AI for Global Challenges

Case Studies in Urban Solar Exposure and Wildfire Management

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Climate Change: A Global Challenge

- Increasing alterations in climate patterns worldwide.
- Effects on human health, safety, and environmental sustainability.
- The WHO 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].
- 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].
- 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 [3].
- Alarming increase in natural disasters.
- 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.
- Pressing need for innovative solutions to mitigate and adapt.

[1] World Health Organization, Billions of people still breathe unhealthy air: New who data, https://www.who.int/news/item/ 04-04-2022-billions-of-people-still-breathe-unhealthy-air- new-who-data, Accessed: 29/08/2024, Apr. 2022.
[2] Our World in Data, Who air pollution deaths, https : / / ourworldindata.org/data-review-air-pollution-deaths, Accessed: 29/08/2024, 2022
[3] European Commission, Focus on energy efficiency in buildings, https://commission.europa.eu/news/focus-energy-efficiency- buildings-2020-02-17_en, Accessed: date-of-access, Feb. 2020.

Aim of this work

- This paper explores how Artificial Intelligence (AI) and High-Performance Data Analytics (HPDA) could serve as crucial tools in addressing global challenges, specifically in two distinct problems - (work in progress).
- **Problem 1**: assessing solar exposure in urban buildings
- **Problem 2**: mitigating wildfire evolution

Problem Formulation

Problem 1: Assessing solar exposure in urban buildings

- Problem Definition: Predicting shading effects between buildings to improve urban planning.
- Context: When a new building is added, how will its defined dimensions (height, width, and depth) affect the solar exposure of surrounding buildings?
- Challenges with Traditional Methods: Rely on computationally intensive simulations that struggle to scale and fail to effectively capture complex interactions, limiting their utility in sustainable urban planning.
- Innovation with AI: AI techniques have been used to address similar challenges but have not traditionally structured data in the form of a graph [4, 5].

[4] S. Subramaniam et al., “Artificial intelligence technologies for forecasting air pollution and human health: A narrative review”, Sustainability, vol. 14, no. 16, p. 9951, 2022.

[5] T. G. Krupnova, O. V. Rakova, K. A. Bondarenko, and V. D. Tretyakova, “Environmental justice and the use of artificial intelligence in urban air pollution monitoring”, Big Data and Cognitive Computing, vol. 6, no. 3, p. 75, 2022.

Problem 1: Assessing solar exposure in urban buildings

- Data Collection: 1,343 samples of building profiles and their solar masks from a section of Strasbourg.
- Detailed Analysis: Includes solar masks of affected surrounding buildings calculated in the absence of the main building; however, current experiments do not account for variables like vegetation which may impact results.
- Network Construction: Constructs the "affected buildings network" by connecting buildings based on changes in solar masks. Implements a mean squared error threshold (≥ 0.01) to refine these connections and more accurately depict the impact of building removal.
- Link Prediction: Employs a transductive approach by removing some connections pre-training. The network then learns from this adjusted graph structure to predict and restore missing links, thus identifying potential shading relationships between buildings.

