Supplementary Material

All analysis maps , histograms and code here:
https://drive.google.com/drive/folders/1ZfaiD6C9VyMmrQn3jkkI8hozCO4dqJN7?usp=sharing

This document discusses the following:

1. Step-1: Assessing the land use model's quality: A) Does the model provide stable results? B) Is the model able to simulate distinct scenarios?
2. Step-2: Assessing the local uncertainty within each scenario: How does the model inform us (and planners) about the uncertainty of the three scenarios?

Step1: Assessment of the Land Use Model's Quality

1. **Monte Carlo Runs**: For each scenario (BAU, PG, and 15MC), we run 100 Monte Carlo simulations using the land use model to generate probability distributions for each land use class. We then merge the probability maps of key land use classes into a single combined probability map for each scenario. We generate three such combined probability maps per scenario (*Fig 1*), so in total, we ran 900 simulations to create 9 combined maps. The key land use classes selected are expected to show the most growth by 2050—residential (high & medium density), commercial, public amenities, recreation, and greenhouses.
2. **Assessment:** We generate combined probability maps for each scenario and assess them using **Visual Comparison** and **Histograms.** The three combined probability maps generated per scenario are visually similar, indicating **stable model behaviour**. We confirm the stability by generating a **histogram** of the scenarios (*Fig 2*). In addition, as shown in *Fig. 1*, we see that the spatial patterns generated by the model show distinct differences between the three scenarios, demonstrating the model's **ability to simulate diverse urban futures**, confirmed by the histograms in *Fig 2*. This distinction confirms the model's utility in assessing global uncertainty and exploring urban transformations under various planning assumptions.

