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DOCTORAL DISSERTATION

Title of doctoral dissertation: From Flood Dynamics to Nature-Based Solutions: A Geospatial AI Framework for Urban Resilience

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Supervisor
prof. dr hab. inż. Michał Szydłowski

Gdańsk, 2026

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DESCRIPTION OF DOCTORAL DISSERTATION

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Keywords of doctoral dissertation in English: climate change, stormwater runoff, nature-based solutions, green infrastructure, Geo-AI, machine learning, urban resilience, spatial planning

Summary of doctoral dissertation in Polish: W rozprawie opracowano zintegrowane, wieloskalowe ramy GeoAI wspierające ocenę zagrożeń powodziowych i planowanie rozwiązań opartych na przyrodzie (NBS) na przykładzie Gdańska. Ramy łączą teledetekcję, modelowanie hydrologiczne HEC-HMS, interpretowalne uczenie maszynowe, ekonometrię przestrzenną oraz analizy GIS.

Wyniki wykazały, że współwystępowanie urbanizacji i zmian klimatu prowadzi do znacznie większego wzrostu odpływu powierzchniowego niż oddziaływanie każdego z tych czynników oddzielnie. Modele SVM, RF i ANN zidentyfikowały kolektory wód opadowych, temperaturę powierzchni terenu, wysokość terenu oraz NDVI jako najważniejsze determinanty podatności powodziowej. Analizy ekonometrii przestrzennej wykazały niedopasowanie rozmieszczenia zielonej infrastruktury do rzeczywistych potrzeb hydrologicznych miasta.

Opracowane podejście umożliwiło identyfikację 20,65% powierzchni dachów odpowiednich dla zielonych dachów oraz potencjału nasadzenia 47 777-48 790 drzew ulicznych. Wykazano również, że zielone dachy mogą ograniczyć całkowity odpływ powierzchniowy o 4,14%. Uzyskane wyniki potwierdzają, że rozwiązania oparte na przyrodzie stanowią kluczowy element adaptacji miast do zmian klimatu i zagrożeń powodziowych, natomiast opracowane ramy GeoAI tworzą uniwersalne, skalowalne i transferowalne narzędzie wspomagające podejmowanie decyzji w nadmorskich miastach, również w warunkach ograniczonej dostępności danych.

Summary of doctoral dissertation in English: This dissertation develops an integrated multi-scale GeoAI framework for urban flood-risk assessment and nature-based solution (NBS) planning

using Gdańsk, Poland, as a case study. The framework combines remote sensing, HEC-HMS hydrological modelling, interpretable machine learning, spatial econometrics, and GIS-based analyses.

The results show that the combined effects of urbanization and climate change produce substantially greater runoff increases than either driver acting independently. Flood susceptibility models (SVM, RF, and ANN) identified stormwater collectors, land surface temperature, elevation, and NDVI as the most important flood-risk determinants. Spatial econometric analyses further revealed a mismatch between the distribution of green infrastructure and areas of greatest hydrological need.

The proposed framework identified 20.65% of rooftops as suitable for green roof implementation and estimated the potential for planting 47,777-48,790 street trees. High-retention green roofs were shown to reduce total citywide runoff by 4.14%. The findings demonstrate that nature-based solutions are a key component of climate adaptation and urban flood resilience, while the proposed GeoAI framework provides a transferable and scalable approach for supporting decision-making in coastal cities facing data limitations.



**GDAŃSK UNIVERSITY
OF TECHNOLOGY**

Faculty of Civil and Environmental Engineering



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Doctoral Dissertation

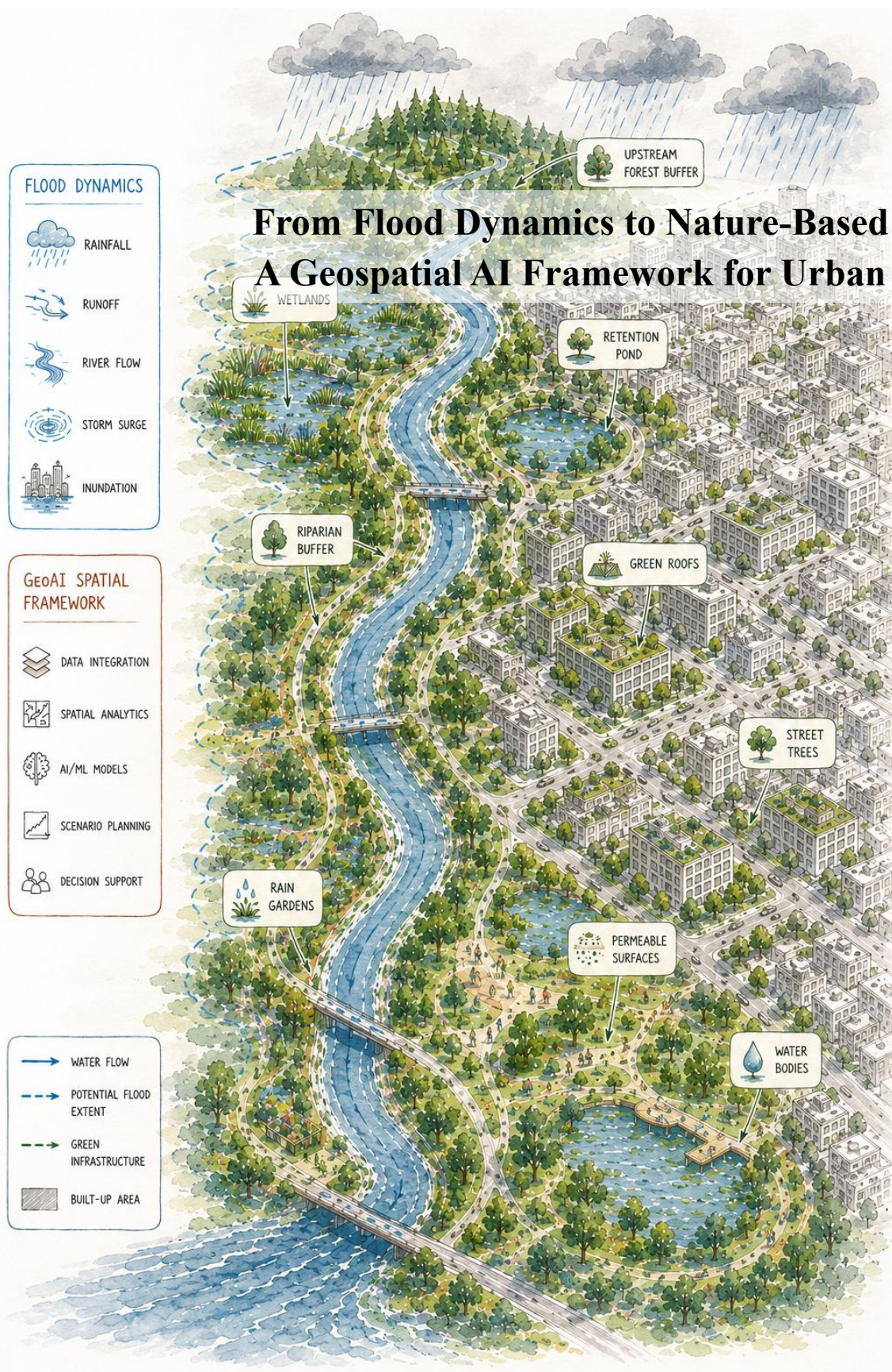
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Abbreviations

Abbreviations	Description
AEP	Annual Exceedance Probability
AI	Artificial Intelligence
AIC	Akaike Information Criterion
ALS	Airborne Laser Scanning
ANN	Artificial Neural Network
AUC	Area Under the Curve
BDOT10k	Polish Topographic Object Database
BGR	Blue-Green Roof
BIC	Bayesian Information Criterion
CAP	Common Agricultural Policy
CEE	Central and Eastern Europe
CLMS	Copernicus Land Monitoring Service
CN	Curve Number
DEM	Digital Elevation Model
DSM	Digital Surface Model
EFFS	Ensemble Filter Feature Selection
ESA	European Space Agency
EU	European Union
EURO-CORDEX	European Coordinated Regional Climate Downscaling Experiment
GEE	Google Earth Engine
GeoAI	Geospatial Artificial Intelligence
GI	Green Infrastructure
GIS	Geographic Information Systems
GIOŚ	Główny Inspektorat Ochrony Środowiska (Chief Inspectorate for Environmental Protection)
GLS	Generalized Least Squares
GPS	Greening Potential Score
GPW	Gdańsk Water Policy (Gdańska Polityka Wodna)
GPZ	Gdańsk Greenery Policy (Gdańska Polityka Zieleni)
GSV	Google Street View
GVI	Green View Index
GWR	Geographically Weighted Regression
HEC-HMS	Hydrologic Engineering Center Hydrological Modeling System
IAI	Impervious Area Index
IDF	Intensity-Duration-Frequency
IMGW-PIB	Institute of Meteorology and Water Management-National Research Institute
KNN	K-Nearest Neighbors
LCM	Land Change Modeler
LID	Low Impact Development
LISA	Local Indicators of Spatial Association
LST	Land Surface Temperature

LULC	Land Use/Land Cover
MAE	Mean Absolute Error
Mask2Former	Masked-Attention Mask Transformer
MAUP	Modifiable Areal Unit Problem
MCDA	Multi-Criteria Decision Analysis
MGWR	Multiscale Geographically Weighted Regression
ML	Machine Learning
MSE	Mean Squared Error
NBS	Nature-Based Solutions
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NO ₂	Nitrogen Dioxide
NRCS	Natural Resources Conservation Service
NRCS-CN	Natural Resources Conservation Service-Curve Number
O ₃	Ozone
OLS	Ordinary Least Squares
OSI	Open Space Index
OSM	OpenStreetMap
OSTAB	Ogólnomiejski System Terenów Aktywnych Biologicznie (City System of Biologically Active Areas)
PM	Particulate Matter
R ²	Coefficient of Determination
RCP	Representative Concentration Pathway
RESILIO	Resilience nEtwork of Smart Innovative cLIimate-adapative rOoftops
RF	Random Forest
RMSE	Root Mean Squared Error
ROC	Receiver Operating Characteristic
RS	Remote Sensing
SDG	Sustainable Development Goals
SEM	Spatial Error Model
SHAP	Shapley Additive Explanations
SLM	Spatial Lag Model
SPI	Stream Power Index
SVI	Street View Images
SVM	Support Vector Machine
SWAT	Soil and Water Assessment Tool
TRI	Terrain Ruggedness Index
TWI	Topographic Wetness Index
UHI	Urban Heat Island
VIF	Variance Inflation Factor
WLS	Weighted Least Squares
XAI	Explainable Artificial Intelligence
XGBoost	Extreme Gradient Boosting

Abstract

Rapid urbanization and climate change are intensifying hydrological and environmental challenges in coastal cities, increasing surface runoff, flood susceptibility, and spatial inequities in green infrastructure (GI) distribution. This thesis develops an integrated, multi-scale GeoAI framework that chains remote sensing, hydrological modelling, interpretable machine learning, spatial econometrics, and AI-driven NBS planning into a sequential diagnostic-to-intervention pipeline, applied to Gdańsk, Poland, a rapidly transforming coastal city with complex historical, environmental, and socio-spatial legacies.

The thesis first quantifies how long-term land use/land cover (LULC) changes and climate forcing have altered city and basin-scale hydrological responses. Google Earth Engine and Land Change Modeler in IDRISI Terrset software were used to analyze historical (1985-2022) and future (2050-2100) LULC. Hydrological impacts were simulated using the Natural Resources Conservation Service curve number method and Hydrologic Modeling System (HEC-HMS) under three scenarios: LULC changes, climate change, and combined LULC and climate change effects. The LULC analysis revealed a marked increase in urban areas, a shift in forest and vegetation cover, and a reduction in agricultural land. HEC-HMS simulations showed an increase in the runoff coefficient across selected decades, attributed to the combined effect of LULC and climate change. The projected increases under RCP 4.5 and RCP 8.5 scenarios for 2050 and 2100 are projected to surpass those observed during the baseline period, establishing the need to examine how these hydrological changes translate into localized flood susceptibility.

Building on these basin-scale findings, the thesis next investigates the spatial manifestation of flood susceptibility within the urban fabric. Flood susceptibility was determined using three ML techniques, Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANN), trained on 265 urban flood episodes with an ensemble filter feature selection (EFS) approach to optimize factor selection. The study incorporates explainable artificial intelligence (XAI), namely the Shapley Additive Explanations (SHAP) model, to enhance transparency and interpretability. The ANN model demonstrated superior performance, outperforming RF and SVM. SHAP analysis identified rainwater collectors, land surface temperature (LST), digital elevation model (DEM), soil, river buffers, and NDVI as dominant contributors to flood susceptibility. The SHAP-identified drivers, particularly LST and impervious surface, reappear as the dominant constraints on GI distribution in the following stage, providing cross-paper validation of the framework's diagnostic sequence.

Recognizing that flood susceptibility patterns intersect with long-standing spatial inequalities, the thesis then examines the distribution of green infrastructure across the city and the factors governing its placement. A grid-based econometric framework was employed to analyze GI spatial distribution in relation to biophysical and sociodemographic factors. Spatial autocorrelation revealed significant clustering, with high-density areas in the western and eastern regions occupying state forests and low-density regions in northern, central urban areas, and parts of

southern regions. Advanced regression models indicated that GI distribution is constrained by the urbanization indicator (impervious surface), while heat exposure (LST) and air quality variables (NO_2 , O_3) act as spatial stress indicators co-occurring with areas of low GI with geographically varying effects. These findings demonstrate that GI provision does not align with hydrological need, reinforcing the necessity for targeted, equity-oriented planning.

Finally, the thesis advances from diagnosis to solution by evaluating the practical potential of nature-based solutions to mitigate runoff under real-world urban constraints. An integrated GIS and machine learning framework was developed to assess GI potential. Green roof suitability was evaluated using building characteristics across three scenarios. At street level, GVI, IAI, and OSI were quantified using Google Street View imagery segmented with Mask2Former. For streets with critically low greenery ($\text{GVI} < 0.2$), hypothetical scenarios were generated to predict tree counts using XGBoost, incorporating environmental variables and physical constraints including street length, spacing (5m, 10m, 15m), and existing trees. Results showed 20.65% of rooftops suitable for greening under a balanced threshold and 38.7% of streets with critically low greenery. XGBoost predicted 47,777-48,790 trees at 5-15m spacing could improve low-GVI corridors, with 75% of segments requiring seven or fewer trees. High-retention green roofs retain 100% of rainfall, mitigating 4.14% of citywide runoff, while medium canopy street trees intercept 0.21-0.22% of runoff.

Overall, the findings confirm that the synergistic effects of LULC and climate change have a more significant impact on urban hydrology than either factor in isolation, shaping both basin-scale runoff responses and localized flood susceptibility. By linking hydrological change, flood risk, GI inequity, and intervention feasibility within a unified GeoAI pipeline, the research provides actionable insights for prioritizing nature-based solutions in Gdańsk, aligning with the Gdańsk Greenery Policy (2023) while identifying additional areas where geospatial and AI-driven approaches can support more equitable and hydrologically effective GI deployment. The proposed GeoAI framework is transferable to data-scarce coastal cities globally and advances the case that nature-based solutions, when deployed with spatial precision and quantified performance evidence within an integrated geospatial AI pipeline, are central rather than supplementary to urban flood adaptation.

Chapter 1

Introduction

1. Introduction and background

Rapid urbanization and climate change have profoundly transformed hydrological systems worldwide, particularly in urban and coastal regions. The expansion of impervious surfaces, vegetation loss, and intensified rainfall events have collectively altered natural runoff processes, leading to frequent and severe flooding (Kahraman et al., 2021; Mikos-Studnicka and Szydlowski, 2022; Rogger et al., 2017). Between 1980 and 2016, extreme weather events caused economic losses exceeding EUR 400 billion across Europe, and projections indicate a further rise in flood risk, especially in Central and Eastern Europe (Ionita et al., 2020; Mrozik, 2022). Cities like Gdańsk, Poland, have become increasingly vulnerable due to their complex geomorphology, coastal exposure, and rapid land use transitions.

Gdańsk faces three flood hazards: surface runoff from post-glacial Moraine hills, river outflow during intense precipitation, and rising sea levels in the Gulf of Gdańsk, necessitating comprehensive research (Cieśliński et al., 2024; Szpakowski and Szydlowski, 2018; Walczykiewicz and Skonieczna, 2020). Additionally, LULC in the Polish Baltic coastal region is sensitive to changing climatic conditions (Zaucha, 2011a). Despite this sensitivity, assessment of LULC changes related to climate change is lacking. Land use and land cover (LULC) changes driven by urban expansion, agricultural decline, and afforestation play a critical role in shaping catchment hydrology and flood dynamics. In Poland and the broader Central-Eastern European region, socio-economic transformations since the 1990s, followed by European Union (EU) accession, have reshaped land use patterns through policies such as the Common Agricultural Policy (CAP) and Cohesion Policy (Cegielska et al., 2018; Tretiak et al., 2021). These changes, along with increasing rainfall intensity, have altered surface runoff behavior even in areas with growing forest cover (Prokešová et al., 2022). However, while LULC dynamics have been widely studied at regional scales, limited research has explored their combined effects with climate change on local hydrology and flood potential in coastal cities like Gdańsk.

Traditional hydrological models, such as SWAT or HEC-HMS, often require extensive calibration data that are unavailable for ungauged basins, posing challenges for urban catchment analysis (Olechnowicz and Weinerowska-Bords, 2014). Consequently, simplified yet robust methods, including the NRCS-CN model, coupled with remote sensing-based LULC mapping (e.g., via Google Earth Engine), offer viable pathways to reconstruct and forecast land use changes and their hydrological impacts (Huang et al., 2017; Kabeja et al., 2020; Noel et al., 2017). The convergence of cloud-based remote sensing platforms, machine learning, and geospatial analysis, increasingly termed GeoAI, offers a more integrated pathway for both diagnosing and predicting urban hydrological change. However, despite technological advancements, uncertainties remain in predicting flood susceptibility and translating model outputs into actionable planning strategies.

Machine learning and explainable artificial intelligence offer a pathway beyond these modelling limitations, but their transformative potential lies not in applying them individually, but in chaining them with remote sensing and hydrological analysis into a coherent analytical pipeline. Machine learning models offer a pathway beyond these modelling limitations, but their transformative potential lies in chaining them with remote sensing and hydrological analysis into a coherent pipeline rather than applying them individually (Islam et al., 2021a; Tehrany et al., 2015a), yet most existing applications treat flood susceptibility mapping as a standalone exercise, disconnected from either the hydrological processes that produce runoff or the spatial planning decisions that follow. Fewer still incorporate explainable AI to identify the dominant drivers of susceptibility and make model outputs legible to urban planners (Garcia and Aznarte, 2020; Tian et al., 2020), but this interpretability step is rarely coupled with the upstream hydrological evidence that motivates it. To the author's knowledge, no study applied to a coastal city has yet integrated these components-remote sensing-based land use analysis, process-based hydrological modelling, and interpretable ML-based risk mapping-as sequential, mutually informing stages of a single geospatial framework. This dissertation does precisely that, treating each methodological layer as both a standalone contribution and a necessary input to the next stage of analysis.

In parallel, nature-based solutions (NBS) including green infrastructure (GI) have emerged as sustainable approaches to mitigate the impacts of urban flooding and climate extremes. GI elements such as green roofs, urban trees, and permeable surfaces improve infiltration, reduce runoff, and provide multiple co-benefits, including air quality enhancement and thermal comfort (Baker et al., 2019a; Gulshad et al., 2024; Li and Ma, 2022). However, GI planning in post-socialist and coastal cities like Gdańsk remains fragmented, driven more by regulatory mandates or available funding than by data-driven spatial prioritization (Ewelina et al., 2021a). The spatial distribution of GI and its relationship with socio-environmental factors therefore require systematic evaluation to guide equitable and resilient urban adaptation strategies.

Understanding the existing spatial distribution of GI and its relationship with socio-environmental drivers is thus a critical first step toward equitable and effective planning. Variations in factors such as slope, elevation, rainfall, population density, and income influence both the feasibility and accessibility of GI across urban areas (Liu et al., 2023a; Pallathadka et al., 2022a; Xu et al., 2019a; Yang et al., 2020a). Analyzing these relationships helps reveal where green infrastructure is unevenly distributed or constrained by dense development, often reflecting underlying socio-spatial inequalities (Cegielska et al., 2017a; Elbakidze et al., 2023b; Ewelina et al., 2021b).

Quantifying where green deficits exist is only the first step; translating that knowledge into spatially explicit, implementable interventions requires a further layer of geospatial AI that existing studies have rarely deployed in combination. Advances in computer vision and street-view imagery have enabled the Green View Index (GVI) to assess vegetation exposure at the street level (Lu et al., 2023, Aikoh et al., 2023; Sánchez and Labib, 2024; Xiao et al., 2021), yet most applications remain descriptive, cataloguing where greenery is low without predicting how many trees could realistically be planted, at what spacing, or with what hydrological effect. This study

pushes considerably further: Advances in computer vision and street-view imagery have enabled street-level greenery assessment through the Green View Index, yet most applications remain descriptive without translating greenery deficits into spatially optimized planting strategies with quantified hydrological performance which is a gap the present research addresses. This integration of computer vision, predictive AI, and geospatial optimization represents a methodological frontier in urban GI planning and is, to author's knowledge, the first application of this pipeline for stormwater management in a Central European coastal city.

Together, these challenges reveal a fundamental gap not merely in data or methods, but in the architecture of urban flood research itself. Remote sensing, hydrological modelling, machine learning, spatial econometrics, and AI-based infrastructure planning each exist as mature fields, yet they are routinely applied in isolation. The result is a fragmented evidence base that cannot support the kind of integrated, spatially explicit decisions that climate-stressed coastal cities urgently need. No unified framework currently exists that links land-use dynamics and hydrological change, flood likelihood mapping, green infrastructure inequity, and NBS implementation feasibility within a single, transparent, and transferable analytical system, particularly for data-scarce coastal urban environments where the consequences of this gap are most acute.

This thesis addresses that gap directly. It develops an integrated, multi-scale GeoAI framework that chains remote sensing-based land use analysis, process-based hydrological modelling, interpretable machine learning, spatial econometric diagnosis, and AI-driven NBS planning into a sequentially coherent system, demonstrated and validated through the case of Gdańsk, Poland. Each component is both a standalone scientific contribution and a building block of the larger framework. The aim is not only to advance methodological capability in urban hydrology and GI planning, but to demonstrate that GeoAI, when structured as an integrated pipeline rather than a collection of tools, can directly support transparent, equitable, and evidence-based urban adaptation.

1.1.Objectives and aims

This doctoral research develops an integrated, multi-scale GeoAI framework for diagnosing urban flood dynamics and planning nature-based solutions under land use and climate change, using Gdańsk, Poland as a representative coastal city case.

Specifically, the research pursues the following objectives:

1. To quantify the historical and projected effects of LULC dynamics and climate change on surface runoff at basin and city scale, using GEE, NRCS-CN, and HEC-HMS modelling under RCP 4.5 and RCP 8.5 scenarios.
2. To develop an interpretable, ensemble machine learning framework, combining SVM, RF, and ANN with EFFE feature selection and SHAP explainability, to map urban flood susceptibility and identify the dominant spatial drivers of flood.

3. To diagnose the spatial inequity of green infrastructure distribution across Gdańsk by examining its biophysical and sociodemographic determinants through spatial autocorrelation and econometric modelling.
4. To quantify urban greening potential at rooftop and street level using GIS, computer vision, and predictive AI, and to assess the cumulative stormwater retention benefits of integrated GI interventions across design storm scenarios.

The thesis is structured as follows. **Chapter 2** reviews the literature on urban flood dynamics, nature-based solutions, and the emerging role of GeoAI in urban planning. **Chapter 3** presents the study area and consolidated data infrastructure. **Chapter 4** quantifies how LULC and climate change have altered hydrological response at basin scale. Chapter 5 maps flood susceptibility using interpretable machine learning. **Chapter 6** diagnoses the spatial distribution and determinants of green infrastructure inequity. **Chapter 7** develops the GeoAI-based NBS suitability and stormwater performance framework. **Chapter 8** synthesizes findings across all components and draws methodological and policy implications. **Chapter 9** concludes the thesis and outlines directions for future research.

Chapter 2

State of the art

2. Introduction

This chapter reviews the body of knowledge underpinning the four analytical stages of the GeoAI framework developed in this thesis. It is organized thematically, progressing from the foundational literature on urban flood dynamics and hydrological modelling, through machine learning approaches to flood susceptibility mapping, to the spatial distribution of green infrastructure and the emerging role of geospatial AI in nature-based solution planning. Each section identifies the state of knowledge, the methodological advances that have shaped it, and the specific gaps that the present research addresses. The chapter concludes with a synthesis paragraph that frames the overarching gap i.e. the absence of an integrated, multi-scale GeoAI pipeline connecting flood diagnosis to spatially targeted NBS intervention, that motivates this thesis.

2.1. Urban flood dynamics, LULC change, and hydrological modelling

Rapid urbanization and climate change have fundamentally altered hydrological systems worldwide, particularly in urban and coastal regions. The expansion of impervious surfaces through roads, rooftops, and hard surfaces reduces infiltration capacity, increases the velocity of overland flow, and shortens the time of concentration in urban catchments, producing more frequent and more intense flood peaks for equivalent rainfall inputs which is a globally observed phenomenon (Rogger et al., 2017; Szydlowski, 2006). Simultaneously, climate change has further exacerbated the frequency and intensity of precipitation events, compounding the hydrological consequences of urban expansion (Busker et al., 2022; Mrozik, 2022). In Europe alone, more than 400 major floods have been recorded in the last two decades, affecting more than 8.7 million people, causing more than 2,000 deaths, and resulting in losses of EUR 72 billion (Ionita et al., 2020b), with extreme weather events between 1980 and 2016 causing EUR 436 billion in total economic losses (Sturiale and Scuderi, 2019). Projections indicate a further rise in pluvial and river floods across Central and Western Europe, including Poland (Mrozik, 2022). Poland has faced severe urban floods in recent years, notably in Elbląg (2017) (Konieczny et al., 2018a), Poznań and Swarzędz (2021) (Mrozik, 2022b), and Gdańsk (2001, 2016) (Majewski, 2016; Szydlowski et al., 2023). By 2050 the urban population is expected to increase by 60%, with a 25% rise in the population living in coastal risk-prone areas (Aziz et al., 2024; Sánchez and Labib, 2024; Szydlowski et al., 2023b). These pressures directly challenge progress towards the Sustainable Development Goals, particularly SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action) (United Nations, 2015), and underscore the urgent need for integrated, spatially explicit frameworks that connect flood diagnosis to nature-based intervention which is the gap addressed by this thesis.

In Europe, however, the relationship between land cover change and flood risk is more complex than the global pattern suggests. Contrary to global deforestation trends, several European countries including Poland have seen net expansion of forest cover since the 1990s, which should theoretically mitigate runoff (Cegielska et al., 2017b; Estonian Ministry of the Environment, 2021; Prokešová et al., 2022b; Tretiak et al., 2021b; Wnek et al., 2021). Despite this, flash flood frequency has risen in recent decades, driven by extreme rainfall events across the European Union (Kahraman et al., 2021b). Between 1980 and 2016, extreme weather events caused economic losses exceeding EUR 400 billion across Europe, and projections indicate a further rise in flood risk, especially in Central and Eastern Europe (Ionita et al., 2020; Mroziak, 2022). This apparent paradox, i.e. increasing forest cover alongside increasing flood frequency, underscores that the spatial configuration of land use change, particularly the concentration of imperviousness in urban cores, matters as much as its aggregate extent.

Political shifts in 1989 and Poland's EU accession in 2004 led to significant transformations of agricultural land into forests and urban areas across Central and Eastern Europe. Supported by EU policies including the Common Agricultural Policy (CAP) and Cohesion Policy, these changes profoundly impacted land use and hydrology (Cegielska et al., 2017b; Estonian Ministry of the Environment, 2021; Prokešová et al., 2022b; Tretiak et al., 2021b; Wnek et al., 2021; Wojkowski et al., 2023), highlighting the need for systematic mapping and quantification to enhance flood risk management. These changes, along with increasing rainfall intensity, have altered surface runoff behavior even in areas with growing forest cover (Prokešová et al., 2022b).

Land use and land cover (LULC) classification is a preliminary step essential for informed hydrological decision-making. Advances in remote sensing and modelling techniques (H. Huang et al., 2017b), facilitated by cloud-based platforms like Google Earth Engine (GEE), have revolutionized LULC analysis by overcoming data accessibility challenges, enabling large-scale geospatial analysis through a reproducible and user-friendly interface (Noel et al., 2017; Saha et al., 2024). Spatiotemporal modelling and simulation techniques have rapidly evolved to study LULC dynamics and forecast future changes (Batty et al., 1997; Verburg et al., 2004). Simulation models for LULC transition and prediction offer effective and replicable methods to assess past, present, and future scenarios under different conditions (Liu et al., 2017; Han et al., 2015), with cellular automata being commonly employed for their versatility in simulating LULC changes (Batty et al., 1997).

Various methods, from simpler rational approaches to more complex models like the Soil and Water Assessment Tool (SWAT) (Briak et al., 2016), have been used to analyze hydrological responses to LULC change at the watershed scale (Mustafa and Szydlowski, 2020; Olechnowicz and Weinerowska-Bords, 2014b). Despite data collection and modelling advances, challenges persist particularly in urban basins with limited measurements (Olechnowicz and Weinerowska-Bords, 2014b). The lack of observational data makes it difficult to employ complex models requiring calibration from extensive discharge records in ungauged basins. Given these constraints,

the Natural Resources Conservation Service curve number (NRCS-CN) method (USDA, 1985) combined with the Hydrologic Engineering Center Hydrological Modelling System (HEC-HMS) (Peters, 1998) presents a viable approach, having been successfully applied in multiple studies to demonstrate the impacts of climate change and LULC on ungauged basin hydrology (Cieśliński et al., 2024b; Kabeja et al., 2020b; Prokešová et al., 2022b; Soulis, 2021).

Previous studies in Central and Eastern Europe have projected LULC changes and analyzed their hydrological impacts across various regions, including the Upper Vistula basin across Poland, Slovakia, and Ukraine (Wojkowski et al., 2023), Romania (Kucsicsa et al., 2019; Mihai et al., 2006), and multiple cities across Poland, Czechia, and Slovakia (Wnek et al., 2021). The effects of spatiotemporal LULC changes on surface runoff have been assessed in Slovakian catchments using the NRCS-CN method (Prokešová et al., 2022b). Locally, significant advances have been made in LULC mapping (Bielecka et al., 2020; Kwoczyńska, 2022), LULC prediction (Dawid and Bielecka, 2022), and LULC impact on surface runoff, including Gdańsk rainfall analysis (Szpakowski and Szydlowski, 2018) and Orunia and Małomiejska basin runoff analysis (Kolarski and Kalinowska, 2019; Olechnowicz and Weinerowska-Bords, 2014). While these studies have provided valuable insights, they have often focused on either historical or future LULC changes in isolation, with limited emphasis on future projections at sub-basin or basin level, and fewer still have integrated both perspectives within a single analytical framework or examined their combined hydrological effects under climate change scenarios.

Gdańsk faces three distinct flood hazards: surface runoff from post-glacial moraine hills, river outflow during intense precipitation events, and rising sea levels in the Gulf of Gdańsk (Cieśliński et al., 2024b; Szpakowski and Szydlowski, 2017; Walczykiewicz and Skonieczna, 2020b). Additionally, LULC in the Polish Baltic coastal region is sensitive to changing climatic conditions (Zaucha, 2011). Despite this sensitivity, systematic assessment of LULC changes in relation to climate change projections for this city remains limited. The gap between regional LULC studies and locally grounded hydrological quantification under both historical and projected scenarios motivates the basin-scale analysis presented in **Chapter 4**.

2.2. Machine learning and explainable AI in urban flood susceptibility mapping

The hydrological literature reviewed above demonstrates that runoff amplifies at basin scale, which raises a more spatially precise question: where within the urban fabric does that runoff translate into actual flood susceptibility? Answering this requires moving beyond process-based modelling toward data-driven spatial flood susceptibility mapping, involving machine learning approaches that made the most significant recent advances.

Flood susceptibility refers to the likelihood of an area experiencing flooding based on intrinsic characteristics such as topographical, hydrological, and meteorological factors (Ahmadlou et al., 2019; Kaya and Derin, 2023; Khosravi et al., 2018). The goal of flood susceptibility assessment is

to develop models that determine the most relevant factors contributing to flood occurrence (Islam et al., 2021b; Parvin et al., 2022; Yaseen et al., 2022). For flood susceptibility modelling, approaches vary from quantitative methods such as artificial intelligence, statistical techniques, and machine learning (Tehrany et al., 2019; Yaseen et al., 2022) to semi-quantitative methods like multi-criteria decision analysis (MCDA) (Khosravi et al., 2018). Computational approaches include hydrologic-hydraulic (Kolarski and Kalinowska, 2019) and hydrodynamic modelling integrated with a geographical information system (GIS). Traditional hydrological and hydrodynamic models are time-consuming and prone to calibration issues (Paprotny et al., 2020), impacting their accuracy in identifying flood-prone regions (Pradhan et al., 2023). MCDA models, although widely used, lack systematic evaluation criteria (Rahman et al., 2019).

In recent decades, machine learning techniques have gained momentum for effectively predicting flood-prone areas (Rahman et al., 2019; Shafizadeh-Moghadam et al., 2018). Among these, Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) have been widely applied to predict flood susceptibility. ANN is widely used for flood modelling because it can process non-linear and multivariate data, demonstrating universal modelling potential (Islam et al., 2021b; Ngo et al., 2018). SVM and RF are also popular among hydrologists due to their prediction accuracy (Islam et al., 2021; Mahdizadeh Gharakhanlou and Perez, 2022; Tehrany et al., 2019; Yaseen et al., 2022).

Despite progress in flood susceptibility modelling (Islam et al., 2021b; Mahdizadeh Gharakhanlou and Perez, 2022; Pradhan et al., 2023; Tehrany et al., 2019; Yaseen et al., 2022), significant challenges remain. A major issue is the lack of a universally accepted model due to varying performances under different conditions and regions (Tehrany et al., 2019). Furthermore, machine learning models are often criticized for being black-box models such as their complexity and opacity hinder practical application, as stakeholders may struggle to understand the factors driving predictions, creating high demand for models that demonstrate how specific outcomes are achieved (Dikshit and Pradhan, 2021; Pradhan et al., 2023; Rudin, 2019). Many studies also fail to consider the interactions between different conditioning factors and classifiers, which are critical components for practical use.

Ensemble feature selection has demonstrated effectiveness across various domains including human activity recognition (Tian et al., 2020), medical data analysis (Ab Hamid et al., 2021), and fish species classification (Effrosynidis and Arampatzis, 2021). Despite its proven utility, its application in flood susceptibility analysis remained unexplored prior to the present research. The ensemble-based filter feature selection (EFFS) approach leverages the strengths of heterogeneous methods to create a more stable and optimal feature subset, unlike methods that rely solely on a single ranking mechanism or a small number of similar techniques. EFFS incorporates a diverse set of feature selection methods, reducing the risk of bias or errors inherent in individual approaches (Effrosynidis and Arampatzis, 2021; Tian et al., 2020), and enhances the performance

of ML models by selecting the most relevant factors, resulting in improved flood susceptibility maps (Osanaiye et al., 2016).

In addition to EFFS, the Shapley Additive Explanations (SHAP) model (García and Aznarte, 2020; Shapley, 1953) provides transparency and interpretability regarding flood susceptibility predictions in decision-making (Dikshit and Pradhan, 2021), allowing quantification of each feature's contribution to flood susceptibility predictions and making results more actionable for urban planners and stakeholders (Aydin and Iban, 2023; Pradhan et al., 2023). This is particularly important in flood risk management, where understanding the influence of various environmental and infrastructural factors is crucial for prioritizing intervention.

Despite these methodological advances, most existing applications treat flood susceptibility mapping as a standalone exercise, disconnected from the hydrological processes that produce runoff or the spatial planning decisions that follow. To the author's knowledge, no study applied to a coastal city prior to the present research has integrated remote sensing-based land use analysis, process-based hydrological modelling, and interpretable ML-based risk mapping as sequential, mutually informing stages of a single geospatial framework which is the gap that **Chapter 5** directly addresses.

2.3.Spatial distribution and determinants of green infrastructure

Flood susceptibility mapping identifies where flood risk concentrates but knowing where likelihood is highest is only actionable if it can be connected to where nature-based mitigation capacity exists or more precisely, where it is absent. This makes the spatial distribution of green infrastructure the logical next analytical question, and one that the literature has addressed with increasing sophistication but persistent methodological fragmentation.

Traditional grey infrastructure proves insufficient to manage urban water problems due to its demand for intensive resources and significant environmental impacts. In response, many nature-based solutions have been proposed across many countries to mitigate urban water problems (Azadgar et al., 2025b). Green infrastructure defined as a "strategically planned network of natural and semi-natural areas with other environmental features designed and managed to deliver a wide range of ecosystem services" (European Commission, 2019) uses green elements to control stormwater runoff (Baker et al., 2019; Gulshad et al., 2024). Environmental benefits, along with the cost-effectiveness of implementation (Gulshad et al., 2024), have made GI an increasingly common design element in urban planning initiatives (Baker et al., 2019b).

Notably, many GI projects have been experimental and opportunistic, often shaped by funding availability, land ownership, or regulatory compliance (Kuller et al., 2017) rather than systematic spatial optimization. While early GI implementation in many cities was strongly motivated by stormwater management and flood mitigation requirements (Baker et al., 2019), a substantial body

of literature has since demonstrated GI's multifunctional role in urban cooling (Xu et al., 2022), air quality improvement (Hewitt et al., 2020), biodiversity support (Sarabi et al., 2022), and human well-being (Labib et al., 2020), and these benefits are increasingly used in spatial prioritization frameworks. However, despite this growing recognition of GI's multi-benefit potential, empirical studies of GI spatial distribution frequently examine individual services in isolation or rely on broad greenness indicators, with limited attention to how multiple biophysical constraints and socio-demographic conditions jointly shape where GI is implemented.

Effective GI planning should be based on driving mechanisms reflecting physical, geographic, socioeconomic, and planning policy factors (Liu et al., 2023). Studies consistently find GI sensitive to physical and geographic characteristics including soil type, elevation, slope, and rainfall patterns (Pallathadka et al., 2022; Yang et al., 2020), runoff, geology (Charoenkit and Piyathamrongchai, 2019), and other hydrological factors (Baker et al., 2019). Yang et al. (2020) found that elevation, slope, and precipitation positively predict urban green space distribution in Wuhan, while proximity to roadways exerts a negative effect. Similarly, Liu et al. (2023) identified slope, precipitation, and distance from built-up areas as positive predictors of regional green space in Nanjing, alongside governance factors such as dedicated fiscal expenditure. Kuller et al. (Kuller et al., 2018) found that lower slope, proximity to waterways, and distance from city centers favor water-sensitive urban design implementation in Melbourne, while urban density constrains it. These biophysical findings confirm that terrain and hydrology are foundational determinants of where GI can and cannot be placed.

Among socio-economic factors, Xu et al. (2019) and Liu et al. (2023) found that places with more capital, technology, and information positively impact GI development and accessibility, highlighting that even where physical conditions favor GI, sufficient resources and supportive policies are crucial for implementation. Equity-focused studies reveal more complex and spatially variable patterns. Ferguson et al. (2018) found that street tree density in Bradford was higher in areas with Asian and Asian British residents and lower socioeconomic status, while public green space favored high-income and white households, suggesting that different GI types follow different equity logics. Pallathadka et al. (2022) found similarly divergent patterns across Atlanta, Phoenix, and Portland, where the relationship between race, income, and GI distribution varied substantially by city context. Chan and Hopkins (2017) identified that green stormwater infrastructure in Portland disproportionately served lower-income areas, while Vogel (2019) found that green infrastructure in Washington D.C. correlated positively with Black and African American and Latinx communities alongside sewer outfall areas, suggesting need-driven rather than preference-driven placement in some contexts. Baker et al. (2019) found that in Baltimore, impervious surface positively predicted green stormwater infrastructure, while in Portland, white residents and higher income were negatively associated, patterns that resist simple generalizations about who benefits from GI investment. Arshad and Routray (Arshad and Routray, 2018) confirmed that high-density housing and population density negatively predict green space availability in Sheikhpura, consistent with the physical displacement argument. Together these

studies demonstrate that the relationship between socio-demographic factors and GI distribution is highly context-dependent, shaped by local planning traditions, governance structures, and the specific GI type under examination.

Most of these studies, however, emphasize either socio-economic or demographic determinants or biophysical determinants, but seldom within a unified spatial modelling framework (Chan and Hopkins, 2017; Ferguson et al., 2018; Pallathadka et al., 2022). Biophysical variables are more extensively treated in separate research streams focused on ecosystem service provision (Almeter et al., 2018), climate adaptation site suitability (Sturiale and Scuderi, 2019), or hydrological modelling (Zhou et al., 2019), but less frequently integrated with social equity assessments. Moreover, fewer studies explicitly distinguish between drivers and constraints of GI placement within a unified modelling framework. The present research addresses this gap by jointly examining biophysical variables, including DEM, slope, and NDVI, built environment characteristics including imperviousness, industrial proximity, stormwater network proximity, and health and education proximity, socio-demographic factors including population density and elderly population, and environmental stressors including LST, NO₂, O₃, PM₁₀, and PM_{2.5}, alongside climate projections and flood hazard exposure, none of which have been widely analyzed together in earlier GI determinant studies.

Socioeconomic transformations that began in the 1980s and accelerated with the post-socialist transition in the early 1990s have profoundly reshaped land use patterns in Central and Eastern Europe (Elbakidze et al., 2023), adding a further layer of complexity specific to the study context. The introduction of a market-based agricultural economy, combined with the influx of Western European subsidized food products, made traditional farming less profitable, causing widespread decline in agricultural activity and expansion of uncultivated land (Cegielska et al., 2018). Similar dynamics have been observed in Poland (Gulshad et al., 2024; Haase et al., 2019; Kukulska-Kozieł et al., 2019), Hungary (Kovács et al., 2019; Kukulska-Kozieł et al., 2019), Austria (Gingrich et al., 2015), Romania (Petrisor et al., 2021), Slovakia and the Czech Republic (Muchová et al., 2016), and more broadly across the CEE region (Gingrich et al., 2015; Marot et al., 2015). After Poland's EU accession, international and national frameworks, including the EU Green Infrastructure Strategy, the Common Agricultural Policy, the Green Surge project, and Poland's Strategic Adaptation Plan (SPA 2030) sought to reintegrate ecological and climate considerations into land use policy (Cegielska et al., 2018; Davies and Laforteza, 2017; Liliana, 2021). At city level, the Gdańsk Greenery Policy (GPZ, 2023) and participatory planning efforts aim to explicitly address climate resilience, ecological connectivity, and equitable GI access (Fikus-Wójcik et al., 2023). The current spatial distribution of GI in Gdańsk therefore reflects both the path-dependent legacies of post-socialist transition and the new multi-level governance layers introduced by EU and climate-driven policies.

Despite these efforts, GI development in Gdańsk often occurs opportunistically, driven by available funding, regulatory mandates such as the mandatory integration of retention features in

new developments under the Gdańsk Small Retention Guide, local geomorphological constraints, and varying levels of public support (Rzeńca et al., 2021). These risks overlooking areas where GI could most effectively mitigate urban heat, air pollution, or flood exposure, underscoring the importance of analyzing spatial patterns of GI on the ground to identify implementation gaps. Furthermore, unlike previous studies that focus on aggregated geographic units such as census block groups or census tracts, a grid-scale approach enables finer spatial resolution and more detailed patterns in GI density, the approach adopted in **Chapter 6**, which examines Gdańsk as a city that has not yet been extensively explored in the GI distribution discourse and represents a valuable case study for understanding GI dynamics in Central-Eastern Europe.

2.4.Nature-based solutions, GeoAI, and urban greening intervention planning

Diagnosing where green infrastructure is misaligned with flooding and environmental need, is a necessary but insufficient condition for urban adaptation. The operational question that follows is where within the city's built fabric, NBS interventions are physically feasible, what form they should take, and how much hydrological benefit they would deliver. These questions have driven a rapidly growing body of geospatial AI research in NBS planning.

Although NBS represent a broad umbrella concept, green infrastructure, strategically planned as a network of natural and semi-natural elements such as parks, green roofs, bioswales, and urban forests, emerges as a key operational focus within infrastructure planning (Sarabi et al., 2022). GI provides tangible and spatial means to implement NBS principles, offering multiple environmental, social, and economic benefits including mitigating the urban heat island (Kabisch et al., 2016; Li and Ma, 2022), improving air quality (Hewitt et al., 2020), reducing noise pollution (Attal et al., 2021), improving quality of life (Labib, 2019), and minimizing stormwater runoff at source (Dowtin et al., 2023). However, GI needs to be retrofitted into dense urban fabric where open space is limited, and retrofitting existing landscapes is challenging (Busker et al., 2022). Creating new large urban parks or green belts within high-density cities is complex given high demand for land for housing and transport (McDonald et al., 2023). In this context, small-footprint solutions such as blue-green roofs (BGR), which occupy unused vertical spaces, and street trees, which occupy underutilized road spaces, offer viable solutions that can be efficiently implemented in dense built-up areas (McDonald et al., 2023; Zhou et al., 2019).

Effective planning of such interventions requires spatially detailed, data-driven assessments to identify where and under which conditions they can be integrated into the existing urban fabric. Not all rooftops are structurally sound due to their shape, slope, area, height, or age, for BGR interventions (T Haer et al., 2022; Peranović, 2025). Similarly, not all streetscapes have equal potential for tree planting. A few existing studies have used GIS to identify potential roofs for BGR interventions (Liu et al., 2022; Santos et al., 2021; Silva et al., 2017), but these provided fixed thresholds without demonstrating the sensitivity of BGR implementation to variations in building parameters and hydrological functionality across alternative scenarios which is a gap that

is critical for evidence-based decision-making. Some experimental studies have indicated that the stormwater retention capacity of green roofs decreases under hydrological extremes, dropping to 5-15% for storms with 5-50-year return periods and decreasing by 0.14% for every 1% increase in intensity (Zheng et al., 2021), leading to the development of BGR, which integrates water storage layers to enhance stormwater buffering (H de Moel et al., 2021; T Haer et al., 2022). However, existing studies have not provided an overarching assessment of the impacts of varying BGR numbers accounting for building parameters across different hydrological scenarios, indicating a methodological gap in creating evidence for effective BGR interventions in pre-built dense urban contexts.

Traditional methods for assessing GI potential involve field surveys and subjective criteria such as visual inspection of roof slope or expert opinion on planting feasibility, which are time-consuming and costly (Ajmi et al., 2023; Liu et al., 2025; Rebecchi et al., 2025; Sanyé-Mengual et al., 2015). Advances in GIS and machine learning offer new possibilities for systematic identification of locations for GI interventions computationally and evaluation of their potential impacts (Li and Ma, 2022), but the current literature shows limited use of data-driven approaches for such GI interventions at scale.

Geolocated street-view imagery (SVI) has become a popular data source for urban analytics (Biljecki and Ito, 2021). Advances in AI modelling have enabled SVIs and deep learning-based image segmentation to quantify street-level greenery through the Green View Index (GVI) (Lu et al., 2023), which serves as a proxy to assess visible street greenery on site (Ki and Lee, 2021). The Treepedia project visualised GVI distribution across 30 global cities (Abbati, 2019), and subsequent studies have used GVI to compare greenness patterns across urban contexts (Aikoh et al., 2023; Sánchez and Labib, 2024; Xiao et al., 2021), examine policy influences (Ye et al., 2019), and reveal social disparities in green access (Li, 2021). While these studies demonstrated the use of SVIs to analyze existing greenery, their use to identify potential space for additional street tree planting has not been examined prior to the present research. It is a missed opportunity to extract information such as open space availability and impervious surface coverage from street-level imagery to identify streets where additional trees can be planted.

Previous studies have focused on tree planting potential assessment through suitability mapping (Kim et al., 2021; Wu et al., 2008), multi-objective spatial prioritization (Almeter et al., 2018; Locke et al., 2011), spatially distributed modelling systems such as i-Tree Landscape, and optimization frameworks (Nyelele and Kroll, 2021). These encountered three critical limitations: they often use a single street as a case study, lacking geographic scalability; they lack specificity regarding the feasibility of tree planting, the impact of existing trees, and the availability of open spaces; and some rely on subjective judgments to determine optimization parameter weights. Furthermore, previous research has primarily evaluated tree planting effectiveness through experimental analyses of physiological rainfall interception (Huang et al., 2017; Yang et al., 2019), while the cumulative stormwater benefits of city-wide tree plantations across different planting

scenarios remain poorly quantified, limiting decision-makers' ability to justify investments and prioritize interventions effectively.

These methodological and evidence gaps collectively indicate a critical need for an approach that supports urban planners and policymakers in creating GI interventions that fit effectively into existing dense urban contexts and help achieve urban greening policy targets. The present research addresses this need by developing an integrated geospatial and AI-based framework to assess the physical suitability of blue-green roofs and street trees and quantify their combined hydrological impacts across multiple design and storm scenarios, moving from descriptive greenness mapping toward actionable planning support for urban climate adaptation.

2.5.Synthesis: the integrated gap this thesis addresses

The four bodies of literature reviewed in this chapter i.e. urban hydrology and LULC modelling, ML-based flood susceptibility mapping, GI spatial distribution analysis, and GeoAI-driven NBS planning, each represent mature and productive research fields. Yet they have developed largely in isolation from one another. Hydrological studies quantify how land use changes amplify runoff but do not identify where within the urban fabric that runoff produces the greatest flood exposure. Flood susceptibility studies map spatial risk patterns but rarely connect them to the GI deficits that explain why those areas lack adaptive capacity. GI distribution studies identify where green infrastructure is absent but do not translate that absence into spatially targeted, performance-verified intervention plans. NBS planning studies evaluate the technical suitability of individual measures but rarely ground them in the upstream flood risk and equity evidence that should motivate their spatial placement.

The result is a fragmented evidence base that cannot support the kind of integrated, spatially explicit decisions that climate-stressed coastal cities urgently need. No unified framework currently exists that links land-use dynamics and hydrological change, flood likelihood mapping, green infrastructure inequity, and NBS implementation feasibility within a single, transparent, and transferable analytical system particularly for data-scarce coastal urban environments where the consequences of this gap are most acute. The present research develops precisely that framework, chaining remote sensing-based LULC analysis, process-based hydrological modelling, interpretable machine learning, spatial econometric diagnosis, and AI-driven NBS planning into a sequentially coherent GeoAI pipeline demonstrated and validated through the case of Gdańsk, Poland.

Chapter 3

Study area and data framework

3. Introduction

The GeoAI framework developed in this thesis requires a case study that embodies the compound flood vulnerabilities, rapid urban transformation, and data availability conditions under which the integrated analytical pipeline is most needed and most testable. Gdańsk, Poland's principal Baltic port city, satisfies these requirements in full due to three structurally distinct flood hazard types, one of the most rapid urban expansions in post-socialist Central Europe, and an institutional data infrastructure that provides the five categories of open access input the framework requires. The analytical complexity and data richness of this context make Gdańsk not only a representative case for post-socialist coastal cities across Central and Eastern Europe but also an appropriate validation environment for a framework designed to be transferable to data-scarce urban contexts globally. The geographical, morphological, and hydrological characteristics of the city that motivate this choice are described in detail in Section 3.1.

This chapter is organized into two parts. Section 3.1 describes the study area, covering Gdańsk's physical geography, urban development history, flood hazard context, and existing green infrastructure and drainage infrastructure. Section 3.2 presents the consolidated data infrastructure supporting the multi-scale GeoAI framework, with all datasets organized thematically in Table 3.1 and annotated with their functional role and the analytical chapter in which they are used. Together these two sections establish the spatial and data foundations upon which **Chapters 4 to 7** are built.

3.1. Study area

In Eastern and Central Europe, including Poland, rapid urbanization, loss of permeable surfaces, limited space for retrofitting have increased the exposure to climate-driven challenges such as urban floods and rising temperatures (Busker et al., 2022b; Mrozik, 2022a). The impact of these changes on Poland became clear in recent years, such as floods in southwestern Poland (2024) (IFRC, 2025), in Elbląg (2017) (Konieczny et al., 2018b), in Poznań and Swarzędz (2021) (Mrozik, 2022a), and in Gdańsk (2001, 2016) (Majewski, 2016; Szydłowski et al., 2023).

Gdańsk, the largest city in northern Poland, is located on the southern coast of the Baltic Sea in the Gulf of Gdańsk, covering an area of 262 km² (Figure 3.1). The western side features the post-glacial hills of the Kashubian Lakeland, rising to 200 m above sea level. The southern part is a dense residential area. In contrast, the eastern part has flat, low-lying polder areas called Żuławy Gdańskie, which are often below sea level (Kuiper Compagnons, 2015a; Szpakowski and Szydłowski, 2018a).

Gdańsk's mean annual precipitation was recorded at 659 mm (Jakusik and Chodubska, 2020). Gdańsk's location at the mouth of the Vistula River and proximity to the Gulf of Gdańsk make it historically and economically significant. However, this coastal positioning also renders Gdańsk highly vulnerable to the impacts of climate change, including sea-level rise and extreme weather events (Staudt et al., 2006; Szydlowski et al., 2023d).

The catchment area of Oruński/Orunia Stream, (Figure 4.2) known as Potok Oruński, has been chosen for local runoff analysis due to the significant LULC changes over the past 37 years. With an area of 16.55 km², the Orunia basin is located in the rapidly developing Południe district of Gdańsk, offering the potential for new construction projects. The Orunia Stream, the largest tributary of Radunia Canal, along with its tributaries, is crucial for draining water from the plateau in the west to the east (Kolarski and Kalinowska, 2019; Pietruszyński and Cieśliński, 2019).

