Cartography M.Sc.

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

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1. Motivation

- Fine-scale population product is essential for many use cases
- The collection of census data is time-consuming and expensive
- Census data is often based on administrative units

Other alternatives: e.g. Gridded population mapping

- Insufficient model evaluation
- Variable optimal scales and spatial heterogeneity are rarely discussed
- Building level population mapping products are not rich

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German Census 2011 provides gridded results at the 1km and 100m levels

Map the population at fine-scale while optimizing the scale for corresponding variables and holding a discussion on spatial heterogeneity and data characteristics.

2. Research Identification

Research Objectives

1) Population estimation at building level

2) Investigate the significance and influence of various datasets

3) Verify if machine learning helps in population mapping

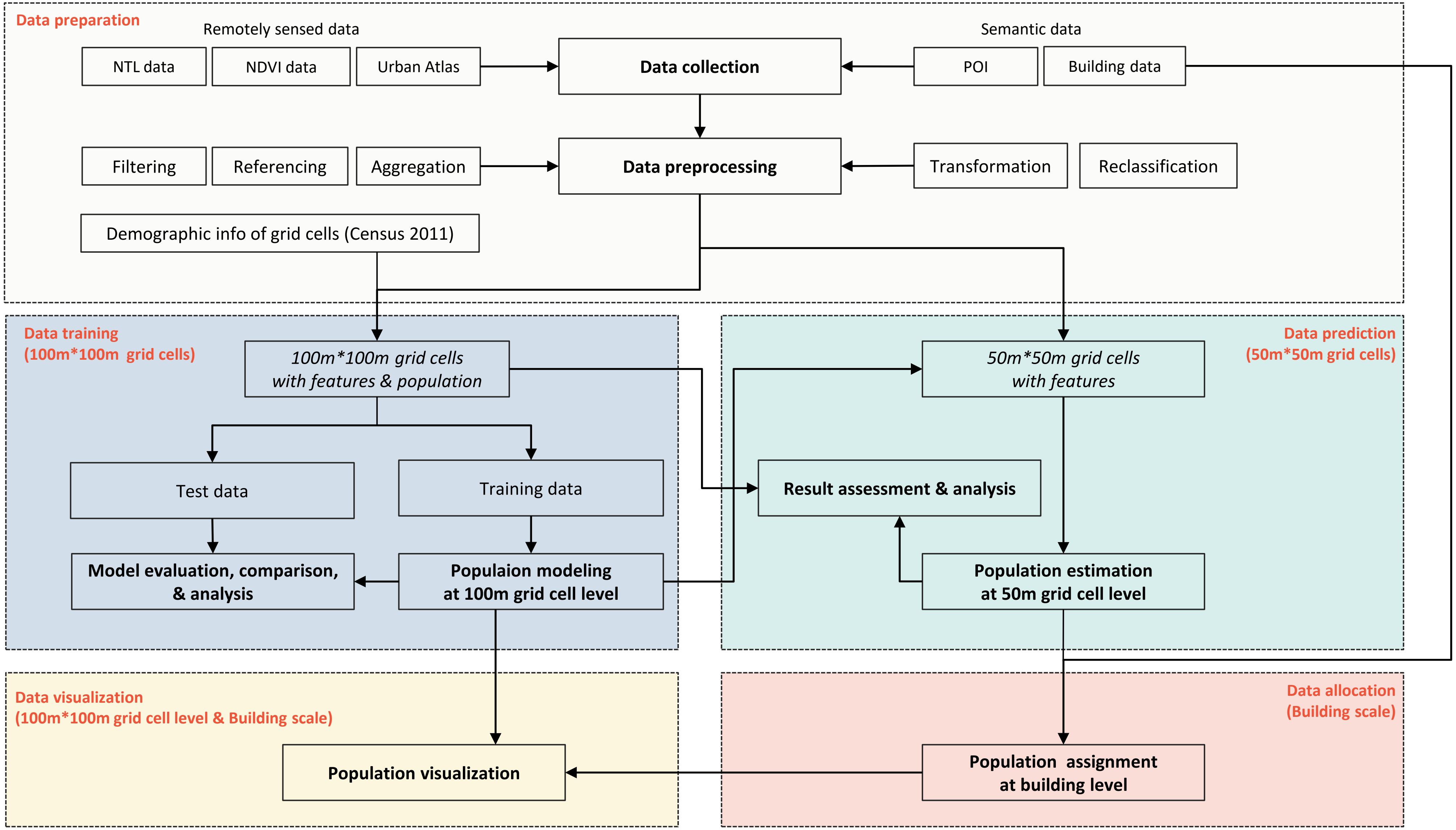
Research Questions

- What is the approach for population mapping at building level?
- What is the optimal scale for each variable?
- Does certain data improve the accuracy of population mapping?
- Do they perform same level of importance in different areas?
- Is the result derived from machine learning methods has reasonable spatial details?

3. Related Work

Perspective	Category		Summary
Methods for Population Mapping	Areal Interpolation	Without ancillary data: assumes evenly distribution	• Overcome multicollinearity, has strong generalization ability, allowing it to handle high-dimensional features and effectively improve population spatialization accuracy (Stevens, Gaughan, Linard, & Tatem, 2015). • Outperform shallow machine learning models like RF but difficult to obtain fine-scale population training samples (Robinson, Hohman, & Dilkina, 2017).
		With ancillary data: dasymetric mapping, involves weights calculation from ancillary data	
	Statistical Modeling	Conventional methods (Linear regression, etc.)	
		Machine learning (Random Forest, etc.)	
		Deep learning (CNN, etc.)	
Integration of Ancillary Data for Population Mapping	Remotely Sensed Products	Land cover/ use data	• Big geo data has higher temporal and spatial resolution thus complementing the lack of semantic information which can indicate various human activities with a more precise location, and widely used while in participation of remotely sensed products (Sutton, Elvidge, & Obremski, 2003). • Most studies ignored the fact that different types of POIs have varying degrees of attractiveness to the population, and instead created quantity/density metrics based on POI data within a fixed same range (Cheng, Zhang, & Huang, 2022). • Some of the datasets used are not freely accessible.
		Night-time light (NTL) imagery	
	Geospatial Big Data	Volunteered Geographic Information (OSM POI, etc.)	
		Location Based Data	
Population Mapping at Building Level			• Few studies.
Population Distribution Visualization	Choropleth map, dasymetric map, proportional symbol map, dot map, cartogram, isarithmic map, heat map, 3D map		• Isarithmic map in population distribution receives a lot of criticisms as population distribution does not fluctuate continuously (Nordbeck & Rystedt, 1970). • Cartogram is more useful in small scales, like global level, country level.

