



Socio-environmental systems participatory models and analysis techniques – Final version

Deliverable 3.3

WP3: Dynamic Multi-Sectoral Resilience Modelling and Assessment Framework

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EXECUTIVE SUMMARY

The Socio-environmental systems participatory models and analysis techniques are a set of methodologies that allow stakeholders and inter-disciplinary scientists to actively collaborate and participate in decision-making processes regarding socio-environmental issues. These models are designed to facilitate collaboration among different groups and to promote the integration of scientific knowledge and local knowledge (e.g., knowledge coming from community science). By incorporating diverse perspectives, these models can lead to more effective and sustainable solutions.

The participatory models and analysis techniques involve a range of tools and approaches that can be adapted to different contexts and scales. These tools can include stakeholder mapping, participatory mapping, scenario planning, and multi-criteria analysis, among others. These techniques aim to create a safe and inclusive space for dialogue and deliberation, where participants can express their views and concerns, identify common goals and interests, and co-create solutions. Overall, the Socio-environmental systems participatory models and analysis techniques can provide a valuable framework for addressing complex socio-environmental issues. By involving stakeholders in the decision-making process, these models can help to build trust, enhance social capital, and foster a sense of ownership and responsibility among participants. Furthermore, these models can contribute to more equitable and sustainable outcomes, by ensuring that the voices of marginalized and vulnerable groups are heard and taken into account.

In this document, the participatory socio-environmental systems modeling techniques that are developed in the ARSINOE project are detailed. Focus is given on the exploitation of the knowledge management infrastructure that is developed in the project to tackle challenges related to participatory socio-environmental systems modeling. A systems innovation approach is adopted to guide the participatory socio-environmental systems modeling process by identifying the underlying structures and processes that contribute to the problem being addressed, and developing solutions that address those underlying causes rather than just treating the symptoms. The detailed participatory socio-environmental models are considered self-explainable and replicable by the scientific community.

1.0 Introduction

A strong interplay exists between human and natural societies, where human societies are exerting a significant influence on natural environments, and conversely, natural phenomena are affecting our communities in an unprecedented manner. To comprehend the underlying factors that will enable us to exercise greater control over this interplay in the future and ensure a more virtuous cycle between human societies and natural environments, it is imperative to jointly model and analyze the fundamental and inescapable interaction between natural and societal systems (Zafeiropoulos et al., 2021). This is particularly relevant in the context of climate change, as it is a complex and multifaceted problem that necessitates a comprehensive and transdisciplinary approach to develop effective solutions to mitigate and adapt to its impact. One possible way to co-create solutions and promote resilience to climate change impacts is through collaboration among scientists from diverse disciplines and the involvement of stakeholders from various sectors and communities.

Towards this direction, socio-environmental systems (SES) modeling integrates knowledge and perspectives across a range of systems, into conceptual and computational tools that explicitly recognize how human decisions affect the environment (Elsawah et al., 2020) and the uncertain nature of the individual systems and their interrelationships. The development of participatory SES models arises as a promising approach to address SES-related problems. In the ARSINOE project, we consider the SES participatory modeling as a process that is related to the adopted Systems Innovation Approach (SIA), while a strong link exists between the SES analysis processes that can be supported through the Data Hub and the SustainGraph (the Knowledge Graph (KG) developed in the project and detailed in D4.6) (Fotopoulou et al., 2022). Specifically, the data collected in the Data Hub and semantically represented in the SustainGraph are fed as input to the analysis processes that are required by the participatory SES models. Vice versa, the output of the analysis processes can populate the Data Hub and the SustainGraph with further data.

In this deliverable, focus is given on detailing the main challenges that have to be faced to effectively support participatory SES modeling and the design of the relevant framework that is adopted within ARSINOE. A set of methods that can be applied for supporting analysis processes of the developed models is listed. Based on this framework, a set of participatory SES models are developed and detailed in the deliverable, including results produced through their application in specific cases.

The structure of the deliverable is as follows. In Section 2, the main challenges faced for the development of participatory SES models are presented following a literature review on the field, while considering the adopted stakeholder engagement process in the project. The part of the challenges that are targeted to be tackled within ARSINOE are identified. In Section 3, the Systems Innovation Approach that is adopted within ARSINOE is shortly described, focusing on the way that it facilitates participatory modeling processes. In Section 4, the developed participatory SES models in the project are presented. Short description of the current version of the models, their main objectives and the participatory approach that is followed is provided. In Section 5, focus is given on the exploitation of the knowledge management infrastructure developed within the project in a twofold scope: taking advantage of the available data as input for the SES models; or populating the ARSINOE knowledge infrastructure with the outputs of the modeling processes. Section 6 concludes the deliverable.

2.0 Challenges and methods for the development of socio-environmental systems participatory models

2.1 Definitions

Participatory modeling for socio-environmental systems involves a collaborative and iterative approach to modeling that engages stakeholders, including community members, policymakers, and researchers, in the modeling process. This approach acknowledges that socio-environmental systems are complex and multifaceted, and recognizes the importance of integrating diverse perspectives, knowledge, and values in modeling efforts. Participatory modeling can help to build trust, facilitate communication, and foster learning among stakeholders, and can lead to more robust and effective decision-making processes that are better aligned with the needs and aspirations of the communities involved. Participatory modeling can help to ensure that modeling efforts are relevant and responsive to the needs and aspirations of the communities involved, ultimately leading to more sustainable and equitable outcomes.

Participatory modeling has become prevalent in various fields such as health, development planning, and environmental research. The main objective is to promote stakeholder interactions and facilitate the development of shared, mutually understood models of complex systems that can be used to inform effective problem-solving and policy decisions. This approach aims to bring stakeholders together to reach a consensus on a common modeling framework, which can enhance the overall decision-making process (Quimby et al., 2023). Various definitions are provided for participatory modeling in the literature. In Stave (2010), participatory modeling is defined as “...an approach for including a broad group of stakeholders in the process of formal decision analysis” (Stave (2010)) while in (Voinov et al. (2018)), PM is defined as “... a purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representations of reality.” Within the ARSINOE project, we consider participatory modeling as a process where various actors are engaged to conceptualize, formally model and analyze complex socio-environmental systems that are identified in the various case studies. The actors include -among others- socio-environmental scientists, data scientists and stakeholders that are participating in the living labs organized by the project.

2.2 Stakeholder Engagement Process

Stakeholder and citizen engagement formed a foundational element of ARSINOE’s modelling framework, ensuring that all analytical components were grounded in the lived realities, operational knowledge, and strategic priorities of those directly affected by climate-related risks. In each case study, a diverse constellation of actors—ranging from public authorities and utilities to local communities, civil society groups, researchers, and private-sector representatives—were actively involved in shaping how systems were defined, how boundaries were drawn, what data were needed, and how digital tools should function to support decision-making. The following sections detail the concrete ways in which this engagement influenced the modelling process, illustrating how stakeholder contributions enhanced the accuracy, relevance, and usability of models and tools across the project.

Refining System Boundaries Through Stakeholder-Driven Conceptualization: Across all ARSINOE case studies, the Living Labs fundamentally reshaped the definition of system boundaries through co-created mental maps and problem statements. Stakeholders consistently revealed hidden drivers, overlooked hazards, and unacknowledged vulnerabilities, prompting modelling teams to expand or reorganize the structure of the models. For instance, in the Athens Metropolitan Area, the Living Lab broadened the hazard system—initially framed as heatwaves and air pollution—to include

biodiversity loss, landscape fragmentation, noise, and socio-economic vulnerabilities, all of which were mapped as both compound and cascading effects. Similarly, in Torbay & Devon (CS8), stakeholders introduced “community” as a new systemic driver, which forced modellers to adapt the modelling structure to allow on-the-fly integration of emergent parameters into socio-technical risk assessments. These iterative refinements ensured that system boundaries reflected actual local complexity rather than pre-defined modelling assumptions.

Living Labs as Drivers of Geographical Boundary Adjustments: Stakeholder participation also played a decisive role in reshaping geographical scales. In several cases, initial modelling extents were proven insufficient once confronted with situated local knowledge. The Athens Living Lab demonstrated that modelling the urban heat island and biodiversity dynamics required inclusion of peri-urban green areas, because these areas provide the reference points necessary to quantify heat island intensity and habitat degradation—insights that drastically improved model realism and confidence. In Case Study 5 (Canary Islands), logistical constraints and stakeholder accessibility considerations during the Living Lab led to shifting from an initial focus on El Hierro and La Palma to modelling the entire archipelago, thus ensuring representativeness and stakeholder continuity. In Main River (CS3), stakeholders validated and corrected the hydrological modelling boundaries by marking critical sub-regions on maps, exposing spatial heterogeneity in water availability and demand that modelers had not fully captured. These examples show how stakeholder knowledge directly influenced not only where models operate, but also why those boundaries matter.

Integrating Temporal Scales and Social-Technical Cycles Through Stakeholder Pathways: Living Lab activities, especially envisioning and back-casting exercises, provided modelling teams with locally grounded temporal frameworks, which then shaped simulation horizons and scenario dynamics. Time horizons were not imposed by the project but were co-defined with stakeholders—often converging around 2050 for long-term visions, while several groups selected 2040 for their final milestones to reflect realistic delays in socio-technical transitions. Moreover, stakeholders identified local governance cycles, climate-related seasonal patterns, and regulatory bottlenecks that influence temporal granularity in model dynamics. The back-casting process revealed that social, environmental, and technological processes move at different speeds; thus, models had to incorporate multiple temporal rhythms, aligning transformation pathways with local institutional and ecological cycles. This participatory determination of temporal parameters ensured that model outputs were both context-sensitive and credible for regional planning.

Data Provision and Integration, With Emphasis on Citizen-Science Contributions: Stakeholders contributed crucial data sets, data validation, and contextual interpretation, significantly enriching the modelling inputs across case studies. Table 5.1 of the deliverable documents the diversity of data sources—including ground sensors, satellite data, drones, simulated datasets, and importantly, citizen-science data, which played an expanding role in ARSINOE’s monitoring schemes. Citizen-generated data were particularly impactful in biodiversity-related modelling, where they were used to map fauna and flora presence, geolocate species, and strengthen or fill gaps in existing datasets for two case studies. The deliverable notes that citizen science proved valuable for producing biodiversity datasets, enhancing spatial accuracy, and reinforcing model calibration and validation. In addition, stakeholders in the Canary Islands provided time-series datasets for water balance components, directly improving hydrological model accuracy. These contributions created richer, more granular datasets and enabled hybrid monitoring schemes combining satellites, sensors, citizen science, and simulated data.

Model Verification, Validation, and Confidence-Building Through Stakeholder Interaction: Living Labs acted as continuous validation interfaces, where modelling teams presented conceptual models, early outputs, and refined simulations to stakeholders for iterative feedback. This multi-phase validation

improved both model credibility and stakeholder trust in the results. Across nearly all case studies, stakeholders confirmed whether models represented the real system, helped correct misinterpretations, and highlighted missing variables. In the Canary Islands, stakeholder engagement was instrumental in validating the water balance model and improving it with new data inputs. More broadly, ARSINOE reports that all high-risk context-related uncertainties identified in early modelling phases were successfully removed from the red danger zone through participatory refinement within Living Labs, demonstrating that co-creation reduced structural and contextual uncertainty more effectively than parameter adjustments alone. Thus, stakeholder involvement was not merely consultative—it was a fundamental mechanism for model correction, uncertainty reduction, and enhanced modelling confidence across ARSINOE.

Stakeholder Input for User Requirements of Digital Tools and Decision-Support Systems: Beyond shaping the modelling framework, stakeholders also played a central role in defining user requirements for ARSINOE's digital tools, ensuring that emerging platforms—such as digital twins, serious games, virtual reality tools, and dashboards—were both usable and relevant for regional decision-makers. Throughout the Living Lab workshops, modelers and tool developers interacted directly with users from municipalities, utilities, environmental agencies, and civil society to understand their operational needs, data literacy, preferred visualization formats, and decision-making workflows. Because Living Labs functioned as co-creation environments, stakeholders were able to articulate what information they needed to support climate adaptation decisions, the granularity required for meaningful interpretation, and the types of interfaces and functionalities that would allow them to explore scenarios or test solutions. For example, the validation sessions—where modelling outputs, digital tool prototypes, and early visualizations were presented—provided crucial feedback on whether the tools sufficiently represented actual system behavior, whether indicators were intuitive, and whether outputs supported the planning horizons and governance cycles of each region. This iterative dialogue ensured that digital tools were not only technically robust, but also aligned with stakeholders' decision contexts, thereby maximizing their adoption potential and real-world impact.

More extensive explanation of how participatory processes supported the mitigation of modelling uncertainties can be found in Deliverable 3.10.

2.3 Challenges

Recently, a lot of work has been done on the specification of the main challenges that have to be tackled for the development of SES participatory models. Following, we provide an overview of the available work on the field. In (Elsawah et al., 2020), the authors detail eight grand challenges that need to be overcome to accelerate the development and adoption of SES modeling. These challenges regard:

- The need to **bridge epistemologies across disciplines** considering the epistemological pluralism in the concepts used and the potential misunderstandings and conflicts that may appear. Semantic alignment of terms is required to enable scientists coming from different disciplines to collaborate. Semantic alignment has to be combined with mechanisms to evaluate the validity and quality of the data. Furthermore, the different methodologies and collaboration norms that may be applied per discipline have to be considered and -where possible- bridged, taking into account the engagement of heterogeneous actors from different backgrounds. Sharing and usage of data in public repositories is required to improve their availability, as well as the potential for reproducibility of experiments.
- The need to **manage the sources of uncertainty** in the data, model structure and model parameters. Different sources of uncertainty may be introduced that in some cases may be

also interlinked. Deep uncertainty is introduced in cases where there is disagreement among the people involved in the modeling process.

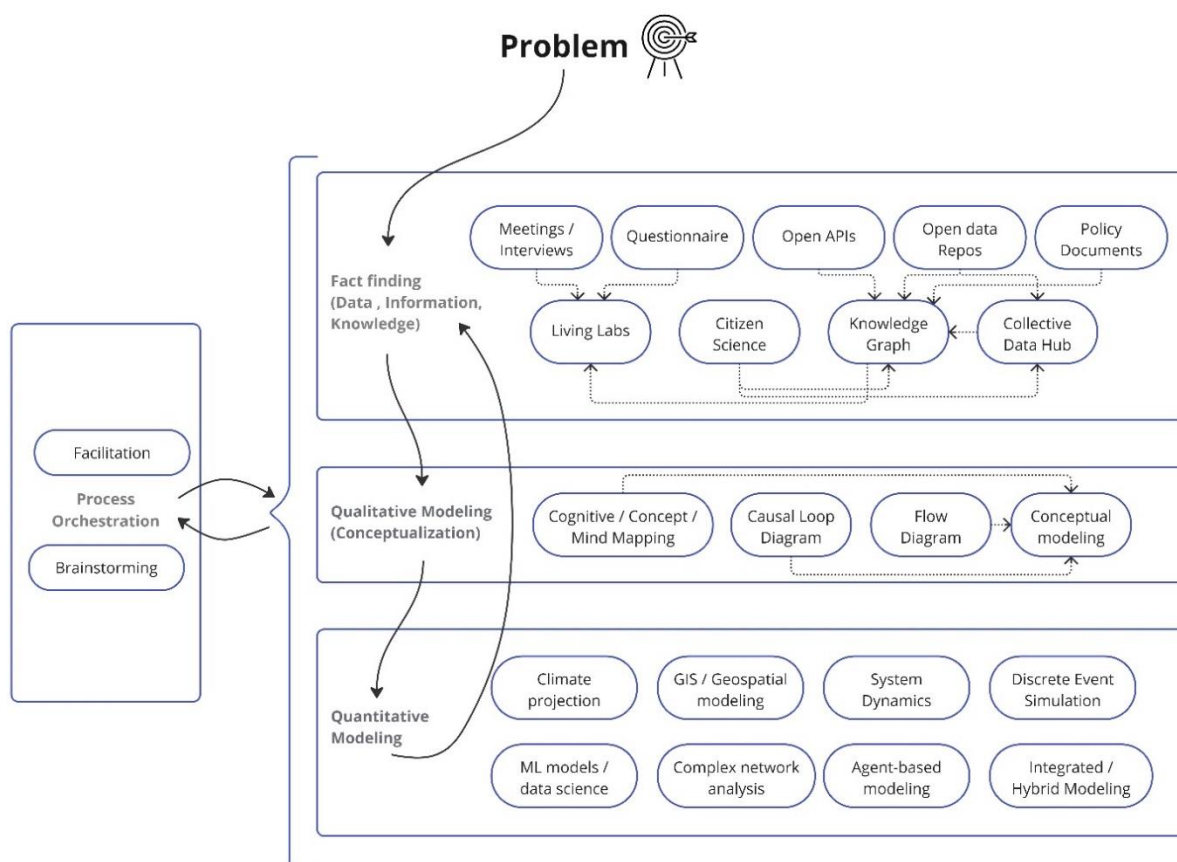
- The need to **combine qualitative and quantitative methods and data** sources, considering quantitative data (e.g., time series data) coming from various data repositories as well as qualitative data (e.g., text, processes description, assessment data). Depending on the research question and the available data, the mix of the quantitative and qualitative information that is fed for analysis has to be decided. Mixed methods are applied for the analysis part.
- The need to cope with **different data scales** from a spatial, temporal and organizational scope. SES modeling may consider different ways of partitioning of the examined geographical areas, while the temporal coverage and resolution may also vary. A coherent matching of the available data in such scales is required to enable their analysis. Human behavior may be examined from an individual or group/community perspective, introducing further complexity in the modeling process.
- The need to develop methods to **capture systemic changes in SES**. SES are dynamic, while gradual changes in their past behavior may affect their future status. It is important to be able to capture dynamic changes and transitions of SES as an integral characteristic of the modeling process. The existing modeling techniques are static in the definition of the system dynamics (e.g., rules or equations that guide the dynamics).
- The need to **integrate the human dimension** in the modeling of SES systems by considering agent-based approaches to represent human behavior by heterogeneous actors (e.g., farmers, households, firms, etc.). Various interdisciplinary research teams investigate coupled natural-human systems, however in a limited scope (Shin et al., 2022). There is a need to better align the theory and the data for guiding social decision rules, as well as to consider behavioral aspects as integral part of the models.
- The need to **elevate the adoption of SES models and impacts on policy design and implementation**. The outcome of the models has to be used to support collaborative decision making. Participatory modeling can combine the innovative capacity of various stakeholders, formalize collective representations of complex problems and promote a sense of ownership by the involved parties. In this way, decision makers may be more likely to adopt the outcomes provided by the models.
- The need to **leverage new data types and sources**, considering data coming from social media, search engines, mobile applications and devices, wearable devices and social networks. Synthesis of heterogeneous data coming from diverse data sources has to be supported.

Following, in Section 4.1.2, we provide details regarding the way that we can tackle part of the aforementioned challenges based on the knowledge infrastructure made available by the project.

2.4 Methods

The tools and methods used during participatory modeling projects are expected to promote system understanding and awareness for all stakeholders (Voinov et al., 2018). There are numerous methods used in participatory modeling projects. In Figure 2.1 a typology of methods is presented as it is made available in (Voinov et al., 2018). In most cases, a combination of methods is taking place in the form of a workflow.

Figure 2.1 Participatory modeling methods



The fact-finding stage of the participatory modeling process regards the collection of data, information and knowledge regarding the system to be modeled. This can be done in various ways based on access to specific data silos, including information coming from interviews, surveys, access to open data repositories and usage of open Application Programming Interfaces (APIs). The fact-finding stage may be revisited multiple times during a participatory modeling process.

The qualitative modeling stage of the participatory modeling process regards the design of conceptual and visual representations of the problem to be tackled, in the form of concepts and relationships among them. The relationships may have spatial and temporal dimensions. Qualitative modeling methods include -among others- the design of mind maps, flow diagrams, causal loop diagrams.

Following, the quantitative modeling stage is taking place (Voinov et al. (2018)). In the quantitative stage, we consider analysis that is based on the values provided to qualitative or conceptual metrics (e.g., scenario building, social network analysis), as well as analysis that is based on values that can be collected per metric with a temporal and/or spatial scale. In this stage, participatory SES modeling can employ various modeling techniques, such as agent-based modeling, system dynamics modeling, and the creation of reinforcement learning environments that simulate SES. These models can investigate environmental, economic, behavioral, and policy-making aspects individually or in combination. Regarding the modeling techniques, agent-based modeling is particularly useful in SES modeling as it simulates the actions and interactions of autonomous agents, allowing for explicit representation of decision-making by human actors (Gotts et al., 2019). It is a valuable tool for exploring the impact of human interactions on social and ecological patterns (Will et al., 2020).

In contrast, system dynamics is a methodology and mathematical modeling technique that provides an overview of complex issues and problems by representing the system as stocks and flows. While agent-based models represent disaggregated parts of a system, system dynamics models represent the aggregated system (Martin et al., 2015). The application of Machine Learning (ML) techniques can also aid in participatory SES modeling. One example is the combination of reinforcement learning (RL) and agent-based modeling (ABM) to better capture the probabilistic nature of the ecological footprint and its impact on environmental sustainability. While ABM relies on pre-defined rules by domain experts, integrating RL agents into the modeling process can better represent real-life scenarios where environmental variables evolve over time and are not always fully understood. Inverse reinforcement learning (IRL) can complement ABM by extracting behavioral rules from data and dynamically shaping them during the learning process (Lee et al., 2017). This approach frames learning behavioral rules as a problem of recovering motivations from observed behavior and generating consistent rules based on these motivations. This can be particularly useful in discovering rules that are difficult to define a priori and require deep insight into an agent's behaviors.

Process orchestration is considered across all the stages of a PM process and includes a set of methods (e.g., brainstorming, facilitation, role playing games) that enable the optimal execution of the various stages and the extraction of outcomes based on collective decisions and actions.

Furthermore, novel techniques are emerging that focus on the identification of patterns in the available data to assist the modeling and analysis processes. When faced with the assumption that every socio-environmental problem is entirely unique, it can be challenging to determine where to start. However, archetype analysis can assist in identifying patterns in the data. Archetypes refer to categories or groups with similar characteristics and patterns, even though individual cases may exhibit distinct traits. Archetype analysis can not only highlight common patterns that frequently arise in SES but also provide strategies for achieving sustainability across different contexts. In the context of SES, archetypes are fundamental and recurring patterns of feedback loops that generate comparable dynamics. Despite variations in individual cases, these archetypes enable researchers to identify comparable attributes and patterns (Palmer, 2022).

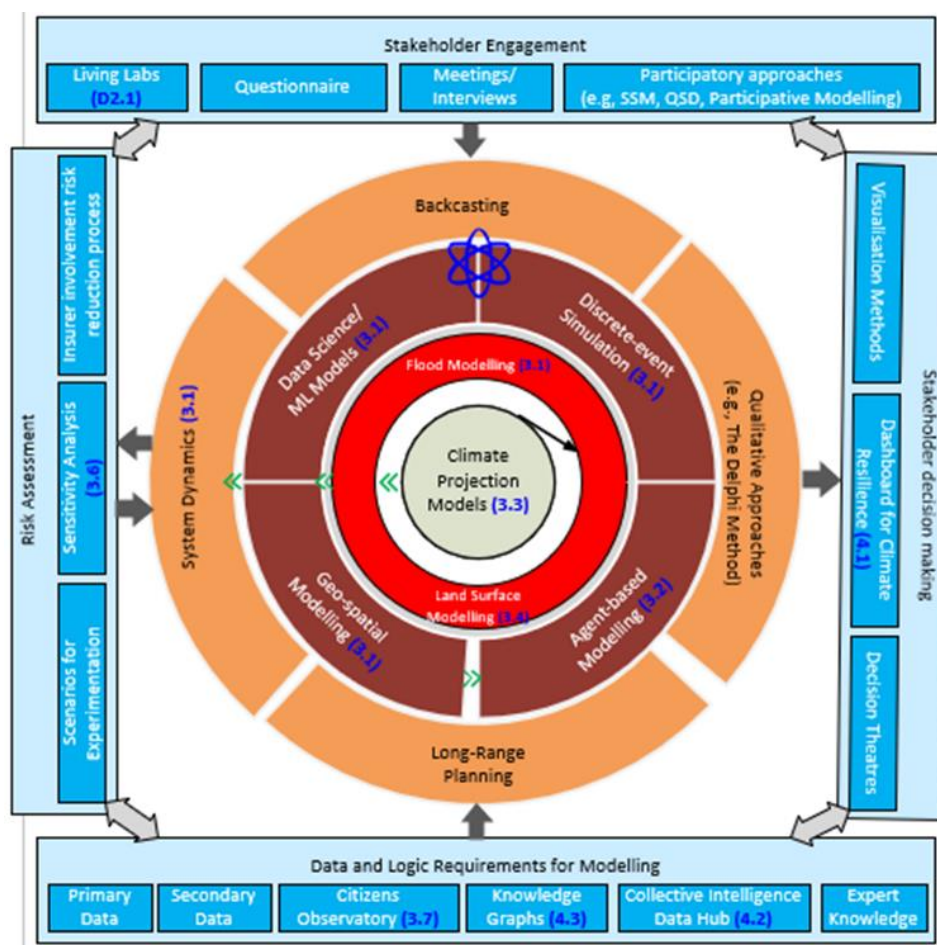
3.0 Participatory modeling based on a Systems Innovation Approach

A systems innovation approach is a holistic method that seeks to identify and implement changes in the underlying structures and processes of a complex system. It recognizes that complex systems are interconnected and dynamic, and that changing one element of the system can have ripple effects throughout the entire system. This approach is particularly useful for addressing complex socio-environmental challenges, such as climate change or resource depletion, that require systemic changes rather than incremental improvements. The systems innovation approach involves engaging stakeholders and using a participatory process to co-create and co-design solutions that address the underlying causes of the problem.

The systems innovation approach can be used to guide the participatory socio-environmental systems modeling process by identifying the underlying structures and processes that contribute to the problem being addressed, and developing solutions that address those underlying causes rather than just treating the symptoms. In practice, the systems innovation approach can be used to facilitate a participatory process in which stakeholders from different sectors and perspectives come together to co-create solutions to a complex socio-environmental challenge. The process involves identifying the key drivers and feedback loops that contribute to the problem, developing scenarios and models to test different intervention strategies, and engaging stakeholders in a continuous process of feedback and iteration to refine the solutions. By involving stakeholders in the process and addressing the underlying structures and processes of the system, the systems innovation approach can lead to more sustainable and equitable solutions to complex socio-environmental challenges.

Regarding the work in the ARSINOE project, we follow a bottom-up approach in many of its activities to optimize the acceptance and uptake of its solutions and develop well-informed analyses of the interactions between bio-physical and socio-economic systems, but also the implications that one system brings another. In this process, the involvement of stakeholders is of critical importance. We adopt an approach where we combine Living Lab workshops to collect feedback and examine participatory approaches for modeling and analysis, existing and emerging innovations and technologies to tackle specific hazards provided by the Climate Innovation Window, as well as custom solutions developed by external parties through the ARSINOE Open Tenders. Specifically, the stakeholders including citizens participate in different threads of the project, such as i) the collection of data, through citizen science, ii) the selection of interventions and providers, through the Climate Innovation Window and the ARSINOE Open Tenders for Innovations, iii) the assessment of willingness to pay, through the choice experiments and virtual reality experience, iv) the capacity building thread, through the train-the-trainers exercise, and v) the participatory modeling, through the interactions between the ARSINOE modelers and stakeholders, in the Living Lab workshops. The participatory approach in the system modeling is also represented in the resilience wheel (Figure 3.1), the ARSINOE Resilience Framework, that enables interactions between the Stakeholder Engagement pillar and the Risk Assessment pillar. This interaction implies that the Stakeholders co-shape the system analysis implemented by the ARSINOE team in different levels. The stakeholders reveal what the geographical, bio-physical, and socio-economic boundaries of the case study are, they indicate hidden synergies and trade-offs that might be not well documented or investigated, or that might be case specific, and, finally, they draw a path towards a vision, through the back-casting exercise choosing the interventions they need to be simulated and tested.

Figure 3.1 Arsinoe's Resilience wheel for participatory modeling.



In the living lab workshops, Arsinoe team distills the stakeholders' knowledge and experience on the respective case study around a specific climate change hazard and the risen vulnerabilities and exposures of the affected systems. The objective of this exercise is to create a mental map that represents the collective knowledge and experience of the stakeholders and then use the mental map to calibrate the conceptual model, which constitutes the roadmap for the modelling approach towards the risk assessment. The feedback of the living lab is translated into the fundamental components of the risk assessment approach: a) hazard, b) vulnerability, c) exposure, and d) capacity (UN, OEWG 2016).

Risk: The potential loss of life, injury or destroyed or damaged assets which could occur to a system, society, or a community in a specific period, determined probabilistically as a function of hazard, exposure, vulnerability, and capacity (i.e., $\text{Risk} = \text{Hazard} \times \text{Vulnerability} \times \text{Exposure/Capacity}$) (UNISDR, 2017).

Hazard: A process, phenomenon, or human activity, including violent conflict and human rights violations, that may cause loss of life, injury or other health impacts, property damage, social and economic disruption, or environmental degradation (UNISDR, 2017).

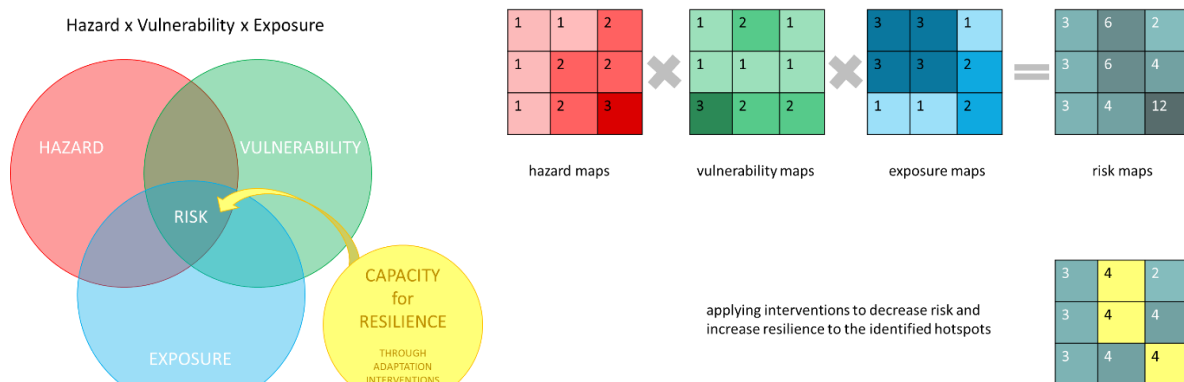
Vulnerability: The conditions determined by physical, social, economic, and environmental factors or processes which increase the susceptibility of an individual, a community, assets, or systems to the impacts of hazards (UNISDR, 2017).

Exposure: The situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas (UNISDR, 2017).

Capacity: The combination of all the strengths, attributes and resources available within an organization, community or society to manage and reduce risks and strengthen **resilience** (UNISDR, 2017).