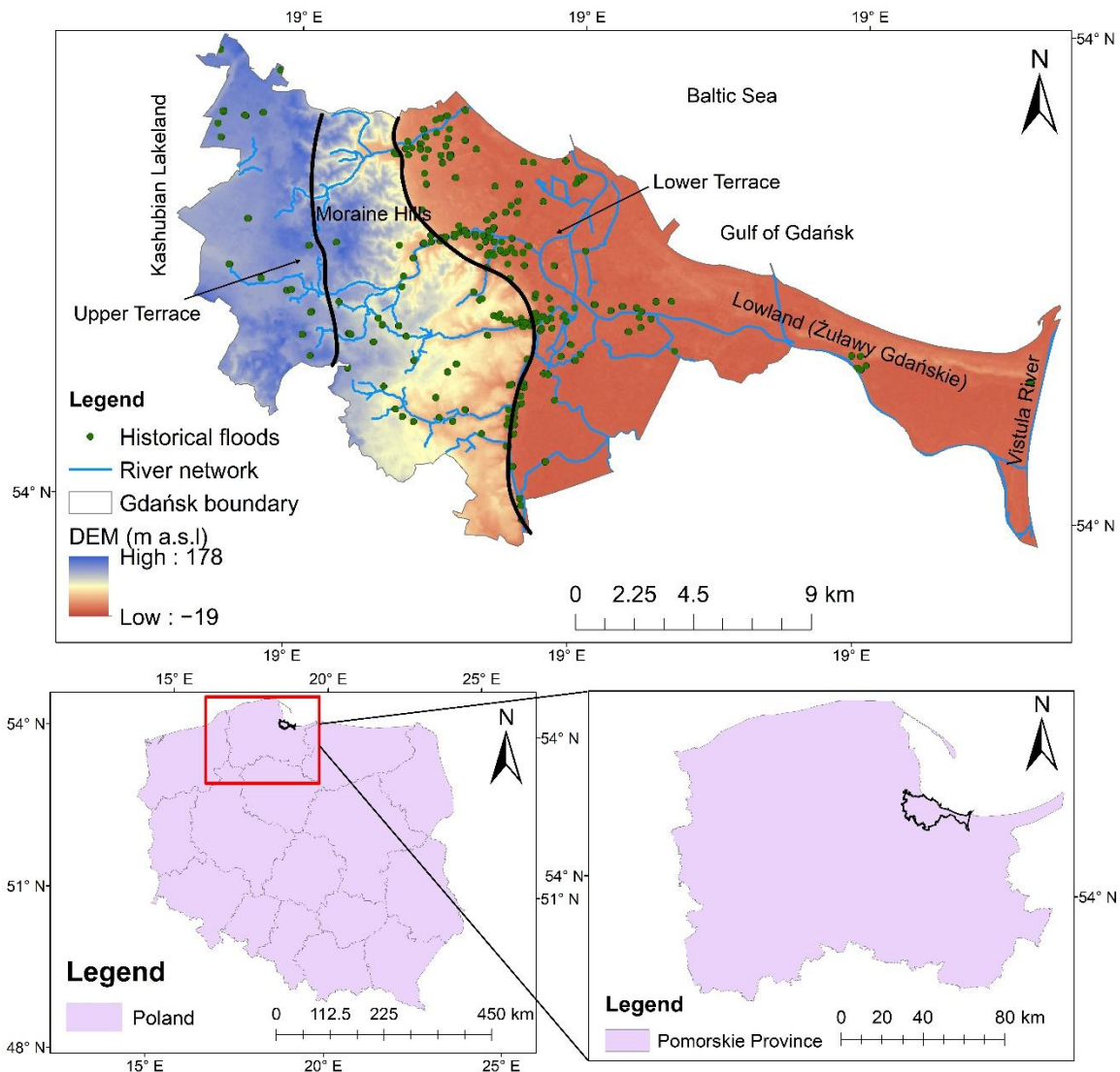


Figure 3.1. The geographical location of the study area: Location map of Gdańsk in Pomerania (bottom right), Gdańsk in Poland (bottom left). Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.

The city experiences land subsidence at an average rate of 1-2 mm per year, exacerbating its susceptibility to flooding (Staudt et al., 2006). Storm surges, driven by strong northern winds, can raise sea levels by over 1.5 ms, with projections indicating potential surges reaching up to 2.5 ms. The frequency of dangerous storms in the Gulf of Gdańsk has nearly quadrupled in recent decades (Jakusik and Chodubska, 2020). From 2010 to 2017, the State Fire Service Headquarters recorded 635 interventions related to sudden rainfall (Walczykiewicz and Skonieczna, 2020a).

In addition, post-socialist countries in Eastern and Central Europe, such as Poland, have historically lagged Western counterparts in integrating GI into urban planning frameworks (Davies and Laforteza, 2017; Gadziński, 2015; Hrdalo et al., 2015). In Polish cities, social perceptions and attitudes toward street trees vary widely, and these opinions can influence decisions to remove or plant street trees. Studies have shown that some residents find trees inconvenient, and that legal changes (Polish Nature Protection Act 2016-2017) (Głowacki, 2017; Maczka et al., 2023) have sparked debates about cutting trees, and that professionals and residents sometimes disagree about their value (Suchocka et al., 2019). Research also shows that views on trees can vary by age group and across cities and rural areas (Giergiczny and Kronenberg, 2014; Jankowski and Świsłocki, 2025), suggesting that social attitudes are an important part of planning GI in Poland.

Nonetheless, Gdańsk's recent policy frameworks, such as the Greenery Policy (GPZ, 2023) (Fikus-Wójcik et al., 2023) and Gdańsk Water Policy (GPW, 2021), reflect institutional interest. However, there remains a lack of systematic assessments that quantify where and how different forms of greening, especially retrofits, can be implemented, and such tools are not yet embedded in local and regional planning practice. Efforts have mainly focused on new development zones, overlooking the retrofitting potential in existing urban fabric facing flood risks and socio-economic disparities, such as rooftops and underutilized streetscapes (Azadgar et al., 2025a). Gdańsk's varied terrain, flash flood episodes, and recent policy efforts (Fikus-Wójcik et al., 2023) make it an ideal setting for applying spatially informed approaches to evaluate and prioritize the stormwater retention potential of green infrastructure.

3.2.Data framework

Table 3.1 combines all datasets used across the four empirical chapters (Chapters 4-7). Datasets are grouped by thematic category and annotated with their role in the analytical framework and the chapter(s) in which they are used. Datasets shared across multiple chapters are listed once with all relevant chapter references noted in the final column. Full methodological details for each analytical stage are provided in the respective empirical chapters.

Table 3.1. Consolidated data infrastructure supporting the multi-scale GeoAI framework: datasets are grouped by thematic category and annotated with their functional role and the analytical chapter(s) in which they are used.

Data	Resolution & Year	Source	Role & Function in Framework	Derived From	Chapter(s)
1. Remote Sensing & Earth Observation Imagery					

Landsat 4-5 Thematic Mapper (TM)	30 m; 1985, 1995	USGS / NASA Earthdata (United USGS, 2021)	LULC classification for historical baseline; runoff curve number derivation	—	Ch. 4
Landsat 7 ETM+	30 m; 2005	USGS / NASA Earthdata (USGS, 2021)	LULC classification; mid-period urban expansion analysis	—	Ch. 4
Landsat 9 OLI/TIRS	30 m; 2022– 2024	USGS / GEE (USGS, 2021)	LST retrieval; NDVI and NDWI derivation; flood susceptibility conditioning variables	→ LST, NDVI, NDWI	Ch. 5, 6
Sentinel-2 MSI	10–20 m; 2015– 2022	ESA / Copernicus / GEE (ESA, 2017; Noel et al., 2017b)	High-resolution LULC classification; NDVI for GI equity analysis	→ NDVI	Ch. 4, 6
Copernicus Global Land Cover (V3.0.1)	100 m; 2019	Copernicus Land Monitoring Service (Buchhorn et al., 2020)	LULC cross- validation; baseline land cover reference	—	Ch. 4
GlobeLand 30	30 m	National Geomatics Center of China (Onilude and Vaz, 2021)	LULC cross- validation	—	Ch. 4
ESA WorldCover	10 m; 2021 v200	ESA WorldCover (Zanaga et al., 2022)	LULC cross- validation; high- resolution reference layer	—	Ch. 4

Google Street View (GSV) imagery	Street-level panoramas; ~50 m interval; 2019–2023	Google Cloud Console (Google, 2025)	Street-level green view assessment; input to Mask2Former segmentation for GVI, IAI, OSI derivation	→ GVI, IAI, OSI	Ch. 7
2. Terrain, Soil & Hydrological Derivatives					
Digital Elevation Model (DEM) / ALS	1 × 1 m; 2024	Geoportal of Poland (Geoportal.pl, 2023a)	Terrain conditioning for flood susceptibility; slope, SPI, TWI derivation; elevation as GI facilitator/constraint; green roof pitch assessment	→ Slope, Aspect, Curvature, SPI, TWI, Roughness	Ch. 4, 5, 6, 7
Digital Surface Model (DSM)	0.5 × 0.5 m; 2024	Geoportal of Poland (Geoportal.pl, 2023a)	Building height extraction for green roof suitability; canopy height estimation	Derived from ALS	Ch. 7
Slope	1 × 1 m	Derived from DEM	Flood susceptibility factor; GI planning constraint	Derived from DEM	Ch. 4, 5, 6
Aspect	1 × 1 m	Derived from DEM	Flood susceptibility conditioning variable; solar exposure proxy for green roof performance	Derived from DEM	Ch. 5
Plan & Profile Curvature	1 × 1 m	Derived from DEM	Flood susceptibility factor; identifies flow convergence	Derived from DEM	Ch. 5

			and divergence zones		
Stream Power Index (SPI)	$1 \times 1 \text{ m}$	Derived from DEM	Erosion and runoff intensity proxy; flood susceptibility input	Derived from DEM, $SPI = \alpha \times \tan \beta$	Ch. 5
Topographic Wetness Index (TWI)	$1 \times 1 \text{ m}$	Derived from DEM	Soil saturation and waterlogging potential; flood susceptibility input	Derived from DEM, $TWI = \ln(\alpha / \tan \beta)$	Ch. 5
Surface Roughness	$1 \times 1 \text{ m}$	Derived from DEM	Terrain irregularity indicator; flood flow resistance proxy	Derived from DEM, $Roughness = (FS_{mean} - FS_{min}) / (FS_{max} - FS_{min})$	Ch. 5
NDVI (Normalized Difference Vegetation Index) - Landsat 9, Sentinel-2	30 m; 2022, 10 m; 2024	Landsat 9 OLI/TIRS via, Sentinel-2 via GEE (ESA, 2017; USGS, 2021)	Vegetation cover proxy; top SHAP driver in flood susceptibility model; heat exposure indicator, Existing vegetation validation for GI distribution analysis; GI density proxy	Derived from Landsat 9, Sentinel-2	Ch. 5, 6, 7
NDWI (Normalized Difference Water Index)	30 m	Landsat 9 OLI/TIRS	Surface water extent mapping; flood susceptibility conditioning variable	Derived from Landsat 9	Ch. 5
Land Surface Temperature (LST)	30 m; 2022	Landsat 9 OLI/TIRS via GEE	Top SHAP driver in flood susceptibility model; heat stress	Derived from Landsat 9	Ch. 5, 6

			need indicator for GI equity		
Soil map (FAO)	30 m	Food and Agriculture Organization (FAO) (FAO, 2009)	Hydrological soil group classification for NRCS-CN runoff modelling	—	Ch. 4
Soil map (Polish Geological Institute)	1:300,000 and 1:50,000; 2019–2021	Polish Geological Institute – National Research Institute (PGI-NRI) (Polish Geological Institute-National Research Institute, 2021)	Detailed local soil type classification; flood susceptibility conditioning variable	—	Ch. 5
Tree point data (ALS-derived)	~1 m grid; 2023	Geoportal of Poland (Geoportal.pl, 2023a)	Existing street tree inventory; baseline for XGBoost tree-planting prediction	Derived from ALS point cloud	Ch. 7
3. Built Environment & Infrastructure					
BDOT10k - Buildings	1:10,000; 2021	Geoportal of Poland (Geoportal.pl, 2023a)	Building footprint geometry for green roof suitability; GI equity analysis	—	Ch. 6, 7
BDOT10k - Road network	1:10,000; 2021	Geoportal of Poland (Geoportal.pl, 2023a)	Street segment delineation; tree-planting spacing scenarios	—	Ch. 7
River network	1:25,000	OpenStreetMap (OSM) (OpenStreetMap, 2017)	Distance-to-river buffer; drainage proximity planning consideration	—	Ch. 4, 5

Distance to stormwater / rainwater collectors	1:25,000	Gdańskie Wody; OSM (Gdańskie Wody, 2024; OpenStreetMap, 2017)	Top SHAP driver in flood susceptibility model; drainage planning consideration	—	Ch. 5, 6
Distance from coastline	—	SIPM – System Informacji Przestrzennej Administracji Morskiej (SIPM, 2021)	Coastal flood exposure indicator	—	Ch. 5
Impervious surface (Urban Atlas)	1:10,000; 2018	Copernicus Land Monitoring Service – Urban Atlas 2018 (European Union’s Copernicus Land Monitoring Service, 2021)	Primary structural constraint on GI distribution; LULC prediction input	—	Ch. 4, 6
4. Socio-demographic Factors					
Population density	1:10,000; 2018	Copernicus Land Monitoring Service – Urban Atlas 2018 (European Union’s Copernicus Land Monitoring Service, 2021)	Space competition proxy for GI distribution; LULC prediction input	—	Ch. 4, 5, 6

Elderly population	District level	Geostatistical Portal (GUS) (GUS, 2021)	Equity indicator for environmental stressors and green space accessibility	—	Ch. 6
5. Environmental Stressors					
Air pollutants (NO ₂ , PM2.5, PM10, O ₃)	500 m; 2021	Główny Inspektorat Ochrony Środowiska (GIOŚ) (GIOŚ, 2021)	Need indicators for GI co-benefits and environmental justice hotspots	—	Ch. 6
6. Climate, Hydrology & Hazard Data					
Synthetic design rainfall (IDF curves)	p = 1%, 10%, 50%; 2022	Gdańskie Wody; IMGW-PIB (Gdańskie Wody, 2024; IMGW-PIB, 2022)	HEC-HMS model forcing; stormwater retention scenario design	—	Ch. 4, 7
Climate projections (RCP 4.5 & RCP 8.5)	5 km; 2050-2100	EURO-CORDEX (Iturbide et al., 2021)	Future rainfall scenario inputs for runoff projections	—	Ch. 4
Urban flood event inventory	Point locations; 2010-2022 (265 events)	State Fire Service (KG PSP); Gdańskie Wody (Gdańskie Wody, 2024)	Flood susceptibility training/validation labels	—	Ch. 5, 6

Chapter 4

Land Use Dynamics and Hydrological Response

4. Introduction

Urban flood risk is not a static condition but an accumulating consequence of how cities transform their land surfaces over time. In Gdańsk, this transformation has been both rapid and spatially consequential: positioned at the convergence of post-glacial moraine hills in the west, low-lying polder areas sitting partly below sea level in the east, and a Baltic coastal exposure in the north, the city faces three structurally distinct flood hazard types whose severity is jointly amplified by the progressive replacement of permeable surfaces with impervious urban fabric. Between 1985 and 2022, Gdańsk's built-up area expanded from 58.64 km² to 88.89 km², with the rate of growth accelerating more than eightfold after 2005, yet existing studies have largely examined LULC dynamics and climate forcing in isolation rather than quantifying their combined hydrological effect within a single framework. This chapter addresses that gap by reconstructing historical LULC transitions across five epochs using multi-temporal Landsat and Sentinel-2 imagery processed in Google Earth Engine, and translating these into surface runoff estimates through the NRCS-CN method and HEC-HMS modelling under three scenario configurations, LULC change alone, climate change alone, and their combined effect, projected forward to 2050 and 2100 under RCP 4.5 and RCP 8.5.

4.1. Methodology

The methodological workflow implemented is depicted in figure 4.1. Initially, the required remote sensing data was collected. LULC maps were classified for the selected years using the GEE platform (Noel et al., 2017). The LCM model (Eastman, 2012) was utilized for predicting future LULC changes for 2050, and 2100.

To evaluate the influence of LULC changes on the hydrology of the entire Gdańsk region, the NRCS-CN method was employed (USDA, 1985). In ArcMap 10.7, a CN grid was generated for each year using the HEC-GeoHMS tool, with soil and LULC maps serving as input data (Figure 4.1). At the basin level, HEC-HMS (Peters, 1998) hydrological analysis was done to simulate the historical and future hydrological response of the basin.

The data source and details of the data used in LULC training, validation and hydrological model are shown in table 3.1.

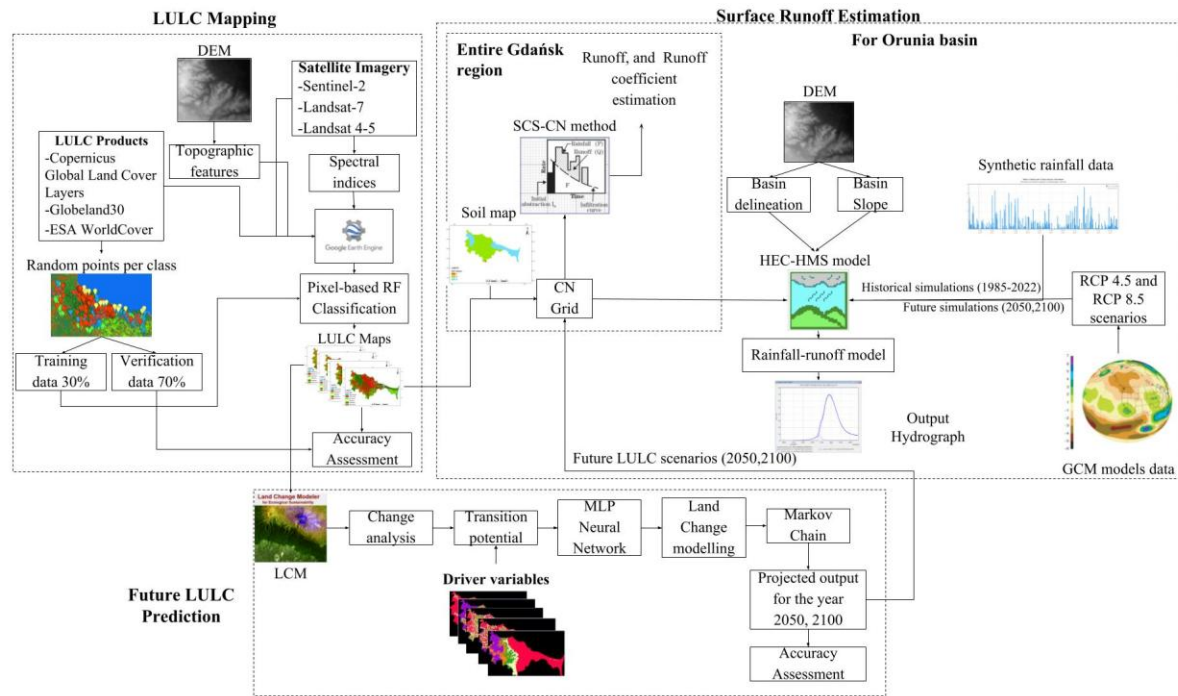


Figure 4.1. Flow chart depicting the methodological framework. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0.*

4.1.1. LULC classification

This study utilized a combination of imagery observation, auxiliary data, and existing LULC products (Table 3.1) to collect training and validation samples. Since these LULC products represented different resolutions and LULC types, it was necessary to resample and reclassify them to a standardized LULC classification scheme using GEE.

In this research, the RF classification (Breiman, 2001) was implemented within the GEE platform. For the RF classifier, to determine the optimal parameters, the LULC classification was performed using different numbers of trees and minimum leaf. Optimum parameters were identified based on the overall classification accuracy. Through repeated experiments, it was determined that setting the number of trees to 100 and the minimum leaf size to 10 produced the best results. Quantitative measures, such as overall accuracy (OA), and the kappa coefficient were employed to evaluate the accuracy of LULC classification using validation data.

4.1.2. Projections for future LULC Change by LCM

For future LULC prediction, the LCM within TerrSet software system (Eastman, 2012) was utilized. LULC scenario modeling facilitates in addressing uncertainty in LULC predictions by enabling the examination of various potential scenarios. Three scenarios were developed considering historical rainfall data from the 20th century, rainfall data up to 2005, and data from 2000 to 2022 along with future rainfall projections. The three different scenarios are: (1) 1985-

2005, (2) 2005-2022, and (3) 1985-2022. Each scenario's LULC maps were imported into LCM for analysis allowing the evaluation of gains, losses, and net changes in land cover.

The selection of driving forces for LULC changes does not have a recommended approach (Mozumder and Tripathi, 2014). In this study, the selected static variables included DEM, slope, aspect, and distance from water bodies while the dynamic variable considered was a distance from the road network. Additionally, population density, a socio-economic factor, was included as a dynamic variable. To map the spatial trend of change, an 8th-order polynomial was employed.

A transition sub-model can represent either single or multiple transitions driven by the same variables (Abuelaish and Olmedo, 2016). Before prediction, the transition maps were derived using an MLP neural network. These maps, together with static and dynamic variables, were used to predict LULC changes for 2050 and 2100 using the CA Markov chain.

In this study, a land cover prediction for the year 2022 (for which we had actual land cover information) was generated using the VALIDATE module of IDRISI Terrset, and its accuracy was evaluated by comparing it to a reference LULC map of the same year.

4.1.3. Local scale hydrological modeling in Gdańsk using NRCS-CN

The NRCS-CN (USDA, 1985) method is an effective approach to calculating rainfall-runoff. This study utilized rainfall with $p=1\%$ (return period 100 years) and $T=24$ h daily maximum rainfall data from 1974 to 2000 (Table 3.1). In ArcMap, a CN grid was prepared by using the LULC and Hydrologic Soil Group (HSG) map of the Gdańsk. CN values, which range between 100 (water bodies) to 30 (permeable soils), were applied to estimate direct runoff depth using the NRCS-CN formula (Eq. 4.1) in ArcMap (Hameed, 2017).

$$Q = \frac{(P - 0.2S)^2}{(P + 0.8S)} \quad 4.1$$

$$S = \frac{25400}{CN} - 254 \quad 4.2$$

where P is the total rainfall (mm), S is the potential maximum retention (mm), CN is the curve number, while Q is the direct runoff (mm).

4.1.4. Hydrological modeling for Orunia basin using HEC-HMS

The HEC-HMS model is widely used for simulating rainfall-runoff processes at different temporal scales (Peters, 1998). HEC-GeoHMS (Feldman, 2000) extension in ArcMap was used to define the basin's topographic and hydraulic characteristics using DEM. The basin was divided into 20 sub-basins for computational efficiency and accuracy. Key attributes such as basin slope, length, and slope of rivers of each sub-basin were identified using DEM. Figure 4.2 illustrates the topography and schematic of the hydrological model for the Orunia basin.

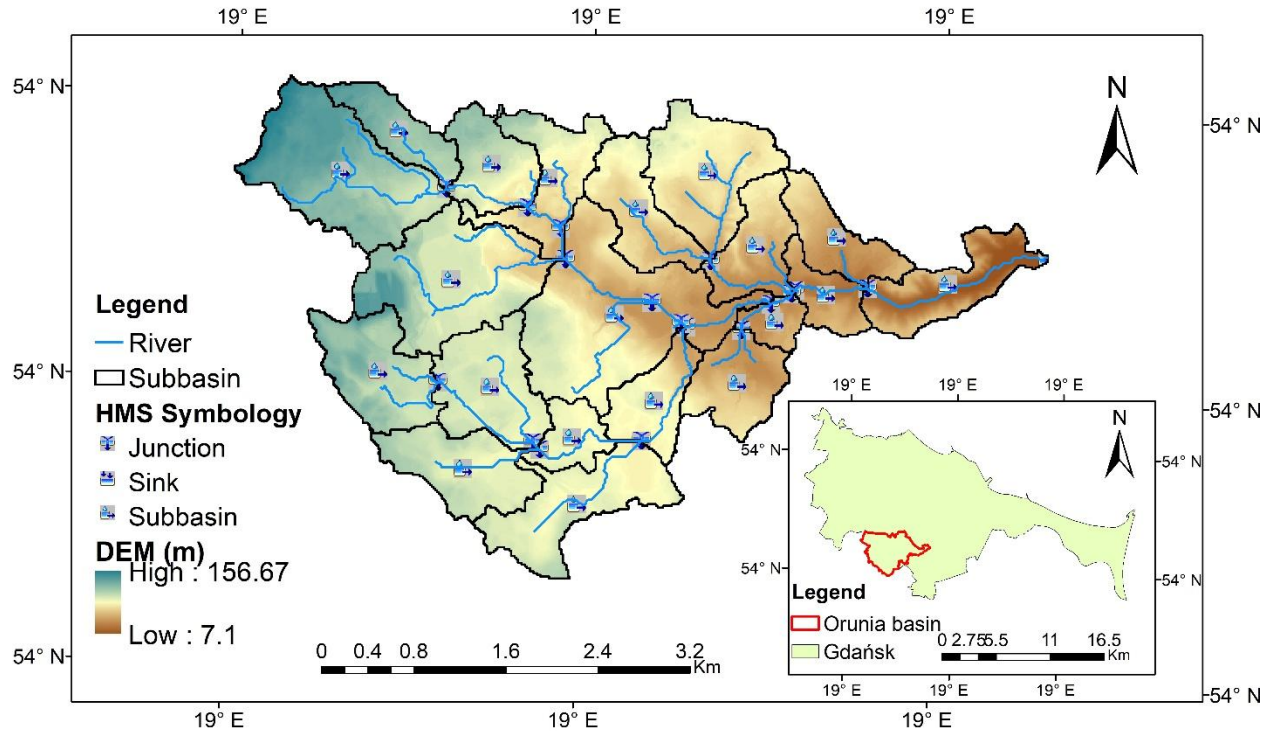


Figure 4.2. Illustration of hydrologic elements in the HEC-HMS model, delineating the Orunia basin. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0.*

In HEC-HMS, the hydrological losses from total rainfall across the basin were computed using the NRCS-CN (USDA, 1985) loss method. To convert rainfall into runoff, the NRCS unit hydrograph transform model was applied. The Muskingum method was utilized for routing water through rivers and channels towards the basin outlet, enabling runoff calculations for each sub-basin.

An important element of hydrological modeling of a catchment area is the verification of the rainfall-runoff model. This process involves a comparison between calculated outflow at the catchment outlet and actual stream flow observations. However, unfortunately, such data is unavailable for the Oruński Stream catchment. Therefore, to ensure the reliability of hydrological estimates, the Oruński Stream catchment model was aligned with the calculation parameters of the previously verified hydrological model of a neighboring Gdańsk catchment, the Strzyża Stream (Cieśliński et al., 2024b; Mikos-Studnicka and Szydlowski, 2022b), based on their hydrological similarity. This approach is reasonable considering the main objective of the research undertaken:

to identify hydrological trend changes in an example urban catchment, and not to build a fully operational hydrological model of the basin.

4.1.5. HEC-HMS Simulation

- First method involved a division of the analysis period from 1974 to 2100 into four periods: 1974-2000 (baseline), 2000-2005 (moderate development), 2005-2022 (human activities), and 2022-2100 (climate change). LULC maps of 1985, 1995, 2005, 2015, 2022, 2050, and 2100 were used to depict evolving LULC over these decades (Table 4.1). The HEC-HMS simulations were conducted using the corresponding land use map, and weather data, with constant DEM and soil data.
- “Fix-changing” method (Mekonnen et al., 2018) was used to assess the impacts of LULC alone on the surface runoff. This employed precipitation data from the baseline period (1974-2000) and LULC maps from 1985 to 2100, with constant DEM and soil data. The HEC-HMS was run seven times for the baseline period, with each run using a different LULC map from the years 1985 to 2100 while maintaining the constant weather dataset from 1974-2000.
- The Third approach is similar to the second one, but it assesses the impact of climate change. It consistently used the 1985 LULC map while altering the climate data across the decades up to 2100.

Table 4.1. Data sets for the HEC-HMS simulation used to analyze the combined and separate effect of LULC and climate changes on surface runoff in the Orunia basin

Model run no	Combined effect		LULC change effect		Climate change effect		Remark
	Climate data set	LULC map	Climate data set	LULC map	Climate data set	LULC map	
1	1974 to 2000	1985	1974 to 2000	1985	1974 to 2000	1985	Baseline period
2	1974 to 2000	1995	1974 to 2000	1995	1974 to 2000	1985	Baseline period
3	2000s	2005	1974 to 2000	2005	2000s	1985	Moderate development
4	2010s	2015	1974 to 2000	2015	2010s	1985	Human activities
5	2020s	2022	1974 to 2000	2022	2020s	1985	Human activities
6	2050s	2050	1974 to 2000	2050	2050s	1985	Climate change
7	2100s	2100	1974 to 2000	2100	2100s	1985	Climate change

In this study, synthetic precipitation events ($T=24h$, $p=1\%$) were used as climate data for each approach which were adopted per the results of previously developed probability distributions (Szpakowski and Szydlowski, 2018c). The baseline period had a rainfall of 93.38 mm, while the period from 2000 to 2005 had a rainfall of 120 mm. For the subsequent periods, a rainfall of 116 mm was used from 2005 to 2015, and 140 mm for 2015 to 2022, considering the corresponding land use conditions of 1985, 1995, 2005, 2015, and 2022.

Additionally, hydrological modeling was conducted for the worst-case scenario for the predicted LULC, i.e., pessimistic: future changes in LULC (2050, 2100) based on the intensification of development observed from 1985-2022. The HEC-HMS was used for future simulations, and the projected maximum daily rainfall data was obtained from bias-corrected Coordinated Downscaling Experiment-European Domain (EURO-CORDEX) (Iturbide et al., 2021) for the medium term (2041-2060) and long term (2081-2100), as presented in table 4.2.

Table 4.2. CORDEX Europe - Maximum 1-day precipitation (RX1day) Change \% - Medium Term (2041-2060) and Long Term (2081-2100) RCP4.5, RCP8.5 (rel. to 1981-2010) - Annual (21 models), Annual (48 models) Regions: Western and Central Europe (Iturbide et al., 2021)

Period	Scenario	Median (%)
Medium Term (2041–2060)	RCP4.5	7.7
Medium Term (2041–2060)	RCP8.5	10.4
Long Term (2081–2100)	RCP4.5	11.8
Long Term (2081–2100)	RCP8.5	22.1

4.2.Results

4.2.1. LULC maps and accuracy assessment

Table 4.3 presents the results of an accuracy assessment conducted using a confusion matrix, which compares the pixel count across various LULC classes in the classified maps of 1985, 1995, 2005, 2015, and 2022. All five classified maps exhibit accuracy levels higher than 90%. The overall accuracy for these classified images, as indicated by the Kappa coefficients, was 94.91% for 1985, 96.98% for 1995, 92.42% for 2005, 93.38% for 2015, and 93.64% for 2022.

Table 4.3. Accuracy assessment of LULC classification

Accuracy measures	1985	1995	2005	2015	2022
Kappa	0.938	0.963	0.90	0.92	0.921
Overall Accuracy (%)	94.91	96.98	92.42	93.38	93.64

Figure 4.3 illustrates the classified LULC maps for Gdańsk across 1985, 1995, 2005, 2015, and 2022 years with six major LULC categories. Table 4.4 presents a quantitative evaluation of the

LULC classes, showing changes in an area measured in km² and the corresponding percentages (%) between 1985 and 2022.

During the period from 1985 to 2022, significant declines were observed in the agricultural land and fallow land categories in Gdańsk. In 1985, the agricultural land covered an area of 51.93 km², accounting for 19.45% of the total area of Gdańsk. Similarly, the fallow land covered an area of 57.65 km². Together, these two categories comprised the largest land cover extent of 109.58 km². The forest and vegetation category, covers an area of 79.66 km², making it the second most prominent LULC category in Gdańsk. In the same year, the built-up, bareland and water bodies covered 58.64 km², 9.86 km², and 9.24 km² respectively.

By 2022, Gdańsk observed a noticeable reduction in agricultural and fallow land to 69.67 km², whereas forest and vegetation expanded to 97.37 km². The built-up area also increased, reaching 88.89 km². This comparison between 1985 and 2022 reveals that the built-up area and forest and vegetation cover have surpassed the extent of agricultural and fallow land in Gdańsk. Additionally, the bare land and water bodies occupied a smaller area in 2022, with 5.11 km², and 7.81 km² respectively (Table 4.4).

Table 4.4. Area occupied by six LULC classes from 1985 to 2022

Classes	1985		1995		2005		2017		2022	
	km ²	%	km ²	%	km ²	%	km ²	%	km ²	%
Waterbodies	9.24	3.46	7.89	2.95	8.35	3.13	7.43	2.78	7.81	2.90
Builtup area	58.64	21.96	58.58	21.94	62.43	23.38	85.48	32.02	88.89	33.06
Agriculture	51.93	19.45	46.28	17.33	45.61	17.08	41.97	15.72	40.34	15.00
Bareland	9.86	3.69	8.14	3.05	9.53	3.57	8.52	3.19	5.11	1.90
Forest and Vegetation	79.66	29.84	93.75	35.11	92.93	34.81	85.69	32.10	97.37	36.22
Fallow land	57.65	21.59	52.38	19.62	48.14	18.03	37.86	14.18	29.33	10.91

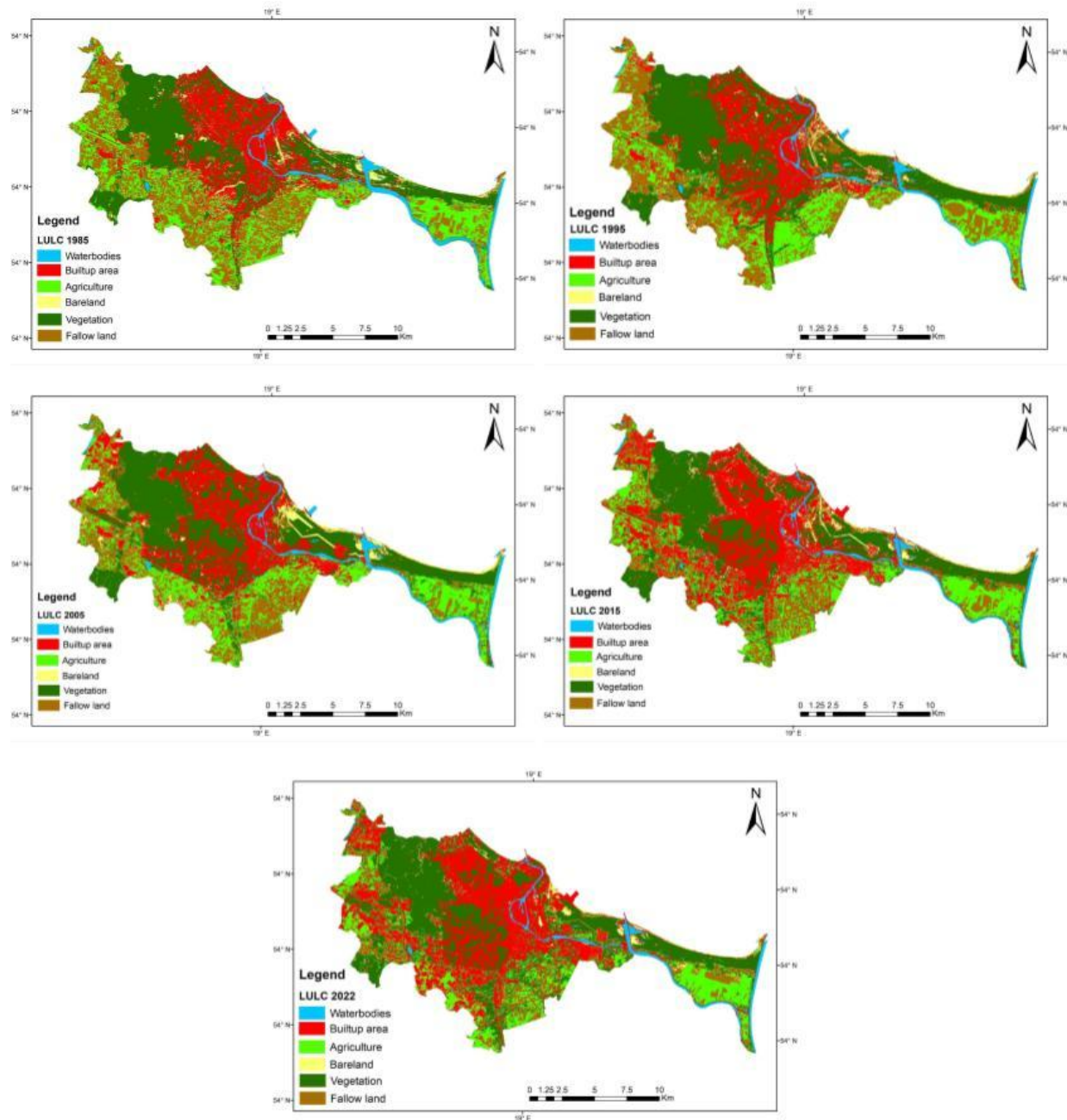


Figure 2.3. LULC map for the years 1985, 1995, 2005, 2015, and 2022. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0.*

4.2.2. LULC change analysis and prediction

A change analysis of LULC classes was conducted during different time intervals: i) 1985–2005 ii) 2005–2022 and iii) 1985–2022 (Figure 4.4). Each time interval exhibited a different quantity of change. This analysis highlights the increase of built-up areas over the years, loss of agricultural land, and increase of forest and vegetation cover. The most pronounced changes occurred during

the second interval from 2005-2022, indicating accelerating urbanization. The detailed interval trend is summarized in figure 4.4.

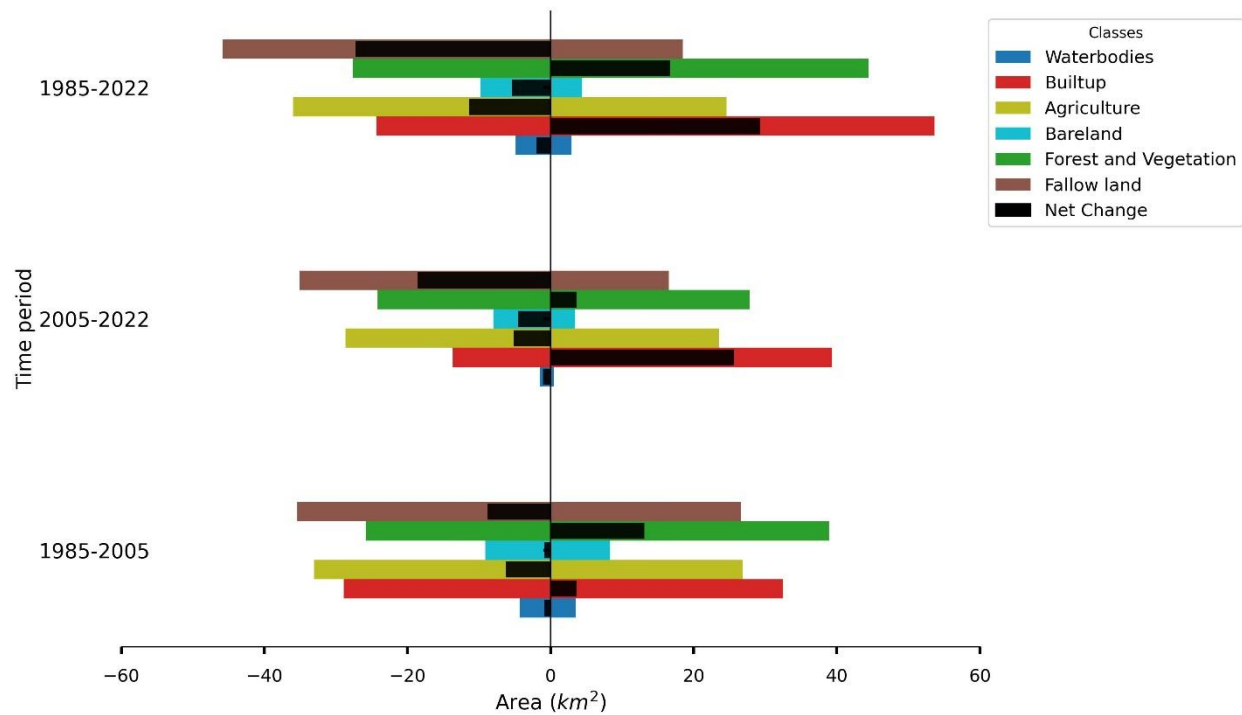


Figure 4.4. LULC gains, losses, and net change for three scenarios: i) 1985–2005 ii) 2005–2022, and iii) 1985–2022. Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0.

4.2.3. Spatial trend of LULC change

In this research, the spatial trend of change in the built-up is of particular importance, due to its significant influence on surface runoff, attributed to its impermeable nature.

The analysis of transitions from other land use classes to the built-up area, depicted in figure 4.5, employs an eight-degree polynomial order. Initially, during 1985–2005, urban growth concentrated in the southern and southwestern Gdańsk, areas rich in arable land and deemed suitable for development. However, over time (2005–2022), the expansion of the built-up area has shifted further southward. Across the span of 37 years, south and southwest expansion has been a key factor in focusing this study on the Orunia basin.

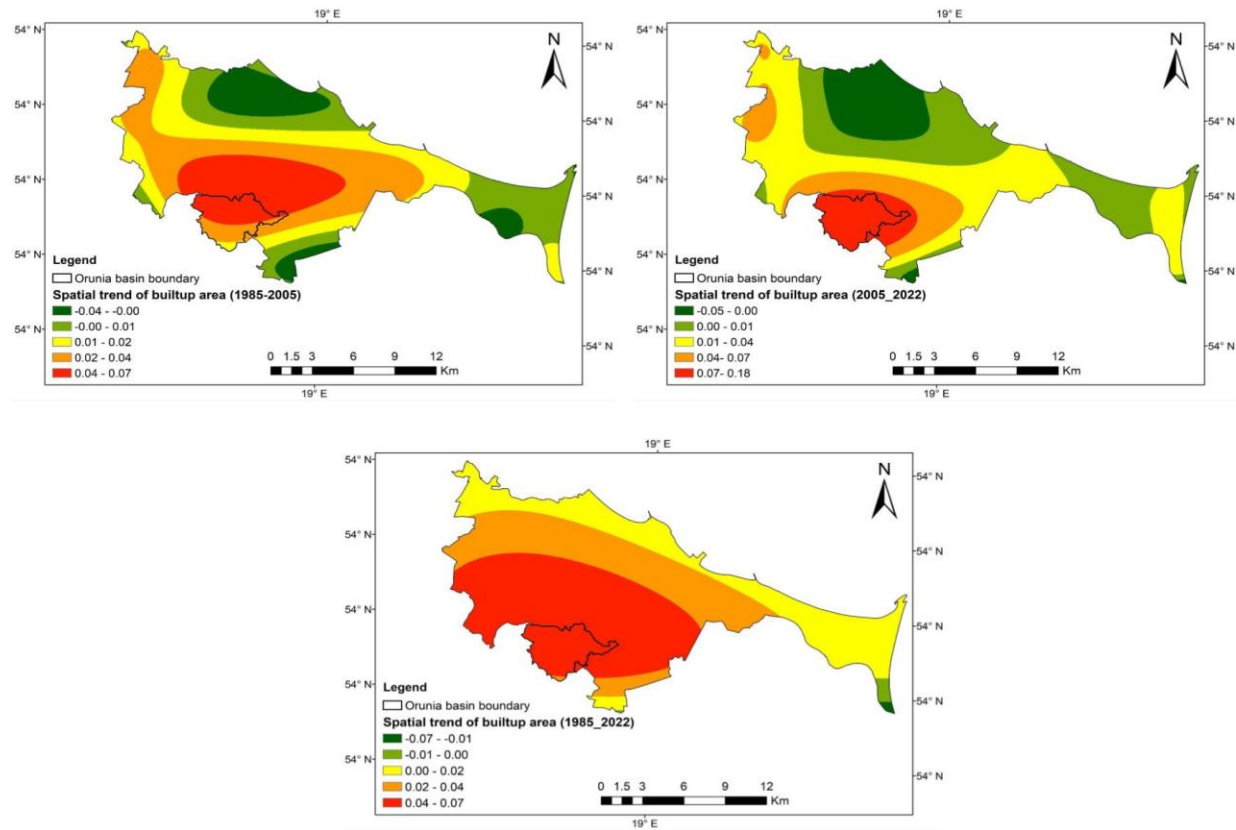


Figure 4.5. Spatial trend of change from other LULC classes to built-up area in Gdańsk across three periods: 1985-2005, 2005-2022, and 1985-2022. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0.*

4.2.4. LULC future prediction

Future LULC changes were projected using the transition probability matrix, obtained through the Markov chain analysis in LCM.

Figure 4.6 shows anticipated LULC for the years 2050 and 2100, generated using a hard prediction model. Additionally, figure 4.7 visually summarizes the distribution of six LULC classes across three scenarios (1985-2005, 2005-2022, and 1985-2022). The scenarios considered were as follows:

- Low demand scenario (1985-2005): This scenario projects the lowest demand for land and the lowest rate of land use change. It predicts a built-up area of 94.33 km² for 2050 and 97.19 km² for 2100.
- Intermediate demand scenario (2005-2022): This scenario projects a higher rate of land use change compared to the low demand scenario. It predicts a built-up area of 129.51 km² for 2050 and 154.47 km² for 2100.

- High demand scenario (1985-2022): This scenario considers cumulative land use change dynamics from the two preceding periods. Therefore, it projects the highest rate of land use change and the overall demand for land during the entire period (1985-2022). It predicts a built-up area of 114.47 km² for 2050 and 157.96 km² for 2100.

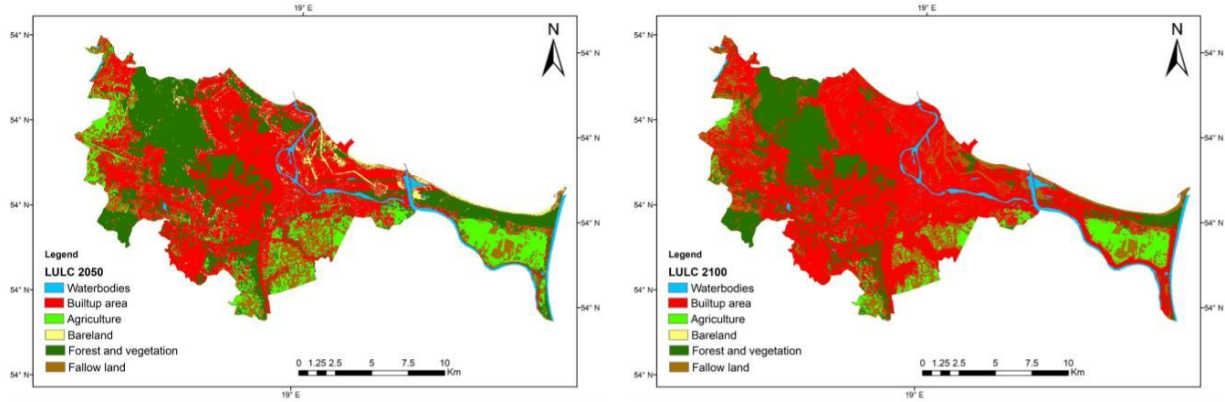


Figure 4.6. Projected LULC map for the year 2050 and 2100 based on time interval 1985-2022. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0*

Table 4.5 provides insights about the level of similarity and dissimilarity between actual and predicted LULC 2022 using the VALIDATE module. It indicates an overall high match, reflecting a reliable prediction while the total disagreement between the maps suggests some discrepancies in the classification due to the allocation errors. The kappa statistics indicate substantial predictive accuracy, with Kno, Klocation, and Kstandard values showing the effectiveness of LULC prediction.

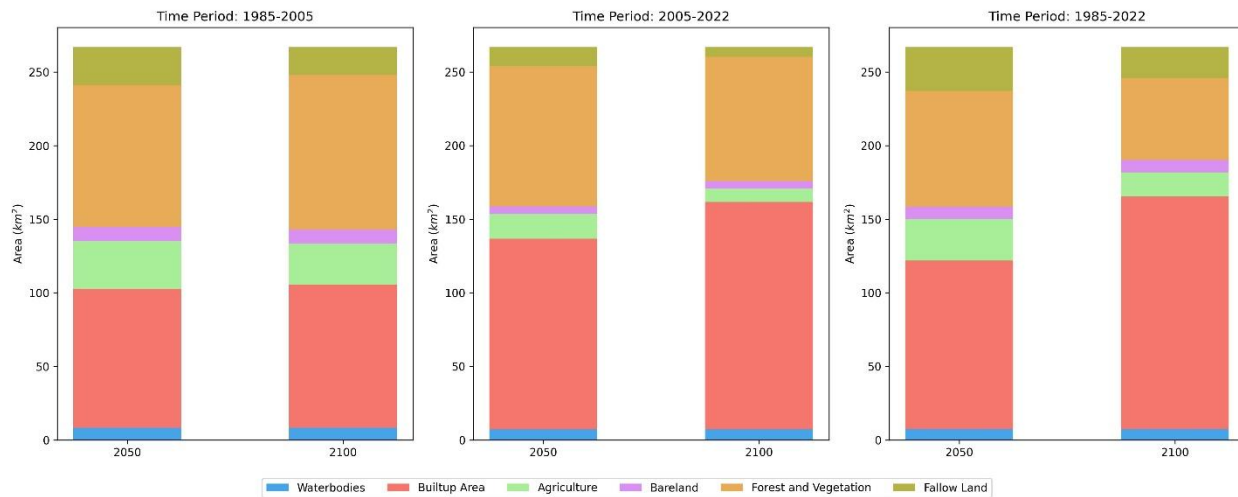


Figure 4.7. Total change in each land cover class (km²) for the projected LULC 2050 and 2100 based on periods 1985-2005, 2005-2022, and 1985-2022. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0*

Table 4.5. Summary statistics of validation for the actual and projected LULC 2022

Agreement/disagreement	% Value
Agreement Chance	14.29%
Agreement Quantity	25.68%
Agreement Gridcell	46.64%
Disagreement Gridcell	11.05%
Disagreement Quantity	2.35%
Kno	84.38%
Klocation	80.85%
Kstandard	77.69%

4.2.5. Influence of urbanization on surface runoff

This study evaluated LULC impacts on Gdańsk's hydrology using the NRCS-CN method, with a detailed focus on the Orunia basin's urban development impacts on surface runoff, using the HEC-HMS model. Three scenarios were considered during the HEC-HMS simulation; i) LULC change effect, ii) climate change effect, and iii) combined LULC and climate change effect (Table 4.1).

4.2.6. LULC change influence on the surface runoff for the entire Gdańsk

Figure 4.8 illustrates the changes in the built-up area and its impact on the surface runoff. From 1985 to 2022, the depth of runoff in Gdańsk increased from 41 mm to 47.03 mm, considering the total daily rainfall of $P=93.38$ mm. Furthermore, the projected LULC for 2050 suggests that this runoff depth could potentially rise to 51.10 mm.

Concurrently, the built-up area in Gdańsk expanded from 58.64 km^2 to 88.89 km^2 , with a projected increase to 114.47 km^2 by 2050. This expansion into impervious areas contributed to most of the runoff, while urbanization resulted in a decline in agriculture and fallow land. Nevertheless, an intriguing result was an increase in forest and vegetation cover, yet the runoff from these areas decreased from 23 mm in 1985 to 22.32 mm in 2022 and will further decrease to 21.96 mm in 2050. In contrast, the runoff depth generated from the built-up area is predicted to increase from 47.66 mm in 1985 to 72.96 mm in 2050.

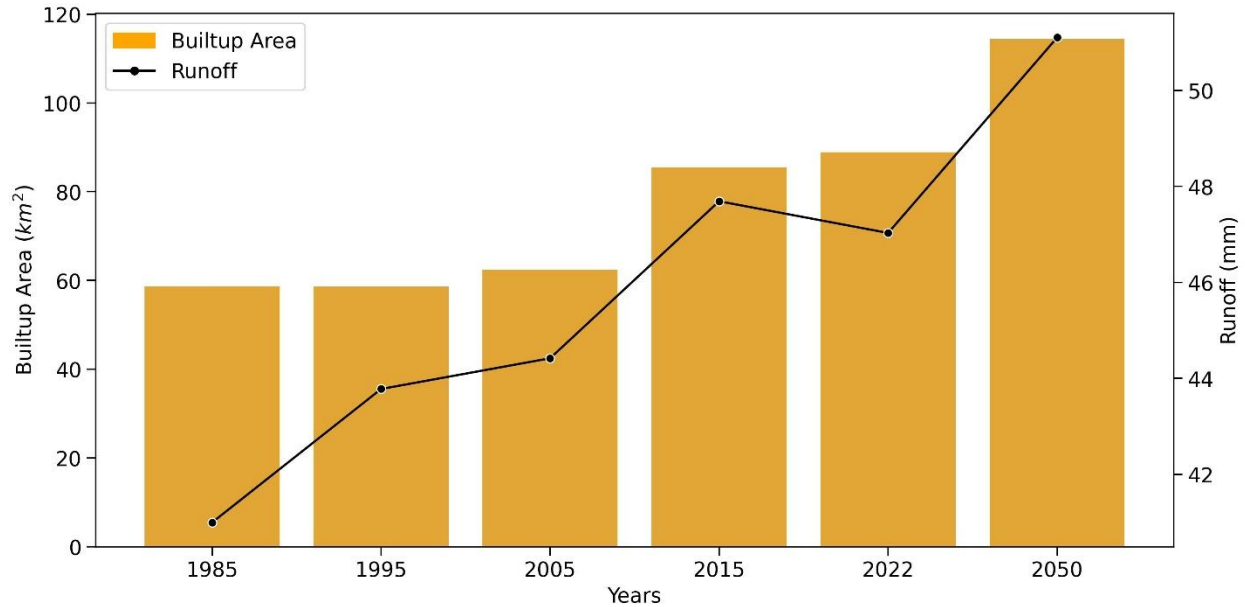


Figure 4.8. Changes in built-up area and runoff depth in Gdańsk between 1985 to 2050. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0*

4.2.7. LULC change effect on Orunia basin's runoff

Under this scenario, parameters from the baseline period (1974-2000), with consistent DEM, soil, and rainfall data (93.38 mm) were used, while LULC maps were altered for different years. During the comparison of the baseline period (1974-2000) and the human activities period (2005-2022), there is a notable increase of 24% in the runoff coefficient particularly from 1985 to 2022. This is attributed to a net increase in built-up area of 6.75 km² in 2022, compared to its initial area of 1.25 km² in 1985 with no reservoir supporting surface runoff storage (Figure 4.9). Notably, considerable 10% of the overall runoff occurred in the last seven years (2015-2022), driven by LULC transformations, surpassing historical LULC changes. This necessitates effective flood management strategies when the capacity of stormwater drainage system conduits is too low.

