AI for Global Challenges: Case Studies in Urban Solar Exposure and Wildfire Management

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***Abstract*—Climate change poses significant challenges to environmental sustainability and human well-being, necessitating advanced tools for effective mitigation and adaptation strategies. Traditional methods for addressing issues like urban solar exposure and wildfire management often fall short due to limited predictive capabilities and inefficiencies in processing large-scale data. This paper addresses these gaps by employing Artificial Intelligence (AI) and High-Performance Data Analytics (HPDA) to enhance predictive accuracy and data handling in two critical areas: predicting shading effects between buildings for sustainable urban planning, and improving wildfire management through precomputed simulations. Our approach utilizes neural networks to model urban shading accurately and leverages HPDA to process extensive wildfire data for better preventive measures and response strategies. The main conclusion is that integrating AI and HPDA significantly enhances our ability to tackle complex climate-related challenges, providing valuable insights and tools for policymakers and urban planners.**

***Keywords*-AI; HPDA; Global Challenges; Urban Solar Exposure; Wildfire Management**

I. Introduction

Climate change is a significant global challenge that impacts many aspects of human life and environmental health. It's evident in the increasing alterations in climate patterns across the world, affecting human health, safety, and environmental sustainability and necessitating prompt and innovative actions. The World Health Organization indicates that nearly all people globally are exposed to air quality levels that exceed safety standards, leading to about seven million deaths annually from outdoor air pollution [1]. Notably, vehicle emissions, which contribute significantly to air pollution with substances like nitrogen dioxide, account for over 40% of some harmful emissions from traffic, underscoring the need for policy and technological improvements [2][3].

The need to address global challenges is further underscored by the inefficiencies within the European Union's building sector, responsible for a substantial portion of energy use and greenhouse gas emissions. Approximately 75% of the EU's building stock is deemed energy-inefficient, presenting a critical opportunity to enhance energy performance in line with the goals of the European Green Deal [4]. Additionally, the ongoing dependence on fossil fuels intensifies these challenges, pressing the shift towards renewable energy sources like wind and solar power, which is especially crucial amidst the recent geopolitical tensions in Eastern Europe.

Moreover, global challenges extend to natural disasters, with an alarming increase in the frequency and severity of events such as wildfires and floods. Wildfires are particularly concerning, not only due to direct exposure but also because of the extensive reach of smoke pollution, which can have profound health implications on vulnerable populations across vast distances. Similarly, floods have emerged as the most frequent natural disaster, with significant human and economic losses. Modeling these phenomena numerically is an immensely complex and computationally intensive task. Computational Fluid Dynamics (CFD) [5][6][7] models, which rely on detailed three-dimensional grids and the calculations of movement within small cells, are employed. These models are highly parallelizable and scalable, making them well-suited for application on HPC architectures [8]. Despite the technological advancements, using these simulations operationally on HPC systems presents considerable challenges, including data capture, pre-processing, and computation, which can take several hours even on the most advanced systems.

This paper explores how advancements in Artificial Intelligence (AI) and High-Performance Data Analytics (HPDA) could serve as crucial tools in addressing global challenges.

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More specifically, we examine how HPDA and AI can be successfully applied to two distinct use cases: assessing solar exposure in urban buildings and mitigating wildfire evolution. We will discuss how these technologies can help address related issues and provide viable solutions.

This paper is organized as follows: Section II reviews the related work. Section III introduces the formulation of the two problems investigated in this paper, namely solar exposure and wildfire management. Section IV presents the experimental results for these two use cases. Finally, Section V summarizes the conclusions of this study.

II. Related work | Methods

Artificial Intelligence (AI) has increasingly been employed to address various environmental challenges, including pollution control and renewable energy optimization. Ye et al. [9] conducted a comprehensive survey analyzing AI applications in environmental pollution control, highlighting the role of machine learning models in monitoring and predicting pollution levels. Kumar et al. [10] explored AI techniques in solar power analysis, focusing on the optimization and control of photovoltaic systems. In urban settings, AI technologies have been utilized to monitor air pollution levels, identify sources, and develop mitigation strategies [11], while machine learning models have been applied to predict future pollution trends based on historical data [12].

