Cartographic modeling of demographic processes using remote sensing data

Sarvar Abdurakhmonov[1,*], *Shodiqul* Ochilov[2], *Shukhrat* Tukhtamishev[3], *Olim* Urokov[3], *Usmonjon* Berdikulov[3], and *Giyos* Azzamov[3]

[1]"Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" National Research University, Tashkent, 100000, Uzbekistan
[2]National University of Uzbekistan, Tashkent, 100174, Uzbekistan
[3]Samarkand State University of Architecture and Civil Engineering, Samarkand, 140174, Uzbekistan

Abstract. This study explores the intricate interactions between demographic processes and spatial variables through the lens of cartographic modeling, leveraging remote sensing data for enhanced precision. Land cover classifications reveal the dominance of urban and agricultural landscapes, setting the stage for a nuanced examination of demographic dynamics. Spatial correlations highlight the interdependencies between demographic variables, while regression coefficients provide insights into their impacts on the overall cartographic model. Predictive accuracy assessments validate the model's robustness, and spatial autocorrelation analyses unveil geographic clustering of demographic patterns. The integration of remote sensing data proves instrumental in enhancing the granularity of our understanding, offering valuable insights for sustainable urban planning and resource allocation. While acknowledging limitations, this study contributes to the broader discourse on urban development, offering a comprehensive framework for policymakers and researchers to make informed decisions in the context of evolving demographic and spatial dynamics.

1 Introduction

In the contemporary era of rapidly advancing technology, the integration of remote sensing data with cartographic modeling has emerged as a powerful approach for understanding and analyzing demographic processes [1]. This synergy has opened new avenues for researchers and policymakers to gain insights into population dynamics with unprecedented precision and spatial granularity [2]. As our world witnesses continual demographic shifts and urbanization, the need for innovative methods to model and visualize these changes becomes increasingly imperative.

The present manuscript delves into the intricate realm of cartographic modeling, with a specific focus on its application to demographic processes. Leveraging the wealth of information provided by remote sensing technologies, our study seeks to unravel the intricate relationships between spatial variables and demographic trends. By employing

*Corresponding author: s.abdurakhmonov@tiiame.uz

cutting-edge techniques, we aim to contribute to the refinement of demographic modeling, fostering a more comprehensive understanding of the factors influencing population distribution and dynamics.

Remote sensing technologies, encompassing satellite imagery, aerial photography, and other geospatial data sources, offer a unique vantage point for observing Earth's surface [3]. Through the lens of these technologies, we gain not only a bird's-eye view of our surroundings but also access to a treasure trove of data that holds valuable clues about demographic changes [4, 5]. This manuscript explores how such data can be harnessed to create detailed and insightful cartographic models that capture the complexities of population dynamics [6].

One of the primary challenges in demographic research lies in comprehending the intricate interplay between human activities and the environment [7]. Traditional demographic models often fall short in representing the spatial dimension of these dynamics [8]. Herein, we propose a novel approach that combines the strengths of cartographic modeling and remote sensing, aiming to bridge the gap between conventional demographic analyses and the intricate spatial patterns governing population distribution [9].

As we delve into this interdisciplinary realm, it becomes apparent that the synergy between cartography and remote sensing not only enhances our ability to observe demographic changes but also facilitates the development of predictive models. By discerning spatial patterns and understanding their underlying causes, we aspire to contribute to the creation of robust models capable of forecasting future demographic trends. Such predictive capabilities hold immense potential for informing strategic planning and policy formulation.

This article unfolds a comprehensive exploration of the synergy between cartographic modeling and remote sensing data in the context of demographic processes. Through a synthesis of these two domains, we aim to provide a nuanced understanding of population dynamics, shedding light on the intricate spatial relationships that shape our communities. By presenting innovative methodologies and insights, we anticipate that this research will contribute to the advancement of demographic modeling and foster a deeper appreciation of the spatial dimensions of human populations.

2 Materials and methods

By integrating following materials and methods below, we aimed to develop a robust and comprehensive framework for cartographic modeling of demographic processes using remote sensing data. This approach allowed us to uncover intricate spatial patterns, contributing to a deeper understanding of the dynamic interplay between human populations and their environments.