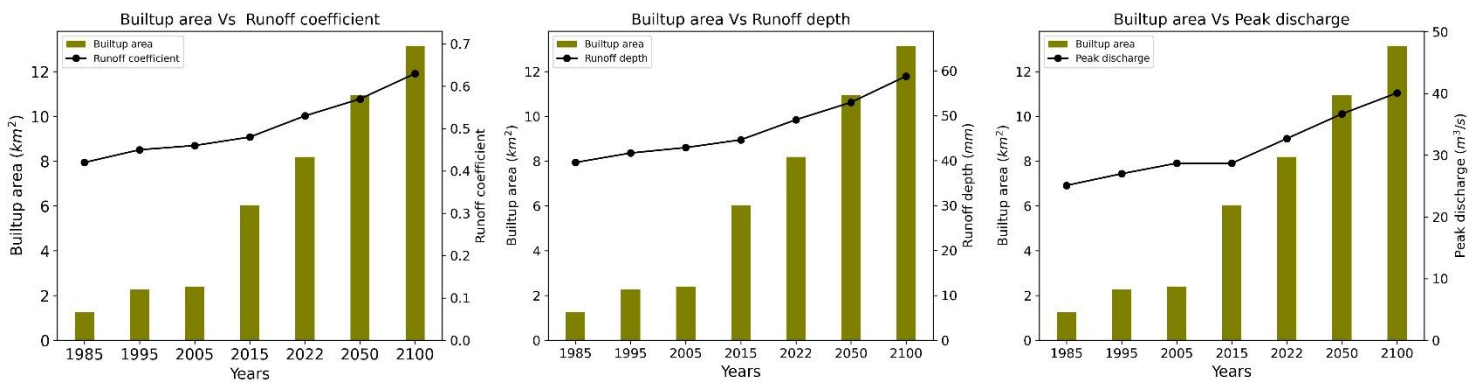


Figure 4.9. Changes in runoff coefficient, runoff depth, peak discharge, and built-up area in Orunia basin under LULC change impact scenario. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0*

Future projections for 2050 and 2100 anticipate further increases to 0.57 and 0.63 respectively, representing 33.80% and 48.55% increase from the baseline period. These projections are driven by the projected expansion of the built-up area, reaching 10.94 km² (2050) and 13.15 km² (2100) under the worst-case scenario (Figure 4.9). A similar trend for runoff depth (mm) and peak discharge (m³/s) can be seen in figure 4.9 for the Orunia basin.

4.2.8. Climate change effect on Orunia basin's runoff

Climate change impacts on runoff were assessed by using a consistent 1985 LULC map and varied weather data sets across several decades (Table 4.1). The analysis showed an overall increasing trend in the runoff coefficient from 0.42 in 1985, and 1995, with 93.38 mm rainfall to 0.55 in 2022 with daily rainfall of 140 mm. From 1985 to 2022, the runoff coefficient increased by 28.70% from the baseline period value to the human activities period.

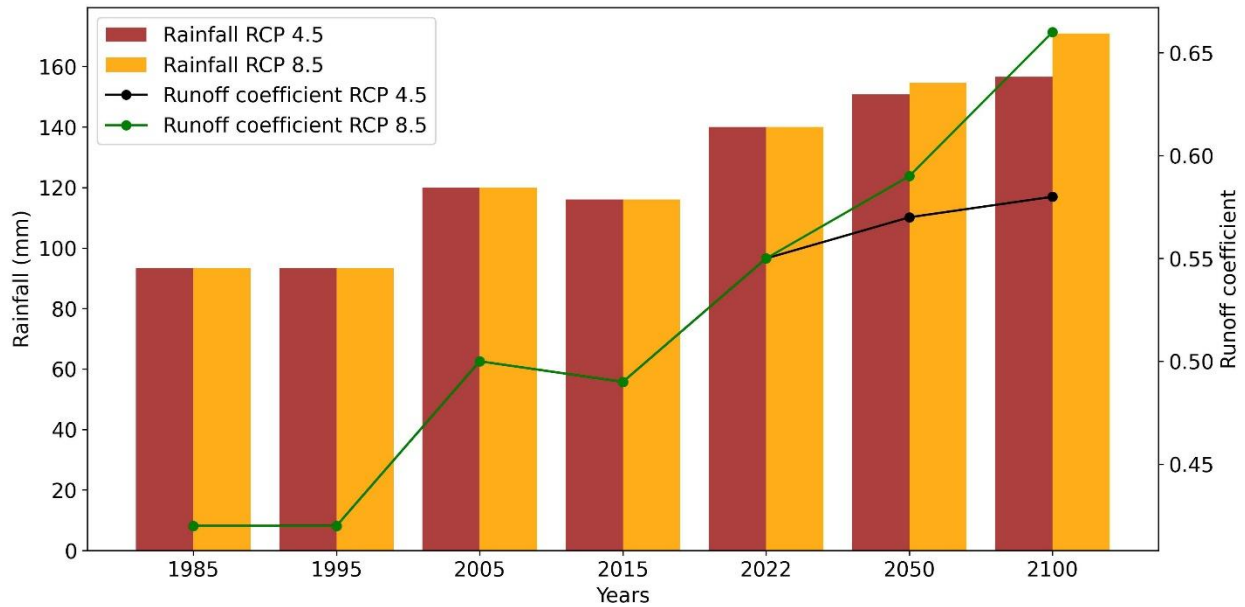


Figure 4.10. Changes in runoff coefficient and rainfall in Orunia basin under climate change impact scenario for RCP 4.5 and RCP 8.5 (1985-2100). Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0

Projections for 2050 and 2100 under RCP 4.5 exhibited a substantial increase of 33.58%, and 36%, resulting in a runoff coefficient value of 0.57, and 0.58. In the case of RCP 8.5, the runoff coefficient exhibited a notable increase of 38.57% in 2050, while 54.57% in 2100. These significant increments are driven by the corresponding rise in estimated synthetic rainfall. The relationship between runoff coefficient and rainfall projections is visually illustrated in figure 4.10.

4.2.9. Combined effects of LULC change and climate change on Orunia basin's runoff

The combined impact of LULC changes alongside climate alternations reveals a significant 49.41% increase in the runoff coefficient from 1985 (0.42) to 2022 (0.63). Notably, the rate of change varied across different decades, which is represented in figure 4.11.

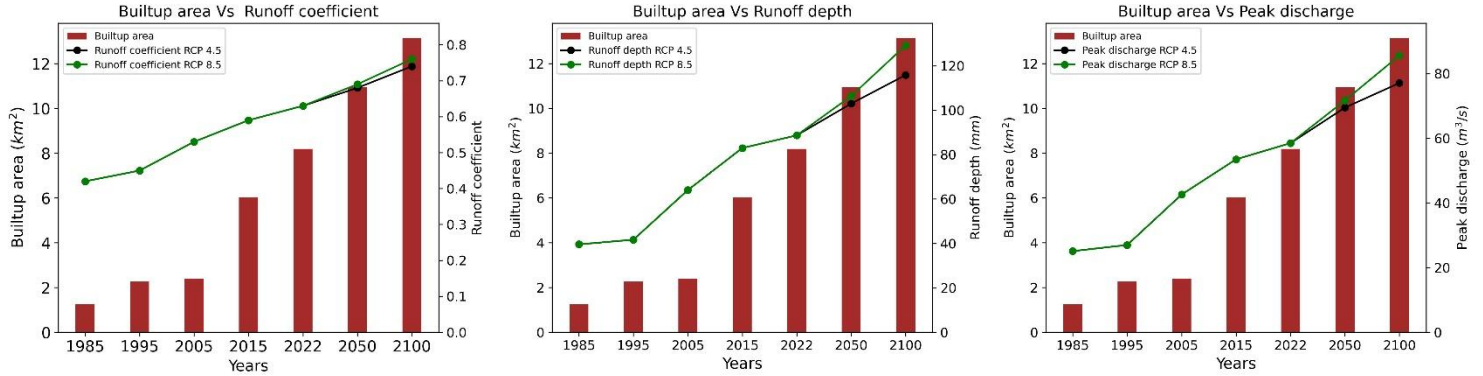


Figure 4.11. Changes in runoff coefficient, runoff depth, peak discharge, and built-up area in Orunia basin under combined LULC and climate change impact scenario for RCP 4.5 and RCP 8.5 (1985-2100) *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0*

A notable gain of approximately 4.12 km² in the built-up area of the Orunia basin was observed between 2005 to 2015. Despite a -3.3% (116 mm) reduction of rainfall for the year 2015, the runoff coefficient experienced a modest 11.09% increase. It showed a subsequent 6.88% increase from 2015 to 2022 which coincided with noticeable rainfall intensity and frequency compared to the 1990s, indicating the synergistic effects of LULC and climate change.

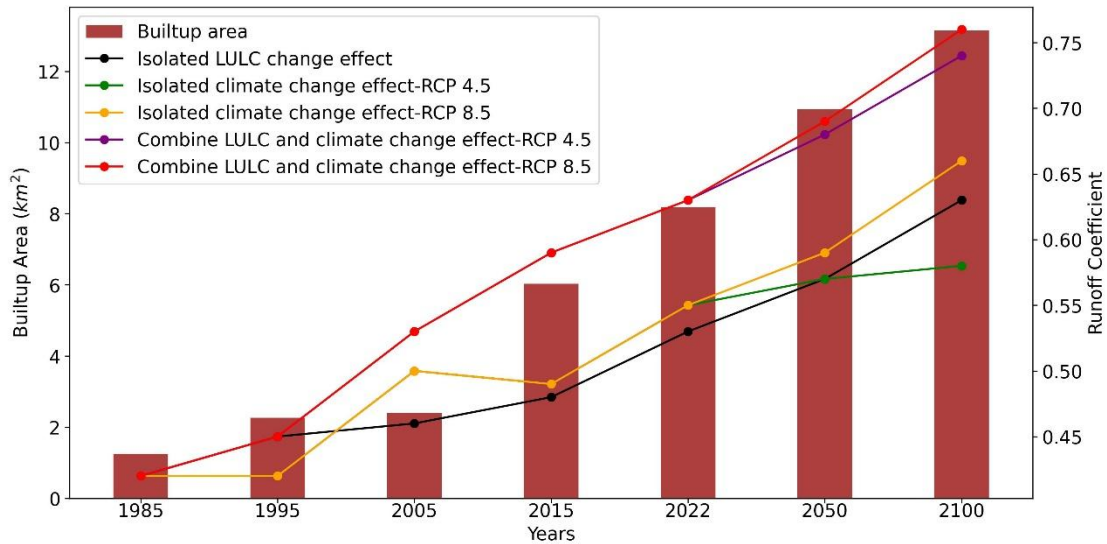


Figure 4.12. Comparison between three simulations in HEC-HMS; i) combined LULC and climate change effect, ii) LULC change effect, and iii) climate change effect. *Reproduced from authors published work (Gulshad et al., 2024a) . © 2024 by the authors. Licensed under CC BY 4.0*

Figure 4.12 depicts the exacerbated combined effects under RCP 4.5 and 8.5. The results obtained reveal a significant increase in the runoff coefficient of 61.08% and 74.58% under RCP 4.5 for

2050 (0.68) and 2100 (0.74), respectively, relative to the baseline period. Under RCP 8.5 scenario, an even more pronounced increase to 62.33% and 78.26% by 2050 (0.69) and 2100 (0.76) is anticipated.

4.3. Discussion

This study analyzed the impacts of historical and projected LULC changes and climate change on surface runoff in Gdańsk, Poland. Using historical LULC data through GEE image classification with an accuracy exceeding 90%, the analysis showed Gdańsk experienced a significant decrease in agricultural land, expansion of built-up areas, and forestation from 1985 to 2022. This trend shows an increase in urbanization and forests at the expense of agricultural land reflecting not only local phenomena but also part of broader regional land-use shifts.

At both local and national levels, the Polish Baltic coastal zone, including Gdańsk, Sopot, and Gdynia, experienced significant urban expansion, and a 17% decline in agriculture over two decades (Kwoczyńska, 2022), alongside increased forestation (Bielecka et al., 2020). It aligns with broader trends in Poland, a study showed expansion of built-up areas by 24.78%, 24.12% growth in forest cover, and 49.62% reduction in agricultural land from 1990 to 2012 (Borowska-Stefańska et al., 2018). The increase in artificial surfaces and forestation also took place in the Małopolskie Province mainly around cities such as Tarnów, Nowy Sącz, Kraków and Wieliczka (Cegielska et al., 2017b). This trend, indicative of changing land use practices and reforestation efforts, is due to changes in national policies and economic conditions (Wnek et al., 2021). The factors influencing the LULC changes in Gdańsk are detailed in table 4.6.

Table 4.6. Factors influencing LULC changes in Gdańsk.

Factor	Influence on LULC	Details
Polish forest policy and EU membership (Wnek et al., 2021)	Increase in forest and vegetation cover	Following World War II and EU membership, Poland's forest policy aimed to increase sustainable forest management and biodiversity.
National Program for Expanding of Forest Cover (KPZL) (Borowska-Stefańska et al., 2018)	Increase in forest and vegetation cover	KPZL aimed to increase forest cover up to 30% by 2020 and further to 33% by 2050.
EU CAP reform (Cegielska et al., 2017b; Wnek et al., 2021)	Decline in agriculture	CAP reform encouraged less economically viable land to transition to other land uses such as forestation.
Post-communist economic transition (Cegielska et al., 2017b; Wnek et al., 2021)	Decline in the agricultural area	Transition to a free-market economy and land privatization in East-Central Europe reduced agricultural interest and promoted

		conversion to forested and developed areas.
Geographical location, industries, tourism	Diversification of LULC	Presence of the shipbuilding industry and tourism significantly influenced land-use diversification.

The trend observed in Gdańsk and other regions of Poland resonates with similar patterns across Europe. For instance, countries like Hungary (Cegielska et al., 2018b, 2017b), Carpathian of Romania (Mihai et al., 2006), Ukraine (Tretiak et al., 2021b; Wojkowski et al., 2023), Estonia (Estonian Ministry of the Environment, 2021), Czech Republic (Wnek et al., 2021), and Slovakia (Prokešová et al., 2022b; Wnek et al., 2021; Wojkowski et al., 2023) indicated increase in forest cover and built-up area. A decrease in agricultural land was observed in southeastern Czech Republic, northern and central Bulgaria, north and southeastern Poland, southern Romania, and the Mediterranean (e.g., central and southern Italy, southern Spain, northern Portugal (Kuemmerle et al., 2016)). These land use changes across Europe underscore the broader environmental and socio-economic shifts impacting LULC, affirming the relevance of Gdańsk's local dynamics within a global context.

The LCM model predicted future LULC in Gdańsk for 2050 and 2100, projecting an increase in built-up area to 114.47 4.12 km² and 157.96 4.12 km² based on 1985-2022 (high demand scenario). Comparative studies in the Tricity region, including Gdański and Kartuzy, confirmed a consistent trend toward the expansion of artificial surfaces and reduction in agricultural areas, emphasizing regional consistency in these changes (Dawid and Bielecka, 2022). Notably, most LULC transformations in Gdańsk are occurring at low elevations (0-100 m), with a less pronounced trend at higher elevations, suggesting future urbanization towards moraine hills to the west, driven by decreasing elevation influence. Furthermore, the role of infrastructure, particularly A1 Highway, in guiding urban growth and shaping neighborhoods in Gdańsk, is evident (Kuiper Compagnons, 2015b).

In the context of the regional trend, the LCM model predicted the expansion of artificial areas and reduction of agricultural land in 33 catchments across Poland, Slovakia, and Ukraine by 2050 and 2100 (Wojkowski et al., 2023). However, modeling based on past transitions has its limitations, particularly the 2005 to 2022 time period in Gdańsk. Past trends may not accurately predict the future, especially in dynamic contexts like Poland's post-EU accession in 2004, which led to significant infrastructural investments and land use changes (Kuemmerle et al., 2016). Although historical data offer insights, it might not be sufficient alone, as evidenced by the pre and post-2004 LULC differences in table 4.4. In areas with complex land-cover patterns influenced by political changes, extended time-frames, and diverse modeling approaches are crucial for accurate analysis. Nevertheless, despite these variations, the model retains substantial predictive power and is applicable to this and similar areas of interest.

Urbanization in Gdańsk significantly impacts the city's hydrology, leading to a comprehensive analysis of how LULC changes affect the hydrological system at a local level. From 1985 to 2022, an increase in runoff depth from 41 mm to 47.03 mm was observed, projected to rise to 51.10 mm by 2050, with the runoff coefficient expected to increase from 0.44 to 0.50. LULC changes, such as the expansion of urban areas and loss of forest cover contribute to increased runoff. However, Gdańsk experienced consistent forest cover increase (46% of total area), a trend that is also evident in other European countries (Cegielska et al., 2018b, 2017b; Estonian Ministry of the Environment, 2021; Prokešová et al., 2022b; Tretiak et al., 2021b; Wnek et al., 2021). Although these changes don't offset the impact of urbanization, they play a significant role at the local scale (Prokešová et al., 2022b). The increase in Gdańsk's impervious area from 58.64 4.12 km² in 1985 to 88.89 4.12 km² in 2022, has raised runoff, emphasizing the need for runoff management strategies.

Currently, Gdańsk surface retention comprises 53 reservoirs with a total capacity of 0.74 million m³. Despite a five-fold increase in capacity between 2001 and 2022 (Gdańskie Wody, 2024), the NRCS-CN method reveals that the total runoff volumes for the chosen daily precipitation in Gdańsk have escalated from 10.74 million m³ to 12.32 million m³ in 2022, with projections reaching 13.39 million m³ by 2050. These figures demonstrate that the existing surface retention system alone is insufficient to fully store rainwater during intense rainfall events, especially under changing climates. In response, Gdańsk's new policy by Gdańsk City Hall has endorsed the city to climate change by 2030, which involves integrating blue-green infrastructure and nature-based solutions at three levels; i) point of origin ii) within municipal reservoirs, and iii) to address rainfall events exceeding 100-year return period (Kasprzyk et al., 2022; Szydłowski et al., 2023b).

Building upon the broader trends, the Orunia basin was assessed for detailed LULC and climate change impacts using HEC-HMS for three distinct scenarios;

- Isolated LULC change effect: The analysis of runoff coefficient, depth, peak discharge, and volume highlights the substantial influence of urbanization within the catchment. The varied soil types in the Orunia basin, ranging from silt loam with better infiltration to sandy clay loam with poor drainage, complicate runoff dynamics (Kolerski and Kalinowska, 2019). The variability in soil types and impervious surfaces affects CN value. As urban areas expand and less permeable surfaces increase, the CN values rise, indicating higher runoff potential. These local observations in the Orunia basin mirror broader regional patterns in Gdańsk and similar urban areas in the Polish Baltic coastal zone. Studies from Orunia (Pietruszyński and Cieśliński, 2019) and Małomiejska basin of Gdańsk (Olechnowicz and Weinerowska-Bords, 2014b) confirm that as urban areas expand, green and undeveloped spaces decrease, leading to increased stormwater volume, affecting both peak discharge value and the speed of transformation processes.
- Isolated climate change effect: The increase in runoff coefficient and depth necessitates enhanced stormwater retention to accommodate the changing precipitation patterns observed since the late 20th century. Historical analysis indicates a significant shift in

Gdańsk's rainfall patterns, where maximum daily rainfall did not surpass 80 mm from 1974 to 2000. Since 2000, there have been several instances where daily rainfall exceeded 100 mm, with a record of 170 mm in 2016- the highest recorded in Poland to date (Szpakowski and Szydlowski, 2018c). These changes reflect broader climatic shifts in the Baltic region (Meier et al., 2021) and highlight the need for updated drainage systems and community awareness for sustainable property development, including water retention solutions.

- Combined LULC and climate change effect: The combined effect of climate change (RCP 4.5 and 8.5) and LULC scenarios are significantly more severe, with rising rainfall intensity and urban area expansion. In the Orunia basin, despite the six retention reservoirs (with a capacity of 0.213 million m³), (Gdańskie Wody, 2024) it is necessary to not only maintain or improve these systems but explore additional strategies like rainwater harvesting techniques, low-impact development practices (LID) and efficient site selection for LID implementation (Gulshad et al., 2024d).

The discussion shows that the synergistic effect of LULC and climate change will significantly impact Gdańsk. However, under high demand scenario (1985-2022), LULC impact on runoff is the same as isolated climate change under RCP 4.5, while by 2100, isolated LULC have a greater impact than isolated climate change effect under RCP 4.5 (Figure 4.12). This finding aligns with previous research assessing LULC impacts on landscape hydric potential (LHP) relative to climate change (Wojkowski et al., 2023). This insight is crucial for water authorities and urban planners to plan and manage land effectively and mitigate hydrological extremes. Land use planning and management can also mitigate the impacts of climate change. A holistic approach, integrating both land use planning and climate change mitigation, is crucial to deal with flood risks. Understanding the local and regional interactions helps in designing more effective land use management and environmental protection strategies that are both responsive to local needs and aligned with regional objectives.

4.3.1. Cross-chapter validation and framework implications

The hydrological findings of this chapter provide the diagnostic baseline upon which the subsequent three analytical stages of the framework are built, and their relevance extends beyond runoff quantification into the spatial and planning dimensions that Chapters 5, 6, and 7 address.

The most direct connection is to **Chapter 5**. The NRCS-CN conditioning variables central to this chapter's analysis, impervious surface extent, LULC class, terrain-derived runoff potential, and drainage infrastructure proximity, overlap substantially with the flood susceptibility conditioning factors applied in **Chapter 5**. This methodological bridge between process-based hydrological modelling and data-driven spatial risk mapping is not coincidental but deliberate: the variables that drive runoff amplification at basin scale are the same variables that determine where flood susceptibility concentrates at city scale. The scenario decomposition finding that the combined effect of LULC and climate forcing exceeds either driver in isolation provides the hydrological context within which **Chapter 5's** susceptibility patterns should be interpreted, the spatial

concentration of high susceptibility in central and lower-terrace districts reflects the cumulative imperviousness accumulation that this chapter quantifies historically and projects forward to 2100.

The forward connection to **Chapters 6** and **7** is equally significant. The projected exceedance of Gdańsk's existing retention infrastructure capacity under both RCP pathways establishes a quantified performance gap, the difference between what the engineered system can absorb and what urban expansion and climate change will generate that nature-based solutions must partially bridge. This gap is not uniform across the city but spatially structured by the same LULC and terrain variables analyzed here, meaning the districts where runoff amplification is greatest are the same districts where GI investment would deliver the highest marginal hydrological benefit. **Chapter 6** examines whether existing GI is positioned to deliver that benefit, and **Chapter 7** quantifies how much of the gap targeted NBS deployment could close. The hydrological baseline established here, specifically the 49.41% combined runoff coefficient increase, and the projected retention infrastructure exceedance provides the quantitative reference against which those chapters' findings should be evaluated.

4.3.2. Limitations and future research

The study faced several limitations:

- The limitations of this research include, lack of comprehensive field data, quality of soil data, overlooked LULC classes, limited range of driver factors, exclusion of climatic factors, and uncertainty associated with climate data used may affect outcomes. Furthermore, uncertainties are also associated with models and forecasts that show simplified representations of complex realities.
- Future research would benefit from employing high-resolution satellite and soil datasets, extending LCM analysis by including climatic variables for accurate outcomes. Additionally, efforts should be made to validate model predictions with extensive field data and to explore the socio-economic implications of land use changes on urban development.

4.4. Conclusion

This study investigated the long-term (1985-2022) LULC changes in Gdańsk, Poland, and predicted future scenarios (2050, 2100) using LCM. It also assessed the impacts of these changes on the surface runoff of Gdańsk using the HEC-HMS model.

LULC results showed urban growth, diminishing agricultural land, and a successive increase in forestation and vegetation. The LCM model for the worst-case scenario (1985-2022) revealed further expansion in built-up areas, and reduced agriculture by 2050 and 2100.

Gdańsk's global runoff analysis for synthetic maximum daily rainfall at a 1% probability, shows an increasing trend of runoff coefficient from 1985 to 2022, projecting further rise by 2050, driven by built-up area expansion.

Using a "fixing-changing" approach, the study highlighted the compound impact of both historical, future LULC and climate changes on hydrological processes. This showed a rise in runoff coefficients for the synergistic effects. The severity increased further by 2050 and 2100 under RCP 4.5 and under RCP 8.5.

The hydrological analysis presented in this chapter establishes that Gdańsk's flood risk is not uniformly distributed across the basin but is structurally produced by the spatial concentration of impervious surfaces, low-lying terrain, and drainage infrastructure deficits in specific sub-catchments. Yet HEC-HMS modelling operates at the basin scale and cannot identify, at the resolution of individual neighborhoods or grid cells, precisely where within the urban fabric this amplified runoff translates into actual flood exposure. Knowing that peak discharge will increase by 34% under combined RCP 8.5 and LULC scenarios by 2100 is necessary but insufficient for targeted intervention, it tells planners that the city faces a worsening problem but not where to act first. Bridging this gap requires shifting the analytical scale from basin-level hydrological modelling to city-level spatial risk mapping, and from process-based simulation to data-driven pattern recognition. **Chapter 5** makes this shift by applying machine learning classification, SVM, RF, and ANN models with SHAP-based interpretability, to map flood susceptibility across Gdańsk, using the 265 fire brigade flood intervention records from 2010 to 2022 as empirical ground truth and the terrain, land cover, and drainage variables established in this chapter as conditioning factors.

Chapter 5

Flood Susceptibility Mapping with Interpretable ML

5. Introduction

The global and basin-scale runoff dynamics established in **Chapter 4** demonstrate that Gdańsk's flood generating processes are intensifying under both land-use and climate pressures but translating this knowledge into spatially targeted intervention requires identifying precisely where within the urban fabric flood susceptibility concentrates. This requires a different methodological register, one capable of learning non-linear relationships between terrain, land cover, drainage proximity, and historical flood occurrence at fine spatial resolution across the urban fabric. This chapter addresses that requirement by developing and comparing three machine learning models, SVM, RF, and ANN, trained on 265 geo-referenced urban flood intervention records compiled from State Fire Service archives for the period 2010 to 2022, and evaluated against twelve physical and anthropogenic conditioning factors including slope, TWI, LST, NDVI, distance to rainwater collectors, and distance to the river network. To move beyond predictive accuracy alone, SHAP is applied to decompose each model's output and identify the relative contribution of individual conditioning factors to flood susceptibility across the city, producing interpretable spatial patterns that connect directly to the green infrastructure equity analysis in **Chapter 6**. The resulting susceptibility maps establish where flood susceptibility concentrates at grid resolution, the spatial evidence base upon which the question of **Chapter 6** becomes possible to ask: whether the city's existing green infrastructure is located where it is most needed.

5.1. Methodology

The methodology framework adopted in this study is shown in Figure 5.1 and encompasses several key steps: (i) flood inventory preparation; (ii) data collection on flood causative factors; (iii) data pre-processing in Python; (iv) multicollinearity analysis; (v) feature selection; (vi) model training and prediction; (vii) model validation and explanation; (viii) flood susceptibility map generation.

Workflow of flood susceptibility mapping using topographical and environmental data, feature selection, machine learning classifiers, and SHAP analysis.

Data for the analyses came from digital records of fire brigade interventions and flood event reports by Gdańskie Wody (Gdańsk Water Company; responsible for rainwater management in Gdańsk) (Gdańskie Wody, 2024). Based on these data, a flood inventory map was prepared, depicting flooded and non-flooded locations, to train the ML models. The premise of the training was that future floods will follow past patterns.

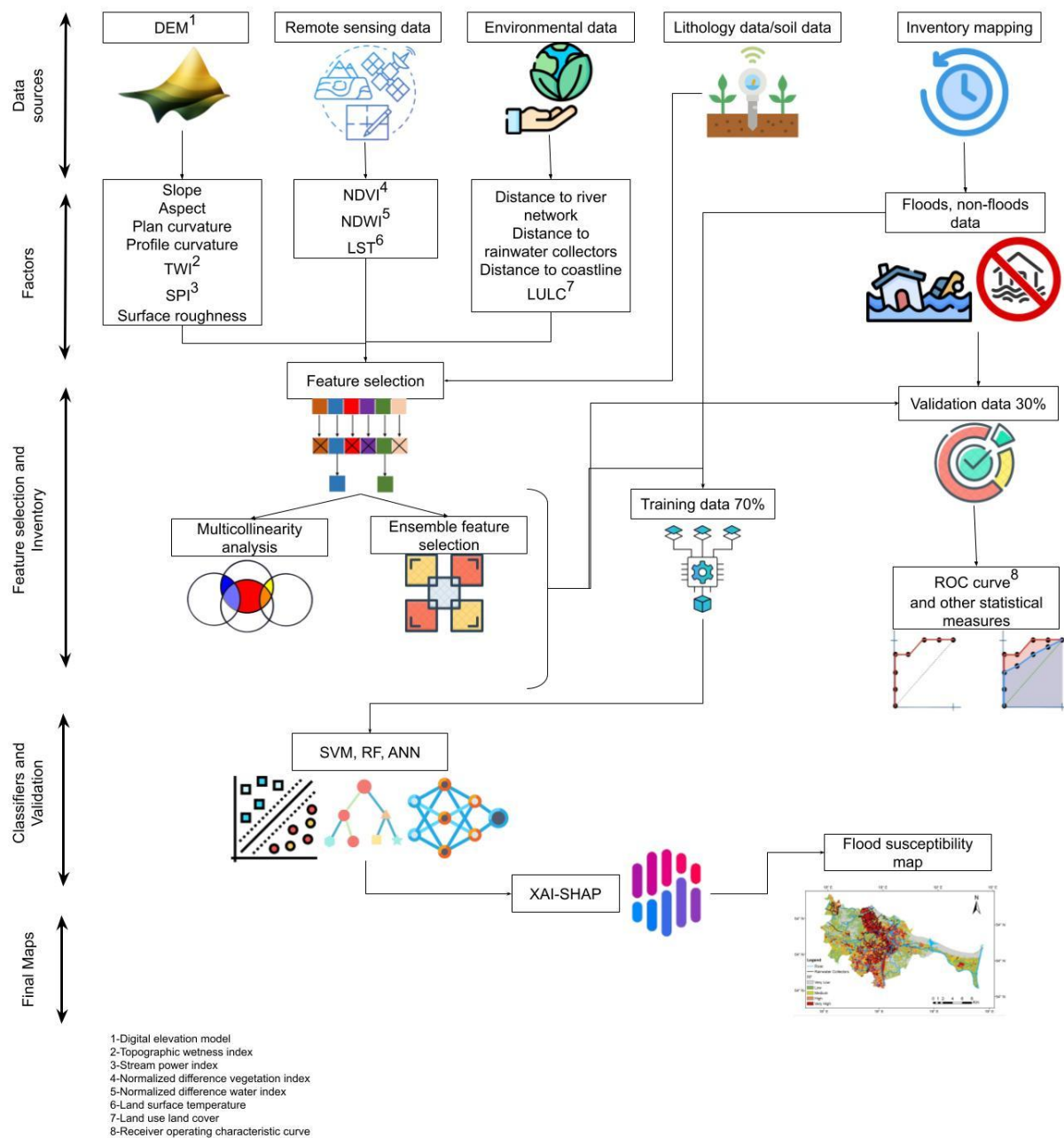


Figure 5.1. Workflow of flood susceptibility mapping using topographical and environmental data, feature selection, machine learning classifiers, and SHAP analysis. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

A total of 265 flood sites and an equal number of non-flood sites were selected, coded as 1 and 0. Following previous studies (Tehrany et al., 2019; Yaseen et al., 2022; Zhu et al., 2024), the dataset was randomly split into training (70%) and test (30%) sets.

Flood intensity and severity depend on topographic, hydrologic, environmental, and geological factors (Diakakis et al., 2016; Rahmati and Pourghasemi, 2017). This study selected flood susceptibility factors based on previous studies (Chakraborty et al., 2021; Mahdizadeh

Gharakhanlou and Perez, 2022; Tehrany et al., 2019, 2015b; Zhu et al., 2024) and coastal city characteristics. The factors considered are presented in table 3.1, chap 3.

5.1.1. Data preprocessing

All factors were standardized to 10m resolution. The spatial database in raster format was created in ArcGIS-10.7, resulting in a matrix of 3380 columns by 1923 rows. Factor values across the study area and flood and non-flood sites were extracted in ArcGIS and exported as .csv files. Subsequently, the data was pre-processed using Python within Google Collab. All factor values were normalized before model training.

5.1.2. Multicollinearity analysis of flood factors

Before training and validating models, evaluating flood factors is crucial to identify noise and assess their predictive power for improving model accuracy (Gulshad et al., 2022; Islam et al., 2021b).

Multicollinearity, assessed using variance inflation factors (VIF), is important in flood susceptibility studies. VIF quantifies how much the variance of a regression coefficient increases due to correlations among predictors (Habibi et al., 2023). A VIF value exceeding 5 suggests significant multicollinearity, which should be evaluated and prompt consideration for removing correlated factors from the model (Beven and Kirkby, 1979; Johnston et al., 2018). VIF is calculated using equation 5.1:

$$VIF(x) = \frac{1}{(1 - R^2(x))} \quad 5.1$$

where $R^2(x)$ is a coefficient of determination when regressing an independent variable x against all other variables. A high $R^2(x)$ indicates a strong correlation between flood and other factors.

5.1.3. The ensemble-based filter feature selection (EFFS) method

The EFFS technique, proposed to optimize feature sets (Solorio-Fernández et al., 2016), is applied in many research fields such as control engineering (Tian et al., 2020b) and cloud computing (Osanaiye et al., 2016). In this study, EFFS is adopted for the first time in flood susceptibility mapping, demonstrating its potential to enhance feature selection by leveraging strengths from individual filter-based methods.

Initial feature importance rankings are obtained from Mutual Information (Yaseen et al., 2022), Gain Ratio (Tian et al., 2020b), Correlation (Tehrany et al., 2019), and ANOVA F-value (Kumar et al., 2015) methods. These rankings form the basis for subsequent ensemble analysis (Tian et al., 2020b). The outcome of feature ranking by each method is expressed as follows:

$$AMI = [XI(1), XI(2), \dots, XI(k), \dots, XI(m)] \quad 5.2$$

$$AGR = [XG(1), XG(2), \dots, XG(k), \dots, XG(m)] \quad 5.3$$

$$ACO = [XC(1), XC(2), \dots, XC(k), \dots, XC(m)] \quad 5.4$$

$$AAO = [XO(1), XO(2), \dots, XO(k), \dots, XO(m)] \quad 5.5$$

where $X(k)$, denotes the ensemble score for the k^{th} feature, calculated as:

$$A = [X(1), X(2), \dots, X(k), \dots, X(m)] \quad 5.6$$

$$X(k) = \alpha XI(k) + \beta XG(k) + \gamma XC(k) + \varepsilon XO(k) \quad 5.7$$

The weights α , β , γ , and ε are empirically determined to balance the contributions from different filter methods. For this study, a weight combination of (2, 1, 2, 1) was chosen based on preliminary results, although several other combinations were tested. Features are then sorted based on their ensemble scores in ascending order to finalize the ranking, ensuring optimal feature selection for flood susceptibility.

5.1.4. Models and algorithms used

Three ML models, i.e., 1) RF, 2) SVM, and 3) ANN, are used for predicting flood susceptibility. RF, an ensemble learning method, constructs numerous decision trees during training. Each tree is trained on a random data subset through “bagging”. The final RF output model, which handles classification and regression tasks, averages the predictions of individual trees:

$$\hat{y}_i = \frac{1}{M} \sum_{j=1}^M f_j(x_i) \quad 5.8$$

where $\hat{y}_i$ is the final output from averaging the classification from individual decision tree prediction $f_j(x_i)$, f_j is the classification model fitted on random dataset samples.

SVM, a supervised machine learning model, creates a hyperplane to maximize class separation using a kernel function. It employs a high-dimensional feature space and minimizes structural risk through cross-validation, often using the Radial Basis Function (RBF) kernel for effective non-linear classification (Table 5.1). Support vectors, the training data points nearest to the hyperplane, help construct this hyperplane, which classifies new data based on the maximized margin between classes. The decision function (equation 5.9) is expressed as:

$$g(x) = \text{sign}\left(\sum_{i=1}^n y_i \alpha_j K(x_i, x_j) + b\right) \quad 5.9$$

where $K(x_i, x_j)$ denotes the kernel function.

Equation 5.10 represents the mathematical expression of RBF:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \quad 5.10$$

Table 5.1. Algorithm parameters selected for SVM, RF, ANN

Algorithm	Parameters
SVM	Complexity parameter = 0.1, kernel = radial basis function, gamma = auto, probability = True
RF	n = 100, max_depth = 20, min_samples_split = 5
ANN	Model = Keras sequential model, hidden layers = 4, nodes for each layer = 100, 40, 30, 1, activation = relu, sigmoid, optimizer = Adam, loss = binary_crossentropy, learning rate = 0.0013, epochs = 50
SHAP	Explainer = SVM: KernelExplainer, RF: TreeExplainer, ANN: DeepExplainer

ANN are computational models inspired by the human brain, comprising an input layer, one or more hidden layers, and an output layer. ANN uses a back-propagation algorithm for learning, adjusting its internal parameters (weights) based on the error between predicted outputs and actual data. It minimizes this error across training cycles (Gulshad et al., 2022; Ngo et al., 2018). The sigmoid function activates and handles non-linear relationships in the data. ANNs approximate complex functions in high-dimensional spaces, making them suitable for various applications, including classification and regression tasks in fields like hydrological modeling (Chakraborty et al., 2021).

The net input to the neuron in the j layer is:

$$net_j = \sum_i w_{ij} \cdot o_i \quad 5.11$$

where w_{ij} is the weight connecting node i to node j , and o_i is the output from node i .

$$O_j = f(net_j) \quad 5.12$$

where f is the activation function applied to the net input.

$$\hat{f}(net_j) = f(net_j) \cdot (1 - f(net_j)) \quad 5.13$$

$$E = \frac{1}{2} \sum_k (d_k - o_k)^2 \quad 5.14$$

where d_k is the target output and o_k is the actual output from the output layer.

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \quad 5.15$$

where η is the learning rate.

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij} \quad 5.16$$

5.1.5. Model explainability

Explainable artificial intelligence enhances transparency in machine learning models, enabling analysts to understand how factors influence model predictions. XAI techniques are categorized into global (permutation feature importance and mean decrease impurity) and local approaches (SHAP and Local Interpretable Model-Agnostic Explanations (LIME)). Global methods show overall significance on average predictions, while local methods reveal specific contributions to individual predictions (Aydin and Iban, 2023; Kim and Kim, 2022). This study employs the SHAP method (Shapley, 1953) to determine how flood conditioning factors impact flood prediction outcomes.

SHAP values, calculated using the Python-based SHAP library, help identify key drivers of the model's outputs, enhancing interpretability in flood susceptibility modeling. The SHAP value $\phi_i(f, x)$ quantifies the influence of factor i on the model prediction f for the input x , as shown in equation 5.17. F represent all features while S is a subset of F excluding i (Aydin and Iban, 2023). The overall influence is measured by mean $|SHAP|$ value value per feature.

$$\phi_i(f, x) = \sum_{S \subseteq F_i} \frac{|S|! (|F| - |S| - 1)!}{|F|!} (f_{S \cup \{i\}}(x_{S \cup \{i\}}) - f_S(x_S)) \quad 5.17$$

$$I_j = -\frac{1}{n} \sum_{k=1}^n |\phi_j^{(k)}| \quad 5.18$$

Table 5.1 shows the explainers used for each model under SHAP.

Previously, research on ML models for flood susceptibility employed variable importance plots to highlight the most and least essential predictors (Aydin and Iban, 2023; Pradhan et al., 2023). However, these plots fail to elucidate crucial aspects, such as variable interactions leading to specific model outputs. Individual force plots and collective summary plots are utilized to address this limitation. These force plots provide a deeper understanding of how variables interact and influence outcomes.

5.1.6. Performance evaluation

Flood susceptibility results are evaluated using several statistical metrics for training and test data: root mean squared error (RMSE), mean absolute error (MAE), accuracy (ACC), sensitivity, specificity, and area under the receiver operating characteristic ROC curve (AUC). The ROC is a standard criterion for evaluating model predictive power, plotting sensitivity on the y-axis and specificity on the x-axis. Sensitivity indicates the proportion of correctly classified flood cells, while specificity suggests the proportion of non-flood cells correctly classified as non-flood sites \cite{islam2021flood}. The area under the ROC curve, the AUC value, ranges between 0 and 1

and measures model performance, with values closer to 1 showing better performance and values closer to 0 indicating a non-informative model (Shafizadeh-Moghadam et al., 2018). AUC, sensitivity, and specificity are given as:

$$AUC = \frac{\sum TP + \sum TN}{P + N} \quad 5.19$$

$$Sensitivity = \frac{TP}{TP + FN} \quad 5.20$$

$$Specificity = \frac{TN}{FP + TN} \quad 5.21$$

P is the total number of flood pixels, and N is the total non-flood pixels. TP (true positives) and TN (true negatives) are correctly classified as flood and non-flood cells. FP (false positives) and FN (false negatives) are incorrectly classified as flood and non-flood cells. The ROC curve validated the final prediction maps for both training and test datasets.

5.2.Results

5.2.1. Flood factor maps

Factor values for flood and non-flood sites were extracted to train, test, and predict flood susceptibility. The histograms (Figure 5.2) represent the factors' frequency distributions with Kernel Density Estimate (KDE) curves, representing historical flood locations in the study area. The x-axis shows the values of each variable for historical flood locations, while the y-axis shows their frequency in the dataset.

Slope: The slope distribution is skewed towards lower values with a long tail extending towards higher values (Figure 5.2). Most historical flooded areas have a gentler slope, with fewer steep slopes (Figure A1, in Appendix A).

DEM: DEM is skewed towards lower elevations. The DEM map of Gdańsk shows elevation from below sea level (-8m) to higher terrain (up to 180m) in the southern and southwestern parts (Figure A1 in Appendix A). This topographic variation divides Gdańsk into three areas: upper terrace, lower terrace, and edge zone.

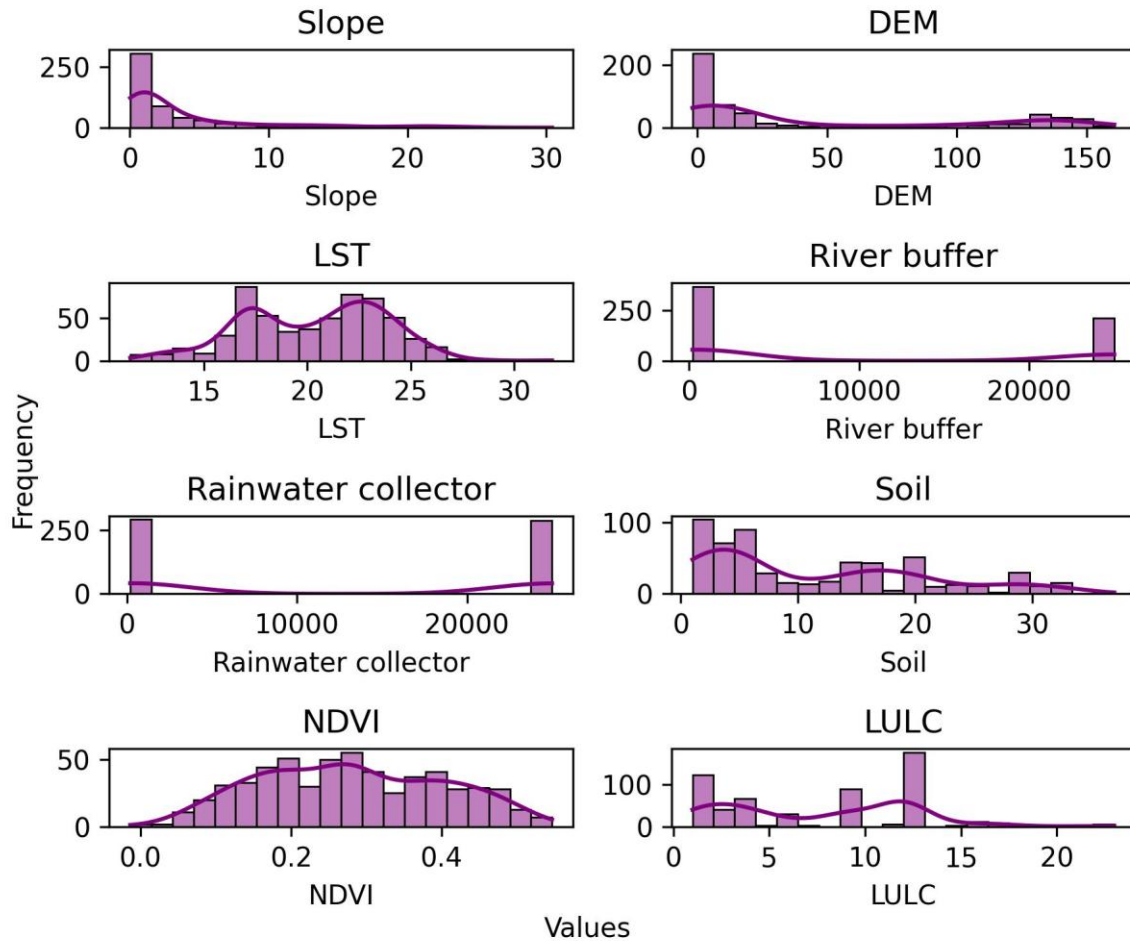


Figure 5.2. Histograms and overlaid kernel density estimates illustrating the distribution of key features critical for flood susceptibility analysis at historical flood sites *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

LST: Gdańsk temperature ranged from 8.3 °C and 36.7 °C, with higher temperatures in urban areas, industrial clusters and agricultural land on the eastern and southwestern sides (Figure A2 in Appendix A). The LST distribution shows a central tendency, indicating an optimal temperature range where flood-related processes or human activity influencing flood susceptibility are more prevalent. In contrast, lower temperatures are associated with rural areas, green spaces, and forests of Gdańsk.

River buffer: Distance from the river histogram shows a bimodal distribution (Figure 5.2), with peaks at both low and high ends. It shows that historical flood locations are either very close to rivers or far from rivers (Figure A2 in Appendix A).

Rainwater collectors: In Gdańsk, the role of rainwater collectors depends on weather conditions and infrastructure capacity. Collectors quickly channel water downhill on steep slopes, reducing accumulation and pressure points. However, in low-lying areas, collectors must handle runoff from upstream basins. If the rainwater surpasses the collectors' capacity during heavy rainfall, overflow can cause nearby flooding. Additionally, rising sea levels can cause backflow into collectors,

reducing their capacity to manage runoff and increasing floods. Higher sea levels also reduce the hydraulic gradient within the collectors, decreasing their capacity to handle runoff. Proximity to rainwater collectors, as shown on the map (Figure A2 in Appendix A), is a crucial indicator of flood susceptibility, particularly in intense precipitation or when sea levels rise.

Soil: Soil distribution shows multiple peaks, indicating varied soil types at flood locations, ranging from sandy, sandy gravel, and alluvial soil on lower terraces (Figure A3 in Appendix A).

NDVI: NDVI has a bell-shaped distribution centered around 0.2, indicating moderate vegetation cover in most areas.

LULC: The LULC map of Gdańsk (Figure A3 in Appendix A) is divided into urban fabric, agricultural land, forests, water bodies, and more. The LULC histogram (Figure 5.2) shows multiple peaks, reflecting diverse land use types (e.g., urban, forest, agriculture). Significant peaks representing historical flood points are found in continuous urban fabric, road networks, and industrial and commercial land.

Moreover, features with broader value ranges provide distinct information for predictive modeling (flood vs non-flood). For instance, slope and DEM are primarily clustered at lower values, contrasting LST, NDVI, soil, and LULC, which display a wider distribution, suggesting that slope and DEM values in historical flood zones remain consistent over time in Gdańsk.

Flood factors analysis shows that each factor uniquely impacts flood susceptibility, depending on their distribution patterns. This insight is essential for effectively identifying and mitigating floods in Gdańsk.

5.2.2. Multicollinearity of factors

Multicollinearity among all 16 factors was assessed (Table 5.2). The minimum VIF value (1.03) was for the aspect, and the maximum value (3.36) was for the slope. All features had VIF values less than 5, indicating negligible collinearity or independence from each other. Hence, all these factors were suitable for further processing.

Table 5.2. Multicollinearity analysis showing VIF values less than five for all the factors of flood susceptibility

Variables	VIF	Variables	VIF
LST	2.23	Coastal buffer	1.46
Aspect	1.03	Soil	1.98
Slope	3.36	DEM	1.86
Plan curvature	1.57	NDWI	1.92
Profile curvature	1.65	SPI	2.60
NDVI	2.04	LULC	1.20
TRI	1.25	TWI	2.40

River buffer	1.15	Rainwater collectors	1.42
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5.2.3. Ensemble feature selection

Factors choice affects machine learning models' accuracy directly or indirectly yet selecting and categorizing appropriate factors is challenging without a universal rule. Therefore, ensemble feature selection identified the most significant factors from the dataset. Feature selection began with various filter methods, each using distinct ranking algorithms.

Figure 5.3 shows the outcome of feature selection, highlighting features' recurrence patterns in predicting flood susceptibility. Key factors such as LULC, proximity to rainwater collectors, Land Surface Temperature (LST), buffer zones around rivers, soil composition, and NDVI consistently appeared as top features across all filter methods. In contrast, features like TRI, SPI, and profile and plan curvature showed less consistent ranking, suggesting lower significance or a more nuanced relationship with the target variable that isn't easily quantifiable or linear.

ANOVA F-value, Mutual Information, Gain Ratio, and Correlation metrics offer varied perspectives while collectively reinforcing specific features' significance. Therefore, the rankings obtained from these methods served as the basis for EFFS method, which aims to eliminate irrelevant or redundant features.

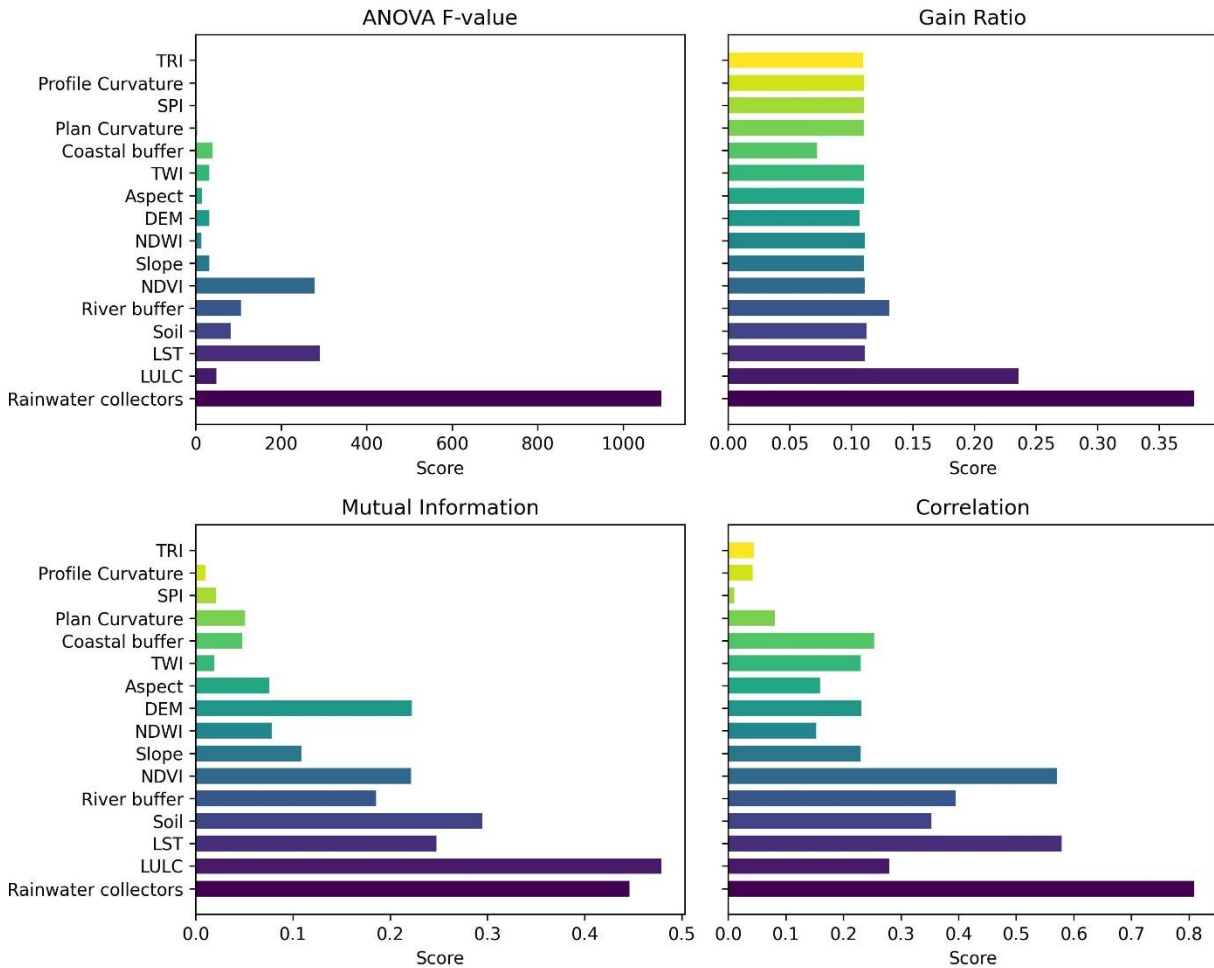


Figure 5.3. Comparative analysis of feature rankings using four filter methods: ANOVA-F, gain ratio, mutual information, and correlation *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

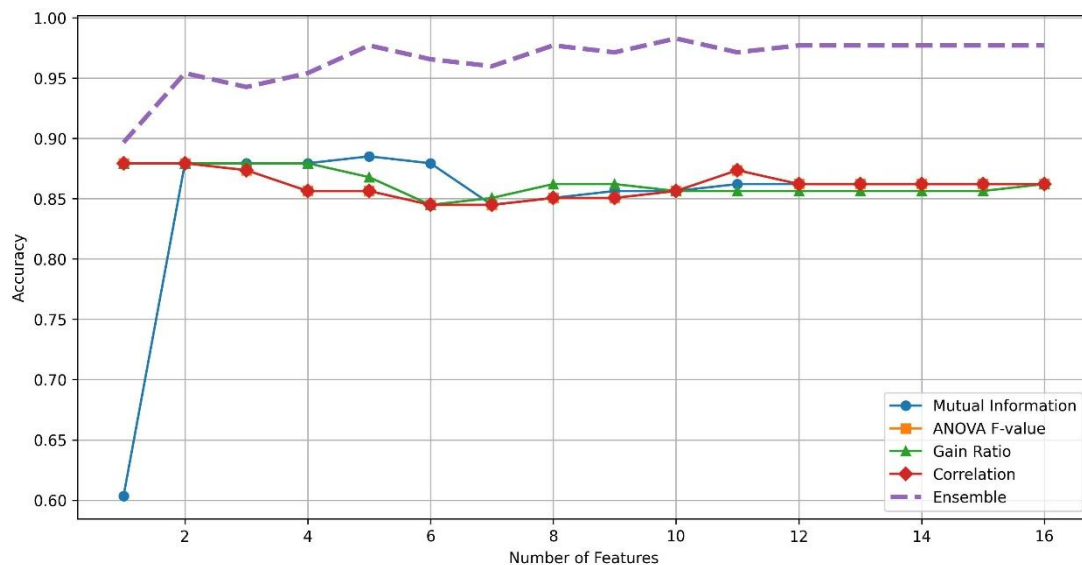


Figure 5.4. Accuracy of ML classifier by different features selection methods and EFFS *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

Figure 5.4 illustrates a trend where accuracy initially rises (88%) when features increase from 2 to 6. Hence, a minimal feature set is inadequate for recognizing the data complexity. Beyond this point, accuracy stabilizes at 86% across four selection methods. It also slightly decreases, suggesting an optimal subset of features that balances model complexity and performance.