Figure 3.2 presents a conceptual schematic of an assessment approach for the identification of risk hotspots, where capacity interventions are required in order to increase resilience in a spatiotemporal risk setting, such as this of Athens case study, where the central investigated hazard is extreme heat. Following, in Section 5, this approach is applied for risk identification in the Athens case study (see Section 5.1).

Figure 3.2 The risk assessment approach on identifying hotspots for interventions.



4.0 Knowledge management infrastructure and SES modeling interplay

The availability of knowledge management infrastructure is crucial for facilitating participatory modeling processes for socio-environmental systems because of the intricate and multifaceted nature of these systems, which necessitate contributions and expertise from a diverse range of stakeholders. Knowledge repositories serve as centralized and accessible locations where stakeholders and interdisciplinary scientists can access relevant data, research, and other resources that can aid in the modeling process. Furthermore, they can promote transparency and accountability by enabling them to monitor the sources and quality of information utilized in the modeling effort. Knowledge repositories can foster informed decision-making processes based on evidence-based research and stakeholder input, which ultimately lead to more effective and equitable outcomes for socio-environmental systems.

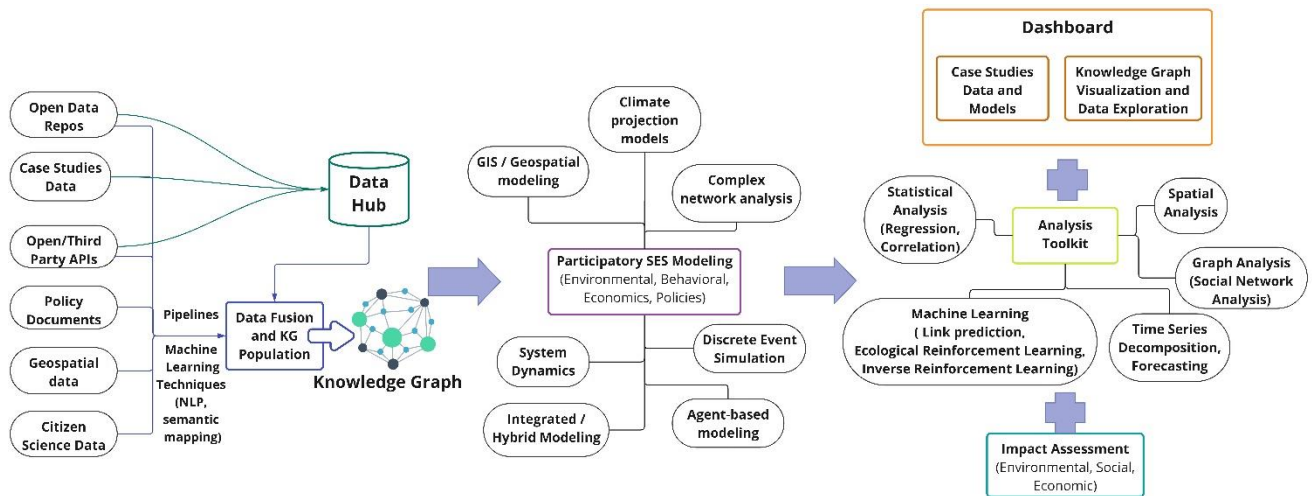
The knowledge management infrastructure in ARSINOE comes from the developments in WP4 and consists of three main tools, namely the Data Hub, the Knowledge Graph (referred to from now on as SustainGraph) and the Dashboard. Each one of the tools, as well as the overall knowledge management infrastructure, contributes to the various steps of a participatory modeling process. On the other hand, the data collected and/or produced through a participatory modeling process can be fed back to the knowledge infrastructure, enriching the available information and enabling the extraction of insights by data scientists.

The Data Hub acts as the main data repository where various datasets of different types and formats (e.g., text documents, time series data, geospatial data) can be hosted and made available to any interested party (e.g., data scientists, environmental scientists, policy makers).

SustainGraph acts as a graph database where the data is represented along with their semantics, enabling their unique representation and the tracking of relationships among them. SustainGraph is an acronym selected for the Knowledge Graph developed in ARSINOE, initially called as Collective Environmental Intelligence Knowledge Graph (KG). It is designed based on the identification of the needs of socio-environmental scientists to support participatory SES modeling. It fuses knowledge coming from a wide range of heterogeneous sources, including information for the SDGs, third-party open data repositories, information coming from the ARSINOE case studies, and information coming from the analysis of policy documents. Detailed description of the SustainGraph is provided in the WP4 deliverables.

The Dashboard provides nice and intuitive interfaces for end users to easily access and exploit the available information and facilitate knowledge sharing and decision-making processes. The interplay between the knowledge management infrastructure in ARSINOE and the participatory SES modeling processes is depicted in Figure 4.1.

Figure 4.1 Knowledge management infrastructure and participatory modeling process interplay.



The approach is separated into three conceptual parts. The first part regards the conceptualization and continuous population of the Data Hub and the SustainGraph, fusing data coming from a variety of data sources. The second part regards the support of participatory SES modeling to capture systemic changes, taking advantage of the knowledge in the ARSINOE knowledge management infrastructure and the existence of mature modeling techniques. The third part regards the support of a set of analysis processes that can be used to assess the impact of various scenarios, based on the outcomes of the modeling process in the second part.

4.1 Data Fusion, Data Hub and Knowledge Graph Population

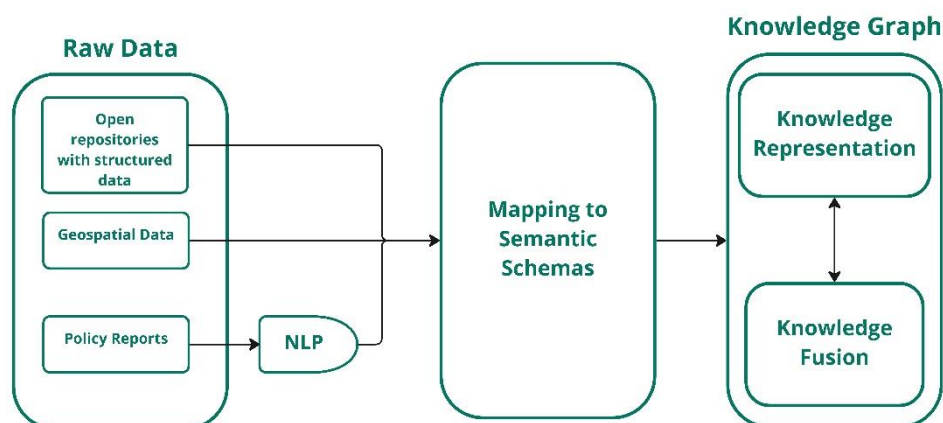
A Knowledge Graph (KG) is a graphical representation that includes specific knowledge and facts. When we refer to "explicit knowledge," we are discussing the conceptualization of the entities within the KG and their interrelationships. Creating a definition of explicit knowledge is typically the initial stage in developing a KG. To achieve this goal, existing knowledge from ontologies, information models, and taxonomies is used. The explicit knowledge that is depicted within the KG is not fixed, as entities can be added or removed dynamically, and relationships can be created or updated. This is an ongoing process that occurs simultaneously with the population of the KG with instance data.

The data referred to as "facts" can be obtained from various structured, semi-structured, or unstructured sources. Such data are made available in the Data Hub. This data encompass open and linked data within open data repositories, including time-series data, textual documents, directives, and policies. These data can be accessed via open or third-party APIs, collected from environmental sensing systems such as IoT nodes, gathered from existing organizations and citizens' observatories, retrieved from satellite systems (e.g., images), and obtained through semantic crawling of web resources. In addition to populating the SustainGraph with data coming from the Data Hub, the data can be processed in real-time or accessed directly through open APIs.

The sources of data used to populate the KG and made available in the Data Hub are diverse in terms of origin, structure, volume, and spatial and temporal granularity. To process and integrate them into the KG, a variety of data fusion and homogenization mechanisms can be employed, as shown in Figure 4.2. Data fusion involves processing techniques that improve the quality of aggregated data, such as removing outliers and aggregating data over time or space, as well as techniques for extracting knowledge from the data. Machine learning techniques can be used to identify hidden relationships, support link prediction, and evaluate the validity and strength of continuous links and relationships.

Textual data can be subjected to entity recognition through natural language processing (NLP) techniques, while computer vision techniques can be used to extract knowledge from images. The collected data are aligned with existing taxonomies and semantic models, leading to the representation of knowledge and the extraction of insights (knowledge fusion).

Figure 4.2 Data Fusion mechanisms.



4.2 Participatory SES Modelling

After creating a unified and comprehensive knowledge graph (KG), participatory modeling of socio-environmental systems (SES) can be carried out. Actually, the KG provides a consistent and rich representation of the collected data, enabling scientists to investigate complex problems resulting from interactions between human and natural systems. The overall knowledge management infrastructure that is developed in ARSINOE can help to tackle part of the challenges for the participatory modeling of SES.

For instance, KGs are powerful tools that can help **bridge epistemologies across different disciplines**. By linking data from different sources, knowledge graphs can provide a unified view of information across different fields, enabling researchers to identify connections and relationships that might otherwise go unnoticed. This can help to break down disciplinary barriers and foster collaboration between researchers from different fields, facilitating the exchange of ideas and knowledge. By making it easier to combine data from different sources and identify patterns and connections, knowledge graphs can also help researchers to develop new insights and theories that cut across different disciplines, leading to more innovative and impactful research outcomes.

The ARSINOE Data Hub and the SustainGraph can help to **manage the sources of uncertainty** in data coming from social, environmental, and economic repositories by providing a framework for representing and linking different types of information. They can help to identify and quantify sources of uncertainty in data, such as missing values or errors, by providing a structured way of representing and analyzing data. By integrating data from different sources, the SustainGraph can also help to identify and manage conflicting or inconsistent information, which is a common source of uncertainty in interdisciplinary research. Additionally, the Data Hub and the SustainGraph can help to track the provenance of data, providing information about where data came from, how it was collected, and how it has been processed, which can help to improve the transparency and reproducibility of research outcomes. Different **data scales** can be captured based on the data population of the Data Hub and the SustainGraph with time series data and spatial data. For such data, the raw information may be made available in existing data repositories, while part of them can be introduced on demand (e.g., through the development of data population pipelines) in the SustainGraph to support analysis processes.

The SustainGraph can also help to **capture systemic changes in socio-environmental systems** by providing a structured representation of the complex interactions and relationships between different elements of the system (e.g., by considering the identified hazards in a specific area; by considering the stakeholders and their areas of financial activity; by considering the mapping of policies documents with the SDGs). By integrating data from different sources and representing it in a consistent and coherent way, it can provide a comprehensive view of the socio-environmental system, including its underlying structure, feedback loops, and interdependencies.

4.3 Analysis Toolkit and Impact Assessment

Researchers will be able to leverage the participatory SES models and the up-to-date information in the KG to gain valuable insights. A diverse set of analysis methods can be utilized for this purpose, including statistical analysis to identify trends and patterns, spatial analysis to explore geographical relationships, graph analysis to analyze the network structure of the data, and time series analysis to examine changes over time. Additionally, supervised and unsupervised ML techniques can be applied to the data to uncover hidden patterns and relationships, classify data, or make predictions. With these powerful analytical tools at their disposal, scientists can more effectively understand and address complex problems arising from the interactions between human and natural systems.

Various analysis techniques can be employed to extract insights from the data and models available in the KG. Pure statistical analysis, for instance, can be used to detect data clusters, classify data into high-level categories, or identify hidden correlations. Spatial analysis, on the other hand, is particularly useful for environmental problems with a clear spatial dimension (Stocks et al.,2000). This type of analysis can track the evolution of environmental phenomena, identify specific locations for objects or events based on well-defined socio-environmental criteria, or survey protected areas that are close to industrial sites. Graph analysis offers a wide range of techniques, including Social Network Analysis (SNA), which can be used to observe social structures through the use of networks and graph theory. SNA can help scientists explain natural resource governance in different settings, examine how decision makers adapt to a changing social and ecological context, and understand the transmission of local ecological knowledge (Salpeteur et al.,2017). Time series decomposition is also a valuable analysis technique as it enables the detection of repeated patterns over time, making it useful for forecasting the future evolution of SES phenomena. Scientists can apply these and other techniques, such as supervised or unsupervised machine learning, to gain a better understanding of complex SES interactions and make informed decisions based on data-driven insights.

The collected data can be analyzed using various machine learning techniques in conjunction with the developed SES models. ML techniques are particularly useful in cases where traditional analysis methods cannot capture the complex relationships between variables. By exploring the data, new knowledge can be generated, and ecological patterns can be recognized and predicted in both space and time. The developed SES models and analysis mechanisms can be used for impact assessment processes. These assessments can include environmental, social, economic aspects, or a combination of them. To facilitate impact assessment, easy-to-understand visualizations can be created to monitor key performance indicators (KPIs) related to different scenarios. Overall, the application of ML techniques can offer a powerful tool for the analysis of the collected data and the development of impactful insights.

5.0 Participatory SES modeling in ARSINOE

5.1 Transdisciplinary approach and co-creation in the Athens case study

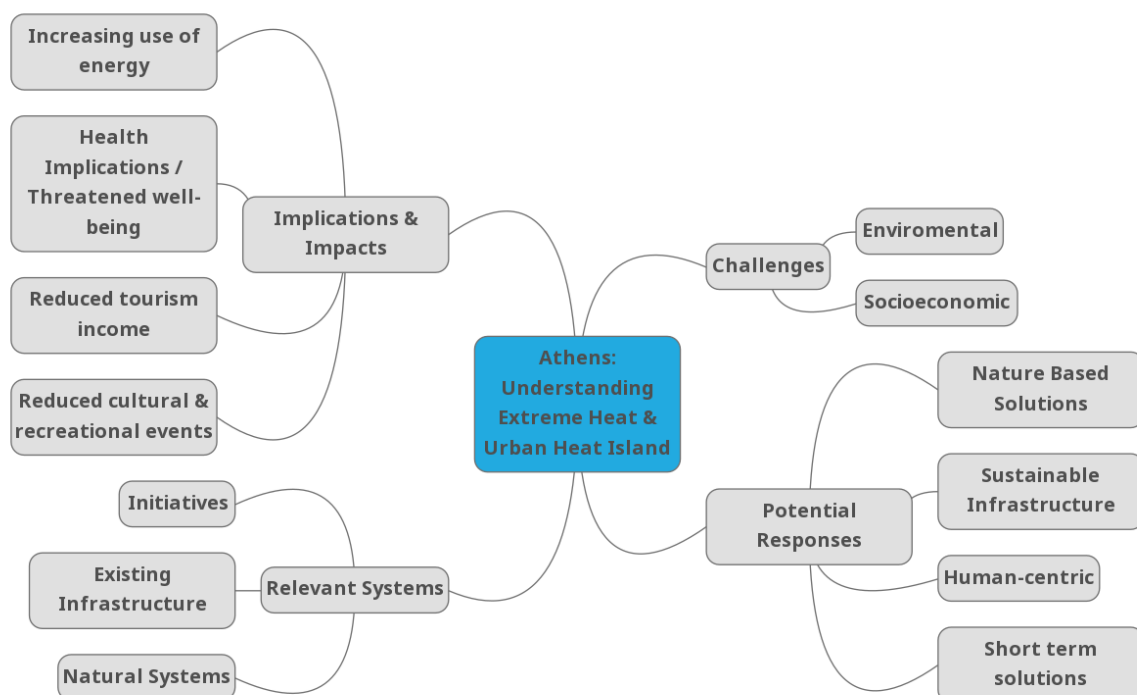
In the Athens case study, a transitional approach was adopted enabling input and scoping across scientific and non-scientific stakeholder communities and facilitating a systemic way of addressing a challenge. This includes initiatives that support the capacity building required for the successful transdisciplinary formulation and implementation of research actions. The challenge was indicated through a co-creation/participatory approach via regular living labs.

The system innovation approach implemented as a bottom-up systemic procedure where the emphasis is given on the functions of the cross-sectoral system “as a whole” and on diversity of actors. Context and solutions to face climate change are identified by qualitative analysis in LLs and through interviews and workshops, where targeted stakeholders and citizens co-design an accepted vision of the future and set a list of possible pathways to reach their goals.

The first live workshop focuses on the objective setting, where the key topic was identified by the SHs through the participatory activity of creating a mind. In the case of Athens, this pointed out that the most critical issue for the locals is extreme heat and in relation to the urban heat island. Additionally, other topics were highlighted by the SHs, such as green areas, interconnection of green spaces, biodiversity, nature-based solutions, health, mobility, accessibility, mapping and data, participatory tools, technologies, and many socio-economic topics etc.

After processing the raw mind map created during LL, a refined map was created describing “the problem (Athens – extreme heat) and its causes – effects – relevant systems – responses (Figure 5.1).

Figure 5.1 Refined mental map.



In the 2nd meeting the aim was to set the problem statement and develop the vision of Athens. The problem was formulated as follows:

“Athens is becoming increasingly hot with significant impacts on health, society and the local economy. What is our vision for dealing, together, with this imminent and invisible threat?”.

The vision for the Athens case study was developed with the SH and presented below through written and visual format (Figure 5.2).

Vision of Athens: *Athens is a green and cool city! It has established a strategic management of urban nature, integrating green and blue infrastructure to enhance the city’s biodiversity and resilience to extreme heat. The management of urban nature ranks high in the city’s priorities, implemented with commitment, continuity, and vision. Athens has a revitalized and vibrant city center, with sustainable mobility and no air or noise pollution. Urban green areas, green and blue corridors are developed and integrated into the city’s cultural routes. Athens actively promotes Green Architecture to cool the city: it is abundant with urban gardens, planted rooms, green roofs, vertical gardens and green buildings. Innovative solutions are fully explored, learning from international experience and mobilizing green funding. Athens is an example of inclusion and equity, its citizens are active and well-informed, and there is social welfare for all, especially the vulnerable; the city knows where they are and responds swiftly to protect them.*

Figure 5.2 The Athens vision in visual format.



After clearly defining the SHs' topic of interest and developing a clear vision for the Athens case study, the scientific team of the Athens case study from NOA, UTH, NTUA, and Athena Research Center, explored the methods and tools that would be needed to model the main topics. For the numerical study and quantification of the vision of Athens, complex models are applied based on the results of LL (mental map, tree map and vision) to assess and combine the extreme heat (section 5.5), the air quality (section 5.3), the connectivity (section 5.6) and accessibility of green areas (section 5.7), and the socioeconomic vulnerability (section 5.8) along with climate change projections aiming at proposing site and challenge specific NbS, by evaluating their performance through micro-climate simulations for the seven districts of the city of Athens (section 5.9), as well as applying an urban biodiversity analysis (section 5.10). In addition, along with bio-physical, socio-economic parameters

were also modeled through other models such as virtual reality. The virtual reality experience was developed with a twofold goal. To support the visualization of the choice experiments developed in the Athens case study, in order to investigate people's willingness to pay for the modification of the urban landscape to a more sustainable and human-friendly one, taking into account the needs of all vulnerable social groups, and for educational purposes.

Following, we summarize some of the main actions that were triggered upon the interaction with the set of engaged stakeholders in the Athens Case Study. A detailed description of such interactions and their impact on the decision-making process is available in the deliverable D3.10 of ARSINOE (D. Kofinas 2024). Stakeholder engagement in the Athens Case Study led to broadening the focus of targeted hazards, moving beyond the initial emphasis on heatwaves to also considering air pollution and biodiversity loss as interrelated risks. The living labs also highlighted the importance of extending the geographic boundaries of the models, to include peri urban areas, in order to capture variations in ecological and demographic features. This prompted adjustments to the spatial resolution of analysis, enabling more localized assessments to sub-zip code scale, supporting more precise intervention planning. Insights gathered during the participatory sessions contributed to shaping the virtual reality (VR) experiment, including the integration of additional contextual elements such as urban violence. Across the modelling process, stakeholders played a continuous role in verification and validation of the provided models and solutions, from conceptual design to data collection and implementation. Each workshop served as a platform for presenting emerging outputs, receiving targeted feedback from local experts, and refining the models to ensure alignment with real-world dynamics and user requirements, including visual consistency features such as unified colouring. Continuous interaction channels have been also established, enabling the collection of feedback on the usage of the provided tools by ARSINOE.

5.2 Interdisciplinary modelling in the Athens case study

5.1.1 Main scope, objectives and participatory processes

In Athens, the ARSINOE case study will concentrate on tackling the impact of Climate Change on both urban biodiversity and public well-being. The focus will be on evaluating the effects of Nature Based Solutions (NBSs) in reducing the Urban Heat Island (UHI) effect in the area. The assessment of adaptation options will involve a multi-criteria analysis, which will consider various factors such as effectiveness, contribution to climate change adaptation, technical and economic feasibility, and public acceptance. To increase public awareness and participation, ARSINOE will adopt three methods: citizen science, youth assemblies to simulate local Green Deal processes and promotion of green practices, and integration of innovation and science into educational curricula.

5.1.2 Conceptual design and analysis processes

The data and model flow diagrams of Figures 5.3, 5.4 and 5.5 are constructed to include the relevant hazard, vulnerability and exposure submodules, the recommended and tested capacity interventions for resilience and the auxiliary layers of data, that are used for the assessment and calibration of the other components. These figures also present the participatory evolution of the modelling structure from an initial preparatory phase, without any inputs by the living lab, to a mature phase with input of two living lab workshops.

Figure 5.3 presents the modeling flow diagram of the initial work hypothesis, constructed collectively by the scientific team for the Athens case study, according to which extreme heat and air pollution are investigated as primary hazards that have cascading effects on morbidity, mortality, and well-being. Since the early 80s, relevant research has established links between heatwaves and health (Jones, et al., 1982) and between increased temperature and shifts in well-being (Hawkins, 1981).

Assessments that relate extreme heat and air pollution to mortality rates exist for the specific case study of Athens (Zafeiratou et al., 2019; Founda, et al., 2022 and Katsouyanni, et al., 2020, respectively). Van der Schriek, et al. (2020) highlight the trade-off of heatwaves and air pollution regarding morbidity, which is also specifically investigated for Athens and for the wider area of the Mediterranean (Founda, et al., 2019). Heatwaves, as defined by the UNDRR hazard taxonomy, as the most neighboring concept to extreme heat events, and their impact on land surface temperature are modeled, through the urban heat island (UHI) phenomenon, as a function of green and grey infrastructure cover, the climate variables, and the expected climate change projections (De Ridder, 2003; Mirzaei, 2015). Air pollution is also assumed to have common predictors with heatwaves (Bertazzon, et al., 2015; Varotsos, et al., 2021). The green infrastructure auxiliary data set is supplemented by a citizen science thread, that specifically builds a tree inventory. Vulnerabilities refer to the related impacts on health and well-being as functions of population vulnerability distribution (age and income) and the exposure refers to residents that are exposed to the two environmental stresses as a function of population density.

Figure 5.3 The initial risk assessment plan.

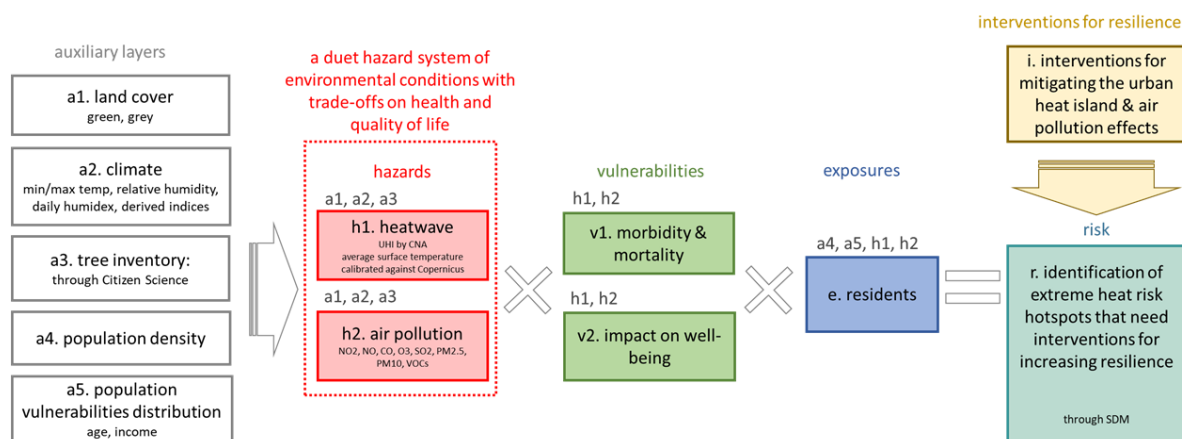


Figure 5.4 presents the modification of the initial plan, after incorporating input of the living lab, after its first workshop. The central topic of the workshop is “extreme heat events”. Stakeholders validated the hypothesis and documentation of the scientific team that air pollution should indeed be coupled to extreme heat, regarding the defined vulnerabilities. Additionally, they added two hazards that have significant trade-offs and interdependencies with heatwaves and air pollution. The first one is the discontinuity of green areas in the city. This is also an urban planning induced stress that is causing degradation of a series of layers linked to the well-being of residents, such as the environmental, the cultural, the aesthetics, and the archaeological layers. The multifunctional properties of green connectivity in urban landscape are investigated and acknowledged by Zhang et al., (2019) and Bai (2018). These layers are not only linked to residents’ vulnerabilities. Alongside with heatwaves and air pollution, they also have an economic impact on tourism due to the exposure of tourists and businesses. Dube & Nhamo (2020) and Rozbicka & Rozbicki (2021) provide some initial evidence to support the hypothesis of the impact of environmental conditions deterioration on tourism. Workers are identified by the living lab as a group specifically exposed to these hazards. Energy consumption increase caused by air conditioning due to the heatwaves is an impact particularly distinguished by the living lab, but also supported by various research works (Viguié, 2020). The second cascading hazard brought into attention by the living lab is the increase of violence reinforced by the

environmental stresses. The hypothesis is also supported by literature with various research works proving correlation of temperature or extreme heat and violence or aggression since the early 80s (Bell, 1981; Harries & Stadler, 1988; Anderson 1989), while recently studies explore the impact that climate change is expected to have on collective violence and aggression (Cane, et al., 2014; Levy et al., 2017; Chersich, 2019). Landscape fragmentation is identified by the scientific team as an auxiliary layer to assess the discontinuity of green. Accessibility to green is introduced as an auxiliary layer to assess the exposures of residents and workers. Energy efficiency of buildings is introduced to assess the vulnerability from energy consumption. Tourist accommodation and businesses distribution in the city can be used for the assessment of tourists and businesses exposures. Additional population vulnerability attributes are added for building more descriptive indexes, such as the social deprivation index, the house ownership, house size and age, profession, nationality and unemployment. Nationality can be used as an index for the migration flow and the relevant vulnerabilities. Regarding the land cover, the living lab brought up the potential importance of blue infrastructure, which might mitigate the hazard of extreme heat locally, and also at a psychological, if not at a bio-physical level. Road network and building heights are also added to the land cover attributes as relevant to the urban heat island. In this workshop of the living lab, discussion on the geographical boundaries of the case study are also set.

The area of the Hadrian Aqueduct, an ancient roman aqueduct that is discussed to be brought back to use for supplementary urban water supply, especially irrigation of green areas, was noted as an area of extreme importance in relevance to the discussed topics.

Figure 5.4 The risk assessment plan after the first living lab workshop.

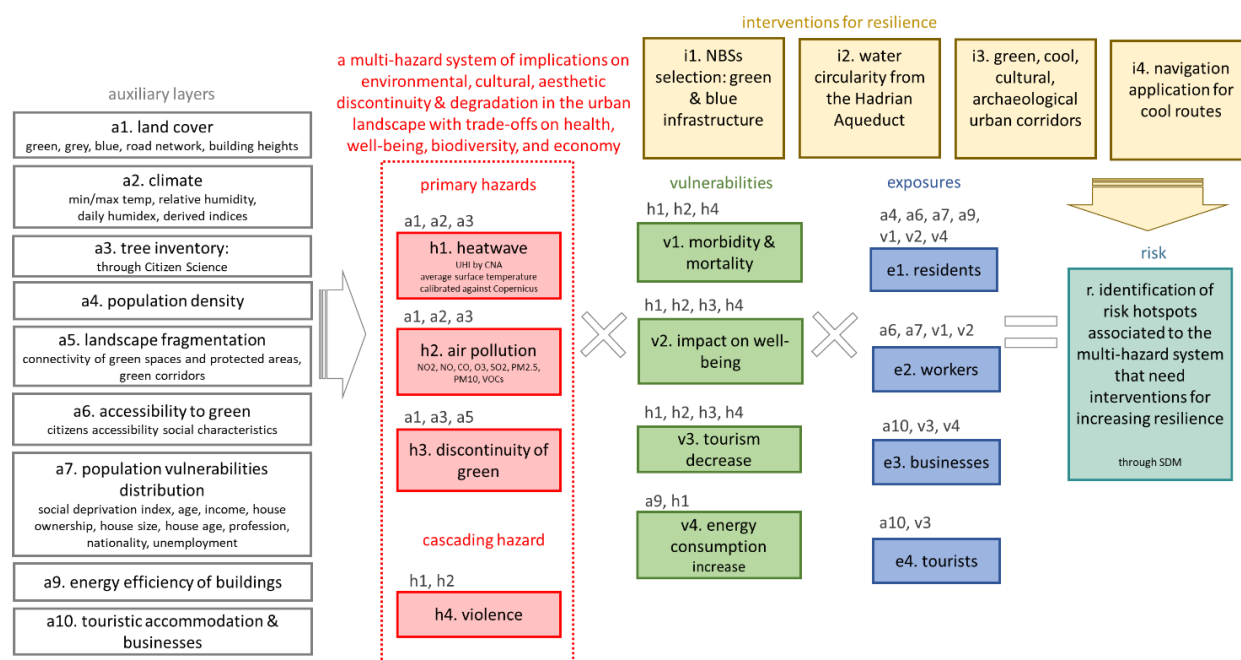


Figure 5.5 presents a more mature modeling and data flow diagram that has been developed after the second living lab workshop. The main objectives of the second workshop with regards to the modeling process are: a) to validate and fine tune the mental map and the conceptual model that have already been constructed and b) to create a collective vision for Athens regarding its resilience capacities against the investigated hazard system. Both objectives' processes feed the modeling flow diagram in

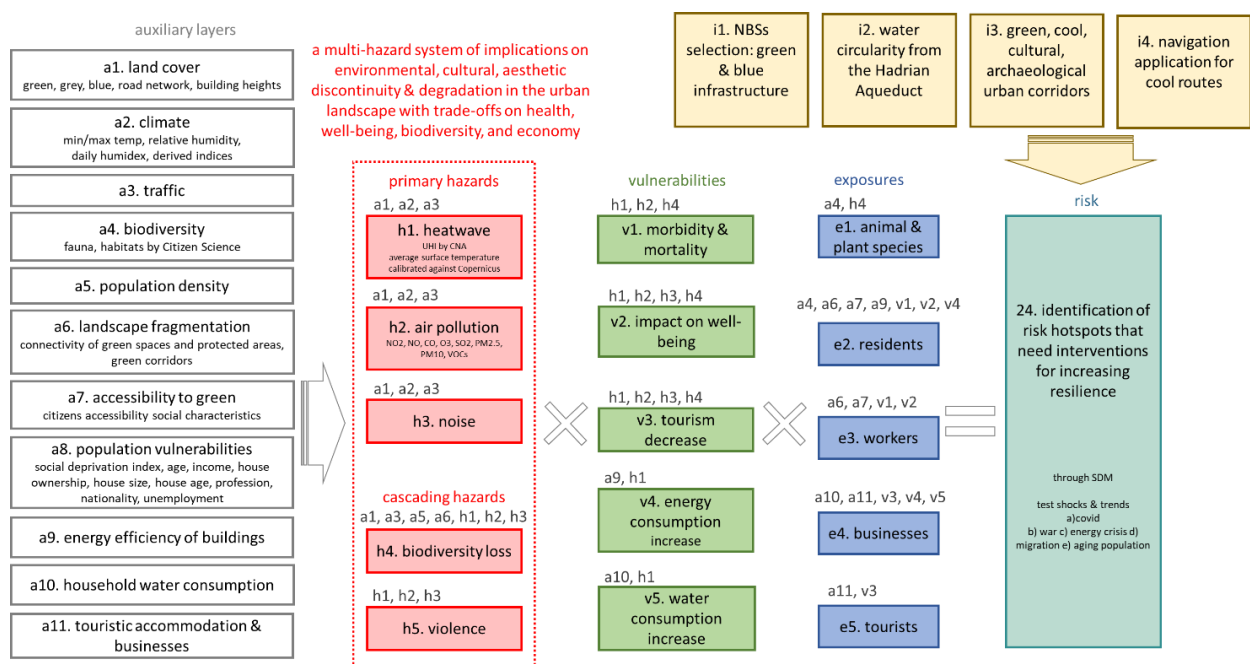
two ways: Firstly, they fine tune the definitions and boundaries of the risk system adding and improving the selection of hazards, vulnerabilities, and exposures and, secondly, they add to the solutions perspectives initiating the brainstorming for recommended technical, technological and socio-economic interventions to be tested, expected to reinforce the capacity of the vulnerable systems. The interventions discussion and selection is planned to be initiated in a later phase of the project, however the stakeholders have already been discussing about existing, planned and imagined solutions, giving an initial hint and direction for scenarios to be tested. A major change that occurred in this phase is the realization that green discontinuity is only part of a much wider hazard, that of biodiversity loss. Such a change was depicted based on the collection of ideas, interests and opinions by the stakeholders engaged in the living lab workshops in the Athens case study.