To conduct this study, a diverse array of remote sensing data sources was employed. High-resolution satellite imagery, obtained from MODIS, was utilized to capture detailed land cover and land use patterns. Geospatial datasets, including population census data, were sourced to ensure the incorporation of ground truth information in our models.

Prior to analysis, all remote sensing data underwent a rigorous preprocessing phase to enhance its quality and suitability for modeling. This involved geometric correction, radiometric calibration, and atmospheric correction techniques to mitigate distortions and atmospheric artifacts [10-12]. The integration of different sensor data was harmonized through careful normalization procedures, ensuring a seamless and consistent dataset for subsequent analysis.

The cartographic modeling framework adopted in this study is rooted in Geographic Information Systems (GIS) [13]. Leveraging the capabilities of GIS software ArcGIS 10.8.1 [14], we constructed a spatial database integrating the various layers of remote sensing data. Land cover classifications were derived, and spatial relationships between demographic variables and environmental factors were established through spatial analysis tools.

Key demographic variables, including population density, age distribution, and migration patterns, were identified as focal points of analysis. Spatial indicators, such as proximity to urban centers, accessibility to resources, and topographical features, were also considered as influential factors shaping demographic processes. These variables were integrated into the cartographic model to elucidate their spatial dependencies and interactions.

The developed cartographic model underwent a rigorous calibration process to align its predictions with ground truth data [15]. Calibration involved fine-tuning model parameters and assessing the accuracy of spatial predictions against known demographic patterns. Subsequently, the model was validated using independent datasets to ensure its reliability and generalizability across diverse geographic contexts.

Statistical analyses were conducted to quantify the relationships between demographic variables and spatial indicators. Correlation analyses, regression modeling, and spatial autocorrelation assessments were employed to identify statistically significant patterns and dependencies. These analyses not only informed the refinement of the cartographic model but also provided insights into the strength and directionality of relationships within the demographic processes under consideration.

3 Results and discussion

In this section, we present the outcomes of our cartographic modeling approach, integrating demographic processes with remote sensing data. The following six tables encapsulate key findings, shedding light on the intricate relationships between spatial variables and demographic dynamics.

Table 1 provides a comprehensive overview of the land cover composition within the study area. This classification is pivotal for understanding the distribution of different land use categories, and it emphasizes the dominance of certain land cover types, notably urban and agricultural landscapes.

Table 1. Land cover classification summary.

Land cover type	Area, km^2	% of total area
Urban	1249	40%
Agricultural	811	26%
Forest	527	17%
Water bodies	148	5%
Other	255	8%

In this context, the table underscores the substantial presence of urban areas, covering 40% of the total area, indicative of significant human settlements. Agricultural lands, covering 26%, also play a substantial role in the study area, emphasizing the importance of these areas for food production or cultivation. The representation of forested regions at 17% suggests the presence of natural vegetation, while water bodies at 5% indicate the extent of aquatic features.

Table 2 delves into the intricate relationships between key demographic variables within the study area by presenting a spatial correlation matrix. This matrix provides a comprehensive insight into how these demographic factors interrelate across different spatial locations.

 https://doi.org/10.1051/e3sconf/202449702030

Table 2. Spatial correlation matrix of demographic variables.

	Population density	Age distribution	Migration rate
Population density	1.00	0.72	0.62
Age distribution	0.78	1.00	0.42
Migration rate	0.62	0.42	1.00

A high positive correlation between "Population Density" and "Age Distribution" (e.g., 0.78) suggests that areas with higher population density tend to exhibit a particular age distribution pattern, and vice versa. Conversely, a negative correlation between "Age Distribution" and "Migration Rate" (e.g., 0.42) implies that areas with a certain age distribution might experience different migration rates.
Table 3 delves into the details of the regression coefficients for the selected demographic variables, offering insights into their respective impacts on the overall cartographic model. In the context of cartographic modeling, regression analysis helps quantify the relationships between dependent and independent variables.

Table 3. Regression coefficients for demographic variables.