Ensemble feature selection outperforms individual methods across all feature sizes. Initially, accuracy increases to 95%, and peaks around ten features. It maintains high accuracy (98%) across all subsequent feature sizes, implying redundant features in the original dataset contribute minimally or not at all to class identification. Therefore, EFFS emerges as a compelling approach for selecting an optimal feature set, maximizing classifier accuracy while maintaining computational efficiency. This efficiency is crucial for large-scale flood susceptibility assessments.

Table 5.3. Selected features by ensemble-based filter feature selection method

Filter method	Selected features
EFFS	Rainwater collectors, LULC, LST, Soil, River buffer, NDVI, Slope, NDWI, DEM, Aspect

Table 5.3 outlines the top 10 attributes identified by the EFFS method for their strong influence on flood susceptibility. These features will be the primary input variables in developing predictive models for future flood events, leading to more reliable maps that can better inform flood management strategies.

5.2.4. Explainability

SHAP explained the outcomes of the selected models in this study. The individual SHAP force plot shows interactions between variables in reaching the predicted target variable (Dikshit and Pradhan, 2021). Force plots (Figure 5.5) have three key characteristics: i) output value, the predicted value for an individual observation; ii) base value, the average prediction across the test dataset; and iii) colors, where red variables push the prediction higher and blue variables push it lower.

Figure 5.5 (a) shows flood susceptibility instance, where the model predicts a high flood probability of 0.73. Features like river buffer rainwater collectors, LST, DEM, and NDVI significantly pushing the prediction toward the flood. In another instance (Figure 5.5 (b)), the model predicts the maximum flood probability of 1.00. Features like river buffers, rainwater collectors, LST, and NDVI strongly influence the model towards predicting floods, indicating their critical role in the model's decision-making process. Soil contributes negatively but is overshadowed by the positive contributions.

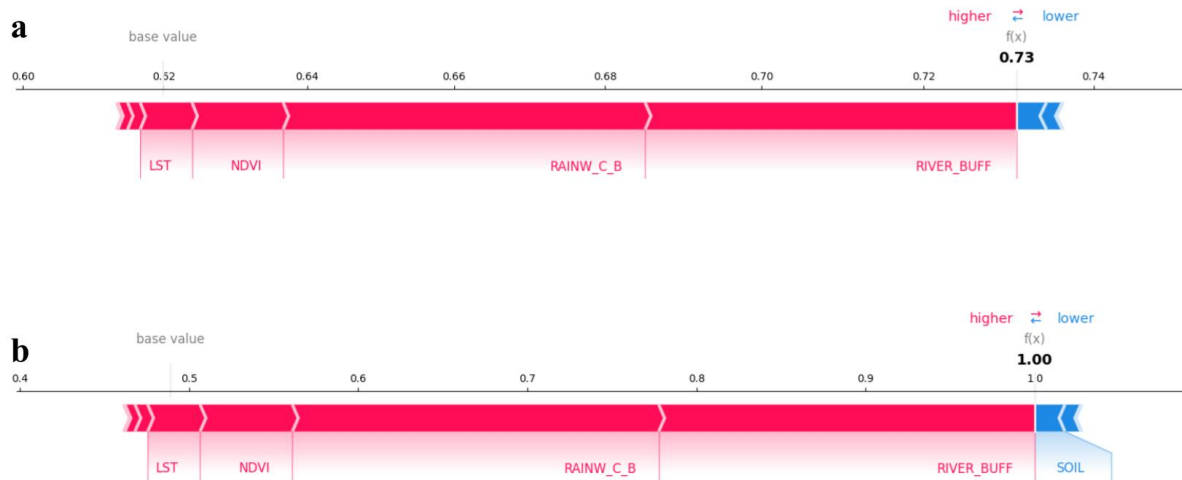


Figure 5.5. SHAP force plots for flood instances, showing key features contribution. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

In this instance (Figure 5.5 (a)), the model predicts a high flood probability of 0.73, implying a lower likelihood of non-flood. Features like LULC, rainwater collectors, LST, DEM, and NDVI contribute positively towards flood prediction (negatively towards non-flood prediction). The river buffer slightly increases the non-flood probability, but its impact is much less significant compared to the different features. In another instance (Figure 5.5 (b)), the model predicts a very high flood probability of 0.99, implying a very low likelihood of non-flood. Features such as rainwater collectors, LST, DEM, NDVI, and LULC firmly push the prediction toward flood (away from non-flood). Similar to plot (a), the negative contribution of the river buffer is minimal compared to the positive influences of the other features.

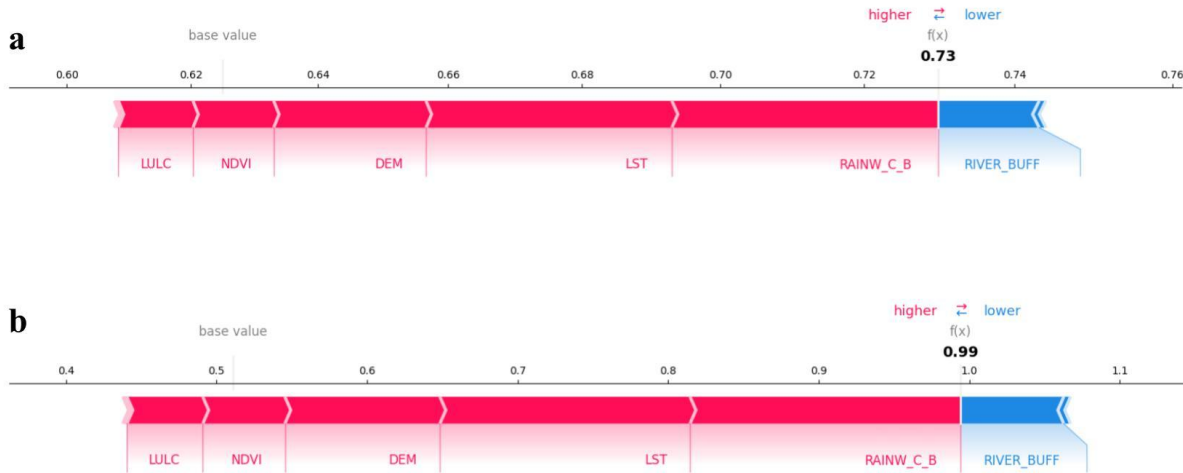


Figure 5.6. SHAP force plots for non-flood instances, showing key features contribution. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

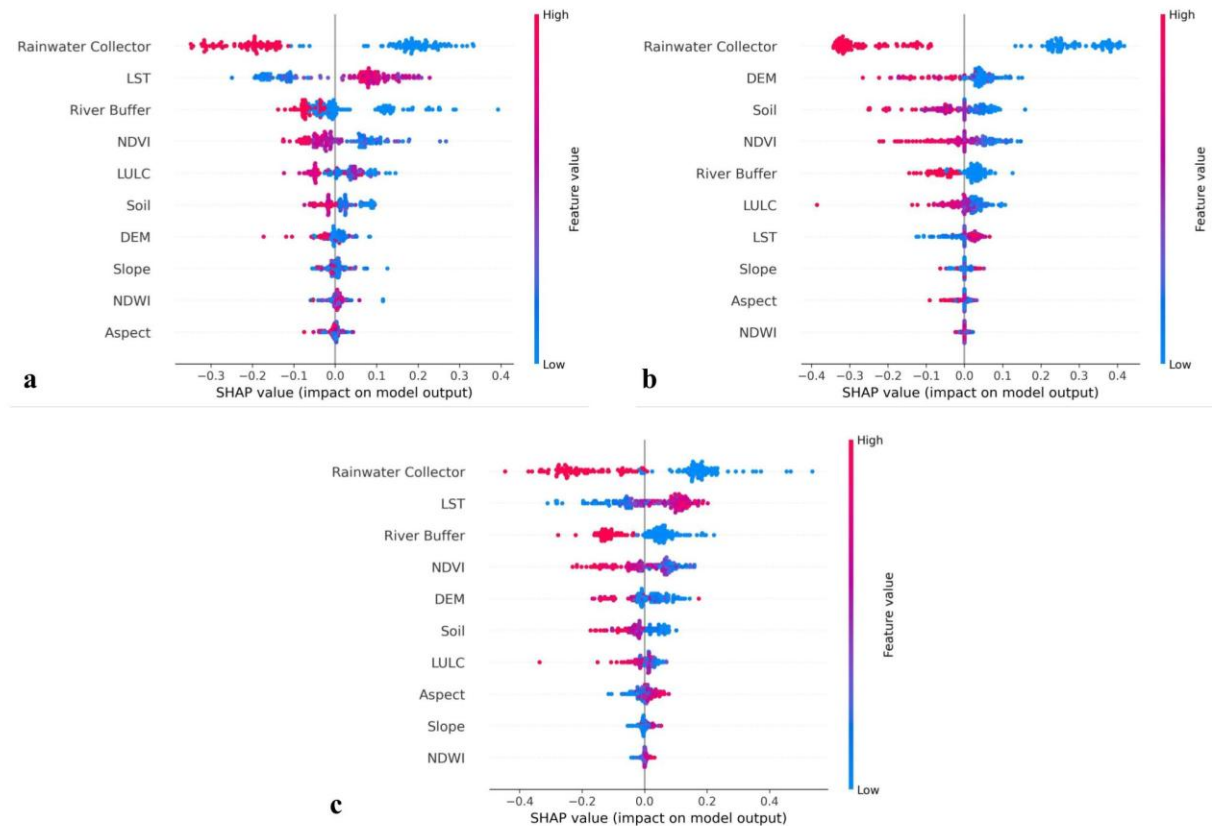


Figure 5.7. Explanation of models a) SVM, b) RF, and c) ANN using SHAP. A cluster of data around the SHAP value of zero indicates a small impact on model output. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

These interpretations underscore the varying influence of features across different instances,

highlighting the importance of rainwater collectors, LST, NDVI, and river buffers in flood prediction. Understanding these feature contributions can refine model performance and enhance interpretability in flood prediction systems.

Figure 5.7 shows SHAP summary plot values for flood factors, ranking their importance in the model prediction from most impactful at the top to least at the bottom. Each point on the plot represents the SHAP value, where its position on the X-axis indicates its impact on a model prediction. A SHAP value of zero means no impact, while values to the right or left suggest higher or lower impacts.

For a classification task, SHAP value > 0 increases the likelihood of a class, while SHAP value < 0 decreases the probability. Colors on the plot represent feature values, with cooler colors for lower values and warmer for higher values or binary class indications. The spread of points represents the variability of the feature's impact; a widespread suggests varied effects, while a narrow spread indicates a more consistent impact. Rainwater collectors, LST, DEM, soil, river buffer, and NDVI strongly impact model predictions, while other factors are mostly centered around zero or slightly positive to negative impact.

5.2.5. Performance of flood prediction

After training, the models were evaluated using statistical measures and ROC curves for training and testing data to assess model fit and generalization. Table 5.4 presents the results.

The RMSE and MAE values for the training datasets are 0.073, 0.016 for ANN, 0.260, 0.182 for RF, and 0.270, 0.133 for SVM, indicating the lowest errors for the ANN model. Similar results were observed for the testing data: ANN (RMSE: 0.168, MAE: 0.057), RF (RMSE: 0.252, MAE: 0.151), and SVM (RMSE: 0.330, MAE: 0.160). ANN achieved an accuracy of 0.992 for training and 0.965 for testing, correctly classifying 96% of pixels as flood and non-flood in the test dataset. RF followed with an accuracy of 0.903 and 0.913, and SVM with 0.905 and 0.862.

Table 5.4. Performance evaluation of models for training and testing datasets using statistical measures.

Methods	SVM Training	SVM Testing	RF Training	RF Testing	ANN Training	ANN Testing
RMSE	0.270	0.330	0.260	0.252	0.073	0.168
MAE	0.133	0.160	0.182	0.151	0.016	0.057
Accuracy	0.905	0.862	0.903	0.913	0.992	0.965
AUC	0.972	0.960	0.965	0.974	0.999	0.994
Sensitivity	0.907	0.892	0.855	0.964	0.989	0.988
Specificity	0.904	0.833	0.947	0.867	0.995	0.944

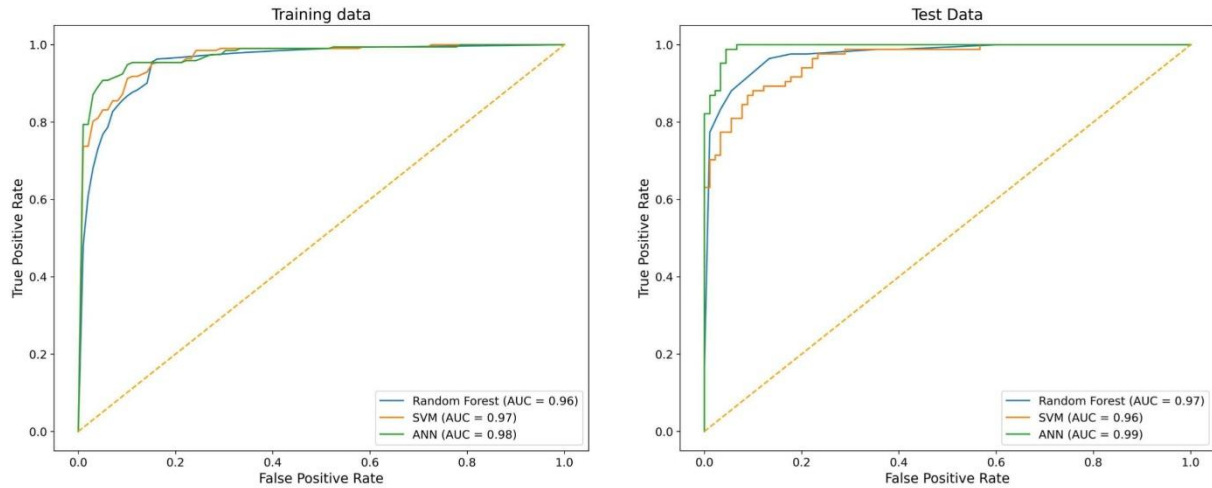


Figure 5.8. ROC curves for training and test datasets for SVM, RF, and ANN under best parameter configuration. Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.

The flood maps produced by the three models were validated using AUROC for training and testing datasets. The success rate curve for training data (Figure 5.8) shows the ANN model with the highest AUC (0.999), followed by SVM (AUC = 0.972) and RF (AUC = 0.965). The prediction rate curve for the validation dataset (Figure 5.8) showed similar results: ANN (AUC=0.994), RF (AUC = 0.974), and SVM (AUC = 0.960).

5.2.6. Flood susceptibility maps

Models were trained using hyperparameter tuning for optimal performance. The RBF kernel with a C value of 0.1 for SVM showed the best performance, with an RMSE of 0.270. Previous research also found the RBF kernel superior for flood susceptibility (Chen et al., 2020; Tehrany et al., 2015b). ANN was tested with various neurons and hidden layers, and the best configuration had four hidden layers, offering the highest accuracy and lowest RMSE (Table 5.4).

Table 5.5. Flood susceptibility classification by SVM, RF, and ANN models

Class	SVM (%)	RF (%)	ANN (%)
Very low	17.686	6.151	9.709
Low	22.197	18.764	18.659
Medium	8.013	17.624	10.886
High	10.302	27.652	24.144
Very High	41.803	29.810	36.601

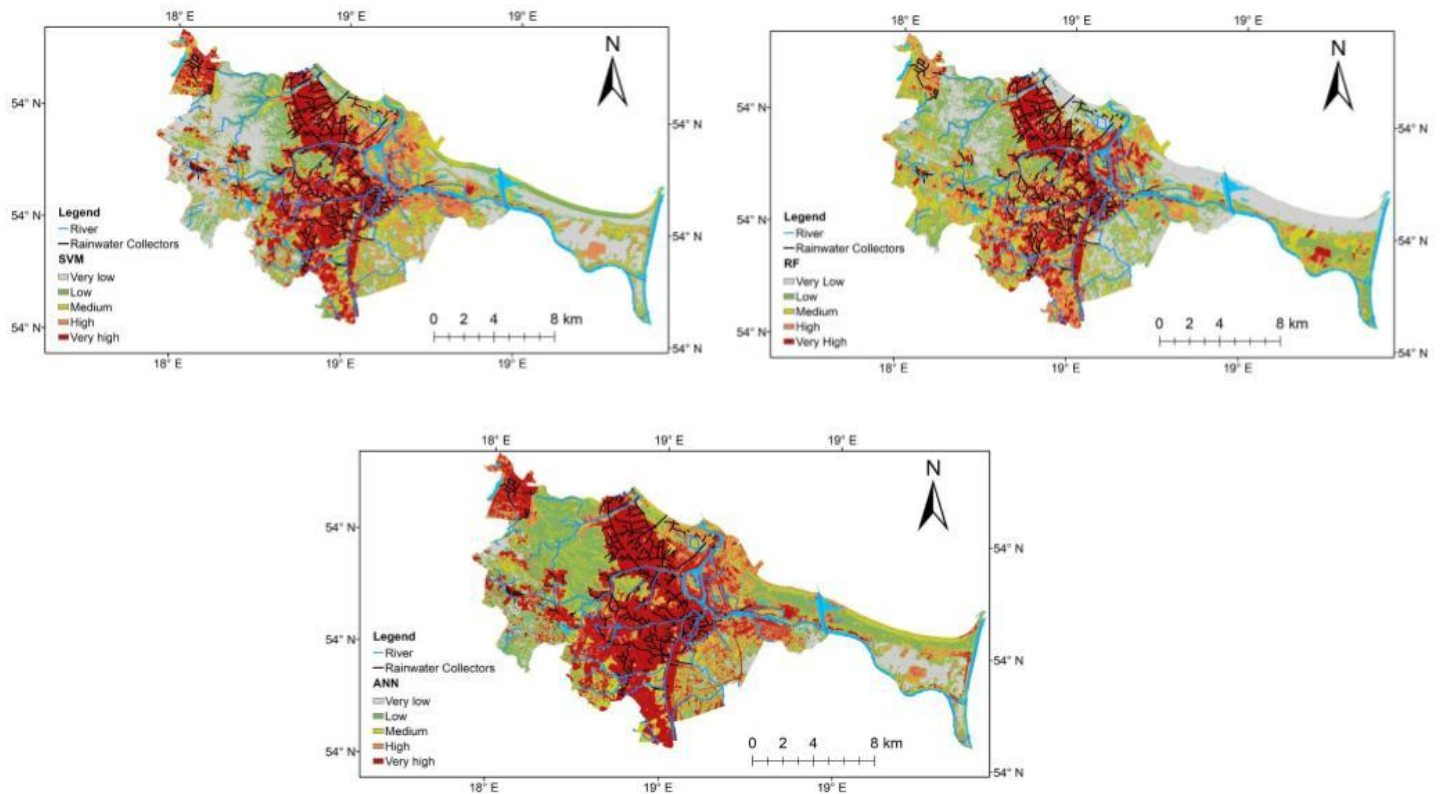


Figure 5.9. Flood susceptibility maps for SVM, RF, and ANN models. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

Each pixel in the flood susceptibility map is assigned a value between 0 and 1, indicating flood probability, with 0 meaning no probability and 1 meaning 100% probability (Tehrany et al., 2019). The probability values must be classified into various classes to create visually effective susceptibility maps. Quantile, natural breaks, equal intervals, and standard deviations can be used (Pham et al., 2017). In this study, the final maps were divided into five classes using quantile classification, ensuring each class contained an equal number of pixels.

Classifiers were categorized into five susceptibility levels: very low, (0.01-0.22), low (0.22-0.39), moderate (0.39-0.57), high (0.57-0.75), and very high (0.75-0.98). Table 5.5 shows the percentage of the area in each class for each classifier. The ANN model indicated that 36.601% of the region falls under very high susceptibility and 24.144% under high susceptibility, totaling 60.745% in the high susceptibility zone (Fig. 5.9). For RF, 29.810% is very high, and 27.652% is high, while for SVM, 41.803% of the area comes under the very high susceptible class, and 10.302% comes under the high class. Low and very low-risk areas together comprise 39.883% (SVM), 24.915% (RF), and 28.368% (ANN).

High and very high flood-susceptible regions are concentrated in the central and northwestern parts of Gdańsk, correlating with fire brigade interventions after heavy rainfall. Figure 5.10 shows flood distribution per district, with color intensity indicating the number of flood events. Wrzeszcz

Górny, Wrzeszcz Dolny, Osowa, Śródmieście, Oliwa, and Orunia recorded the most interventions. High-risk areas are near rainwater collectors and watercourses, especially near the edge zone and the lower terrace. Densely built and flat regions receive runoff from the upper terrace during heavy rainfall. The main areas vulnerable to flash floods in Gdańsk are divided into three regions: the moraine hills (upper terrace), subdivided into plateau and slopes; the polders; and Canal Radunia.

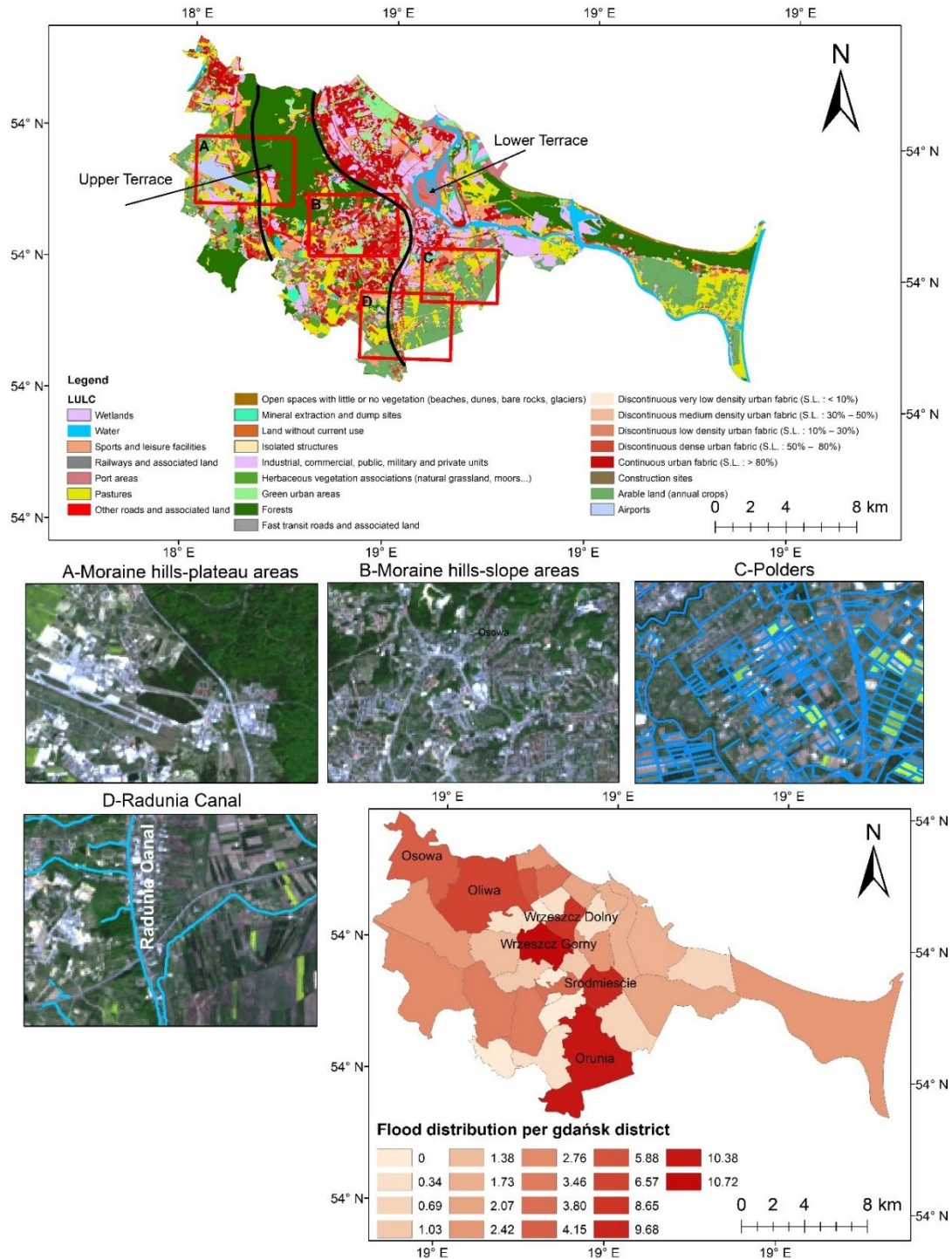


Figure 5.10. Flash flood susceptible areas in Gdańsk; Top map showing LULC with upper and lower terraces, the lower section features satellite images of specific areas (A-D), and a map indicating flood distribution across different districts, with color gradients representing the number of floods. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

5.3.Discussion

This chapter mapped urban flood susceptibility across Gdańsk using three machine learning classifiers, SVM, RF, and ANN, combined with ensemble feature selection and SHAP explainability. The results demonstrate that ANN outperforms the other classifiers across all evaluation metrics, that a ten-variable EFFS-selected subset captures the essential predictive information more effectively than individual feature selection methods, and that rainwater collectors, LST, DEM, soil, river buffer, and NDVI consistently emerge as the dominant susceptibility drivers. This section interprets these findings in four stages: first, by examining why these specific variables dominate and what their prominence reveals about Gdańsk's flood generation mechanisms; second, by contextualizing model performance against comparable studies in the literature; third, by interpreting the spatial patterns of susceptibility across the city's three structurally distinct vulnerability zones and their implications for urban planning; and fourth, by establishing how these findings connect to and validate the analytical stages preceding and following this chapter within the integrated GeoAI framework. The section concludes by acknowledging the principal limitations of the analysis and their implications for interpreting and transferring the results.

5.3.1. Interpretation of dominant flood drivers

The EFFS and SHAP analyses converge on a consistent set of dominant flood susceptibility drivers, rainwater collectors, LST, DEM, soil, river buffer, and NDVI, whose prominence reflects the specific hydrological character of Gdańsk rather than generic flood conditioning factors.

Rainwater collectors emerge as the single most influential predictor across all SHAP configurations. This finding reflects Gdańsk's structural flood vulnerability: the city's stormwater network was designed against pre-2000 rainfall distributions, and during heavy precipitation events, collectors in low-lying areas must simultaneously manage runoff from upstream basins while resisting backflow from rising sea levels, which reduces hydraulic gradient and therefore drainage capacity. When rainfall surpasses collector capacity, overflow causes localized flooding in precisely the areas where collector density is highest, a counterintuitive spatial pattern that the SHAP analysis captures but that conventional distance-based susceptibility variables would miss. This finding has direct planning implications: collector proximity is not merely a passive indicator of drainage infrastructure but an active proxy for the threshold exceedance dynamics that drive Gdańsk's most damaging flood episodes.

LST ranks consistently among the top SHAP drivers across all three models, a finding that extends beyond its direct physical role in flood generation. High LST in Gdańsk is spatially concentrated in continuous urban fabric, industrial clusters, and agricultural land in the eastern and southwestern districts, precisely the areas with greatest imperviousness and lowest vegetation cover. LST therefore functions as a compound proxy variable integrating surface sealing, heat retention, and reduced evapotranspiration, all of which amplify runoff generation (Chakraborty et al., 2021). Its prominence in the susceptibility model corroborates the hydrological analysis of Chapter 4, where

the imperviousness-driven runoff amplification mechanism was identified as the primary driver of basin-scale flood risk, the SHAP result provides spatially explicit, data-driven confirmation of the same process at city scale.

DEM's influence reflects Gdańsk's multilateral topographic structure. Lower terraces, including the coastal belt and polder areas of Żuławy Gdańskie, sit partly below sea level and face compound flood exposure from both surface runoff and coastal inundation (Staudt et al., 2006b). The skewed distribution of historical flood locations toward lower elevations confirms that topographic position is a fundamental determinant of flood exposure, consistent with findings across multiple regional contexts (Mahdizadeh Gharakhanlou and Perez, 2022; Tehrany et al., 2019; Yaseen et al., 2022). The edge zone between upper and lower terraces represents a particularly critical transition area where runoff accelerates from gentle plateau slopes into densely built lower districts, concentrating discharge at points where the drainage network is already under stress.

Slope's role operates through two distinct mechanisms. In the moraine hill areas of southwest Gdańsk, steep slopes hinder infiltration and accelerate runoff into downstream networks (Mahdizadeh Gharakhanlou and Perez, 2022), while in the low-lying polder areas, near-zero slopes restrict gravitational drainage and promote waterlogging. The wide distribution of slope values at historical flood locations, skewed toward lower values but with a long tail toward higher values, reflects this dual mechanism and explains why slope, while a significant predictor, is not the dominant one: its effect varies fundamentally by terrain zone in ways that the unified susceptibility model partially conflates.

NDVI's contribution reflects the well-established role of vegetation in moderating infiltration, reducing soil erosion, and increasing water retention capacity (Yaseen et al., 2022). In Gdańsk's context, low NDVI values correspond to the densely built central and northern districts where impervious cover is greatest and green infrastructure is most sparse. The bell-shaped NDVI distribution centered around 0.2 at historical flood locations indicates moderate vegetation cover in most affected areas, reflecting the mixed urban-green character of Gdańsk's flood-exposed neighborhoods rather than uniformly bare or uniformly vegetated terrain.

The river buffer variable exhibits a bimodal distribution at historical flood locations, with peaks at both low and high distances from river channels. This pattern indicates two distinct flood generation mechanisms operating in Gdańsk: proximal flooding driven by river overflow and channel capacity exceedance during intense precipitation, and distal flooding driven by surface runoff accumulation in low-lying areas far from channels but poorly connected to drainage networks. The prominence of this variable in SHAP analysis corroborates findings from comparable urban flood susceptibility studies (Mahdizadeh Gharakhanlou and Perez, 2022; Tehrany et al., 2019, 2015b), where river network proximity consistently ranks among the top predictors.

Soil and LULC contribute through their combined influence on infiltration capacity and surface runoff generation. Multiple soil type peaks at flood locations, ranging from sandy and sandy gravel

to alluvial soils on lower terraces, reflect the spatial heterogeneity of Gdańsk's subsurface conditions, with alluvial soils in polder areas offering particularly limited storage capacity. LULC's peaks at continuous urban fabric, road networks, and industrial and commercial land confirm that land use type is a critical determinant of flood dynamics (Habibi et al., 2023), with impervious surfaces generating overland flow even under moderate rainfall intensities. The positive correlation between LULC and LST visible in the spatial data reinforces that urban expansion and heat stress are spatially co-located and jointly amplify flood susceptibility.

Features with broader value ranges, LST, NDVI, soil, and LULC, provide more discriminative information for predictive modelling than slope and DEM, whose values at historical flood zones remain relatively consistent over time. This reflects the temporal dynamics of Gdańsk's flood risk: topographic structure is fixed, but LST, NDVI, and LULC change as the city develops, meaning the variables that drive future changes in susceptibility are precisely those that reflect ongoing urban transformation rather than static terrain characteristics.

5.3.2. Model performance and comparative assessment

The ANN model achieved superior performance across all evaluation metrics. This hierarchy is consistent with findings from comparable urban flood susceptibility studies (Islam et al., 2021b; Rahman et al., 2019; Tehrany et al., 2019, 2015b; Yaseen et al., 2022). ANN's advantage reflects its capacity to model complex non-linear and multivariate relationships among conditioning factors (Gulshad et al., 2022), which is particularly relevant in Gdańsk where the three topographically distinct flood zones generate fundamentally different variable interaction patterns. RF's strong performance, competitive with ANN on test accuracy, reflects its robustness to overfitting through ensemble averaging (Breiman, 2001), while SVM's lower test accuracy relative to training accuracy suggests slightly greater sensitivity to the spatial autocorrelation patterns in the conditioning variable dataset.

The RBF kernel configuration for SVM is consistent with prior flood susceptibility research demonstrating the RBF kernel's superiority for non-linearly separable environmental data (Chen et al., 2020; Tehrany et al., 2015b; Yaseen et al., 2022). The ANN configuration of four hidden layers with the lowest RMSE reflects the complexity of the feature interaction space, shallower networks underfit the multi-zone topographic variability while deeper networks risk overfitting to the spatially clustered training sample.

The EDFS method's demonstrated superiority over individual feature selection approaches maintained across all feature sizes beyond ten features compared to peak accuracies for individual methods, confirms the value of ensemble approaches in reducing selection bias. This finding aligns with ensemble feature selection literature in cloud computing and human activity recognition (Osanaiye et al., 2016; Tian et al., 2020), and extends it to the flood susceptibility domain where, to the author's knowledge, EDFS had not previously been applied. The stability of EDFS accuracy beyond ten features also confirms that the original sixteen-variable dataset contained redundant

predictors, and that a ten-variable subset captures the essential information while maintaining computational efficiency for large-scale urban flood assessment.

Recent studies have demonstrated that explainable models significantly enhance understanding of model outcomes and stakeholder acceptance (Aydin and Iban, 2023; Dikshit and Pradhan, 2021; Kim and Kim, 2022; Pradhan et al., 2023). The SHAP results validate the ANN model by confirming that its most influential features, elevation, slope, river network proximity, and land cover, align with established flood risk factors identified across independent studies (Mahdizadeh Gharakhanlou and Perez, 2022; Tehrany et al., 2019; Yaseen et al., 2022), providing confidence that the model's high accuracy reflects genuine learning of flood-generating processes rather than overfitting to spatially biased training samples.

5.3.3. Spatial patterns of flood susceptibility and urban policy and planning implications

The ANN model identifies 60.7% of Gdańsk's area as falling within high or very high susceptibility classes, with spatial concentration in the central and northwestern districts. The analysis reveals three structurally distinct vulnerability zones whose flood generation mechanisms differ fundamentally and require different management responses.

The moraine hill slopes in southwest Gdańsk are increasingly urbanized and prone to flash floods due to steep terrain, heavy rainfall, and accelerating imperviousness. Unlike low-lying areas, these zones are not vulnerable to storm surges but face rapid runoff generation that overwhelms the capacity of old combined sewage systems and directs concentrated discharge into channels like Canal Radunia (Walczykiewicz and Skonieczna, 2020b). Retention basins are crucial in reducing peak flows from these slopes (Cieśliński et al., 2024b), and while many have been constructed with more planned on the plateau, rising land costs in this area diminish the cost-effectiveness of purely infrastructural solutions, a finding that reinforces the case for supplementary nature-based retention at source. The plateau component of the moraine hills is comparatively less urbanized with gentler slopes and slower runoff, but increased urban expansion poses a future threat by raising peak flow beyond existing retention basin capacity. Gdańsk has implemented strict development regulations in this zone (Cieśliński et al., 2024b), though enforcement varies by sub-region.

The polder areas southeast of the city were initially designed for agriculture with controlled water level regulation and have sufficient buffering capacity to manage short, intense rainfall without significant impact under current conditions. Although flooding occurred in 2001 when Canal Radunia's capacity was exceeded, the polder drainage system generally handles water flow effectively. However, accommodating increased runoff from any future urbanization in these areas would require enhancing drainage and pumping infrastructure (Kuiper Compagnons, 2015).

Canal Radunia, an artificial channel dating to the Middle Ages, designed to drain the polder and supply water to Gdańsk, receives discharge from small natural streams in the moraine hills and has

a maximum design capacity of 20 m³/s. During the 2001 flash flood, the canal was overwhelmed by a combined discharge of approximately 100 m³/s from streams, stormwater, and overland flow, resulting in breaches at five locations and extensive flooding east of the channel (Kuiper Compagnons, 2015b; Majewski, 2016a). This event represents the clearest empirical evidence of the drainage capacity exceedance that the susceptibility model quantifies probabilistically across the city and establishes why rainwater collectors and river buffer proximity emerge as the model's dominant predictors.

High and very high susceptibility concentrates in districts including Wrzeszcz Górny, Wrzeszcz Dolny, Osowa, Śródmieście, Oliwa, and Orunia, which record the greatest correspondence with historical fire brigade interventions (IMGW-PIB, 2022). These central and lower-terrace districts receive concentrated runoff from the upper terrace during heavy rainfall, and their densely built fabric combined with flat topography limits the gravitational drainage gradient available to remove accumulated water. The Historic Centre of Gdańsk, located in this lower terrace area, is also prone to flooding (Gdańskie Wody, 2024), suggesting that rainwater collectors and watercourses structurally struggle to manage extreme runoff under the rainfall intensities now projected under both RCP pathways established in Chapter 4. The elevated sea level risk adds a further dimension to Gdańsk's compound flood exposure. Rising sea levels endanger coastal beaches and nearby aquifers, and if flash floods coincide with storm surges, the city faces combined pluvial-coastal inundation scenarios for which current drainage design criteria were not developed. Evaluating the resilience of existing design standards to projected climate change trajectories is therefore an urgent research and policy priority.

Gdańsk has developed a comprehensive institutional response to its compound flood exposure. A three-stage rainwater management strategy, encompassing on-site water management, municipal stormwater systems, and retention reservoir operation, provides the current operational framework for managing pluvial flood risk (Szydłowski et al., 2023b). On the moraine hill plateau, strict development regulations have been implemented to pause some expansion plans, though enforcement varies by sub-region (Cieśliński et al., 2024b). New developments across the city are required to retain up to 30mm of rainwater on-site, representing a source-control approach that directly addresses the imperviousness-driven runoff amplification documented in this chapter. Community engagement through social platforms, the Citizens' Panel, and the Gdańsk Climate Change Forum has also sought to build public understanding of pluvial flood risk and co-produce adaptation responses (Szydłowski et al., 2023b). While these measures represent meaningful institutional progress, the susceptibility mapping results presented here suggest that spatially targeted, data-driven prioritization of the kind developed in the subsequent chapters of this thesis, is necessary to ensure that infrastructure investment and GI deployment are directed toward the highest-risk zones rather than distributed uniformly or opportunistically.

5.3.4. Cross-chapter validation and framework implications

The dominance of LST and rainwater collectors as SHAP drivers independently corroborates the imperviousness-driven runoff amplification mechanism established in **Chapter 4**, where the urban heat-imperviousness feedback was identified as the primary driver of basin-scale flood risk increases between 1985 and 2022. That these variables emerge from a data-driven ML analysis, without reference to the hydrological model, using a different dataset, at a different spatial resolution, and converge on the same underlying process constitutes a cross-methodological validation of the framework's diagnostic logic. The convergence is not coincidental: it reflects a genuine spatial structure in Gdańsk's flood risk that is recoverable through multiple independent analytical approaches, which is precisely what a robust GeoAI framework requires.

This cross-chapter validation extends forward to **Chapter 6**. The SHAP-identified drivers, LST, impervious surface as reflected in LULC and rainwater collector proximity, and low NDVI, reappear in the spatial econometric analysis of green infrastructure distribution as the dominant constraints on GI presence. The districts identified here as highest flood susceptibility zones, Wrzeszcz Dolny, Letnica, Nowy Port, Orunia, are the same districts that **Chapter 6** identifies as most GI-deficient and most environmentally stressed. This variable-level continuity across two methodologically independent analyses is the framework's strongest cross-chapter validation point and provides the spatial foundation for the targeted NBS planning in **Chapter 7**.

5.3.5. Limitations

A recognized limitation of the flood susceptibility analysis concerns the use of a single unified model across Gdańsk's spatially varied topography. The city faces three structurally distinct flood hazard types, surface runoff from moraine hills, river outflow during intense precipitation, and coastal inundation driven by sea-level rise, each governed by different physical processes. A single model applied across this heterogeneity risks conflating flash flood susceptibility in upland areas with inundation susceptibility in lowland polders, potentially misattributing the importance of terrain and drainage variables across zones where their effects operate through fundamentally different mechanisms. Future research should develop separate susceptibility models tailored to each hazard type, particularly as sea-level rise scenarios become increasingly relevant for Gdańsk's eastern and coastal districts under the RCP 8.5 pathway projected in Chapter 4.

A second limitation concerns the training data. The flood inventory was compiled from historical fire brigade intervention records, which may underrepresent localized flooding events that were either unreported or resolved without emergency response, introducing a systematic bias toward more severe and publicly visible flood episodes. This bias is most likely to affect the model's performance in peripheral residential areas with lower reporting rates, where actual susceptibility may be higher than the model estimates. Future research should supplement fire brigade records with insurance claims data, citizen-reported flood observations, and remote sensing-derived inundation extents to produce a more complete and spatially balanced training dataset.

5.4. Conclusion

Flood susceptibility mapping in Gdańsk, Poland, employing SVM, RF, and ANN models, ensemble-based filter feature selection, and explainability techniques, has provided valuable insights into flood susceptibility.

Ensemble feature selection identified critical factors influencing flood susceptibility in Gdańsk, including LULC, proximity to rainwater collectors, LST, river buffer zones, soil composition, and NDVI. These factors were consistently highlighted across multiple feature selection methods as pivotal in predicting flood-prone areas.

The predictive performance of the SVM, RF, and ANN models was evaluated using AUC, with the ANN model demonstrating superior performance (AUC 0.992) compared to RF (AUC 0.965) and SVM (AUC 0.905), underscoring the efficacy of machine learning approaches in accurately delineating flood susceptibility zones in Gdańsk.

To tackle the issue of model interpretability, SHAP clarified the impact of specific features on model predictions. This approach improves transparency by providing insights into how particular factors (rainwater collectors, LST, NDVI, River buffer) contribute to flood risk assessments and facilitating informed decision-making in flood mitigation strategies.

Future research should focus on creating separate prediction models that consider risks associated with sea level rise and climate change.

Urban planners, policymakers, and disaster management authorities can prioritize interventions and distribute resources effectively using practical insights from this study. Using machine learning techniques and geospatial data, stakeholders can anticipate flood risks and improve community resilience.

The flood susceptibility maps produced in this **Chapter 5** reveal a clear spatial grammar of urban flood risk in Gdańsk: high-susceptibility zones cluster systematically in low-lying, densely impervious, poorly drained neighborhoods where LST is elevated and vegetation cover is minimal. These are precisely the conditions under which nature-based solutions would deliver the greatest hydrological and thermal co-benefits. Yet susceptibility mapping alone cannot determine whether the city's existing green infrastructure is positioned to intercept this risk. A high-susceptibility neighborhood that already contains abundant green infrastructure presents a different planning challenge than one that is both flood-prone and green infrastructure-deficient and it is the latter condition, the spatial coincidence of flood exposure and green infrastructure absence, that represents the most urgent intervention priority. Whether such coincidence is systematic or incidental, and whether it correlates with socio-demographic vulnerability, cannot be answered from susceptibility maps alone. **Chapter 6** addresses this directly by shifting the analytical focus from where flood risk concentrates to where green infrastructure exists, how it is distributed across the city, and what structural factors, physical, socio-economic, and environmental explain the inequalities in that distribution.

Chapter 6

Spatial Distribution and Determinants of Green Infrastructure

6. Introduction

The flood susceptibility analysis in **Chapter 5** established that Gdańsk's highest-risk zones are characterized by elevated land surface temperature, minimal vegetation cover, and proximity to overwhelmed drainage infrastructure, a constellation of conditions that green infrastructure is specifically designed to address through stormwater retention, evapotranspiration cooling, and surface runoff interception. Yet the capacity of green infrastructure to mitigate these conditions depends entirely on where it is located relative to where the risk concentrates. If green infrastructure follows the spatial logic of urban development, accumulating in affluent, low-density, already-green neighborhoods while remaining absent from dense, impervious, flood-exposed areas, then its citywide distribution may be systematically misaligned with the very problem it is meant to solve. This **Chapter 6** examines that alignment directly by assessing the spatial distribution and determinants of existing green infrastructure across Gdańsk at 1 km² grid resolution, using a multi-indicator framework that integrates bio-physical constraints, built environment characteristics, socio-demographic factors, and environmental stressors. Spatial lag and spatial error models are applied to identify which structural factors most strongly predict green infrastructure presence and density, and bivariate spatial analysis is used to detect grid cells where high flood susceptibility and low green infrastructure coverage co-occur, the environmental justice hotspots that **Chapter 7** will target with a GeoAI-based suitability framework for nature-based solution deployment.

6.1. Methodology

The methodology adopted in this study is shown in Fig. 6.1. It encompasses five steps: (i) Input data: input data from multiple sources was downloaded, (ii) Data preprocessing: all data was standardized to 1km grid, then it was normalized, and multicollinearity was calculated using correlation and VIF (iii) Spatial analysis: spatial autocorrelation was calculated using Moran I analysis, (iv) Regression models: a sequence of global and spatial regression models were implemented.

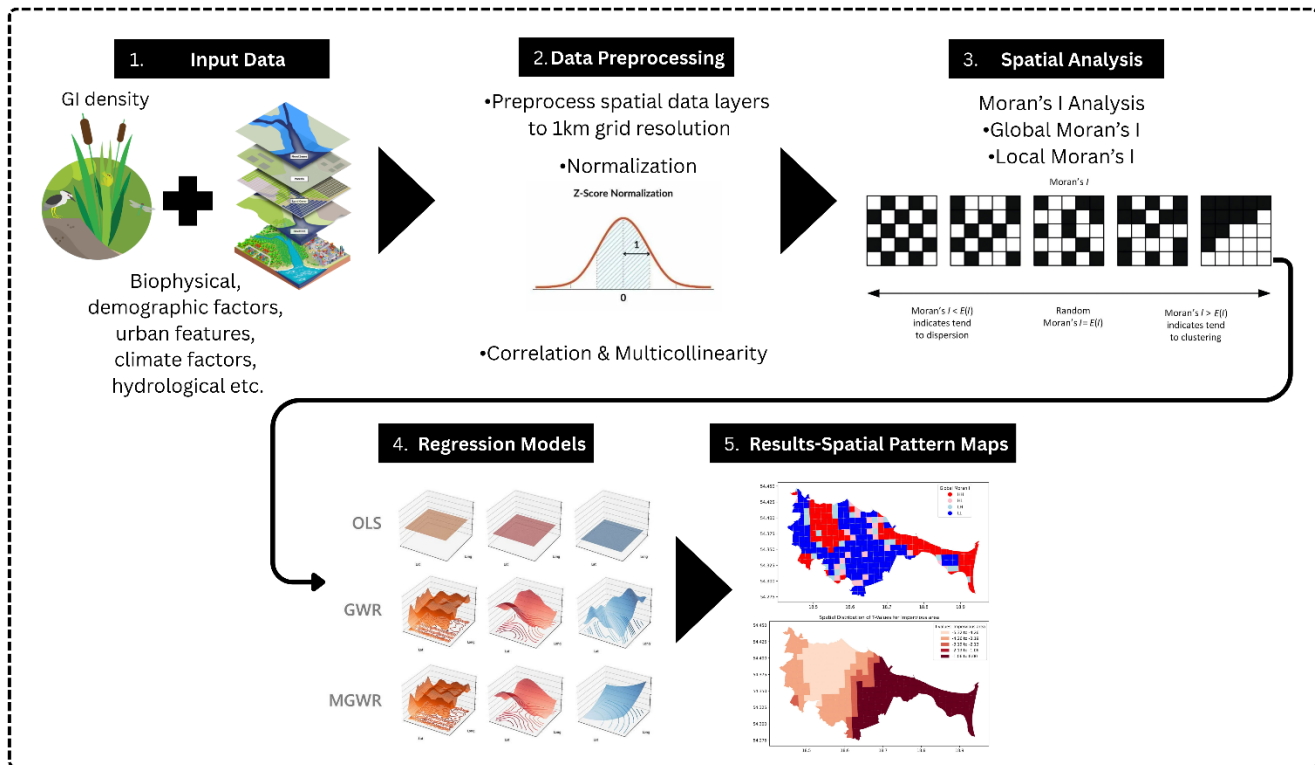


Figure 6.1. Methodological framework for assessing existing GI pattern in Gdańsk. *Reproduced from authors published work (Gulshad and Szydlowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.*

6.1.1. Constraints versus indicators for GI Implementation

In the first stage of methodology, biophysical and socio-demographic factors (Table 3.1) were selected based on their relevance to GI distribution in Gdańsk. Some factors act as constraints, limiting the GI implementation due to urbanization, infrastructure, or other physical barriers. Others serve as indicators, highlighting the need for GI in areas facing environmental stressors such as air pollution, heat islands, or flood risk.

6.1.2. Data preprocessing

In the second stage of methodology, a regular 1 km grid was generated covering the administrative extent of Gdańsk. This grid resolution was selected as a compromise between data availability and statistical requirements. Several predictors (air pollutants, climate projections) are only available at 500 m-5 km resolution, so using cells finer than 1 km would not introduce additional independent information but would increase spatial autocorrelation. At the same time, the 1 km grid provides many more analysis units ($N = 342$ cells) than district-level aggregation ($N = 35$ districts), improving statistical power for multivariate and spatial regression. Administrative districts as units were not considered because they vary greatly in size and land-cover composition, which would exacerbate the modifiable areal unit problem (MAUP). While small GI features such

as pocket parks are partially generalized at this scale, the 1 km grid preserves the dominant contrasts between forest complexes, industrial corridors, and dense urban districts that are relevant for identifying city-wide spatial disparities that inform strategic planning priorities.

For regression analysis, all green infrastructure classes (forests, wetlands, parks, cemeteries, allotments, etc., (Appendix B, figure B1, table B1)) (European Union's Copernicus Land Monitoring Service, 2021; Fikus-Wójcik et al., 2023; Geoportal.pl, 2021) were aggregated into a composite GI variable representing total green infrastructure per 1 km grid cell to enable robust statistical modeling. This structural aggregation aligns with prior spatial econometric studies of GI distribution (e.g., in Baltimore, Maryland and Portland, Oregon; in Phoenix, Atlanta, and Portland; Washington D.C (Baker et al., 2019b; Pallathadka et al., 2022b; Vogel, 2019)), where the objective is to model spatial patterns of overall GI provision rather than differentiate ecosystem service performance by type. Hence, all GI polygons, regardless of size, were intersected with the 1 km grid. All GI polygons were merged into a single composite layer and GI density per grid was calculated as the proportion of area of GI features within a grid by the area of the grid (Baker et al., 2019b; Pallathadka et al., 2022b):

$$GI_density_i = \frac{area_GI_i}{area_grid} \quad 6.1$$

Consequently, small GI elements contribute proportionally to grid-level density values. While very small or isolated green patches may have limited influence on this strategic scale, the approach ensures that cumulative GI provision is fully represented across the city. The resulting GI density (continuous 0-1) within each grid served as the dependent variable for all spatial analyses.

All factors (e.g., LST, impervious surfaces, NO₂ emissions, precipitation) were standardized to a 1 km × 1 km grid cells, served as independent factors and exported for further processing. All statistical and spatial modeling was performed in Google Colab. Independent variables were normalized using z-score method. Multicollinearity was assessed using Pearson correlation and variance inflation factors (VIF) to eliminate noise and redundancy. The refined variables were analyzed using multiple regression models.

6.1.3. Spatial autocorrelation

In the third stage of methodology, spatial autocorrelation was performed to assess whether GI density values are spatially clustered, dispersed, or randomly distributed (Pan et al., 2021). For this purpose, both Global and local Moran I were implemented for GI density at a grid-scale using Python libraries. Global Moran measured overall spatial pattern of GI density in Gdańsk (Rodriguez et al., 2021) and is defined by equation 1. Values range from +1 (strong spatial clustering) to 0 (randomness) and -1 (strong dispersion) (Anselin, 2019).

$$I = \frac{N}{w_o} \cdot \frac{\sum_{i=1}^N \sum_{j=1, j \neq i}^N w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2} \quad 6.2$$

where N is the number of spatial units, x_i and x_j are GI density values at locations i, j , $\bar{x}$ is the mean GI density, and w_{ij} is the spatial weight. The total weight w_0 is given by:

$$w_0 = \sum_{i=1}^N \sum_{j=1}^N w(i, j) \quad 6.3$$

Local Moran's I, LISA, identified spatial clusters (High-High, Low-Low) and outliers (High-Low, Low-High), capturing localized spatial heterogeneity of GI density in Gdańsk (Anselin, 1995). It is calculated as:

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1}^N w_{ij} (x_j - \bar{x}) \quad 6.4$$

where I_i is the Local Moran's I for location i , S_i^2 is the variance of x , given by:

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^N x_j^2}{N - 1} - \bar{x}^2 \quad 6.5$$

To assess sensitivity to neighborhood structure, five spatial weights matrices (Adaptive KNN, Fixed KNN, Queen Contiguity, Rook Contiguity, Distance Band) were tested to determine the best fit for GI density patterns. Resulting maps highlight high and low-density clusters across space. However, Moran I does not explain whether the pattern is due to spatial dependence (lag) or spatially correlated residuals (error). Hence, regression analysis is required to further interpret the underlying spatial processes.

6.1.4. Multiple regression models

In the fourth stage of methodology, to model the relationship between GI density and explanatory factors, a sequence of global and spatial regression models was implemented in Google Colab. The modelling pipeline consisted of: Ordinary least squares (OLS), weighted least squares (WLS), generalized least squares (GLS), spatial lag model (SLM), spatial error model (SEM), and geographically weighted regression (GWR) models. All models used the 1 km grid GI density as the dependent variable.

OLS served as a baseline global model, assuming no spatial dependence in residuals (Pan et al., 2021). However, Moran's I test on residuals revealed spatial autocorrelation, necessitating spatial regression. Residual diagnostics indicated violation of OLS assumptions. Significant heteroscedasticity motivated WLS and GLS estimation. Spatial dependence was subsequently diagnosed using Lagrange Multiplier tests, which indicated that both SLM and SEM were suitable.

SLM and SEM were estimated using multiple spatial weight matrices. The SLM (equation 6.6) accounts for spatial dependence on the dependent variable (GI density):

$$Y = \rho WY + \alpha I_N + X\beta + \epsilon \quad 6.6$$

SEM (equation 6.7) corrects spatial dependencies in residuals:

$$Y = \alpha I_N + X\beta + u, \text{ with } u = \lambda Wu + \epsilon \quad 6.7$$

Y represents GI density. $X\beta$ represents independent variables (LST, impervious area, etc.), I_N is the identity matrix, W is the spatial weights matrix, ρ and λ is capture spatial lag and error dependence (Badetiya and Barale, 2024).