Despite these advancements, gaps remain in applying AI to predict urban shading effects, where traditional methods often rely on computationally intensive simulations that fail to scale or capture complex interactions effectively, hindering sustainable urban planning.

In wildfire management, traditional methods, dependent on historical and empirical data, lack the necessary spatial and temporal resolution for accurate forecasts, leading to outdated and non-responsive models [13]. Integration challenges with diverse data sources, such as weather indices and vegetation moisture levels, persist, reducing model adaptability [14]. Leveraging AI to enhance data processing and utilize real-time environmental data [15] has shown promise in improving decision-making accuracy [16][17], but computational constraints remain a significant hurdle.

The wish-list in both domains includes developing AI models capable of handling complex, large-scale data efficiently and providing accurate, real-time predictions to inform decision-making processes. Our contribution addresses these gaps by employing neural networks to predict urban shading effects, facilitating sustainable urban planning, and utilizing pre-computed wildfire simulations processed through HPDA to enhance wildfire management strategies. This approach aims to overcome current limitations by improving scalability, accuracy, and responsiveness in tackling climate-related challenges.

III. Problem Formulation

This section outlines the problem formulation for the addressed problems.

A. Solar exposure

In this use case, we investigate the dynamic interplay between urban development and solar exposure. Specifically, the focus is on understanding how shading from surrounding buildings influences the solar energy received by a target construction. Such shading effects can significantly alter temperature, humidity, and incident light levels within an area. The primary objective here is to quantify how new constructions modify solar intake and create solar masks that affect the surrounding environment. This analysis is crucial for urban planning and sustainability efforts, ensuring that new developments harmonize with their natural and built environments to optimize energy efficiency and living conditions. HPC plays a crucial role in this task, as this analysis will be conducted on a pre-calculated set of simulations of solar masks for an area before and after new construction.

B. Wildfire Management

In this use case, we explore the integration of High-Performance Computing (HPC) and Artificial Intelligence (AI) in managing severe forest fires. Simulating fires based on real-time field data is crucial for informed responses. To achieve this, we utilize a set of pre-calculated fires, employing CFD models that consider various scenarios, such as ignition points, wind speed, direction, and moisture conditions of forest fuels. These simulations could be invaluable in both designing strategies to identify vulnerable points by analyzing simulations and responding to new fires. Since simulating a new fire in real-time is impractical, we reformulate this problem as a search through a vast database of pre-computed fire simulations. Specifically, when a real-world fire is detected, its characteristics—captured through satellite or aerial imagery—are input into an AI engine that conducts a shape similarity analysis with stored simulations. This process is essential for rapidly identifying the most relevant simulations that match the current fire conditions. If no suitable matches are found, the system must swiftly compute and integrate a new simulation to aid firefighting efforts.

IV. Results

This section details findings for each problem investigated.

A. Solar exposure

To tackle the use case of predicting shading relationships between buildings, a neural network is trained using a custom dataset corresponding to the building topology of a section of Strasbourg. The dataset consists of 1,343 samples of buildings and their solar masks, accompanied by the solar masks of affected surrounding buildings which are computed in the absence of that particular building. These masks only include values that change due to the building's absence or presence. The neural network's training focuses on how solar masks evolve when new buildings are introduced, though current experiments do not consider additional factors like vegetation.