4. Workflow, Data & Methodology



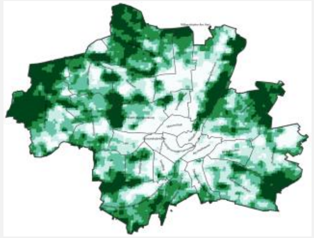
4. Workflow, Data & Methodology

Overview of Dataests Used in This Study

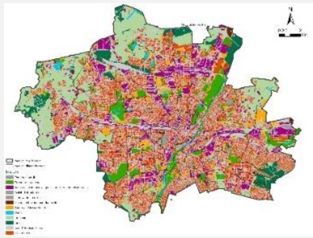
Type	Official Name	Data Provider	Reference Year
Population	German Cencus 2011	Federal Statistical Office	2011
Administrative Units	Verwaltungsgebiete 1:250 000 (kompakt), Stand 31.12. (VG250 31.12.)	Federal Agency for Cartography and Geodesy	2011
Geographical Grids for Germany	DE_Grid_ETRS89-LAEA_100m DE_Grid_ETRS89-LAEA_500m DE_Grid_ETRS89-LAEA_1km		2018
NDVI data	MOD13Q1.061 Terra Vegetation Indices 16-Day Global 250m	NASA LP DAAC at the USGS EROS Center	2014
NTL data	VIIRS Stray Light Corrected Nighttime Day/Night Band Composites Version 1	Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines	2014
Land use	CORINE Land Cover 5 ha, as of 2018 (CLC5-2018)	Federal Agency for Cartography and Geodesy	2018
	Urban Atlas 2012 - München	Copernicus EU Land Monitoring Service	2012
Points of Interest **Building attributes**	OpenStreetMap data OSM Building	OpenStreetMap contributors	2022

Nighttime light data

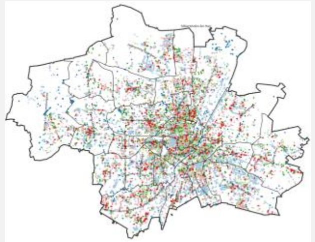
NDVI data



Urban Atlas

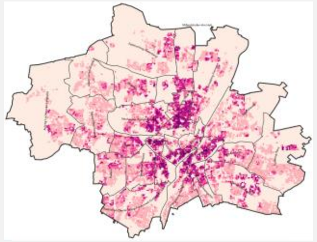


POI data



Building info

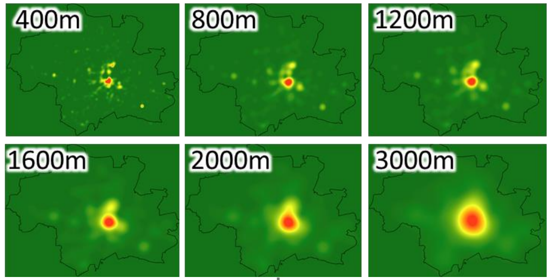
Population density



Data collection → Data filtering → Data referencing → Data reclassification → Data transformation → Data aggregation →

POI & Urban Atlas 2012 → Data reclassification

POI



→ Data transformation

Part of the table after data preprocessing

	id	Anzahl	ntl_mean	ndvi_mean	build_area	volume
1	100mN27777E44384	16	14.809857	5097.22042	3485.255449	28299.312061
2	100mN27779E44359	242	14.419295	4188.467141	3107.902749	44461.748281
3	100mN27834E44286	0	8.835617	5468.782609	522.365378	2463.521097
4	100mN27887E44304	0	5.182189	5754.366623	0	0
5	100mN27816E44255	0	10.402209	4061.64673	0	0
6	100mN27762E44440	0	24.470251	3935.730531	0	0
7	100mN27913E44375	0	4.907396	6624.058532	0	0
8	100mN27839E44271	0	9.974982	4061.652174	305.225338	2814.086694
9	100mN27894E44342	0	2.674414	5419.770124	0	0
10	100mN27830E44346	154	27.274048	3360.639779	2042.75161	27250.246131

4. Workflow, Data & Methodology

Data modeling

Use five models to train and choose the best one

- Random Forest Regression
- Ridge Regression
- Decision Tree Regression
- Support Vector Regression
- K Nearest Neighbors (KNN) Regression

Model evaluation

- R^2
- mean absolute error (MAE)
- mean relative error (MRE)

$$MAE = \frac{1}{N}\sum_{i}^{N}|P_i - R_i|$$

$$MRE = \frac{1}{N}\sum_{i}^{N}\frac{|P_i - R_i|}{R_i}$$

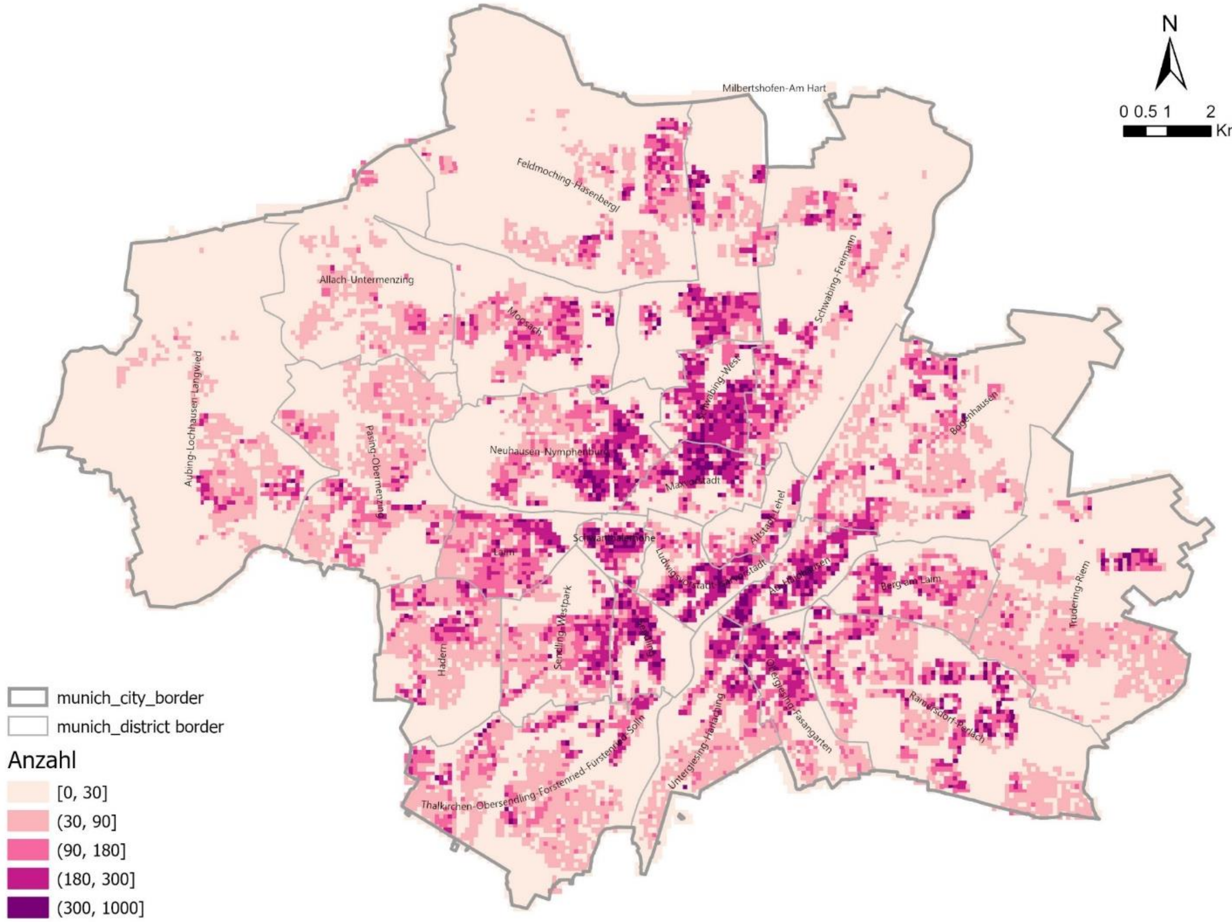
Population visualization

- Choropleth map
- Dasymetric map
- Dot map
- Proportional symbol map
- Heat map
- 3D hexbin map

5. Case Study & Results

- Study area: Munich
  - 31783 100m*100m grid cells
  - 1.35M residents (Census 2011)
  - Population density: 4254 /Km^2 (Census 2011)