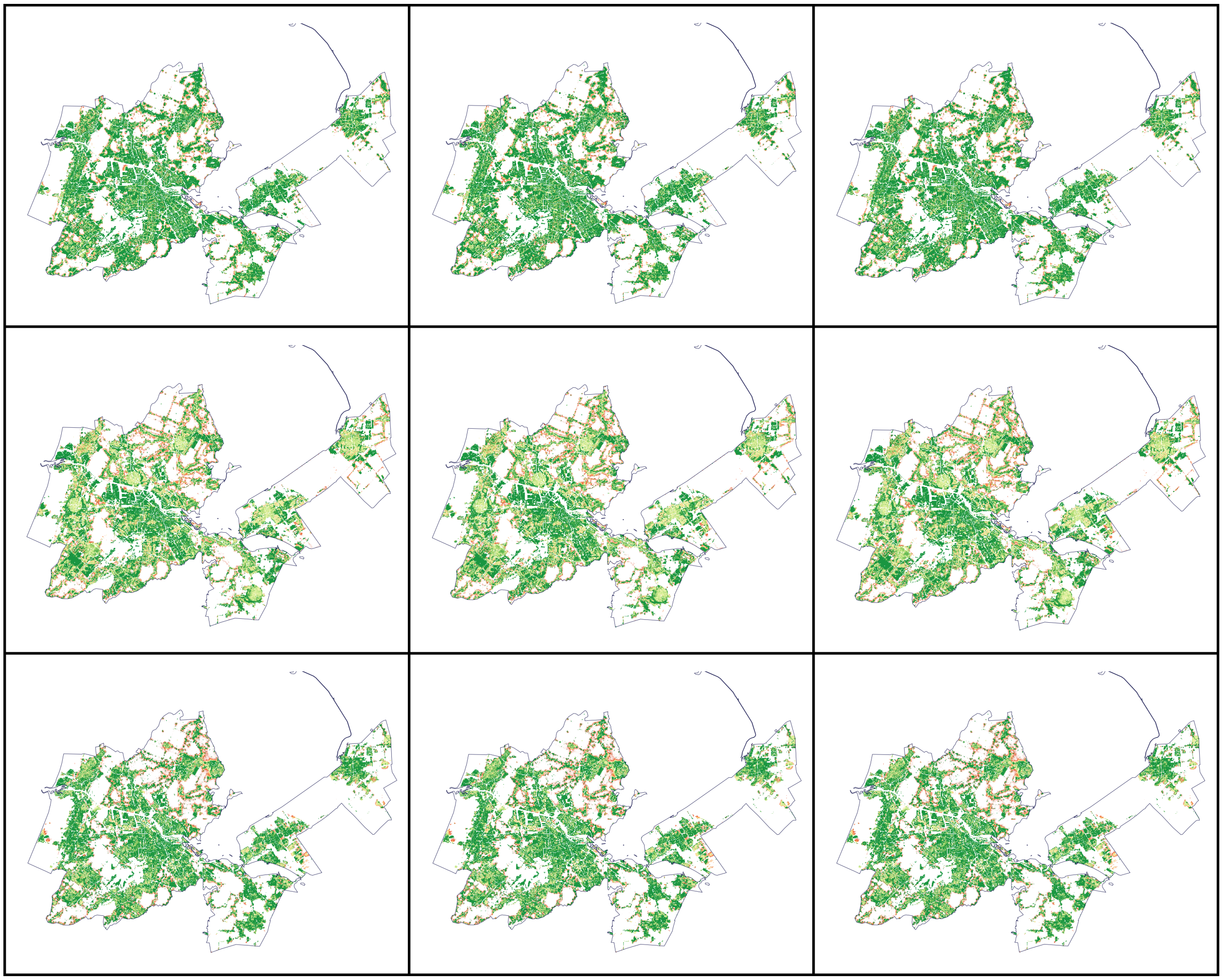


Fig 1: Combined probability maps - 3 per scenario (from top: BAU, PG, 15MC). Each probability map was created using 100 simulations.