Biodiversity loss is also recognized by the Sendai framework (UNDRR, 2020) as an environmental type and environmental-degradation cluster hazard. Heatwaves, air pollution, and noise share common drivers with habitat loss in the urban setting, such as impervious grey surfaces and green areas fragmentation (Shochat et al., 2010), but also constitute drivers to biodiversity loss themselves (Proppe, et al., 2013; Newport, et al., 2014; Fenoglio et al., 2021).

Biodiversity loss, in this context could as well be classified as a vulnerability, however it is chosen to classify as a hazard with tradeoffs to the primary hazards. The second workshop also added another primary hazard of multiple tradeoffs with the existing hazard system, that of noise (Slabbekoorn, 2019). To the increase of energy consumption, increase of water consumption is also added to the system of vulnerabilities.

Apart from the structural interventions of the living lab to the modeling approach, there is also correction of the geographical boundaries of the case study. In the first workshop, the Hadrian Aqueduct was indicated as the heart of the case study, also capable of offering a series of synergies, technical, funding, cultural, administrative and many more. In the second workshop, the boundaries of the case study are extended to include a much wider area to showcase more intense variability regarding the biophysical properties, but also the socio-economic vulnerabilities.

Figure 5.5 The risk assessment plan after the second living lab workshop.



5.1.3 Development status

At the current phase, the main objectives of the case study are clarified and a set of conceptual maps for representing the tackled concepts are produced. Initial modeling work has taken place. Based on the metrics that have to be fed to the analysis processes, data population in the ARSINOE knowledge management infrastructure is taking place.

In the context of WP3, in an effort to detect and quantitatively evaluate the spatial and temporal patterns related to Urban Heat Island (UHI) effect, an analysis of time series of temperature, humidity, wind speed as well as the land covers and land uses of a region, using mainly complex network analysis based on time series is conducted. The data have been collected from the Copernicus database, for the area of the central region of Athens, point by point in a 100-meter grid. At each point, the temperature, humidity and wind speed have been recorded.

The methodology initially employs the construction of complex networks based on univariate analysis (use of each variable separately: temperature, humidity, and wind speed). The aim of the analysis is to identify the nodes of the network that correspond to points of increased interaction with other points (hubs); the presence of hubs in a system indicates points of importance in the system under study and could be linked to the UHI effect. Next the relationship of such points with land uses and land covers, as well as their spatial location, are explored. Since a hub represents a point of strong interaction such points may also be candidate points for natural green interventions in the frame of the project, since affecting such points means a large number of linked points-locations are affected too.

In addition to this approach, using the multilayer network methodology, we construct networks using simultaneously all variables at each point, in such a way that the relationships and interactions between the individual networks (representing properties) can be explored. This type of analysis can reveal non-linear or complex interactions of the various variables with the temperature as well as their spatial location and land use. This analysis applies both to the whole dataset simultaneously, and to individual time series based on their seasonality and periodicity, in order to examine and possibly comment on different results, since the available data have hourly records for a period of six months, from April to in September of four consecutive years.

An important aspect to be investigated is the temporal evolution of the complex networks which can provide important information on the seasonal or time-dependent behavior as well or the effect of an external parameter which will lead to further conclusions. At the same time an alternative strategy to identify specific points and behaviors will be used as a complementary approach. We apply the hierarchical clustering methodology so that time series from different locations are sorted into clusters and then using these subgroups we perform more detailed complex network analysis as described above for the specific series in order to identify more fine scaled dynamics/interactions.

5.3 Interdisciplinary model to support air quality predictions

5.3.1 Main scope, objectives and participatory processes

This modeling effort refers to the participatory development of a model, with the scope to support the numerical predictions of air pollution concentrations over Athens (in the frame of the Athens case study within ARSINOE).

The atmospheric scientists (NOA) have initiated interaction with Information Technology (IT) experts (ICCS), towards the understanding of the needs of the former and the capabilities of the latter, relevant to the known and well-established challenges faced by the numerical atmospheric modelers.

In particular, numerical modeling systems necessitate credible observational timeseries for their accuracy assessment. Access to such time series data can be provided through queries over the data infrastructure made available in the ARSINOE project, where up to date data can be made available for analysis purposes. Thus, easy access to in situ time series data can be provided by automating the procedures for data retrieval and processing and the incorporation of data analysis. Custom visualizations for both the input and the output data for the model can be provided, enabling the atmospheric scientists to get a quick overview of the parameters to be used in the analysis processes. Where applicable, some data analysis pipelines may be also developed and adopted.

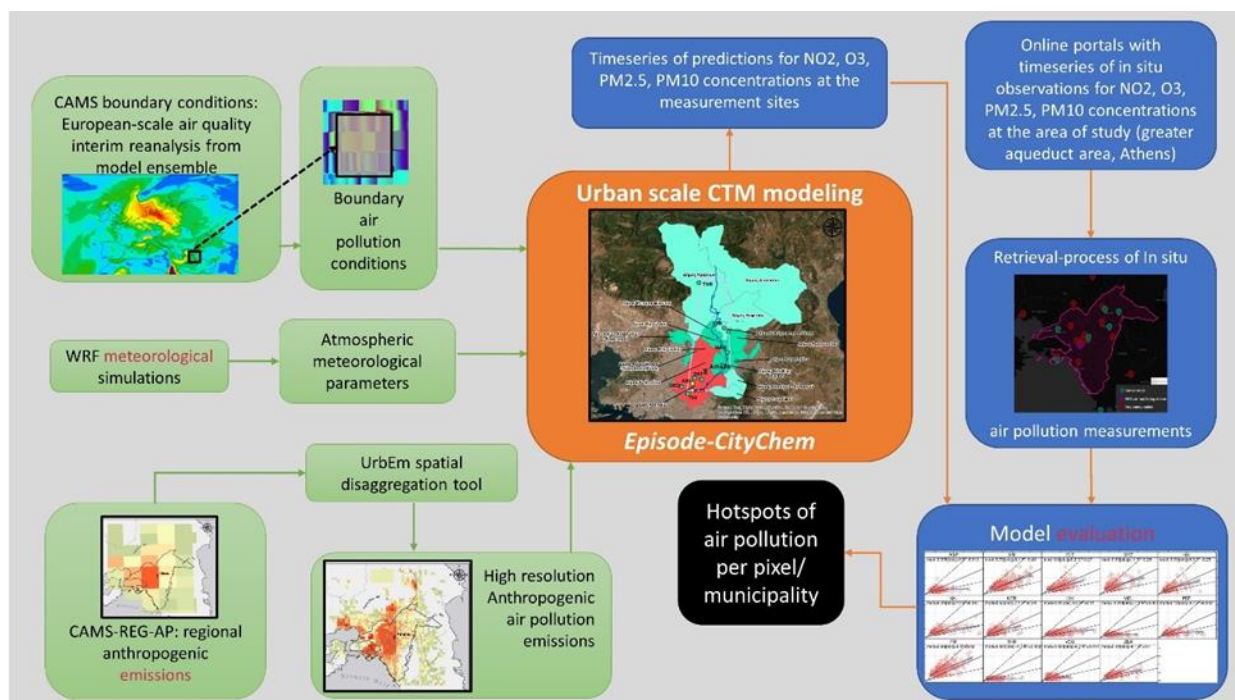
So far, interaction among the participants has followed the conventional methods in the form of virtual meetings and exchange of e-mails. The participatory processes are currently being studied so that the most suitable and efficient approach for the structure and scope of the model are selected to support development in the later stages.

5.3.2 Conceptual design and analysis processes

The overall concept of this inter-disciplinary model is to combine targeted IT processes with the atmospheric numerical model system, towards the evaluation of air pollution outputs against in situ measurements (Figure 5.6). To this end, the atmospheric numerical component of the system (green boxes in Figure 5.6) is supported by the IT component of the system (blue boxes in Figure 5.6), towards the evaluated estimation of the air pollution hotspot areas of the case study Athens. Specifically, the set of time series data will be made available by the SustainGraph, while custom queries and Application Programming Interfaces (APIs) will be provided for easily getting access to these data, based on the configuration (e.g., time period, sampling frequency, geolocation characteristics) selected by the atmospheric scientists. The statistical analysis of the comparisons between predictions and observations will be supported by the participatory model under development.

The atmospheric simulation period covers 2019, being a contemporary and conventional (lockdown-free) year. The meteorological conditions of 2019 were found representative of the 5year period 2015-2019. Hourly outputs for the whole year are used for the evaluation of model performance. Representative months of elevated air pollution for the cold and the warm period of 2019 are January and October, respectively, according to a comparative study of the mean monthly values of NO_2 , $\text{PM}_{2.5}$, SO_2 , PM_{10} . These months will be used to identify the air pollution hotspots proposed for assessing the positioning of NBS.

Figure 5.6 The conceptual design of the Inter-disciplinary model to support air quality predictions. The green boxes represent the atmospheric numerical component of the system, while the blue boxes represent the IT component. The outcome is the evaluated estimation of the air pollution hotspots areas (here, of the case study Athens)



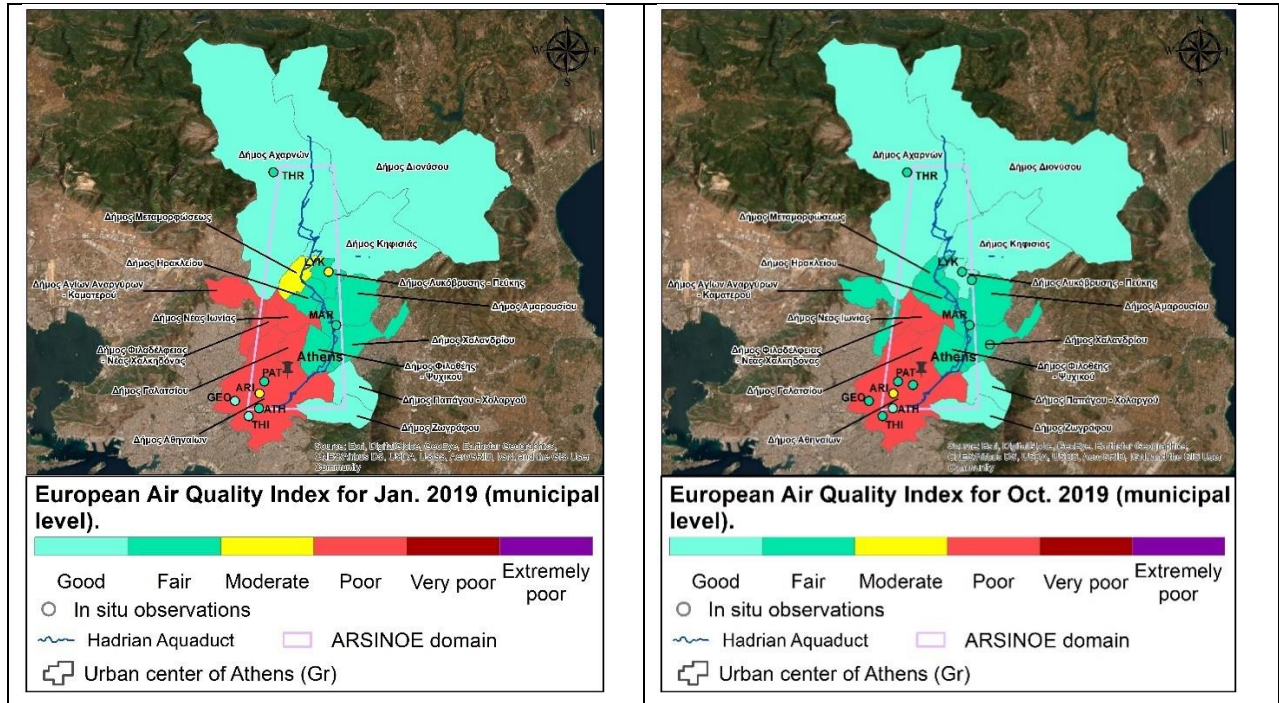
5.3.3 Development status

The current development status of the designed model is first the definition of the area of study (here, the greater aqueduct area, Athens) and the period under study (2019). Then, the identification of the atmospheric parameters in need for evaluation (meteorology and air pollution) against the publicly available timeseries of in situ observational data, has been completed.

The identification of the sources of this data (online portals) has also been performed. The portals of national (here, Greece) coverage are located (e.g., Ministry of Environment, National Meteorological Service), in addition to the portals of European coverage (e.g., EEA, NOAA), so that the model can be replicable for any European city of interest. Initial work has taken place for the population of SustainGraph with such data, where challenges for providing access to a plethora of time series and spatial data are identified and tackled. These challenges include the need to manage a large volume of data, as well as the need to develop spatial data management functions to provide aggregated data values for specific regions. The usage of external time series and spatial databases is considered as an option for optimal data storage.

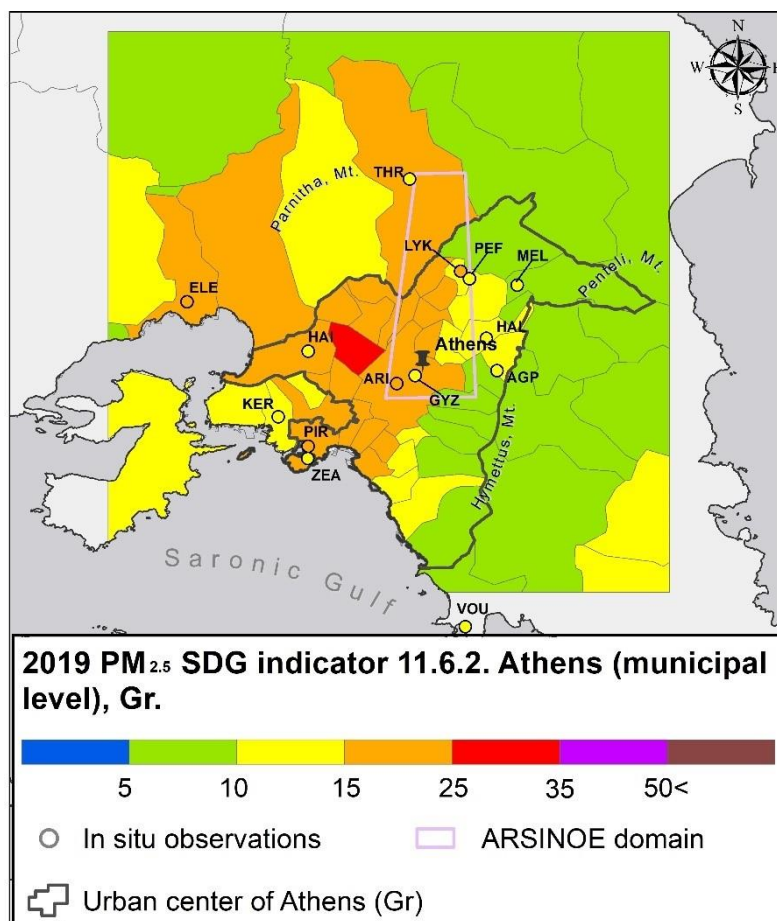
The Air Quality Index (AQI, from measurements and model results) is calculated in consistency to the European Environment Agency (<https://airindex.eea.europa.eu/Map/AQI/Viewer>). Figure 5.7 shows AQI values per municipality for the most polluted month of the cold and the warm period of 2019.

Figure 5.7 Mean monthly Air Quality Index (AQI) predictions per municipality for January (left) and October (right) 2019. Points correspond to the respective measured values. The embedded polygon reflects the focus area.



The population weighted annual mean levels of $PM_{2.5}$ mass concentrations, when provided at the spatial analysis of concentration predictions and population density retrievals (1 km), correspond to an equivalent of the official SDG 11.6.2 National value, but in a localized manner. The spatial aggregation of the high-resolution predictions at the municipal level reveals an SDG Indicator 11.6.2 (2019) is shown in Figure 5.8.

Figure 5.8 The predicted localized UN SDG 11.6.2 (population weighted annual mean levels of PM_{2.5} mass concentrations in $\mu\text{g}/\text{m}^3$) for 2019, aggregated at the municipal level. Points correspond to the respective measured values. The embedded polygon reflects the focus area.



5.4 High resolution climate change projections for the Attica region

5.4.1 Main scope, objectives and participatory processes

The main scope of this modeling procedure is the quantification of human discomfort and its evolution under climate change. Climatic indicators relevant to the urban environment and human health will be calculated. Such indicators include number of days classified according to temperature, as well as discomfort indices utilizing state of the art regional climate model data. Downscaling techniques will be implemented, to obtain the appropriate climatic data for Athens, at a higher horizontal resolution (1km). Additionally, hot spots of extreme temperatures will be identified under current as well different future climatic conditions. Similarly, to the previous model, data population and analysis pipelines are going to be made available in the SustainGraph to support the participatory analysis processes.

5.4.2 Conceptual design and analysis processes

In the framework of this activity daily data from a five-member sub-ensemble of GCM (Global Climate Model)/RCM (Regional Climate Model) couples developed within the EURO-CORDEX initiative will be

utilized. More Information on these GCM/RCM couples is provided in Table 5.1. The climatic data are available in the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) for a continuous period ranging from 1950 to 2100. The horizontal resolution of the models is 0.11°, while the simulated data will cover three 20-yr periods: the period 1981–2000, which will be used as the reference period and the future periods 2031– 2050 and 2081-2100. To cover a range of possible futures, three Representative Concentration Pathways (RCPs) will be examined, i.e., **RCP2.6**, **RCP4.5** and **RCP8.5**.

Table 5.1 GCM/RCM couples utilized for the development of high-resolution climate change projections for Attica.

Driving Global Climate Model (realization)	Regional Climate Model	Institute
MPI-ESM-LR (r1i1p1)	RCA4.v1	Swedish Meteorological and Hydrological Institute (SMHI)
HadGEM2-ES (r1i1p1)	RCA4.v1	Swedish Meteorological and Hydrological Institute (SMHI)
HadGEM2-ES (r1i1p1)	RACMO22-E.v2	Royal Netherlands National Meteorological Institute (KNMI)
CNRM-CM5 (r1i1p1)	RACMO22-E.v2	Royal Netherlands National Meteorological Institute (KNMI)
EC-EARTH (r3i1p1)	HIRHAM5.v2	Danish Meteorological Institute (DMI)

Further processing of the climatic data will be performed, and statistical downscaling techniques will be implemented in order to obtain the appropriate climatic data for Attica with a higher horizontal resolution (1km). To this aim, the following steps will be followed:

Step 1: Development of a daily high resolution (1kmx1km) gridded dataset (for the period 1981-2000) based on observations for temperatures (Tmax, Tmin) and relative humidity.

Step 2: Statistical downscaling of the RCM daily model variables to the high-resolution observational grid and implementation of bias correction and disaggregation framework as used in (Varotsos et al., 2022).

Step 3: Calculation of climatic indices, quantification of human discomfort and identification of hot spots of extreme temperatures for the different time frames and scenarios.

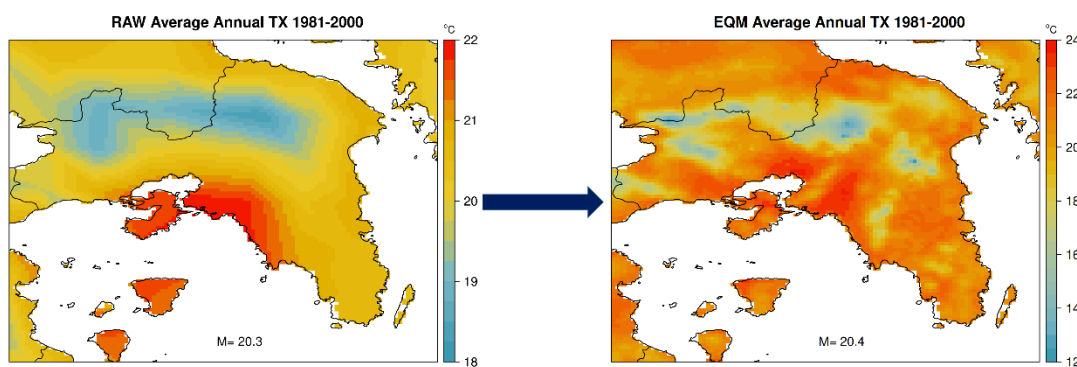
Step 4: Identification of regions affected by UHI and quantification of its evolution under different climate change scenarios.

5.4.3 Development status

The high resolution (1kmx1km) gridded dataset (for the period 1981-2000) based on observations for temperatures (Tmax, Tmin) and relative humidity for Attica (step 1) has been developed. To downscale the RCM daily model variables a two-step post processing procedure is used following the methodology of Varotsos et al. (2021). In particular, the RCM daily data are remapped on the gridded

observational data grid using bilinear interpolation and consequently the models' output is bias adjusted using the gridded observational dataset as the reference dataset. Bias adjustment is applied using empirical quantile mapping (EQM). This two-step approach is the reversed order of the bias correction and spatial disaggregation framework, which has been previously used to statistically downscale both regional and global models for climate change and seasonal forecast studies, respectively (Varotsos et al, 2023; Karali et al. 2023). Regarding the bias adjustment method, EQM works by adjusting the 1st–99th percentiles of the predicted empirical probability density function (PDF) based on the observed empirical PDF, while for lower or higher values falling outside this range, a constant extrapolation is applied using the correction obtained for the 1st or 99th percentile, respectively (Figure 5.9).

Figure 5.9 Indicative map depicting the average annual maximum temperature before (left) and after (right) the statistical downscaling implementation in the area of interest.



5.5 UHI - Distribution of temperatures and associated factors

5.5.1 Main scope, objectives and participatory processes

The specific work aims to provide information about the distribution of air and land surface temperatures and the associated parameters like the building heights, land use and tree cover. For the conceptual design for this work, a presentation was provided during the 1st Living Lab in Athens to trigger discussion among participants on the solutions/ interventions. Suggestions and feedback were collected by the participants, that helped us to better formulate the system to be managed.

5.5.2 Conceptual design and analysis processes

The model calculates the mean distribution of summer temperatures for the months June, July and August over five years. It covers the area of Hadrian aqueduct with a buffer zone around it. The data used for the land surface temperature distribution comes from a Landsat satellite (several missions) with a spatial resolution of 100m. The air temperature comes from Copernicus Climate Change Service (C3S) and a climate urban model again using temperatures from 5 summers like before. The difference is that the data comes hourly allowing us to study the diurnal variability of air temperatures within the area of interest. In addition, we have used the Urban Atlas data set from Copernicus Land Monitoring Service (CLMS) and the land use, the street trees, and the building height. We have showcased the hotspots along the Hadrian aqueduct at different times of the day to support mitigation activities. All the codes used for this analysis are developed in-house by the National Observatory of Athens/IAASARS (Figure 5.10, Figure 5.11).

Table 5.2 Model parameters

Model input parameter(s):	Source:	Resolution:
<i>Landsat images</i>	https://www.usgs.gov/landsat-missions/landsat-collection-2-level-2-science-products	30-160m, depending on spectral band and satellite mission
<i>Urban climate model</i>	<i>Copernicus C3S</i>	100m
<i>Urban Atlas</i>	<i>Copernicus CLMS</i>	Vector – building block level

Figure 5.10 The workflow for UHI mapping.

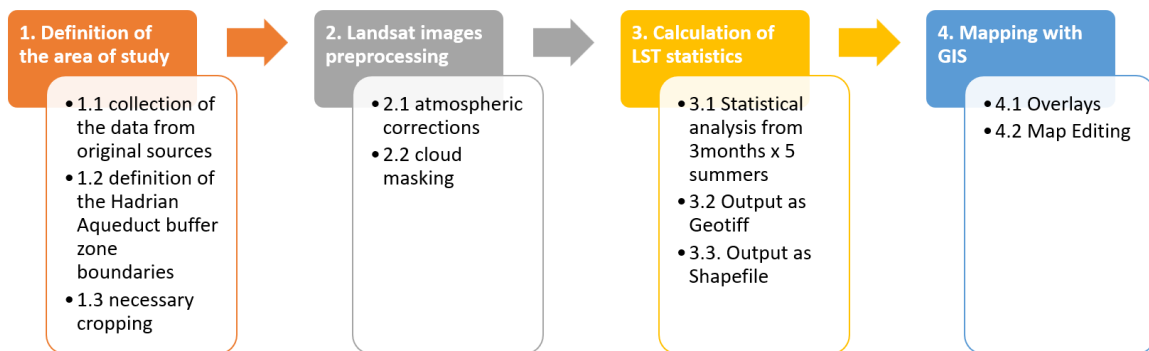
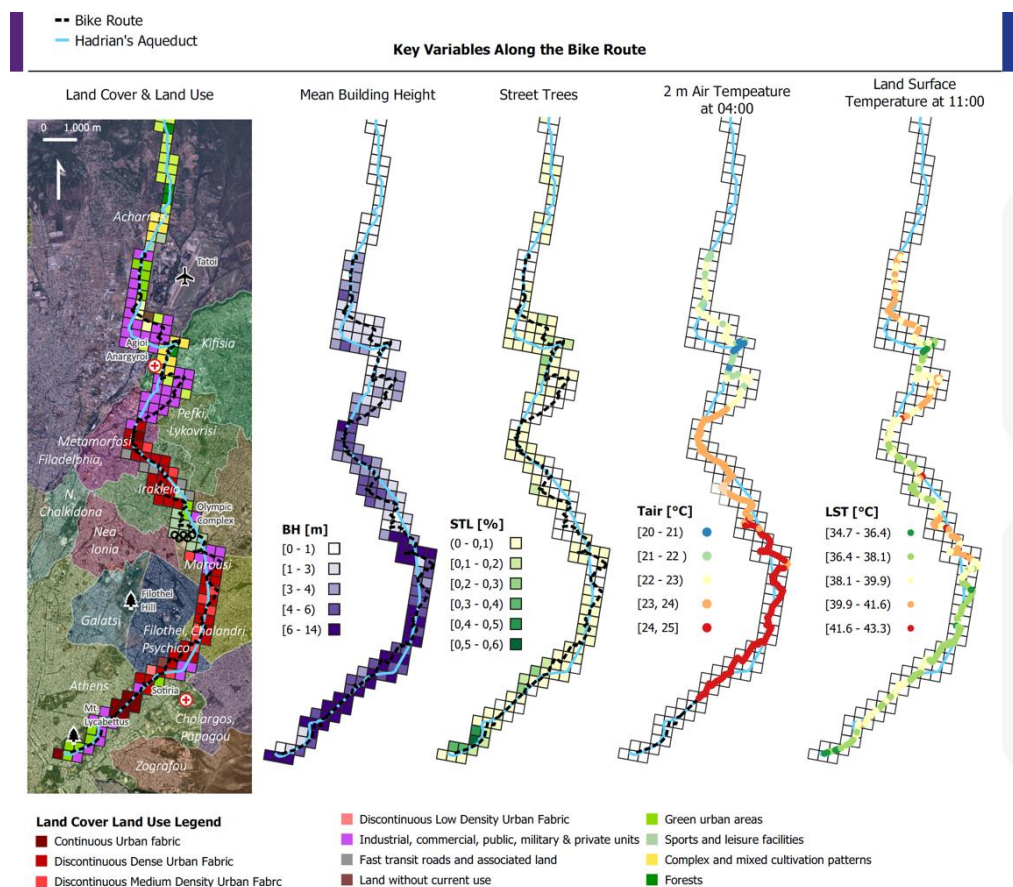


Figure 5.11 The output for Hadrian Aqueduct in AMA.



Tair and LST are the mean summertime Air temperature and Land Surface Temperature at 11:00 Local Time. The source of the LCLU, BH and STL data is the Copernicus Land Service. The source of the Tair data is the Copernicus Climate Service and the source of the LST data is the National Observatory of Athens.

The model output consists of the following variables: Average Land Surface Temperature; Average hourly Air Temperature; Land Use; Street trees; Building height. All at 100m spatial resilience. The output provides information about UHI and hot spots along the Hadrian Aqueduct in AMA, which is necessary for future planning and urban design and strategic priorities regarding the greening of the city along the aqueduct (Figure 5.12, Figure 5.13).

Figure 5.12 The mean summertime air temperature (Tair) and land surface temperature (LST) along the Hadrian aqueduct.

