

Fine-scale Machine Learning Based Population Mapping: A Case Study of Munich

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Fine-scale population mapping is critical to a wide range of public interests [1]. Because census data is time-consuming and expensive, and machine learning has emerged as a hotspot as a result of increased access to big data [2], it is critical to apply it to population mapping and evaluate its performance in order to enrich fine-scale population products.

BACKGROUND

Gridded population mapping has been an important alternative of population mapping for decades, however, there are some problems in previous studies: 1) datasets used are not always accessible; 2) optimal scales are rarely discussed, ignoring the fact that different features may have different acting ranges [3]; and 3) fine-scale population mapping results are frequently disaggregated from census data, rather than estimation. Therefore, proposing another approach for population prediction is of great value.

OBJECTIVE

This study aims to integrate multiple freely available remote sensing products and semantic data using machine learning methods, while optimizing the scale of different variables and holding a discussion on spatial heterogeneity and data characteristics.

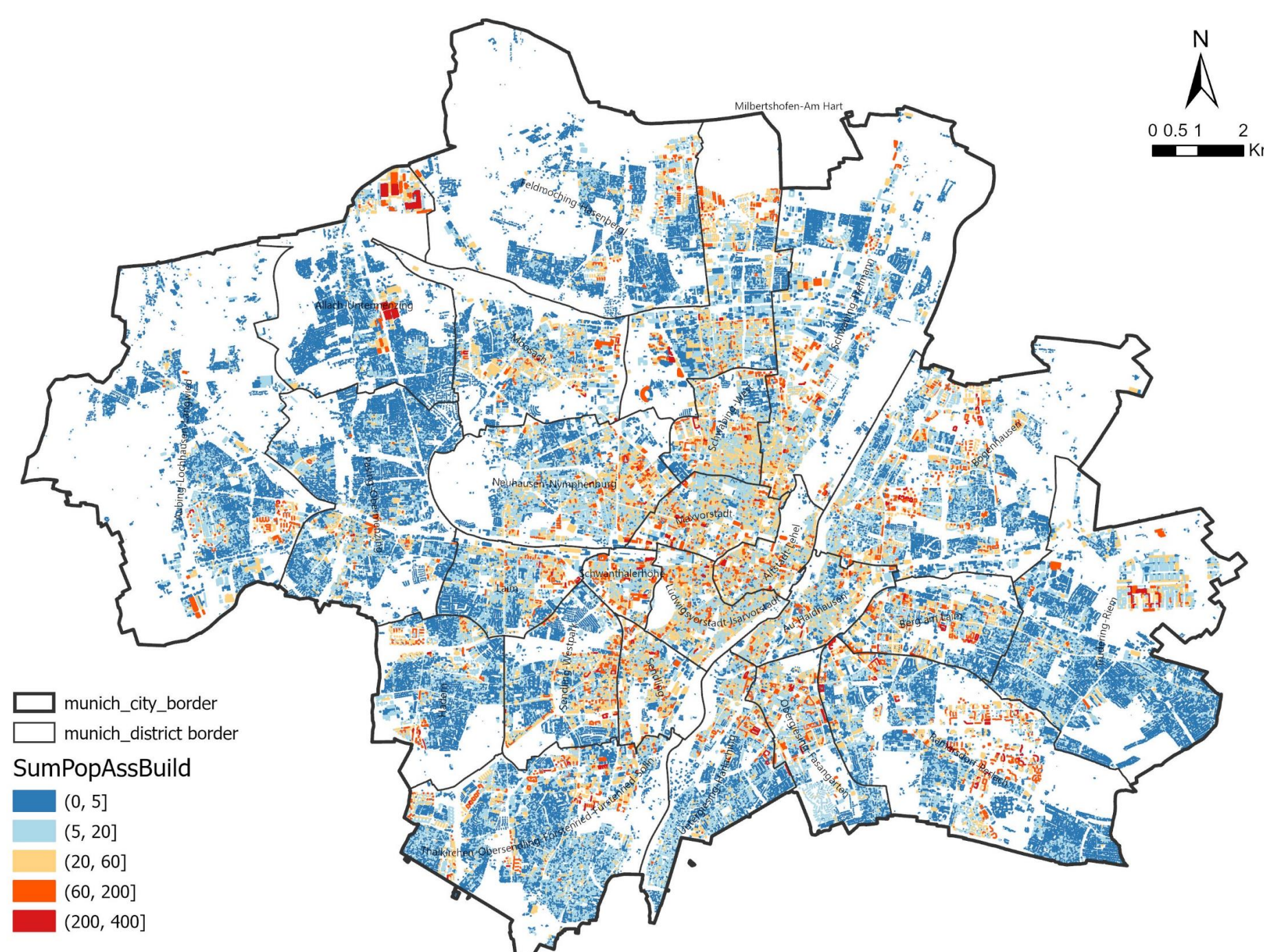


Figure 2. Choropleth map of population distribution at building scale of Munich from estimation results.

RESEARCH QUESTION

1. What is the approach for fine-scale population mapping?
2. What is the optimal scale for each variable?
3. Does certain data improve the estimation accuracy in population mapping?
4. Do they perform same level of accuracy in different areas?
5. Is the result derived from machine learning methods has reasonable spatial details?