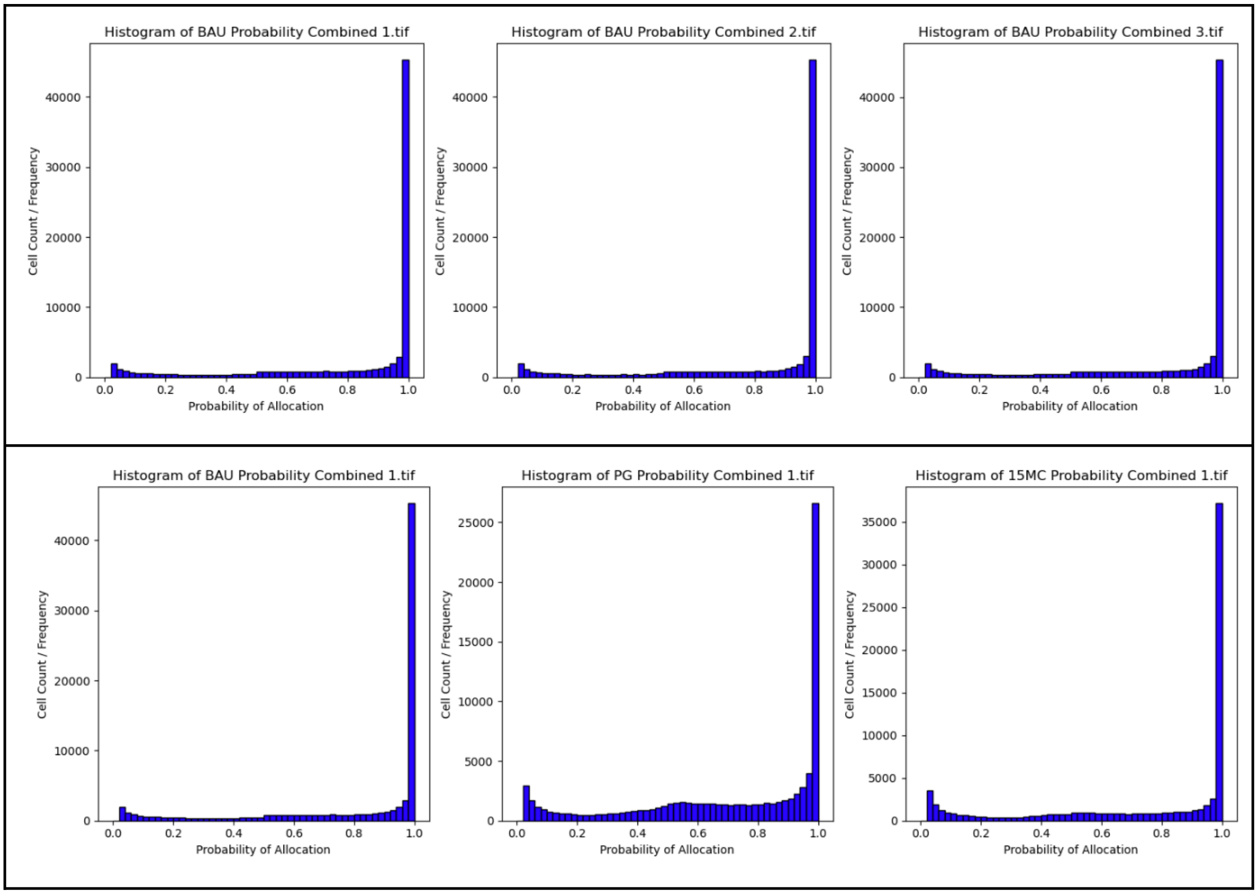


Fig 2: Histograms of the combined probability maps per scenario (1) (top) Combined probability maps for the BAU scenario, indicating stable runs. (2) (bottom) Histograms of combined probability maps generated for the BAU, PG and 15MC scenarios, indicating differences in distribution.

Step 2: Assessing the local uncertainty within each scenario

This section explores the local uncertainty in the modelled scenarios, providing insights into the degree of certainty or uncertainty associated with the model's results. High uncertainty in the scenario output suggests the potential for more significant uncertainty in real-world conditions, making it crucial to assess how such uncertainties can inform urban planning. By examining these uncertainty patterns, planners can identify areas where the model aligns or deviates from expected outcomes, thus enhancing decision-making processes. Ultimately, this approach enables us to extract valuable lessons from the model that can guide more resilient and adaptive planning strategies.

2.1 Visual Assessment:

When we visually assess the combined probability map of each scenario (*Fig 1*), we identify areas of high, moderate and low probability of allocations (corresponding to areas of low, moderate and high uncertainty) :

- **High Probability areas (Dark Green, Value = 1):**
  These areas represent stable zones (**low uncertainty**) where land use is unlikely to change over time, typically found in urban cores or city centres. In the **BAU** scenario, the dark green regions dominate, reflecting continuity and stability in urban form, with minimal land use transformation expected.
- **Moderate Probability areas (Yellow to Light Green, Values 0.5 to 0.9):**
  These areas signify gradual transitions or urban intensification, such as shifts from residential to commercial or lower- to higher-density housing. In the **PG scenario**, many of these zones fall within designated growth hubs, highlighting **moderate uncertainty** in the exact location of changes but indicating development potential. Similar to the PG scenario, the **15MC (15-Minute City)** scenario shows cores that are aligned with the 15-minute accessibility model where moderate transformations are expected but with uncertainty in the exact location of the different (urban) land use types. Further investigation of the model results shows that the probability of these areas becoming urban is very high and that these areas are expected to have a mix of urban land use types. However, the exact location of the various land use types varies per simulation run and hence contributes to the local uncertainty.
- **Low to Moderate Probability areas (Orange to Red, Values 0.1 to 0.4):**
  These zones represent potential urban expansion areas, typically clustering around existing developments. While these areas indicate plausible future growth, the exact locations of expansion remain uncertain. Coordination with local planners can help clarify development preferences in these zones, as they represent possible but undecided expansion corridors.

Next, we assess the **stability** and **uncertainty** of allocation for each land use class within a scenario using their individual probability maps.

2.2 Standard Deviation (SD)

To evaluate stability, we calculate the standard deviation (SD) for a probability map per land use for each scenario on a cell-by-cell basis. We then compare the SDs for a single land use class across the three scenarios (*ref: codebook*). Lower standard deviation values indicate greater stability, meaning land use allocations are consistent across runs for that pixel. High stability suggests that the scenario generation reliably predicts land use in specific locations, enhancing confidence in those outcomes. As shown in *Table 1 (which summarises SD's for land uses in each scenario)*, the minimum standard deviation for all land uses is 0, meaning that for some pixels, the predictions are identical across all runs—these are the most stable regions in the study area. Across all three scenarios, the maximum standard