GWR was implemented to address spatial heterogeneity, allowing model coefficients to vary across space rather than assuming uniform relationships (Brunsdon et al., 1998) (equation 6.8). An adaptive bi-square kernel was used, and bandwidth was selected via cross-validation.

$$y_i = \beta_0(u_i, v_i) + \sum_k^p \beta_k(u_i, v_i)x_{ik} + \epsilon_i \quad 6.8$$

where y_i is GI density at location i , $\beta_0(u_i, v_i)$ are location specific coefficients, $\beta_k(u_i, v_i)x_{ik}$ represents the local slope parameter, x_{ik} are the independent variables, (u_i, v_i) are the spatial coordinates. ϵ_i is the error term (Badetiya and Barale, 2024; Brunsdon et al., 1998). The weight function for GWR is given by equation 6.9:

$$w(d_{ii'}) = \exp \left(-\frac{1}{2} \left(\frac{d_{ii'}}{h_i(k)} \right)^2 \right) \quad 6.9$$

where $w(d_{ii'})$ is the weight based on its distance between location i and i' , $h_i(k)$ is the adaptive bandwidth defined by the number of k^{th} nearest neighbors (Badetiya and Barale, 2024; Brunsdon et al., 1998).

To identify the most suitable spatial configuration, five spatial weight matrices (Adaptive KNN, Fixed KNN, Queen, Rook, and Distance Band) were tested. Model performance was evaluated using metrics (pseudo R^2 , AIC, BIC Log-Likelihood) and spatial dependence indicators (ρ for SLM, λ for SEM). Local statistical significance was evaluated using the adjusted critical t-value provided by the MGWR procedure ($|t| \geq 2.579$ at 95% confidence). Unlike the conventional ± 1.96 threshold used in global regression, GWR applies a multiple testing correction to account for the large number of local coefficient estimates. This adjustment reduces the risk of inflated Type I error arising from spatially varying parameter estimation. Resulting coefficient and t-values maps

were created using Python 3.11 matplotlib library. Detailed model output and diagnostic summaries are provided in Appendix B.

6.1.5. GI priority areas

To enhance the practical relevance of the grid-based analysis, a priority map (detailed method in Appendix B, note B1 (Derivation GI priority map) was derived. For this purpose, GI density map and environmental stress indicators (LST, impervious surface, NO₂, flood occurrence) maps were selected. Priority cells were identified where GI density values were below the 25th percentile and were classified as “low GI supply”. Environmental stress indicators above the 75th percentile were classified as “high stress”. To avoid subjective weighting and ensure comparability across variables with different units and distributions, a percentile-based thresholding approach was applied. Cells exhibiting low GI density and at least two concurrent stress indicators were classified as high-priority areas.

6.2. Results

6.2.1. Spatial distribution of biophysical, socio-demographic factors

LST: The highest mean temperatures, ranging from 22.62 °C to 23.46 °C (Append B Fig. B2) are primarily concentrated in the central and northern parts (Przymorze Małe, Wrzeszcz Dolny, Letnica, and Młodeo Miasto) of the city which also have been identified as priority areas in Gdańsk Greenery Policy with temperature being one of the key factors influencing this designation (Fikus-Wójcik et al., 2023). These regions are likely to experience higher average temperatures due to dense urbanization, impervious surfaces, and lower levels of GI.

DEM: The mean elevation ranges from below sea level (-0.41) (eastern and southeastern regions) to 144.66 (western and northwestern parts) (Appendix B Fig. B2). The plateau of the Gdańsk moraine hills (western part) is less urbanized, covered with state forests, and with gentler slopes (Gulshad et al., 2024d, 2024e; Kuiper Compagnons, 2015b). Urban planning should protect and enhance GI on moraine hills (upper terrace) and focus on integrating GI into the low-lying urban areas (lower terrace) for flood management.

Flood: Fig. B2 (Appendix B) shows flood distribution, with color intensity indicating the number of flood events. Wrzeszcz Górny, Wrzeszcz Dolny, Osowa, Śródmieście, Oliwa, and Orunia districts had the most interventions (Jakusik and Chodubska, 2020; Walczykiewicz and Skonieczna, 2020b) during rainfall events. Densely built and flat regions near the edge zone and the lower terrace receive runoff from the upper terrace during heavy rainfall like Historic Center of Gdańsk (Gdańskie Wody, 2024). The eastern part of Gdańsk and the upper terrace show low flood occurrences due to high GI density and higher elevations (Kuiper Compagnons, 2015b).

Population density: Population densities, ranging from 0 to 574.38 person per square kilometer (Appendix B Fig. B2) Highest densities occur in Chełm (south) and Zaspą (north), with the lowest in Stogi Portowe and Lasy Oliwskie. Between 2008 and 2021, population growth in south and western urban districts reflected ongoing urban development (Azadgar et al., 2025b; Gulshad et

al., 2024a; Mariusz et al., 2022), leading to more demand for infrastructure and services and low GI density.

Pollutants: Appendix figure B2 shows NO_2 and O_3 concentrations, key pollutants from industrial activities and vehicles. NO_2 concentrations are highest in north-central-eastern region (Stogi and Nowy Port districts) while O_3 concentrations are highest in the northern regions. Due to complex atmospheric chemistry, O_3 concentrations vary spatially and are not always directly proportional to NO_2 levels. These maps highlight the environmental pressures on GI due to industrial proximity, NO_2 emissions, and ozone levels. This can guide targeted interventions in high-stress areas. The maps for the rest of the factors are available in the Appendix B (Fig. B3, B4).

6.2.2. Spatial patterns of GI

GI density varies spatially across the city, as illustrated by GI density map (Fig. 6.2), showing the raw density values across a 1 km grid scale. Highest GI density is found in western (Trójmiejskiego Parku Krajobrazowy/Tricity Landscape Park), eastern (forests along coastal belt/Lasy Pasa Nadmorskiego, z Parkiem Reagana, Parkiem Jelitkowskim, Parkiem Brzeźnieńskim) and southwestern parts (Lasy Otomińskie) forested areas. Central urbanized zones (Przymorze Małe, Wrzeszcz Dolny, Letnica, Wzgórze Mickiewicza, Letnica, Zaspa Młyniec and Rozstaje) show the lowest greenery.

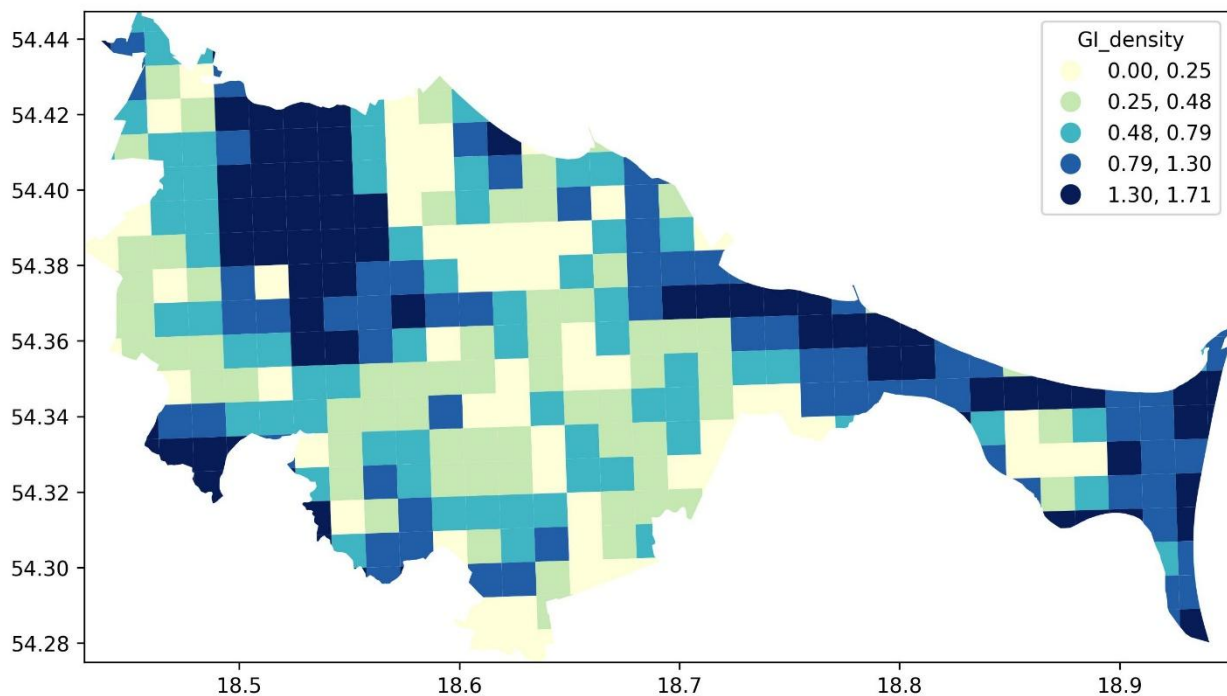


Figure 6.2. GI density map of Gdańsk showing low, medium, and high-density areas. *Reproduced from authors published work (Gulshad and Szydlowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.*

GI density was used to calculate spatial autocorrelation through Global Moran, and Local Moran's I. For Global Moran's I, among five weight matrices, Rook Contiguity weights produced moderate-

to-strong positive global clustering (Global Moran's I (0.63, p-value=0.001) (Appendix B table B3) and provided stable adjacency-based structure appropriate for regular grid data. Figure 6.3a presents this global spatial pattern of GI density, confirming that GI is concentrated in forested areas.

Following Global Moran's I analysis, Local Moran's I analysis provided more detailed insights into local variations. For Local Moran's I, among five weight matrices, Adaptive KNN was selected because it produced the highest proportion of statistically significant local clusters (61.4%) while maintaining stable neighborhood structure across peripheral grid cells (Appendix table B3). Fig. 6.3b shows LISA results, identifying High-high (HH) and Low-low (LL) clusters and spatial outliers (Low-high (LH) and High-low (HL)).

HH cluster with high GI densities surrounded by similar areas are found in the northwest (Tricity Landscape Park), eastern coastal forests (near Sobieszewo Island and Stogi Beach) and western Lasy Otomińskie forest.

LL regions (low GI densities surrounded by similar areas) are distributed in the north, center, south and some western parts. Industrial and commercial areas (Przymorze Małe, Wrzeszcz Dolny, Aniołki, Letnica, Przeróbka, etc.). Areas with non-significant local Moran's I ($p > 0.05$) mean no strong clustering was detected in those locations. These areas show negative local Moran's I values between -1.04 to 0.15 (Appendix B Fig. B5).

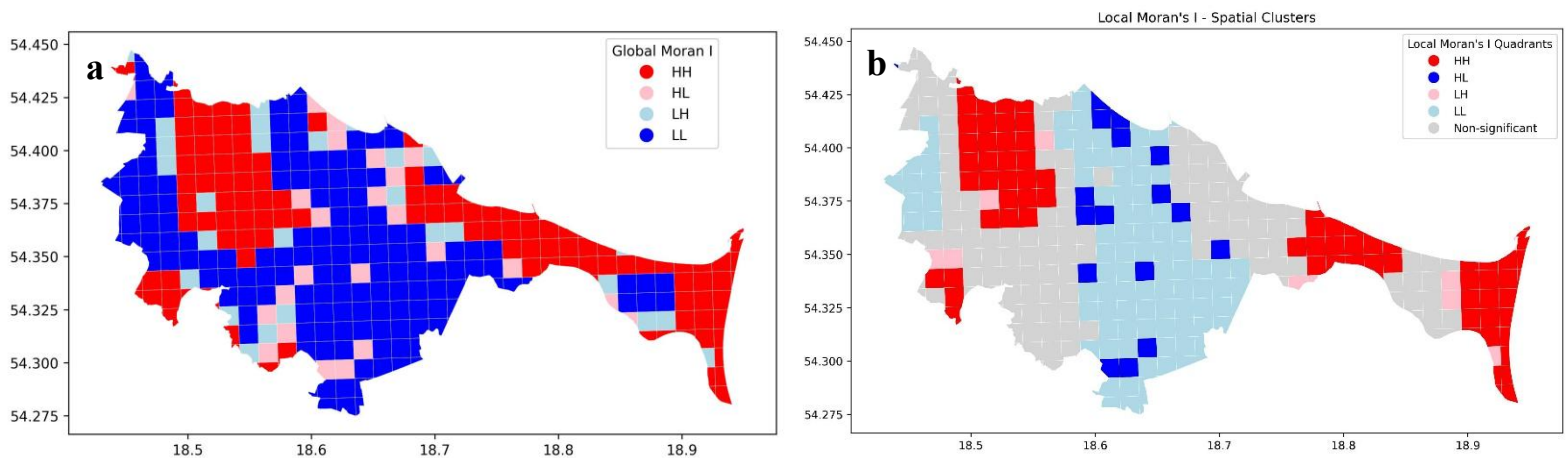


Figure 6.3. a) Global Moran's I map for GI density in Gdańsk. The color-coded clusters reveal areas with significant concentrations of GI and outliers where low-density regions are surrounded by high-density areas or vice versa. b) Local Moran's I cluster analysis. Reproduced from authors published work (Gulshad and Szydlowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.

HL clusters (high GI densities adjacent to low GI densities) represent isolated green spaces in center and southern areas, such as small urban parks or cemeteries: Oliwskie Łąki/Oliwa Meadows in the north of Letnica and south of Nowy Port, Park Imienia Ronalda Reagana in Przymorze Wielkie, Cmentarz Łostowicki/cemetery in the Ujeścisko-Łostowice and Siedlce districts. LH areas (low densities surrounded by high GI densities) are sparse appearing in the northwest of Gdańsk in Matarnia, around Tricity Landscape Park, beside Lasy Otomińskie forest in the

southwest, and along the eastern coastal belt of Wyspa Sobieszewska. Their scarcity suggests that low-GI areas transition gradually to high-GI areas through non-significant regions. These non-significant areas represent mixed land-use mosaics where neither greenery nor built surfaces dominate. In Gdańsk, these correspond to edge zones between forest complexes (e.g., Tricity Landscape Park, coastal forests) and compact residential districts such as Wrzeszcz-Oliwa and the mid-terrace corridor. Together local Moran's I result and the global Moran's I give a comprehensive view of GI distribution in Gdańsk, revealing both the general trend and local deviations from this trend.

6.2.3. Spatial patterns of coefficients and explanatory variables

6.2.3.1. Relationship of factors with GI

The correlation analysis between factors and GI density revealed several significant negative relationships (Figure 6.4b). PM10 (-0.50), PM2.5 (-0.53), NO₂ (-0.42), LST (-0.60), impervious surface (-0.52), and population density (-0.36) showed moderate to strong negative correlations with GI density. To determine whether population concentration itself constrains GI density or whether population serves as a proxy for built-up urban form., partial correlation analysis was conducted between population density, impervious surface, and GI density. After controlling the impervious surface, the correlation between population density and GI density became weak and statistically non-significant from $r = -0.36$ to $r = -0.06$ with $p = 0.26$, an 83% reduction. In contrast, impervious surface only modestly reduced impervious-GI correlation from $r = -0.52$ to $r = -0.39$, (a 25% reduction) with $p < 0.001$ when controlling the population density.

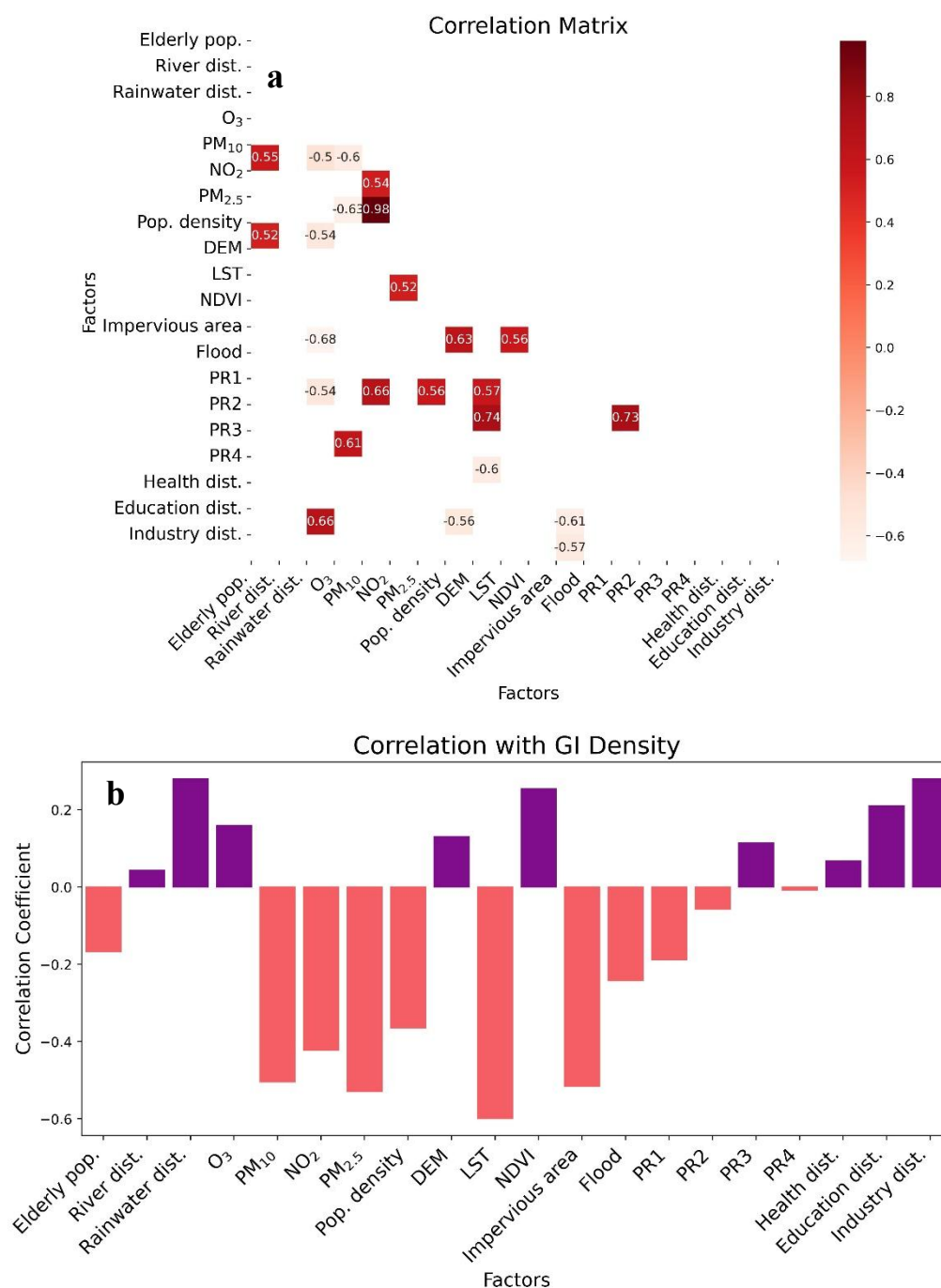


Figure 6.4. a) Correlation matrix showing relationships among independent factors influencing GI distribution in Gdańsk; positive correlations >0.5 are shown in red color, while negative correlation >-0.5 is shown in light colors. b) Graph showing the correlation between GI density and independent factors. *Reproduced from authors published work (Gulshad and Szydłowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.*

Among positive correlations, none emerged as a strong driver of GI. Weak positive correlation included rainwater collectors (0.28), O₃ (0.16), NDVI (0.25), distance from educational institutes

(0.21), distance from industrial areas (0.28), and DEM (0.13). Other factors showed no significant relationship with GI density.

6.2.3.2. Relationship between factors

To assess collinearity among predictors and ensure regression model interpretability, pairwise correlations were computed between all factors (Figure 6.4a). Several strong associations indicated redundancy within groups of variables. $PM_{2.5}$ and PM_{10} showed a high correlation of 0.98. Future precipitation scenarios were also correlated (0.73), DEM and future precipitation (2071-2100 under RCP 4.5) were highly correlated (0.74). Impervious areas and population density showed a moderate correlation of 0.63. Based on these correlations, $PM_{2.5}$, PM_{10} and the precipitation scenario for 2021-2050 (RCP 4.5) were identified as potentially redundant predictors.

These were further verified by multicollinearity results (Appendix B table B1). PM_{10} (VIF=96.93), $PM_{2.5}$ (VIF=81.72), future precipitation 2021-2050 under RCP 4.5 (VIF=10) exceeded multicollinearity threshold and therefore were removed from the analysis to avoid issues in estimating regression coefficients. After removing, all remaining factors had VIF below 10, indicating negligible collinearity and suitability for regression analysis.

6.2.4. Global determinants of GI density

The OLS model provides a baseline model with an R^2 value of 0.484 and adjusted R-squared of 0.457, indicating that about 48.4% of the GI density variability is explained by model (Table 6.1). The lower R^2 value highlights OLS inability to capture spatial dependencies, suggesting the need for advanced models. Diagnostic tests revealed significant heteroscedasticity and autocorrelation as shown in table 6.1, violating OLS assumptions. Key predictors with significant negative impacts are given in Table 6.1.

To address heteroscedasticity, WLS was applied and its results showed high R^2 (0.989) and adjusted R^2 (0.99), reflecting variance re-weighting rather than substantive explanatory improvement. However, residual diagnostics (low Durbin-Watson, high R^2 , and significant Omnibus test-p value, Table 3) indicated persistent spatial autocorrelation, confirming that WLS does not resolve spatial dependence hence, need for GLS to better handle spatial correlation. While GLS improved heteroscedasticity correction but failed to account for the spatial dependence (Table 6.1). This confirms the need for spatial models, such as SLM or SEM, as a more appropriate approach to handling spatial dependencies in geographically referenced data. Table 6.1 shows the coefficient values of explanatory variables having major impact on GI density.

Negative coefficients for impervious surface, LST, NO_2 and O_3 were consistent across models. Population density, NDVI, DEM and precipitation projections remained positive in WLS/GLS. These results indicate that global regression models fail to fully account for spatial dependency in GI density, motivating the use of spatial models.

Table 6.1. Results of OLS, WLS and GLS models.

Statistic	OLS	WLS (Inv. sq. residuals)	WLS (Inv. abs. residuals)	GLS
R²	0.484	0.999	0.961	0.989
Adj. R²	0.457	0.999	0.959	0.988
AIC	331.7	-84.87	61.48	-83.55
BIC	400.7	-19.68	126.7	-14.52
F-statistic	17.86	2.129×10 ⁴	473.1	1718
Residuals behavior	BP p<0.05, BG p<0.05	High R ² ; DW=1.155; BP p<0.05	BP p<0.05; DW=0.912	BP p>0.05 (corrects heteroscedasticity); DW=1.157
Coefficient				
Impervious surface	-0.21	-0.52	-0.55	-0.53
LST	-0.20	-0.68	-0.72	-0.70
NO₂	-0.16	-0.30	-0.27	-0.32
O₃	-0.12	0.32	0.32	0.27
Population density	—	-0.37	-0.34	-0.36
Elderly population	—	0.31	0.27	0.31
DEM	—	0.33	0.31	0.32
NDVI	—	0.43	0.47	0.40
2021–2050 RCP 8.5	0.14	0.58	0.60	0.58
2071–2100 RCP 8.5	—	1.03	1.03	1.00
• AIC = Akaike Information Criterion • BIC = Schwarz Criterion • BP = Breusch-Pagan (heteroscedasticity test) • BG = Breusch-Godfrey (autocorrelation test) • DW = Durbin-Watson (autocorrelation statistic)				

The results show that Rook Contiguity provided the best overall model fit for both Spatial Lag and Spatial Error models, with the lowest AIC values and highest pseudo R² (Appendix B Table B3, B4, B5). The spatial lag model showed high explanatory power, with a pseudo R² value of 0.72 and a spatial pseudo R² of 0.45, explaining approximately 72.08% of the GI density variance (Table 6.2). The positive spatially lagged variable ($\rho = 0.65$) indicates a strong spatial dependence. In contrast, the spatial error model shows a low explanatory power of 0.44 (Table 6.2). The spatial lag model captures dependence through spatially lagged dependent variables, whereas the spatial error model accounts for spatial autocorrelation in the residuals.

LST and impervious area negatively impact GI density with coefficients of -0.13 and -0.19 (lag model), -0.26 and -0.18 (error model). Distance from industries (-0.0803 lag model, -0.0661 error model), and Ozone (-0.0897 lag, -0.1129 error) also show negative impacts. The total impact includes direct effects (local) and indirect effects (spillover). Urbanization through impervious areas (-0.55 lag) and LST (-0.38 lag) impose both local and spillover effects on GI density. Other variables are not statistically significant at the 5% level for both models.

Table 6.2. Comparison of regression models: Spatial Lag, Spatial Error, Global, and GWR

Statistic	Spatial Lag	Spatial Error	Global Model	GWR
R²	0.72	0.44	0.484	0.84
Adjusted R²	—	—	0.46	0.78
Residual Sum of Squares	—	—	47.53	14.81
Log Likelihood	-69.17	-38.73	—	—
AIC	176.35	113.47	331.66	72.94
BIC	249.21	182.49	—	—
ρ (Spatial Lag Coefficient)	0.65	—	—	—
λ (Spatial Error Coefficient)	—	0.80	—	—

6.2.5. Spatial heterogeneity in GI drivers (GWR)

The GWR model provides a detailed spatial analysis of the relationship between predictors and GI density, revealing significant local variations. Although GWR provided an R^2 of 0.84 and an adjusted R^2 of 0.78, explaining 84% of the GI density variation, this improvement is expected due to its local fitting nature. The reduction in AIC to 72.94 and residual sum of squares from 47.53 (global model) to 14.81, indicates improved model fit (Table 6.2) than other models as supported by other studies (Xu et al., 2019b; Yang et al., 2020b). However, GWR results are interpreted primarily as evidence of spatial non-stationarity rather than as a definitive replacement for global models. The GWR highlights spatial heterogeneity in the effects of predictors. For instance, impervious areas showed negative coefficient with a mean of -0.210, and LST with mean effect of -0.165. Conversely, O_3 exhibits both positive and negative effects depending on the region, with a mean of 0.161 and a range from -0.20 to 0.71.

6.2.5.1. Spatial patterns of coefficients and explanatory variables

The coefficient and t-value maps with adjusted critical threshold of $|t| \geq 2.579$ (Figures 6.5,6.6) illustrate the spatial variation in the relationship between the GI density and key predictors, as modeled by the GWR. The results show distinct positive and negative regions, emphasizing the localized influence of predictors on GI density.

LST: The LST coefficient and t-value maps (Figure 6.5a,b) illustrate the strength and statistical significance of the relationship with GI density. The coefficient map shows a predominantly negative relationship between LST and GI density, particularly in the southern and eastern regions

(blue, negative -0.4 to -0.1), where UHI and limited greenery prevail. In contrast, the northern and central areas show a weaker relationship (red/orange), suggesting spatial heterogeneity. The t-value map complements this by indicating the statistical significance of these coefficients. Lighter color areas correspond to stronger negative regions (t-values from -7.58 to -3.03) with $|t| \geq 2.579$, while darker areas indicate regions where t-values are closer to zero (-1.52 to 0.00) below significance threshold, indicating a weaker relationship.

Impervious areas: The coefficient map (Figure 6.5c,d) indicates a consistent negative relationship between impervious surfaces and GI across most regions, especially in the central and northern parts (shown in blue color, -0.45 to -0.30), dominated by built-up area in the center (Gdańska Biuro Rozwoju, 2019). The t-value map confirms the robustness of the negative coefficients in these regions. The central and northwestern regions of the study area exhibit the lightest colors in the t-value map, corresponding to t-values ranging from -5.32 to -3.19, which substantially exceed the critical threshold of $|t| \geq 2.579$. These areas represent areas where impervious areas have a statistically significant negative effect on GI density.

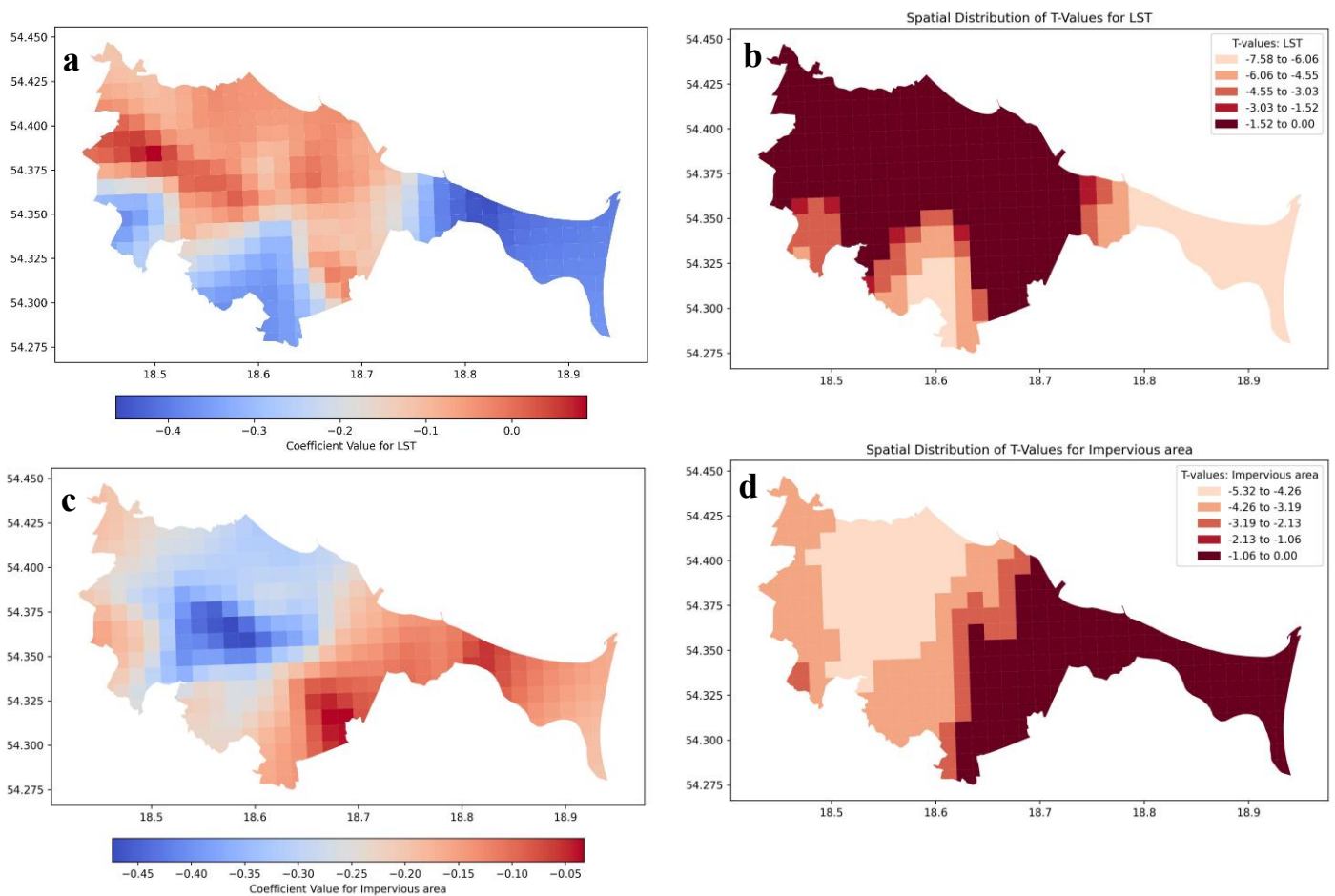


Figure 6.5. Coefficient values from the MGWR (left) and their corresponding areas of significance (right) in Gdańsk: a,b) LST, c,d) Impervious area. Reproduced from authors published work (Gulshad and Szydłowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.

O₃: The GWR model indicated spatial heterogeneity in the relationship between O₃ and GI density (Figure 6.6a,b). Positive coefficients occurred with near-zero to slightly positive coefficients (0.0 to +0.2) in the western region transitioning to stronger positive coefficients (+0.4 to +0.6) in the eastern areas mainly in eastern districts, whereas central and northern districts showed near-zero coefficients. The t-value map confirmed statistical significance for the positive effects in the east with t-values ranging from 3.47 to 7.63 which substantially exceed the critical threshold of +2.579 and weaker or non-significant relationships elsewhere.

NO₂: The NO₂ coefficients exhibited spatial variation (Figure 6.6c,d). Local coefficients ranged from -0.20 to 0.5. Positive coefficients were concentrated in the eastern part of the study area, while negative or near-zero coefficients dominated central and western areas. The eastern portion representing t-values ranging from 3.07 to 5.12, which clearly exceed the critical threshold of +2.579 and indicate significant positive relationships between NO₂ and GI density.

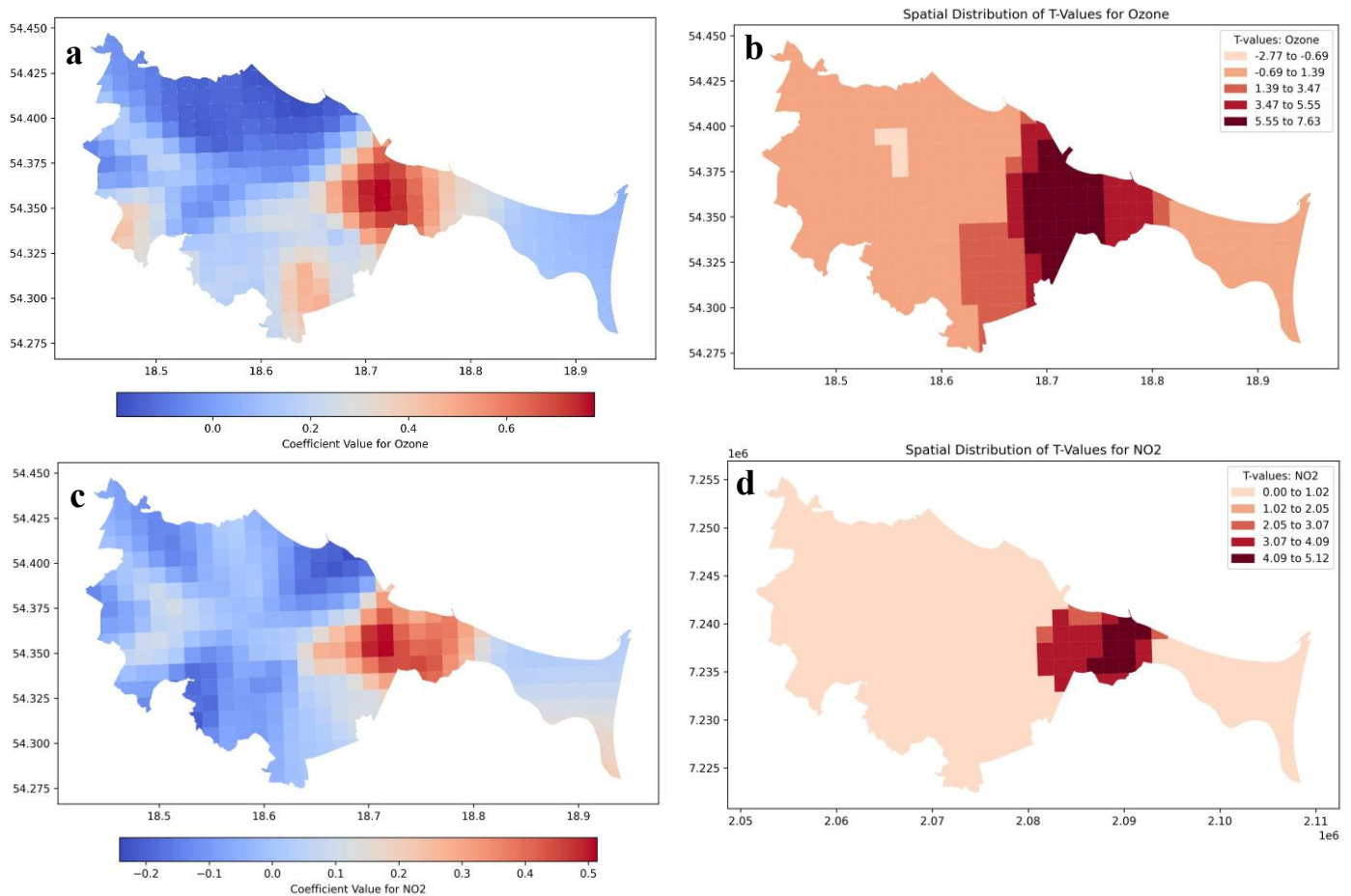


Figure 6.6. Coefficient values from the MGWR (left) and their corresponding areas of significance (right) in Gdańsk: a,b) O₃, c,d) NO₂. Reproduced from authors published work (Gulshad and Szydlowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.

6.2.6. GI priority areas

The results indicate that the environmental need for GI (cooling, filtration, runoff absorption) is not spatially aligned with its current provision, underscoring priority areas where GI could deliver disproportionately high environmental benefits. The GI priority map (Fig. 6.7) identifies spatially concentrated intervention zones in central and lower-terrace districts, including Wrzeszcz Dolny, Letnica, Nowy Port, Zaspą-Młyniec, Śródmieście, and Orunia-Św. Wojciech-Lipce. These areas exhibit both GI deficits and multiple environmental stressors. In contrast, western upland forest districts remain low priority. The spatial clustering of priority cells highlights systematic mismatch between GI supply and environmental pressure at the municipal scale.

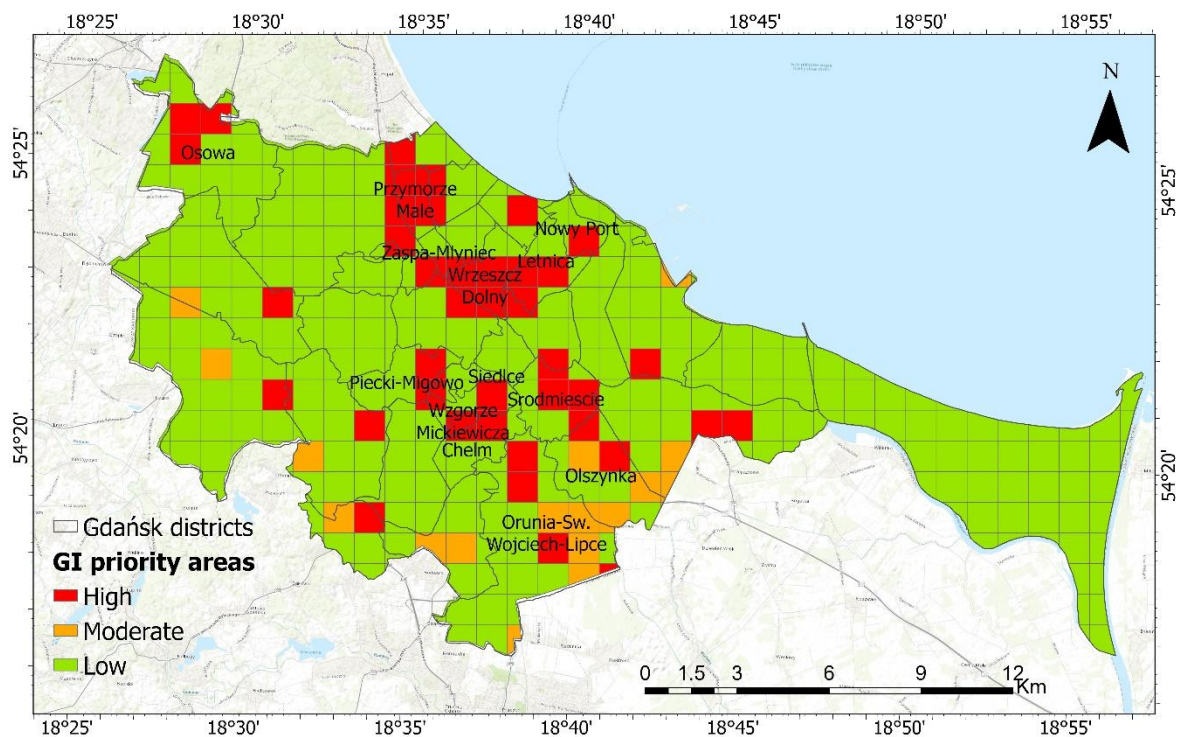


Figure 6.7. GI priority areas in Gdańsk using the grid-level results. *Reproduced from authors published work (Gulshad and Szydlowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.*

6.3. Discussion

Urban green infrastructure is a keyway to implement nature-based solutions (NBS), while providing measurable benefits. However, GI distribution across cities is often shaped by topography, historical development, and current planning priorities. Understanding these patterns and what drives them is essential for evidence-based urban greening strategies that target areas of greatest need. Therefore, this study examines how topography, urban form, environmental stressors, and sociodemographic factors relate to GI density in Gdańsk, Poland.

The spatial patterns observed in Gdańsk indicate that GI distribution is not random but strongly shaped by physiographic and urban morphological structures. Forested upland areas on the moraine hills and coastal belts exhibited the highest GI density, as confirmed by Moran's I clustering analysis, while the central, northern, and southern urbanized districts formed persistent low-density clusters. This is confirmed by temporal LULC analysis (1985-2024) in Gdańsk which showed that forests remained stable at the periphery, while interior districts underwent densification and industrial conversion, reinforcing the spatial GI patterns identified by the LISA analysis (Gulshad et al., 2024a). These patterns reflect interactions between terrain (upper terrace vs. lower terrace), hydrological pathways, and historical land conversion (Gulshad et al., 2024d, 2024e; Kuiper Compagnons, 2015b).

The upper terrace acts as a GI reservoir, with high permeability, large forest complexes, and low flood occurrence while low lying areas between terraces are flood prone and have less GI due to dense development and runoff from higher elevations (Mariusz et al., 2022). This shows how natural landforms influence current GI distribution and create unequal access to ecosystem services such as cooling, runoff mitigation, and recreation. In southeastern and eastern Gdańsk, lowland polders (agricultural areas of Żuławy Gdańskie and Wyspa sobieszewska) serve agriculture, control water-level regulation and manage short, intense rainfalls without significant adverse impacts (Kuiper Compagnons, 2015b). However, their future role in GI planning must be evaluated, especially as urban expansion and climate change may increase runoff from adjacent built-up areas.

Previous district scale studies in Gdańsk revealed similar results: Oliwa (west) and Wyspa Sobieszewska (east) districts have the largest nature-based solutions. While Rudniki, Olszynka, Orunia-Św. Wojciech-Lipce districts in the east, Wzgórze Mickiewicza in the center and Nowy Port in the north exhibited low GI density (Azadgar et al., 2025b; Brosz et al., 2023). Recent development trend in Gdańsk further suggest that northern side (Wrzeszcz, Oliwa, Zaspa, and Przymorze), and the south-western band (Śródmieście, Chełm, Gdańsk-South, and Piecki-Migowo) (Azadgar et al., 2025b; Mariusz et al., 2022) could benefit from further urban planning interventions to address the GI disparities.

While land use and topography explained broad GI patterns, correlation analysis clarified the underlying drivers. Population density correlates negatively with GI but also correlates strongly with impervious surface suggesting it reflect development intensity rather than exerting a direct effect on GI. To test this, partial correlations were examined by controlling for impervious surface. When impervious cover is held constant statistically, the population-GI correlation weakens, while impervious-GI remains strongly negative. This suggests that built surfaces and pavement are the primary mechanism limiting GI, while population density reflects the degree of urbanization. Similar relationships have been documented in cities with diverse urban morphologies, including Bradford, UK (Ferguson et al., 2018), Baltimore, Washington DC, USA (Baker et al., 2019b; Vogel, 2019), Melbourne, Australia (Kuller et al., 2018), Sheikhpura (Arshad and Routray, 2018), Pakistan, indicating that the relationship is not unique to Gdańsk.

Not all associations are unidirectional, the negative associations between GI density and environmental stressors (LST, NO₂, PM₁₀, PM_{2.5}) require careful interpretation because the underlying relationships are bidirectional. Previous studies found that GI plays a significant role in mitigating urban heat islands through shading and evapotranspiration at different scales of analysis (Rahaman et al., 2022). GI also improves air quality via deposition and filtration (Kuller et al., 2017; Zuniga-Teran et al., 2021), so higher GI can lead to lower LST and pollutant concentrations. The cross-sectional regression models therefore capture existing spatial configurations rather than one-way causal effects. In this study, we interpret LST and air pollutants as environmental stress indicators that co-occur with low GI, rather than as factors that directly constrain GI implementation.

Apart from strong negative correlations, several weak positive correlations need additional interpretation. Rainwater collectors show positive correlation with GI density because they are located along ravines and valley bottoms draining upland forests towards lower terrace rivers. They often are adjacent to forest complexes, parks and other vegetated corridors. In contrast, low lying port and industrial zones are dominated by closed underground drainage and offer little room for vegetated retention (Gdańskie Wody, 2024; Kuiper Compagnons, 2015b; Mariusz et al., 2022). The positive association therefore captures the co-location of GI with hydrological infrastructure in priority zones. NDVI showed modest positive associations with GI density, indicating its role as general indicator of vegetation cover.

DEM is weakly positive due to the location of upland forests in the western part of Gdańsk. Although, bivariate correlation shows positive correlation between GI density and distance from industrial areas reflecting Gdańsk's spatial structure rather than a direct causal effect. However, the spatial lag and spatial error models produce negative coefficients for this variable. This difference arises because simple correlation reflects the overall spatial pattern of the city, where GI appears adjacent to industrial zones as buffers and wetlands on the low terrace, and far from them as large forest complexes on the upland moraine terraces (Kuiper Compagnons, 2015b; Mariusz et al., 2022) with a low GI residential belt in between. However, once other variables such as impervious surface, LST, NDVI, DEM, and spatial dependence are included in the regression models, the coefficient represents the independent effect of industrial proximity while holding these other factors constant. As a result, the regression models capture a more localized relationship than the simple correlation (Dormann et al., 2007).

Correlation analysis doesn't account for spatial dependence; therefore, the regression models were used to capture spatial dependence in GI analysis. The OLS and WLS/GLS models provided baseline associations but failed to capture spatial autocorrelation and heteroscedasticity, indicating that GI density is not spatially independent. Spatial Lag models suggest that GI density in a given location is influenced by GI in neighboring cells confirming that urban form variables such as impervious cover and LST generate both local and spillover impacts, consistent with the idea that urban heat, sealed surfaces, and development patterns form continuous spatial fields rather than discrete patches consistent with First Law of Geography (Dormann et al., 2007). The Spatial Error

model showed lower explanatory power, indicating that spatial dependence in GI distribution arises from substantive spatial processes rather than unobserved spatial noise. Across all models, population density, impervious area and LST showed negative effects on GI, while NO₂ and O₃ showed slight positive and negative impact (SLM and SEM estimate a single global average coefficient across the entire study area, which is negative, while the GWR model allows coefficients to vary spatially,) reflecting spatial heterogeneity. This indicates that the negative global coefficient represents an average effect across heterogeneous local processes, where strong positive relationships in eastern districts are offset by negative or weak effects elsewhere. The divergence between global and local NO₂ and O₃ coefficients indicates spatial non-stationarity, while the overall city-wide effect is negative, eastern districts exhibit significant positive local relationships, demonstrating that global averages mask localized environmental dynamics which is better explained by GWR model.

GWR analysis revealed substantial spatial heterogeneity in how different factors affect GI density across Gdańsk. Impervious surfaces and LST showed consistently negative coefficients across the city, but with stronger effects in dense central and northern districts with urban fabric, limited soil exposure, and pronounced urban heat. In east, weaker relationship of impervious area correspond to less urbanization and more green areas as identified in the Gdańsk Greenery Policy (GPZ, 2023) as ecologically valuable green corridors (Fikus-Wójcik et al., 2023). Southern districts (e.g., Chełm, Ujeścisko-Łostowice) showed similar weaker relationship due to ongoing development where private gardens and fragmented green patches buffer the negative effect of new impervious surfaces, producing a weaker local relationship (Fikus-Wójcik et al., 2023). Population growth in south and western urban districts (2008 and 2021) confirmed ongoing urban development (Azadgar et al., 2025b; Gulshad et al., 2024a; Mariusz et al., 2022), leading to infrastructure demand while limiting GI density. Similar trends are observed in different cities of world like Melbourne (Kuller et al., 2018), Pest County, Hungary, Małopolskie Province, Poland (Cegielska et al., 2018b; Kukulska-Kozieł et al., 2019), Łódź and Prague (Haase et al., 2019) and Western, Central, Eastern European cities (Halecki, 2024).

Previous studies on UHI in Gdańsk confirms the impact of urban structure and land use on temperature variations such as central urban areas (Wrzeszcz Dolny) contributing to elevated temperatures (Czarnecka and Nidzgorska-Lencewicz, 2014). Moreover, similar negative relationships between LST and urban greenery have been observed in Polish cities (Rzeńca et al., 2021), both eastern and western European countries (Halecki, 2024), reinforcing the critical role of GI in mitigating urban heat. In this study, the spatially varying LST coefficients should be interpreted as reflecting GI need. Higher LST values occur where GI is absent or sparse due to biophysical cooling processes, producing a negative association through reverse causality. Thus, LST acts as a heat exposure indicator, identifying districts where cooling services provided by GI are most needed but currently insufficient.

O₃ showed bidirectional effects, reflecting the complex interaction between vegetation and air pollution. In northeastern districts (Stogi, Krakowiec-Górki Zachodnie, Rudniki) with forests and

coastal green spaces, positive coefficients suggest GI interacts with ozone through natural processes. Plants release biogenic volatile organic compounds (BVOCs) such as isoprene which participate in ozone formation under sunny conditions (Li et al., 2025). At the same time, GI can help remove pollutants. Similarly, industrial and port districts (Nowy Port, Stogi, and Port of Gdańsk) exhibit complex pollutant interactions. These areas have high emissions from traffic and industry. Although coastal forests are present but as historically documented in Gdańsk (Raińska et al., 2007; Szczepaniak et al., 2006), contamination and industrial emissions can reduce the functional efficiency of vegetation (Azadgar et al., 2025b).

A previous study in Gdańsk showed ozone formation is linked to NO_x and VOC concentrations under high solar radiation (Marć et al., 2014). Here, the spatial co-occurrence of industrial zones, high NO₂, elevated O₃ and GI presence in industrial and coastal districts aligns with the known ozone formation process involving NO_x emissions, anthropogenic VOCs and biogenic VOCs. Monitoring data from ARMAG (2022) (Kołakowski et al., 2022) confirm recurrent exceedances of permissible NO₂ levels in port-adjacent districts (Nowy Port and Stogi), further supporting the local influence of industrial and traffic emissions. The positive GWR coefficients in these areas suggest that GI tends to be located where pollutant loads are highest, likely because these areas require environmental mitigation. These patterns emphasize the importance of considering atmospheric processes, industrial morphology and pollutant transport when interpreting spatial drivers of GI density and highlight the need for localized environmental interventions.

The spatial patterns, correlations, and modeling results documented above have direct implications for urban planning policy, particularly in the context of climate adaptation and nature-based solutions frameworks.

6.3.1. Policy planning and implications

Green infrastructure represents a key operational strategy within the broader nature-based solutions umbrella, which emphasizes working with natural processes to address challenges including climate change, disaster risk reduction, and human well-being (Kuller et al., 2017; Labib et al., 2020; Vogel, 2019). The spatial analysis presented here demonstrates how GI provision can be systematically assessed and targeted to maximize climate adaptation benefits. By identifying areas where environmental stressors (heat, pollution, flood risk) coincide with GI deficits, the analysis supports prioritization and strategic allocation of resources at the municipal level. This will be helpful to achieve policy targets such as the EU Green Infrastructure Strategy (European Commission, 2019), EU Biodiversity Strategy (European Commission, 2020), the implementation of the Nature Restoration Law (European Parliament & Council of the European Union, 2024) and the UN Sustainable Development Goals (SDGs 11 and 13) (UNEP, 2022), which call for integrated spatial planning that embeds nature-based solutions into urban development trajectories.

Locally, Gdańsk Water Policy/Gdańska Polityka Wodna (GPW, 2021), and the GPZ (2023) focus on developing waterside areas, flood protection and increasing the greenery (Fikus-Wójcik et al., 2023) such as in Przymorze Małe, Wrzeszcz Dolny, Młodeo Miasto and Letnica (Fikus-Wójcik et

al., 2023; Mariusz et al., 2022). This study aligns with these priorities exhibiting high land surface temperatures, low GI density, and higher impervious surfaces, reinforcing the need for targeted interventions in line with GPZ objectives. However, due to the 1km grid scale analysis, this study suggested some more areas like central districts of Wzgórze Mickiewicza, Zaspą Młyniec, and Rozstaje, suggesting that these regions have yet to benefit from GPZ's prioritization fully (Fig. 6.7). These areas represent spatial mismatches between GI provision and environmental need and may serve as candidate zones under municipal policies. However, the grid scale used in this study serves as a standardized analytical frame for diagnosing spatial patterns in GI provision and environmental stress across Gdańsk. These insights can support municipal-level strategic planning and other policy instruments. While the study identifies priority areas for GI, the selection of specific GI types requires site-specific planning, ecological assessment, and design-level analysis, which is beyond the scope of this city-wide spatial assessment.

While the GPZ considers key environmental stressors, this study indicates that planners may benefit from integrating additional bio-physical and socio-demographic factors, such as population density, proximity to industrial areas, LST and air quality. From a normative planning perspective, the strong negative correlations indicate spatial mismatch between need and supply. For instance, industrial and port-adjacent districts (e.g., Nowy Port, Stogi) experience high pollutant concentrations but relatively sparse GI, while high-density residential districts (e.g., Chelm, Zaspą) exhibit limited public green space per capita. Continuous geospatial monitoring could support equitable distribution of GI and targeted climate adaptation.

Comparable patterns have been documented in other Central and Eastern European cities (e.g., Bucharest, Kraków, Budapest, Warsaw), where suburbanization, and industrial restructuring influenced green space distribution (Kukulska-Kozieł et al., 2019; Petrisor et al., 2021). However, results do not establish causality regarding governance transitions. Disentangling natural constraints (topography, hydrology) from institutional choices (zoning, privatization policy) requires temporal analysis tracking how GI patterns changed before, during, and after the transition period. Nonetheless, the clustering of low-GI districts and negative coefficients of impervious cover and LST reflect similar pressures identified in Poznań, Dubrovnik and Ljubljana (Gadziński, 2015; Hrdalo et al., 2015; Marot et al., 2015; Pichler-Milanovič and Foški, 2015), where fragmented governance, transport priorities and limited funding mechanisms complicate GI implementation. To address these issues, Gdańsk could learn from Western European approaches (e.g., Netherlands green roof project (H de Moel et al., 2021)) to mitigate urban flood risk and work towards a more sustainable and equitable urban environment. However, direct policy transfer requires careful adaptation to local institutional capacities, funding mechanisms, and public acceptance. Successful GI implementation depends not only on technical suitability but also on governance structures, stakeholder engagement, and long-term maintenance commitments, factors that vary substantially across urban contexts.