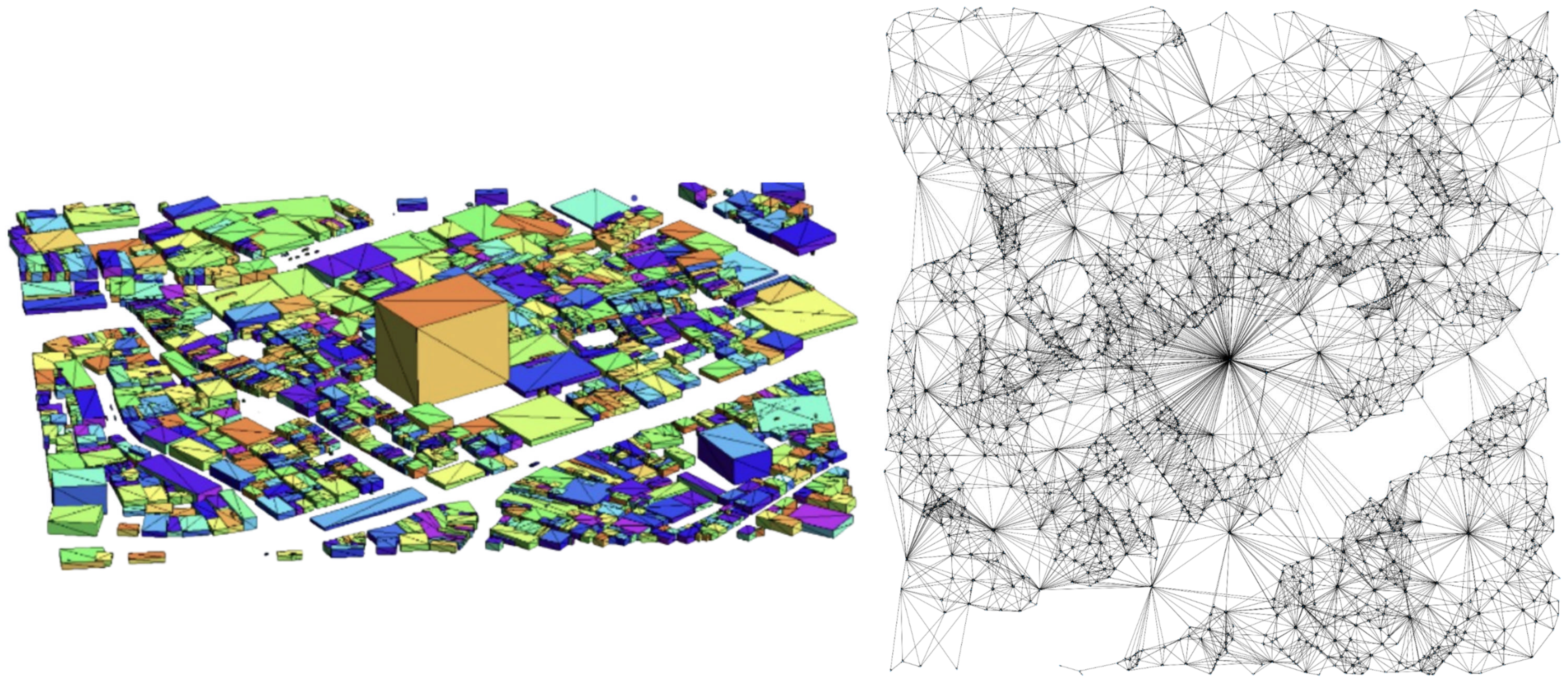

Figure 1. The affected buildings network using the proposed threshold on solar mask difference between buildings

Problem 1: Assessing solar exposure in urban buildings

- **Data Preparation:**
  - Removes a portion of existing edges while retaining all nodes (buildings) to simplify the graph.
  - The modified graph is then processed by a Graph Neural Network (GNN) for training.
- **Model Architecture:**
  - Utilizes a two-layer Graph Convolutional Network (GCN) to encode node interactions through message passing.
  - Employs a decoder that performs binary classification to determine the existence of an edge between nodes, configurable as a hyperparameter.
- **Experimental Settings:**
  - Graph Structure: Explores both directed and undirected graph configurations.
  - Classifier Type: Compares the effectiveness of a Simple Dot Product versus a Multi-Layer Perceptron (MLP).
  - Node Features: Assesses the impact of using building location versus building height as node features.
  - Threshold for Solar Mask Difference: Implements a threshold to refine edge creation based on the impact on solar exposure.

Problem 1: Assessing solar exposure in urban buildings

- Initial Experiment Results: Demonstrates strong performance with Area Under the Curve (AUC) scores often exceeding 70%.
- Key Observations: Undirected graphs and using building location as node features enhance model accuracy.
- Ongoing Refinements: Focus on further optimizing these results to improve prediction reliability and accuracy.