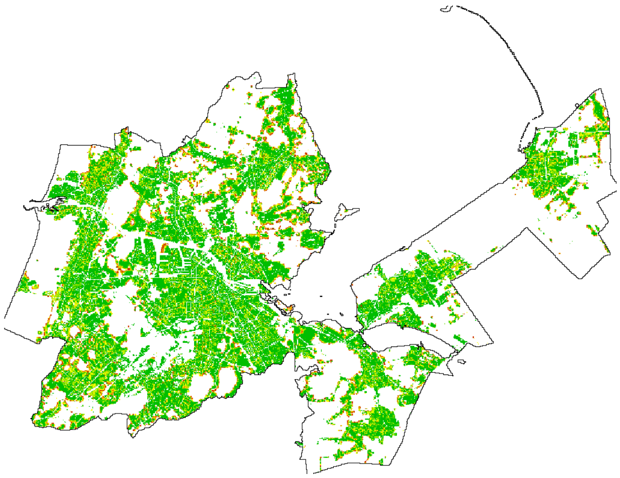
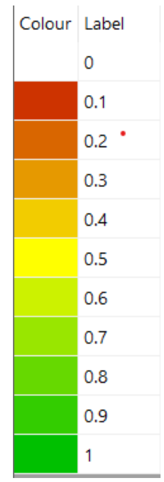
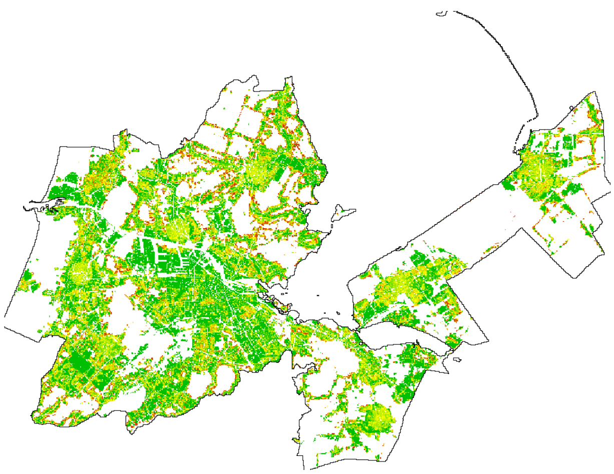
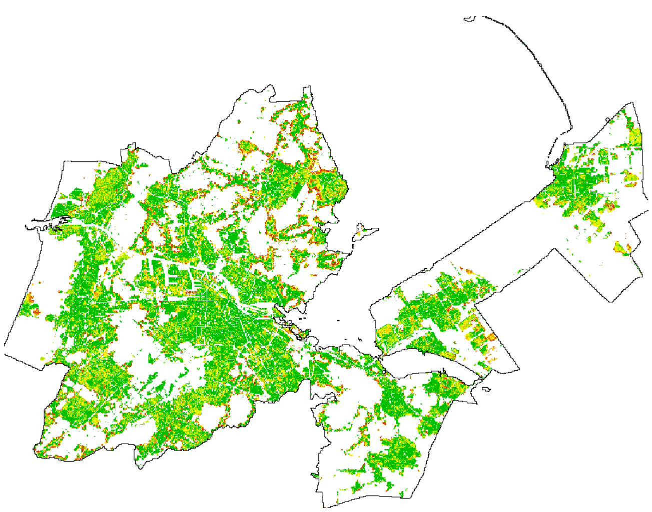
	**BAU** 
	**PG**
	**15MC**

Fig 3: Combined probability maps (including all functional land use classes) for the three scenarios

deviation (also see maps), 0.119, indicates some areas with high variability across runs, indicating low stability or high uncertainty about the type of land use allocation. However, the mean SD for land uses across the 3 sets of probability maps for all scenarios ranges from 0.008 to 0.03, suggesting that predictions are generally stable across the region (*refer: codebook*).

1. **Histograms**: Along with the min, max, and mean values, we visualise the distribution of standard deviation across all pixels using histograms (*Fig. 3*). For Residential (H) and Commercial, the distribution is concentrated around low standard deviation values (0 to 0.1), indicating that most predictions are stable.
2. **Stability Maps**: We also generate standard deviation maps for each land use class in each scenario (*Fig. 3*). In both existing and proposed urban cores, low standard deviation values reflect high predictability (e.g., city centres unlikely to change). Conversely, transitional or growth areas, especially along the urban periphery, show higher standard deviation (green/yellow), indicating prediction variability. This variability arises in locations with (new) mixed land use developments as the general direction of development is the same across the various simulation runs within a scenario, but the exact allocation of the mix of urban land uses within new growth hubs differs in different simulation runs..