Munich population distribution at 100m gridded level of Census 2011



5. Case Study & Results

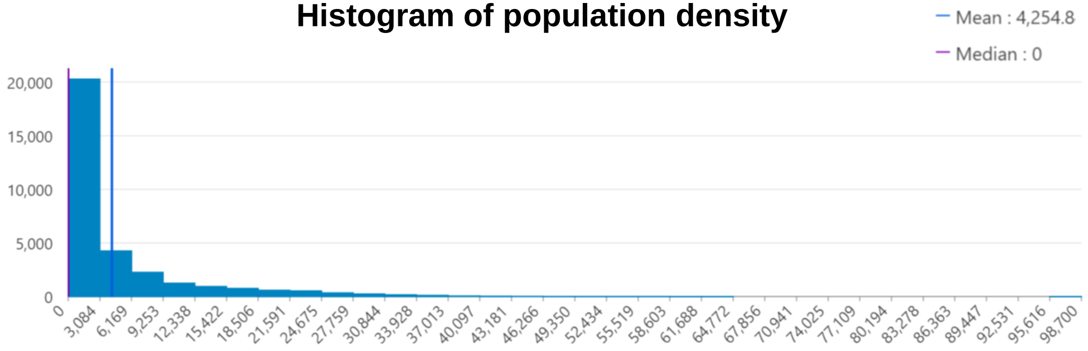
Data modeling & evaluation (100m*100m grid cell level)

- RF has the best overall performance.

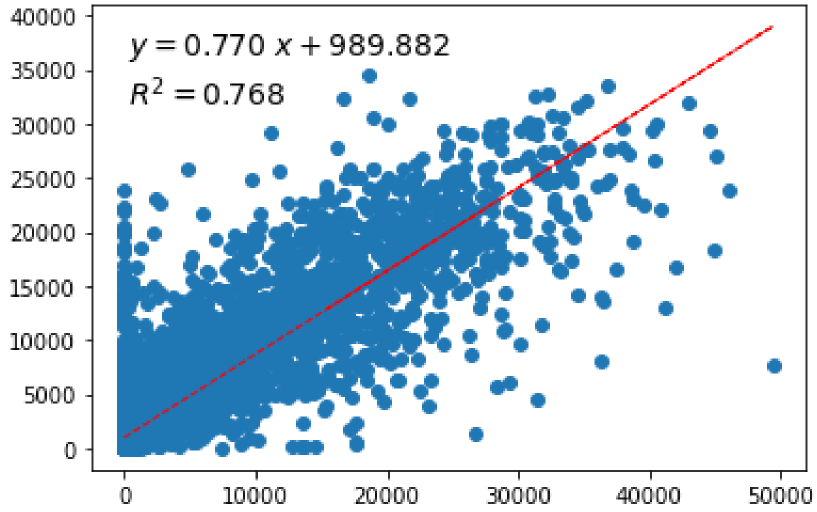
Evaluation of the applied five models

Performance	Random Forest	Ridge Regression	Decision Tree Regression	Support Vector Regression	K Nearest Neighbors Regression
R^2	**0.77**	0.58	0.49	-0.24	0.59
Mean absolute error (/km²)	**1520**	2815	2145	3774	2029
Median absolute error (/km²)	**242**	1647	0	452	200
Max error (/km²)	**42112**	40086	43900	48947	51050

Histogram of population density



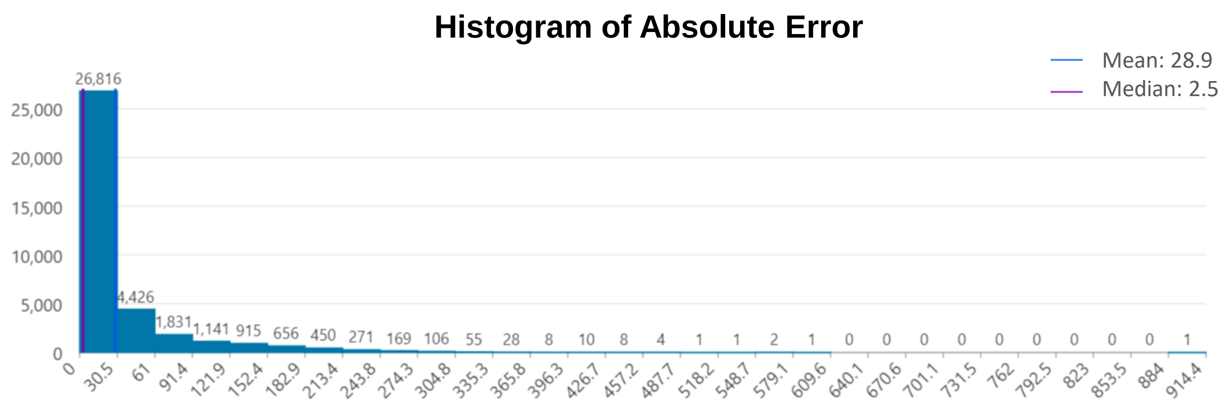
Scatter plot of true and predicted values (RF)

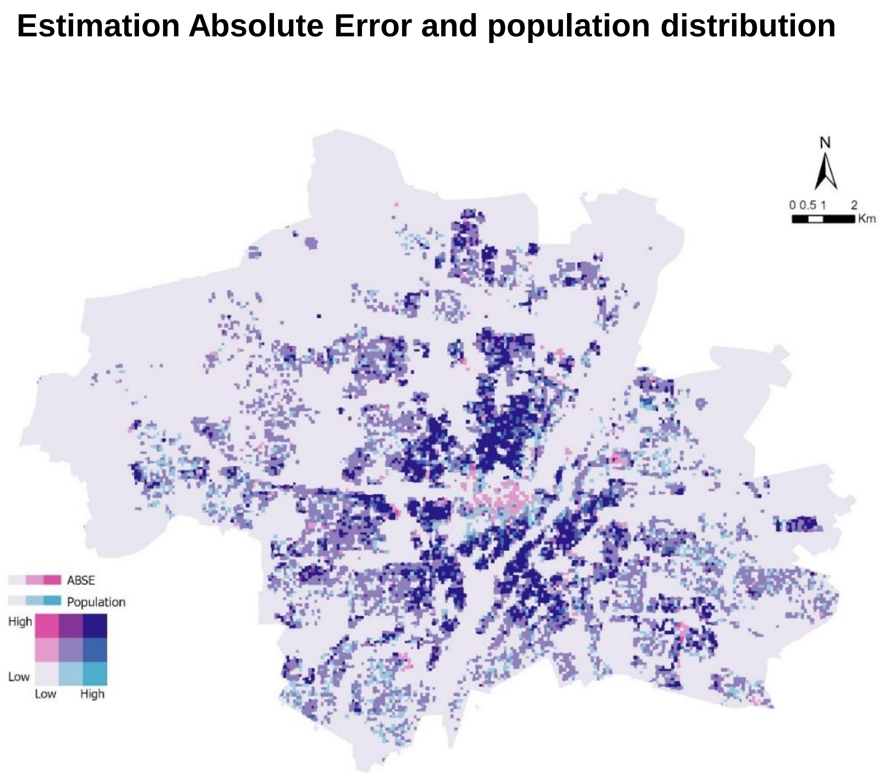


5. Case Study & Results

Data estimation & evaluation (50m*50m grid cell level)

- 76.4% are smaller than the mean population, indicating that the estimation result is good.
- High density areas have higher estimated errors.