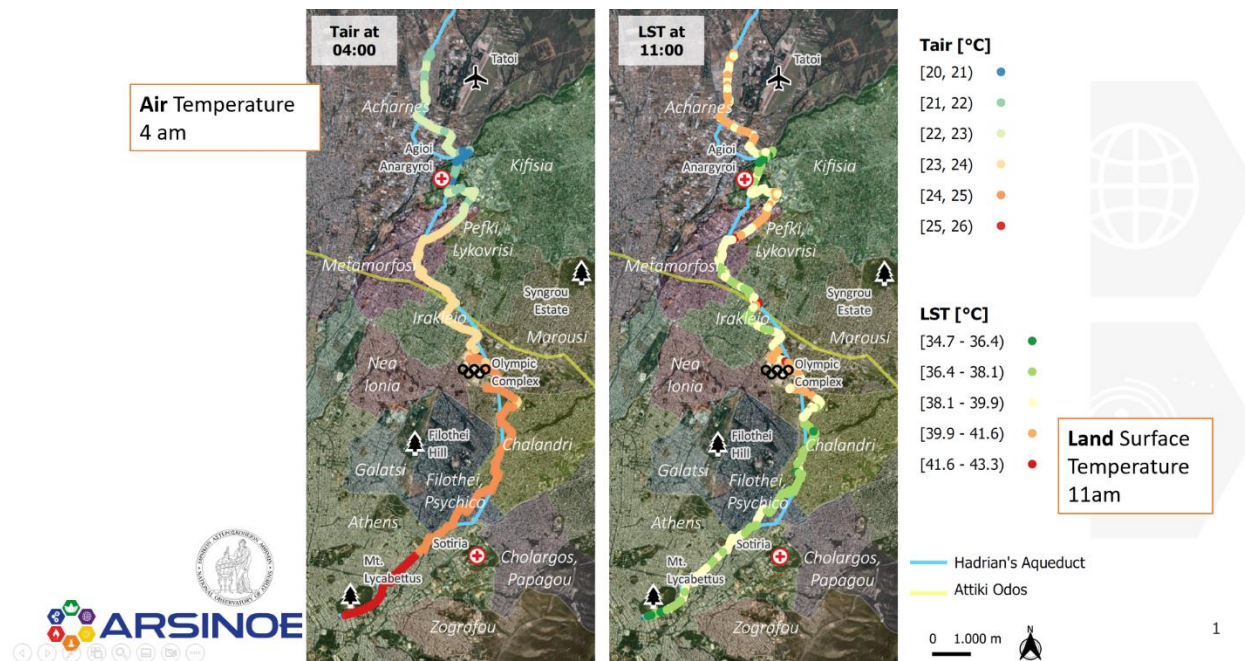
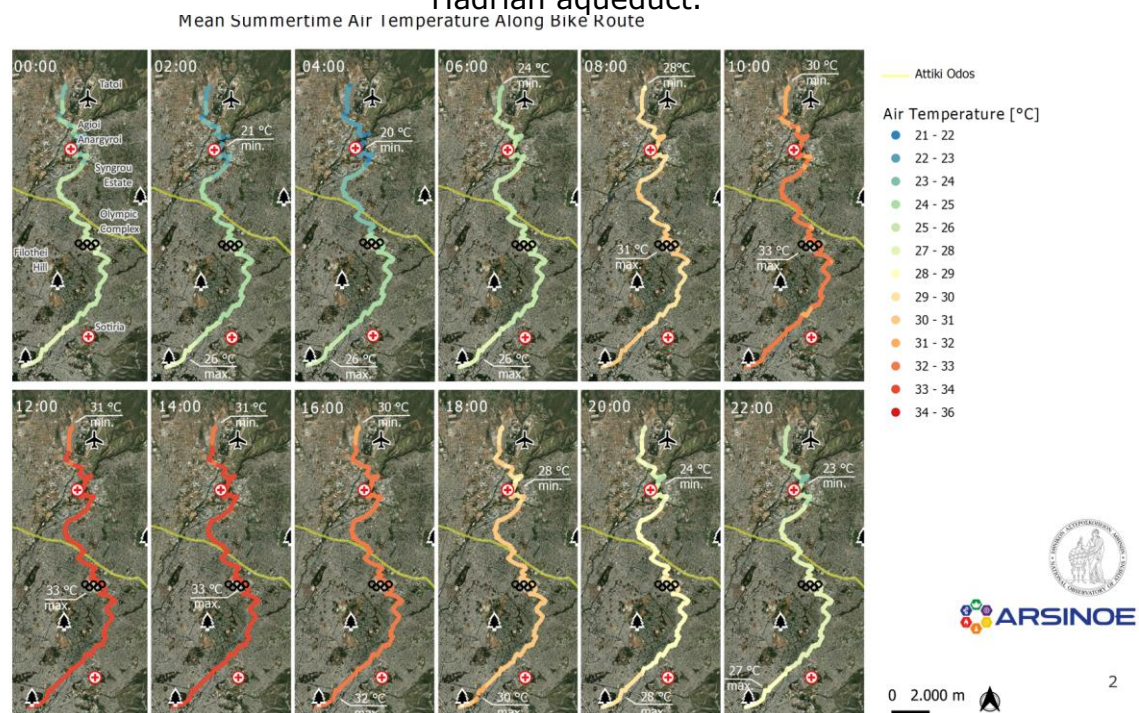


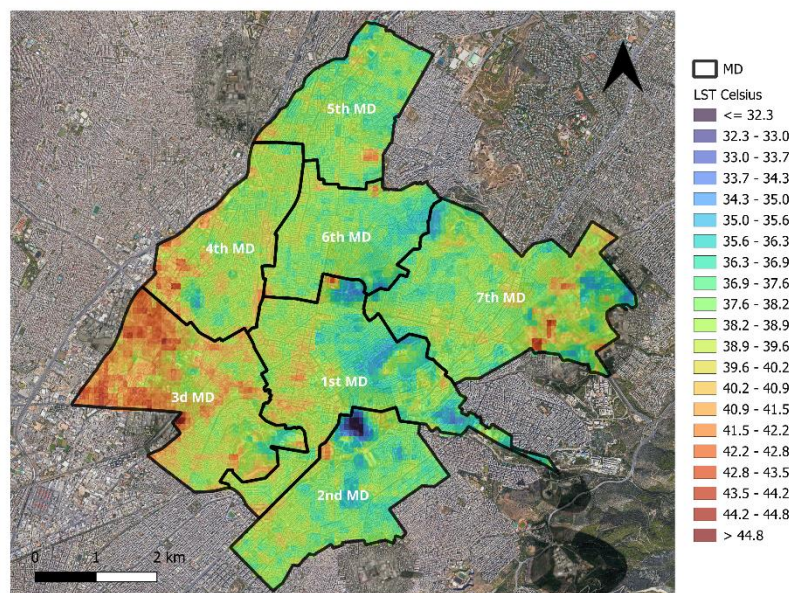
Figure 5.13 The mean summertime day and evening air temperature along the Hadrian aqueduct.



5.5.3 Development status

Remote sensing monitoring of land surface temperature (LST) over cities is commonly used to assess the impact of urbanization, land-use dynamics and climate change. Here, Landsat satellite imagery (Wulder et al., 2019) is being employed to derive LST measurements. LST is derived through the conversion of digital numbers to radiance, using sensor specific calibration parameters. Also, an important step is the correction procedure regarding the influence of atmospheric constituents on the thermal signal by using atmospheric correction algorithms. For the Athens Case Study (CS1) hotspot analysis, 185 images from available Landsat data, for months June, July and August over a period of 3 years (2020-2023), are selected and processed to acquire a representative mean distribution of LST with a spatial resolution of 100 m (Figure 5.14).

Figure 5.14 . Satellite (Landsat) derived 3 months (June-July-August) mean land surface temperature (LST in Celsius), over 3 years (2020-2023), at a spatial resolution of 100 m.



The TN95p indicator is used to measure the urban heat island effect (Figure 5.15). The indicator is based on the difference in temperature between urban and rural areas for warm nights, where warm nights are defined as the 95th percentile (TNp95) of the daily JJA minimum temperature (Tmin). For a place like Attica, where dry conditions prevail in the summer, it is critical to incorporate nighttime temperatures while analyzing UHI (UHI hereafter) intensity. Here, the rural value is defined as the spatial 10th percentile of the TN95p in the domain under study while the spatial 90th percentile is used to establish the urban value (Lauwaet et al. 2015). According to this, the UHII for the reference period (1981-2000) is projected 4.27 °C, while for the near future period (2031-2050) 4.37 °C, 4.78 °C and 4.66 °C under RCP2.6, RCP4.5 and RCP8.5, respectively. For the distant future (2081-2100) the UHII values are 4.83 °C, 4.73 °C and 4.95 °C under RCP2.6, RCP4.5 and RCP8.5, respectively. From the results it is evident that UHII does not alter significantly under climate change with the highest change being lower than about 0.7 °C under RCP8.5 and by the end of the century (Figure 5.16). Similar results have been found in previous studies (e.g. Sharma et al. 2019 and references therein). Nevertheless, because urban areas are roughly 4.5 °C warmer than rural ones, they are subjected to more severe heat hazards than their rural counterparts. In other words, if rural regions experience 26 °C during warm nights in the future, cities will be exposed to 30.5 °C, posing significantly higher health risks.

Figure 5.15 Summer TN95p averaged over the periods and scenarios examined. In each panel M in black color denotes the spatial average for the whole domain under study, whereas M in blue color denotes the spatial average of the densely populated areas (7 municipal units of Athens municipality).

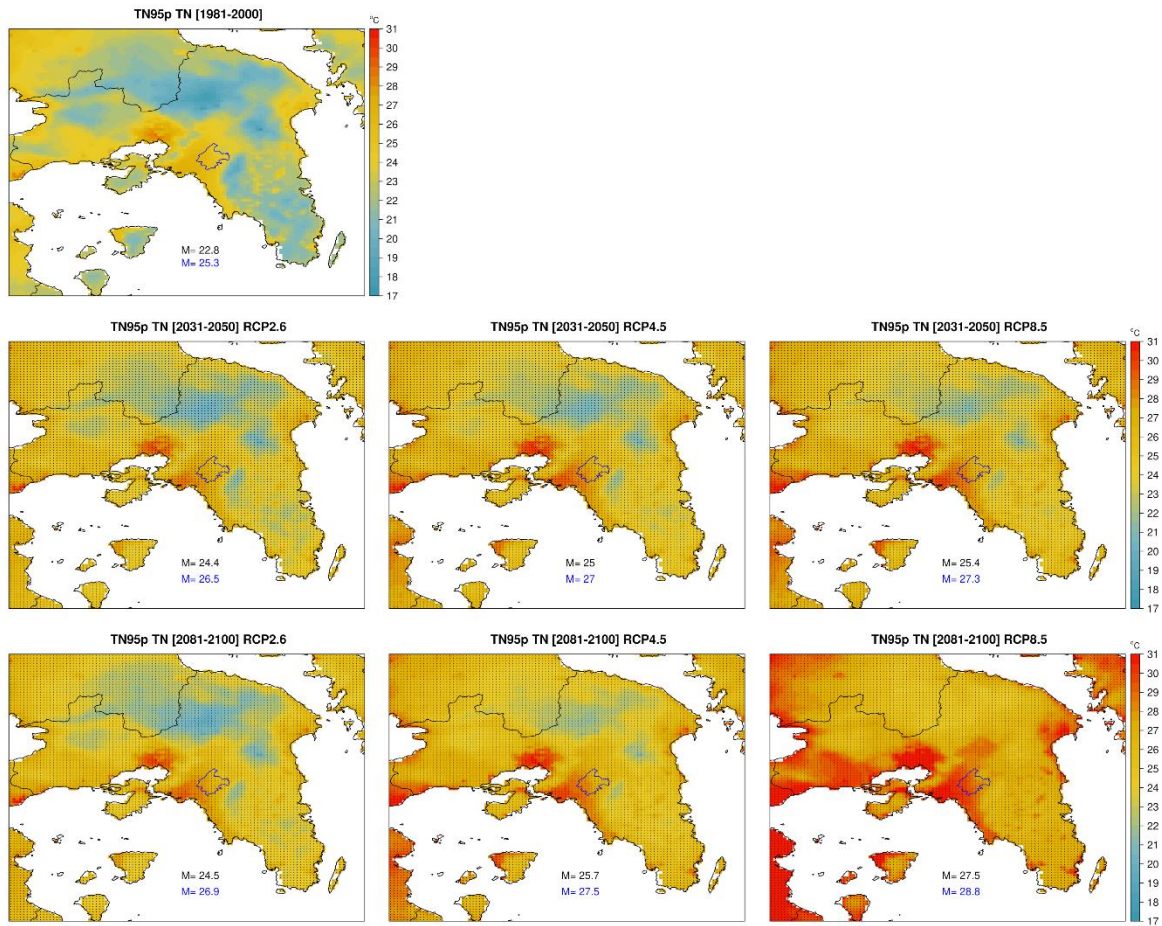
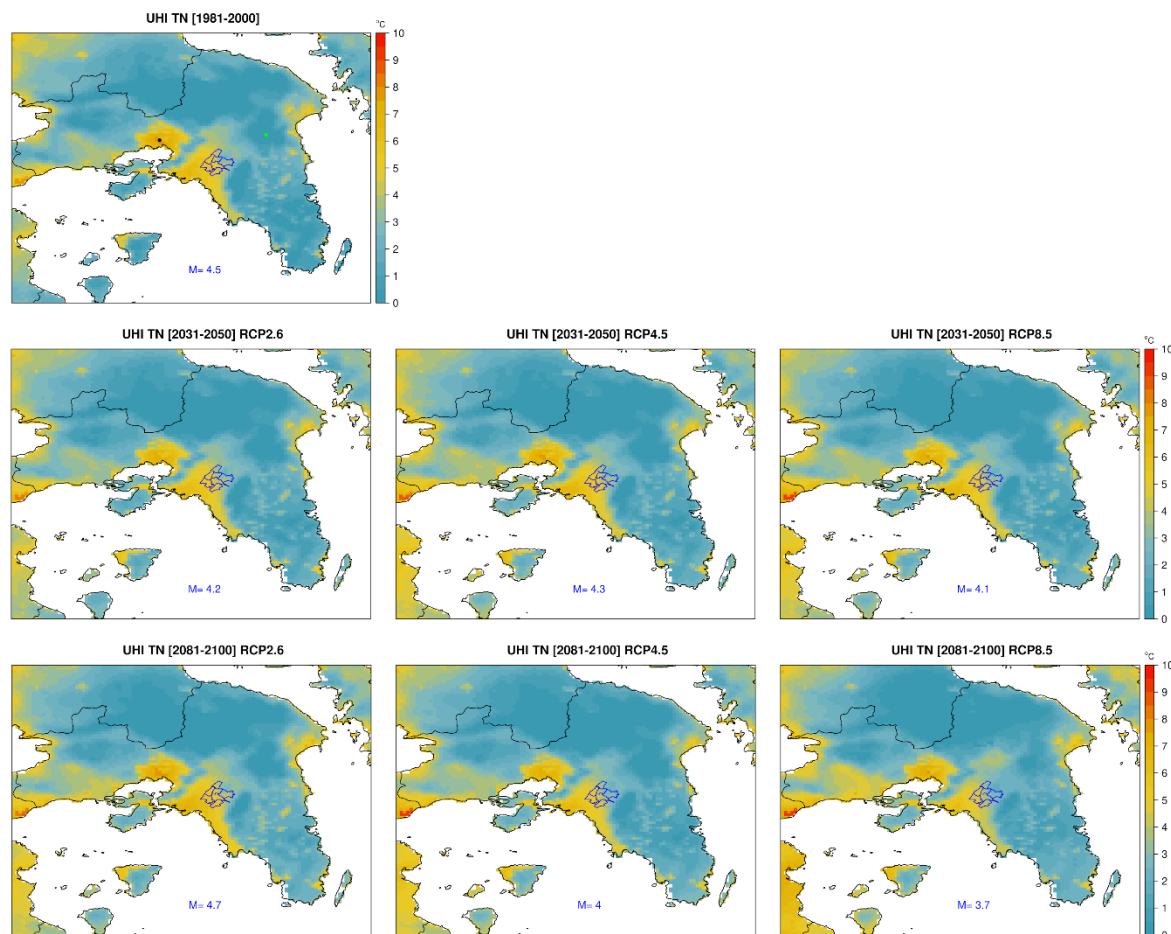


Figure 5.16 Spatial distribution of UHI intensity based on TN95p. From each grid point the spatial 10th percentile of TN95p is subtracted. Negative values have been replaced by zeros



5.6 Connectivity of green areas – Landscape fragmentation

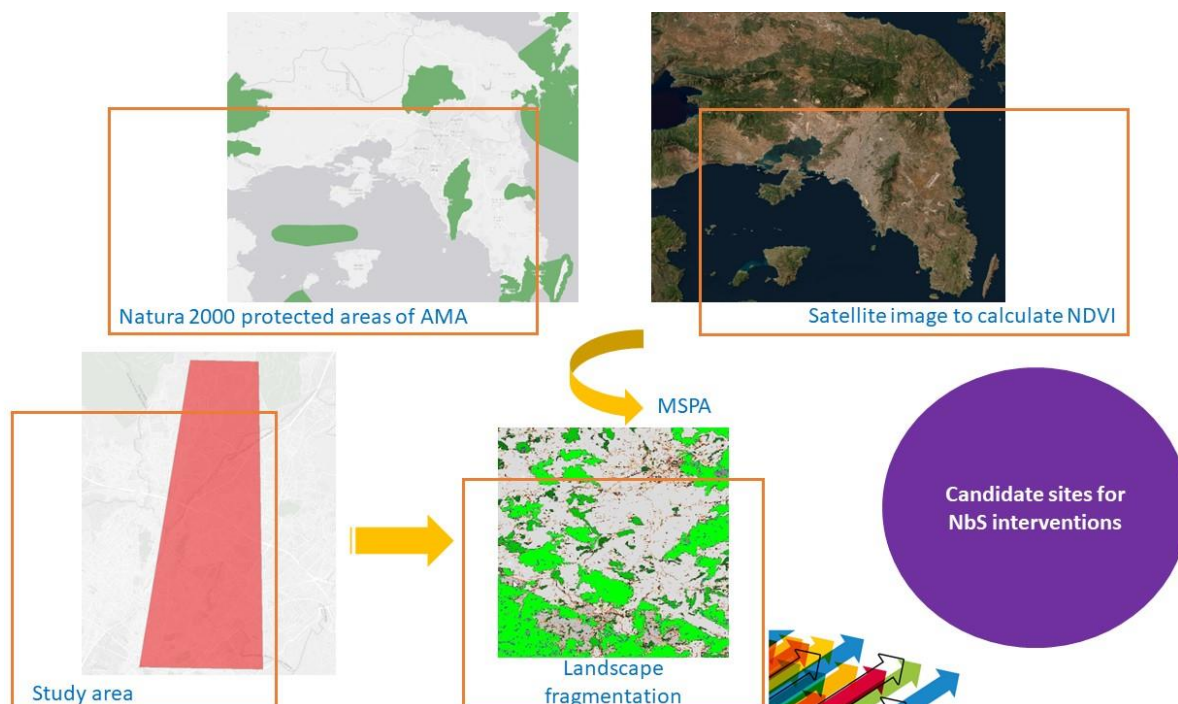
5.6.1 Main scope, objectives and participatory processes

The assessment of the connectivity of protected and green areas in AMA will pave the ground for a coherent nature network, fully complying with the EU Biodiversity Strategy for 2030. In this way, landscape fragmentation for AMA will be assessed.

5.6.2 Conceptual design and analysis processes

The model aims at measuring the connectivity of protected areas and the landscape fragmentation in AMA. The model is a GIS-based toolbox, named GuidosToolbox (Graphical User Interface for the Description of image Objects and their Shapes - GTB) with a wide variety of generic raster image processing routines, including related free software such as GDAL (to process geospatial data and to export them as raster image overlays in Google Earth), and FWTools (pre/post-process and visualize any raster or vector data). The GuidosToolbox Workbench (GWB) contains the most popular image analysis modules set up as command-line-only scripts for automated mass-processing on Linux 64bit servers. The model is performed using ESRI ArcGIS tool (Figure 5.17).

Figure 5.17 The conceptual design of green and protected areas connectivity.



The analysis includes the following steps:

- definition of protected areas in AMA: overlapping the Natura 2000 network with AMA boundaries the protected areas are geographically identified, along with the most valuable species and habitats according to the 1979 Birds Directive and the 1992 Habitats Directive.
- spatial pattern analysis of AMA's landscape: the model estimates isolated small fragments, core areas, connecting pathways among the landscape of AMA, after calculating the Normalized Difference Vegetation Index (NDVI), thus identifying vegetation greenness and understanding vegetation density and plant health.
- assessing landscape fragmentation in the study area: taking into account the biodiversity status through Natura 2000 protected areas of AMA and the vegetation patterns by NDVI, the Morphological Spatial Pattern Analysis (MSPA) will allow us to evaluate the connectivity of green spaces in the study area and thus recognize fragmented regions, top priority for NbS interventions.

5.6.3 Development status

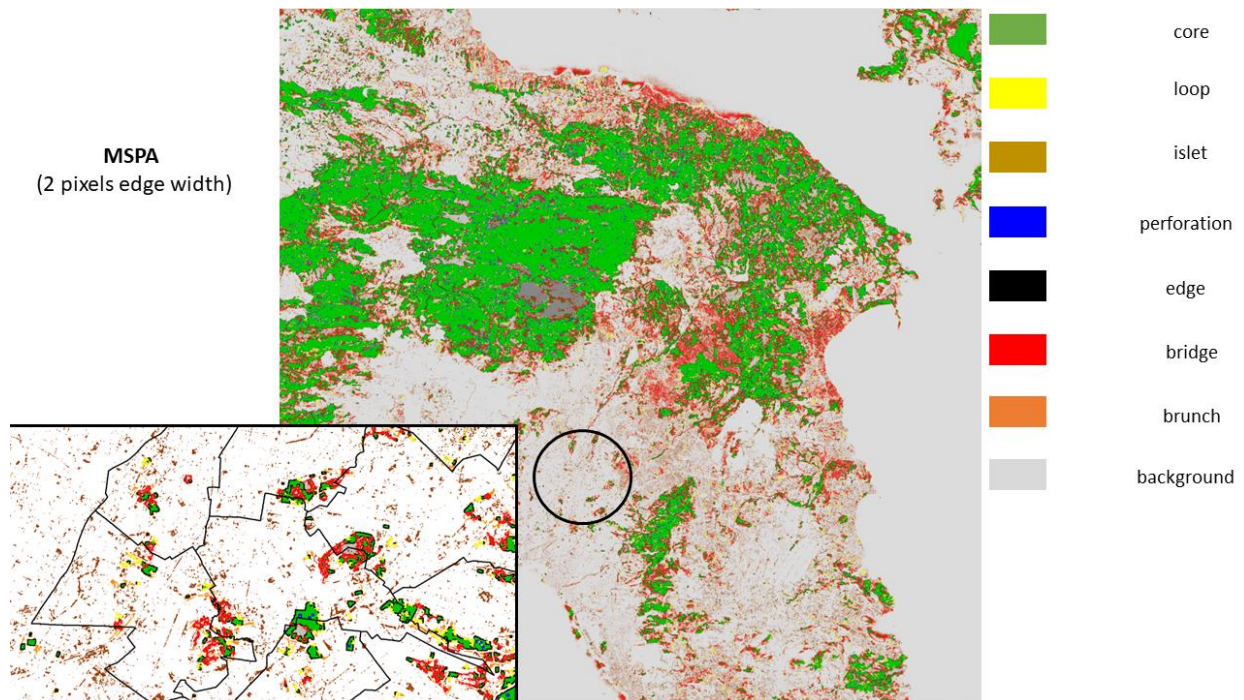
Apart from the efficient management of protected areas, there must be natural corridors that enable local populations to coexist and adapt. Landscape connectivity is a measure to evaluate the status of biodiversity conservation in a region, ecosystems' health, and thus their adaptive capacity and resilience. Climate change will definitely have a significant influence on Greece's unique biodiversity and taking into account the socio-economic background of the country but also the topographical complexity, landscape connectivity will play a crucial role as a restoration/protection strategic tool.

Though the Attica basin includes the capital of Greece, still 6 different sites of the Natura 2000 network are hosted within. Ensuring the connectivity of these important for biodiversity conservation sites, is of top priority to achieve urban resilience under the current climate crisis. Recent studies and policy initiatives highlight the climate change-biodiversity loss nexus, so the assessment of the landscape patterns in the Athens region is a strategic step to be able to identify the ecological corridors that can

significantly contribute towards preserving or even improving ecological processes in the urban environment, and thus the preservation of ecosystems' health and citizens' well-being.

Focusing on the city of Athens, at the urban center, though landscape fragmentation is high, bridges and core areas are identified that could play a prime role in restoration, preservation or improvement urban greenery actions, under the frame of green planning and related interventions (Figure 5.18).

Figure 5.18 Connectivity map of the FUA (Functional Urban Area) of Athens with 2 pixels edge width, focusing on the center of Athens



5.7 Accessibility of Green Urban Areas

5.7.1 Main scope, objectives and participatory processes

The concept of 15-minute walking distance will be adopted (Pafi et al., 2022) (Poleman, 2016) (EIT KIC Urban Mobility S.L., 2022) to investigate if citizens of Athens have access to urban green spaces through pedestrian, citizen-friendly routes. In this way, social inclusion and the connectivity of neighborhoods to green areas will be assessed.

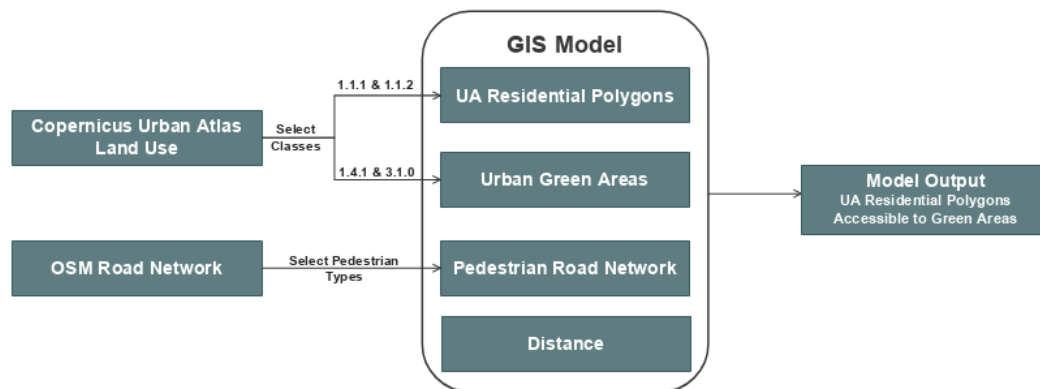
5.7.2 Conceptual design and analysis processes

Before processing, it is necessary the preprocessing of the datasets to obtain the final inputs of the model. The main datasets used for this purpose are (i) Urban Atlas (UA) Land Use 2018 and (ii) OpenStreetMap (OSM) Road Network.

UA provides reliable, inter-comparable, high-resolution land use and land cover data with integrated population estimates. The nomenclature includes 17 urban classes and 10 Rural Classes. To define our residential polygons layer, only UA polygons from the classes 1.1.1 and 1.1.2 were selected. For the Urban Green Areas polygons from classes 1.4.1 and 3.1.0 were selected. For the final Urban Green Areas layer to be created, further effort was put in removing narrow roads or paths inside parks or other urban green areas and calculating the area of each polygon and then buffered at 1.5m.

OSM Road Network parts are tagged based on their road category (motorway, primary, secondary, residential, unclassified, etc.). For our model only pedestrian related tags (pedestrian, living street, etc.) were selected and used as input in our model (Figure 5.19).

Figure 5.19 Data preprocessing as model inputs.

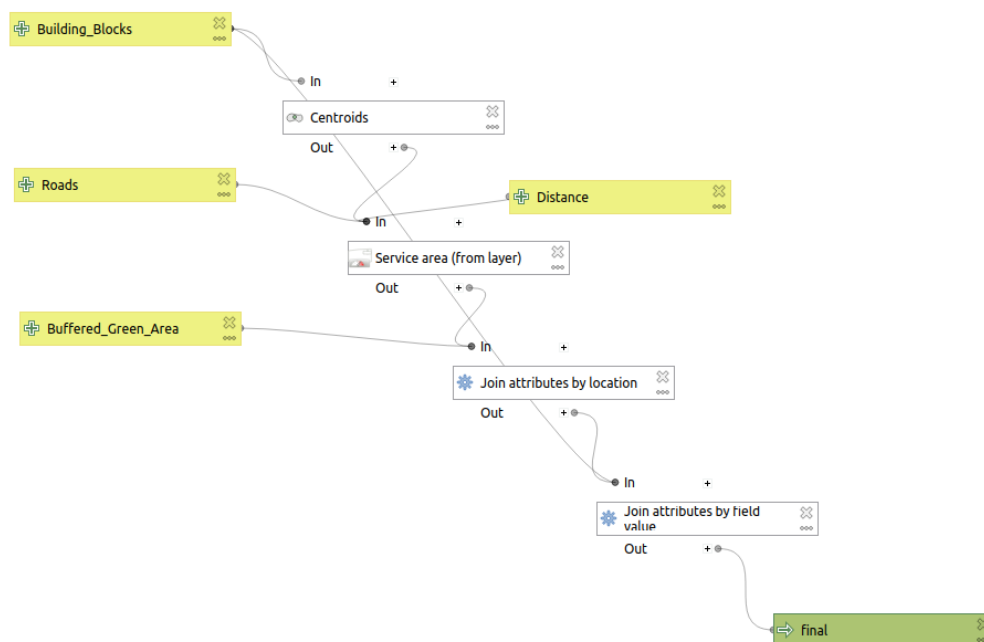


A QGIS model was created that incorporated all the steps of the analysis. The input of the model are the datasets created in the preprocessing stage (UA Residential Polygons, Urban Green Areas, Pedestrian Road Network) as well as the distance (in meters) between the UA Residential Polygons and the accessible Urban Green Areas. The distance was calculated for a 5 minute and a 15 minute walk with a walking speed of 5km/h.

The main steps of the analysis are:

- Calculating the centroids of each Residential UA polygons
- Executing a Network Analysis to extract the Service Areas of each centroid, namely the part of the road network that can be covered in the given distance/time
- Service Areas are spatially joined with the largest intersected Urban Green Area polygon
- Residential UA polygons are joined with the service areas based on a common attribute (UA ID) (Figure 5.20).

Figure 5.20 Model development for the accessibility of Green Urban Areas.