Table 1: Statistics of Standard Deviation for All Land-Use Classes in all scenarios (900 runs)

Land Use	Min Std Dev	Max Std Dev	Mean Std Dev
Residential H BAU	0	0.105	0.0159
Residential H PG	0	0.109	0.0207
Residential H 15MC	0	0.108	0.0169
Residential M BAU	0	0.104	0.018
Residential M PG	0	0.106	0.021
Residential M 15MC	0	0.110	0.019
Recreation BAU	0	0.114	0.0126
Recreation PG	0	0.117	0.016
Commercial BAU	0	0.106	0.008
Commercial PG	0	0.116	0.017
Commercial 15MC	0	0.119	0.038

Public Amenities BAU	0	0.106	0.014
Public Amenities PG	0	0.105	0.013
Public Amenities 15MC	0	0.112	0.030

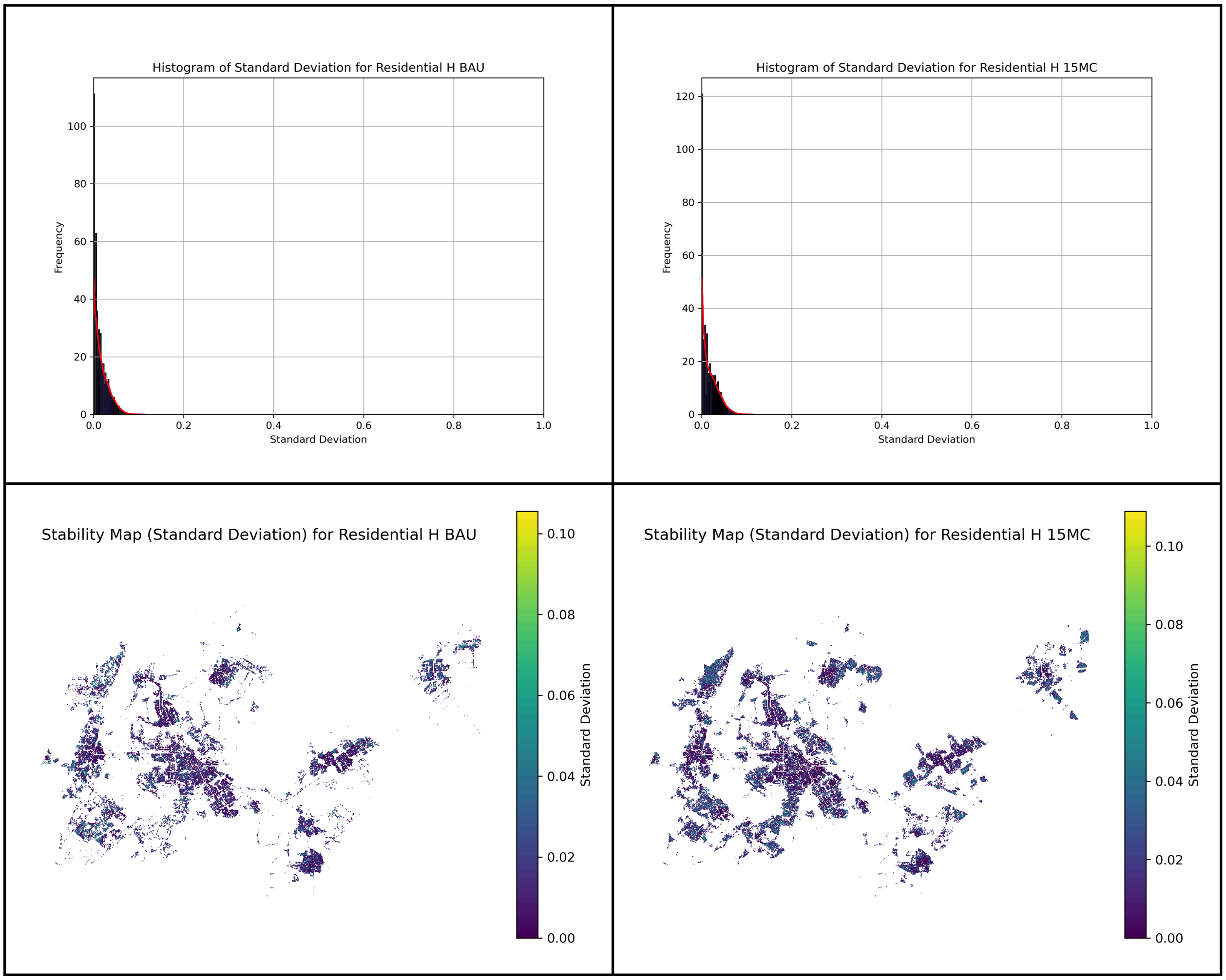


Fig 3: Sample Histograms (top) and Standard Deviation Maps (bottom) for Residential (high density) for BAU and 15MC scenarios (all maps here)

2.3 Entropy

To assess **uncertainty**, we calculate **entropy** across Monte Carlo runs for every scenario. Entropy measures the uncertainty of land use allocation: if a pixel has similar probabilities for allocating multiple land use classes, its entropy will be high, indicating that the model is uncertain about the specific land use for that pixel. This metric is particularly useful in highlighting areas where multiple land use outcomes are equally plausible, reflecting ambiguity in the predictions (*Table 2)*.

- **Min Entropy (-0.0)**: Close to zero, indicating high certainty in land use classification.
- **Max Entropy (~1.5-1.6)**: Indicates areas of high uncertainty where multiple outcomes are equally likely.
- **Mean Entropy (~0.17-0.3)**: Reflects overall uncertainty in the model.

Table 2: Summary of Entropy for All Scenarios

Scenario	**Min entropy**	**Max entropy**	**Mean entropy**