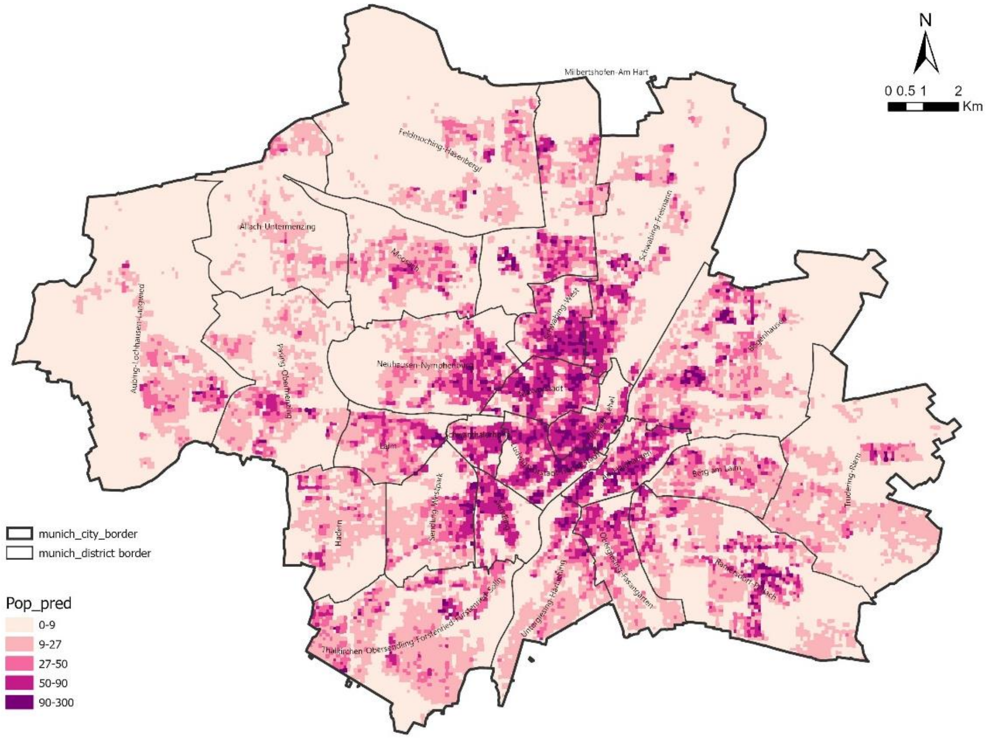




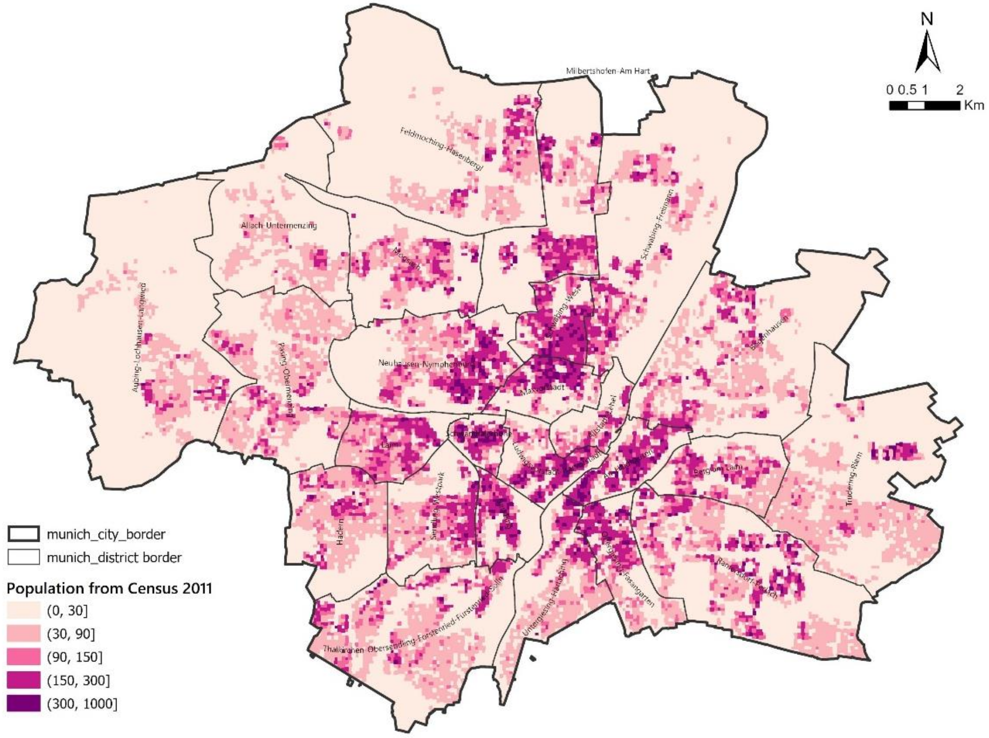
5. Case Study & Results Data estimation & evaluation (50m*50m grid cell level)

- The population values obtained by the trained model are not reliable but their relationship is.

Spatial distribution of predicted population



Spatial distribution of true population from Census 2011



5. Case Study & Results

Data allocation to buildings & visualization

Population recalculation of 50m*50m grid cells

50m*50m grid cell weight calculation based on same level prediction results

↓

Allocation of census data to 50m*50m grid cells based on its weight

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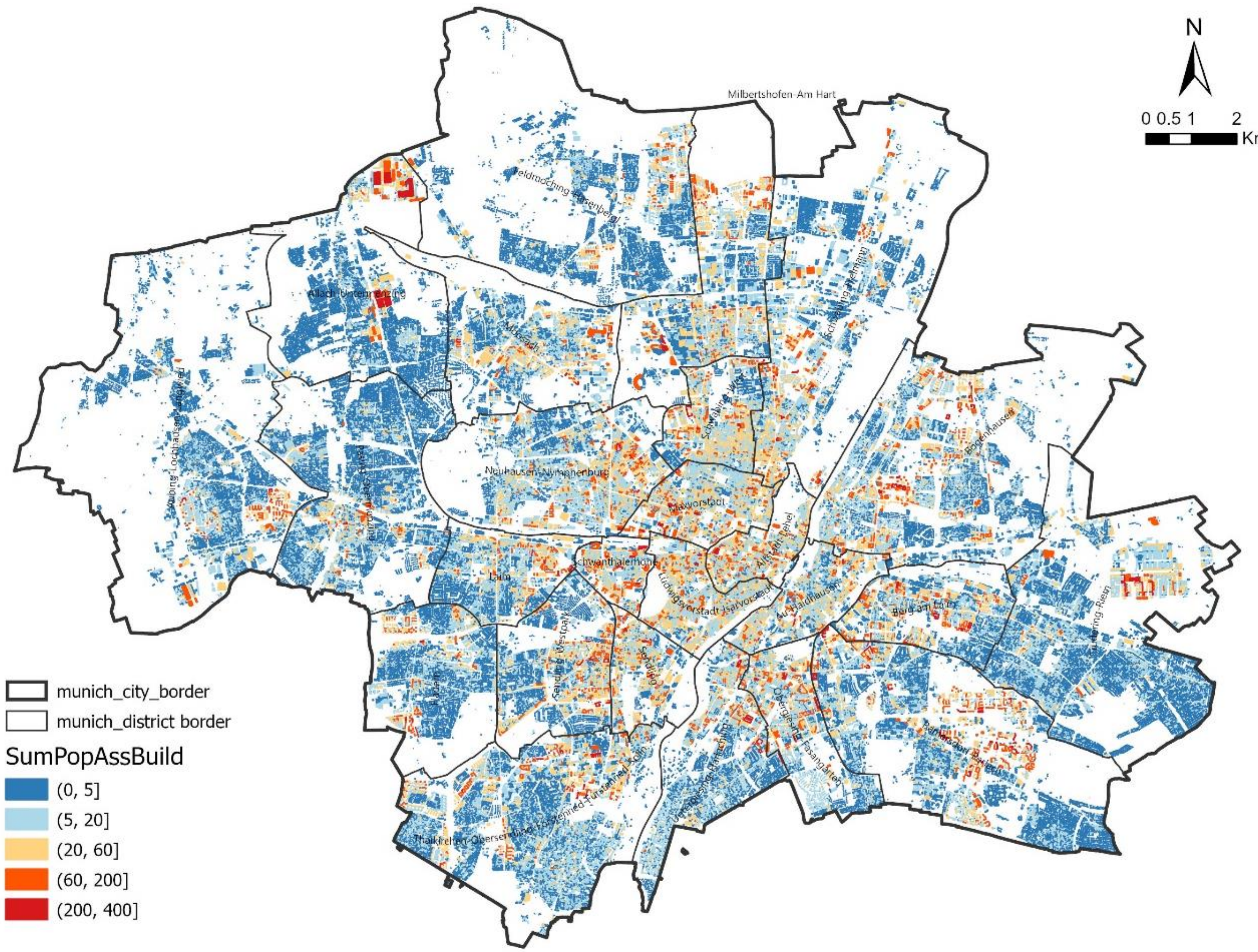
Weight calculation of each building