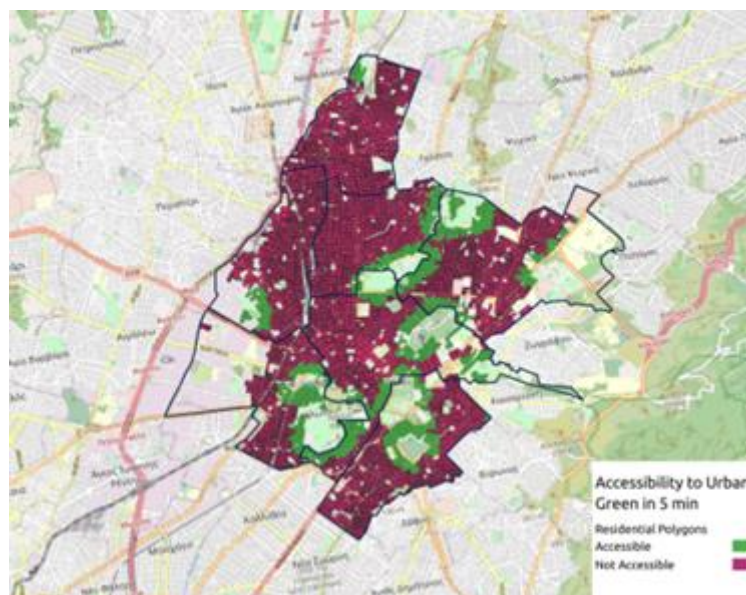
The final output of the model is a vector geopackage file of the UA Residential Polygons with the extra information of the area of the accessible Urban Green Area polygon.

Finally, the output will be combined with additional socio-economic data (population and deprivation index) to examine the spatial correlation of those datasets.

5.7.3 Development status

The results of the network analysis, to identify the accessibility of citizens (by means of number of residential polygons and population density) within a 5-minute (300 m) walking distance were used as the final incorporated layer to conduct the hotspot mapping. The QGIS model of the geospatial analysis was developed by using Urban Atlas datasets (i.e., residential polygons, urban greenery and forests) overlapped with the road network (OpenStreetMap). The network analysis extracts the Service Areas of each centroid of the residential urban area polygons that can be covered in 5-minute (300 m) walking distance. Then, Service Areas are spatially joined with the largest intersected urban green and urban area polygons (Figure 5.21).

Figure 5.21 Accessibility of residential polygons of the city of Athens to Green Urban Areas larger than 5 ha, within a distance of 5 minutes (300m).



5.8 Vulnerability assessment in country, regional and city level

5.8.1 Main scope, objectives and participatory processes

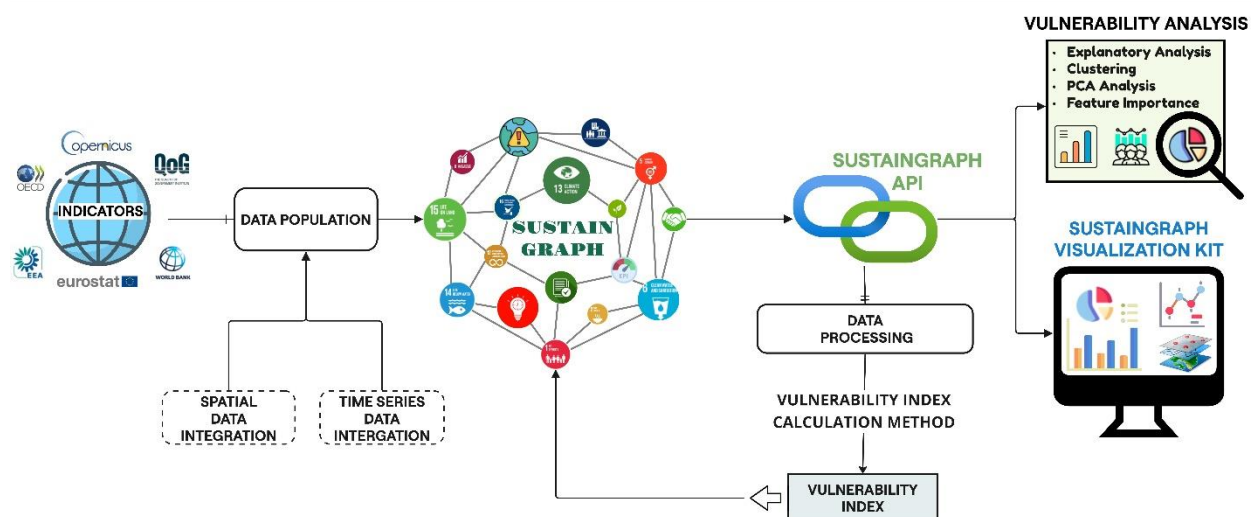
Climate change vulnerability assessment (CCVA) is crucial to understand how different regions, communities, and ecosystems are susceptible to the impacts of climate change. The main scope is to develop framework to enable open and interoperable CCVA taking advantage of a knowledge management infrastructure and specifically a Knowledge Graph, the SustainGraph, that tracks information for various indicators around the Sustainable Development Goals. We follow an indicator-based vulnerability assessment approach for various temporal and spatial scales, while considering hazard-independent and hazard-dependent analysis processes. Indicative analysis results are provided in national scale for the countries of the European Union, in regional scale for the various regions across Greece, and in local scale for urban environments across cities in Greece.

5.8.2 Conceptual design and analysis processes

Overview Framework

The proposed CCVA framework is centered around the knowledge that can be offered through a Knowledge Graph that is populated with data for various indicators in different spatial and temporal scales. The SustainGraph (Fotopoulou Eleni et al., 2022) aims to track information for various indicators related to the SDGs and assist social and environmental scientists to design solutions for the development of climate-resilient regions. The proposed framework is generic enough and can be adopted for the support of Indicator-Based Vulnerability Analysis (IBVA). Scientists can take advantage of the collection of data for various indicators and the provision of open and extensible interfaces to manage such data and inject them into analysis processes. A high-level view of the proposed framework is depicted in Figure 5.22.

Figure 5.22 Climate Change Vulnerability Assessment Framework High Level View.



The SustainGraph is populated with data from a set of indicators coming from diverse sources, including databases from Eurostat, the European Environmental Agency (EEA), the Organization for Economic Cooperation and Development (OECD), the Copernicus Data Space Ecosystem and the World Bank. Time series data are introduced in different spatial scales (e.g., national level, regional level, city level). To support the integration of the raw data, a set of data population workflows are developed in Python, targeted to the aforementioned databases and considering the type, the format and the spatial resolution of the data. Time series data, originally in tabular format, are introduced into the SustainGraph through specifically developed data population pipelines. On the other hand, spatio-temporal data, regarding land cover or land use, are represented in high grid-cell resolution in raster or vector formats of various scales. They are filtered based on the geometry of the corresponding administrative unit, aggregated and introduced in the SustainGraph (Christina-Maria Androna 2024). Upon the data population to the SustainGraph, access to the available data is provided through a set of Application Programming Interfaces (APIs). These APIs enable information retrieval and seamless interaction of the SustainGraph with further data management and analysis processes or components of the CCVA framework.

In the proposed CCVA framework, the SustainGraph APIs are used for processing the available data based on a set workflows. These workflows support processes such as data quality assessment, data cleaning, detection of outliers, filling in of missing values and data normalization. Following, the processed data is provided as input to processes for the calculation of vulnerability indexes. Different methodologies can be applied for the calculation of the indexes (e.g., calculation of weighted

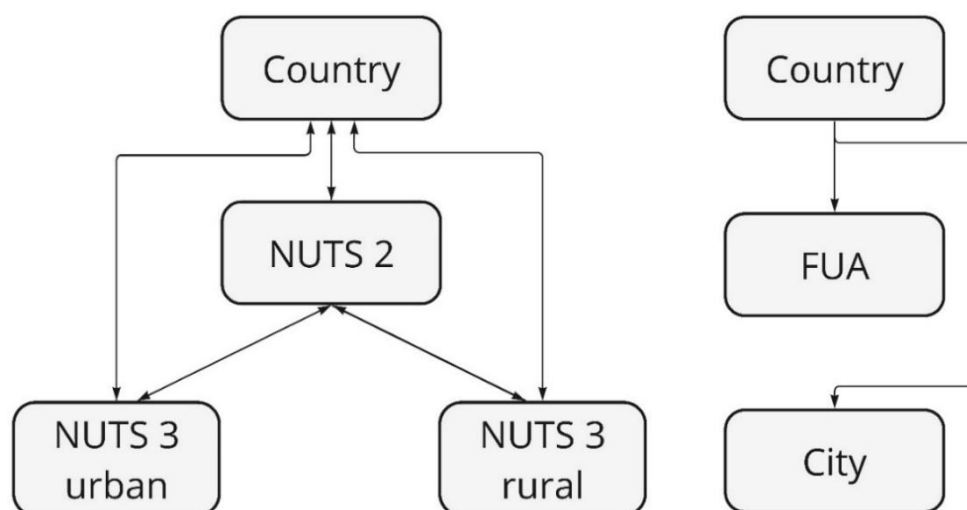
averages) depending on the exact CCVA process to be followed. Composite indexes can be calculated that may refer to hazard-dependent or hazard-independent vulnerabilities. The calculated vulnerability indexes are stored and made available through the SustainGraph.

By having access to the vulnerability indexes, a set of analysis and visualization processes can be executed, once again by taking advantage of the SustainGraph APIs for the interaction with the Knowledge Graph. This is one of the main advantages of offering the knowledge in a structured way and through open and interoperable interfaces, since different analysis scripts can be onboarded and executed on demand. In case of updates in the collected data (e.g., introduction of recently collected data), the supported analysis processes can be easily re-executed, while comparability of the produced results is easily performed. For instance, the analysis processes may regard explanatory analysis and machine learning techniques, including clustering and Principal Component Analysis (PCA), that can provide valuable insights, support decision making, and enhance comprehensive and holistic planning for managing the identified vulnerabilities. Furthermore, visualisation tools can be used to provide user-friendly visualisations from the available time-series data, as well as visualisations of vulnerability indexes in geomaps based on different spatial and temporal resolutions. Interoperability with external tools and analysis scripts is also possible through the development of the appropriated APIs.

Hazard Independent

Hazard-independent vulnerability assessment and analysis aims to monitor and describe the inherent susceptibility of population and areas when exposed to hazards and extreme conditions, considering their characteristics at social, political, economic, and environmental dimensions. In the proposed framework, based on the European wide vulnerability framework (Eklund 2024), vulnerability is expressed as a compound cross-scale index calculated on various geographical levels. The index on each level considers a set of indicators on each dimension (social, political, economic, environment). In the analytical framework presented, the compilation of indicators within each dimension, originally proposed by (Eklund 2024), underwent detailed scrutiny. It was filtered based on the data quality and availability of each indicator and further enriched with new indicators. This process aimed to thoroughly and comprehensively represent each dimension and capture a broader spectrum of its characteristics.

Figure 5.23 Multilevel Vulnerability Approach



The tables in the Appendix A provide an overview of the dimensions and sub-dimensions in which indicators are systematically categorized. The social dimension aims to represent the living conditions

of a population, encompassing facets such as the quality of life regarding healthcare services, education, transportation, population distribution, and gender equality. Social disparities, inadequate healthcare infrastructure, and limited access to education compromise the resilience and adaptive capacity of communities to the adverse effects of hazards. The political aspect of a community regarding the quality of the political system and the government is also a key factor in resilience and its ability to apply emergency planning and policies. The economic dimension considers the financial resources and stability, the cost of living, production, and employment. Resilience demands a strong and independent economy to invest in critical infrastructure and be able to prepare for, respond to, and recover from various hazards. The state of the ecosystem (green spaces, protected areas, biodiversity), its preservation and the government's measures towards environmental issues are holistically represented through the environmental dimension that aims to describe the environmental quality of an area. The effect of each indicator on the total vulnerability (increasing or decreasing effect) is specified in the tables in the Appendix A, with a positive or a negative sign accordingly.

The indicator-based vulnerability index is calculated across 5 different administrative levels (Country, NUTS 2, NUTS 3, FUA, Cities) within 27 Member States of the European Union. The main objective follows a hierarchical approach, where the final vulnerability index for each level (Country, NUTS 2, NUTS 3, FUA, City) considers the impact of indicators of all the levels of higher or lower hierarchy. This approach highlights the interdependencies among the different administrative levels and considers vulnerability in a more holistic way. To refine the analysis, NUTS 3 areas were further categorized into "urban" or "rural" according to the territorial typology of Eurostat. Regions characterized as predominately rural or intermediate were classified as "rural", whereas predominately urban regions were categorized as "urban". The categorization of NUTS 3 regions was incorporated to capture the different conditions between urban and rural areas, especially in the environmental and economic dimensions. As depicted in Figure 5.24, the vulnerability index for levels Country, NUTS 2 and NUTS 3 (urban and rural), follows both a top-down and a bottom-up approach. However, in the hierarchy of FUA and Cities, it is not applied due to limited indicator diversity between these levels, stemming from data availability constraints. Therefore, the vulnerability index calculation for FUA and City levels considers only the overarching impact of their respective national level.

Based on the proposed vulnerability assessment framework, a data processing workflow is performed for the calculation of the vulnerability index. The data processing workflow is based on the respective one in (Eklund 2024), with enhancements where needed. The primary objective is to transform the data retrieved from the SustainGraph API into a suitable format for the computation of the vulnerability indices. This approach is delicately divided into 4 segments, each methodically constructed to handle certain aspects of the overall procedure.

1. Filling in missing values

Since we combine indicator data from diverse sources, we encounter instances of missing data, necessitating the careful selection of appropriate techniques to ensure that the original data structure remains unaltered. At first, an interpolation method in forward and backward directions is performed per indicator in each geoArea with missing values across the years. In more detail, we perform the time-interpolation technique, which considers a linear relationship between the known data points for the estimation of the missing values.

However, the lack of data across all years for particular geoAreas requires a different interpolation technique to be used. The k-Nearest Neighbors imputation method is a powerful technique used in machine learning for handling the missing values. The idea behind KNN imputation is to fill in the missing values with the mean value from the k nearest neighbors. In this context, neighbors refer to geoAreas with similar values across the indicators. The procedure for determining the optimal k begins

with the normalization of the data across all geoAreas and years. Following that, we examine a range of k values, applying k -fold cross-validation to test the imputation algorithm's efficiency. The average Root Mean Square Error (RMSE) is computed for each fold, and the optimal k is the one associated with the lowest average RMSE. Due to the diversity of indicators across the administrative levels, the optimal k may differ for each level.

2. Outliers Detection

At this stage of the workflow, the computation of two statistical measures, the skewness and the kurtosis of the data distribution, is necessary to limit the presence of outliers that may hinder the informative potential of individual indicators. Thus, by examining these two measures, we can evaluate the normality of the distribution of each indicator's data across all years and geoAreas. As in the workflow in (Eklund 2024), if the absolute skewness surpasses 2 or the kurtosis exceeds 3.5, then a winsorization approach is applied, in which the outliers are limited. More specifically, the values above the 98th percentile are set to the 98th percentile, and those lower than the 2nd percentile are raised to the 2nd percentile. After applying this step, the values of skewness and kurtosis metrics are reexamined and if either metric still exceeds its limit, a log transformation is applied.

3. Normalization

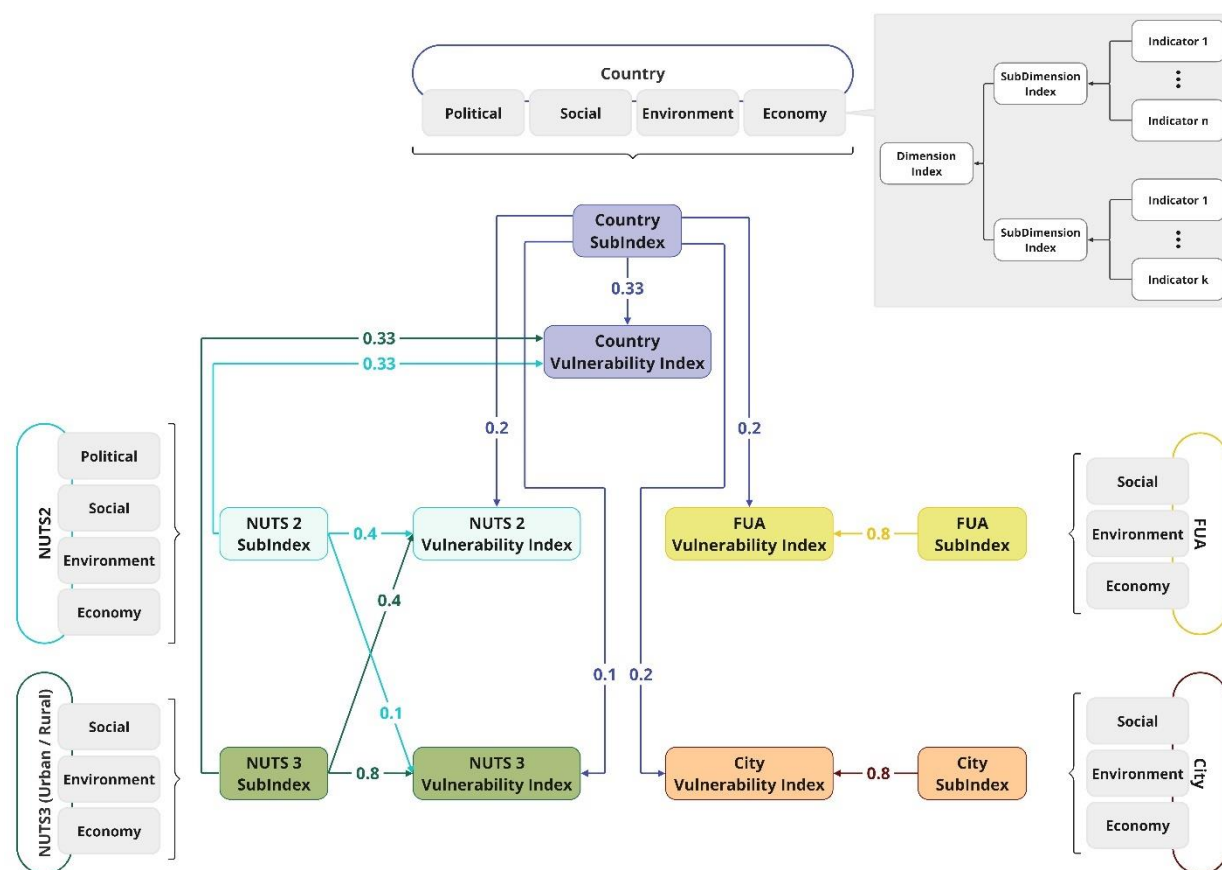
One of the most crucial steps in our workflow is the normalization of data. The normalization step is necessary for the comparability of indicators measured on different scales. The MinMaxScaler estimator is used to transform the indicators data across all years and geoAreas in the range (0,10). The indicators vary in their impact on the vulnerability; for some of them, an increase corresponds to higher vulnerability (increasing effect), while for others corresponds to reduced vulnerability (decreasing effect). For this reason, the indicators with a decreasing effect on the vulnerability (signed with "-" on the tables in the Appendix A, i.e. higher values lower the vulnerability, undergo a two-step transformation. Initially, they are scaled to the range (0,10), and then their values are reversed by subtracting them from 10 within this range.

4. Vulnerability index calculation method

The calculation method regarding the computation of the hazard-independent vulnerability indices follows a hierarchical approach, developed in a four-step process (Figure 5.24). The first step regards averaging the indicators data per subdimension on each level to determine the subdimension indices. In the second step, the subdimension indices are aggregated per Dimension (Political, Social, Environment, Economic) resulting in the Dimension vulnerability index for each level. The third step of the process involves averaging the dimensions indices values to determine each administrative level's (Country, NUTS2, NUTS3, FUA, City) vulnerability subindex. Once the subindices are calculated, the last step of the workflow regards the calculation of the vulnerability index at each level. The computation of the vulnerability index involves utilizing the subindices of different administrative levels of higher or lower hierarchy, each contributing with different weights, as shown in Figure 5.25. The vulnerability index is computed using both top-down and bottom-up approaches at the Country and NUTS levels, whereas, at the FUA and City levels, only the top-down approach is applied. At lower administrative levels, the vulnerability index for a given geoArea is derived by taking into account the subIndices of its superior administrative levels. Conversely, at superior administrative levels, the index is determined by considering the mean of the subindices of the geoAreas at lower levels within the geoArea assessed.

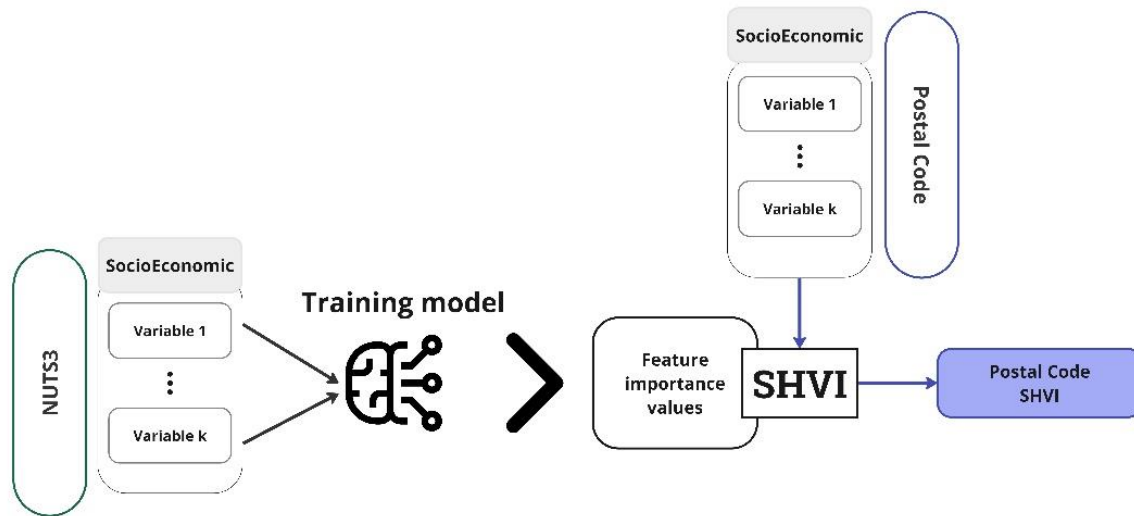
Figure 5.25 shows the weight of impact of each administrative level at the vulnerability index of the corresponding level. The weight of each administrative level's subindex reduces as we move up the administrative levels. For this reason, the vulnerability index of a given geoArea at the country level

Figure 5.24 SubDimension, Dimension, SubIndex, and Vulnerability Index calculations



The hazard specific vulnerability assessment and analysis is conducted, focusing on the socio-economic vulnerability to extreme heat events. The vulnerability study involves selecting and training a model on socio-economic vulnerability variables at a low-scale administrative level, in our case NUTS 3 regions, and extracting the feature importance values of the model to formulate a weighted average composite index, the Socio-Economic Heat Vulnerability Index (SHVI). The SHVI can be applied and calculated at higher granularity levels, contingent upon the availability of the corresponding socio-economic variables. The vulnerability assessment was focused on the extreme heat events within the Attica region of Greece. Therefore, the model was trained utilizing socio-economic vulnerability variables for all NUTS 3 regions of Greece and further applied at the postal code level within the Attica region.

Figure 5.25 Flowchart of Hazard Dependent Vulnerability Analysis, Socioeconomic Heat Vulnerability Index (SHVI).



Indicators data are retrieved from the SustainGraph API and transformed through data processing procedures to define the independent and dependent variables of the model's training process. The independent variables were selected for each NUTS 3 region of Greece based on their contribution to socioeconomic vulnerability, as per (Seema G Nayak 2018). To formulate the final independent variables, which are presented in Table 5.3 Socio-economic Vulnerability Features, the indicators data were aggregated where needed and normalized to the percentage relative to the population per NUTS 3 region. The dependent variable of the model refers to the "Daily average mortality rate during heat wave events per 100k population". To construct this variable the country is partitioned into ten climatic zones that are meteorologically similar and are expected to record concurrent temperature extremes, based on the information published by the Greek Ministry of Environment and Energy (Ministry of Environment and Energy n.d.). The heatwave events within each zone, which is comprised of several NUTS 3 regions, are identified using temperature data, according to (Simone Russo 2015). Then, mortality weekly timeseries data is collected for each NUTS 3 region in Greece and linearly interpolated to a daily timestep, to match the temperature time series to calculate the rate.

Table 5.3 Socio-economic Vulnerability Features

% Elderly
% Retired
% People living in houses built before 1980
% Unemployed
% Renting
% Living alone
% Living in houses smaller than 60 sq. m.
% People as immigrants from developing countries

The vulnerability index SHVI considers the feature importance values from an ensemble decision tree model. Several ensemble decision tree models were examined, and through cross-validation and hyperparameter optimization the Extreme Gradient Boosting (XGB) model was selected, according to

the squared mean error, averaged across 5 folds. As depicted in Figure 5.26, the XGB model with the selected hyperparameters, was trained on the socioeconomic variables of the NUTS 3 regions (Table 5.3), and the feature importance values are utilized in a weighted average to construct the SHVI, according to the equation:

$$SHVI_j = \sum_{i=0}^n x_i v_i, \forall j \in C$$

, where x : feature importance value of feature i and v is the value of the feature i

for each j region in the C case study area

The final SHVI along with the socioeconomic variables on the postal code level are used to calculate the vulnerability for 266 postal code regions in Attica.

5.8.3 Development status

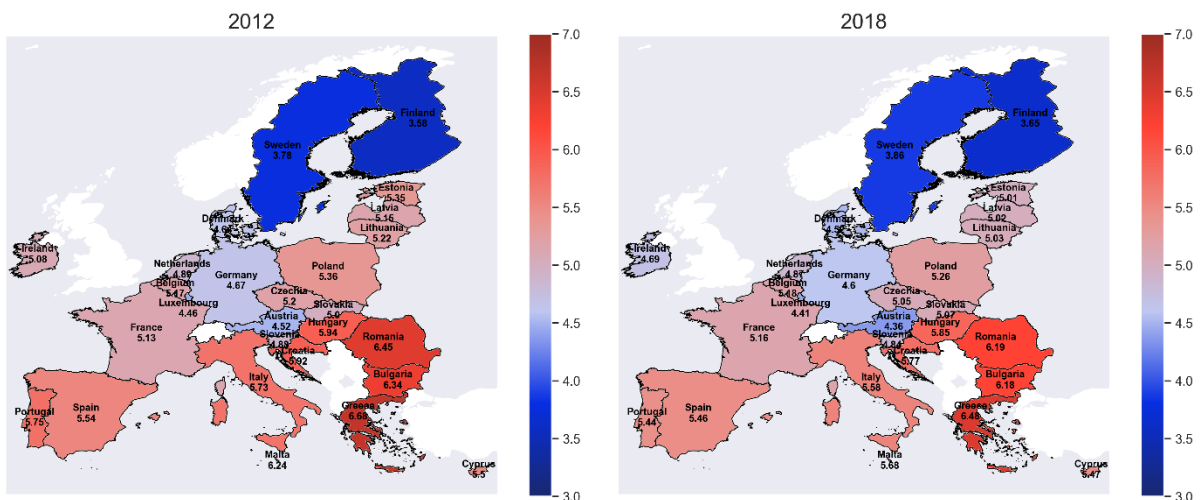
Hazard Independent

To validate and evaluate the method proposed in section 5.8.2, the hazard-independent vulnerability index is calculated annually at European, national, and local levels through the years 2011 to 2023. The indicators selected were gathered for the years 2010 to 2023 from open data authoritative sources: Eurostat, Copernicus, United Nations Economic Commission for Europe (UNECE), United Nations Development Programme (UNDP), World Health Organization (WHO), Worldwide Governance Indicators (WGI), World Bank, The QoG Institute, European Environment Agency (EEA), Global Human Settlement Layer (GHSL), and Organisation for Economic Co-operation and Development (OECD). Following the framework proposed in Figure 5.22, the indicators were collected from the SustainGraph API and processed accordingly.

European Level

The hazard-independent vulnerability index is calculated for the 27 member states of the European Union across the years, as presented in the maps in Figure 5.26. The resultant values are systematically distributed on a scale ranging from 1 to 10, and reflect a nuanced vulnerability at the country level with values from 3.0 to 7.0. The visual representation in Figure 5.26, reveals distinguishable patterns in vulnerability between the Mediterranean/Southern countries and their counterparts in Scandinavia and Central Europe. To further validate and examine this indicated clustering, a clustering algorithm is applied to the vulnerability indices within Europe across the period of 2011 to 2023.

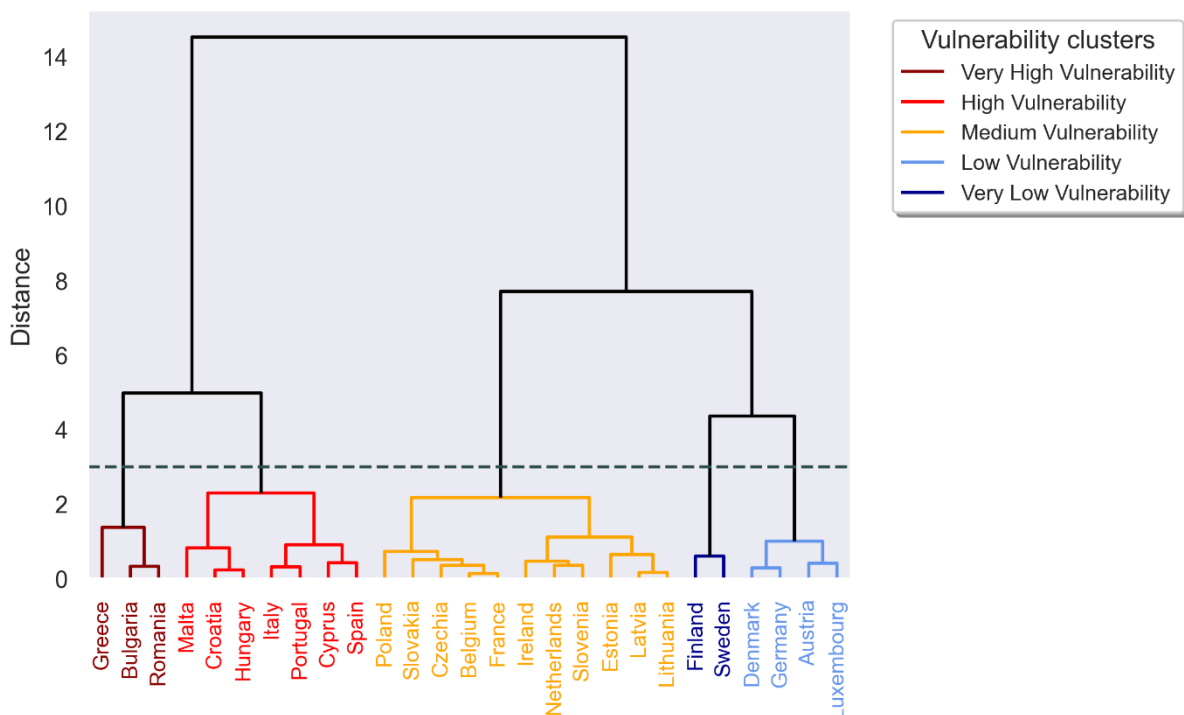
Figure 5.26 The vulnerability index across the years (EU-27 countries)



An unsupervised machine learning technique is used to cluster the EU-27 countries according to their socio-economic vulnerability. We perform an agglomerative (bottom-up) hierarchical clustering, which divides the European countries into clusters based on a linkage method that minimizes the variance within each cluster, namely Ward variance minimization algorithm.