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

Problem 2: Mitigating wildfire evolution

- **Dataset Overview:**
  - Consists of 10,584 pre-calculated wildfire simulations for a 3x3 km^2 area in Barcelona.
  - Includes detailed geospatial data, wind simulations in various directions and speeds, and derived from high-resolution LiDAR data.
- **Simulation Details:**
  - Features 441 strategically placed ignition points to model different wildfire scenarios effectively.
- **Risk Assessment Using HPDA:**
  - BP Definition: Burn Probability in percentage, where NF is the number of times fire passes through a specific point, and NS is the total number of simulations.
  - This metric, combined with data on buildings, roads, and other infrastructure, helps assess potential adverse impacts and is visualized on a risk map.

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

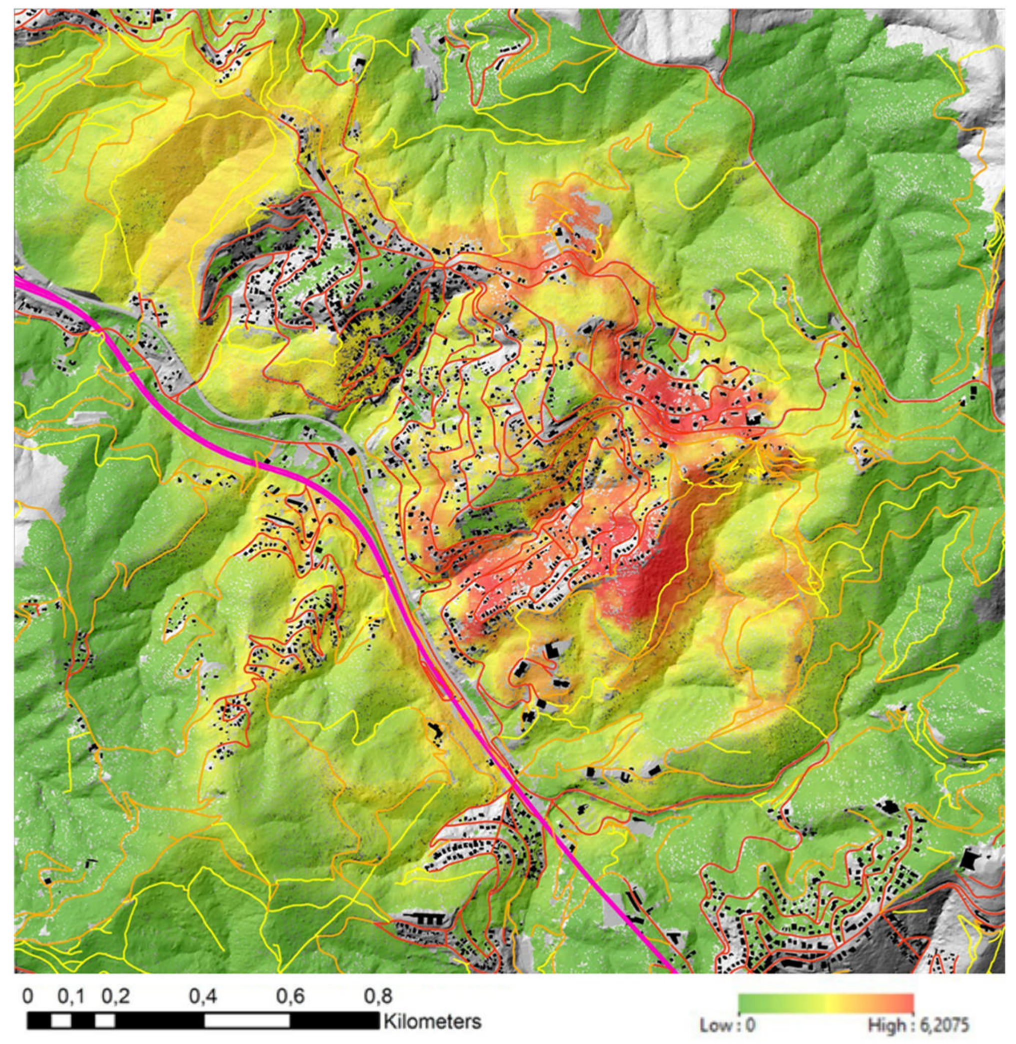

Figure 2. An example of Burn Probability (%), visualized on a map. The areas in red indicate a higher likelihood of fire spread.