RESULTS

1. Shown in Figure 1.
2. For the majority of POI classes, the optimal scale is within an 800m acting range, which is about a 10-minute walk.
3. Land use is the most important information in population mapping, following by POI and building.
4. In neighborhoods, there are clear patterns of overestimation and underestimation.
5. The spatial pattern of the population distribution has been learned by the regression model as the value distribution almost show the same pattern.

CONCLUSION

The research objectives and research questions were generally met and widely discussed by evaluating the results from various perspectives. However, this study has many limitations that are obvious in retrospect. The obtained datasets, for example, have a broad meaning of population, not just registered residents, however, they are only used to estimate residents, which could be a future research path.

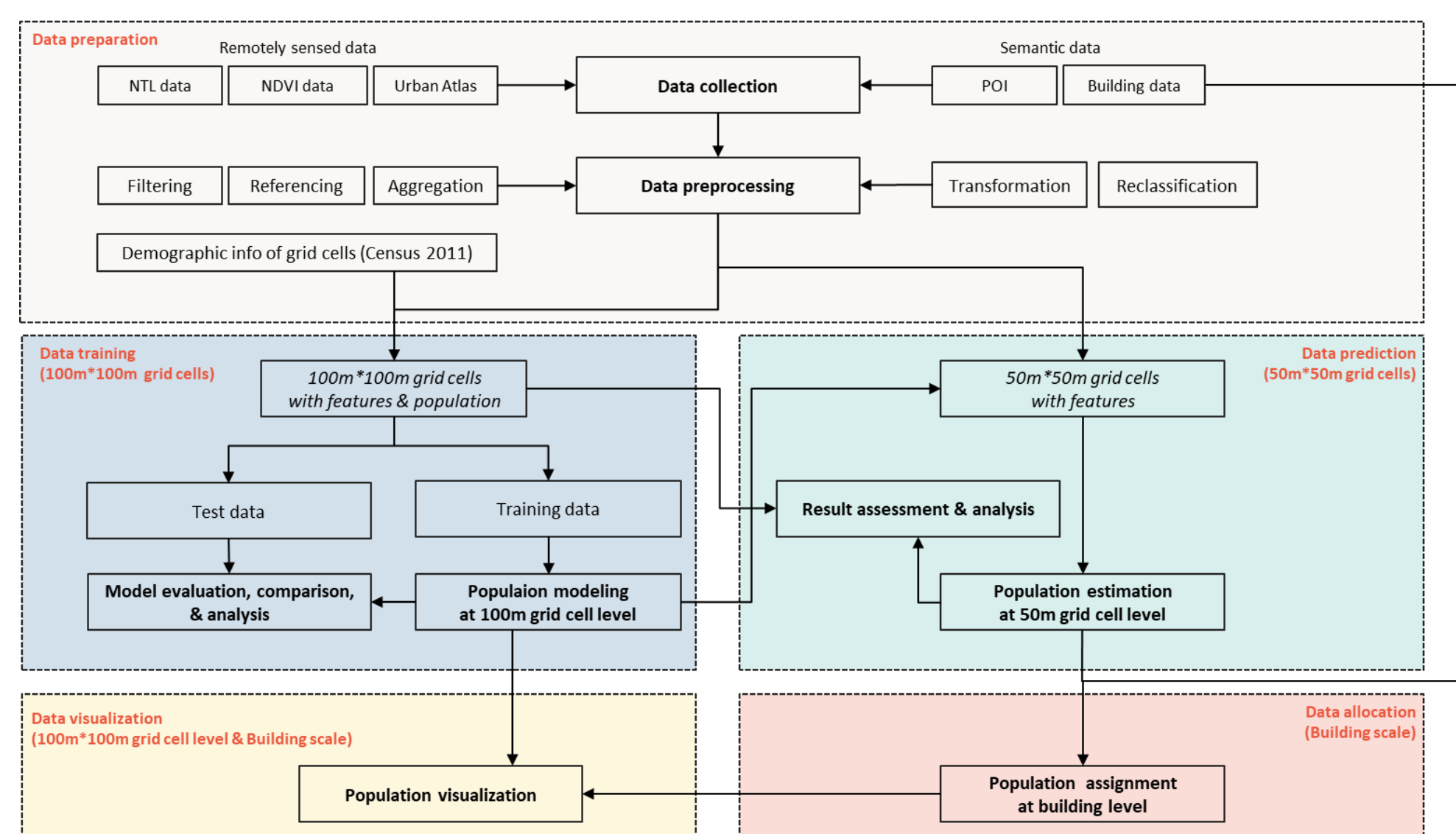


Figure 1. Flowchart of this study. To achieve the research objectives, the framework mainly contains five sections, data preparation, data modeling at 100m*100m grid cell level, gridded population estimation at 50m*50m grid cell level, population allocation at building level, and population visualization.

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REFERENCES

- [1] Stevens, F. R., Gaughan, A. E., Linard, C., & Tatem, A. J. (2015). Disaggregating Census Data for Population Mapping Using Random Forests with Remotely-Sensed and Ancillary Data. PLOS ONE, 10, pp. 1-22.
- [2] Šimbera, J. (2020). Neighborhood features in geospatial machine learning: The case of population disaggregation. Cartography and Geographic Information Science, 47, 79-94.
- [3] Cheng, J., Zhang, X., & Huang, J. (2022). Optimizing the spatial scale for neighborhood environment characteristics using fine-grained data. International Journal of Applied Earth Observation and Geoinformation, 106, p. 102659.