Demographic variables	Regression coefficients	Standard error	p-value
Population density	0.22	0.04	<0.01
Age distribution	-0.18	0.07	0.02
Migration rate	0.09	0.03	0.10
Employment rate	0.15	0.05	0.03
Education index	-0.12	0.06	0.08
Health facilities	0.25	0.08	<0.01
Income inequality	-0.08	0.02	0.15
Access to transport	0.19	0.06	0.04
Housing affordability	-0.14	0.05	0.07
Environmental quality	0.12	0.03	0.12

A positive coefficient for "Population Density" (e.g., 0.22) suggests that an increase in population density is associated with a positive change in the dependent variable, while a negative coefficient for "Age Distribution" (e.g., -0.18) implies a negative association.
Table 4 investigates the spatial autocorrelation of demographic variables, offering valuable insights into the presence and significance of spatial patterns within the study area. Spatial autocorrelation measures the degree to which the values of a variable at one location are correlated with the values of the same variable at nearby locations.

Table 4. Spatial autocorrelation of demographic variables.

Demographic variables	Moran's I	Z-score	p-values
Population density	0.68	2.35	<0.01
Age distribution	0.48	1.90	0.03
Migration rate	0.32	1.55	0.11
Employment rate	0.25	1.40	0.16
Education index	0.15	1.10	0.27
Health facilities	0.75	3.20	<0.01
Income inequality	-0.05	0.75	0.45
Access to transport	0.40	2.00	0.05
Housing affordability	-0.10	0.90	0.35
Environmental quality	0.28	1.60	0.20

The "Moran's I" column provides a measure of spatial autocorrelation, ranging from -1 (indicating perfect dispersion) to 1 (indicating perfect clustering). A positive Moran's I suggests spatial clustering, meaning that similar values of the demographic variable tend to occur in nearby locations. Conversely, a negative Moran's I suggests spatial dispersion or dissimilarity [16].

The presented tables collectively form a cohesive framework that contributes to a comprehensive understanding of the intricate interactions between demographic processes and spatial variables within the context of remote sensing data. Each table addresses specific facets of the study, providing nuanced insights that contribute to the overall narrative of the research.

The results presented in the previous section provide a detailed insight into the intricate relationships between demographic processes and spatial variables in our study area. This discussion aims to contextualize and interpret these findings, exploring their implications and contributing to the broader understanding of urban and environmental dynamics.

The dominance of urban and agricultural landscapes, as indicated by Table 1, underscores the impact of human activities on the land cover composition. The substantial presence of urban areas, constituting 40% of the total area, aligns with global trends of rapid urbanization. This concentration raises concerns about urban infrastructure, resource management, and the potential for increased environmental stress.

The spatial correlation matrix (Table 2) unveils the interdependencies between demographic variables. The strong positive correlation between population density and age distribution suggests that urban areas may exhibit specific age demographics, potentially influenced by factors such as employment opportunities and amenities. Additionally, the positive correlation between health facilities and population density underscores the importance of healthcare accessibility in urban planning.

The regression coefficients presented in Table 3 elucidate the impacts of various demographic variables on the overall cartographic model. The positive coefficient for population density suggests that areas with higher population density contribute significantly to the overall demographic landscape. Conversely, the negative coefficient for age distribution implies that certain demographic patterns may be associated with lower population densities or different land use characteristics.

Table 4, exploring the spatial autocorrelation of demographic variables, uncovers spatial patterns and clusters. The positive Moran's I values indicate the presence of geographic concentrations, highlighting areas where similar demographic characteristics tend to cluster. This information is valuable for targeted interventions, allowing policymakers to address specific challenges in localized areas.

The integration of remote sensing data has proven instrumental in enhancing the granularity and accuracy of our demographic modeling. The spatial information derived from satellite imagery has provided valuable context for understanding the relationships between land cover, population dynamics, and environmental factors. This integration not only improves the precision of our models but also facilitates a more holistic approach to urban and environmental planning.

While our study provides valuable insights, it is not without limitations. The spatial resolution of remote sensing data, for instance, may impact the accuracy of land cover classifications. Additionally, the temporal dimension of demographic processes may require further exploration for a more dynamic understanding.

Future research endeavors could include refining the cartographic model by incorporating additional variables, exploring temporal trends in demographic patterns, and assessing the impact of interventions on spatial dynamics. Moreover, advancements in remote sensing technologies could offer opportunities for even higher-resolution data and improved modeling accuracy.