Problem 2: Mitigating wildfire evolution

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.

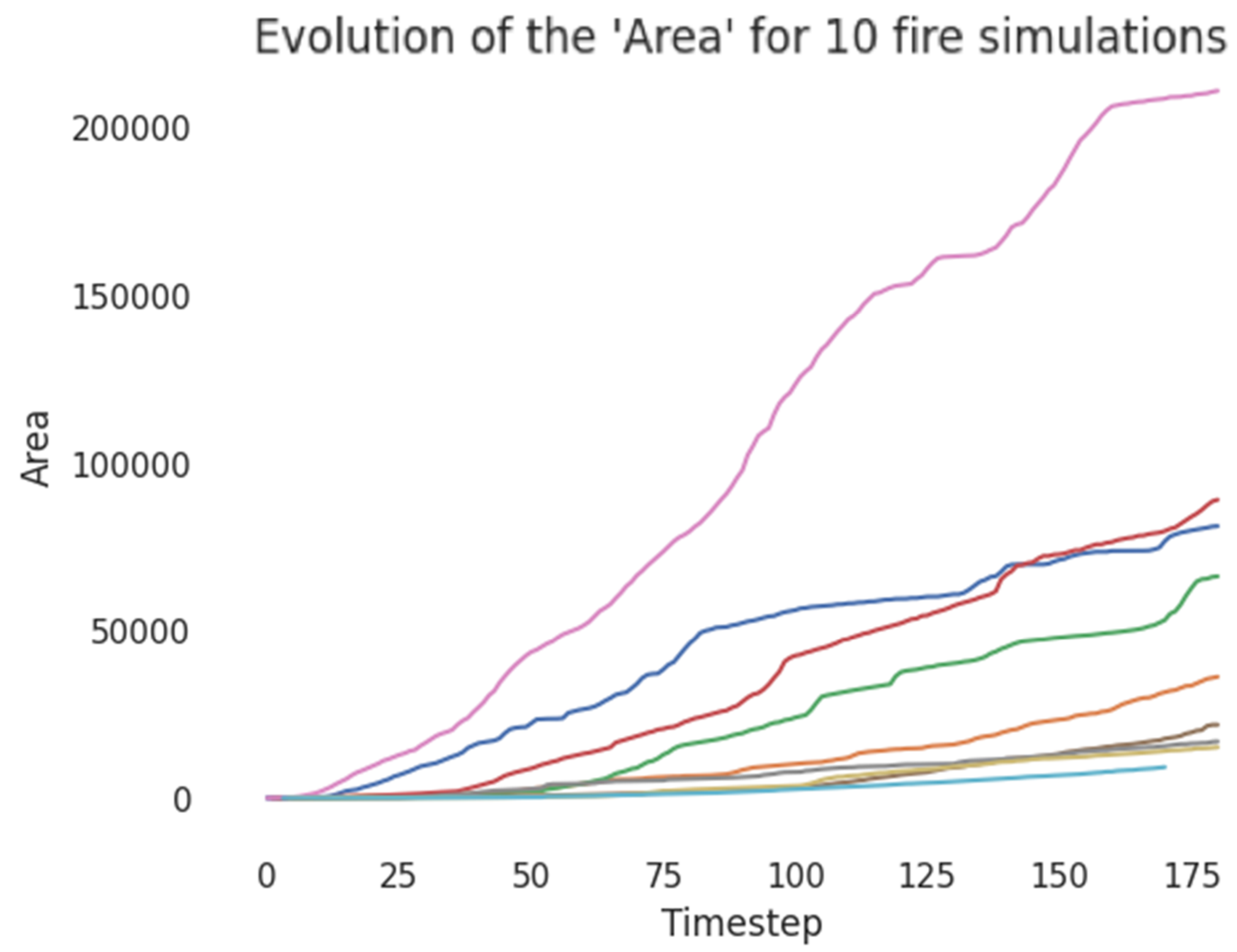

Figure 3. The evolution of the “Area” feature across ten different forest fires.