BAU	0	1.51	0.17
PG	0	1.59	0.30
15MC	0	1.60	0.22

In the **BAU** (Business-as-Usual) scenario, **low mean entropy (0.17)** suggests that the model predicts established land use patterns with confidence. The **maximum entropy of 1.51** shows some localised uncertainty, but overall, the model indicates a low local uncertainty in the BAU scenario (*Fig 4*). The **PG** (Planned Growth) scenario has the **highest mean entropy (0.30)**, reflecting greater uncertainty due to new interventions, zoning changes, and growth strategies. Areas of high entropy correspond to proposed mixed-use hubs, where several land use types (residential, commercial, public amenities) compete for allocation, and the exact allocation of land uses is uncertain. The **15MC** (15-Minute City) scenario shows **moderate mean entropy (0.22)**, higher than BAU but lower than PG. Like the PG scenario, the model indicates the allocation of mixed urban development in the growth hubs with high confidence but also indicates uncertainty regarding the exact allocation of the different land use types within the mixed developments (*Fig 4*).

Across all scenarios, high maximum entropy values (1.5-1.6) suggest localised areas of uncertainty, likely due to conflicting land use patterns, edges or peripherals of growth hubs, or possibly sparse data. Part of planning and policymaking would be to focus on the areas of uncertainty, as these will show dynamic growth and will be sensitive to interventions (in both a positive and negative way). Reducing uncertainty in these areas may require additional policies but could also involve further refining model assumptions and data quality.