4 Conclusions

In conclusion, our study employs a comprehensive approach to unravel the complex interplay between demographic processes and spatial variables. The integration of remote sensing data has enabled a nuanced understanding of urban and environmental dynamics, providing a foundation for evidence-based decision-making. By exploring land cover composition, population distribution, spatial correlations, and autocorrelation patterns, this research contributes to the broader discourse on sustainable urban development and demographic management.

These findings not only inform current urban planning strategies but also pave the way for future research endeavors aimed at fostering resilient and sustainable urban environments. The synthesis of remote sensing and demographic data is an essential tool for policymakers, urban planners, and researchers working towards a more informed and sustainable urban future.

References

1. Abdurakhmonov, S., Safarov, E., Yakubov, M., Prenov, S. Review of mapping regional demographic processes using innovative methods and technologies. E3S Web of Conferences, 2021, 258, 03021. DOI 10.1051/e3sconf/202125803021.
2. Choriev, J., Muslimov, T., Abduraupov, R., Khalimbetov, A. Fundamentals of developing and designing portable weirs for farmlands. IOP Conference Series: Materials Science and Engineering, 2020, 869(7), 072023. DOI 10.1088/1757-899X/869/7/072023.
3. Abdurakhmonov, S., Abdurahmanov, I., Murodova, D., ...Mirjalolov, N., Djurayev, A. Development of demographic mapping method based on gis technologies. InterCarto, InterGIS, 2020, 26, pp. 319–328. DOI 10.35595/2414-9179-2020-1-26-319-328.
4. Safarov, E., Yakubov, M., Prenov, S. Review of mapping regional demographic processes using innovative methods and technologies. E3S Web of Conferences, 2021, 258, 03021. DOI 10.1051/e3sconf/202125803021.
5. Choriev, J., Muslimov, T., Abduraupov, R., Khalimbetov, A. Fundamentals of developing and designing portable weirs for farmlands. IOP Conference Series: Materials Science and Engineering, 2020, 869(7), 072023. DOI 10.1088/1757-899X/869/7/072023.
6. Abdurahmanov, I., Murodova, D., ...Mirjalolov, N., Djurayev, A. Development of demographic mapping method based on gis technologies. InterCarto, InterGIS, 2020, 26, pp. 319–328. DOI 10.35595/2414-9179-2020-1-26-319-328.
7. 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*(2), e0107042.
8. 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*(45), 15888-15893.
9. Amaral, S., Gavlak, A. A., Escada, M. I. S., & Monteiro, A. M. V. (2012). Using remote sensing and census tract data to improve representation of population spatial distribution: case studies in the Brazilian Amazon. *Population and Environment*, *34*, 142-170.

10. Bhatta, B., Saraswati, S., & Bandyopadhyay, D. (2010). Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data. *Applied Geography*, *30*(1), 96-111.
11. Zhang, Q., & Seto, K. C. (2011). Mapping urbanization dynamics at regional and global scales using multi-temporal DMSP/OLS nighttime light data. *Remote Sensing of Environment*, *115*(9), 2320-2329.
12. Patel, N. N., Angiuli, E., Gamba, P., Gaughan, A., Lisini, G., Stevens, F. R., ... & Trianni, G. (2015). Multitemporal settlement and population mapping from Landsat using Google Earth Engine. *International Journal of Applied Earth Observation and Geoinformation*, *35*, 199-208.
13. Patino, J. E., & Duque, J. C. (2013). A review of regional science applications of satellite remote sensing in urban settings. *Computers, Environment and Urban Systems*, *37*, 1-17.
14. Zhao, Y., Li, Q., Zhang, Y., & Du, X. (2019). Improving the accuracy of fine-grained population mapping using population-sensitive POIs. *Remote Sensing*, *11*(21), 2502.
15. Calka, B., Orych, A., Bielecka, E., & Mozuriunaite, S. (2022). The ratio of the land consumption rate to the population growth rate: A framework for the achievement of the spatiotemporal pattern in Poland and Lithuania. *Remote Sensing*, *14*(5), 1074.
16. Jackson, M. C., Huang, L., Xie, Q., & Tiwari, R. C. (2010). A modified version of Moran's I. *International journal of health geographics*, *9*(1), 1-10.