Problem 2: Mitigating wildfire evolution

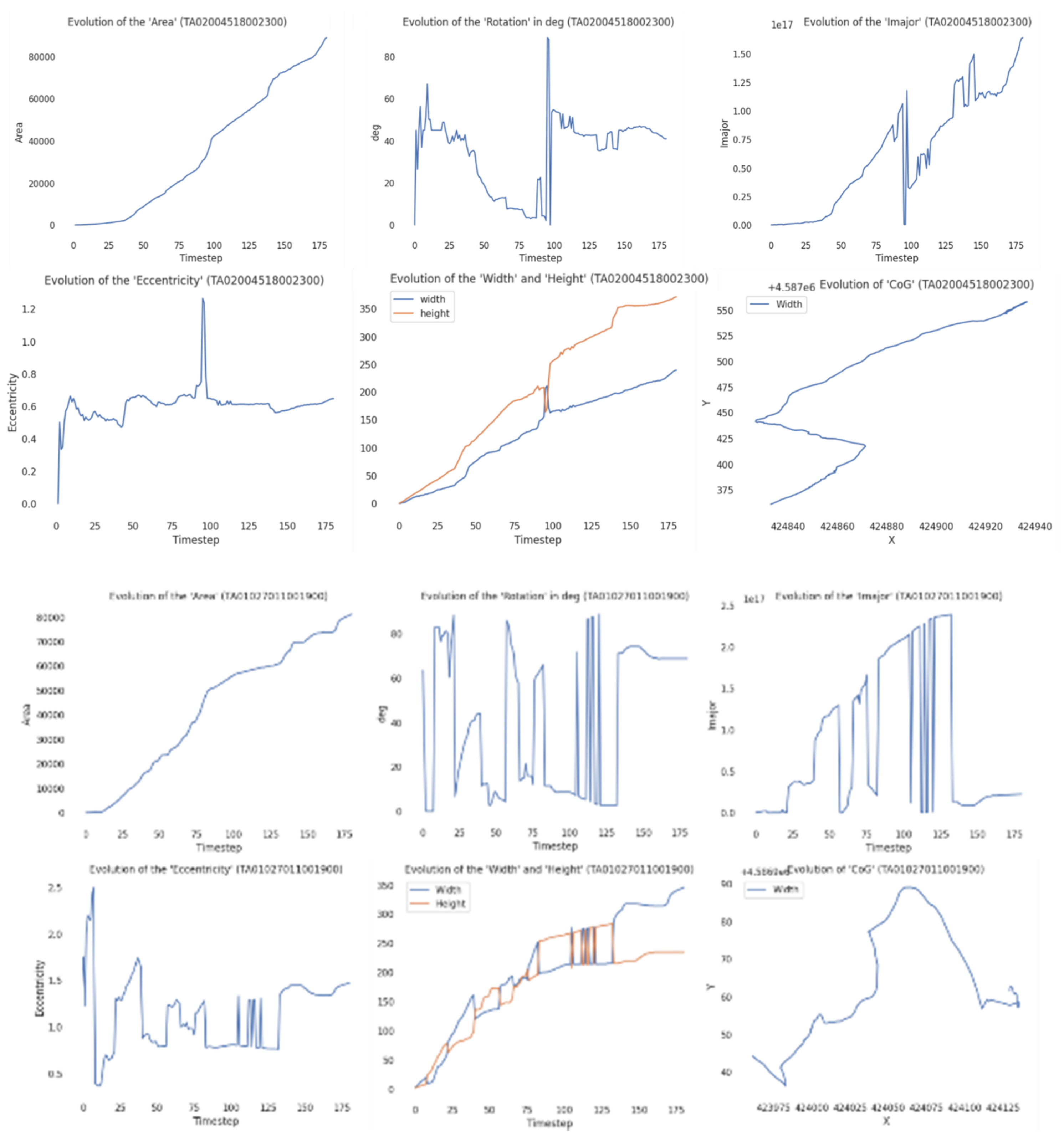

Figure 3. Illustrates the evolution of the six features: “Area,” “Rotation,” “Imajor,” “Eccentricity,” “Width,” “Height,” and “Center of Gravity of the contour” for each timestep.