In order to predict shading relationships between buildings in a cityscape, a graph is constructed where nodes represent buildings and edges represent shading interactions. The graph

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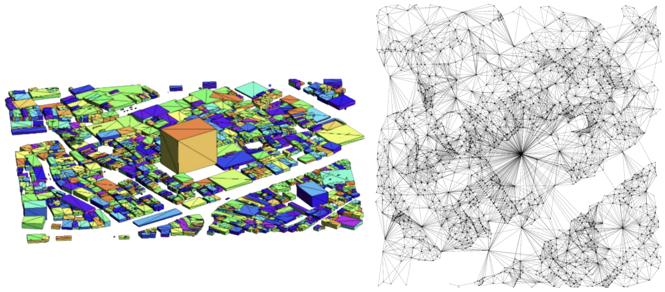

Figure 1. The affected buildings network using the proposed threshold on solar mask difference between buildings.

focuses on visualizing the topological arrangement of buildings, highlighting how they are interconnected based on their proximity and the shading they cast on each other.

The graph, termed the "affected buildings network" (Figure 1), is constructed by connecting buildings only if the removal of one affects the solar mask of another. This network can be either directed, with edges pointing toward affected buildings, or undirected. Initial observations showed that the network was dense, with edges even between distant buildings. This unexpected density was due to small changes in solar masks during dataset creation. To refine the network, a threshold was introduced: an edge is only created if the difference in solar masks, measured by the mean squared error before and after a building's deletion, is greater than or equal to 0.01, resulting in a more realistic depiction of the network.

After the creation of this graph, a transductive link prediction approach is employed to predict which structures each building shades. Link prediction involves inferring missing or potential edges between nodes in a graph. In the transductive approach, some edges are removed before training. The neural network is trained on the incomplete graph to learn patterns, and after training, it attempts to rediscover the removed edges, predicting which buildings shade each other.

The methodology employed in this study can be summarized as follows:

- **Data Preparation:** A portion of existing edges is removed while retaining all nodes (buildings). The remaining graph is then fed into a Graph Neural Network (GNN) for training.
- **Model Architecture:** A two-layer Graph Convolutional Network (GCN [18]) is utilized to encode the graph's nodes through message passing [19]. The decoder component, which performs binary classification to determine the existence of an edge between two nodes, is treated as a hyperparameter.
- **Experimental Settings:** Various experimental settings are explored, including:
  – The structure of the graph: directed vs. undirected.
  – The type of classifier: Simple Dot Product vs. Multi-Layer Perceptron (MLP).
  – Node features: Building location vs. building height.
  – The threshold on solar mask difference.

Table I reports the Area Under the Curve (AUC) for transductive Link Prediction on the affected buildings network from the initial set of experiments. This metric, commonly used in the field, measures edge classification performance. A higher ROC AUC score indicates better model performance, with a value of 1.0 representing perfect classification and 0.5 indicating a performance no better than random guessing. The table compares outcomes from two configurations: one using a threshold for solar masks and one without, allowing for a direct evaluation. Higher ROC AUC scores indicate better performance, with bolded percentages highlighting the top results in each configuration.

The initial experiments with GNN models show strong performance, with most configurations achieving high AUC scores (over 70%) even before full optimization. Early trends suggest that building location is a particularly useful feature, and undirected graphs generally perform better. Although cases with thresholded solar masks yield slightly lower AUC scores, they show better alignment with proximity, indicating promising potential for predicting affected buildings. Further optimization of the GNNs will be pursued to refine these results.

B. *Wildfires*

The core idea behind this use case is the use of a dataset of precalculated simulations for a specific area, under different scenarios. Specifically, this dataset centers on a 3x3 km² Wildland-Urban Interface (WUI) area in Barcelona, featuring detailed geospatial data such as Digital Terrain Models and fuel models, primarily derived from LiDAR data with 2-meter resolution. The dataset includes wind simulations for eight directions and three speeds, and 441 systematically placed initial ignition points for wildfire scenarios, culminating in a total of 10,584 simulations.