Weight of each building in a 50m*50m grid cell based on building volume

↓

Population of each building

Choropleth map of population distribution at building scale of Munich



5. Case Study & Results
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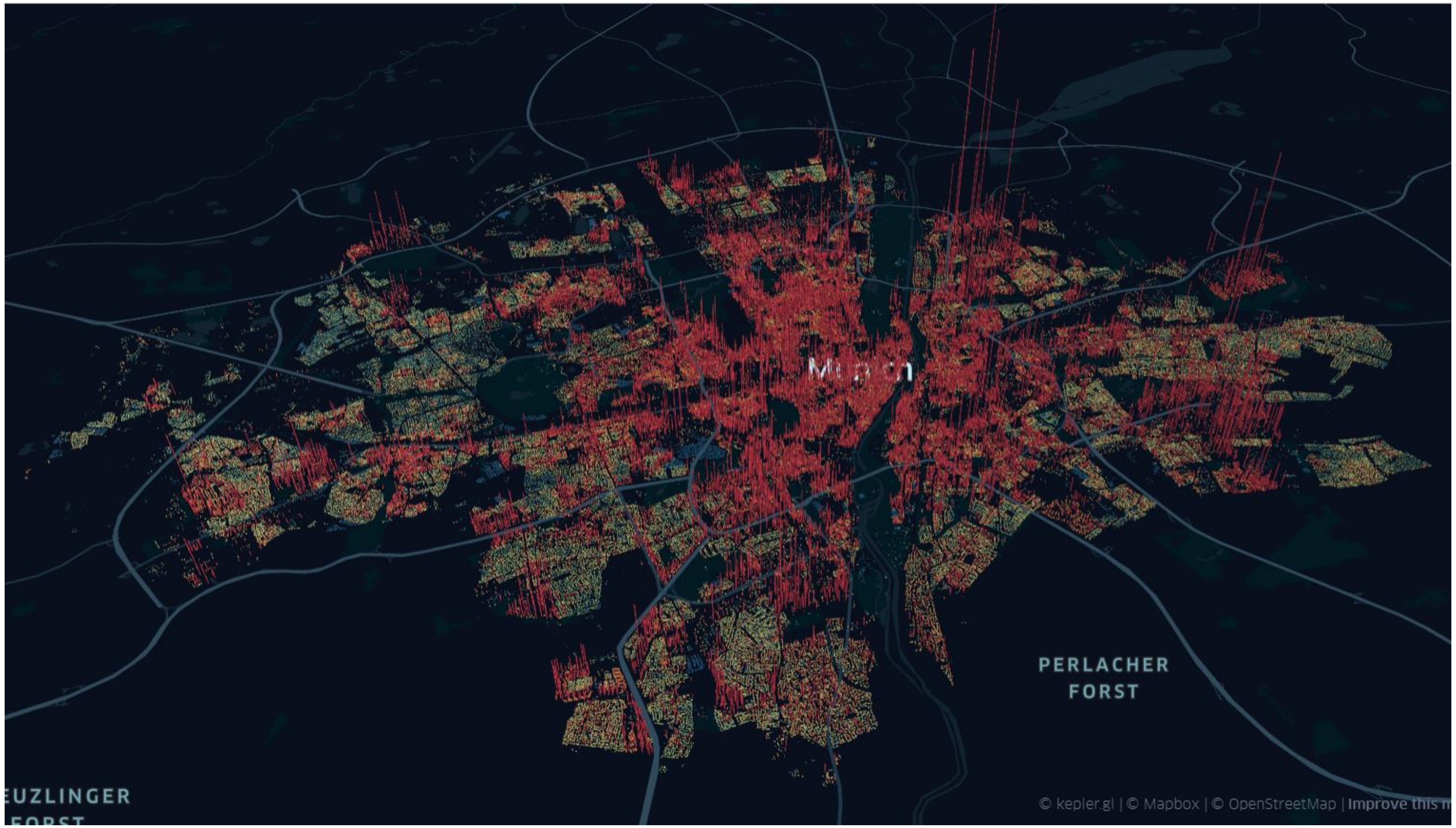
Weight calculation of each building