6.3.2. Cross-chapter validation and framework implications

The spatial econometric findings of this chapter connect to the preceding analyses through two specific validation points that reinforce the framework's internal coherence. First, the identification of impervious surface as the primary structural constraint on GI distribution, with a total spatial impact of -0.55 including spillover effects, directly corroborates **Chapter 4's** finding that late-stage imperviousness accumulation produced disproportionately large non-linear runoff increases at basin scale. Both analyses, one process-based hydrological modelling at basin scale and the other spatial econometric GI analysis at 1 km² grid resolution, independently converge on the same underlying mechanism: continuous urban fabric displacing permeable surfaces is the dominant driver of Gdańsk's flood risk and GI deficit simultaneously. Second, the environmental stress indicators identified here as co-occurring with GI absence, LST, low NDVI, and drainage proximity, are precisely the variables that SHAP attribution in **Chapter 5** identified as the dominant predictors of flood susceptibility. This variable-level continuity across two methodologically independent analyses confirms that the spatial logic of flood risk in Gdańsk is consistently traceable to the same underlying urban form characteristics regardless of the analytical approach used to detect it.

Together these two validation points produce the framework's core diagnostic finding: the districts that generate the most amplified runoff, concentrate the highest flood susceptibility, and exhibit the greatest GI deficit are spatially the same, which is a triple overlap that required three independent analytical stages to establish and that is not retrievable from any single chapter alone. This convergence directly conditions **Chapter 7**: the structural constraints on GI identified here define the feasibility boundaries within which NBS suitability is assessed, ensuring that greening scenarios are evaluated against the actual urban conditions that this chapter has characterized rather than against theoretical open space availability.

6.3.3. Limitations and future research

Several limitations and considerations exist in the current study. For example, there were limitations to data acquisition in Gdańsk, particularly the unavailability of fine-scale income and education data that would allow a more comprehensive GI equity assessment. In this study, the elderly population was used as a proxy socio-demographic vulnerability indicator, given evidence that older residents are more sensitive to heat stress and more dependent on accessible nearby green space. However, other vulnerable groups (e.g., low-income households or children) could not be evaluated due to data constraints. GI density represents a structural indicator of green space presence and availability, not a functional indicator of ecosystem service provision. Aggregating heterogeneous GI types into a single density measure introduces functional uncertainty, because different GI forms vary in cooling capacity, pollutant removal, hydrological regulation, accessibility, and planning constraints. Therefore, spatial associations identified in this study should be interpreted as reflecting patterns of overall green space availability, rather than equivalent ecological performance.

There is also uncertainty associated with climate data (future precipitation) used for the analysis. This study used existing flood inventory data to create a flood map to evaluate the current conditions for the GI assessment. However, for future research aimed at optimizing GI site selection, using a flood susceptibility map, generated in chapter 5 of this thesis using climate data together with other factors, will be more effective. This approach can help ensure better optimization and more resilient GI planning.

In the future, it would be beneficial to differentiate between two types of green spaces: undeveloped green spaces, like intact forests or natural areas, and intentionally designed green spaces, like parks or landscaped areas. This will provide a clearer picture of the distribution and role of natural versus human-made green areas.

Spatial scales for examining GI are also important. Previously conducted studies examined these relationships aggregated up to the census tract scale (Kuller et al., 2018; Pallathadka et al., 2022b; Vogel, 2019) or city scale (Xu et al., 2019b). This study considered a finer scale when exploring the distribution of GI. However, for future research, it is essential to compare different scales of analysis (district scale, census tract, sewer-shed scale) as some relationships only appear at specific scales while others remain consistent.

6.4. Conclusion

Nature-based solutions play a critical role in making cities more resilient, equitable, and climate-adaptive. This study advances their implementation by revealing how biophysical and socio-demographic factors shape GI distribution in Gdańsk. Using statistical modeling, the study moves beyond descriptive assessments to systematically distinguish between factors that constrain GI development and indicators that show need for GI implementation.

By jointly considering environmental stressors, urban form, population characteristics, the framework offers new insights into how urbanization pressures, and policy interventions shape present-day GI patterns. Furthermore, the framework highlights opportunities for targeted GI expansion to be done in low-density/high-stress zones, retrofitting impervious areas with greenery to cool microclimates, integrating air-purifying GI in industrial zones.

Together, this research provides a reproducible pathway for diagnosing gaps in GI provision, supporting more equitable spatial distribution, and aligning local planning with broader climate and sustainability goals (SDG 11 and SDG 13).

The spatial econometric analysis presented in this **Chapter 6** confirms that green infrastructure distribution in Gdańsk is not governed by hydrological need but by structural urban conditions impervious surface accumulation, heat exposure, and socio-demographic vulnerability systematically predict GI absence rather than GI presence, producing a city where the neighborhoods most exposed to flood risk and environmental stress are precisely those least served by nature-based mitigation. Yet identifying this misalignment, while necessary, is insufficient on its own. The next logical question is not simply where green infrastructure is missing but where it

is physically feasible to introduce it, what form it should take given the built environment constraints of each location, and how much hydrological benefit its deployment would deliver. Answering these questions requires moving from diagnosis to intervention, from mapping what exists to planning what could exist, and from statistical explanation to scenario-based quantification. **Chapter 7** addresses this transition directly by developing a GeoAI-based suitability framework that evaluates two complementary nature-based solution typologies, green roofs at building scale and street trees at corridor scale, across Gdańsk's urban fabric, quantifying their combined stormwater retention potential under multiple deployment scenarios.

Chapter 7

GeoAI Framework for NBS Suitability & Stormwater Analysis

7. Introduction

The preceding **chapters** have progressively narrowed the analytical focus from basin-scale hydrological dynamics to city-scale flood susceptibility to neighborhood-scale green infrastructure inequity, each stage adding a layer of spatial precision to the understanding of where urban flood risk concentrates and why existing green infrastructure fails to address it. **Chapter 7** completes this diagnostic-to-intervention transition by asking not where the problem is, but what can be done about it, and where. Building on the flood susceptibility hotspots identified in **Chapter 5** and the GI deficit zones mapped in **Chapter 6**, this chapter develops an integrated GeoAI framework to evaluate the suitability and stormwater performance of two nature-based solution typologies operating at complementary spatial scales: green roofs assessed at the individual building level using morphological and structural characteristics derived from BDOT10k and airborne LiDAR data, and street trees assessed at corridor level using Google Street View imagery segmented through the Mask2Former deep learning model to derive Green View Index, Impervious Area Index, and Open Space Index. For streets with critically low greenery, XGBoost models predict feasible tree counts under three spacing scenarios, and RESILIO retention parameters translate these deployments into quantified stormwater mitigation estimates, connecting the spatial precision of the GeoAI framework directly to the hydrological baseline established in **Chapter 4**.

7.1. Methodology

The study's overall analysis comprises four steps, as outlined in Figure 7.1. These stages include: (i) Potential green roofs assessment: Building data was analyzed to identify rooftops suitable for green roof installation under multiple scenarios, (ii) street-level greenery assessment: SVI was segmented using deep learning enabling classification of streets by greenery levels, (iii) predictive modeling of street trees: A machine learning model, combined with hypothetical greening scenarios and physical constraints, was used to estimate feasible tree planting potentials, and (iv) Estimation of runoff retention and interception: Hydrological analysis was conducted to quantify the potential reduction in stormwater runoff from green roofs and street trees under varying scenarios. The framework is designed to be transferable across cities but is demonstrated here using Gdańsk, Poland, as a test case. The data used for this methodological framework are provided in Table 3.1.

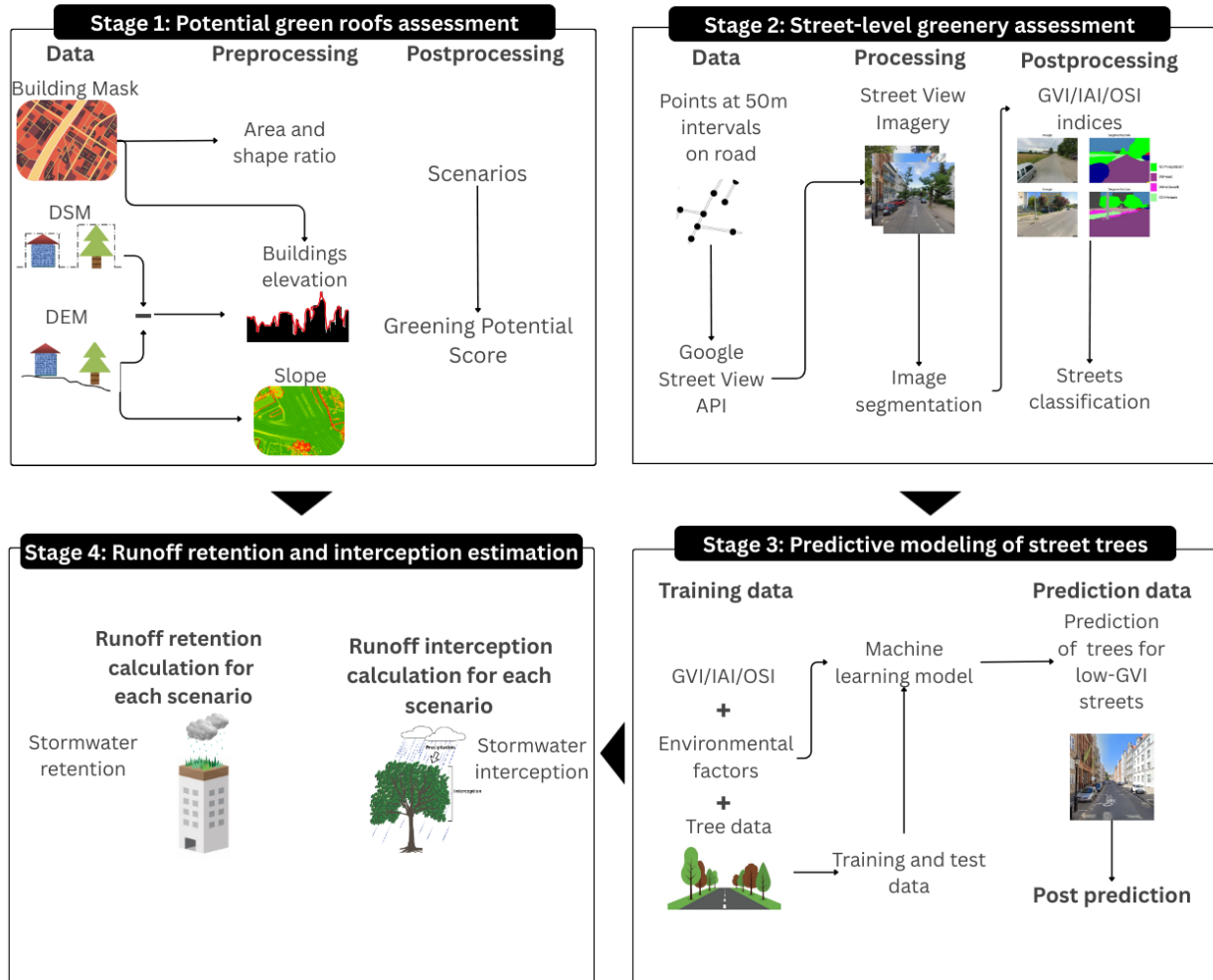


Figure 7.1. Methodological framework for assessing green GI potential in Gdańsk. *Reproduced from authors work Gulshad et al. (under review).*

7.1.1. Assessment of BGR potential

In the first stage of the methodology, a GIS-based method was adopted to assess the potential of BGR interventions. Based on existing research, several building-related criteria, including building height, slope, area, and shape ratio, were considered (H de Moel et al., 2021; Dong et al., 2025, 2024; T Haer et al., 2022; Kim et al., 2021; Peranović, 2025). Additionally, planning and heritage-related characteristics, such as heritage buildings and industrial zones, were also included in the BRG evaluation process.

To analyze the BGR potential, building polygon records from BDOT10k topographic data of Poland and OSM was used as the unit of analysis. For each building polygon, the building height and slope was estimated utilizing the DSM and DEM records. DEM height was subtracted from the DSM height within the building polygon to obtain the building height. Using the DSM layer, slope of each roof was also estimated. Additionally, from the polygon record, roof's total surface area was calculated and estimated the surface-to-perimeter ratio to obtain the shape ratio. Using

this information for each building, the greening potential score (GPS) was estimated using equation 7.1.

$$GPS = H.w_H + S.w_S + A.w_A + SR.w_{SR} \quad 7.1$$

where H is height, S is the slope, A is the roof area, SR is the shape ratio, and w_H, w_S, w_A, w_{SR} are the corresponding weights for each factor. When estimating the GPS score using equation 7.1, three scenarios were created following (Peranović, 2025) to demonstrate the sensitivity of BGR potential based on building parameters and planning considerations. Notably, historical buildings were removed from each scenario due to heritage protection constraints. These scenarios are as follows:

- **Scenario 1:** Several threshold values were set for the building parameters based on the literature (H de Moel et al., 2021; Kim et al., 2021; Mulder, 2025; Peranović, 2025). The maximum selected building height was 40 m (Wang et al., 2023), the maximum slope was 20°, the minimum roof area was 50 m², and the shape ratio threshold was 0.75. Each criterion was normalized, and equal weights of 0.25 were given to each criterion to obtain the greening potential score (GPS).
- **Scenario 2:** Slope was grouped into five categories (i.e., 0-5°, 5-10°, 10-15°, 15-20°, and above 20°) while the other criteria remained the same. Each of these slope categories was assigned weights ranging from 1 to slopes of 0-5°, 0.75 to slopes of 5-10° (low-medium slope), 0.5 to slopes of 10-15° (medium-high slope), 0.25 to slopes of 15-20° (less suitable), and 0 to slopes above 20° (not suitable). After normalizing all criteria, we assigned equal scores to get the GPS.
- **Scenario 3:** The criteria and weights were the same as scenario 1, except that industrial buildings were excluded from the analysis to obtain scores.

7.1.2. Street-level greenery assessment

In the second stage of the modelling framework, the existing greening conditions around the streets were evaluated using street-view images (SVIs). To operationalize the process, image sampling points were generated at 50 m intervals using road network data for Gdańsk to collect Google Street View images (GSV). At each point, a four-directional panoramic SVI was acquired using the GSV static API (Google, 2025) in compliance with the Google Maps Platform Terms of Service. Imagery was used solely for non-commercial academic research. We acknowledge the ongoing debate regarding the legal and licensing implications of proprietary imagery (Helbich et al., 2024).

After image collection, an image segmentation deep learning model was utilized based on the pretrained Masked-attention Mask Transformer (Mask2Former) model (Cheng et al., 2022a).

Earlier studies indicated that the Mask2Former model trained on the Cityscape dataset showed very high reliability in analysis (Cheng et al., 2022b; Sánchez and Labib, 2024). This model classifies each pixel into urban classes such as roads, vegetation, buildings, sky, and others. To determine the suitability of each image for analysis, the process developed by Danish et al. (Danish et al., 2025) was utilized. Of 24,341 street segments, 17,448 had valid imagery after filtering, and a final cleaned dataset of 22,156 segments was used to calculate several image-based indicators that provide information on existing green spaces, vacant land, and open space availability around each street. These indicators include the Green View Index (GVI), impervious area index (IAI), and open space index (OSI).

First, the GVI quantifies the proportion of visible greenery in street-level imagery (Yang et al., 2009). GVI was calculated as the ratio of green pixels to the total number of pixels across four directional images. However, due to the potential unavailability of all four images at each location, a modified version of the GVI (Sánchez and Labib, 2024) was used:

$$GVI = \frac{1}{N} \sum_{i=1}^N \frac{Area_{green\ pixels,i}}{Area_{total\ pixels,i}} \quad 7.2$$

where $Area_{green\ pixels,i}$ is the number of green pixels in the image i , $Area_{total\ pixels,i}$ is the total number of pixels in the image i , and N is the number of images at the sample point.

Second, IAI was computed, which measures the proportion of impervious surfaces (e.g., roads, pavement) visible in the street view images. It was calculated similarly to the GVI as:

$$IAI = \frac{1}{N} \sum_{i=1}^N \frac{Area_{impervious,i}}{Area_{total\ pixels,i}} \quad 7.3$$

where $Area_{impervious,i}$ is the number of impervious pixels in the image i .

Third, OSI was computed, which reflects the visible open, non-built, and non-vegetated areas (often bare ground or terrain) in the images. It was computed as:

$$OSI = \frac{1}{N} \sum_{i=1}^N \frac{Area_{terrain,i}}{Area_{total\ pixels,i}} \quad 7.4$$

where $Area_{terrain,i}$ is the number of terrain pixels in the image i .

The mean values of GVI, IAI, and OSI were calculated from point-level data and assigned to each corresponding road or street segment. These values ranged between 0 (no greenery/impervious/terrain) and 1 (high greenery/impervious/terrain). Altogether, these

indicators provided not only the existing greenery conditions but also the spatial constraints and opportunities for future greening around each street.

7.1.3. Assessing current street trees

The next stage of this methodology was designed to assess how many trees could be added for streets with poor current greening conditions. To achieve this, first the current state of the trees along each street was analyzed. For this purpose, existing tree data of Gdańsk were extracted from 3D-tree model data of Poland (Geoportal.pl, 2023b). A buffer of 20 m was created around each road segment that was used to retrieve SVI from GSV. The existing tree count was then calculated for each street within a 20 m buffer. Tree count was used as the dependent variable, and the covariates were NDVI, LST, street length, air pollutants (NO₂, PM_{2.5}, PM₁₀), and population density. Covariates captured ecological suitability (NDVI, LST, air pollutants) (Locke et al., 2011) and urban form (street length, population density), as these factors influence microclimate conditions, planting space availability, environmental stress, and potential demand for urban greenery (Almeter et al., 2018; Kim et al., 2021; Wu et al., 2008). The mean value of each covariate was calculated for each street segment using a 20m buffer. Furthermore, data preprocessing involved normalization and outlier removal. After that, a correlation analysis was conducted between independent and dependent factors. The dataset was randomly split into training (70%) and test (30%) sets.

To identify the most suitable algorithm, a model comparison was performed including linear regression, random forest, and eXtreme Gradient Boosting (XGBoost). XGBoost (Chen and Guestrin, 2016) achieved higher overall predictive performance for this dataset and was therefore selected. Compared to linear regression, tree-based models such as XGBoost offer the advantage of capturing non-linear relationships and variable interactions (Zhou et al., 2022), which are important for complex environmental drivers of urban tree distribution. A grid search cross-validation was used for hyperparameter tuning. The final model was configured with a squared error objective function, 100 estimators, a learning rate of 0.1, and a random state of 42 to ensure reproducibility. In addition, feature importance values were extracted from the trained XGBoost model using the split frequency ("weight") metric to assess the relative contribution of each explanatory variable to the tree count prediction. Model accuracy was evaluated using several statistical metrics for test data: Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R².

7.1.4. Hypothetical street tree greening scenarios

In addition to analyzing patterns in existing street trees, a trained model was used to estimate how many additional trees could have been planted on each street if we increased greenery. Notably, for streets with poor greening conditions, a GVI threshold of <0.2 was selected to identify streets with insufficient greenery ("poor streets"). This threshold was selected from the lower half of the GVI distribution (values ≤ the 50th percentile). On these streets, the need to plant more trees was assessed to increase greenery by adding trees.

Hence, the hypothetical street greening scenario was created by increasing the GVI value to > 0.4 for selected poor streets. This threshold was selected based on the observed distribution of GVI values across the study area, where the median GVI is approximately 0.20, and the upper quartile is around 0.30, meaning that a value above 0.4 represents a substantial but still realistic improvement in street-level greenery, acknowledging the available planting space, street geometry, and infrastructure limitations commonly considered in urban tree planting guidelines (Borowska-Stefańska et al., 2018; E Szopińska and Zygmunt-Rubaszek, 2010). Modified GVI values, along with other factors, were provided to the trained XGBoost model to predict improved tree counts for hypothetical streets, with modified greening values. Because model predictions may exceed what is physically feasible (e.g., suggesting more trees than can realistically fit along a short or already well-planted street), a scaling factor (SF) was applied. The SF for each street segment was calculated as the ratio of the maximum number of trees that could physically fit along the street (based on segment length, planting spacing, and existing tree count) to the model's predicted tree count, ensuring that the final recommendations do not exceed the available planting capacity. The detailed method for defining the scaling factor SF is given in Appendix C, note C1. This approach was implemented for three spacing scenarios (5m, 10m, and 15m between trees), following Polish road-vegetation guidelines (E Szopińska and Zygmunt-Rubaszek, 2010), yielding three different tree counts for each scenario. Hence, finally, three tree planting scenarios were defined to increase greenery around poor streets: (i) New trees at 5 m spacing; (ii) new trees at 10 m spacing; (iii) new trees at 15 m spacing. Results are presented as maps and can be explored using interactive web maps [GreenRoofs](https://khansa-gulshad.github.io/GreenRoofs/)³ and [GreenStreets](https://khansa-gulshad.github.io/GreenStreets/)⁴.

7.1.5. Runoff retention and interception estimation

In the fourth stage of the methodology, the hydrological performance of BGR and street trees was assessed across different scenarios. This stage summarized the potential impact of future greening on stormwater and flood management under varying urban greening scenarios.

7.1.5.1. Stormwater retention for blue-green roofs

To assess the theoretical hydrological impact of potential blue-green roofs, the runoff retention method was adopted from the Resilience nEtnetwork of Smart Innovative cLIimate-adaptive rOoftops (RESILIO) model (H de Moel et al., 2021). Apart from RESILIO's reference parameters (drainage factor = 0.9 and storage depth = 71mm), two additional drainage factors (0.8 and 0.7) and storage depth layers (50mm, 30mm) (Appendix C, Table C1) were considered to represent different blue-green roof design capacities (low and moderate) (Zhang et al., 2021) and for sensitivity analysis.

Three rainfall events were selected from the local intensity-duration-frequency (IDF) dataset (IMGW-PIB, 2022) to represent different levels of storm intensity. The 1% annual exceedance

³ <https://khansa-gulshad.github.io/GreenRoofs/>

⁴ <https://khansa-gulshad.github.io/GreenStreets/>

probability (AEP), also known as a 100-year storm, represents a rare but extreme rainfall event (44.02 mm). The 10% AEP (10-year storm, 26.50 mm) corresponds to the design-standard rainfall commonly used in urban drainage planning. The 50% AEP (2-year storm, 17.28 mm) reflects a relatively frequent but moderate rainfall event. Together, these three events cover extreme design and routine storm conditions. The adopted hypothetical blue-green roof design parameters are given in Table A1 in Appendix C, note C2. The percentage runoff reduction ($\%Reduction$) and city-scale retention impact ($\%I$) were calculated as:

$$\%Reduction = \left(\frac{D_{retained}}{P} \right) \times 100 \quad 7.5$$

$$City - scale \%I = \left(\frac{V_{retained}}{V_{total}} \right) \times 100 \quad 7.6$$

where $D_{retained}$ is retained rainfall depth (mm), $V_{retained}$ is total retained volume (L), V_{total} is the city runoff volume (L), and P is the rainfall depth (mm). Derivations of intermediate terms ($D_{retained}$, $V_{retained}$, V_{total}) are provided in Appendix C, note C2.

7.1.5.2. Runoff interception estimation for hypothetical street trees

To estimate the potential of urban tree canopies along the streets to mitigate stormwater runoff, a quantitative interception method was applied (Hirabayashi, 2015, 2013). In this approach, rainfall falling on the tree crown is partially held on leaves and branches before evaporating or slowly dripping to the ground, reducing the effective runoff volume (Dowtin et al., 2023a). The method uses tree canopy size (small, medium, large) and interception efficiency values (the proportion of incident rainfall typically retained by trees) for sensitivity analysis (Table C2 in Appendix C).

The method calculates the intercepted rainfall volume and the resulting reduction in runoff using the parameters in Table CA2 of Appendix. The runoff coefficient and selected storm events are the same as those used for runoff retention by the blue-green roof method. The percentage of runoff reduction η due to tree interception is calculated as:

$$\eta = \frac{I_{total}}{Q_{total}} \times 100 \quad 7.7$$

The net runoff Q_{net} is calculated by subtracting the intercepted volume from the total runoff.

$$Q_{net} = Q_{total} - I_{total} \quad 7.8$$

Derivations of I_{total} (based on crown area A_c , interception efficiency E_i , and tree counts N) and Q_{total} (using runoff coefficient C and city area A_{city}) are provided in Appendix, note C3.

Table 7.1 presents the key scenarios considered in the primary analysis. A full combination of green roof storage layer depth (high, medium, low) and tree characteristics (spacing and diameter) (Table C4) was explored in a sensitivity analysis, with detailed results provided in Appendix C.

Table 7.1. Representative scenarios considered in the main analysis: high green roof retention and medium tree diameter

Rainfall Scenario	Green Roof Scenario (High retention)	Tree Spacing (Medium Diameter)
1% (100-year): 44.02 mm	GR1: Baseline	T1: 5 m spacing
	GR2: Slope-weighted subcategories	T2: 10 m spacing
	GR3: Industrial buildings excluded	T3: 15 m spacing
10% (10-year): 26.50 mm	GR1: Baseline	T1: 5 m spacing
	GR2: Slope-weighted subcategories	T2: 10 m spacing
	GR3: Industrial excluded	T3: 15 m spacing
50% (2-year): 17.28 mm	GR1: Baseline	T1: 5 m spacing
	GR2: Slope-weighted subcategories	T2: 10 m spacing
	GR3: Industrial buildings excluded	T3: 15 m spacing

7.2. Results

7.2.1. Potential blue-green roofs

The potential blue-green roof suitability analysis results show that Gdańsk has substantial, spatially concentrated rooftop potential, with suitability highest in lowland and central districts across all scenarios. In Scenario 1, 20.65 % of the city's buildings were suitable for blue-green roofs, adding up to 5.4 km² of potential green roof area. Scenario 2 produced nearly identical results, while scenario 3 reduced the number to 17.49% and the total area to 3.8 km². This 30% reduction indicates that large industrial buildings account for a large share of the city's green-roof potential.

Across all three scenarios, the candidate rooftops share very similar geometric characteristics, making them excellent for extensive greening. Most roofs are flat with gentle slopes of 3° to 5°, so little soil retention is required. Buildings are low- to mid-rise (5-20 m), making them easy to access and reducing structural concerns. Rooftops are small to medium in size (over 90% under 1000 m²) and are easy to retrofit with compact, regular shapes (values 0.93-4). Figure 7.2 presents examples of buildings with different GPS. The images highlight key attributes such as height, slope, roof area, and shape ratio, showing how these factors influence the suitability for green roof installation.

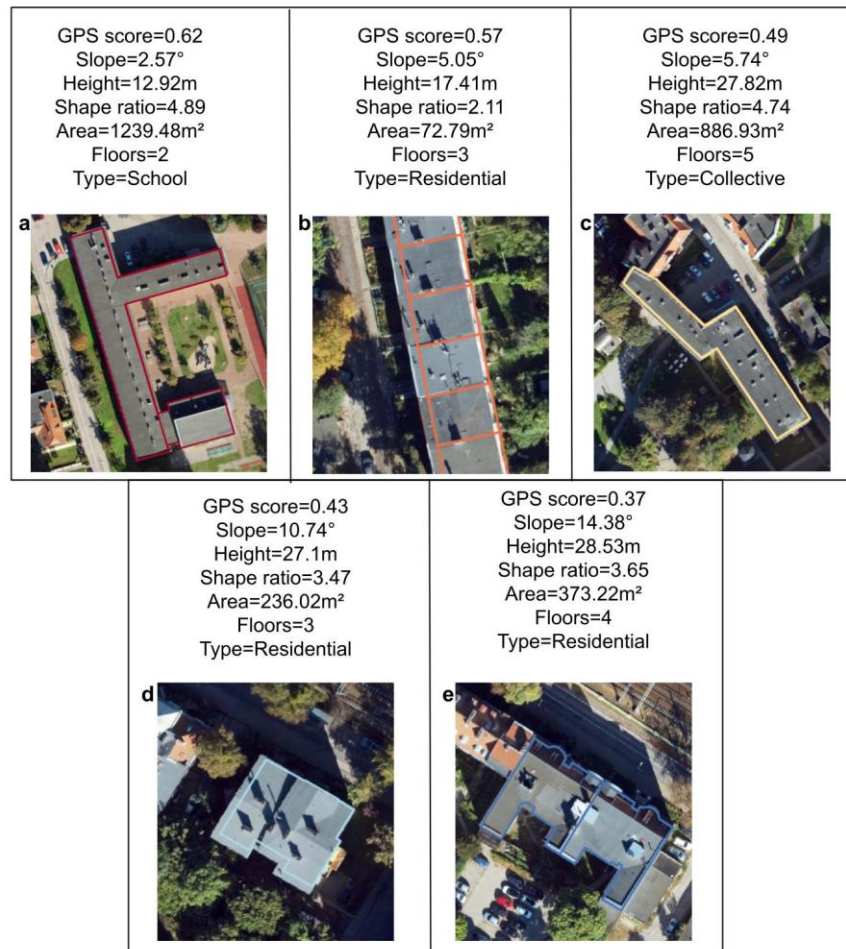


Figure 7.2. Representative examples of buildings evaluated for green roof suitability. The GPS is shown along with key building attributes (slope, height, perimeter, shape ratio, area, floors, and type) to illustrate variation in suitability across different building types. *Reproduced from authors work Gulshad et al. (under review).*

Across all three scenarios, buildings in Gdańsk range from low to high suitability for blue-green roofs (GPS 0.25-0.74). In scenario 1 (mean 0.55), when all four factors are equally weighted, most buildings fall within the middle-to-high suitability range (0.60-0.66), with many clustering around moderately high potential. This shows that green roofs are broadly feasible across the city when no single factor dominates. Scenario 2 (mean 0.58), with categorized slope scores, shows more buildings shift into the higher-potential range (GPS scores 0.60-0.70), suggesting that roofs with moderate slopes are still good candidates. In scenario 3 (mean 0.54), when industrial buildings are excluded, average suitability dropped a bit with more buildings grouped in the moderate range (0.50-0.60). This shift suggests that industrial buildings, often with large, flat roofs, play an important role in raising the city's green-roof potential, even though many non-industrial buildings remain suitable.

The city-wide GPS maps for scenarios 1-3 (Figure 7.3) show that buildings suitable for potential green roofs are concentrated in Gdańsk's lowland (i.e., central, north central, and east), while

buildings in the south and east parts did not qualify. In scenarios 1 and 3, the highest suitability ($GPS \geq 0.56$, red and dark red) is clustered mainly in the central areas, i.e., central east, forming a continuous belt along the main water corridors and the historic core. High and medium-high suitability (0.56-0.73) roofs occur in the northern and northwestern districts, whereas lower suitability buildings ($GPS < 0.55$, pale yellow through blue) dominate the western edges. In scenario 2, high-potential clusters (dark red; GPS 0.60-0.74) are scattered across the central, north central, and eastern districts, with moderate-high zones (orange; GPS 0.52-0.59) and low-potential buildings (light and dark blue; GPS 0.51-0.29) interspersed among them. A low potential patch was found in the western area, consistent with the patterns seen in Scenarios 1 and 3. Maps for scenario 2 (Figure C3) and scenario 3 (Figure C4) are provided in Appendix C.

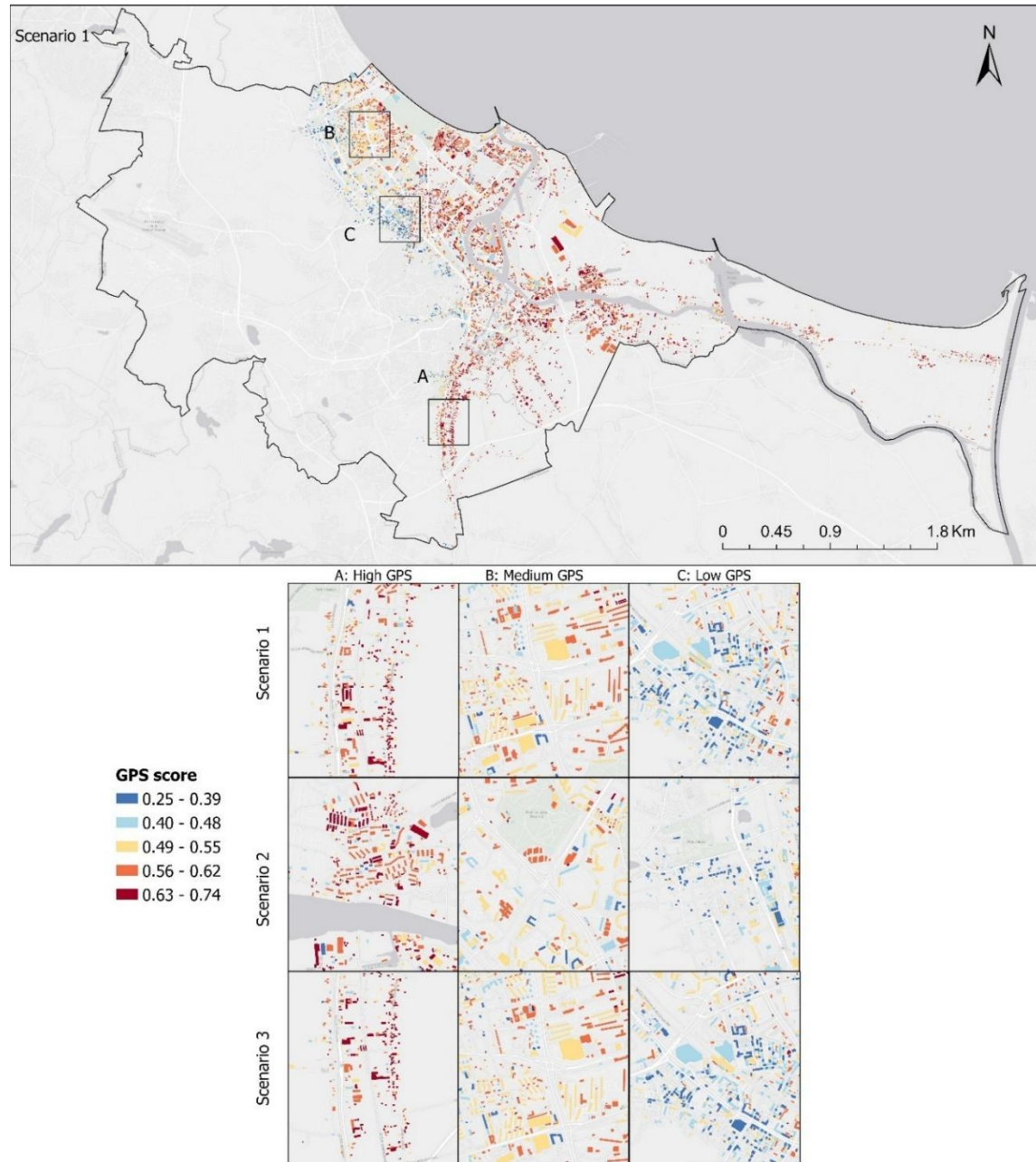


Figure 7.3. Spatial distribution of potential green roofs in Gdańsk with their respective greening potential score under Scenario 1,2,3. *Reproduced from authors work Gulshad et al. (under review).*

7.2.2. Street-level greenery assessment

Overall, our analysis shows that most streets offer limited exposure to greenery from a pedestrian perspective, are dominated by paved surfaces, and provide very little open or undeveloped ground. These results are supported by segmentation analysis. GVI values ranged from 0 to 0.99, with a mean of 0.223, meaning on average, only about one-fifth of the street view consists of vegetation, as shown in Figure 7.4. Three-quarters of all street segments have a $GVI \leq 0.30$, indicating that

most locations have relatively sparse vegetation, though some reach nearly full coverage (maximum = 0.993).

Street view	Streetscape Indices
	Good street Street name=68 Słupska GVI=0.64 IAI=0.19 OSI=0.00 Existing tree count=37
	Medium street Street name=43 Ludwika Waryńskiego GVI=0.16 IAI=0.33 OSI=0.00 Existing tree count=3 Additional trees needed=2
	Poor street Street name=31 Ogarna GVI=0.02 IAI=0.35 OSI=0.00 Existing tree count=0 Additional trees=5

Figure 7.4. Example of streetscape analysis showing the street view (left) and calculated greenness indicators (right) for good, medium and poor streets, including GVI, IAI, OSI, and existing tree count. *Reproduced from authors work Gulshad et al. (under review).*

By contrast, impervious surfaces are the most visually dominant element, with high values ranging from 0 to 0.99, and an average of 0.355. 75% of street segments have an $IAI \leq 0.44$, confirming that paved surfaces, roads, sidewalks, and other hardscape are the dominant visible elements. Open space (i.e., terrain) is minimal and could accommodate new planting; OSI values range from 0 to 0.64, with a mean of only 0.080. 75% of street segments have an $OSI \leq 0.12$, showing that bare earth or gravel is rarely exposed in the public right-of-way. Taken together, these statistics highlight that while impervious cover is pervasive, there remains substantial room to increase street-level greening where GVI is low and open-space interventions could be most impactful.

Across Gdańsk, geographic patterns reveal unequal access to street greenery (Figure 7.5). Peripheral areas experience tree-lined streets, while dense central districts are dominated by concrete corridors with minimal greenery. The western and eastern peripheral areas with forested or semi-natural surroundings exhibit the highest GVI values (0.43-0.99, dark green) and lower

impervious areas (0.0-0.32), forming continuous corridors of dense street greenery. Intermediate values (0.15-0.42, orange, light green) characterized mixed residential and commercial zones in the central and northern parts, while dense central areas showed the lowest GVI (0.00-0.14, red lines) and high impervious areas (0.43-0.99), with only sparse roadside planting (inset C). Overall, segments with $GVI \leq 0.20$ indicate the potential to enhance street-level greenery. Based on this distribution, all streets with $GVI < 0.20$ (the lower quartile) were classified as “poor streets.” This selection identified 8,579 segments ($\approx 38.7\%$ of the dataset) as candidates for further greening through hypothetical tree-planting scenarios.

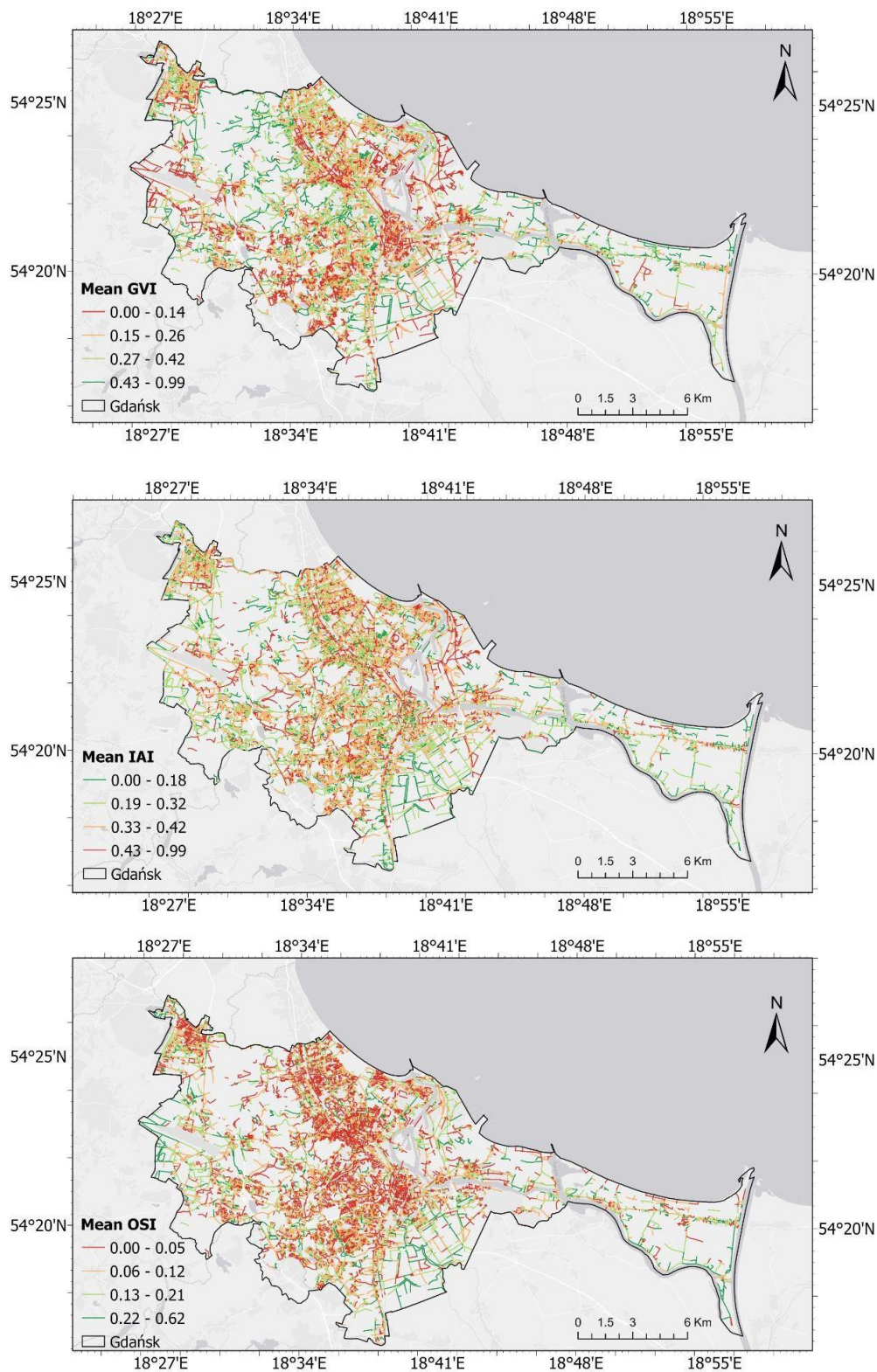


Figure 7.5. Average GVI, IAI, OSI across streets in Gdańsk. *Reproduced from authors work Gulshad et al. (under review).*

7.2.3. Potential street greening scenarios

Multicollinearity was assessed using VIF and correlation analysis before model training (Appendix C, table C3, figure C1), confirming acceptable levels of collinearity among the selected variables. The model demonstrated strong predictive performance on the test dataset (MAE: 2.71, MSE: 27.76, RMSE: 5.25, R^2 : 0.82). These results suggest that the combination of street-level factors (length, GVI, IAI, OSI, NDVI, LST, population density, NO_2 , and PM_{10}) offers substantial explanatory power for predicting existing tree counts and thus can serve as a reliable basis for estimating potential tree planting scenarios. This was also confirmed by the feature importance of XGBoost given in Figure C2 in Appendix C

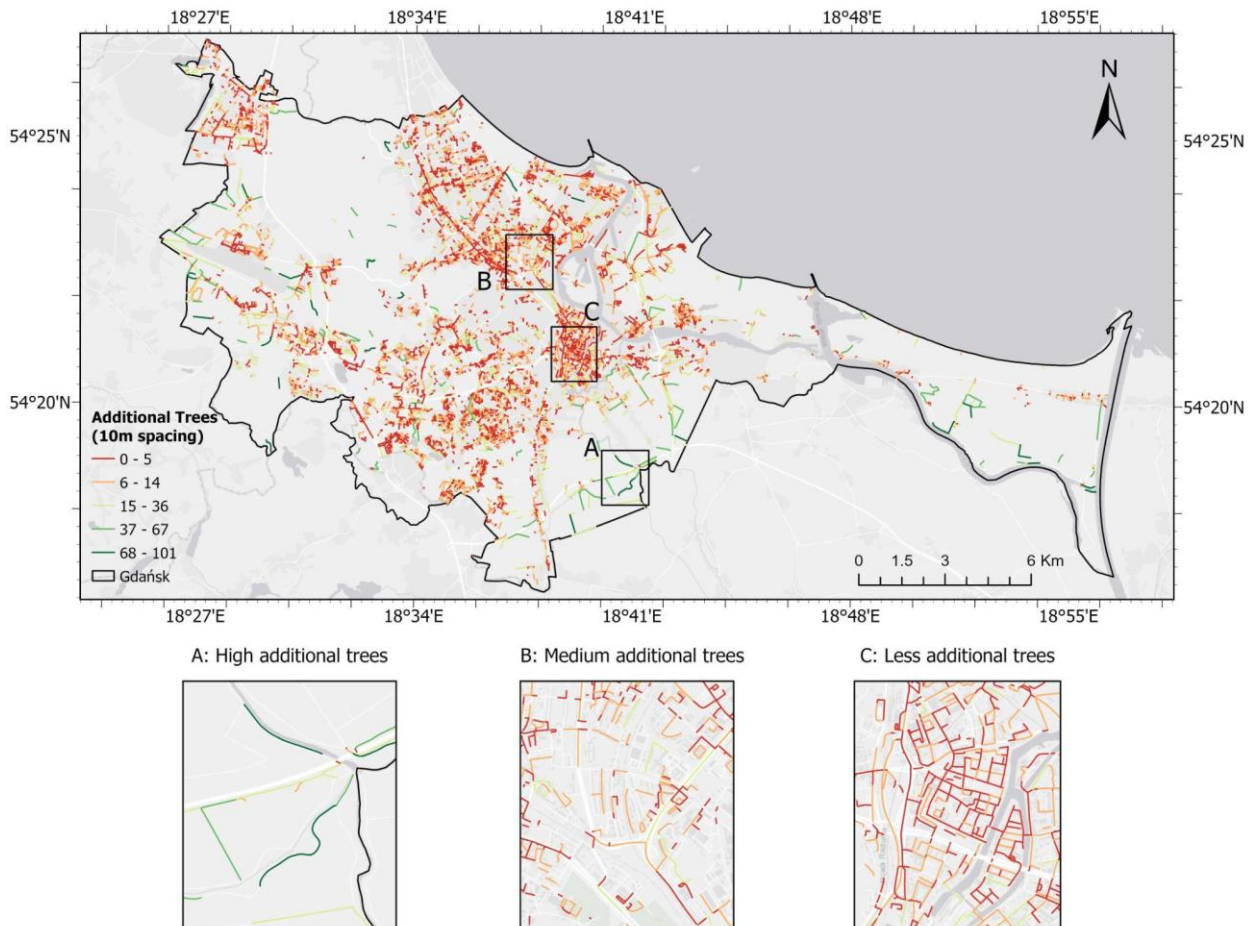


Figure 7.6. Spatial distribution of hypothetical streets with predicted additional trees for 10m spacing. *Reproduced from authors work Gulshad et al. (under review).*

The modeling results indicated substantial capacity for expanding street trees in Gdańsk, even under conservative spacing assumptions. Across 8,579 poor street segments, the analysis found 48,790 additional trees at 5 m spacing, 48,653 at 10 m spacing, and 47,777 at 15 m spacing, representing potential increases of ~201%, ~200%, and ~197% over the existing 24,279 trees along these streets. The spacing between trees (5, 10, or 15 m) makes very little difference to the total

number needed, and the results are consistent across all options. On average, each street would need about five new trees at each spacing, with 75% of streets receiving seven or fewer new trees. In practical terms, most streets can be substantially greened with fewer than ten new trees, and only a handful of street segments require very large numbers of trees.

The additional-trees (10 m spacing) map (Figure 7.6) shows where Gdańsk's poorest streets would benefit most from new trees. Lines colored dark red (0-5 trees) cover the old town and dense built-up areas, with narrow, tightly built streets where only a handful of trees will fit per block. Orange (6-14 trees) appear in the north and west of the city. Light green (15-36 trees) and dark green (37-101 trees) segments trace longer boulevards and parks in the southeastern and eastern parts, where sufficient space exists for a substantial planting belt (Inset A), highlighting a trade-off between urgency and feasibility. Maps for 5m (Figure C5) and 15m (Figure C6) spacing are provided in Appendix C.

7.2.4. Hydrological Impact of Greening: runoff retention and interception

Table 7.2 presents the runoff retention potential of green roofs across three scenarios with varying roof coverages and rainfall depths. All scenarios model blue-green roofs with high retention design parameters that retain 100% of incident rainfall up to their storage capacity, with scenario 1 providing the greatest retention volumes and citywide impact. Scenario 1 yields the highest runoff retention volumes across all three rainfall depths (Table 7.2). For a rare but extreme storm event (44.02mm), approximately 238.48 ML is retained, translating to a citywide impact of 4.14%. This retention capacity decreases slightly for lower rainfall depths but remains consistent in terms of citywide impact. In scenario 2, the retention volumes and citywide impact are nearly identical to scenario 1. Scenario 3, with a reduced green roof area, shows a smaller overall retention volume, with 166.31 ML retained under the 44.02 mm rainfall scenario. The citywide impact is reduced to 2.88%, reflecting the lower total green roof area. The results of the sensitivity analysis are given in Table C5 in Appendix C. Retention capacity is highly sensitive to blue-green roof design. Reducing storage depth and drainage efficiency from high to medium retention results in an approximate 9.13% decrease in retention for large storm events (44.02 mm). Low retention scenarios reduce volume by over 52.29% for the 44.02 mm rainfall event, 20.75% for the 26.50 mm rainfall event, and no change for the 17.28 mm rainfall event, compared to the high retention scenario. These findings underscore the importance of selecting the appropriate retention capacity for green roofs, especially for managing stormwater runoff.

Table 7.2. Runoff retention under varying green roof scenarios and rainfall design storms for the high retention scenario (storage layer depth 70mm, drainage factor 0.9).

Scenario	Green roof area (m ²)	Rainfall (mm)	Total runoff (Billion L)	Retained volume (ML)	City impact (%)
GR1	5,417,580.6	44.02	5.77	238.48	4.14
		26.50	3.47	143.57	4.14
		17.28	2.26	93.62	4.14

GR2	5,417,502.2	44.02	5.77	238.48	4.14
		26.50	3.47	143.56	4.14
		17.28	2.26	93.61	4.14
GR3	3,778,154.3	44.02	5.77	166.31	2.88
		26.50	3.47	100.12	2.88
		17.28	2.26	65.29	2.88

Table 7.3 presents data on tree interception of runoff across different scenarios, with medium-sized trees (5.6m in diameter) at varying tree counts. Scenario 1 demonstrates a consistent runoff interception percentage (22%) across different rainfall depths (44.02 mm, 26.50mm, and 17.28mm). Total interception volumes for Scenario 1 range from 4.92 ML for the lowest rainfall to 12.54 ML for the highest. Scenario 2 yields similar to Scenario 1, with the same interception percentage but slightly lower total interception volumes. Scenario 3 has a slightly lower rainfall interception percentage (21%) and a smaller total interception volume than the previous two scenarios.

These results indicate that increasing tree cover can lead to greater runoff interception, with slightly diminishing returns as the spacing between trees increases from 5m to 15m. Results of the sensitivity analysis for runoff interception (Table C6) are provided in Appendix C. Compared to the medium canopy diameter class (5.6m), interception values for the small diameter class (3.4m) are consistently 63.64% lower across all scenarios and rainfall conditions. In contrast, the large diameter class (6m) yields an increase of 13.64% in Scenario 1 and Scenario 2, and 14.29% in Scenario 3 across all rainfall events. These differences highlight the strong influence of canopy size on urban tree ecosystem services, particularly stormwater management capacity.

Table 7.3. Runoff interception under varying tree counts (based on spacing scenarios), rainfall design storms for medium diameter class.

Scenario	Number of Trees	Rainfall (mm)	Total runoff (Billion L)	Rainfall Interception (%)	Total Interception (ML)
T1	48,790	44.02	5.77	0.22	12.54
		26.50	3.47	0.22	7.55
		17.28	2.26	0.22	4.92
T2	48,652	44.02	5.77	0.22	12.50
		26.50	3.47	0.22	7.53
		17.28	2.26	0.22	4.91
T3	47,775	44.02	5.77	0.21	12.28
		26.50	3.47	0.21	7.39
		17.28	2.26	0.21	4.82

7.3.Discussion

GI is a critical implementation pathway for NBS, which is increasingly recognized for enhancing urban resilience to climate change. This study contributes to the operationalization of GI by developing an integrated GIS and machine-learning-based framework that operates across multiple scales, from building rooftops to streetscapes, to enhance urban climate resilience in terms of stormwater and flood management. By treating green roofs and street trees not as independent interventions but as complementary elements of a single urban system, GI can buffer cities against extreme flooding while delivering co-benefits for society. Notably, this study advances existing approaches fourfold.

First, the scenario-based green roof suitability model introduces flexibility in defining roof eligibility criteria and planning constraints. By using multiple scenarios within the GPS framework, we identified numerous opportunities to retrofit green roofs, even when accounting for structural and land-use constraints. Rather than adopting a binary or single variable approach, the slope-weighted method (Scenario 2) captures additional green roof opportunities that strict thresholds would miss (Dong et al., 2025; Peranović, 2025). Notably, results showed that low-rise, moderate-slope, and compact roofs were the most suitable. These findings aligned with Landscape Development and Landscaping Research Society-FLL green roof guidelines for extensive systems (Landschaftsbau, 2018), suggesting that widespread implementation may depend more on supportive policies than on specialized engineering. Furthermore, scenarios showed how factors such as excluding industrial buildings or applying stricter slope requirements can alter the number of potential green roofs. This reflects patterns found in Amsterdam, where 27% of roofs were suitable under strict limits but 38% under relaxed limits (de Moel et al., 2022; T Haer et al., 2022). Taken together, this approach shifts green-roof suitability analysis from a rigid, one-size-fits-all assessment to a nuanced, scenario-based framework that connects technical feasibility with policy decisions.

Second, we provide a streetscape assessment by introducing new visual indicators. While GVI has been used globally (Abbati, 2019; Aikoh et al., 2023; Lu et al., 2023b; Sánchez and Labib, 2024; Xiao et al., 2021; Ye et al., 2019), IAI and OSI are introduced here for the first time at the street level. Together, these indicators provide a more complete view of the urban visual environment, showing the balance between visible greenery, paved surfaces, and open terrain. The results highlight a clear contribution: while GVI values align with global benchmarks (Aikoh et al., 2023; Sánchez and Labib, 2024; Ye et al., 2019), adding IAI and OSI reveal the dominance of paved surfaces and lack of open space, a pattern common in post-socialist cities that often prioritize infrastructure over greenery (Davies and Laforteza, 2017; Gadziński, 2015; Hrdalo et al., 2015). Consistent with previous findings that urban greening is limited by the distribution of pervious and impervious surfaces (Nyelele and Kroll, 2021), our results showed that dense urban areas with low greenery and more impervious surfaces have few options for interventions, suggesting the need for green walls or roof greening (Peranović, 2025). This is the opposite of conventional tree planting programs, which often focus on peripheral areas where implementation is easier but

benefits are lower, highlighting the value of data-informed frameworks applicable across diverse urban settings. Areas with low greenery and more open space may signal easier opportunities for ground-level interventions. However, since most streets have very little open space, planting trees in built-up areas will require engineered solutions, such as structural planters, tree grates, or permeable paving, rather than natural soil exposure. This finding has direct implications for costs and maintenance requirements, as engineered solutions are more expensive (Berland et al., 2017) but necessary in heavily paved urban environments, a common condition in cities globally.