Figure 5.27 illustrates the dendrogram that represents the hierarchy of clusters formed during the agglomerative clustering process. In order to form distinct and meaningful clusters, a cutting threshold of 3 is chosen, resulting in 5 clusters. Greece, Bulgaria, and Romania emerge with the highest vulnerability index, according to Figure 5.27, and form the Very High Vulnerability cluster. On the other side, Finland and Sweden exhibit analogous behavior having the lowest values in vulnerability, forming the Very Low Vulnerability cluster. The rest of the Mediterranean and Southern European countries (Spain, Cyprus, Portugal, Italy, Malta, Croatia) along with Hungary, are collectively grouped in the cluster that indicates high values of the vulnerability index (High Vulnerability cluster). Western European countries (Denmark, Germany, Austria, and Luxembourg) are considered as the Low Vulnerability cluster. The Medium Vulnerability cluster consists of countries from Western Europe (France, Belgium, Netherlands), Central Europe (Poland, Slovenia, Czechia, Slovakia), and Northern Europe (Ireland, Latvia, Lithuania, Estonia).

Figure 5.27 Hierarchical clustering of countries as a dendrogram.

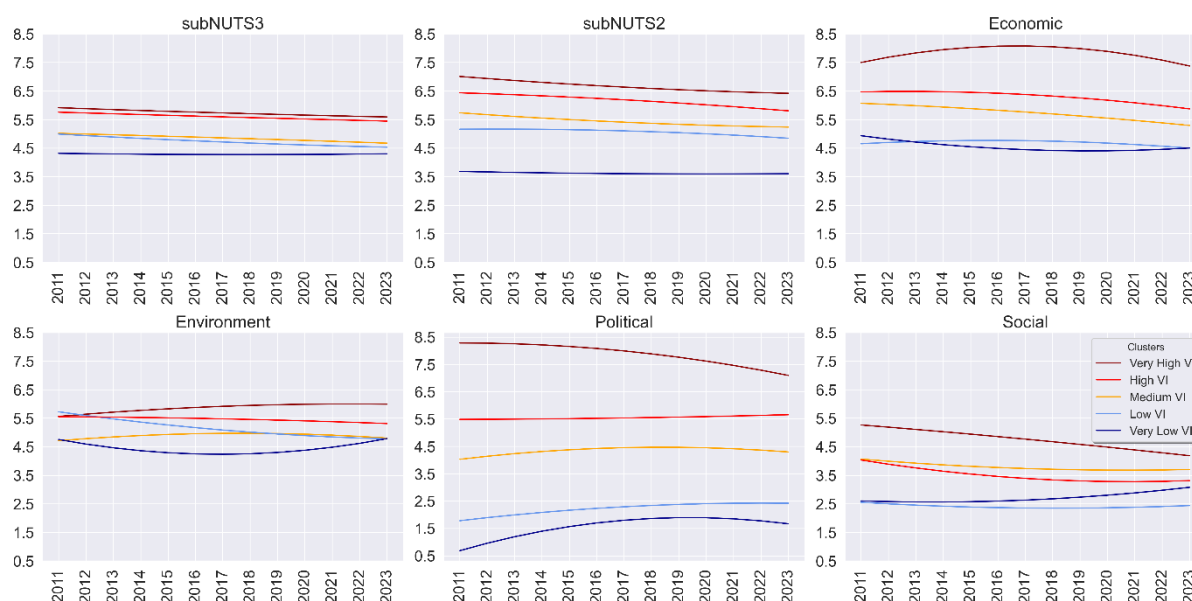


The vulnerability index at the country level is defined by the subindices of its dimensions (Political, Economic, Social, Environment) and the lower administrative levels of sub-NUTS 2 and sub-NUTS 3 (urban and rural).

The plots presented in Figure 5.28 illustrate the evolution of each subindex per cluster across time. In more detail, a quadratic polynomial regression is conducted on the subindices values for all countries of each cluster. The outcome of this regression is a set of coefficients encapsulating the underlying patterns in the data. The quadratic polynomial regression was selected since it can fit non-linear relationships between variables and provide a more accurate representation of the data.

Figure 5.28 reveals that the political and economic dimensions reach the highest vulnerability among all the subindices, for the Very High and High Vulnerability cluster. Conversely, the lowest vulnerability subindices are observed in the political and social dimensions of the countries with Very Low and Low Vulnerability. The sub-NUTS 3 and environment dimensions have relatively close values among all the clusters, in the range of 4 to 6. Within the Very High Vulnerability cluster, the social and political vulnerability indices display a declining trend over time, while the economic vulnerability peaked for the year 2017. The Low vulnerability cluster appears with lower vulnerability values in the social dimension compared to the Very Low cluster and is the only one that decreases environmental vulnerability over the years.

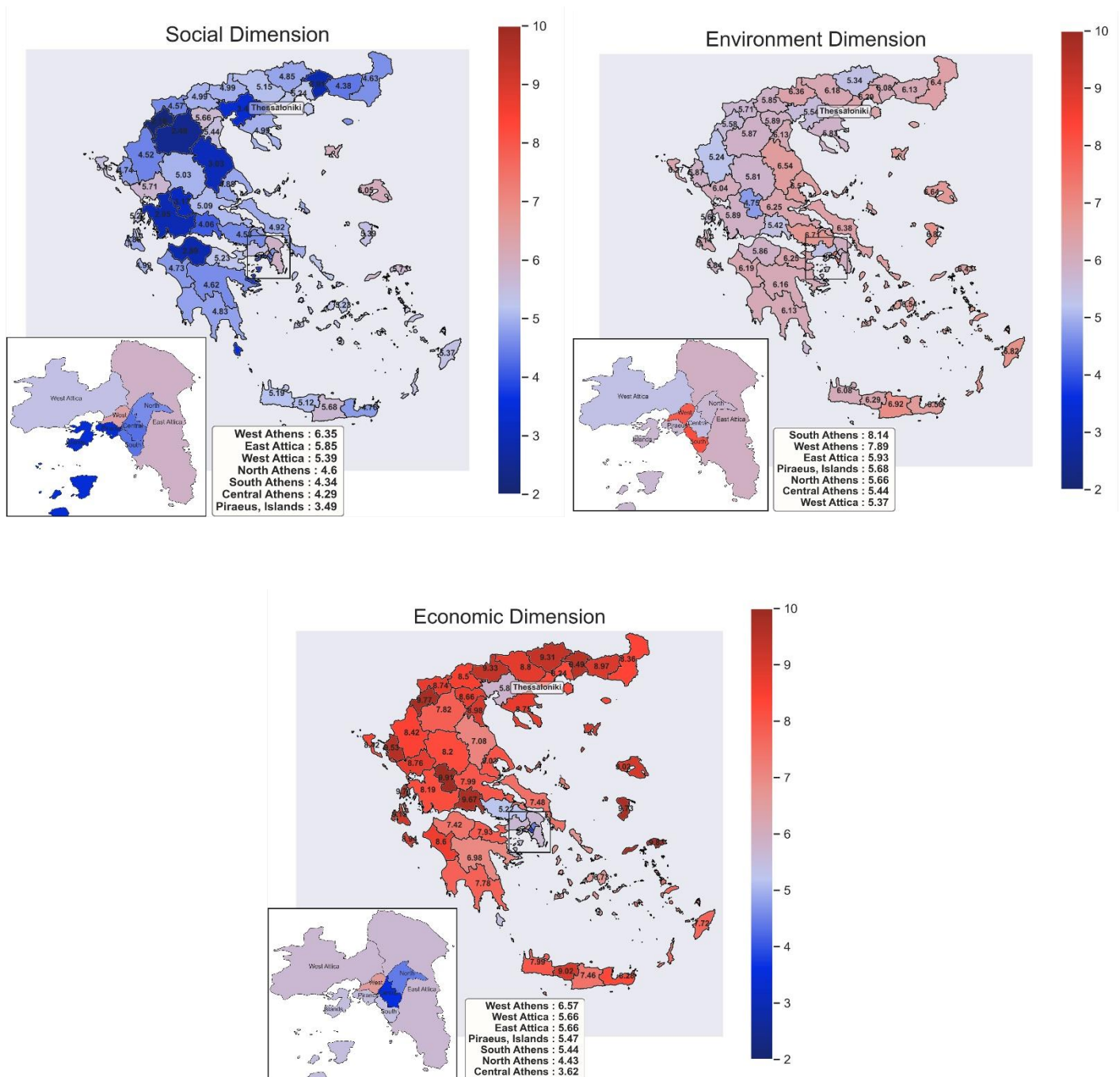
Figure 5.28 The evolution of subindices across time per cluster.



National level

In the context of a national-level analysis, NUTS 3 administrative units of urban and rural typology are assigned a vulnerability index that considers the economic, social, and environmental dimensions along with the vulnerability status of the higher administrative levels (NUTS 2 and country). Figure 5.29 illustrate the vulnerability index of each dimension across NUTS 3 regions in Greece.

Figure 5.29 The Dimension values of Greece.



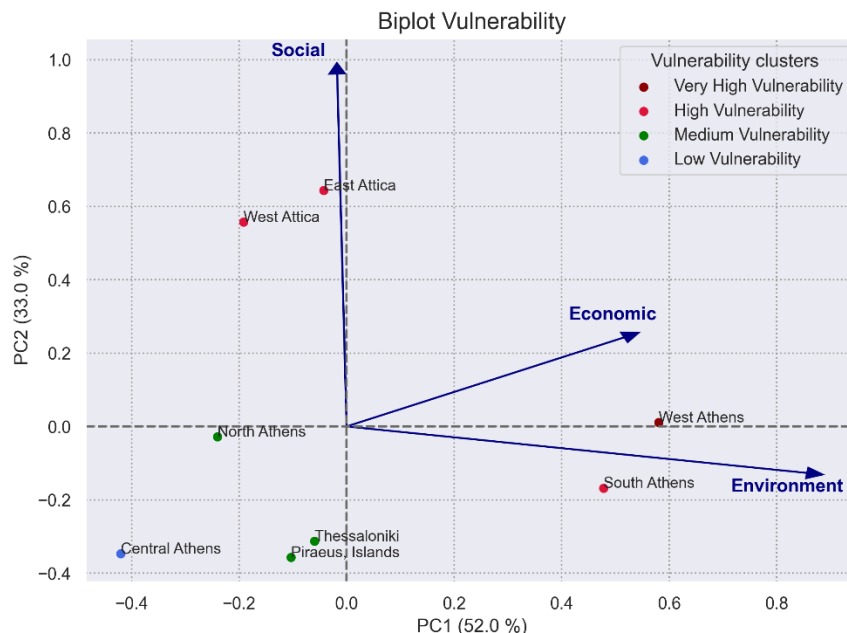
At this level, the social dimension, influenced by factors such as population density, migration, young and old age dependency (see Appendix tables), exhibits the lowest values in vulnerability, ranging from 2.2 to 6.3, compared to the other two dimensions in urban and especially rural areas. The urban areas of Greece, include Athens, regions of Attica, and Thessaloniki, the second largest city in Greece. The economic development of these areas is superior to rural Greek areas since they offer more business opportunities and better market access. Therefore, the vulnerability in urban areas is relatively low in the economic dimension. Rural areas of Greece, on the contrary, appear with the highest vulnerability

values in their economic dimension, indicating the financial inequality between urban and rural areas. The environmental dimension is where urban areas, especially West and South Athens, are more vulnerable, compared to the rural areas that appear with more moderate values in this dimension.

The **urban** areas of Greece are classified into 4 clusters, according to their vulnerability index across the years. The cluster with vulnerability values in the range of 4.6 to 5.1, is considered the low-vulnerability cluster which is composed of the NUTS 3 region of Central Athens. The medium-vulnerability cluster covers vulnerability values from 5.1 to 5.4 and consists of North Athens, Thessaloniki, and Piraeus along with the Saronic Islands. South Athens, East and West Attica belong to the high-vulnerability cluster (vulnerability values from 5.6 to 6.2), whereas West Athens comprises the very high-vulnerability cluster with vulnerability values reaching up to 6.7.

To further explore the dimensionality of the vulnerability and identify patterns in these clusters, a Principal Component Analysis (PCA) is performed. The first two principal components (PC 1 and PC 2) collectively explain 85% of the total variance in the vulnerability values of the areas and therefore are selected as the biplot axes demonstrated in Figure 5.30. Based on the projection of the 3 vector dimensions (Social, Economic, Environment), PC 1 is positively correlated with high Economic and Environment Dimension values in vulnerability, while PC 2 is mainly correlated with High Social Dimension vulnerability values. Areas that belong to the same cluster of vulnerability values, when grouped together in the biplot, indicate similarity in their characteristics. This is evident in the high vulnerability cluster, where both East and West Attica exhibit high positive PC 2 values indicative of elevated Social Dimension vulnerability. However, South Athens, also part of the high vulnerability cluster, has relatively low social vulnerability (negative PC 2), but higher values in the Economic and Environment Dimension (high PC 1 value). The highest vulnerability is found in West Athens (Very High Vulnerability Cluster), primarily driven by high vulnerability in the Environment and the Economy (highest PC 1 value).

Figure 5.30 Biplot of Vulnerability Dimensions in Urban NUTS 3 of Greece.



Local level

The vulnerability indexes calculated at the FUA and City level enable an analysis of the vulnerability at the local scale of a country. In Figure 5.31 is presented the vulnerability index along with its

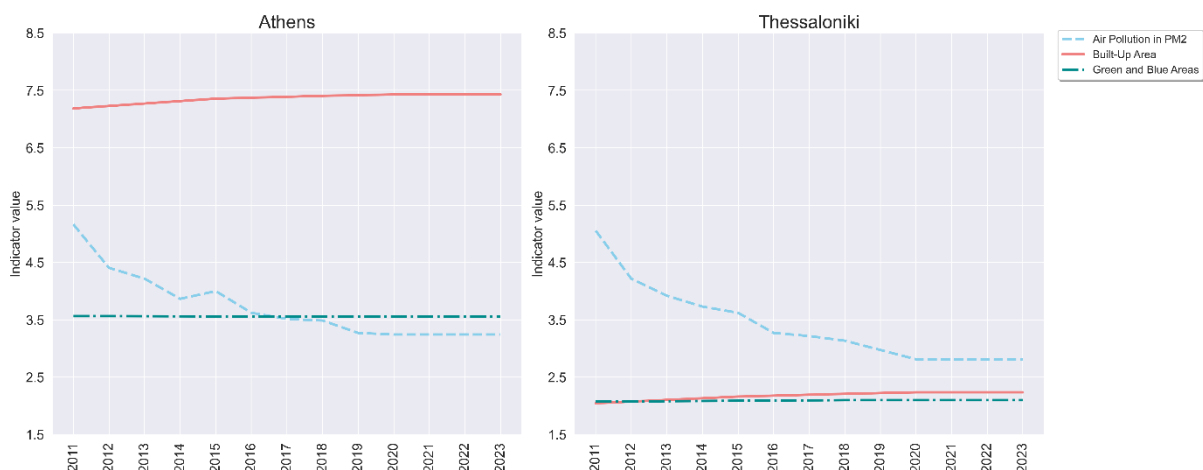
dimension's values for the FUA of the two biggest cities of Greece, Athens and Thessaloniki. The vulnerability index of these FUAs fluctuates in the same range of values, approximately around 5, but is influenced by different factors. Even though there are no significant differences in their social vulnerability, the economic vulnerability of Thessaloniki appears with higher values compared to Athens across the years, with both reaching their peak in 2012. On the contrary, Athens demonstrates greater vulnerability in the environmental dimension, which can be further evaluated by scrutinizing the corresponding indicator values.

Figure 5.31 Evolution of vulnerability indices across time in Athens and Thessaloniki.



Figure 5.32 illustrates the evolution of the three indicators of the environment dimension of the FUA over time. The crucial differentiation between Athens and Thessaloniki derives from the indicator that measures the distribution of built-up surfaces. It fluctuates between 6.5 to 7.5 in Athens, while in Thessaloniki takes lower values between 1.5 to 2.5. The air pollution in PM2 has a decreasing trend in both cities, especially after 2014 when Thessaloniki maintains lower values than Athens. The Green and Blue Areas indicator is a composite indicator that, according to the EEA, refers to the amount of discontinuous urban fabric, green urban areas, coniferous, broad-leaved and mixed forests, sport and leisure facilities, water bodies and courses of the FUA. The lower values of Thessaloniki in this indicator are attributed to the limited extent of discontinuous urban fabric and green urban areas compared to Athens. The FUA of Athens has a larger area considered urban, which can be characterized by discontinuous and green spaces.

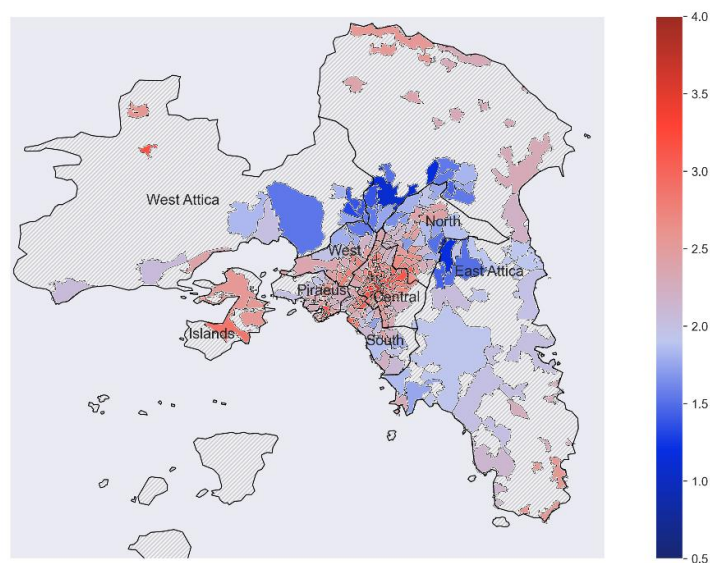
Figure 5.32 The Environment Dimension of Functional Urban Area



Hazard dependent

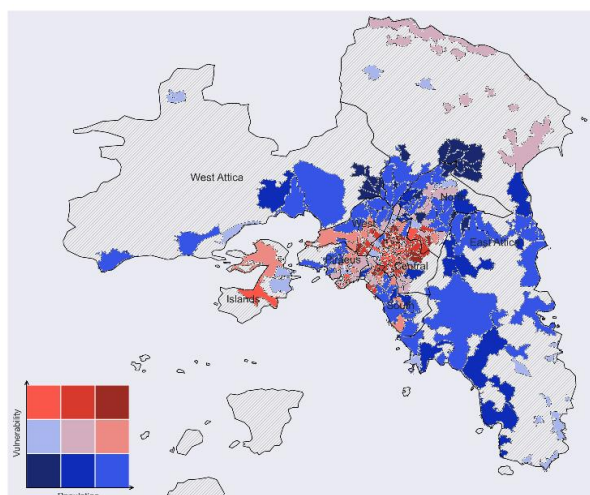
The SHVI is calculated for the Postal Codes in the region of Attica, as depicted in Figure 5.33. When examining the vulnerability of the Attica region as a whole, we see that the SHVI ranges between [0,935- 3,936], with a mean of 2,437 (population weighted mean of 2,306) and a standard deviation of 0,55. The population ranges between [1085 – 49856] with a mean of 13989,41 and a standard deviation of 7997,13. The highest vulnerabilities are observed in the central sector (as shown in Figure 5.33) mainly due to the high concentration of immigrants and people living in older buildings

Figure 5.33 The SHVI of Postal Codes in Attica region.



In Figure 5.34, exposure to extreme heat events is also assessed, by combining the SHVI, which is a measure of socioeconomic vulnerability, with the population exposed to extreme heat. The combination of high exposure and high vulnerability (dark red color) that presents the worst-case scenario of highest risk is observed in eight zip codes in Attica and they are all the central sector. The latter has a high concentration of high vulnerabilities, either with or without high populations. Suburbs and communities away from the center show either lower exposure, low vulnerabilities, or both.

Figure 5.34 The SHVI and population exposure for the Attica region, by Postal Code.



5.9 Atmospheric numerical model to support microclimatic simulations and nature-based solutions

5.9.1 Main scope, objectives and participatory processes

The application of a numerical model for weather and microclimate research will provide meteorological output regarding present climatic conditions over the area of study (Athens Metropolitan Area – AMA). Short term and long term, high spatial horizontal resolution (200m) microclimatic simulations will be performed with the aim to validate the outcomes of all the prerequisite models (sections: 5.3 - 5.8) -meaning sites with absence of green urban areas, low urban biodiversity value and air quality, and significant levels of urban thermal stress and socioeconomic vulnerability- with the ultimate goal to identify sites of the city of Athens that require mitigation/adaptation measures to implement NbS. Specific NbS per site of Athens will be selected based on existing repositories and relevant platforms (e.g., [BISE](#), [ClimateScan](#), [ClimateADAPT](#), [DRMKC](#), [Natural Hazards — Nature-based Solutions](#), [Nature-based Solutions Initiative platform](#), [Naturvation Urban Nature Atlas](#), [NWRM](#), [OPPLA](#), [ThinkNature](#), [weADAPT](#), [Connecting Nature](#), [Global Program on Nature-based Solutions for Climate Resilience](#)) and/or proposal of new interventions, if needed, according to local characteristics, environmental status and current climatic conditions.

Next, the potential impact of selected NbS on the city's microclimate, such as the enhancement of green and blue infrastructures, will be investigated by simulating different land use scenarios. Model runs need accurate and updated land use, vegetation and soil type input data that will be sourced from the Copernicus Land Service – Pan-European Component. Specifically, Corine Land Cover ([CLC](#)) and Urban Land Cover Land Use data ([Urban Atlas](#)) will be utilized. The microclimate simulation scenarios will contribute towards testing the effectiveness of NbS, thus concluding on the most suitable NbS to be implemented in each site to improve climate resilience in the city of Athens.

5.9.2 Conceptual design and analysis processes

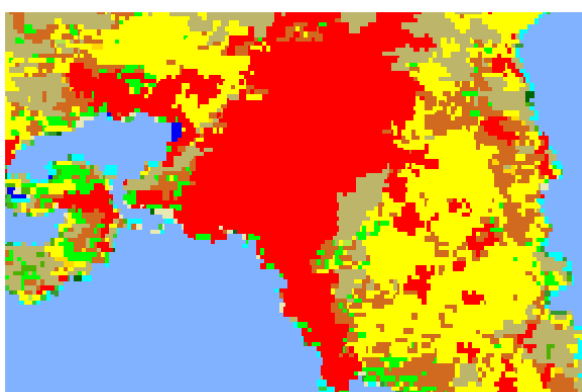
The Weather Research and Forecasting (WRF) regional model (Version 4.4 (Skamarock et. al, 2021)), is a numerical weather prediction and atmospheric simulation system, which integrates the Advanced Research WRF (ARW) dynamics solver. WRF incorporates the Noah-Multiparameterization Land Surface Model (Noah-MP LSM) allowing the representation of several physical processes, such as canopy radiative transfer with shading geometry considered, separate treatment of the vegetation canopy based on vegetation element density, distribution and crown radius (vertical and horizontal), leaf reflectance and transmittance properties, surface run-off, soil moisture flux, and more. Noah-MP LSM is coupled with the single-layer urban canopy model UCM (Tewari et al., 2007). The single layer UCM uses a simplified two-dimensional urban geometry approach considering building height, roof and road width to represent heat fluxes over impervious surfaces and inside the street canyon environment. It includes trapping/reflection of radiation and shadowing effects defined by the street canyon dimensions and orientation. By computing roof, wall and road surface temperatures and their resulting heat fluxes, it is possible to calculate the energy and momentum transfer between an urban environment and the atmosphere. The coupling of the single-layer UCM with the Noah-MP LSM completes the urban surface energy balance by calculating fluxes from the vegetated portion of the urban surface in a given grid cell. Therefore, the WRF-LSM modelling system allows for a multi-parameter approach when investigating the urban climate in high resolution applications.

Predefined datasets of Moderate Resolution Imaging Spectroradiometer (MODIS) with 21 land use classes and 16 soil categories are generally used by the WRF preprocessor (WPS). At the same time, numerical simulations can also be optimized by ingesting high-resolution vegetation and urban land use data, derived from satellite image analysis, national/European urban databases and land cover databases. To this aim, Corine Land Cover ([CLC](#)) and Urban Land Cover Land Use data ([Urban Atlas](#) - UA) from [Copernicus](#), will be integrated to the WRF system and a detailed analysis of urban land use

categories (UCM model), following the Local Climate Zone (LCZ) classification (Stewart et al., 2012)(Oliveira et al., 2020) will be incorporated to represent the Athens Metropolitan Area in greater detail. The steps of improving land use and land cover in WRF, compared to the default land use dataset (in this case MODIS 21 class land use data), by ingesting higher resolution (200 m) and updated geospatial data (CLC + UA), is shown in Figure 5.35. This allows for a detailed analysis of the city's microclimate under current conditions and at the same time it will facilitate the implementation of urban planning mitigation scenarios (e.g., increase of urban green and water bodies, green roofs, use of reflective materials). The impact of the urban solutions proposed will be quantified by contrasting the model's output between the simulated current conditions and the mitigation scenarios (e.g., differences in surface temperature, air temperature, humidity).

Figure 5.35 WRF simulation domain (200m horizontal resolution) depicting the optimization steps for land use and land cover representation, beginning from the default MODIS 15s resolution data (a), followed by the ingestion of Corine Land Cover reclassified to the MODIS categorization (b) and the ingestion of Urban Atlas urban land use under the Local Climate Zone (LCZ) urban classification (c). MODIS and LCZ categories are described in the attached legend.

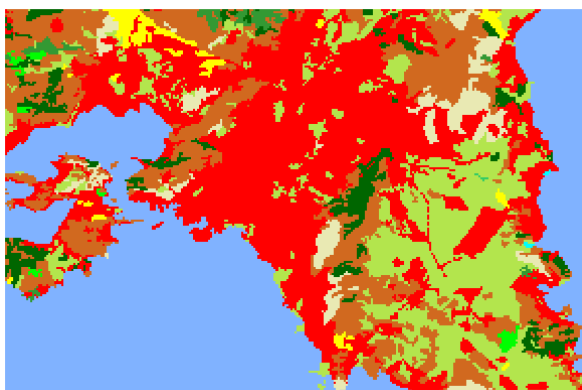
a)



MODIS 21 classes

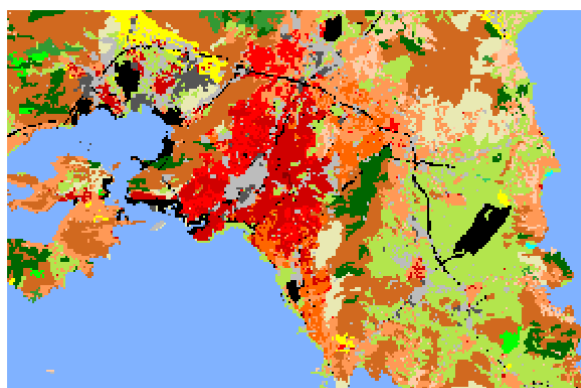
- Evergreen Needleleaf Forest
- Evergreen Broadleaf Forest
- Deciduous Needleleaf Forest
- Deciduous Broadleaf Forest
- Mixed Forests
- Closed Shrublands
- Open Shrublands
- Woody Savannas
- Savannas
- Grasslands
- Permanant Wetlands
- Croplands
- Urban and Built-up
- Cropland/Natural Vegetation Mosaic
- Snow and Ice
- Barren or Sparsely Vegetated
- Water (like oceans)
- Wooded Tundra
- Mixed Tundra
- Barren Tundra
- Lake

b)



LCZ urban classes

c)



5.9.3 Development status

Currently, the ingestion of improved land use and land cover for urban and non-urban areas over the region of interest, has been completed. Additionally, a series of preliminary simulations have been carried out (at NOAA's server) to test the robustness of the model's configuration. Next steps include the designing of the urban land use scenarios and their implementation through the microclimatic simulations. Also, the WRF modelling system will be ported to the high-performance computing facilities (HPC) of GRNET ([National Infrastructures for Research and Technology](http://www.grnet.gr)) for further testing and to facilitate the computationally demanding numerical applications. Next, simulations of the city's current microclimate will be validated against available meteorological observations and the modelling system will be optimized accordingly before proceeding with the final production runs and output analysis.

A multidimensional approach is opted for the hotspot mapping, which is highly multidisciplinary and includes the following diverse modeling approaches: Climatology (see 5.3), satellite thermal infrared (TIR) data processing (see 5.4), air quality modelling (see 5.2), geospatial analysis of green areas (see 5.5), and vulnerability assessment (see 5.8).

Our hotspot identification method consists of the prioritization of sites with the worst conditions, within the Athens Municipality, related to urban heat and air pollution, as well as the lack of Green Urban Areas and socio-economic vulnerability levels. A detailed evaluation and quantification of the above parameters provides the necessary input framework to determine multi-hazard hotspots at the city-scale.

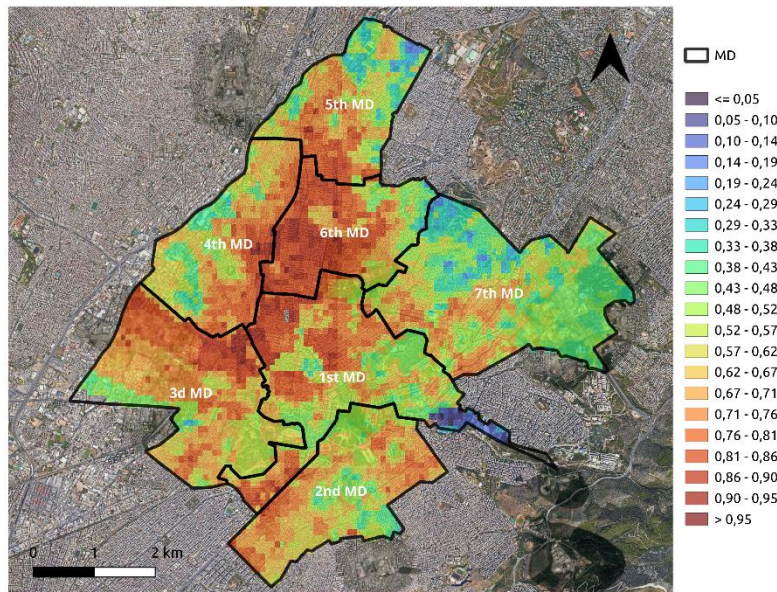
A three-stage prioritization approach is followed to map the most vulnerable and multi-threatened sites. First, the five produced layers of CHT index, mean LST, AQI, accessibility of GUAs and socioeconomic vulnerability (sections 5.3 - 5.8) are post-processed, using the QGIS software, to enable their spatial combination. This post-processing establishes the appropriate integration of the examined environmental threats and socio-economic vulnerability and includes the following steps:

- i. Definition of a common coordinate reference system (CRS) projection, EPSG:4326 - WGS 84.
- ii. Rasterization of layers (100 m² cell size).
- iii. Clip to the extent of our case study (Athens Municipality).
- iv. Normalization of layers (unweighted).