Weight of each building in a 50m*50m grid cell based on building volume

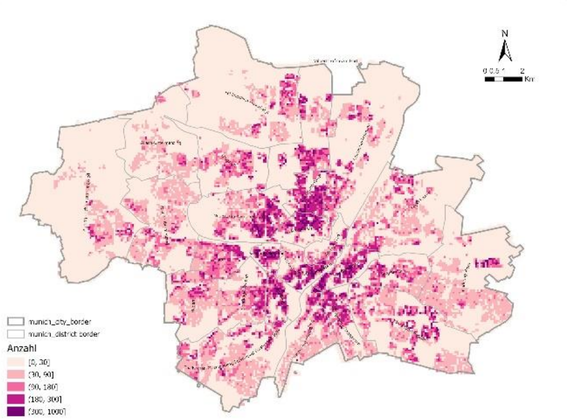
Population of each building

3D hexbin map of population distribution at building level of Munich

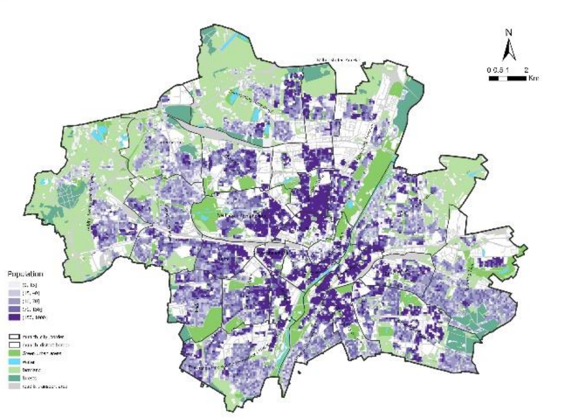


5. Case Study & Results
Data visualization (100m*100m grid cell level)

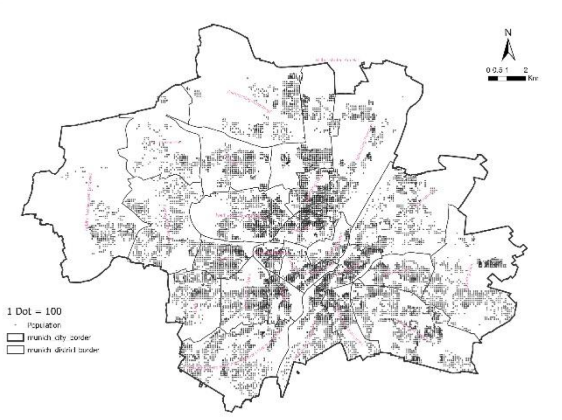
Choropleth map



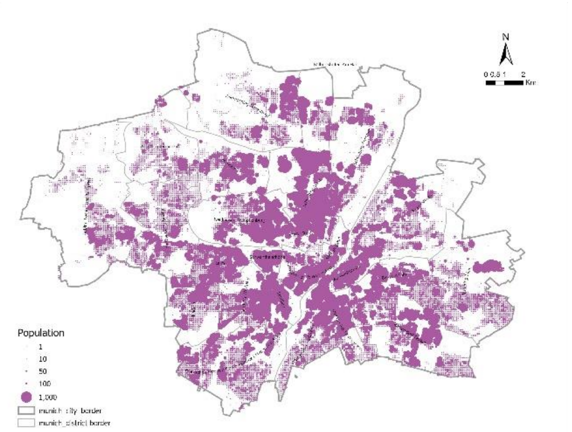
Dasymetric map



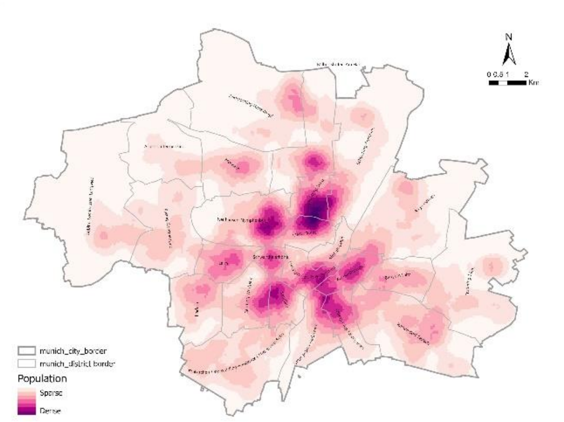
Dot map



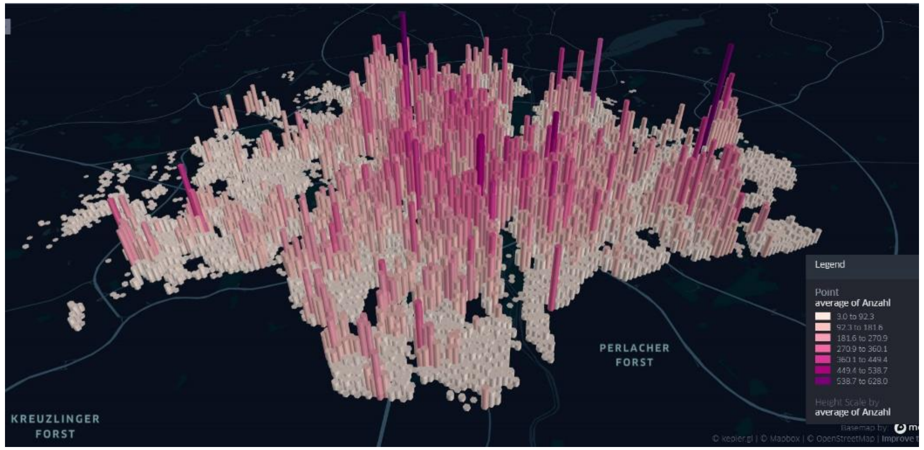
Proportional symbol map



Heat map



3D hexbin map



5. Case Study & Results Responding to research questions

- RQ1: What is the approach for fine-scale population mapping?
- RQ2: What is the optimal scale for each variable?
  - For the majority of the categories, the optimal scale is within an 800m acting range, which is about a 10-minute walk.
- RQ3: Does certain data improve the accuracy in population mapping?
  - Land use is the most important information in population mapping, following by POI.

POI category and its optimal scale

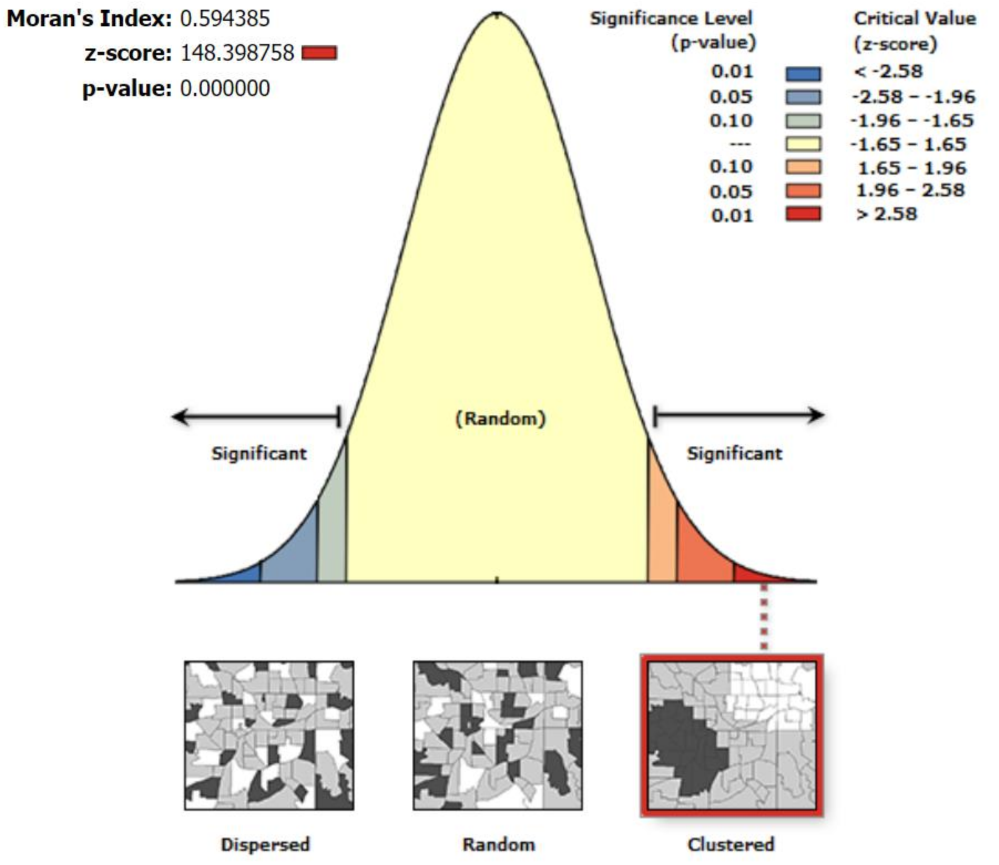
Category	Optimal Scale	Category	Optimal Scale
Accommodation	3000m	Park	3000m
Airport	3000m	Public Transport Stops	400m
Culture Facilities	800m	Railway Stops	1600m
Education Facilities	400m	Recycling Facilities	400m
Government	3000m	Resorts	800m
Health Care Facilities	400m	Restaurant & Beverages	400m
Helipad	3000m	Retail	400m
Leisure Facilities	3000m	Sport Area	400m
Life Services	400m		

Results of different datasets

Attribute	Datasets used	R^2	Mean absolute error (/km²)	Median absolute error (/km²)	Max error (/km²)
---	NTL NDVI Urban Atlas 2012 OSM Building OSM POI	0.767	1520	242	42112
Without building information	NTL NDVI Urban Atlas 2012 OSM POI	0.720	1753	300	36382
Without land use data	NTL NDVI OSM Building OSM POI	0.703	1854	393	41794
Without NTL data	NDVI Urban Atlas 2012 OSM Building OSM POI	0.767	1517	232	42165
Without NDVI data	NTL Urban Atlas 2012 OSM Building OSM POI	0.766	1518	240	41890
Without POI data	NTL NDVI Urban Atlas 2012 OSM Building	0.708	264	1706	39606

- RQ4: Do they perform same level of accuracy in different areas?
  - Clear patterns of overestimations and underestimations in the neighbourhood area
- RQ5: Is the result derived from machine learning methods has reasonable spatial details?
  - The spatial pattern of the population distribution has been learned by the regression model.