By analyzing the dataset, useful information can be extracted for informed decision-making, both in designing preventative measures against massive wildfires and in responding to new fires. For prevention, one can utilize metrics like **Burn Probability** (BP), calculated as:

$$BP = 100 \times \frac{NF}{NS} \tag{1}$$

Here, BP is the Burn Probability in percentage, NF represents the number of times fire passes through a specific point, and NS is the total number of ensemble simulations. This BP index, along with data on buildings, roads, and other vulnerable infrastructures in the area, helps assess the probability of adverse impacts. This assessment can be visualized on a risk map, as shown in Figure 2.

To make informed decisions during a new fire, it is essential to predict the fire's evolution in real time. However, conducting a new simulation under real-time conditions is unfeasible. Therefore, we propose an algorithm that employs a search mechanism on a dataset of pre-calculated simulations. Based on this dataset, the algorithm for real-time fire behavior projection is illustrated in Algorithm 3.

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TABLE I. TEST AUC RESULTS FOR LINK PREDICTION (SURROUNDING AFFECTED BUILDING DISCOVERY) USING DIFFERENT HYPERPARAMETERS.

	Test AUC		Test AUC (with threshold)	
	Height	Location	Height	Location
Undirected Graph + Simple Classifier	**79.2**	**80.9**	**71.3**	71.6
Directed Graph + Simple Classifier	77.0	74.4	69.8	64.9
Undirected Graph + MLP Classifier	74.6	75.1	65.9	**78.4**
Directed Graph + MLP Classifier	71.6	74.9	55.6	77.5

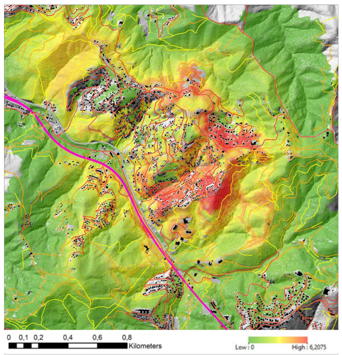

Figure 2. An example of Burn Probability (%), visualized on a map. The areas in red indicate a higher likelihood of fire spread.

Algorithm 1 Real-Time Fire Behavior Projection

Input: Fire front position captured at a specific time using satellite-borne sensors (e.g., MODIS, SUOMI, etc.)[23].
Output: Projected fire behavior based on the closest matching simulation, or a suggestion to perform a new simulation if no match is found.

Step 1: Extract the shape of the current fire front from the active (burning) areas.
Step 2: Calculate the shape descriptors for the given time.
Step 3: Consider other variables for the analysis: wind speed, wind direction, and coordinates of the point of origin (if known).
Step 4: Apply a search and discovery algorithm to a large database of simulations. The same shape descriptors and other variables are used as indexes.
Step 5: Run similarity routines to extract simulations that are closest to the observed fire front at the given time.
Step 6: Use the extracted pre-calculated simulations to project the expected fire behavior.
Step 7: If no similar simulation is found, the system suggests performing a new simulation and adding it to the database for future use.

Figure 3. The algorithm for the real-time fire behaviour prediction.

To perform similarity analysis (Steps 4 and 5), the following method is suggested for deriving basic descriptors of fire spread shapes: Extract the relevant contour from the 2D grid of the simulation, which captures fire access time at a specific point [20]. Determine the center of gravity and calculate the oriented minimum bounding box using the rotating calipers method. Identify the shape's major and minor axes, termed Length and Width, and ascertain the orientation of the major axis to indicate fire propagation direction. Finally, compute the eccentricity

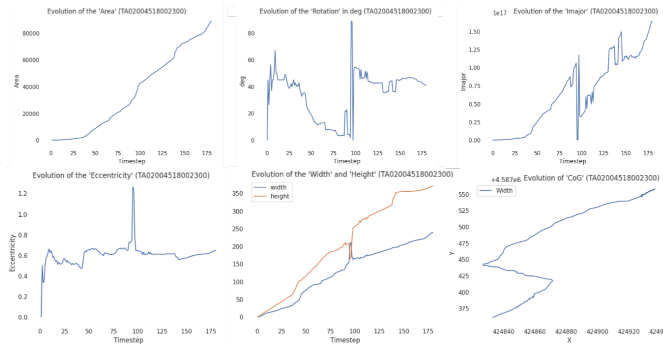

Figure 4. Illustrates the evolution of the six features: "Area," "Rotation," "Imajor," "Eccentricity," "Width," "Height," and "Center of Gravity of the contour" for each timestep.