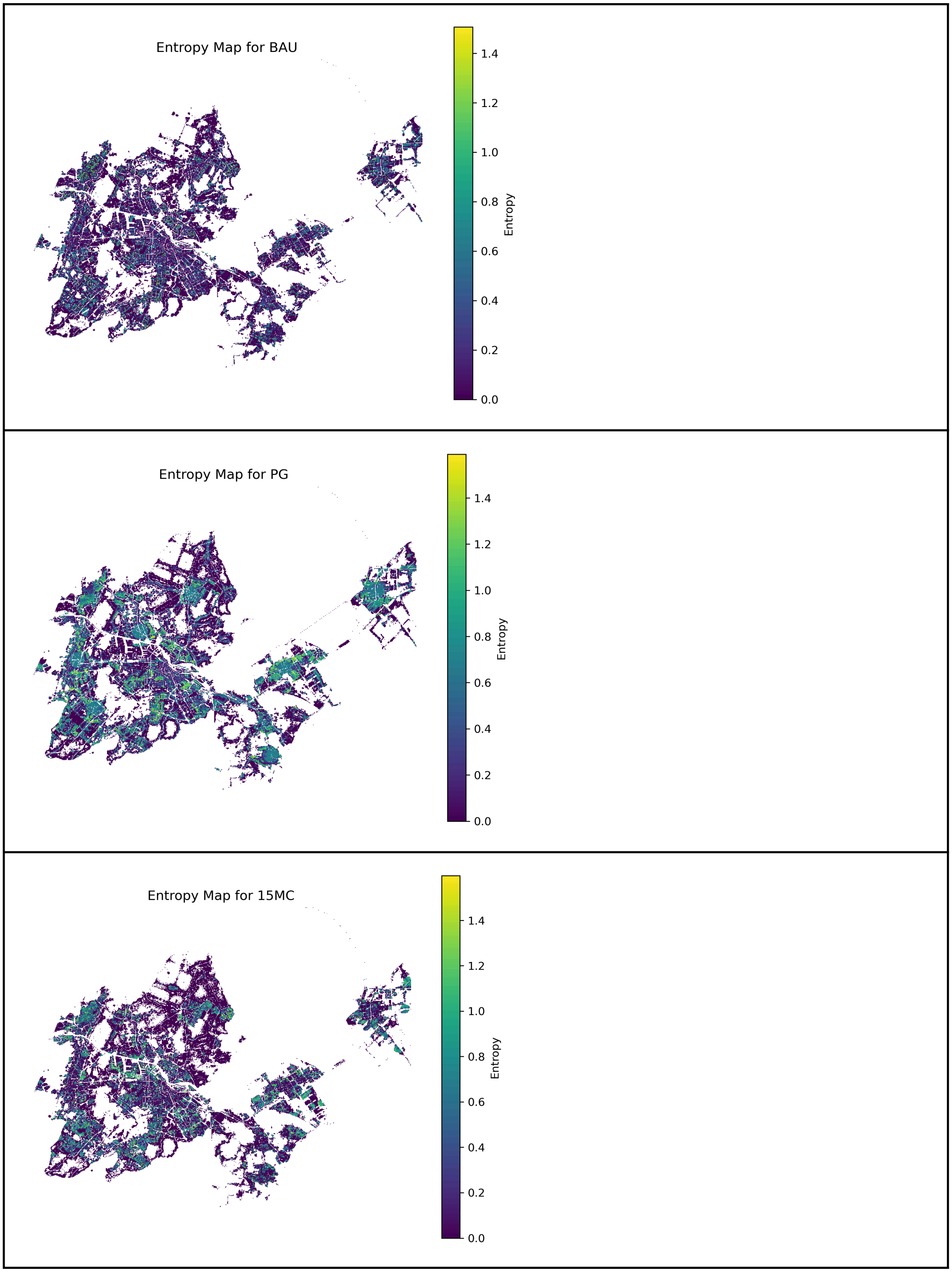


Fig 4: Entropy maps for each scenario (all maps [here]).

Step-3: Discussion on the method [Future Work]

While standard deviation and histograms provide useful insights into the distribution of probabilities across land use allocations, current metrics are unable to capture the **spatial configuration** of these allocations. The standard deviation treats the locations as independent, meaning that if land use is allocated slightly differently in another run, it will still be counted as unequal, even if the land use is only shifted to a neighbouring location. This fails to account for the **spatial 'nearness'** of allocated land uses, a critical factor in urban planning.

To better understand the model's output, it is important to not only use histograms but also analyse the **spatial patterns in the output maps**. For example, areas expected to develop with land use type X may not be identical across scenarios, but if the allocations are spatially close to each other, this suggests a consistent trend that histograms alone cannot reveal.

A more effective metric to assess the distribution of probabilities across land use allocations would consider both the **proximity** and **spatial configuration** of the allocated land uses, providing a deeper understanding of how land use may evolve across scenarios. Since the model is intended for exploratory purposes—such as identifying parts of the city likely to experience new development—it's essential that the metric accounts for spatial patterns, not just raw counts of probability distributions. Without this, the analysis may overlook important trends related to the **clustering** or **dispersion** of land use changes, which are crucial for understanding urban dynamics and making informed planning decisions.

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