Spatial auto correlation report



Given the z-score of 148.398758, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

6. Conclusions

Summary

- A framework for population mapping at 50m*50m grid cell level and building scale has been proposed and evaluated.
- RF was found to be the best model when compared to the other four popular shallow machine learning algorithms.
- Optimal scales for each POI category are identified.
- OSM POI, OSM Building, and land use data help to improve accuracy.
- Estimation errors are highly clustered, these variables do not perform at the same level of accuracy in different population density areas.
- Machine learning can have a good result of pattern recognition instead of population value alone.

6. Conclusions

- Limitations in Methodology
  - Deep learning has been shown to be more capable than shallow machine learning at acquiring and learning multisource data, achieving higher quality population spatialization (Zhao, Liu, Zhang, & Fu, 2020).
- Limitations in Study Area
  - Only includes Munich city as a study area, with no rural or suburban areas.
- Limitations in Data Uncertainty Discussion
  - Much of the data explored is inherently uncertain due to limited knowledge, randomness and indeterminism, and vagueness (Chuprikova, 2019).
- Limitations in True Population Data Obtain
  - The obtained datasets have a broad meaning of population, not just registered residents.

Thank you :)

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References

- Bakillah, M., Liang, S., Mobasheri, A., Jokar Arsanjani, J., & Zipf, A. (2014). Fine-resolution population mapping using OpenStreetMap points-of-interest. International Journal of Geographical Information Science, 28, 1940–1963.
- Batista e Silva, F., Freire, S., Schiavina, M., Rosina, K., Marín-Herrera, M. A., Ziemba, L., . . . Lavalle, C. (2020). Uncovering temporal changes in Europe's population density patterns using a data fusion approach. Nature communications, 11, 1–11.
- Batista e Silva, F., Gallego, J., & Lavalle, C. (2013). A high-resolution population grid map for Europe. Journal of Maps, 9, pp. 16-28.
- Breiman, L. (2001). Random forests. Machine learning, 45, pp. 5-32.
- Cabello, S., Haverkort, H., Van Kreveld, M., & Speckmann, B. (2010). Algorithmic aspects of proportional symbol maps. Algorithmica, 58, pp. 543-565.
- Chen, K. (2002). An approach to linking remotely sensed data and areal census data. International Journal of Remote Sensing, 23, 37–48.
- 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.
- Cheng, Z., Wang, J., & Ge, Y. (2022). Mapping monthly population distribution and variation at 1-km resolution across China. International Journal of Geographical Information Science, 36, pp. 1166-1184.
- Chu, H.-J., Yang, C.-H., & Chou, C. C. (2019). Adaptive non-negative geographically weighted regression for population density estimation based on nighttime light. ISPRS International Journal of Geo-Information, 8, p. 26.
- Chuprikova, E. (2019). Visualizing Uncertainty in Reasoning. Ph.D. dissertation, Technische Universität München.
- Cockx, K., & Canters, F. (2015). Incorporating spatial non-stationarity to improve dasymetric mapping of population. Applied Geography, 63, pp. 220-230.
- Deville, P., Linard, C., Martin, S., Gilbert, M., Stevens, F. R., Gaughan, A. E., . . . Tatem, A. J. (2014). Dynamic population mapping using mobile phone data. Proceedings of the National Academy of Sciences, 111, 15888–15893.
- Doxsey-Whitfield, E., MacManus, K., Adamo, S. B., Pistolesi, L., Squires, J., & Baptista, O. B. (2015). Taking Advantage of the Improved Availability of Census Data: A First Look at the Gridded Population of the World, Version 4. Papers in Applied Geography, 1, pp. 226-234.
- Eicher, C. L., & Brewer, C. A. (2001). Dasymetric mapping and areal interpolation: Implementation and evaluation. Cartography and Geographic Information Science, 28, 125–138.
- Evans, R., Oliver, D., Zhou, X., & Shekhar, S. (2019). Spatial Big Data: Case Studies on Volume, Velocity, and Variety. Big Data: Techniques and Technologies in Geoinformatics, pp. 163-190.
- Flowerdew, R., & Green, M. (1994). Areal interpolation and types of data. Spatial analysis and GIS, pp. 121-145.
- Frantz, D., Schug, F., Okujeni, A., Navacchi, C., Wagner, W., van der Linden, S., & Hostert, P. (2021). National-scale mapping of building height using Sentinel-1 and Sentinel-2 time series. Remote Sensing of Environment, 252, 112128.
- Frye, C., Wright, D. J., Nordstrand, E., Terborgh, C., & Foust, J. (2018). Using classified and unclassified land cover data to estimate the footprint of human settlement. Data Science Journal, 17.
- Gallego, F. J., Batista, F., Rocha, C., & Mubareka, S. (2011). Disaggregating population density of the European Union with CORINE Land Cover. International Journal of Geographical Information Science, 25, pp. 2051–2069.
- Gaughan, A. E., Stevens, F. R., Linard, C., Jia, P., & Tatem, A. J. (2013). High resolution population distribution maps for Southeast Asia in 2010 and 2015. PloS one, 8, e55882.
- Goodchild, M. F. (2007). Citizens as sensors: the world of volunteered geography. GeoJournal, 69, pp. 211-221.
- Goodchild, M. F., & Siu-Ngan Lam, N. (1980). Areal interpolation: a variant of the traditional spatial problem. Geo-Processing, 1, pp. 297--312.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote sensing of Environment, 202, pp. 18-27.
- He, M., Xu, Y., & Li, N. (2020). Population spatialization in Beijing city based on machine learning and multisource remote sensing data. Remote Sensing, 12, p. 1910.
- Healy, K. (2018). Data visualization: a practical introduction. Princeton University Press.
- Hu, Q., Wang, M., & Li, Q. (2014). Urban hotspot and commercial area exploration with check-in data. Acta Geodaetica et Cartographica Sinica, 43, pp. 314-321.
- Huang, Z., Ottens, H., & Masser, I. (2007). A Doubly Weighted Approach to Urban Data Disaggregation in GIS: A Case Study of Wuhan, China. T. GIS, 11, pp. 197-211.
- Jackson, S. P., Mullen, W., Agouris, P., Crooks, A., Croitoru, A., & Stefanidis, A. (2013). Assessing completeness and spatial error of features in volunteered geographic information. ISPRS International Journal of Geo-Information, 2, pp. 507-530.
- Jain, D., & Tiwari, G. (2017). Population disaggregation to capture short trips--Vishakhapatnam, India. Computers, Environment and Urban Systems, 62, pp. 7-18.
- Kang, C., Liu, Y., Ma, X., & Wu, L. (2012). Towards estimating urban population distributions from mobile call data. Journal of Urban Technology, 19, pp. 3-21.
- Kimerling, A. J. (2009). Dotting the dot map, revisited. Cartography and Geographic Information Science, 36, pp. 165-182.
- Langford, M. (2006). Obtaining population estimates in non-census reporting zones: An evaluation of the 3-class dasymetric method. Computers, environment and urban systems, 30, pp. 161-180.
- Langford, M. (2007). Rapid facilitation of dasymetric-based population interpolation by means of raster pixel maps. Computers, Environment and Urban Systems, 31, pp. 19-32.
- Leyk, S., Gaughan, A. E., Adamo, S. B., de Sherbinin, A., Balk, D., Freire, S., . . . others. (2019). The spatial allocation of population: a review of large-scale gridded population data products and their fitness for use. Earth System Science Data, 11, 1385–1409.
- Liu, Y., Liu, X., Gao, S., Gong, L., Kang, C., Zhi, Y., . . . Shi, L. (2015). Social Sensing: A New Approach to Understanding Our Socioeconomic Environments. Annals of the Association of American Geographers, 105, pp. 512-530.
- Luo, P., Zhang, X., Cheng, J., & Sun, Q. (2019). Modeling population density using a new index derived from multi-sensor image data. Remote Sensing, 11, 2620.