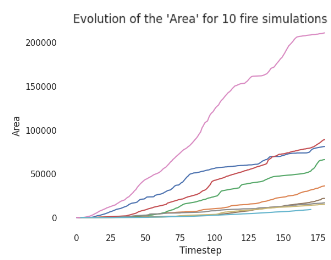

Figure 5. The evolution of the "Area" feature across ten different forest fires.

(length-to-width ratio) and the moment of inertia relative to the major axis. Additional shape descriptors proposed for use in similarity analysis include the total area enclosed by the shape, the total length of the shape's perimeter, its eccentricity, orientation angle, and moment of inertia.

Figures 4 illustrate the evolution of features during a single fire, aimed at evaluating the effectiveness of handcrafted features in capturing fire progression. Figure 5 depicts the "Area" feature across 10 different fire simulations, revealing varying rates of fire spread—some expand rapidly, while others progress more slowly. This comparison highlights the diverse behaviors of wildfires under different conditions.

The distinct trajectories of handcrafted shape descriptors across these fires demonstrate that each fire follows a unique path. While this uniqueness aids in identifying a fire's progression based on these features, it complicates locating similar fire simulations for new fires. To further explore this uniqueness,

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Principal Component Analysis (PCA) was applied to reduce the dimensionality of the fire data for visualization. Figure 6 shows the PCA results: the left panel displays PCA features color-coded by fire simulation filenames, while the right panel color-codes them by the timestep from which each vector was extracted. The fire data follows a consistent linear trajectory, indicating close relationships between features at each timestep. However, the lower and central parts of the diagram reveal a distinct cluster of blue points at timestep zero (as shown in the right panel where blue points correspond to the positions at timestep zero), seemingly unrelated to the rest of the fire's evolution. This poses a challenge in identifying similar wildfires when only early-stage data is available.

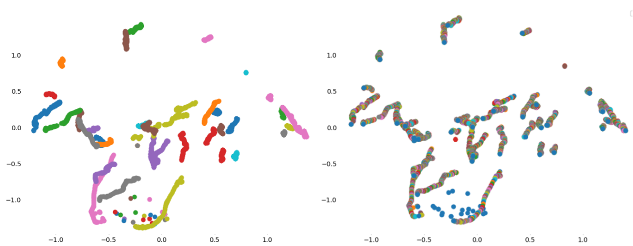

Figure 6. The results of PCA for each timestep of fire simulation.

In this pipeline, user preferences dictate the search algorithm and its features. The key contribution is showing how pre-calculated simulations facilitate proactive and reactive wildfire management.

V. Conclusion and Future Work

This study explores approaches for two distinct challenges—predicting solar shading effects and managing wildfires—using AI and HPC. Corresponding tools effectively correlate shading relations between buildings through characteristics like building proximity and height, or respectively aid in designing preventive measures against wildfires by analyzing the Burn Probability (BP) and supporting rapid response strategies by matching real-time fire scenarios with pre-calculated simulations. For wildfires, the next steps include testing various similarity algorithms and enhancing accuracy with visual features, terrain data, and multimodal inputs. For solar exposure, the focus will be on tuning GNNs, node features, and exploring shading mask evolution over time.

Acknowledgment

This work has been developed as part of the HiDALGO2 project, which has received funding from the European High Performance Computing Joint Undertaking (JU) and Poland, Germany, Spain, Hungary, France and Greece under grant agreement No 101093457.

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