In the second stage, the integration of the examined environmental hazards to determine priority areas by superimposing the four post-processed layers, is carried out. This is achieved by overlaying and adding together all layers to rank cells (4818 cells) and measuring the collective environmental and socio-economic vulnerability within the extent of our case study. Cells with the least combined

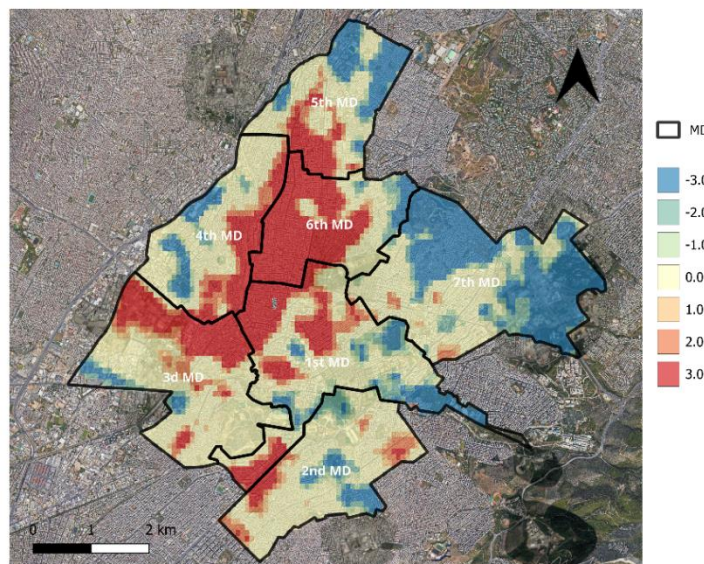
values (closer to 0) are characterized by good overall environmental conditions and those with the highest values (closer to 1) are considered more vulnerable (Figure 5.36).

Figure 5.36 Normalized combined hot spot map from climatic, land surface temperature, air-quality, accessibility and vulnerability layers. Values closer to 0 denote good environmental conditions while values closer to 1 denote a degradation of overall conditions.



In the third and final stage, the local Getis-Ord (G_i^*) indicator is applied over the final normalized hotspot map. G_i^* is a common indicator used for the exploration of spatial patterns (Getis and Ord, 1992), and specifically clusters of high or low values that are hot or cold spots of environmental and socio-economic vulnerability, respectively (Zartarian et al., 2024). This indicator compares the local weighted average of values in a cell and its neighborhood to the total sum of all cells to distinguish significant differences and returns the corresponding standard deviation (z-score). In this case, we specified as neighborhood the focal cell and the nine cells around it (Moore neighborhood) and performed 999 permutations to test significance. The analysis was performed in R (version 4.3.2) (R Core Team, 2024). The results (Figure 5.37) indicate a large cluster of high overall vulnerability in the center of the study area ranging from north to south. This cluster overlaps partially with 5 municipal districts, namely 1, 3-6. Two more degraded areas can be observed in the first municipal department (in Exarchia and north of Monastiraki). In the south, there is a vulnerable area on the limits between the first and second municipal department and a smaller one in the 3rd municipal department. On the other hand, the least vulnerable areas can be found at the periphery of Athens municipality, while larger clusters are limited to the north.

Figure 5.37 Getis-Ord (G_i^*) indicator results for the 7 Municipal Districts of Athens.



Focusing on the most environmentally and socio-economically vulnerable sites [hotspot mapping scoring > 2.36 (Getis-Ord z-score)], two distinctly spatial clusters are observed in the seven districts of Athens, i) the Metaxourgeio area, where a considerable number of open, public places exists and ii) the densely populated area around the Attica Metro station (Figure 5.38). These two diverse geographical structures provide the opportunity for a wide range of NbS proposals according to the specific local characteristics. More precisely, in open public spaces, interventions like urban parks and community gardens can be designed, whereas in cases of densely spatially located buildings, green roofs and road verge interventions can be applied.

Figure 5.38 The worst areas of the seven districts of Athens, scoring more than 0.9 in the hotspot prioritization process.

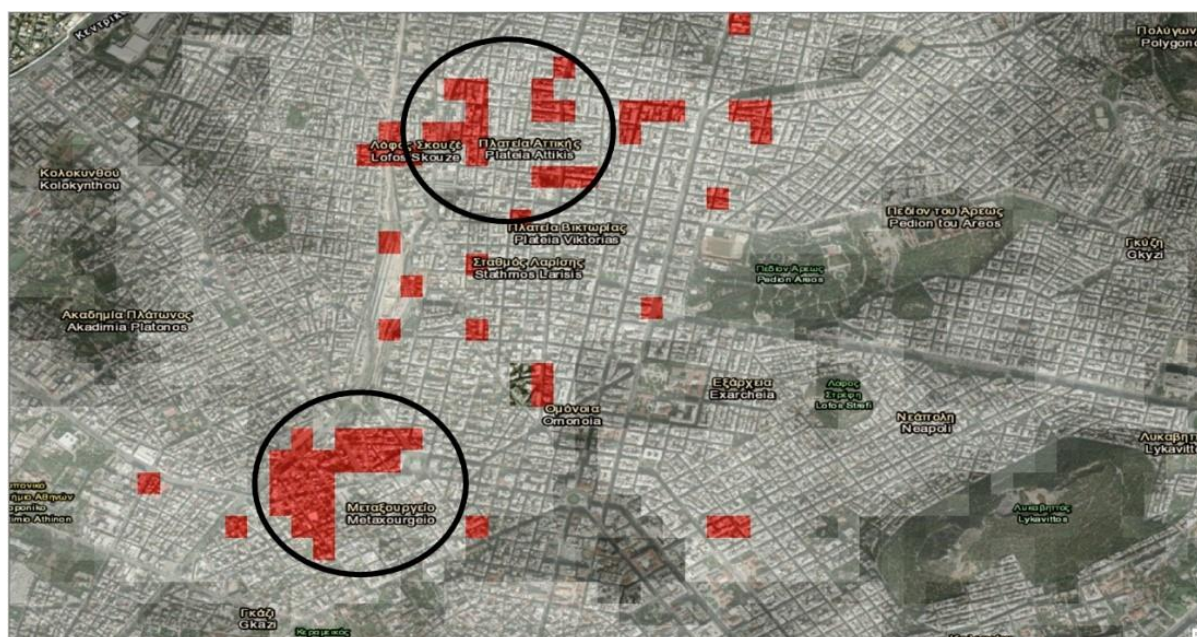
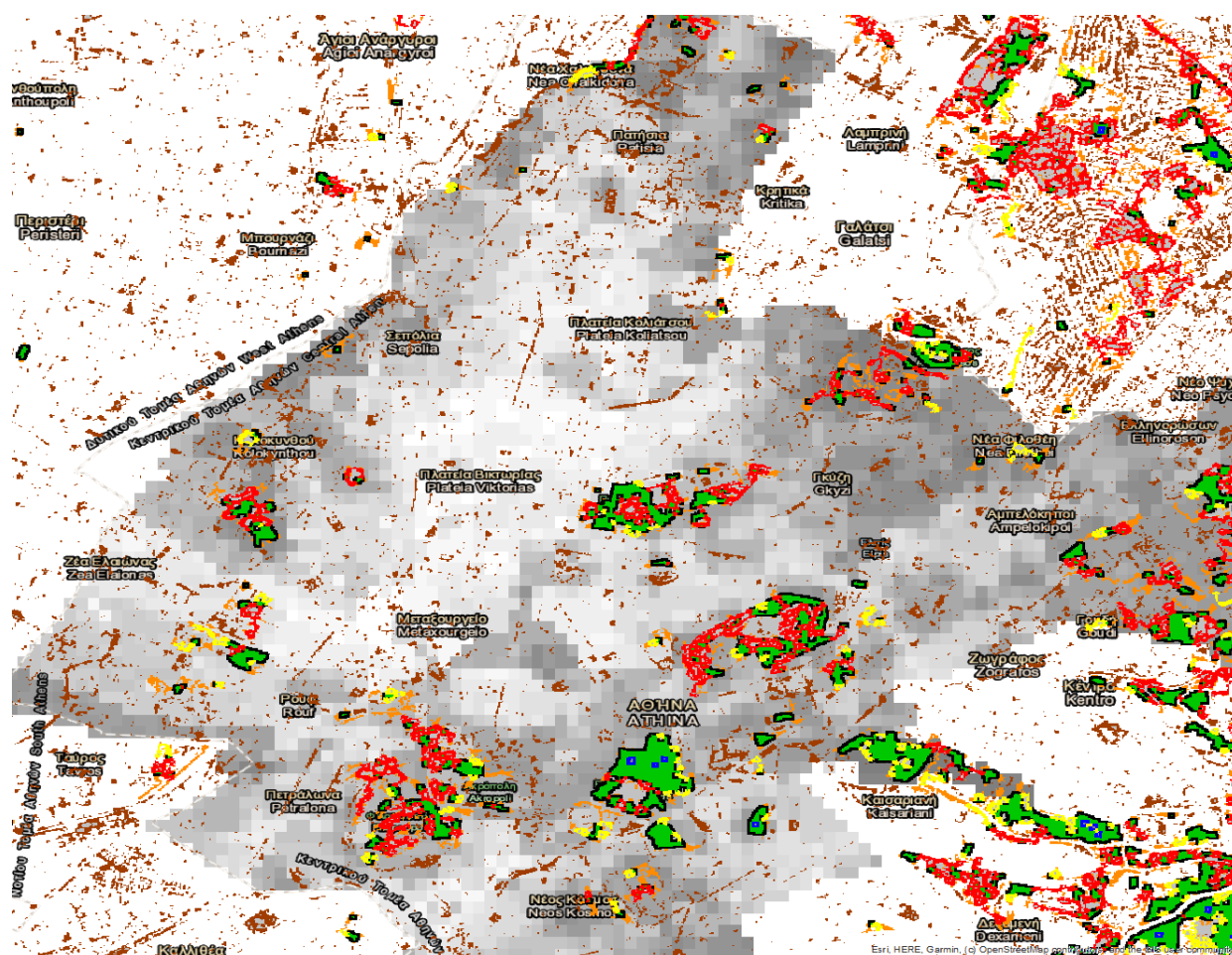
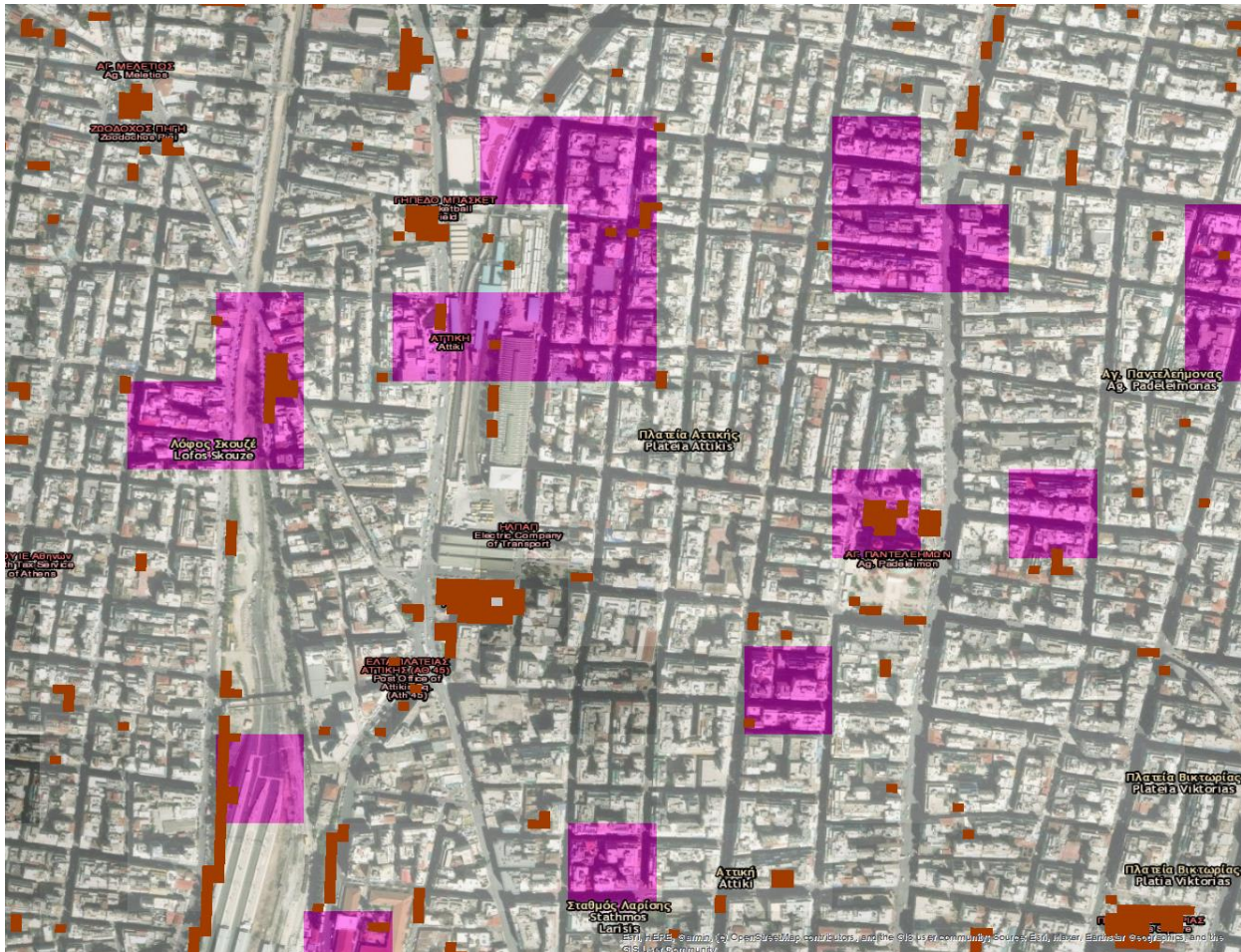


Figure 5.39 Connectivity map of the prioritized (based on the hotspot mapping) seven districts of Athens, where the structure of the vegetation patterns and the landscape fragmentation of the city is revealed through the different MSPA classes.



[illegible]

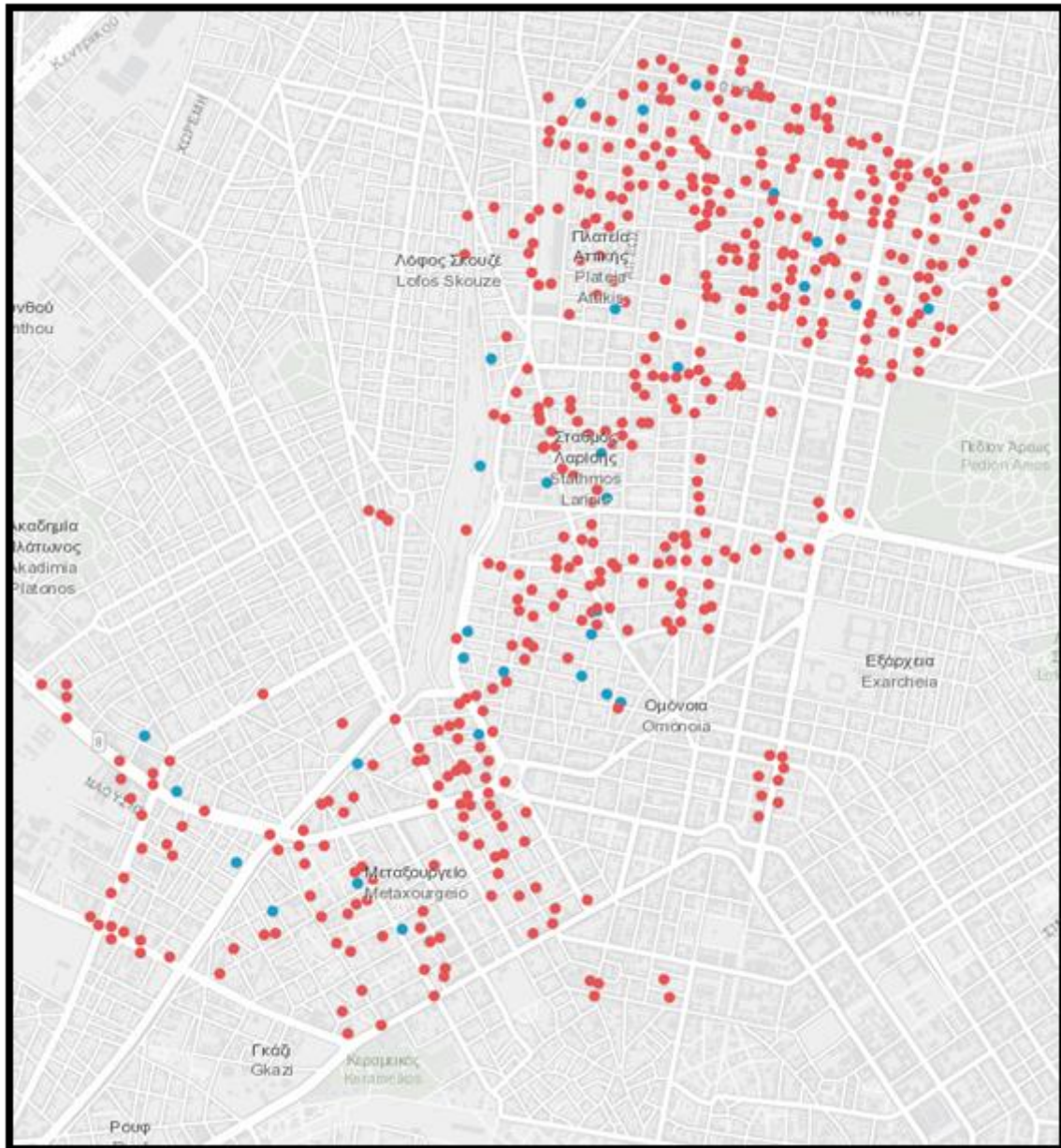
Figure 5.41 Connectivity map of the prioritized (based on the hotspot mapping) Attiki Metro station region, where according to the MSPA, only islets are observed. Purple pixels represent the highest scores (first cluster) of the multi-hazard assessment.



Yet, these unconnected group of pixels act as steppingstones at the landscape, thus their location in accordance with the geographical appointment of NbS is of high importance to achieve the most effective green infrastructures for the city addressing the multiple examined hazards (Wang et al., 2019).

Our contribution lies in identifying the specific points of interventions that will ensure, through NbS selected per case, the mitigation of all the recognized environmental and socio-economic hazards as well as the restoration of landscape connectivity. Thus, based on the combined outcomes of the hotspot mapping and the connectivity analysis, we delimited initially the entire area of intervention and then the specific points of interventions, based on the local characteristics (i.e., availability to apply NbS) (Figure 5.42). We identified 498 potential points of intervention, where NbS could be applied. After a thorough study of the specific points of intervention, we excluded 31 points due to issues concerning their property and the current status.

Figure 5.42 After the in-depth study of the availability of the high priority area, 498 points of intervention were identified. The red points (467 points) are the accepted points of interventions, where NbS will be proposed, taking into account the local characteristics of each point. The blue points are the rejected points of interventions, where NbS are not feasible due to the property status and the current situation of these points.



The next step includes the identification and proposal of specific NbS per point of intervention, that will be selected in accordance with the identified environmental and socio-economic hazards, but also aiming at enhancing landscape connectivity and improving the status of urban biodiversity in the city of Athens.

Following the proposal of NbS over the identified urban areas, microclimatic simulations (WRF) will be carried out so as to assess present climatic conditions. Next, NbS scenarios that are applicable and

reproducible by the regional WRF model will be investigated and compared against the control microclimatic simulations in order to validate the effect of the proposed interventions.

The impact assessment of NbS, as well as the combined methodology of integrating various environmental threats and socioeconomic challenges serves the vision of Athens expressed by the interested parties during the LL workshops. More precisely, the proposed and tested NbS will be designed to address, at least, two of the main problems in the city: the extreme heat and the lack of greenery (and biodiversity in general). NbS will constitute the tool that could be applied to transform Athens into a cooler, cleaner, and greener city through the use of green and blue infrastructures, but also the inclusion of and equity for all of its citizens by means of co-designing, involvement during the decision-making, monitoring and improvement of the applied NbS.

5.10 Urban Biodiversity Analysis

5.10.1 Main scope, objectives and participatory processes

Urban ecosystems, composed of a unique mosaic of natural and built environments, are home to a vast array of flora and fauna that contribute significantly to overall ecological health and human well-being. However, these ecosystems are often under considerable stress, facing threats such as habitat fragmentation, pollution, and climate change. The framework developed refers to an urban biodiversity analysis, through which patterns and underlying factors that affect biodiversity in cities are highlighted. The framework is adapted for the municipality of Athens, Greece, a city that is facing its own unique challenges in preserving biodiversity while accommodating urban growth. The analysis's granularity is at the zipcode level. The data incorporated in the analysis originates both from earth observation data and citizen science data, engaging local communities in data collection efforts.

5.10.2 Conceptual design and analysis processes

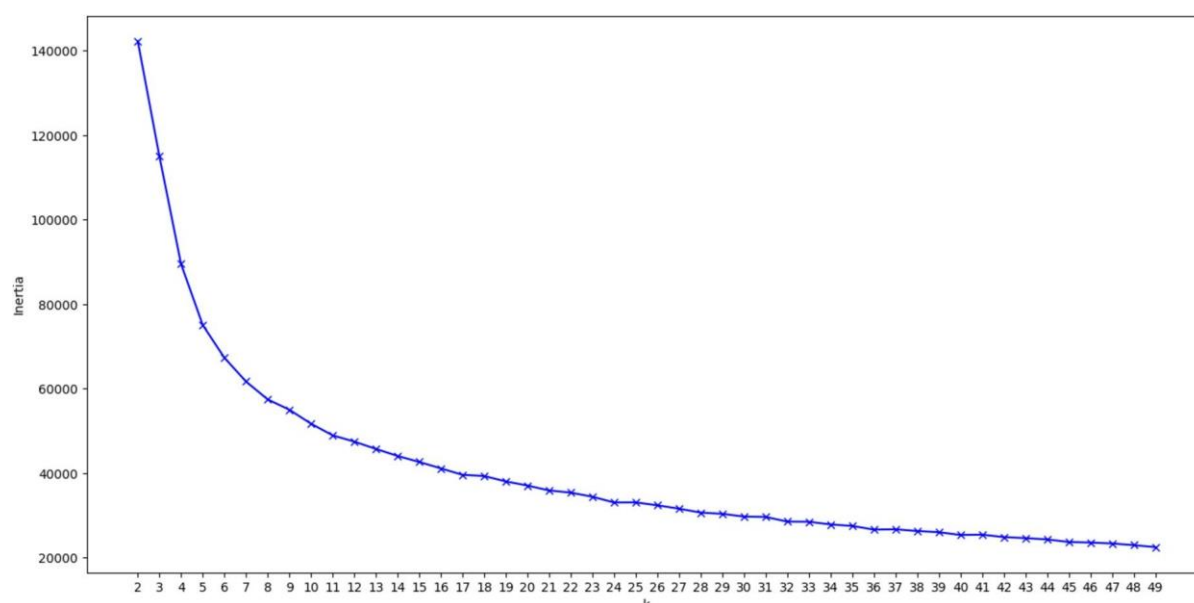
In order to classify urban habitats according to the characteristics they have in relevant variables that drive biodiversity in the city, the important features were extracted after data analysis. These features were used to identify which urban system properties are relevant to biodiversity, so they can be included by the city in a system that automatically classifies the city to habitats. For this purpose, K-means clustering was used, the unsupervised machine learning algorithm that creates clusters of neighboring points with similar features. A long list of variables was considered; in the Table A.7 in Appendix A, we list the features that were chosen: they include population density as well as residential and non-residential density, Urban Land Cover and imperviousness, vegetation, road network, tree coverage, noise level and some meteorological variables such as temperature, precipitation, etc. Data granularity was at zip code level; the dataset contained a total of 494 zip codes in the municipality of Athens. All data were obtained by remote-sensing open datasets, while the units, specific source and corresponding resolution for each variable is listed in the Table A.7 in Appendix A. All data was normalized using the following normalization function:

$$x_{norm} = \frac{(x - \mu)}{\sigma}$$

where x is the feature value, μ is the mean of the feature and σ is the standard deviation of the feature. The data of each layer was overlaid over the geospatial layer of neighborhoods of central Athens, Greece. The data points of each gridded layer were then translated to corresponding centroids and aggregated for each neighborhood of the case study region. For layers with a resolution that was too sparse to have a corresponding centroid in each neighborhood, for example the 1 km by 1 km layer of mean precipitation, each neighborhood was assigned the value of the nearest centroid. For polygon layers, such as the green areas from the Copernicus Urban Atlas 2018, the percentage of the overlapping polygons was used as the variable, or in the case of the noise maps, the percentage of the overlapping polygons was used in conjunction with the value of each noise polygon to assign an average noise value to each neighborhood.

The elbow method was used to decide the optimal number of clusters that the data should be divided into. Based on Figure 5.43 clustering was performed for 4, 5 and 6 clusters and the silhouette score (s) was calculated for each, in order to evaluate the separation distance between clusters and the cohesion of each cluster. Score s is a clustering efficiency metric that quantifies how close points are in the cluster; it ranges from -1 to 1, with a high positive value indicating that the object is well-matched to its own cluster and poorly matched to neighboring clusters. The silhouette score for the number of clusters being 4, 5 and 6 was calculated at 0.4, 0.406 and 0.407 respectively. Even though there is an improvement as the number of clusters is increased, the improvement is deemed marginal, and the optimal number of distinct clusters with satisfying clustering cohesion was decided at 4 clusters, which coincided with 4 distinct urban habitats.

Figure 5.43 Elbow method for finding the optimal number of clusters.



Citizen science data (biodiversity data) were collected from the Global Biodiversity Information Facility (GBIF, <https://www.gbif.org/en/>) portal, which includes 10,184 observations (1803 species) including a variety of taxa (e.g., birds, plants, insects, reptiles, mammals, gastropods, arachnids, fungi, etc.) reported between 2010 and 2023—the data set is open and available (GBIF 2023)—to detect biodiversity and species patterns across our study area. These observations were cross-mapped on the four different urban habitats identified through the clustering process.

5.10.3 Development status

Urban habitat typology

The categorization of urban habitats is based on remote sensing data that are related to the built environment and associated bio-physical characteristics, rather than species found in the cities. The species are mapped to validate the habitat typology that emerges from the data and clustering analysis. Following the clustering procedure, four distinct clusters were identified with different characteristics each. To further develop this into an urban habitat typology and identify what differentiates the clusters among them, we analysed the mean values of the features per zip code in each cluster. The mean values of the feature variables for each cluster are shown in Table 5.4., while a description of the clusters follows.

Table 5.4 Mean Values pf feature variables per zip code in each cluster

Feature variables	Low-residential	Urban green	Dense urban fabric	Urban arterials
Average noise level (db)	69.43	67.33	69.64	67.91
Number of trees per square meter (-)	0.003	0.003	0.004	0.004
Vegetation (NDVI)	0.108	0.222	0.083	0.092
Roads (%)	8.79	5.17	9.78	3.05
Water (%)	0	0.3	0	0
Residential density (%)	25.47	36.80	52.92	55.17
Residential height (m)	5.46	6.99	10.65	11.91
Non-residential density (%)	30.31	3.93	0.56	0.40
Non-residential height (m)	6.62	0.78	0.12	0.09
Population density (people/m ²)	0.014	0.010	0.030	0.034
Green area (%)	3.8	30.4	1.6	1.5
Imperviousness (%)	79.3	52.2	85.8	87.1
Mean precipitation (mm)	66.69	69.03	66.79	70.59
Maximum temperature (deg. C)	44.84	44.63	44.58	44.14
Mean temperature (deg. C)	29.71	29.17	29.60	29.09
Number of hot days (-)	13.15	12.09	11.31	10.32

Low-residential cluster

According to Table 5.4, Cluster 1 demonstrates significant non-residential density and building height, suggesting the concentration of commercial or industrial activities.

The corresponding low population density implies limited residential activity in these areas. The limited green space, potentially attributed to the spatial requirements of non-residential structures, aligns with the highest occurrence of hot days, possibly due to an urban heat island effect. Geographically, this cluster is located predominantly to the west. Based on these characteristics, we name Cluster 1 as the *“Low- Residential Cluster”*

Urban green cluster

Contrastingly, Cluster 2 is characterized by a high percentage of green areas and vegetation. This could indicate a balance between urban development and green space preservation, thus resulting in limited roads and water bodies. The cluster also displays low non-residential density and height, and reduced imperviousness, indicative of predominantly lowrise residential areas and efficient water management practices. Based on these characteristics, we name Cluster 2 as the *“Urban Green Cluster”*.

Dense urban fabric and urban arterials cluster

These two clusters share characteristics, namely high residential density and building height, suggesting densely populated residential areas. The reduced non-residential density and height imply a predominance of residential spaces over commercial or industrial establishments. The two clusters have a lot of similarities, but we see that one of them has a significantly higher road density, as it encompasses densely populated neighborhoods in Athens with relatively narrow streets and dense structuring— named *“Dense Urban Fabric.”* The other cluster has a lower road density as it includes some of the large arterials of Athens, thus it is termed *“Urban Arterials.”*

A data correlation analysis is also performed to explore correlations among features, shown in Figure 5.44. We see that Road density is highly correlated with Noise level, while green area percentage coincides with vegetation, as expected. The former also has a high negative correlation with imperviousness, which in turn is negatively correlated with vegetation. Precipitation results in cooler temperatures in the city, which explains the strong negative correlation of precipitation with mean and maximum temperature. The data correlation matrix verifies the quality of data, as all correlations are reasonable, while also shows that some urban features are highly related, as expected. All sixteen features are mapped separately for the municipality of Athens at a zip code level in Figure 5.45, while Figure 5.46 maps the four clusters as they were derived, without and with the species occurrence observations obtained by citizen scientists and found in GBIF.

Figure 5.44 Correlation plot of the variables used in the analysis.