Third, we bridge the gap between identifying need and defining action through predictive modeling. This data-driven approach addresses a critical question for urban forestry: where and how many new trees can we plant, given the physical and spatial constraints? Traditional suitability studies rely on GIS or rule-based criteria (Almeter et al., 2018; Kim et al., 2021; Locke et al., 2011; Nyelele and Kroll, 2021; Wu et al., 2008), which are useful but prescriptive. Machine learning addresses this gap by learning patterns between environmental features and existing tree distributions, enabling predictive estimation of greening potential across entire city networks. Rather than a scattershot million trees approach, we introduced a scaling factor that accounts for segment length, existing trees, and planting guidelines, ensuring that predictions translate into feasible planting numbers. Thus, this framework provides segment-by-segment targets for urban planners seeking to move streets out of the lowest quartile of visible greenery. Furthermore, machine learning can indirectly support equity and resilience by helping planners identify under-green streets and make better, evidence-based policy decisions.

Moreover, the consistency of results across different tree-spacing scenarios suggests that small variations in planting distance have only a minor effect on overall outcomes. What matters more is identifying and improving street segments with low tree cover. This approach gives planners flexibility to adapt spacing guidelines according to local species, maintenance capacity, and design preferences. However, T2 (10-meter) spacing is appropriate for residential streets with moderate heat risk and typical pedestrian volumes, while T3 (15-meter) spacing should be avoided in populated areas because it reduces benefits. This prioritization supports environmental justice by directing intensive interventions toward communities with the greatest need and vulnerability, rather than applying the same standards that cause existing green space inequalities. Importantly, our results also revealed that the potential for tree planting is uneven across the city. Some streets could accommodate many additional trees, whereas central downtown areas have little available space. This reflects a broader pattern where suburban-style neighborhoods often have the greatest potential for green corridor development, while denser urban cores require creative solutions beyond street trees (McDonald et al., 2021). Similar space limitations exist worldwide, hence using multiple strategies is often necessary.

Fourth, our integrated framework shows the synergistic benefits for stormwater management. Green roofs act as small, distributed retention basins, capturing large volumes of rainfall, which is important in urban cores where ground-level greening is limited. Their impact is greater when combined with other complementary interventions, emphasizing the importance of integrated GI

strategies rather than relying on a single component, a principle applicable to stormwater planning globally (Berland et al., 2017). In scenario 3, industrial buildings were excluded, hence lowering stormwater retention. While many industrial rooftops are technically suitable, operational barriers such as heavy equipment, chemical handling, or maintenance needs make implementation difficult. This highlights that addressing non-technical barriers through targeted policies or incentives can increase retention, especially in flood-prone districts. Furthermore, the high sensitivity of retention performance to design parameters carries critical implications for policy design and implementation standards. If green roof programs do not specify minimum performance requirements or incentivize high-retention designs, the actual benefits will be lower than expected (Zheng et al., 2021). This finding underscores the need for performance-based standards rather than simple presence/absence requirements in GI policies, ensuring that installed systems deliver the intended hydrological services.

The modest contribution of street trees to stormwater interception should be understood in the broader context of urban tree benefits. While trees make limited direct contributions to runoff reduction, their co-benefits like thermal regulation, air quality, carbon sequestration, habitat provision, water quality protection, and human wellbeing justify investment (Berland et al., 2017; Donovan et al., 2013; Mullaney et al., 2015). This finding reinforces the importance of valuing street trees for their multifunctionality. The strong influence of canopy size on interception capacity highlights a temporal dimension often neglected in static assessments (Berland et al., 2017; Downton et al., 2023a). Similar to concerns raised by Chazdon and Guariguata (2018) and Nyelele and Kroll (2021) regarding temporal lags in ecosystem services, our analysis highlights that newly planted trees provide minimal hydrological services until canopies mature. This temporal lag underscores the need to initiate tree-planting programs, as delays lengthen the time required to achieve full canopy coverage and the associated benefits. Such temporal dynamics should be factored into long-term urban greening, and climate adaptation plans worldwide. Furthermore, the combined potential of green roofs and street trees suggests that these interventions should be used together as components of hybrid systems that combine gray and green approaches, enhancing rather than substituting for centralized drainage systems (Berland et al., 2017). This perspective aligns with urban water management approaches that promote resilience through a combination of solutions and applies to cities worldwide as they adapt to the challenges of climate change.

7.3.1. Planning and policy implications

This integrated framework provides a practical, data-driven way to translate urban climate and sustainability goals into implementable green infrastructure projects. By combining spatial indicators (GVI, IAI, OSI) with predictive modeling, it enables planners for location-based identification of GI interventions, and efficient allocation of resources. It helps municipalities meet EU policy targets by identifying exactly which rooftops and streets can be greened and how many trees or green roofs are feasible, turning general commitments into real action (Li and Ma, 2022b; McDonald et al., 2021; Zhou et al., 2019). The framework supports investment planning by

showing expected benefits, such as stormwater retention, making it easier to secure funding from public or private sources.

The framework also supports phased investment planning by helping municipalities prioritize low-cost, near-term opportunities, such as flat, low-rise rooftops and streets with higher open space, while accepting more complex, engineered interventions in dense urban cores. At the institutional level, effective implementation requires coordination across departments, as green roofs and street trees are often managed separately despite their interdependent benefits. The proposed indicators (GVI, IAI, OSI, and retention estimates) can also serve as baseline metrics for monitoring progress and evaluating outcomes over time. Finally, the identified feasibility and performance thresholds provide a basis for policy instruments, such as tax incentives, development regulations, or density bonuses, paired with maintenance requirements to ensure long-term effectiveness of GI interventions.

However, technical suitability alone does not guarantee successful greening. Social acceptance, participation, stewardship, or long-term maintenance play a critical role (Carmichael and McDonough, 2018; Geron et al., 2023). Incorporating results into participatory planning processes ensures technically robust recommendations also align with governance realities and community priorities. Visual indicators make plans understandable to residents, supporting participatory decision-making, and may contribute to assessing distributional inequalities across neighborhoods. Overall, this framework accelerates implementation, maximizes benefits, and provides clear, evidence-based guidance for cities to build greener, more resilient urban environments.

7.3.2. Cross-chapter validation and framework implications

The NBS suitability and stormwater performance findings of this chapter complete the framework's diagnostic-to-intervention sequence, and their validity is strengthened by the degree to which their spatial outputs align with the risk and equity patterns established independently in the three preceding chapters.

The most direct validation is spatial. Suitable rooftops for blue-green roof installation concentrate in the lowland central, north-central, and eastern districts, the same areas that **Chapter 4** identified as experiencing the greatest runoff amplification under combined LULC and climate forcing, that **Chapter 5** identified as highest flood susceptibility zones, and that **Chapter 6** identified as most GI-deficient and most environmentally stressed. This spatial correspondence was not built into the suitability model; it emerges from building morphology and terrain characteristics independently of the flood risk and GI equity analyses, yet it reproduces the same spatial structure. Similarly, the 38.7% of street segments classified as critically low greenery are concentrated in the dense central districts where **Chapter 6's** environmental stress indicators are highest. The fact that physical feasibility and spatial need converge on the same locations across four independently conducted analyses, each using different data sources, methods, and spatial resolutions, constitutes the strongest cross-chapter validation point in the entire framework.

The hydrological performance results also connect back to **Chapter 4** directly. The 4.14% citywide runoff reduction from high-retention green roofs and the 0.21-0.22% interception from street trees represent quantifiable contributions to closing the retention infrastructure gap established in **Chapter 4**, where projected runoff volumes under both RCP pathways were shown to exceed the combined capacity of Gdańsk's 53 retention reservoirs. These figures confirm that GI alone cannot close that gap, green roofs and street trees most effectively attenuate sub-extreme frequent events rather than the extreme events that overwhelm engineered capacity, but they establish that spatially targeted NBS deployment delivers measurable, performance-verified contributions that complement rather than substitute for grey infrastructure. This grey-green complementarity argument is only visible because **Chapter 4** established the quantitative capacity gap against which **Chapter 7's** retention figures can be evaluated.

Chapter 7 also closes the cross-chapter validation chain by confirming the policy implication that runs through all four empirical chapters: the spatial precision of the GeoAI framework transforms GI from a general urban sustainability aspiration into a spatially targeted, performance-verified flood adaptation instrument. The findings are synthesized across all framework components in **Chapter 8**.

7.3.3. Limitations and Future Research

This study presents a promising approach for estimating the potential of green infrastructure but is subject to limitations. First, the analysis is based on hypothetical suitability scenarios rather than realized interventions. Social acceptance, governance, economic feasibility, and policy constraints were not incorporated, even though they are critical to translating technical suitability into real-world implementation. The tree model also needs to account for more physical constraints, such as utilities, street width, or site-specific suitability.

Second, the street-level greenery assessment relied on GSV imagery, which is captured at different times of year and across multiple years. Seasonal variability and inconsistencies in imagery may cause bias in the calculated greenness indicators. Green roof estimates are limited by data availability, such as building age, structural integrity, rooftop load-bearing capacity, and potential for long-term maintenance requirements; therefore, these factors should be included, as they could influence the decision to install a green roof.

Third, the runoff retention analysis for green roofs was adopted from the RESILIO project in Amsterdam. While the methodology is robust, local differences in rainfall patterns, roof construction practices, and urban hydrology may lead to deviations in actual performance. Simplified interception formulas should incorporate tree-specific features such as species, age, and environmental variability.

Finally, there is also a trade-off between green roofs and street trees. Green roofs offer immediate stormwater retention, while street trees require years to mature and therefore provide slower, long-term environmental benefits. This highlights the need for balanced planning strategies that weigh

short-term versus cumulative impacts. In practice, prioritization decisions should consider criteria such as cost-effectiveness, maintenance requirements, structural feasibility (for roofs), available space (for trees), and co-benefits for climate resilience. Future research should integrate multi-criteria to consider short-term hydrological gains against long-term ecological and social outcomes, enabling planners to balance these interventions in practice.

Consequently, future research should integrate socio-political and economic factors such as policy, funding, and community acceptance; employ alternative remote-sensing data; and validate hydrological assumptions with local runoff monitoring. It should also include fine-scale site information (soil, utilities, street design) for tree models, expanded building-level datasets on structural and maintenance attributes for green roofs, and exploration of additional greening opportunities, such as parking lots and vacant lots.

7.4. Conclusion

This research advances NBS implementation by developing an integrated framework for optimizing GI in urban environments. We combined the potential for rooftop and street greening into a single spatial planning tool to guide planning decisions. By focusing on small-footprint interventions, such as blue-green roofs and street trees, the framework offers practical solutions for dense cities with limited space. It combines GIS-based rooftop suitability assessment across multiple scenarios. It also estimates street greenery from street-view imagery and identifies how many trees could be added to low-greenery streets, accounting for physical constraints, using machine learning. Hydrological analysis quantifies the added value of blue-green roofs and street trees in mitigating runoff. Together, this work provides: i) a transferable pathway for NBS prioritization in data-scarce cities, ii) support equitable distribution of green spaces, and iii) actionable standards. While addressing trade-offs requires further work, converting underutilized rooftops and constrained streetscapes into climate-adaptive systems can help cities advance SDG 11 and SDG 13 through evidence-based deployment of NBS.

The results presented in this **Chapter 7** demonstrate that nature-based solutions are not aspirational additions to Gdańsk's urban fabric but spatially feasible, quantifiably effective, and deployable at scale within the constraints of an existing built environment. Across 20.65% of rooftops identified as suitable for greening, high-retention green roofs can mitigate 4.14% of citywide runoff, while the 47,777 to 48,790 street trees predicted as feasible in critically low-greenery corridors would extend canopy cover precisely into the impervious, heat-exposed neighborhoods that **Chapter 6** identified as structurally underserved. Taken individually, these numbers are modest. Taken together and targeted with spatial precision at the flood susceptibility hotspots established in **Chapter 5**, they represent a meaningful first layer of nature-based flood adaptation that conventional grey infrastructure alone cannot deliver at equivalent cost or co-benefit breadth. The GeoAI framework developed here does not prescribe a single solution but produces a spatially explicit decision support layer, one that tells planners not only what is possible, but where it matters most. With the diagnostic sequence complete, from hydrological baseline through susceptibility

mapping and GI inequity to intervention suitability, **Chapter 8** synthesizes these findings into a unified framework assessment, examining how each analytical stage reinforces the others and what the integrated pipeline means for urban flood adaptation beyond Gdańsk.

Chapter 8

Synthesis, Implications & Transferability

From Flood Dynamics to Nature-Based Solutions: A Geospatial AI Framework for Urban Resilience

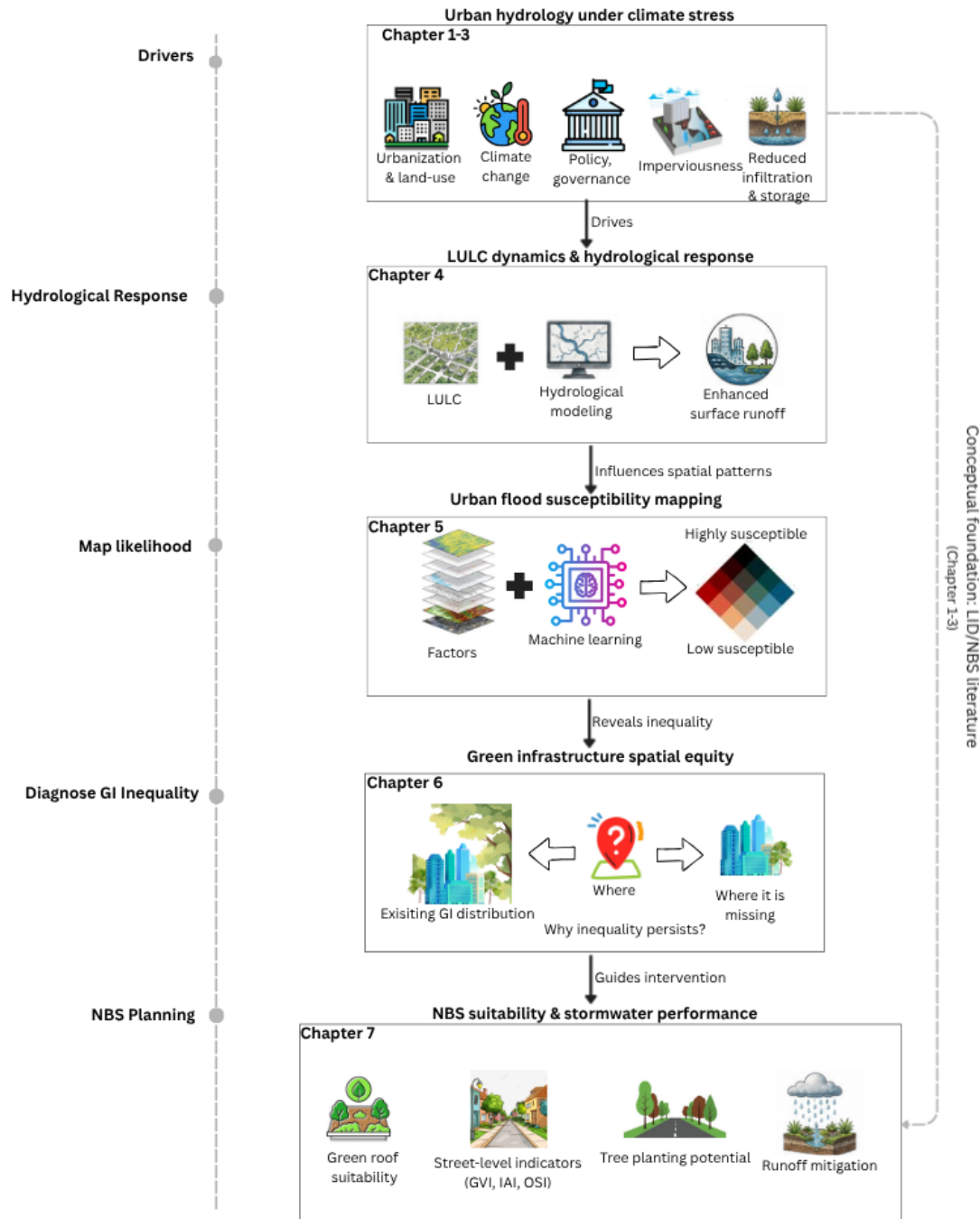


Figure 8.1. Conceptual framework illustrating the integrated research pathway linking land-use and climate drivers, hydrological processes, flood susceptibility, green infrastructure spatial dynamics, and actionable nature-based solution planning.

8. Introduction

The preceding four empirical chapters have progressively constructed a spatial understanding of urban flood risk in Gdańsk, from the hydrological consequences of land-use transformation at basin scale, through the city-scale concentration of flood susceptibility, to the structural misalignment between green infrastructure provision and hydrological need, and finally to the quantified feasibility of nature-based solutions at rooftop and street level. Each chapter was analytically self-contained, contributing a standalone scientific finding, yet each was also deliberately positioned as a necessary input to the stage that followed. **Chapter 8** steps back from individual findings to examine what they produce collectively. This chapter synthesizes the connections between analytical stages, interprets what the framework reveals that no single chapter could establish alone, and draws out the methodological, planning, and transferability implications of the integrated GeoAI pipeline. **Section 8.1** presents the cross-chapter synthesis, tracing how findings from **Chapters 4 to 7** reinforce and extend one another. **Section 8.2** reflects on the GeoAI framework as a methodological contribution. **Section 8.3** addresses uncertainty and robustness across the framework. **Section 8.4** translates findings into policy recommendations and an implementation roadmap for Gdańsk. **Section 8.5** examines the conditions under which the framework is transferable to other urban contexts.

8.1. Cross-chapter synthesis

Taken together, the five chapters comprising this thesis form a sequential GeoAI framework that advances from diagnosing how urban flood risk emerges, through mapping where it concentrates spatially, to demonstrating how it can be mitigated through targeted, data-driven green infrastructure planning. Rather than treating flooding as a uniform or purely hydrological phenomenon, the collective findings show that urban floods are spatially heterogeneous outcome shaped by interacting land-use dynamics, hydrological processes, and urban morphology that determine where adaptive capacity exists and where it does not. This integrated perspective, linking remote sensing, interpretable machine learning, spatial econometrics, and AI-driven NBS planning within a single analytical chain, constitutes the central methodological and empirical contribution of the thesis. Figure 8.1 illustrates this sequential architecture, showing how each analytical stage generates outputs that condition the next, from basin-scale hydrological drivers through susceptibility mapping and GI equity diagnosis to street-level NBS planning

8.1.1. Urban flood drivers

Chapter 4 establishes that urban flooding in Gdańsk is driven primarily by the long-term amplification of surface runoff through land-use and land-cover change, rather than climate forcing alone, though their combined effect consistently exceeds either driver in isolation. The scenario decomposition analysis is the key finding here: LULC change alone produced a 24% increase in the runoff coefficient between 1985 and 2022, climate forcing alone drove 28.70%, but the combined effect reached 49.41%, a synergy that confirms urbanization is not a secondary amplifier but a co-equal primary driver of flood risk. Critically, this relationship is non-linear: as catchments

approach full imperviousness, incremental additions of sealed surface produce disproportionately large increments in peak discharge, meaning the hydrological consequences of continued urban expansion will accelerate rather than stabilize even under moderate growth scenarios. By 2100, projected total runoff volumes under both RCP pathways will exceed the combined capacity of Gdańsk's 53 retention reservoirs by a margin that the existing drainage infrastructure, designed against pre-2000 rainfall distributions, cannot absorb. These findings reframe the policy question: stormwater runoff management in Gdańsk is not primarily a climate adaptation problem but an urban development governance problem, and land-use regulation is therefore a first-order flood management instrument.

This diagnostic finding gains additional weight from its independent confirmation in **Chapter 5**, where SHAP attribution identified land surface temperature, NDVI, and drainage proximity, all direct proxies of the imperviousness-driven processes quantified in **Chapter 4**, as the dominant predictors of flood susceptibility. The convergence of evidence across process-based hydrological modelling and data-driven machine learning, two methodologically independent analyses, constitutes the first cross-chapter validation point of the framework and provides the spatial foundation for everything that follows.

8.1.2. Spatial heterogeneity of flood susceptibility

Where **Chapter 4** established that flooding is intensifying across Gdańsk as a whole, **Chapter 5** reveals that flooding is not evenly distributed but spatially concentrated in a pattern that reflects the city's underlying urban morphology. The ANN model identifies 60.7% of the city's area as falling within high or very high susceptibility classes, with three structurally distinct vulnerability zones emerging: the urbanized moraine hill slopes in the southwest, where steep terrain accelerates runoff into downstream networks; the low-lying polder areas of Żuławy Gdańskie in the east, which sit partly below sea level with limited drainage gradient; and the Canal Radunia corridor, where drainage capacity exceedance during intense events has been repeatedly documented. This spatial polarization is not incidental, it is the direct spatial expression of the imperviousness accumulation patterns quantified in **Chapter 4**, now visible at neighborhood resolution.

The more significant synthesis contribution of **Chapter 5**, however, lies in what SHAP attribution reveals about the drivers of that susceptibility. Rainwater collectors, LST, DEM, and NDVI emerge as the dominant predictors, variables that are not independent flood factors but proxies for the same urban heat-imperviousness feedback that **Chapter 4** identified as the primary runoff amplification mechanism. Critically, these same variables reappear in **Chapter 6** as the dominant structural constraints on green infrastructure distribution, a variable-level continuity across two methodologically independent analyses that constitutes the framework's strongest cross-chapter validation point. The spatial logic of stormwater runoff in Gdańsk is consistently traceable to the same underlying urban form characteristics, whether approached through process-based hydrology, machine learning susceptibility mapping, or spatial econometric GI analysis and this

convergence is precisely what justifies treating the four empirical chapters as a unified diagnostic system rather than a collection of separate studies.

8.1.3. Misalignment between flood prone areas and green infrastructure provision

Chapter 6 completes the diagnostic sequence by asking whether Gdańsk's existing green infrastructure is positioned where the stormwater runoff and environmental stress identified in **Chapters 4** and **5** are greatest. The answer is unambiguous: it is not. GI distribution is strongly clustered in peripheral, historically forested areas, the Tricity Landscape Park, coastal forests near Sobieszewo Island, and southwestern Lasy Otomińskie, while persistent low-density zones occupy precisely the central and northern urbanized districts that **Chapters 4** and **5** identified as highest risk. This misalignment is not random but structurally produced: impervious surface is the primary constraint on GI distribution, with a total spatial impact of -0.55 including spillover effects, and this relationship holds even when population density is controlled. It is the built environment itself, not population pressure, that physically displaces green space, a finding with direct implications for where planning intervention must be directed.

The more important synthesis contribution of **Chapter 6**, however, is what it adds to the cross-chapter validation chain. The variables that SHAP identified as dominant flood susceptibility drivers in **Chapter 5** i.e., LST and drainage proximity reappear in **Chapter 6** as environmental stress indicators that co-occur with GI absence rather than GI presence. The districts most exposed to heat stress and poor air quality are the same districts least served by green infrastructure and most susceptible to flooding. This triple spatial overlap i.e. high flood susceptibility, high runoff generation, and low GI density, is the framework's core diagnostic finding, one that required four independently conducted analytical stages to establish and that is not retrievable from any single chapter alone. It is also the finding that makes **Chapter 7** not merely a logical next step but a necessary one: identifying where intervention is needed is only meaningful if followed by identifying where it is feasible.

8.1.4. Toward targeted, data-driven adaptation strategies

Chapter 7 completes the diagnostic-to-intervention transition by answering the question that the triple spatial overlap of **Chapter 6** makes urgent: where within the city's flood-exposed, GI-deficient districts is nature-based intervention actually feasible, and how much hydrological benefit would it deliver? The analysis operates at two complementary scales i.e. rooftop and street, treating blue-green roofs and street trees not as alternative measures but as components of a single integrated system whose combined effect is spatially targeted rather than uniformly distributed.

The spatial targeting result is the most important synthesis finding of **Chapter 7**: suitable rooftops concentrate in the lowland central, north-central, and eastern districts, precisely the areas that **Chapters 4** and **5** identified as highest flood susceptibility zones and **Chapter 6** identified as most

GI-deficient. This correspondence is not coincidental but structurally produced by the same urban morphology that drives flood risk i.e., flat, low-rise, compact buildings in densely impervious neighborhoods are both the most hydrologically exposed and the most geometrically suitable for green roof retrofitting. Similarly, the 38.7% of street segments classified as critically low greenery are concentrated in the dense central districts where **Chapter 6's** environmental stress indicators are highest. The GeoAI framework does not merely identify where interventions are needed and where they are feasible as separate outputs. It demonstrates that these two spatial sets substantially overlap, which is the operational basis for evidence-based prioritization.

On hydrological performance, two findings carry synthesis weight beyond **Chapter 7** itself. First, high-retention green roofs delivering 4.14% citywide runoff reduction and street trees intercepting 0.21–0.22% represent modest but quantifiable, performance-verified contributions, numbers that shift GI from a symbolic planning aspiration to an evidence-based infrastructure component. Second, and more importantly for planning, GI and grey infrastructure are not alternatives but complements operating at different points of the rainfall-runoff relationship: green roofs and street trees most effectively attenuate the sub-extreme, frequent events that constitute the majority of annual runoff volume and accelerate drainage system deterioration, while engineered retention remains necessary for extreme events exceeding GI storage capacity. The appropriate planning frame emerging from the full four-chapter sequence is therefore a hybrid grey-green system, one in which GI is deployed with spatial precision guided by the diagnostic layers of **Chapters 4 to 6**, and conventional infrastructure is sized for the residual that GI cannot absorb.

8.1.5. The GeoAI framework as a methodological contribution

A defining contribution of this thesis lies not in any individual finding but in the analytical architecture that connects them. By chaining remote sensing-based land use analysis, process-based hydrological modelling, interpretable machine learning, spatial econometric diagnosis, and AI-driven NBS planning into a sequential and mutually informing system, the thesis operationalizes a GeoAI framework for urban flood adaptation, one in which each stage provides both a standalone scientific contribution and a necessary input to the next.

This chaining logic is what distinguishes the framework from the fragmented literature it responds to. The hydrological baseline of **Chapter 4** is not merely context for **Chapter 5**, it provides the runoff patterns against which ML-derived susceptibility maps are spatially validated, and the convergence between independently derived process-based and data-driven evidence strengthens both. The susceptibility patterns in **Chapter 5** define where adaptive capacity matters most, making the GI equity diagnosis of **Chapter 6** spatially motivated rather than arbitrary. The constraints revealed in **Chapter 6** condition the feasibility boundaries within which **Chapter 7** NBS planning operates, ensuring that greening scenarios are modelled against actual urban form rather than theoretical open space. **Figure 8.1** visualizes this sequential architecture, mapping each methodological stage to its analytical output and showing how outputs flow forward as inputs to the next stage across four spatial scales from basin to street.

The GeoAI designation is not cosmetic. Interpretable machine learning enabled susceptibility mapping at a spatial resolution and with a driver-attribution transparency that process-based models alone could not achieve for an ungauged urban catchment. Deep learning segmentation of street-level imagery produced greenery indicators, GVI, IAI, OSI, at a spatial granularity inaccessible to satellite remote sensing. XGBoost with physically constrained inputs, generated city-wide tree planting predictions that neither rule-based GIS suitability analysis nor classical regression could produce at equivalent accuracy. Each AI component was selected not for novelty but because it solved a specific analytical problem that conventional methods could not.

This sequential dependency across four empirical chapters, at scales ranging from the basin scale to individual street segments, demonstrates that GeoAI, when structured as an integrated pipeline rather than a collection of tools, can directly support transparent, equitable, and evidence-based urban flood adaptation. The methodological pluralism across each chapter is structural: each method was selected precisely because it generates the output that the following stage requires, and no single paradigm could have produced the complete diagnostic-to-intervention chain that the framework delivers. In doing so, it advances the case that GeoAI is not merely a technical upgrade to existing urban planning workflows but a structurally different approach to generating the spatial intelligence that equitable flood adaptation requires.

8.1.6. Uncertainty and robustness of the framework

This thesis chains five methodologically distinct analytical stages into a single sequential pipeline, uncertainties do not remain isolated within individual models but propagate forward. For instance, a classification error in LULC mapping affects CN values in HEC-HMS, which affects the spatial baseline against which ML susceptibility predictions are validated. Acknowledging this propagation explicitly is necessary to correctly interpret the robustness and applicability of the framework's outputs.

The hydrological analyses presented in **Chapter 4** are subject to uncertainty associated with both rainfall representation and runoff modelling assumptions. The NRCS-CN approach was selected because of its suitability for ungauged and data-scarce urban catchments; however, the method simplifies several hydrological processes, including infiltration variability, subsurface flow interactions, and spatial heterogeneity of antecedent moisture conditions. Runoff estimates are additionally influenced by the use of synthetic design rainfall scenarios and future climate projections under RCP 4.5 and RCP 8.5 pathways, which themselves contain uncertainty related to greenhouse gas trajectories, regional climate model parameterization, and precipitation downscaling. Furthermore, the absence of long-term discharge observations for the Oruński Stream limited direct hydrological calibration and required indirect validation using neighboring hydrological studies and observed urban flood patterns. Consequently, the hydrological outputs should be interpreted primarily as spatially comparative and scenario-based estimates rather than deterministic forecasts of future runoff volumes.

Remote sensing-based analyses introduce additional uncertainty related to spatial and temporal data consistency. Historical land-use classifications derived from Landsat imagery are affected by sensor resolution, seasonal vegetation variability, atmospheric effects, and classification generalization. Although Google Earth Engine enables large-scale and reproducible land-cover analysis, classification uncertainty may propagate into subsequent hydrological modelling through curve number assignment and impervious surface estimation. Similarly, Google Street View imagery used in **Chapter 7** was collected across different years and seasons, potentially influencing GVI, IAI, and OSI measurements due to differences in vegetation phenology, lighting conditions, and image availability.

A further source of uncertainty arises from the scale transitions between analytical stages: basin-scale hydrological outputs were not directly downscaled to the 1 km² grid used in **Chapter 6**, and GI equity findings were not formally linked to individual building suitability assessments in **Chapter 7**. These scale discontinuities are managed through spatial consistency of input datasets but represent a structural limitation of the multi-scale design.

The machine learning components of the framework also involve several sources of uncertainty. Flood susceptibility modelling in **Chapter 5** relied on historical fire brigade intervention records, which may underrepresent localized flooding events that were either unreported or did not require emergency response. Spatial autocorrelation within environmental variables may additionally influence model learning behavior and artificially increase predictive performance if not interpreted carefully. While ensemble feature selection and SHAP explainability improve model transparency, they do not eliminate uncertainty associated with feature interactions, data imbalance, or transferability to cities with different hydrological and urban characteristics. The high predictive accuracy of the ANN model therefore reflects strong performance within the study context but should not be interpreted as evidence of universal applicability without local recalibration.

The green infrastructure suitability and performance analyses in **Chapter 7** also represent planning-scale estimates rather than engineering-scale implementation assessments. Green roof suitability was evaluated primarily from geometric and spatial criteria and did not incorporate structural load-bearing assessments, ownership constraints, or detailed maintenance feasibility. Similarly, runoff retention estimates were based on standardized retention assumptions adapted from the RESILIO framework and therefore may differ from real-world performance under local construction practices, maintenance conditions, and long-term vegetation dynamics. The hydrological contribution of street trees is also temporally dynamic because newly planted trees require extended maturation periods before reaching canopy sizes capable of delivering the estimated interception benefits.

Despite these uncertainties, several characteristics of the framework improve its overall robustness. First, the framework combines multiple independent methodological approaches, including process-based hydrological modelling, interpretable machine learning, spatial

econometrics, and computer vision, allowing cross-validation of spatial patterns across analytically distinct methods. Second, the framework emphasizes spatial consistency and comparative interpretation rather than reliance on single deterministic outputs. Third, the use of open-access datasets and transparent analytical workflows improves reproducibility and adaptability across other urban contexts. This framing is not a limitation but a design choice: the framework is built to inform planning decisions under uncertainty, not to eliminate uncertainty, a distinction that is central to its transferability to data-scarce urban contexts.

8.2. Policy planning and implications for urban flood management and GI planning

The Gdańsk Greenery Policy (GPZ 2023) (Fikus-Wójcik et al., 2023) provides the primary regulatory instrument through which these recommendations can be operationalized, establishing city-wide greening targets and an annual monitoring cycle that the GI priority map developed in **Chapter 6** can directly inform. This shifts GPZ implementation from uniform district-level targets to spatially differentiated, flood-susceptibility-weighted allocation. Translating GeoAI-derived outputs into municipal adaptation practice requires not only spatial prioritization but also institutional, regulatory, and financial alignment. The following recommendations synthesize the policy implications emerging from **Chapter 4-7** and identify pathways for integrating the framework into Gdańsk’s existing planning instruments.

The policy framework is presented across three complementary instruments. Table 8.1 translates analytical findings into specific policy recommendations organized by planning domain. Table 8.2 sequences these recommendations into a phased implementation roadmap tied to spatial priority zones. Table 8.3 identifies the principal spatial conflicts requiring resolution before district-scale deployment can proceed. Together they constitute a governance pathway from spatial evidence to municipal action.

Table 8.1. Policy recommendations covering spatial targeting, green roof standards, development control, street greening, and transferability

Policy area	Recommendation	Regulatory instrument	Evidence base
Spatial targeting	Allocate greenery budgets using the GI priority map-directing investment toward central lowland districts where flood susceptibility, runoff amplification, and GI deficit intersect	GPZ 2023 annual monitoring cycle; spatial planning directives	Chapter 4-6

Green roof standards	Mandate minimum storage layer depth ($\geq 70\text{mm}$) and drainage factor for green roofs, retention drops 9.13% at medium design and 52%+ at low design relative to high-retention specification	Building regulations; municipal green roof grant conditions	Chapter 7
Development control	Introduce minimum green coverage requirements tied to flood susceptibility zoning; impervious surface is the primary constraint on GI distribution (total spatial impact -0.55)	Local spatial development plan (MPZP); environmental impact assessment thresholds	Chapter 6
Street greening	Explicitly enable and fund engineered solutions (structural planters, tree grates, permeable paving) in high-imperviousness priority corridors; set street-level targets using GVI/IAI/OSI rather than uniform planting quotas	Street design standards; GPZ annual tree planting program	Chapter 7
Transferability	Framework relies entirely on open-access data (GEE, GSV, BDOT10k, free ML tools), deployable without advanced hydrometric sensor infrastructure in post-socialist coastal cities where urban transformation has outpaced institutional capacity	EU Green Deal funding instruments; LIFE program applications	Chapter 4-7

Table 8.2. A three-phase implementation pathway for translating the GeoAI framework's outputs into municipal planning action in Gdańsk

Phase	Spatial focus	Key actions	Barriers to address
Phase 1	City-wide-integrate framework outputs into GPZ and GPW planning instruments	-Embed GI priority map and suitability layers into municipal GIS -Enact performance-based green roof standard (min. 70mm storage layer) -Differentiate GPZ targets by flood susceptibility zone -Complete BDOT10k utility overlay for street greening feasibility	-Utility data gap for street planning
Phase 2	Priority districts: Wrzeszcz Dolny, Letnica, Nowy Port, Zaspamłyniec, Śródmieście, Orunia	-Green roof retrofit on public buildings with GPS ≥ 0.60, no heritage constraint -Street tree planting on segments with OSI ≥ 0.10; engineered solutions where OSI < 0.08 -Incentive scheme for industrial rooftop greening -Participatory engagement via Citizens' Panel and Climate Change Forum	-Heritage protection in historic core -Industrial rooftop operational barriers -Variable public attitudes (Polish Nature Protection Act) -Engineered solutions may involve substantially higher installation costs than conventional planting approaches

Phase 3	City-wide + secondary districts: Wzgórze Mickiewicza, Zaspa-Młyniec, Rozstaje	-Recalculate GVI/IAI/OSI every 3-5 years as standard monitoring metric -Apply for EU Structural Funds / LIFE using 238.48 ML retention evidence -Adopt minimum green coverage in development control (MPZP) -Budget maintenance at 1-3% installation cost/year for green roofs; enhanced care during 3-5 yr tree establishment period	-Green roof vs. solar PV competition for rooftop space -Long-term maintenance funding gaps -Tree maturation lag (near-term benefit below Chapter 7 estimates)
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Table 8.3. Spatial conflicts that require explicit resolution before district-scale deployment.

Conflict	Nature of conflict	Resolution approach
Green roofs vs solar PV	-High-suitability rooftops (flat, low-rise, central lowland) are simultaneously targeted under climate adaptation and energy transition policy	-Prioritize rooftops > 500 m ² where both uses coexist; develop combined BGR–PV co-installation guidance within GPZ framework
Street trees vs utilities	-Underground gas, water, electrical and telecoms infrastructure constrains planting location and root development in central priority corridors	-Integrate BDOT10k utility mapping into street greening analysis before district-scale rollout; structural root barriers and engineered pits as default in constrained corridors
Industrial rooftops	-Technically suitable (large, flat, high GPS) but operationally constrained by equipment, chemical handling, and maintenance access	-Voluntary incentive scheme rather than mandate; publicly owned industrial sites as demonstration cases in Phase 2
GI vs development pressure	Central lowland priority zones are economically active mixed-use areas with high demand for land for housing and commercial development	Flood susceptibility zoning as legal basis for minimum green coverage requirements; compensatory GI mechanisms (e.g. green roofs offsetting ground-level loss) in dense redevelopment zones

Together, the implementation roadmap and conflict-resolution framework demonstrate that effective deployment of GI/NBS interventions depends not only on hydrological suitability but also on governance capacity, regulatory flexibility, spatial compatibility, and long-term

maintenance planning. This reinforces the thesis argument that urban flood adaptation requires hybrid, multi-sectoral strategies integrating geospatial intelligence with engineering and planning practice.

8.3. Transferability

The framework is transferable because its architecture-sequential, scale-progressive, interpretability-centered, is independent of its case study. Post-socialist coastal cities across Central and Eastern Europe, where LULC transitions since the 1990s have followed trajectories comparable to Gdańsk's, represent the most direct application context. The most direct transfer candidates are Baltic and Central European coastal cities that have undergone comparable post-socialist urban expansion: Szczecin, Poland's second Baltic port, shares Gdańsk's polder topography and drainage legacy infrastructure (Bielecka et al., 2020); Riga and Tallinn have experienced similarly rapid imperviousness accumulation since EU accession with limited flood monitoring infrastructure (Prakapienė, 2026); and Gdynia, sharing the same Tricity metropolitan area and hydrological regime (Galata et al., 2026), represents an immediate replication opportunity using datasets already compiled for this thesis.

More broadly, any data-scarce coastal city navigating the intersection of accelerating imperviousness, intensifying rainfall, and constrained adaptation budgets can apply the pipeline with locally calibrated inputs. The modular design means individual stages can be updated or replaced as local data improves without rebuilding the framework. Replication requires five categories of open-access input: a high-resolution DEM for terrain derivatives; multi-temporal satellite imagery for LULC classification; a historical flood event inventory of documented incidents for ML training; building footprint and road network data; and street-level imagery with sufficient spatial coverage for GVI assessment. All five are available globally through Copernicus (European Union's Copernicus Land Monitoring Service, 2021), USGS Earth data (USGS, 2021), OpenStreetMap (OpenStreetMap, 2017), and Google Street View (Google, 2025), the same sources used in this thesis. Cities lacking a flood event inventory represent the most significant constraint, though fire service intervention records, insurance claims data, or citizen-reported flood records provide viable alternatives.

Three policy principles emerging from this thesis are generalizable beyond Gdańsk regardless of local institutional context: performance-based retention standards are necessary to ensure green roof installations deliver their intended hydrological services; and flood susceptibility-differentiated green coverage requirements in development control are a more effective mechanism than uniform city-wide greening targets. Most critically, engineered street-greening solutions must be explicitly enabled by policy in high-imperviousness districts where conventional tree planting is physically infeasible, which is a constraint that urban greening programs in post-socialist cities routinely underestimate.

Chapter 9

Conclusion and Future Research

9. Key findings and contributions

This thesis developed and applied an integrated GeoAI framework for urban flood adaptation, advancing from hydrological diagnosis through flood risk mapping, green infrastructure equity analysis, and NBS feasibility assessment to quantified stormwater performance, demonstrated through the case of Gdańsk, Poland. The framework's central contribution is not any individual finding but the sequential architecture connecting five methodologically distinct empirical chapters into a coherent diagnostic-to-intervention pipeline, in which each stage's output conditions the next and no single paradigm could have produced the whole. Three contributions emerge from this work.

Empirically, the thesis provides the first integrated evidence base for Gdańsk that links runoff amplification, flood susceptibility, GI inequity, and NBS feasibility within a single spatial system. The triple spatial overlap between flood exposure, runoff generation, and GI deficit, required four independently conducted studies to establish and is not retrievable from any single chapter and constitutes the thesis's core diagnostic finding.

Methodologically, the thesis advances the operational toolkit of urban GeoAI through four specific innovations: the first application of EDFS ensemble feature selection to urban flood susceptibility mapping; the introduction of IAI and OSI alongside GVI as a multi-indicator street-level greenery assessment system; the use of XGBoost with a physically constrained scaling factor for city-wide street tree planting prediction; and a scenario-based GPS framework that links green roof technical feasibility to planning constraints rather than treating suitability as a binary threshold. Each of these extend existing methods in ways directly motivated by the practical limitations of single-method approaches identified in the systematic review presented in Chapter 2.

Applied, the framework is designed for data-scarce, lower-capacity urban environments, relying entirely on open-access data and freely available tools. This is a deliberate response to the implementation gap between technically sophisticated flood research and the planning capacity of the municipalities that most need it. The framework removes the data-infrastructure barrier to spatially explicit GI planning in post-socialist coastal cities where urban transformation has outpaced institutional capacity.

Collectively, the four empirical chapters address the thesis objectives in sequence: **Chapter 4** quantifies how LULC and climate change have altered hydrological response at basin scale; **Chapter 5** identifies where flood susceptibility concentrates within the urban fabric; **Chapter 6** establishes why green infrastructure is misaligned with hydrological need; and **Chapter 7**

determines where nature-based solutions are feasible and what stormwater benefit they deliver. Together they fulfil the overarching objective of developing a transferable GeoAI pipeline that connects urban flood diagnosis to spatially targeted, performance-verified intervention.

9.1.Limitations and future research

No analytical framework of this scope is without limitations and acknowledging them precisely is necessary both for correctly interpreting the findings and for identifying where future research should focus. Five limitations apply across the framework, each of which also points toward a concrete research direction.

The first concerns validation constraints in hydrological modelling. **Chapter 4** relied on indirect validation for the Orunia basin, aligning the model with the neighboring, well-studied Strzyża Stream catchment rather than observed streamflow data, due to the absence of long-term gauging records for Oruński Stream. This approach qualitatively validates the model's behavior but introduces uncertainty in absolute runoff magnitudes. Similarly, the stormwater retention estimates in **Chapter 7** were derived from the RESILIO framework developed for Amsterdam, and while its parameters are widely applied in urban hydrology, local differences in rainfall patterns, roof construction practices, and drainage behavior in Gdańsk may produce deviations from theoretical performance. Both limitations are characteristic of data-scarce urban catchments and are acknowledged as sources of uncertainty rather than methodological flaws, but they mean the quantitative outputs should be interpreted as planning-order estimates rather than engineering precision values. As Gdańsk's hydrometric monitoring infrastructure matures and green roof installations accumulate performance records, direct calibration and empirical validation of both model components represent the most immediate future research priority.

The second limitation concerns data availability and resolution. The flood susceptibility model in **Chapter 5** was trained on historical fire brigade intervention records, which may underrepresent localized flooding events that were unreported or did not trigger emergency response, introducing a systematic bias toward more severe and publicly visible flood episodes. **Chapter 6** could not incorporate fine-scale income or education data, limiting the socio-demographic dimension of the GI equity analysis to elderly population as a vulnerability proxy, low-income households and children, both recognized as disproportionately exposed to urban environmental stressors, could not be evaluated. **Chapter 7** green roof estimates are based on building geometry from topographic databases and do not account for structural load-bearing capacity, ownership constraints, or maintenance requirements, all of which affect real-world installation feasibility. Google Street View imagery used for street-level greenery assessment was captured across different years and seasons, introducing phenological bias in GVI measurements that future studies should address through temporally controlled image acquisition. Extending the GI equity analysis with fine-scale income and household vulnerability data would test whether the spatial mismatches in GI provision

identified in **Chapter 6** also map onto social vulnerability which is a question the current data could not answer but that is directly relevant to environmental justice planning in Gdańsk.

The third limitation is the single hazard focus of the flood susceptibility analysis. **Chapter 5** developed a unified model across Gdańsk's spatially varied topography, but the city faces three structurally distinct flood hazard types: surface runoff from moraine hills, river outflow during intense precipitation events, and coastal inundation driven by sea-level rise, each governed by different physical processes and requiring different GI responses. A single model applied across this heterogeneity risks conflating flash flood susceptibility in upland areas with inundation susceptibility in lowland polders, potentially misattributing driver importance across hazard types. Future research should develop separate susceptibility models tailored to each hazard type, particularly as sea-level rise scenarios become increasingly relevant for Gdańsk's eastern and coastal districts under the RCP 8.5 pathway projected in **Chapter 4**.

The fourth limitation is the implementation gap between technical suitability and real-world deployment. The framework quantifies where interventions are physically feasible and how much hydrological benefit they would deliver, but it does not model the social, economic, and governance factors that determine whether technically suitable interventions are implemented. In Polish cities specifically, attitudes toward street trees vary considerably across age groups and between planning professionals and residents, and legal changes affecting tree removal under the Polish Nature Protection Act have complicated urban greening efforts in ways that spatial analysis cannot capture. The transition from spatial identification to real-world implementation requires participatory planning processes and governance structures that the framework supports but does not replace. Future research should integrate social acceptance modelling and participatory scenario development into the NBS planning stage, testing whether the spatially optimal interventions identified by the GeoAI framework align with community preferences and institutional capacity in priority districts.

The fifth limitation concerns the static nature of the framework. The analysis assesses current conditions and future scenarios without modelling temporal change in infrastructure performance. This is most consequential for street tree interventions: newly planted trees provide minimal hydrological services until canopies mature, a process that may take decades, meaning the 0.21-0.22% citywide runoff interception estimated in **Chapter 7** reflects mature medium-canopy trees rather than near-term planting outcomes. Long-term urban greening and climate adaptation plans need to account explicitly for this temporal lag, weighting green roof interventions more heavily for immediate stormwater impact and tree planting for long-term cumulative benefit. Future research should develop dynamic NBS performance models that incorporate tree maturation trajectories and green roof ageing curves, enabling municipal planners to set realistic near-term targets while maintaining long-term investment in canopy expansion.

Each of these five research directions is enabled by the diagnostic infrastructure this thesis has established. The framework does not exhaust the research agenda, it builds the spatial and methodological foundation from which the next generation of urban GeoAI studies can proceed with locally grounded, empirically validated, and socially embedded approaches to nature-based flood adaptation.

9.2. Conclusion

Urban flood risk is spatially structured, shaped by where land has been developed, where green space has been withheld, and how both interact with intensifying rainfall. Responding to that structure requires a framework that connects these processes across scales and translates diagnosis into feasible, performance-verified action. This thesis has built that connection, demonstrating through the case of Gdańsk that the question of where floods occur, why green infrastructure is absent, and what nature-based solutions can deliver are not three separate research problems but sequential dimensions of a single spatial system, one that only becomes visible when remote sensing, hydrological modelling, machine learning, spatial econometrics, and AI-driven planning are structured as a unified pipeline rather than applied in isolation.

The framework's most important finding is not any individual number but the triple spatial overlap that required all four empirical chapters to establish: the same neighborhoods that generate the most runoff, concentrate the highest flood susceptibility, and exhibit the greatest green infrastructure deficit are also the neighborhoods where nature-based intervention is most physically feasible. This convergence transforms the planning problem from one of general urban greening to one of spatially precise, performance-verified, equity-oriented intervention and it is a transformation that GeoAI, unique among available analytical approaches, is capable of producing at the resolution and transparency that municipal planning requires.

In doing so, the thesis demonstrates that nature-based solutions, deployed with spatial precision and grounded in quantified performance evidence, are not supplementary to urban flood adaptation but are central to it.

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Appendix A

1. Figures

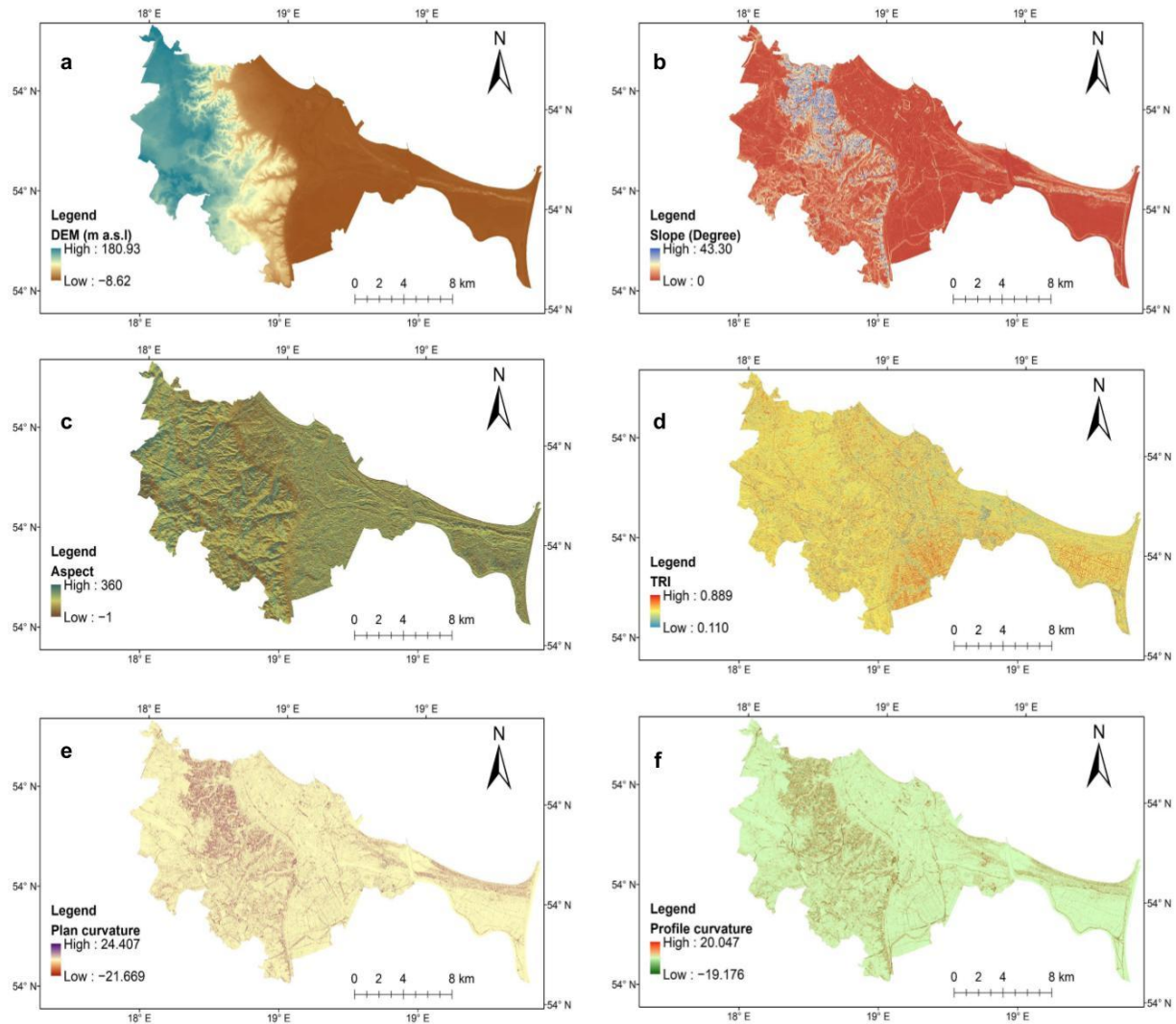


Figure A1. Spatial distribution of flood susceptibility factors: a) DEM, b) Slope, c) Aspect, d) TRI, e) Plan curvature, and f) Profile curvature. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

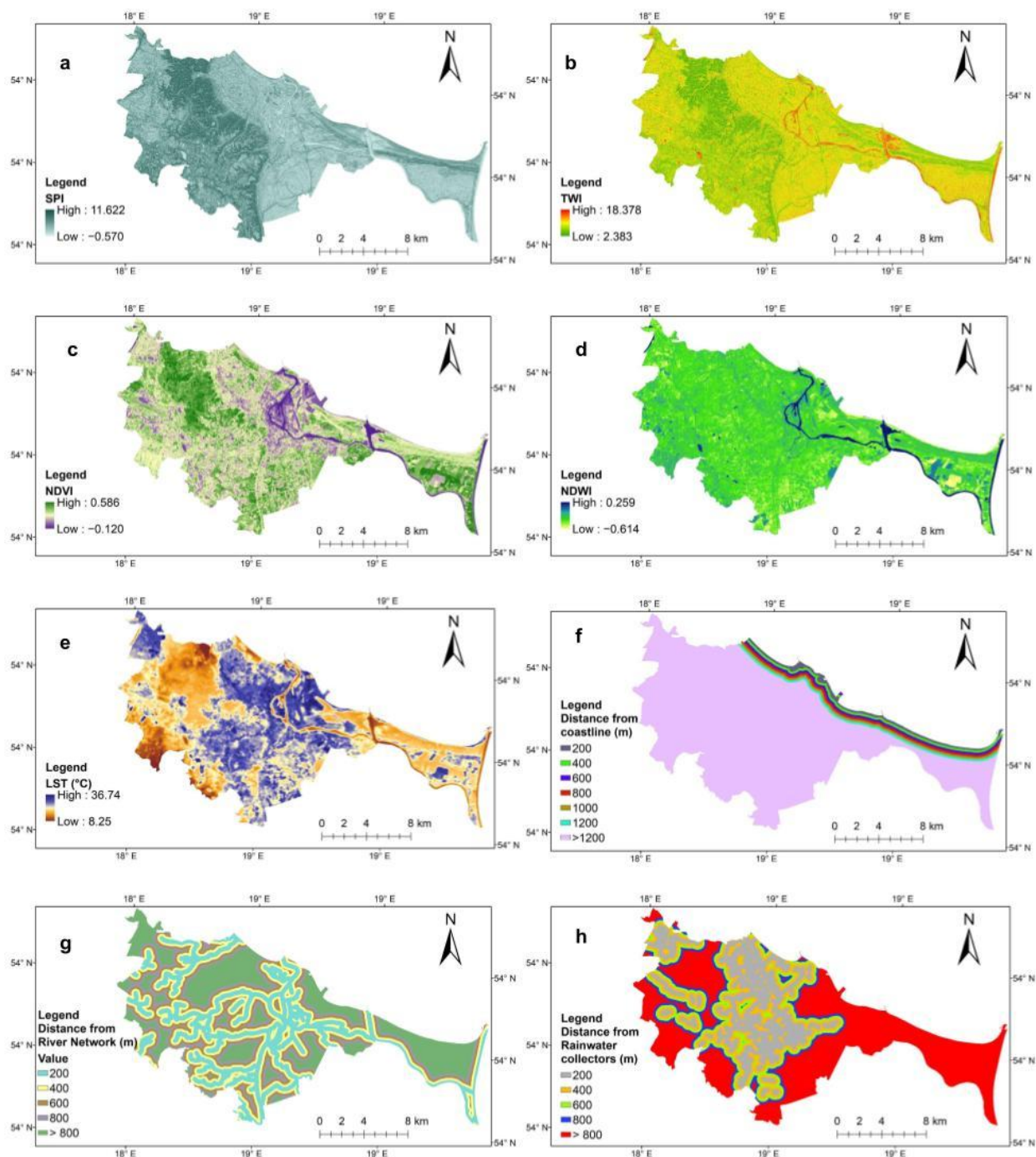


Figure 3. Spatial distribution of flood susceptibility factors: g) SPI, h) TWI, i) NDVI, j) NDWI, k) LST, l) Distance from the coastline, m) Distance from river network and, n) Distance from rainwater collectors. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

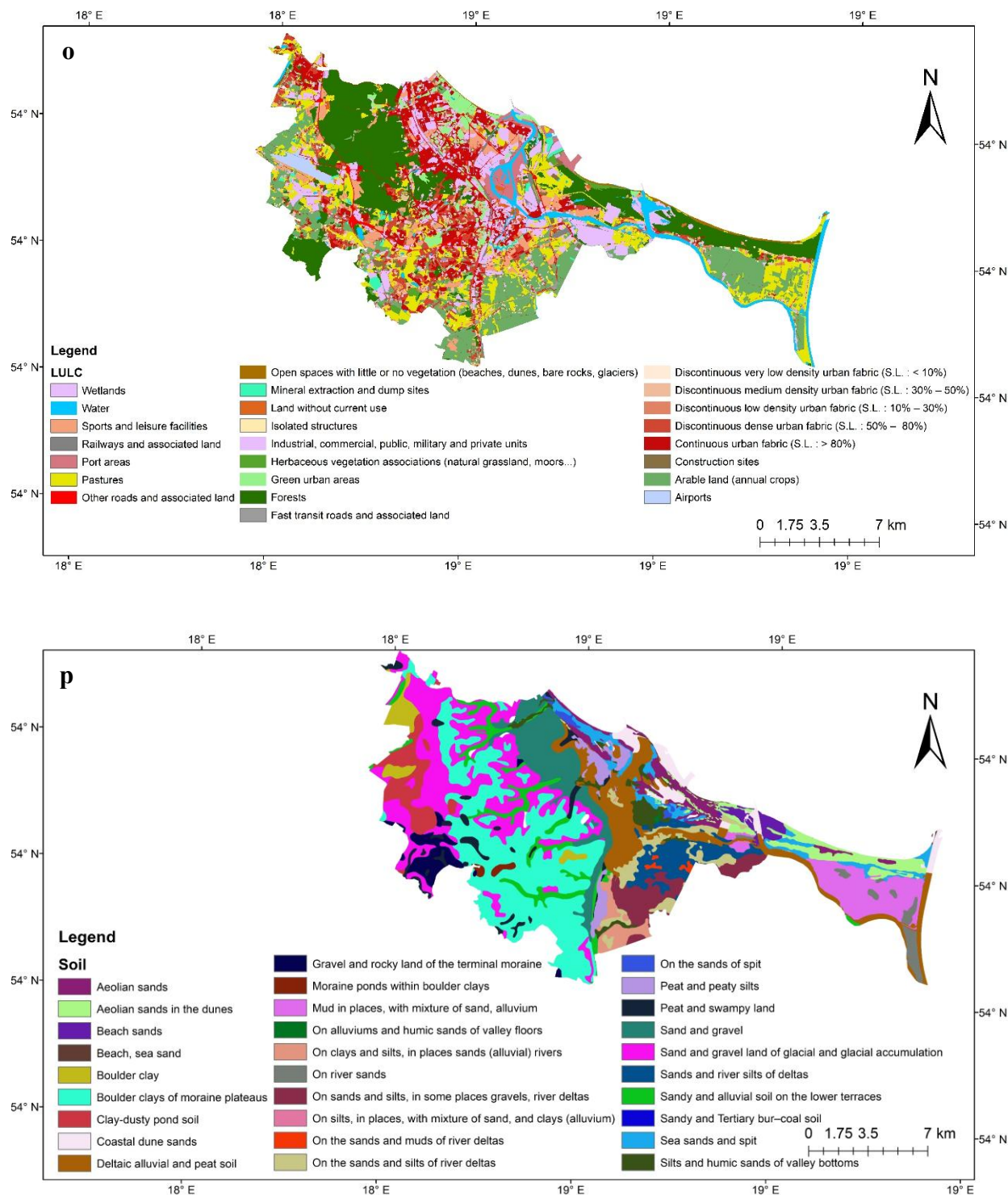


Figure A3. Spatial distribution of flood susceptibility factors: o) LULC, and p) Soil. *Reproduced from authors published work (Gulshad et al., 2024e). © 2024 by the authors. Licensed under CC BY 4.0.*

Appendix B

1. Note B1-Derivation of GI priority map

To enhance the practical relevance of the grid-based analysis, a spatial priority map was derived from the 1 km grid dataset. The objective was to identify areas characterized by low GI provision and elevated environmental stress, representing spatial mismatches between GI supply and environmental need. The priority classification was based on variables identified in the statistical analysis as relevant constraints or stress indicators:

- GI density (supply indicator; proportion of GI area per 1 km grid cell),
- Land Surface Temperature (LST) (heat stress indicator),
- Impervious surface area (urbanization pressure indicator),
- NO₂ concentration (air pollution indicator),
- Flood occurrence (hazard exposure indicator).