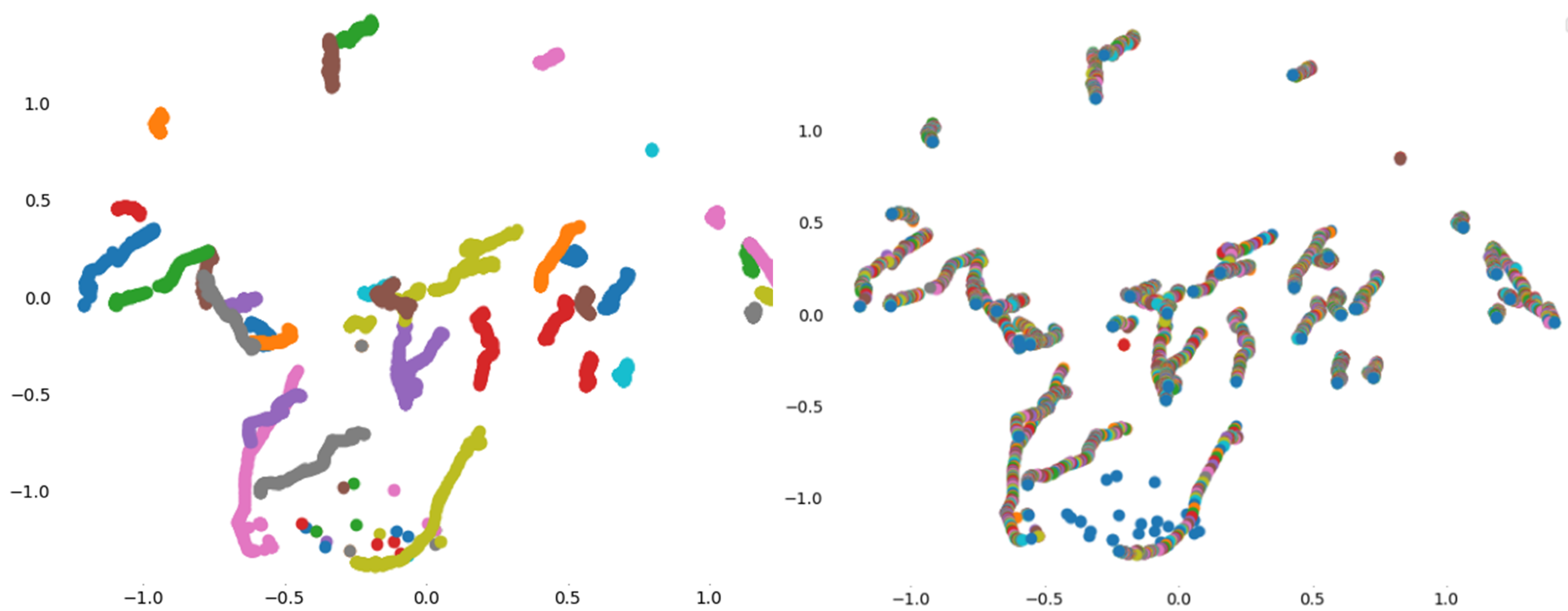

Figure 4. The results of PCA for each timestep of fire simulation.

Conclusion and future steps

- **Problem 1: Assessing Solar Exposure in Urban Buildings**
  - **Current Approach:**
    - Utilized AI and High-Performance Computing (HPC) to predict shading relations between buildings, considering factors like building proximity and height.
  - **Future Steps:**
    - Focus on fine-tuning Graph Neural Networks (GNNs), enhancing node features, and exploring how shading masks evolve over time.
- **Problem 2: Mitigating Wildfire Evolution**
  - **Current Approach:**
    - Employed tools to analyze Burn Probability (BP) and extract features from simulations, using these in real-time fire scenarios with pre-calculated simulations to support rapid response strategies.
  - **Future Steps:**
    - Plan to test various similarity algorithms and enhance model accuracy by incorporating visual features, terrain data, and multimodal inputs.

Thank you for your time!

Questions?