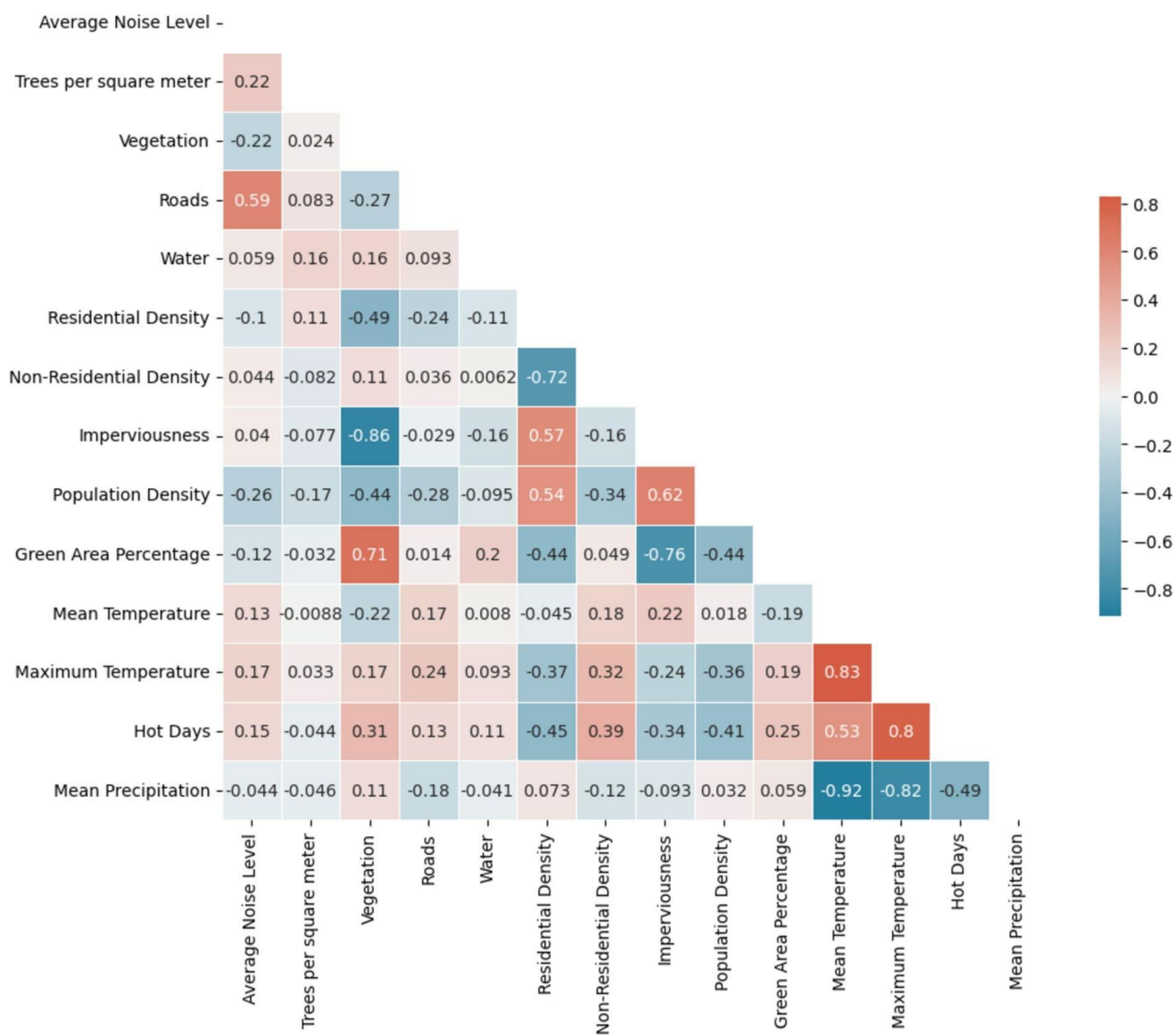


Figure 5.45 Values of sixteen features used for clustering analysis of Athens municipality.

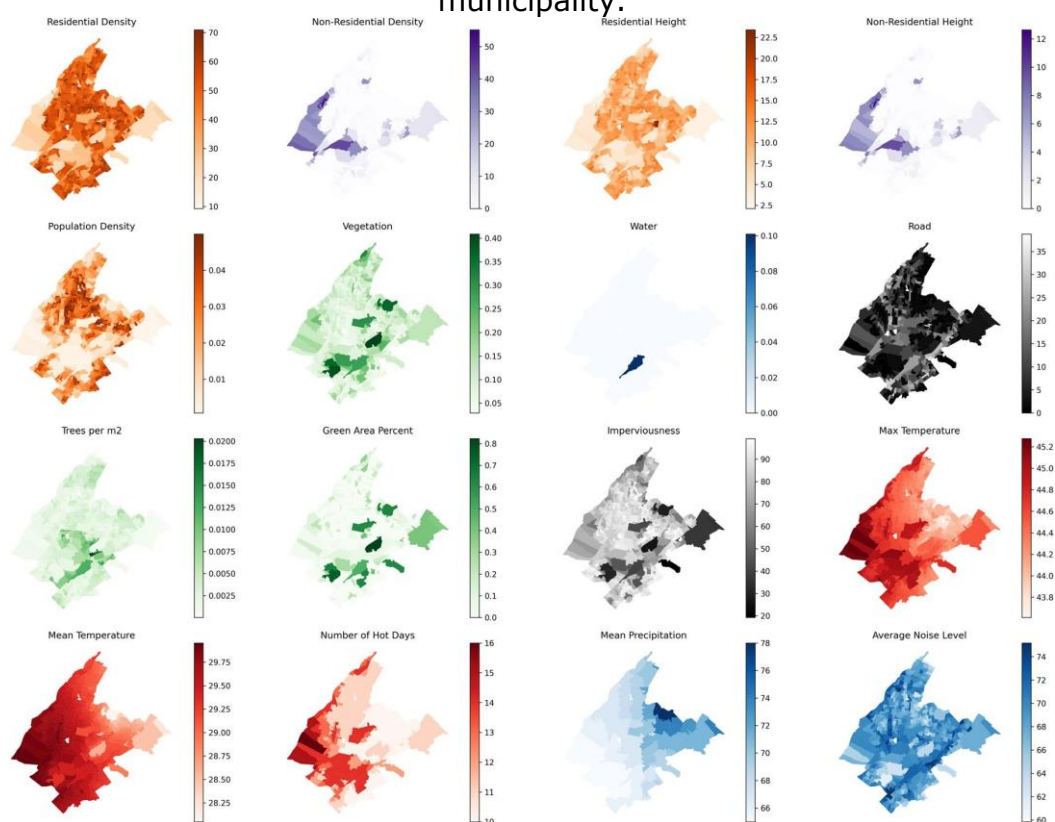
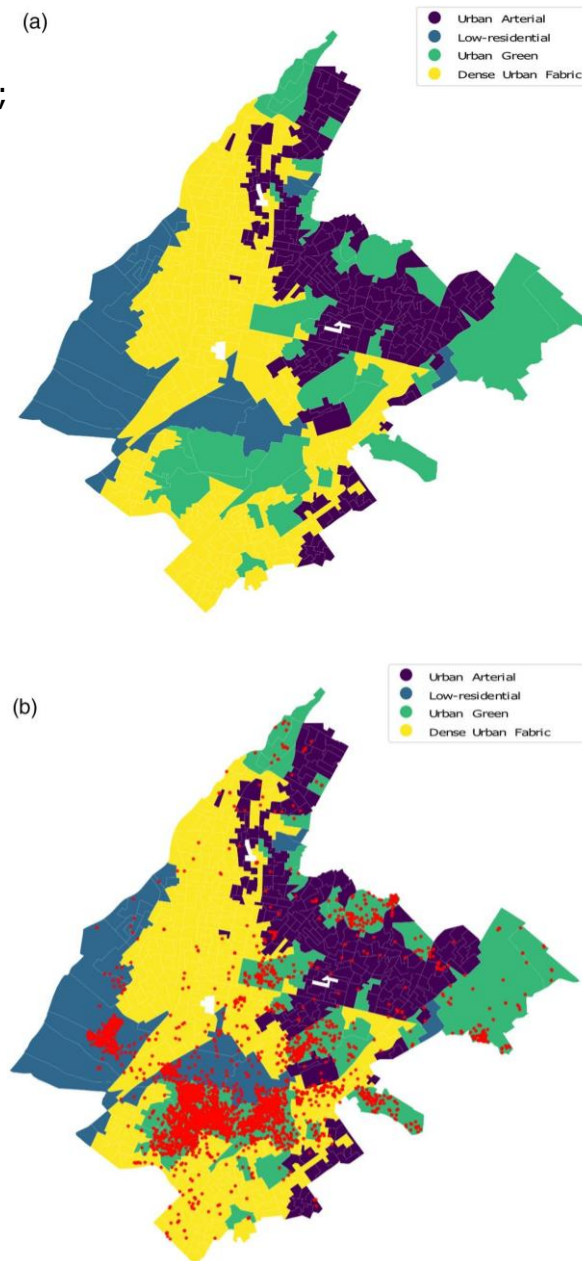


Figure 5.46 Athens (a)
clusters,
four urban habitats;
overlaid with GBIF
data (GBIF 2023)



municipality—four
corresponding to
b same as (a)
species occurrence

We further analyzed the results by conducting the Analysis of Variance (ANOVA) test to statistically validate the differences among the means of the clusters and to test the null hypothesis that the means are equal. This statistical method is particularly useful in our analysis as it allows for the simultaneous comparison of more than two groups or clusters, thus permitting the assessment of a multitude of urban characteristics for the different urban habitats across the city. Table 5.5 presents the sorted ANOVA scores for each characteristic within the clustered zip codes—larger ANOVA scores signify that the feature variable is important in cluster differentiation. These scores and corresponding p-values quantify the differences across clusters and test the statistical significance of these differences.

Table 5.5 ANOVA scores and associated p-values for all feature variables

Feature variables	ANOVA score	p-value
Non-residential density	6.89E + 02	2.81E-175
Non-residential height	6.78E + 02	5.47E-174
Maximum temperature	2.30E + 02	4.42E-93
Residential density	2.26E + 02	6.78E-92
Mean temperature	1.95E + 02	2.86E-83
Green area percentage	1.68E + 02	1.03E-74
Imperviousness	1.65E + 02	5.13E-74
Vegetation	1.50E + 02	4.89E-69
Mean precipitation	1.50E + 02	8.78E-69
Residential height	1.10E + 02	2.47E-54
Hot days	8.94E + 01	3.82E-46
Population density	6.30E + 01	1.81E-34
Roads	2.63E + 01	8.59E-16
Average noise level	2.54E + 01	2.89E-15
Water	4.46E + 00	4.18E-03
Street trees per square meter	1.94E + 00	1.22E-01

The top scoring characteristic is Non-Residential Density with an ANOVA score of 6.89E+02 and a corresponding p-value of zero demonstrates significant variation across clusters and rejects the null hypothesis of equal means. Similarly, Non-Residential Height, with an ANOVA score of 6.78E + 02 and a p-value of zero, shows significant differentiation across clusters. It is noteworthy that climatic attributes like Maximum Temperature and Mean Temperature also show statistically significant variations across the clusters, with p-values far below the conventional threshold of 0.05. The presence of significant variation in Green Area Percentage, Imperviousness, and Vegetation is indicative of the varied nature of land use across the clusters. On the other end of the spectrum, characteristics such as Water and Street trees per square meter show lower ANOVA scores, suggesting a more uniform distribution of these features across the city's habitats. Notably, Street trees per square meter has a p-value greater than 0.05 ($p = 0.12$), which does not reject the null hypothesis, indicating no significant difference in means across the clusters for this characteristic.

Species occurrence data

In Table 5.6, we see the mean number of species occurrence observations per zip code in each cluster, as they were downloaded from the GBIF platform for the period between 2010 and 2023. This is by no means meant to say that we have an exact record of biodiversity and species occurrence in Athens. The GBIF (2023) dataset is only what has been recorded by citizens throughout the years. It is very possible that species occur in other locations, and it has not been recorded by citizens. We only use this information as an indication of the biodiversity across the Athens zip codes. A general overview of the types of organisms that were spotted across Athens is shown in a Sankey diagram in Figure 5.48, in which species occurrence observations obtained

by citizen scientists through the GBIF platform are shown for kingdoms, phyla, and classes mapped to the 4 different urban habitat clusters. We see that the number of observations of plants and animals are about equally split, with the plants being dominated by tracheophyta and fungi being found at very small numbers. Animals are split into 3 phyla: arthropoda, chordata and mollusca, with chordata dominating. Overall, a low number of biodiversity observations are found in non-green areas, which cover the largest surface area of the city. When it comes to total number of observations, the Urban Arterials cluster is the one with the lowest number of observations.

Table 5.6 Mean number of observations per zip code in each cluster

Low-residential	Urban green	Urban arterials	Dense urban fabric
22.77	99.17	1.87	0.74

We also performed a species frequency analysis, which includes a species count statistical analysis that is shown in Table 5.7. In Table 5.8, we include a list of species and their corresponding observation counts in a frequency decreasing order, showing all species that had over 100 observations. This is a total of 3252 observations, about a third of the total number of observations in the data set. The corresponding frequency plot is shown in Figure 5.47, in which we see that the highest frequency is for species that appear only once, while a large number of species appear twice in the dataset. This is also supported by Table 5.7, in which we see that 25% and 50% of our data includes species that have only one or two observations, respectively, while 75% of the data include species that are observed up to 4 times. The highest number of observation counts for a single species is 301 and it is found for *Ceratonia siliqua* (Table 5.8).

Table 5.7 Statistics of species occurrence counts.

Count	1803
Mean	5.65
Std	16.35
25% of data	1
50% of data	2
75% of data	4
Max	301

Figure 5.47 Species occurrence frequency analysis—density plot.

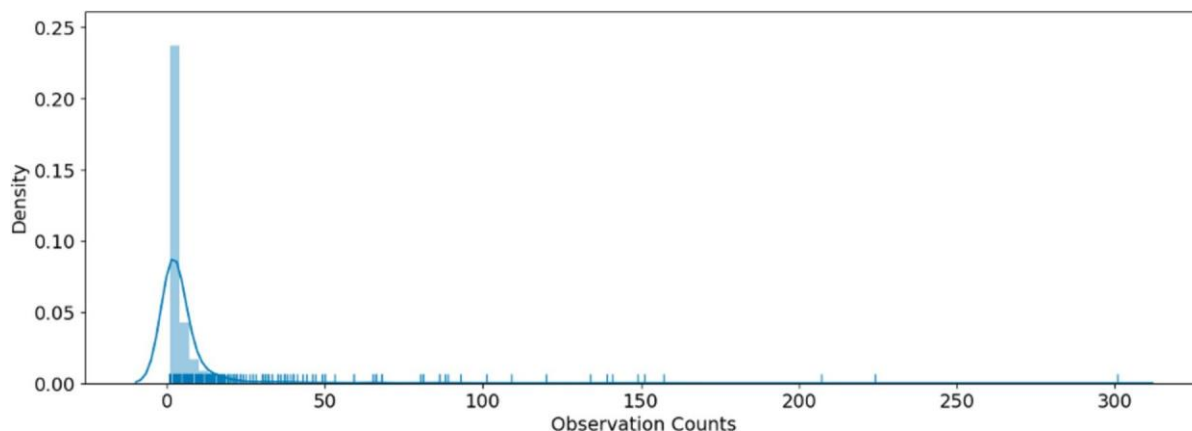
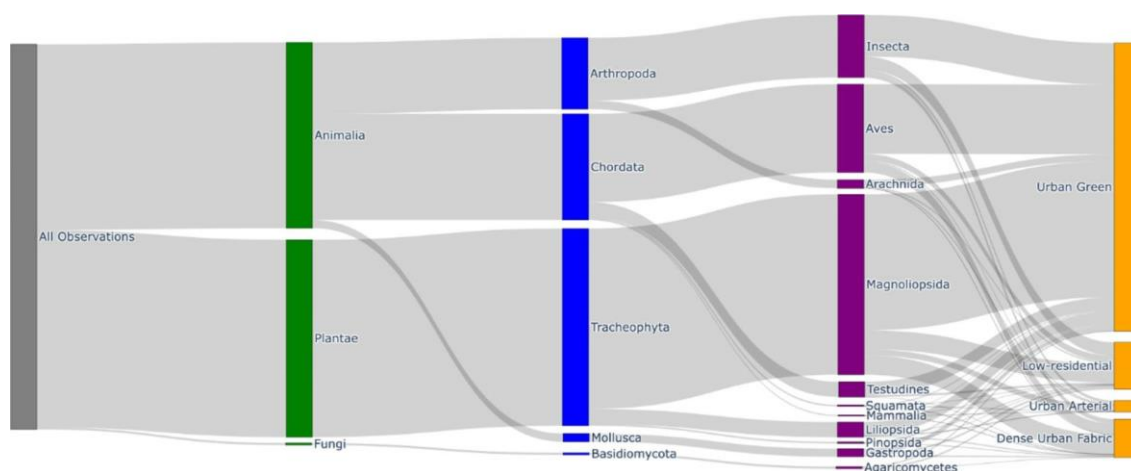


Table 5.8 Frequency of species occurrence.

Ceratonia siliqua	301
Testudo marginata	224
Medicago arborea	207
Streptopelia decaocto	157
Upupa epops	151
Nerium oleander	149
Parkinsonia aculeata	141
Pica pica	139
Solanum elaeagnifolium	134
Otus scops	120
Olea europaea	109
Pistacia lentiscus	101

Clustering results matched well the reality on the ground for Athens. A large number of observations (compared to the other clusters) are found in the “Urban Green” cluster, which is also where the National Garden is located in the center of the city and where the only zip code with a water body exists (see the “water” graph in Figure 5.45). Pockets of species observations can be found scattered in other locations that are characterized as belonging to the same cluster. The Urban Green cluster is indeed “Green”, since it has the highest percentage of green area and vegetation (Table 5.4) and has a critical amount of biodiversity observations (Table 5.6). No other cluster has as many observations as those of the Urban Green cluster. The Urban Arterials and Dense Urban Fabric cluster areas have a high degree of cementification and either large boulevards (Urban Arterials), or narrow streets and high buildings (Dense Urban Fabric), so they are expected to have fewer biodiversity observations and to have the conditions conducive for low species occurrence rates. A significant group of observations is found in the low-residential cluster, which is, at a first glance, surprising. The area includes the Athens Agricultural University that houses tree nurseries and other green parts. Furthermore, in this last cluster, the “Elaionas” district is found. According to the Athens Resiliency Strategy, this urban district is a post-industrial area that has a significant fraction of green open spaces (a result of a Presidential decree) distributed among the urban fabric, even though it is currently regulated to house various light industries. This justifies the existence of species occurrence observations in this low residential part of Athens.

Figure 5.48 Species occurrence observations obtained by citizen scientists through the GBIF platform: All species observations (grey color) are distinguished for kingdoms (green color), phyla (blue), and classes (purple) and they are cross-mapped to the four different urban habitat clusters (orange)



When comparing the number of observations in Athens with what is reported in the literature, e.g. for Los Angeles (LA) in the USA (Li E 2019), we see the following: The urban green area has the most observations in the urban environment (just like in Athens). The Urban Arterials area in Athens has about 50 times less observations than the Urban Green area, while the latter respective area in LA has only 6 times fewer observations. When the most developed areas in Athens and LA are compared (called Dense Urban Fabric in Athens), we see that it is only 4 times fewer in LA and about 100 times fewer than the Urban Green cluster in Athens. The Low-Residential area in Athens has 5 times fewer observations than the Urban Green, while in LA only 3 times fewer. We see that biodiversity in Athens outside the Urban Green cluster is very limited, but this is easily justified when the very limited percentage of green in the whole city is considered, which also exists in isolated patches and is not spread throughout the city. Green corridors, green roofs and continuity in green spaces would enhance biodiversity, but this is not the case in Athens with over 80% of its land being impervious and most open streams being covered. It is hard to compare LA and Athens, as LA has large surface areas, large lots, detached houses and is widely spread out in the urban space. On top of this, we need to consider that the observations that are listed herein are the ones captured by citizens. LA is a city that has run bioblitz events and challenges repeatedly (Los Angeles Public Library n.d.) and is expected to have large citizen engagement in capturing biodiversity occurrences via apps like the iNaturalist. For Athens, these events are relatively new, and the citizens are less accustomed to going out and taking part in such citizen science initiatives. A limited number of them are happening in the framework of research projects, mainly with school children, thus the number of citizen science observations is expected to be limited. Efforts should be directed towards creating links of citizens with the natural environment in the city, so they can enjoy the benefits of nature to society, but also to promote their ecological identities and the feeling of “One with Nature” for current and future generations (Laspidou 2023).

6.0 Conclusions

In conclusion, participatory design of socio-environmental systems is a challenging task that requires careful consideration of various factors. The challenges faced include issues related to stakeholder engagement, data availability, communication, and coordination. Overcoming these challenges requires a robust methodology that can support participatory modeling of socio-environmental systems. The methodology should be able to facilitate collaboration among stakeholders, integrate different types of data, and provide a platform for stakeholders to share their perspectives and insights.

The methodology proposed in this document aims to support participatory modeling of socio-environmental systems. It comprises of several steps, including scoping, stakeholder identification, and communication, which are referred to briefly in this report and dealt with in more detail in WP2 (Moujan, 2022), and data collection, model development, and validation, presented here to full extent. Each step is designed to address specific challenges and ensure that stakeholders are involved throughout the modeling process. The knowledge management infrastructure that is developed in the ARSINOE project is exploited in the various steps. The methodology has been applied for the development of socio-environmental models, and the provided feedback shows that it can effectively support participatory modeling of socio-environmental systems.

The participatory models presented in this document demonstrate the potential of the methodology to support participatory design of socio-environmental systems. The models cover different socio-environmental systems, including natural resource management, urban planning, and disaster risk reduction. The models showcase how stakeholders' inputs can improve the accuracy and relevance of the models, leading to better-informed decision-making. The participatory models can also help build trust and foster collaboration among stakeholders, leading to more sustainable and equitable socio-environmental systems.

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Appendix A

Appendix Table A.1 List of Indicators - Country level

Dimension	Sub-Dimension	Indicators	Effect
Social	Population	Projected population change ¹	+
		Number of refugees per 100,000 population ²	+
		Change in age-dependency ¹	+
	Population(Social Participation)	Children at-risk-of-poverty ¹	+
		Gender inequality index ³	+
		Domestic general government health expenditure as percentage of general government expenditure ⁴	-
	Health	Self-reported unmet need for medical care ¹	+
		Perceived good health ¹	-
Political	Quality of political system	Regulatory quality ⁵	-
		Control of corruption ⁵	-
	Government and political situation	Political stability ⁵	-
Economic	Financial resources	Gross national saving ⁵	-
		GDP per capita ¹	-
	Economic / Environmental	Climate related economic losses ¹	+
		Production, value added and exports in the environmental goods and services sector ¹	-
	Inequality	Income Inequality ¹	+
Environment	Environmental / Government	Environmental protection expenditure ¹	-
		Share of renewable energy in gross final energy consumption ¹	-
	Environmental	Common farmland bird index ¹	-
		Natura 2000 protected areas ¹	-

¹ Eurostat

² United Nations Economic Commission for Europe

³ United Nations Development Programme - Our World in Data

⁴ World Health Organization

⁵ The World Bank

		Water exploitation index ¹	+
		Marine waters affected by eutrophication ¹	+
		Generation of waste ¹	+

Appendix Table A.2 List of Indicators - NUTS2 level

Dimension	Sub-Dimension	Indicators	Effect
Social	Health	Life expectancy ¹	-
	Health / Access	Hospital beds per 100'000 population ¹	-
	Population (Education)	Less than primary, primary and lower secondary education (levels 0-2) ¹	+
		People with tertiary education (levels 5-8) ¹	-
Political	Government	Regional quality of government index ⁶	-
Economic	Financial resources	Household income ¹	-
	Inequality (Employment)	Employment rate ¹	-
	Access	Motorways ¹	-
		Railways ¹	-
Environment	Environmental	Land cover for FAO forest ¹	-

Appendix Table A.31 List of Indicators - NUTS3 Urban level

Dimension	Sub-Dimension	Indicators	Effect
Social	Population	Population density ¹	+
		Net migration ¹	+
		Young dependency ¹	+
		Old dependency ¹	+
Economic	Financial resources	NUTS3 GDP per capita vs country average ¹	-
		Gross value added (at basic prices) ¹	-
	Environmental	Cooling degree days ¹	+
		Heating degree days ¹	+
Environment	Environmental	Tree cover density ⁷	-
		Urban area classified as green space ⁷	-
		Urban land cover ⁷	+

⁶ [The QoG Institute](#)

⁷ [Copernicus](#)

		Air pollution ⁸	+
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Appendix Table A.42 List of Indicators - NUTS3 Rural level

Dimension	Sub-Dimension	Indicators	Effect
Social	Population	Population density ¹	+
		Net migration ¹	+
		Young dependency ¹	+
		Old dependency ¹	+
Economic	Financial resources	NUTS3 GDP per capita vs country average ¹	-
		Gross value added (at basic prices) ¹	-
Environment	Environmental	Tree cover density ⁷	-
		Number of days with high fire danger ⁷	+
		Soil erosion ¹	+
		Population weighted air pollution ⁸	+

Appendix Table A.53 List of Indicators - FUA level

Dimension	Sub-Dimension	Indicators	Effect
Social	Population	Population density ⁹	+
		Youth dependency ratio ¹⁰	+
		Elderly dependency ratio ¹⁰	+
Economic	Financial resources	Gross domestic product per capita ¹⁰	-
	Environmental	Heating degree days ¹⁰	+
		Cooling degree days ¹⁰	+
	Inequality (Employment)	Unemployment rate ¹⁰	+
Environment	Environmental	Air pollution in PM2 ¹⁰	+
		Built-up area ⁹	+
		Green and blue areas ⁷	-

Appendix Table A.64 List of Indicators - City level

Dimension	Sub-Dimension	Indicators	Effect
Social	Living conditions	Number of people in accommodation for the homeless ¹	+
		Number of murders and violent deaths ¹	+

⁸ [European Environment Agency](#)

⁹ [Global Human Settlement Layer](#)

¹⁰ [Organisation for Economic Co-operation and Development](#)

	Population	Population Density ¹	+
		Old-age dependency ¹	+
		Young-age dependency ¹	+
	Education	Proportion of population aged 25-64 qualified at level 5 to 8 ISCED, from 2014 onwards ¹	-
		Share of students in higher education in the total population (per 1000 persons) ¹	-
		Share of early leavers from education and training, total -% ¹	+
	Health / Access	Share of population connected to potable drinking water system - % ¹	-
		Share of population connected to sewerage treatment system - % ¹	-
	Transport / Access	People killed in road accidents per 10000 pop. ¹	+
		Average time of journey to work - minutes ¹	+
		Share of journeys to work by car or motorcycle -% ¹	+
		Share of journeys to work by public transport (rail, metro, bus, tram) -% ¹	-
		Length of bicycle network (dedicated cycle paths and lanes) - km ¹	-
Economic	Inequality (Employment)	Unemployment rate ¹	+
	Environment	Share of the urban waste water load (in population equivalents) treated according to the applicable standard % ¹	-
		Price of a m ³ of domestic water ¹	+
Environment	Environmental	Municipal waste generated (domestic and commercial), total - 1000 t ¹	+
		Number of days particulate matter PM10 concentrations exceed 50 µg/m ³¹	+
		Green and blue areas ⁷	-
		Street tree density ⁷	-
		Built-up area ⁹	+

Appendix Table A.7 Features chosen for urban habitat cluster analysis

Feature variable	Units	Source	Resolution
Residential density—the percentage of land that is residential	%	GHSL—Global Human Settlement Layer—Built up characteristics 2018 https://doi.org/10.2905/3C60DDF6-0586-4190-854B-F6AA0EDC2A30	10m × 10m grid
Non-Residential density—the percentage of land that is non-residential	%	GHSL—Global Human Settlement Layer—Built up characteristics 2018 https://doi.org/10.2905/3C60DDF6-0586-4190-854B-F6AA0EDC2A30	10m × 10m grid
Residential height: the average height of residential buildings in the area	m	GHSL—Global Human Settlement Layer—Built up characteristics 2018 https://doi.org/10.2905/3C60DDF6-0586-4190-854B-F6AA0EDC2A30	10m × 10m grid
Non-residential height: the average height of non-residential buildings in the area	m	GHSL—Global Human Settlement Layer—Built up characteristics 2018 https://doi.org/10.2905/3C60DDF6-0586-4190-854B-F6AA0EDC2A30	10m × 10m grid
Population density: the population density of the area	People/m ²	GHSL—Global Human Settlement Layer—Population Grid 2020 https://doi.org/10.2905/2FF68A52-5B5B-4A22-8F40-C41DA8332CFE	10m × 10m grid
Vegetation: the vegetation of the area	NDVI	GHSL—Global Human Settlement Layer—Built up characteristics 2018 https://doi.org/10.2905/3C60DDF6-0586-4190-854B-F6AA0EDC2A30	10m × 10m grid
Water: percentage of land as surface water	%	GHSL—Global Human Settlement Layer—Built up characteristics 2018 https://doi.org/10.2905/3C60DDF6-0586-4190-854B-F6AA0EDC2A30	10m × 10m grid
Roads: percentage of land as roads	%	GHSL—Global Human Settlement Layer—Built up characteristics 2018 https://doi.org/10.2905/3C60DDF6-0586-4190-854B-F6AA0EDC2A30	10m × 10m grid
Street trees per square meter	Number of street trees	Copernicus Urban Atlas— Street Tree Layer 2018 https://land.copernicus.eu/local/urban-atlas/street-tree-layer-stl-2018	Polygon layer
Hot days: number of days with temperatures above 38 degrees Celsius in one summer	Days	Copernicus—Climate variables for cities in Europe—2017 https://doi.org/10.24381/cds.c6459d3a	100m × 100m grid
Mean precipitation: the mean precipitation of the area	mm	WorldClim 2—1 km spatial resolution climate surfaces for global land areas— https://www.worldclim.org/data/worldclim21.html	1000m × 1000m grid
Average noise level: the average noise level of the area	Decibel	Ministry of Environment and Energy— https://ypen.gov.gr/	Polygon layer
Geospatial layer of neighborhoods of central Athens	N/A	Hellenic Statistical Authority— https://www.statistics.gr/en/home/	Polygon layer

Systems Innovation Approach (SIA) addresses the growing complexity, interdependencies and interconnectedness of modern societies and economies, focusing on the functions of the cross-sectoral system as a whole and on the variety of actors. The Climate Innovation Window (CIW) is the EU reference innovations marketplace for climate adaptation technologies. ARSINOE shapes the pathways to resilience by bringing together SIA and CIW, to build an ecosystem for climate change adaptation solutions. Within the ARSINOE ecosystem, pathways to solutions are co-created and co-designed by stakeholders, who can then select either existing CIW technologies, or technologies by new providers (or a combination) to form an innovation package. This package may be designed for implementation to a specific region, but its building blocks are transferable and re-usable; they can be re-adapted and updated. In this way, the user (region) gets an innovation package consisting of validated technologies (expanding the market for CIW); new technologies implemented in the specific local innovation package get the opportunity to be validated and become CIW members, while the society (citizens, stakeholders) benefits as a whole. ARSINOE applies a three-tier, approach: (a) using SIA it integrates multi-faceted technological, digital, business, governance and environmental aspects with social innovation for the development of adaptation pathways to climate change for specific regions; (b) it links with CIW to form innovation packages by matching innovators with end-users/regions; (c) it fosters the ecosystem sustainability and growth with cross-fertilization and replication across regions and scales, at European level and beyond, using specific business models, exploitation and outreach actions. The ARSINOE approach is show-cased in nine widely varied demonstrators, as a proof-of-concept with regards to its applicability, replicability, potential and efficacy.



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