References

- Lwin, K., & Murayama, Y. (2009). A GIS approach to estimation of building population for micro-spatial analysis. Transactions in GIS, 13, 401–414.
- McDonald, G. C. (2009). Ridge regression. Wiley Interdisciplinary Reviews: Computational Statistics, 1, pp. 93-100.
- Mei, Y., Gui, Z., Wu, J., Peng, D., Li, R., Wu, H., & Wei, Z. (2022). Population spatialization with pixel-level attribute grading by considering scale mismatch issue in regression modeling. Geo-spatial Information Science, pp. 1-18.
- Murakami, D., & Yamagata, Y. (2019). Estimation of gridded population and GDP scenarios with spatially explicit statistical downscaling. Sustainability, 11, 2106.
- Nagle, N. N., Buttenfield, B. P., Leyk, S., & Spielman, S. (2014). Dasymetric modeling and uncertainty. Annals of the Association of American Geographers, 104, 80–95.
- Nong, Y., & Du, Q. (2011). Urban growth pattern modeling using logistic regression. Geo-spatial Information Science, 14, pp. 62-67.
- Nordbeck, S., & Rystedt, B. (1970). Isarithmic maps and the continuity of reference interval functions. Geografiska Annaler: Series B, Human Geography, 52, pp. 92-123.
- Pajares, E., Muñoz Nieto, R., Meng, L., & Wulfhorst, G. (2021). Population Disaggregation on the Building Level Based on Outdated Census Data. ISPRS International Journal of Geo-Information, 10, 662.
- Pozzi, F., & Small, C. (2005). Analysis of urban land cover and population density in the United States. Photogrammetric Engineering & Remote Sensing, 71, pp. 719-726.
- Qiu, Y., Zhao, X., Fan, D., & Li, S. (2019). Geospatial Disaggregation of Population Data in Supporting SDG Assessments: A Case Study from Deqing County, China. ISPRS International Journal of Geo-Information, 8, p. 356.
- Riffe, T., Sander, N., & Klüsener, S. (2021). Editorial to the Special Issue on Demographic Data Visualization. Demographic Research, 44, pp. 865-878.
- Robinson, C., Hohman, F., & Dilkina, B. (2017). A deep learning approach for population estimation from satellite imagery. Proceedings of the 1st ACM SIGSPATIAL Workshop on Geospatial Humanities, (pp. 47-54).
- Schug, F., Frantz, D., van der Linden, S., & Hostert, P. (2021). Gridded population mapping for Germany based on building density, height and type from Earth Observation data using census disaggregation and bottom-up estimates. Plos one, 16, e0249044.
- Šimbera, J. (2020). Neighborhood features in geospatial machine learning: The case of population disaggregation. Cartography and Geographic Information Science, 47, 79–94.
- Sinha, P., Gaughan, A. E., Stevens, F. R., Nieves, J. J., Sorichetta, A., & Tatem, A. J. (2019). Assessing the spatial sensitivity of a random forest model: Application in gridded population modeling. Computers, Environment and Urban Systems, 75, pp. 132-145.
- Slocum, T. A., McMaster, R. B., Kessler, F. C., & Howard, H. H. (2022). Thematic cartography and geovisualization. CRC Press.
- 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.
- Stewart, J., & Kennelly, P. (2010). Illuminated Choropleth Maps. Annals of the Association of American Geographers, 100, pp. 513-534.
- Sun, H., & Li, Z. (2010). Effectiveness of cartogram for the representation of spatial data. The Cartographic Journal, 47, pp. 12-21.
- Sun, W., Zhang, X., Wang, N., & Cen, Y. (2017). Estimating population density using DMSP-OLS night-time imagery and land cover data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10, pp. 2674-2684.
- Sutton, P. C., Elvidge, C., & Obremski, T. (2003). Building and evaluating models to estimate ambient population density. Photogrammetric Engineering & Remote Sensing, 69, pp. 545-553.
- Sutton, P., Roberts, D., Elvidge, C., & Baugh, K. (2001). Census from Heaven: An estimate of the global human population using night-time satellite imagery. International Journal of Remote Sensing, 22, 3061–3076.
- Tiecke, T. G., Liu, X., Zhang, A., Gros, A., Li, N., Yetman, G., . . . others. (2017). Mapping the world population one building at a time. arXiv preprint arXiv:1712.05839.
- Ural, S., Hussain, E., & Shan, J. (2011). Building population mapping with aerial imagery and GIS data. International Journal of Applied Earth Observation and Geoinformation, 13, 841–852.
- Wang, M., Wang, Y., Li, B., Cai, Z., & Kang, M. (2022). A Population Spatialization Model at the Building Scale Using Random Forest. Remote Sensing, 14, 1811.
- Wu, S.-s., Qiu, X., & Wang, L. (2005). Population Estimation Methods in GIS and Remote Sensing: A Review. GIScience & Remote Sensing, 42, pp. 80-96.
- Xia, C., Nie, G., Fan, X., & Zhou, J. (2020). Research on the estimation of the real-time population in an earthquake area based on phone signals: A case study of the Jiuzhaigou earthquake. Earth Science Informatics, 13, 83–96.
- Xiong, J., Thenkabail, P. S., Gumma, M. K., Teluguntla, P., Poehnelt, J., Congalton, R. G., . . . Thau, D. (2017). Automated cropland mapping of continental Africa using Google Earth Engine cloud computing. ISPRS Journal of Photogrammetry and Remote Sensing, 126, pp. 225-244.
- Yang, X., Ye, T., Zhao, N., Chen, Q., Yue, W., Qi, J., . . . Jia, P. (2019). Population mapping with multisensor remote sensing images and point-of-interest data. Remote Sensing, 11, p. 574.
- Yang, X., Yue, W., & Gao, D. (2013). Spatial improvement of human population distribution based on multi-sensor remote-sensing data: An input for exposure assessment. International journal of remote sensing, 34, pp. 5569-5583.
- Yao, Y., Liu, X., Li, X., Zhang, J., Liang, Z., Mai, K., & Zhang, Y. (2017). Mapping fine-scale population distributions at the building level by integrating multisource geospatial big data. International Journal of Geographical Information Science, 31, 1220–1244.
- Ye, T., Zhao, N., Yang, X., Ouyang, Z., Liu, X., Chen, Q., . . . others. (2019). Improved population mapping for China using remotely sensed and points-of-interest data within a random forests model. Science of the total environment, 658, 936–946.
- Zeng, C., Zhou, Y., Wang, S., Yan, F., & Zhao, Q. (2011). Population spatialization in China based on night-time imagery and land use data. International Journal of Remote Sensing, 32, pp. 9599-9620.
- Zhang, C., & Qiu, F. (2011). A point-based intelligent approach to areal interpolation. The Professional Geographer, 63, pp. 262-276.
- Zhao, G., & Yang, M. (2020). Urban Population Distribution Mapping with Multisource Geospatial Data Based on Zonal Strategy. ISPRS International Journal of Geo-Information, 9, p. 654.
- Zhao, S., Liu, Y., Zhang, R., & Fu, B. (2020). China's population spatialization based on three machine learning models. Journal of Cleaner Production, 256, p. 120644.