These indicators represent complementary dimensions of environmental stress and urban pressure relevant for strategic GI planning. To avoid subjective weighting and ensure comparability across variables with different units and distributions, a percentile-based thresholding approach was applied.

Identification of GI deficit: GI density values below the 25th percentile was classified as “low GI supply”.

Identification of environmental stressors: Environmental stress indicators above the 75th percentile were classified as “high stress”. This percentile-based approach standardizes variables without requiring direct normalization and is commonly used in spatial vulnerability and environmental prioritization studies. It allows identification of relative spatial extremes within the study area.

Cumulative stress index: For each stressor exceeding the upper quartile threshold, a binary value of 1 was assigned. These binary indicators were then summed to generate a cumulative stress score for each grid cell, ranging from 0 to 4.

Priority classification: Priority levels were defined as follows:

- Low priority: GI density $\geq$ 25th percentile
- Moderate priority: GI density $<$ 25th percentile and stress count = 1
- High priority: GI density $<$ 25th percentile and stress count $\geq$ 2

The resulting priority map identifies grid cells where multiple environmental stressors coincide with insufficient GI provision, thereby supporting spatially explicit strategic planning and policy prioritization at the municipal scale. This procedure is intended for strategic-level screening rather than parcel-scale intervention design.

2. Figures

Proportional contribution of GI

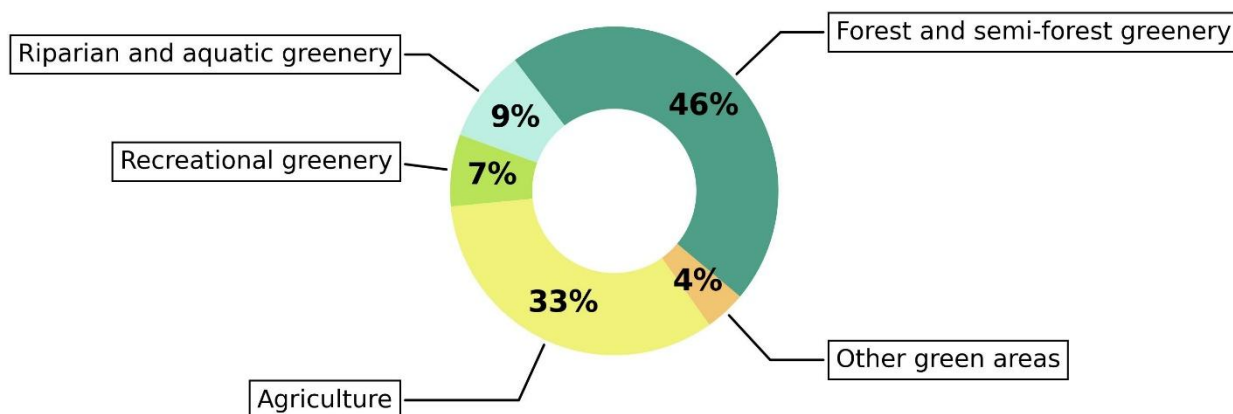


Figure B1. Proportional contribution of GI in Gdańsk. *Reproduced from authors published work (Gulshad and Szydlowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.*

Bio-physical and socio-demographic factors maps

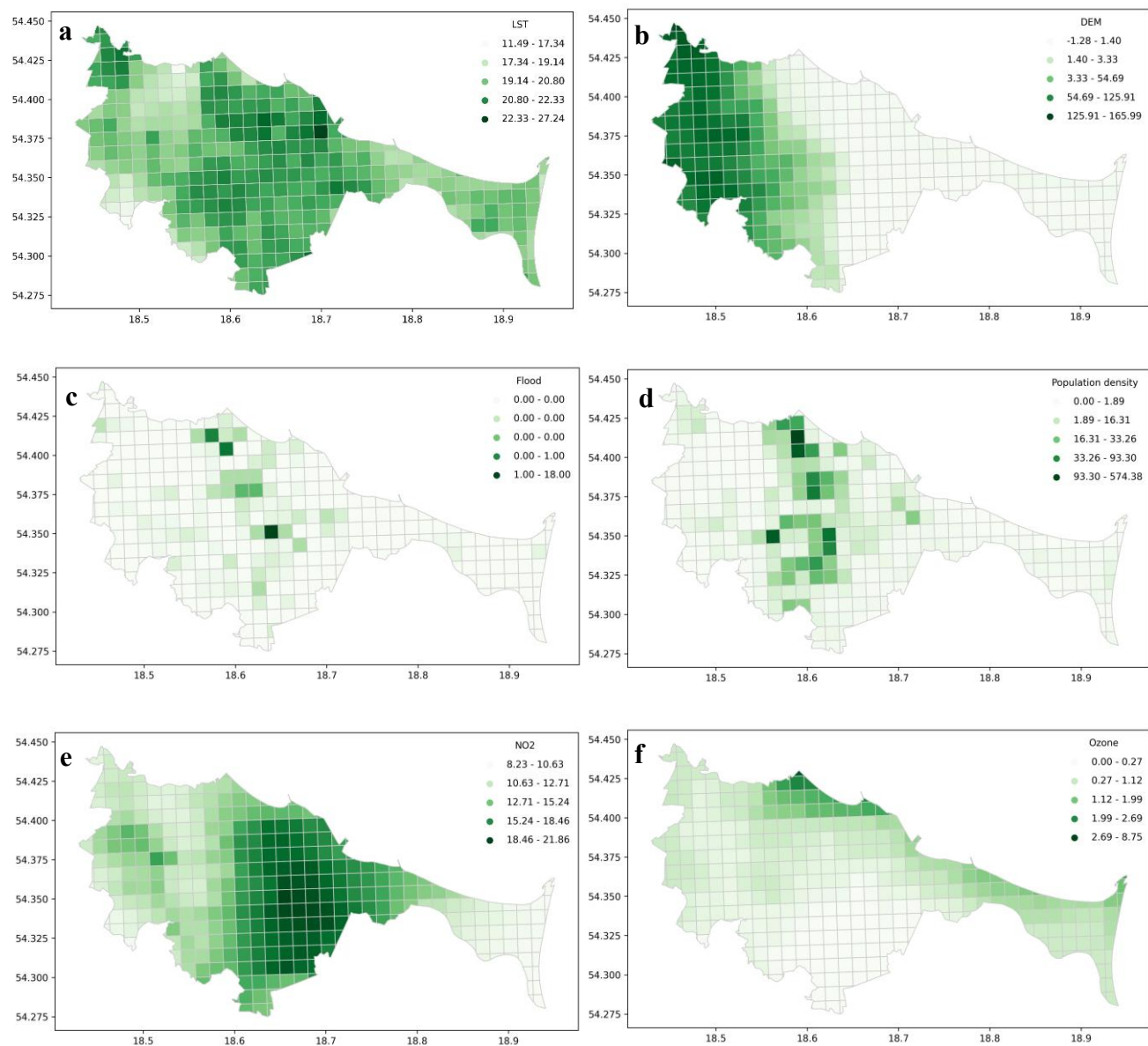


Figure B2. Spatial distribution of bio-physical and socio-demographic factors at grid scale: a) LST, b) DEM, c) Floods, d) Pop.density, e) NO₂, and f) O₃. Reproduced from authors published work (Gulshad and Szydłowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.

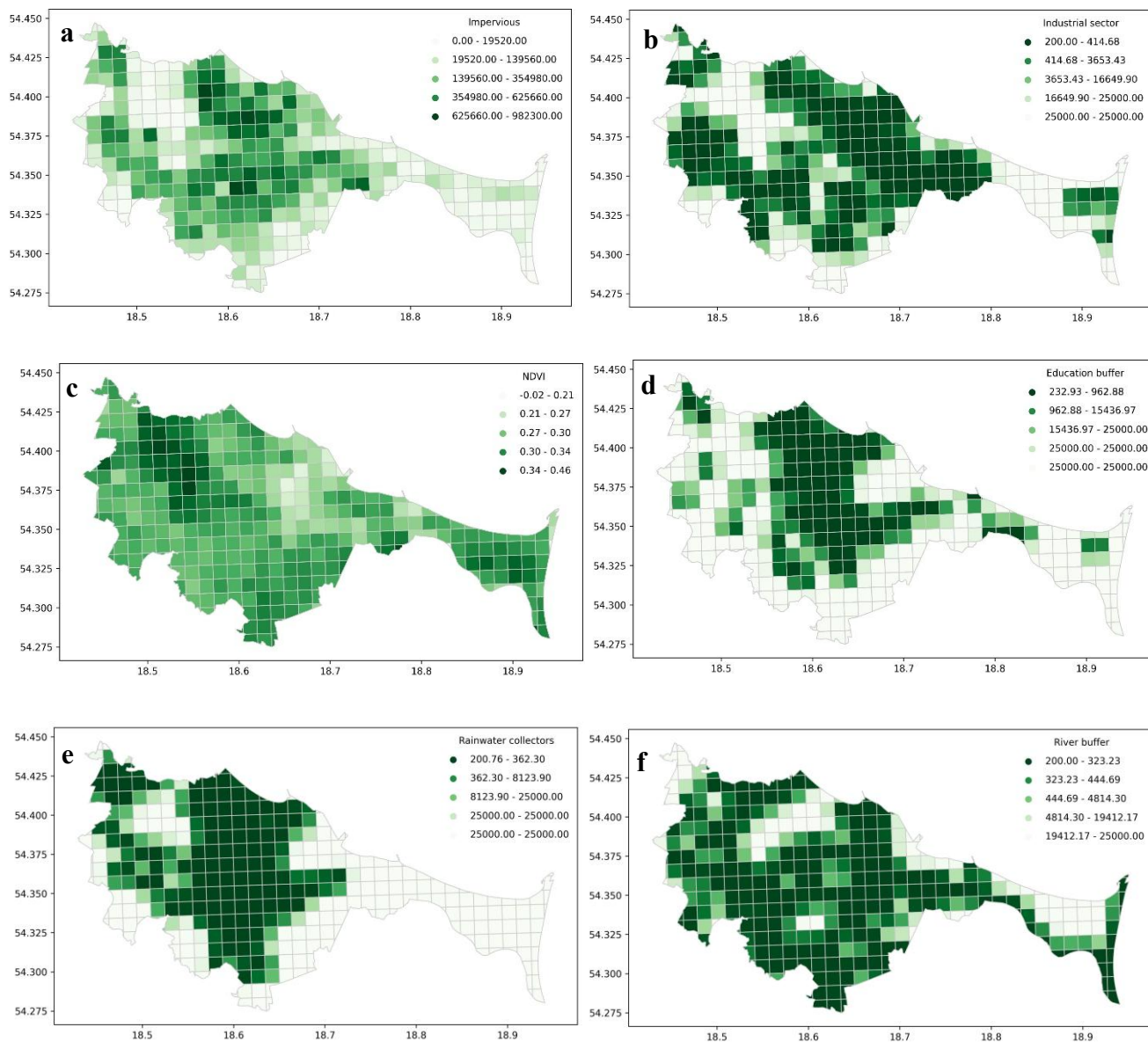


Figure B3. Spatial distribution of bio-physical and socio-demographic factors at grid scale: a) Impervious area, b) Distance from industrial areas, c) NDVI, d) Distance from educational institutes, e) Distance from rainwater collectors, and f) Distance from river. *Reproduced from authors published work (Gulshad and Szydlowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.*

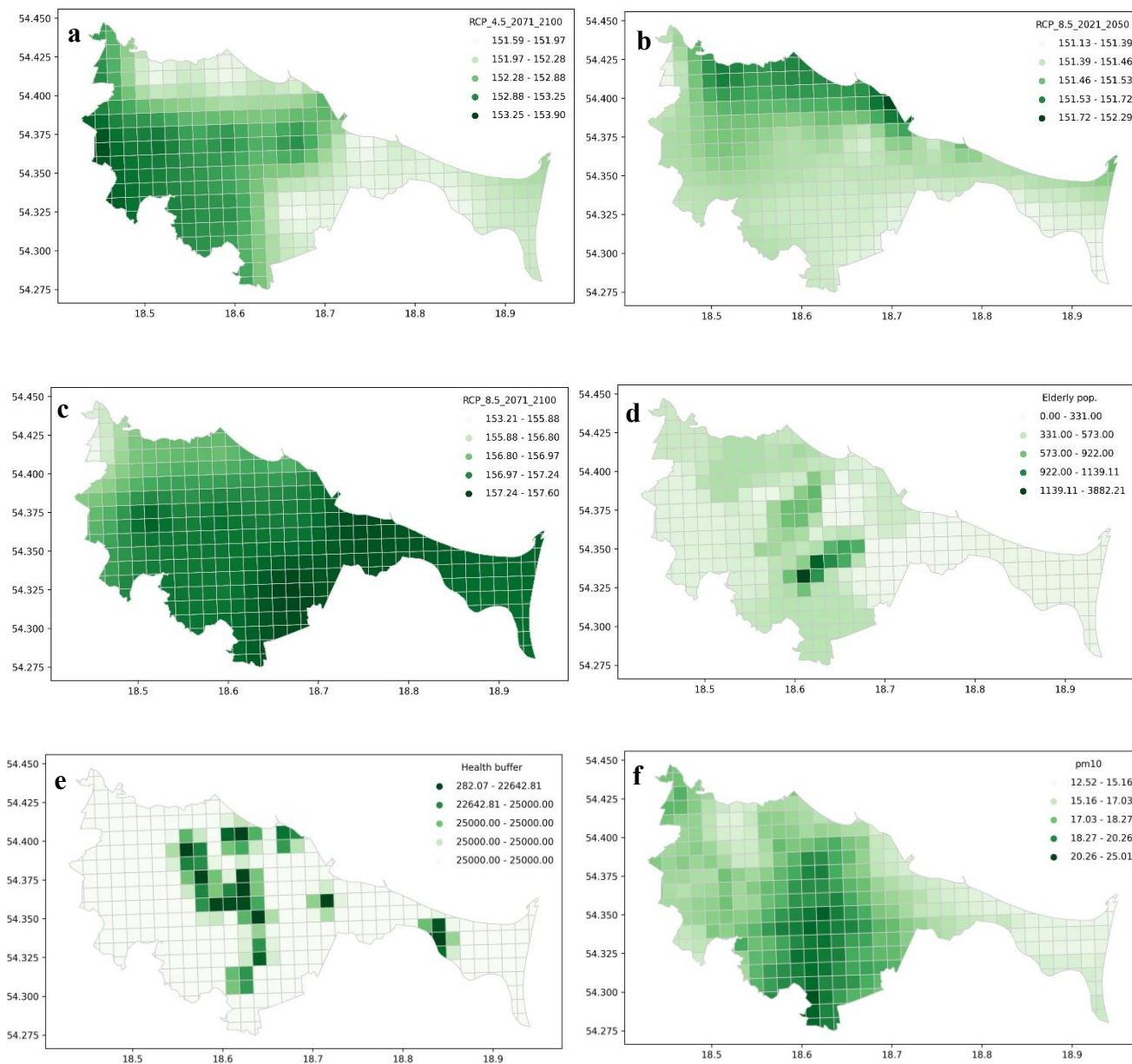


Figure B4. Spatial distribution of bio-physical and socio-demographic factors at grid scale: a) RCP 4.5 2071-2100, b) RCP 8.5 2021-2050, c) RCP 8.5 2071-2100, d) Elderly pop., e) Distance from health care, and f) PM₁₀. *Reproduced from authors published work (Gulshad and Szydlowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.*

Spatial distribution map-Local Moran's I

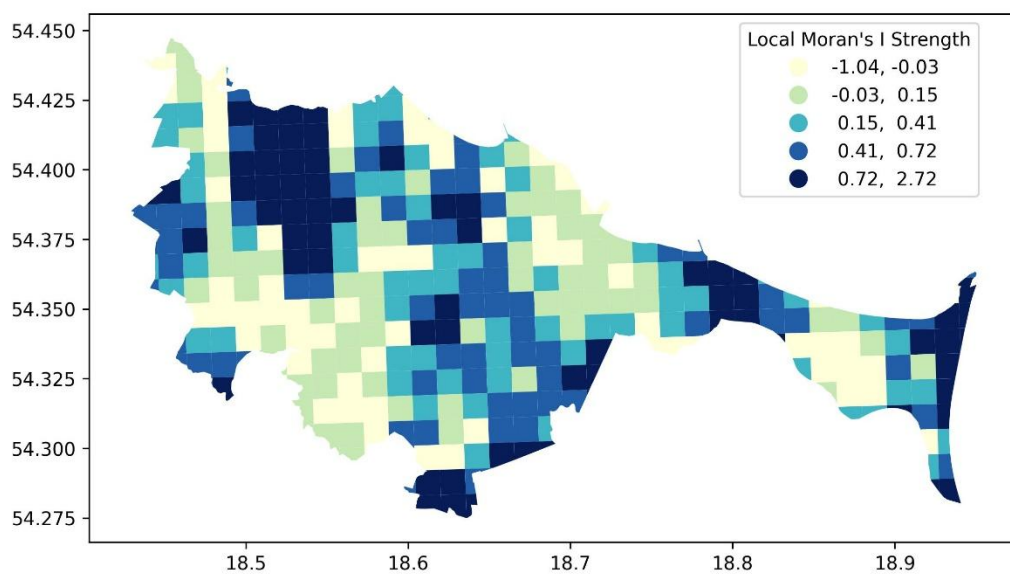


Figure B5. Local Moran's I value map for GI density in Gdańsk. *Reproduced from authors published work (Gulshad and Szydłowski, 2026). © 2026 by the authors. Licensed under CC BY 4.0.*

3. Tables

GI typology

Table B1. GI typology, functions and examples in Gdańsk.

GI type	Urban function	Examples in Gdańsk
Forest & semi-forest	Large patches, biodiversity, carbon storage	Tricity Landscape Park
Riparian/aquatic	Drainage, flood	Vistula riverbanks
Recreational	Public leisure	Parks, sports fields
Agriculture & allotments	Production, semi-private green	Allotment gardens
Other	Institutional green	Cemeteries, zoo

Multicollinearity analysis

Table B2. Multicollinearity analysis showing VIF values less than ten for all environmental factors considered for GI assessment.

Variables	VIF	Variables	VIF
Elderly population	2.18	LST	2.33
River density	1.33	NDVI	2.05
Rainwater collectors	3.43	Impervious density	4.30
Ozone	5.70	Floods	1.53
NOx	3.97	Precipitation 2071–2100 RCP 4.5	3.60
DEM	7.25	Precipitation 2021–2050 RCP 8.5	2.90
Population density	2.44	Precipitation 2071–2100 RCP 8.5	3.09
Industries	1.80	Health services	1.45
Educational services	2.78	–	–

Comparison of different spatial weights

Table B3. Comparison of different spatial weights methods for Global and Local Moran's I analysis.

Weights Methods	Local Moran's I Mean	% Significant Cells (Local Moran's I)	Global Moran's I	p-value (Global Moran's I)
Adaptive KNN	0.38	0.39	0.001	61.40
Fixed KNN (k=8)	0.49	0.49	0.001	49.12
Queen Contiguity	0.55	0.56	0.001	43.57
Rook Contiguity	0.63	0.63	0.001	29.53
Distance Band (1000 m)	-0.00	-0.00	0.414	77.49

Table B4. Comparison of different spatial weights methods for Spatial Lag model.

Weights Methods	Spatial Lag R²	Spatial Lag AIC	Spatial Lag Log-Likelihood	Spatial Lag ρ
Adaptive KNN	0.60	264.39	-113.20	0.72
Fixed KNN (k=8)	0.64	233.90	-97.95	0.66
Queen Contiguity	0.69	198.51	-80.26	0.67
Rook Contiguity	0.72	176.35	-69.17	0.65
Distance Band (1000 m)	0.49	332.27	-147.13	-1.00

Table B5. Comparison of different spatial weights methods for Spatial Error model.

Weights Methods	Spatial Error R²	Spatial Error AIC	Spatial Error Log-Likelihood	Spatial Error λ
Adaptive KNN	0.41	251.90	-107.95	0.84
Fixed KNN (k=8)	0.40	211.43	-87.72	0.79
Queen Contiguity	0.43	153.23	-58.62	0.80
Rook Contiguity	0.44	113.47	-38.73	0.80
Distance Band (1000 m)	0.48	330.27	-147.13	-1.00

Appendix C

1. Note C1-Scaling predictions

This section provides the equations for scaling factor explained in section 7.1.4.

Given the street length L and the desired tree spacing s , first the maximum number of trees that can be planted along both sides of the street were computed. The number of trees per side is calculated as:

$$\text{Max trees per side} = \left\lceil \frac{L}{s} \right\rceil + 1 \quad (\text{C1})$$

Then, the total maximum number of trees M is:

$$M = 2 \times \text{int}(\text{Max trees per side}) \quad (\text{C2})$$

Let E represent the number of existing trees, and P represent the predicted tree count. The remaining planting capacity is:

$$\text{Remaining capacity} = M - E \quad (\text{C3})$$

The scaling factor SF is then defined as:

$$SF = \begin{cases} 0, & \text{if } P = 0 \\ \max\left(0, \min\left(1, \frac{M - E}{P}\right)\right), & \text{if } P \neq 0 \end{cases} \quad (\text{C4})$$

The recommended number of trees is calculated as:

$$\text{Recommended Trees} = E + (SF \times P) \quad (\text{C5})$$

In the end, for a given spacing $s \in \{5, 10, 15\}$, the number of additional trees needed is calculated as:

$$\text{Additional}_s = \text{Recommended Trees} - E \quad (\text{C6})$$

2. Note C2-Stormwater retention for green roofs

This section provides parameters used in analysis and full derivations for equations (7.5 and 7.6) in section 7.5.1.

Table C1. Parameters used in calculating runoff retention by green roofs.

Parameter	Value	Notes / Source
Storage layer depth ($D_{storage}$)	71 mm (High retention), 50 mm (Medium retention), 30 mm (Low retention)	The storage layer depth is the total depth of the green roof's water-retaining substrate layer, which temporarily stores rainfall before drainage occurs (Busker et al., 2022c; Hans de Moel et al., 2021; Toon Haer et al., 2022).
Retention factor ($D_{retention}$)	0.9, 0.8, 0.7	10% drained, fraction of storage retained post-drainage (Busker et al., 2022c; Hans de Moel et al., 2021; Toon Haer et al., 2022)
Design storms (60 min)	1% = 44.02 mm, 10% = 26.50 mm, 50% = 17.28 mm	2, 10, 100-year return period (IMGW-PIB, 2022).
Runoff coefficient (C)	0.5	Based on SCS-CN method (Gulshad et al., 2024b).
Green roof coverage areas	3 scenarios	Scenarios explained in section 7.5.1.

To calculate the retention capacity of green roofs, first, the effective retention depth was calculated as:

$$D_{retention} = D_{storage} \times f_{pre-drainage} \quad (C7)$$

where $D_{storage}$ is the storage layer depth (mm), $f_{pre-drainage}$ is the fraction of storage retained $1 - \text{drainage factor}$. Next, the retained rainfall by green roofs is calculated as:

$$D_{retained} = \min(P, D_{retention}) \quad (C8)$$

where P is rainfall depth (mm). Actual retained rainfall cannot exceed either the rainfall event depth or the retention capacity. The return periods were selected to evaluate green roof performance across a range of storm frequencies, from routine rainfall events to extreme flooding scenarios.

Runoff reduction percentage at green roof scale was calculated as:

$$\%Reduction = \left(\frac{D_{retained}}{P} \right) \times 100 \quad (C9)$$

where $\%Reduction$ is the percentage of rainfall retained by the green roof system. Whereas, retained volume at green roof scale is calculated as:

$$V_{retained} = D_{retained} \times A_{total \text{ green roof area } i} \quad (C10)$$

where $A_{total\ green\ roof\ area\ i}$ is the total green roof area for scenario i . As 1 mm of rainfall over 1 m² equals 1 liter, all volume-related outputs are directly calculated in liters for consistency and ease of interpretation. To calculate potential city-scale impact of green roof retention per scenario i :

$$V_{total} = P \times A_{city} \times C \quad (C11)$$

$$\%I = \left(\frac{V_{retained}}{V_{total}} \right) \times 100 \quad (C12)$$

where A_{city} is Gdańsk area in (m²), C is runoff coefficient, and $\%I$ is the percentage of total city rainfall volume retained by green roofs.

3. Note C3-Runoff interception for hypothetical trees

This section provides parameter values and full derivations for equations (7.7 and 7.8) in section 7.1.5.2

Table C2. Parameters used in calculating runoff interception by hypothetical trees

Parameter	Value	Notes / Source
Interception efficiency (E_i)	0.237 (range: 0.15–0.25)	Deciduous trees in temperate climates (Dowtin et al., 2023b)
Tree canopy diameters (D_c)	Small: 3.4 m, Medium: 5.6 m, Large: 6.0 m	Polish guidelines (Elżbieta Szopińska and Zygmunt-Rubaszek, 2010)
Tree count scenarios (N)	3 scenarios	Scenarios explained in section 7.1.5.2

The crown area was calculated using the formula:

$$A_c = \pi \left(\frac{D_c}{2} \right)^2 \quad (A13)$$

where A_c is the crown area in m², D_c is the crown diameter in m.

For each tree, the rainfall volume intercepted is a product of its canopy area and the effective interception depth, defined as:

$$I_d = E_i \times P \quad (A14)$$

$$I_t = A_c \times I_d \quad (C15)$$

where I_t is the intercepted volume per tree (liters), A_c is the crown area, I_d is interception depth (mm), E_i is interception efficiency and P is rainfall depth (mm). The total intercepted volume for N trees is:

$$I_{total} = N \times I_t \quad (C16)$$

The total runoff volume for the city during the storm calculated by runoff coefficient method:

$$Q_{total} = A_{city} \times \left(\frac{P}{1000} \right) \times C \times 1000 \quad (C17)$$

where A_{city} is the total area of Gdańsk in m^2 , C is runoff coefficient.

4. Note C4-Multicollinearity and correlation analysis

Prior to model training and testing, the presence of multicollinearity among the independent factors was assessed using VIF values (Table A3). $PM_{2.5}$ got VIF of 20, so it was removed from the analysis, and after removing it all VIF values were well below the common threshold of 10, indicating an acceptable level of multicollinearity and supporting the inclusion of all selected features in the model.

Table C3. Multicollinearity analysis showing VIF values less than ten for all factors considered for trees prediction.

Variables	VIF
Length	1.13
GVI	1.55
IAI	1.28
OSI	1.15
NDVI	2.09
LST	2.03
Pop. density	1.13
PM_{10}	1.53
NO_2	1.27

A correlation analysis was performed to further understand the relationships between the independent factors, as well as between these factors and the target variable (tree count).

The correlation matrix of independent variables (Figure C1 a) revealed a strong positive correlation (0.44) between NDVI and GVI, and a positive correlation (0.48) between PM_{10} and LST, indicating a positive association between air pollution and land surface temperature. A negative correlation (-0.63) was found between NDVI and LST, reflecting the role of vegetation in urban cooling. There was also a negative correlation (-0.39) between GVI and IAI and slight negative correlation (-0.13)

between GVI and OSI showing streets with more greenery had less impervious areas and less open space (terrain).

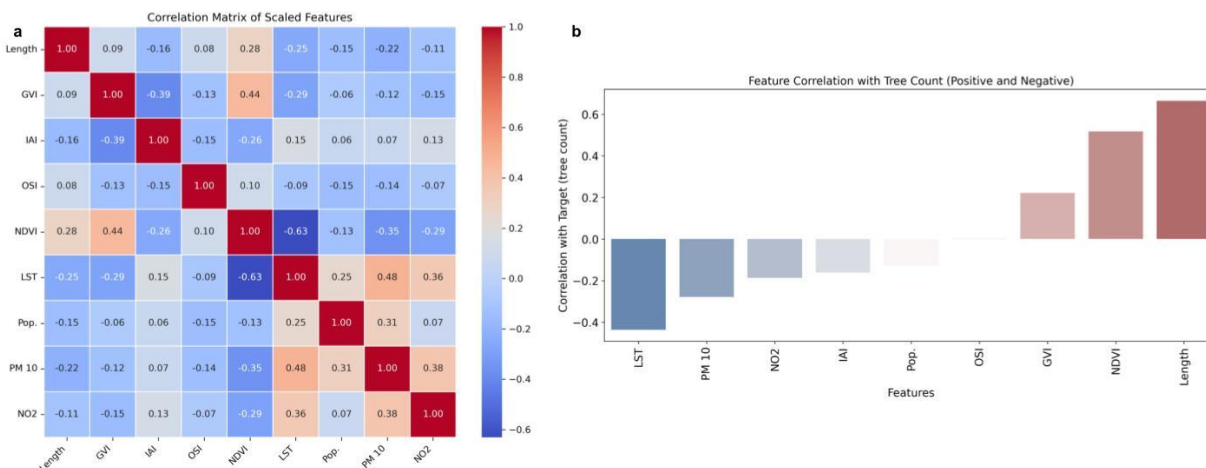


Figure C1. a) Correlation matrix of independent factors b) Correlation of independent factors with dependent variable i.e., existing trees. *Reproduced from authors work Gulshad et al. (under review).*

The independent factors correlate with dependent factors i.e., tree count (Figure A1 b) identified street length and NDVI as the most positively correlated factors with existing tree count, followed by GVI. Conversely, LST, PM₁₀, and NO₂ exhibited negative correlations with tree count, suggesting that more trees reduce air pollution and surface temperature.

These analyses confirmed that the selected features provide diverse and meaningful information for modeling tree count along streets and justified their use in subsequent machine learning models.

5. Note C5-Feature Importance

Feature importance analysis showed that street length, NDVI, LST, air pollutants and GVI contributed most strongly to prediction, while other covariates had comparatively lower influence (Figure A2). This ranking confirms that the selected street-level and environmental factors provide a robust explanatory basis for estimating tree planting potential.

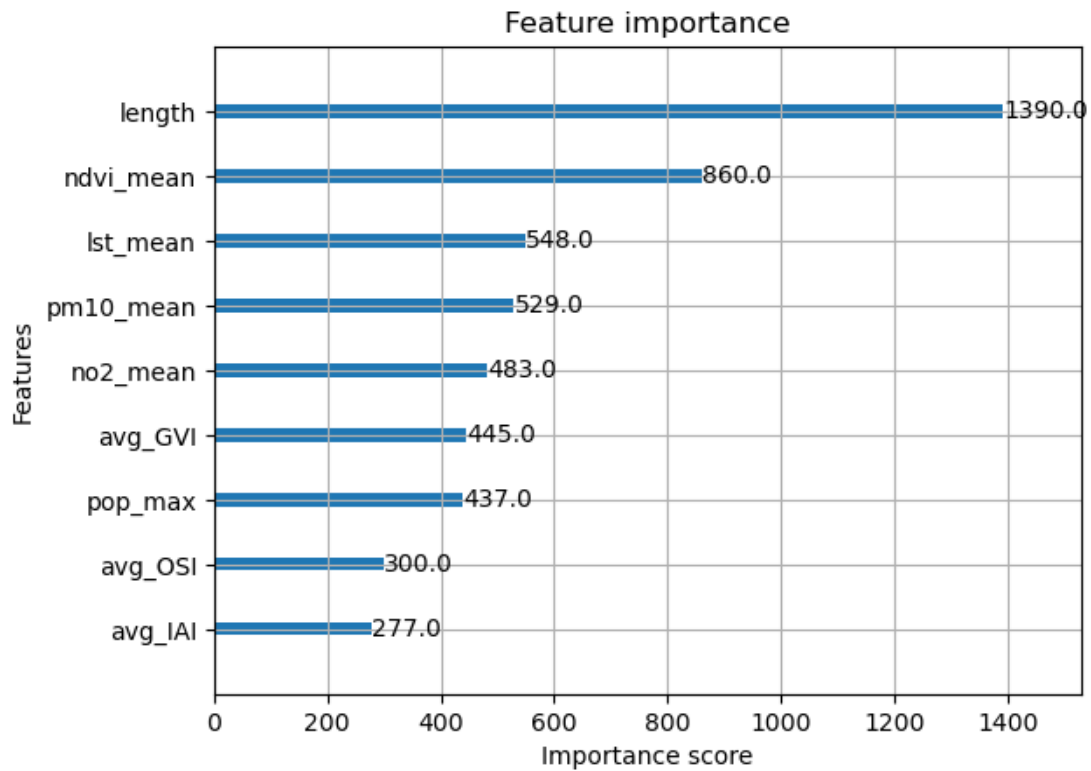


Figure C4. Feature importance of XGBoost model *Reproduced from authors work Gulshad et al. (under review).*

6. Tables

Table C4. Full scenario matrix for sensitivity analysis (green roof retention and tree diameter variations)

Rainfall Scenario	Green Roof Variants (Retention)	Tree Spacing & Diameter
1% (100-year): 44.02 mm	GR1, GR2, GR3 × High, Medium, Low	T1, T2, T3 × Small, Medium, Large
10% (10-year): 26.50 mm	GR1, GR2, GR3 × High, Medium, Low	T1, T2, T3 × Small, Medium, Large
50% (2-year): 17.28 mm	GR1, GR2, GR3 × High, Medium, Low	T1, T2, T3 × Small, Medium, Large

Table C5. Runoff retention under varying green roof scenarios and rainfall design storms for medium (M) and low (L) retention scenarios (storage layer depth of 50mm and 30mm, drainage factors of 0.8 and 0.7, respectively).

Scenario	Green roofs area (m ²)	Rainfall (mm)	Total runoff (Billion L)	Rainfall retention (%)	Retained Volume (ML)	City Impact (%)
GR1 (M)	5,417,580.6	44.02	5.77	90.87	216.70	3.76
		26.50	3.47	100	143.57	4.14

		17.28	2.26	100	93.62	4.14
GR2 (M)	5,417,502.2	44.02	5.77	90.87	216.70	3.76
		26.50	3.47	100	143.56	4.14
		17.28	2.26	100	93.61	4.14
GR3 (M)	3,778,154.3	44.02	5.77	90.87	151.13	2.62
		26.50	3.47	100	100.12	2.88
		17.28	2.26	100	65.29	2.88
GR1 (L)	5,417,580.6	44.02	5.77	47.71	113.77	1.97
		26.50	3.47	79.25	113.77	3.28
		17.28	2.26	100	93.62	4.14
GR2 (L)	5,417,502.2	44.02	5.77	47.71	113.77	1.97
		26.50	3.47	79.25	113.77	3.28
		17.28	2.26	100	93.61	4.14
GR3 (L)	3,778,154.3	44.02	5.77	47.71	79.34	1.38
		26.50	3.47	79.25	79.34	2.29
		17.28	2.26	100	65.29	2.88

Table C6. Runoff interception under varying tree counts (based on spacing scenarios) and rainfall design storms for small (S) and large (L) diameter classes (3.4m and 6m).

Scenario	Number of Trees	Rainfall (mm)	Total runoff (Billion L)	Rainfall Interception (%)	Total Interception (ML)
T1 (S)	48,790	44.02	5.77	0.08	4.62
		26.50	3.47	0.08	2.78
		17.28	2.26	0.08	1.81
T2 (S)	48,652	44.02	5.77	0.08	4.61
		26.50	3.47	0.08	2.77
		17.28	2.26	0.08	1.81
T3 (S)	47,775	44.02	5.77	0.08	4.53
		26.50	3.47	0.08	2.72
		17.28	2.26	0.08	1.78
T1 (L)	48,790	44.02	5.77	0.25	14.39
		26.50	3.47	0.25	8.66
		17.28	2.26	0.25	5.65
T2 (L)	48,652	44.02	5.77	0.25	14.35
		26.50	3.47	0.25	8.64
		17.28	2.26	0.25	5.63
T3 (L)	47,775	44.02	5.77	0.24	14.09

		26.50	3.47	0.24	8.48
		17.28	2.26	0.24	5.53

7. Figures

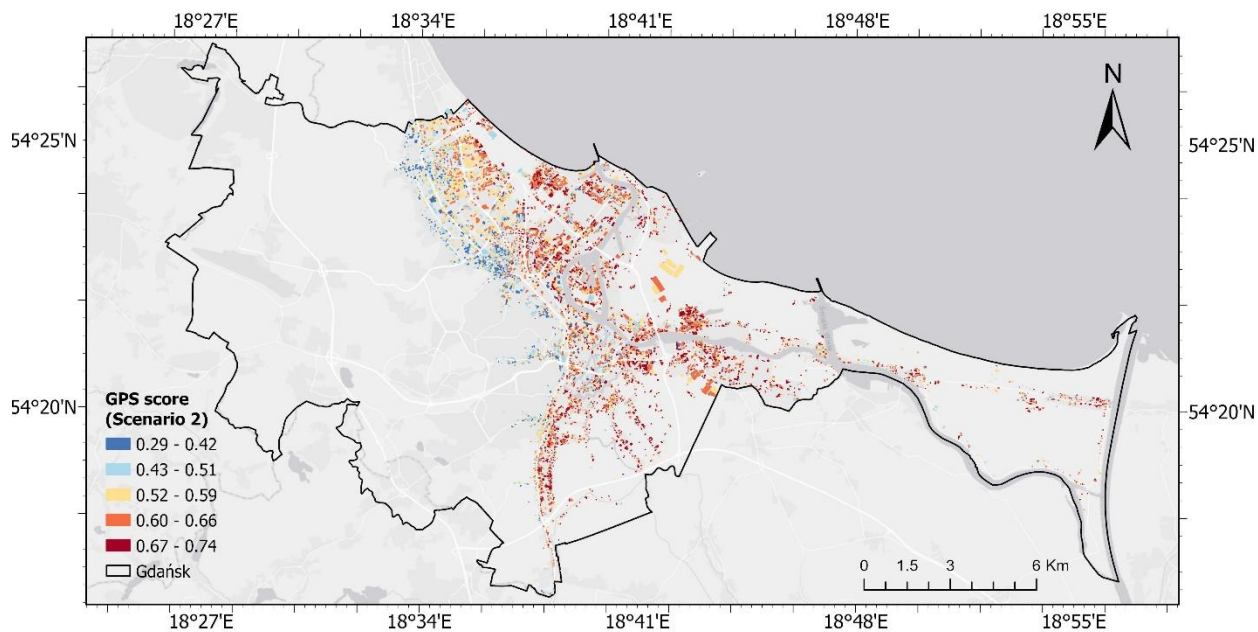


Figure C3. Spatial distribution of potential green roofs in Gdańsk with their respective greening potential score under Scenario 2. *Reproduced from authors work Gulshad et al. (under review).*

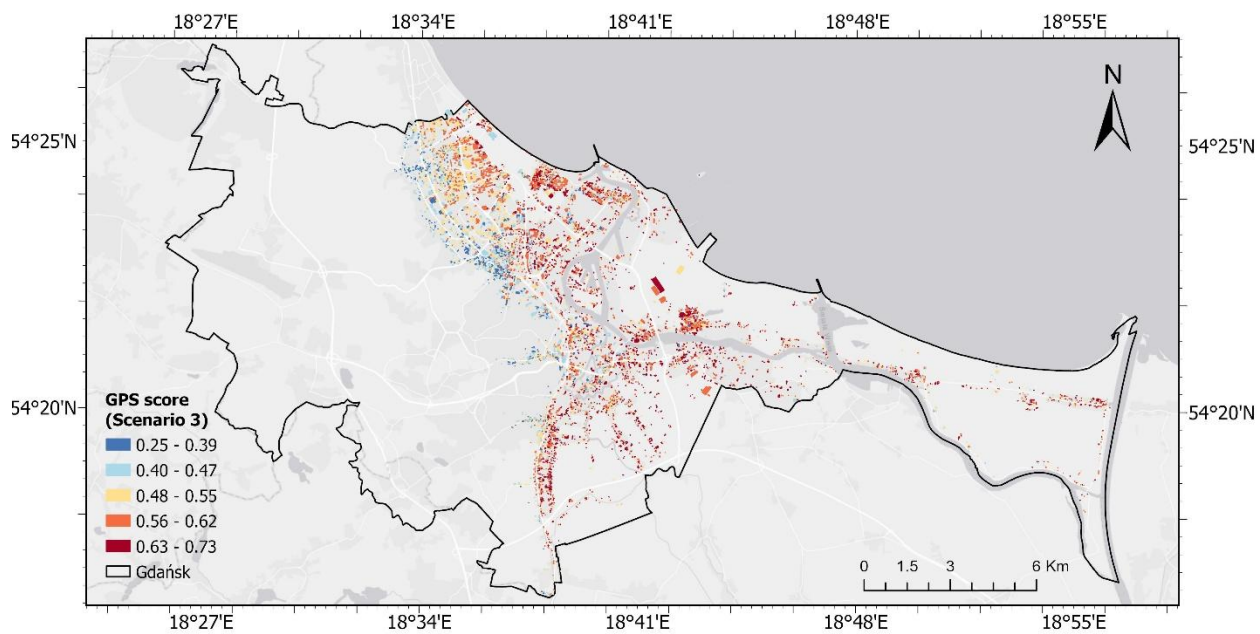


Figure C4. Spatial distribution of potential green roofs in Gdańsk with their respective greening potential score under Scenario 3. *Reproduced from authors work Gulshad et al. (under review).*

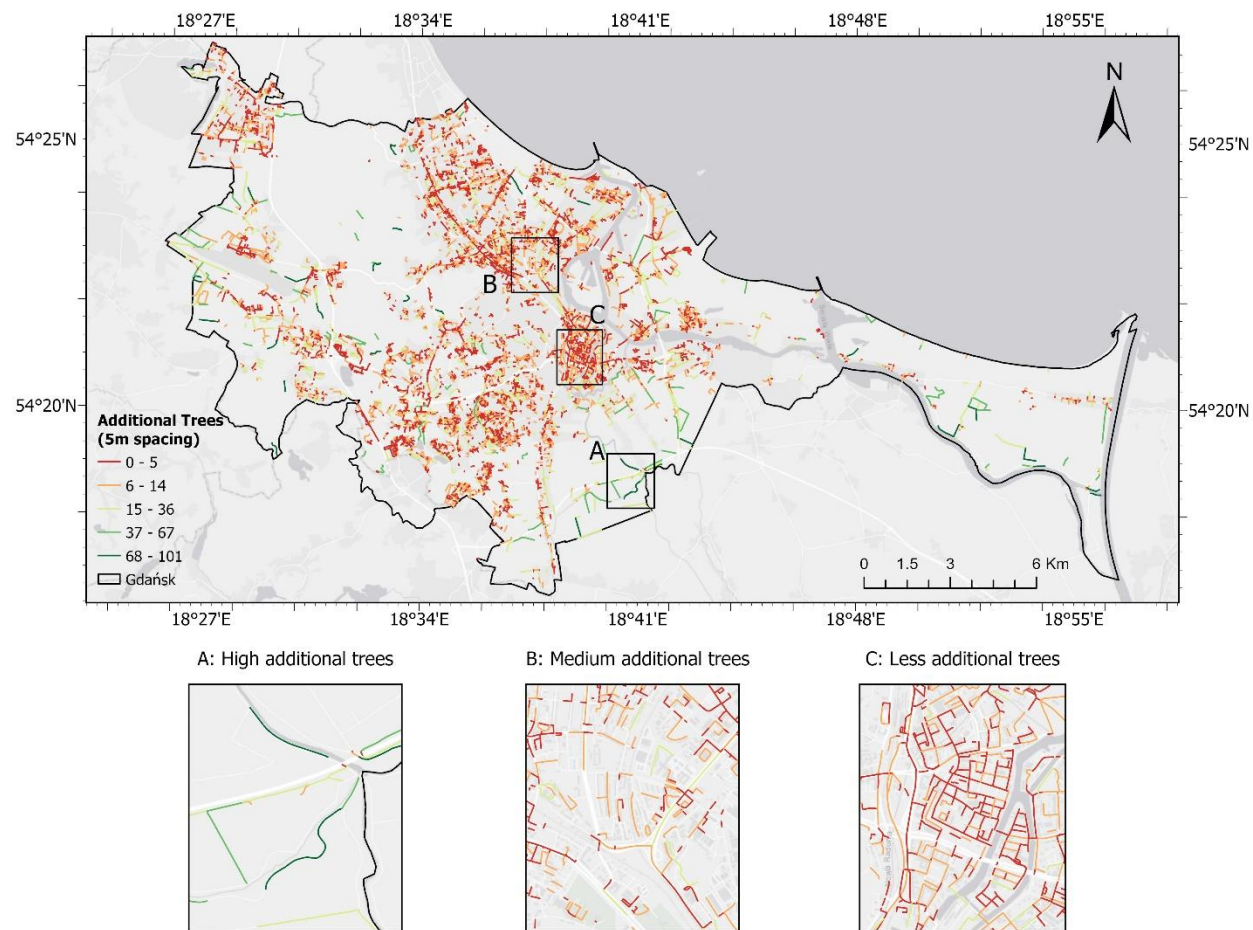


Figure C5. Spatial distribution of hypothetical streets with predicted additional trees for 5m spacing. *Reproduced from authors work Gulshad et al. (under review).*

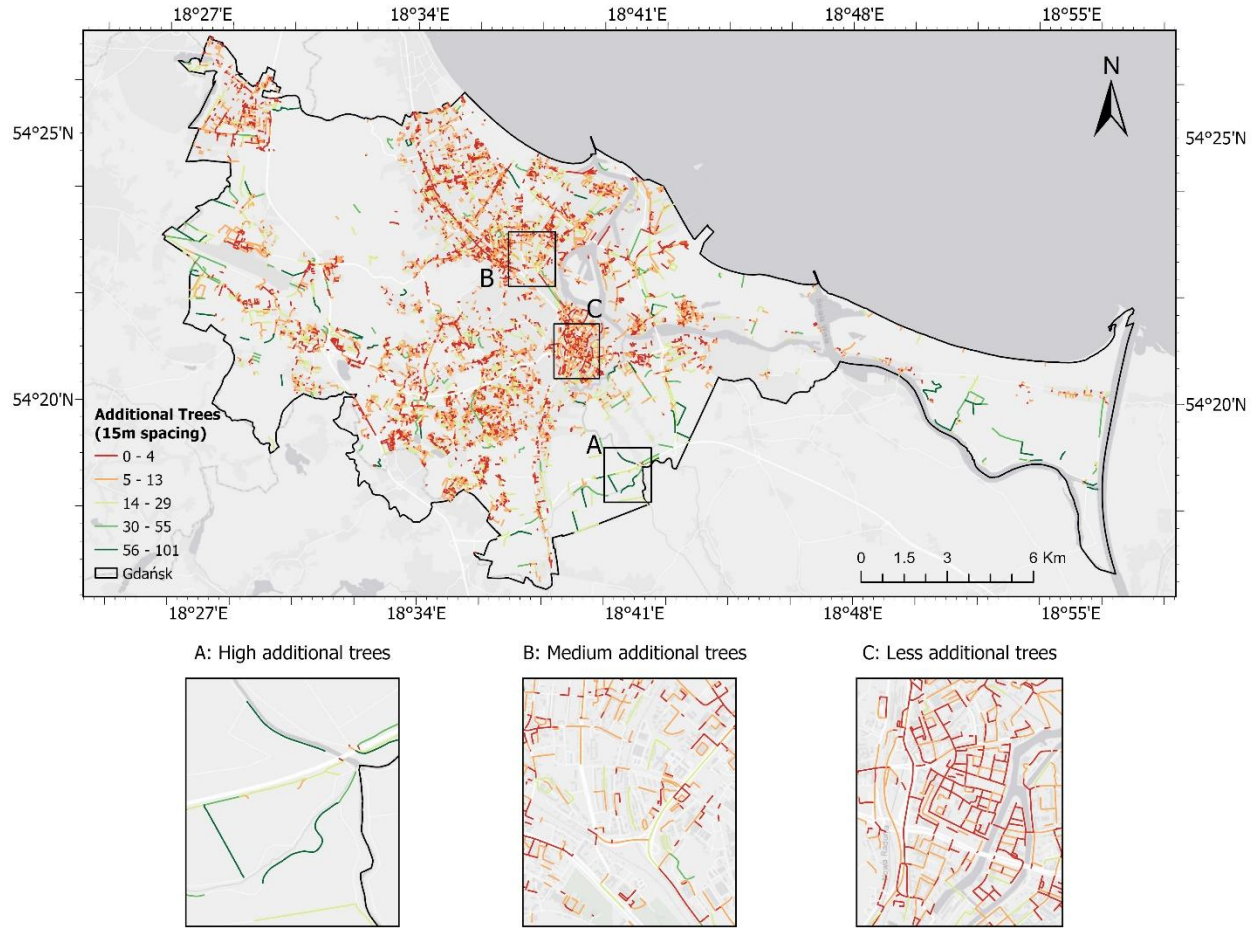


Figure C6. Spatial distribution of hypothetical streets with predicted additional trees for 15m spacing. *Reproduced from authors work Gulshad et al. (under review).*