



GIS-Based Land Price Modelling for Housing Affordability Assessment: A Pilot Study in Volos, Greece

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Abstract: Land costs play a pivotal role in housing affordability but are often misrepresented in urban research. This pilot study assesses land price shifts and their implications for housing affordability in Volos, Greece, through GIS-based interpolation. Price surfaces were modelled using 2022 land plot price data and geostatistically validated to be used as a baseline. Comparison with 2024 data reveals rising land prices in areas where land was previously affordable, highlighting a growing challenge to housing affordability. This study also shows that land costs can be effectively monitored using geostatistics and price mapping, even in smaller and imperfect markets. This research contributes to the literature on spatially informed real estate analysis in less-studied areas with limited real estate data.

Keywords: land prices; affordable housing; GIS interpolation; price modelling; real estate.



Theoretical Context

From Land Prices to Housing Affordability

To assess housing affordability, economic parameters such as income, rent levels, mortgage rates, and housing maintenance costs are commonly considered. Regarding real estate factors, the discussion usually revolves around the affordability of the existing housing stock for leasing or homeownership purposes. However, the cost of land acquisition is often underexplored, even though the link between land and housing may seem self-evident. This is somehow expected since the impact of land acquisition costs on housing affordability is not straightforward. Anthony (2022) argues that housing affordability is better monitored by incorporating income measures, despite acknowledging land prices as a factor per se. In their study, Costello and Rowley (2015) found a clear, albeit weak, link between land supply and house prices. Yii et al. (2022) argued that urban land prices are a key component in housing price prediction, noting that the effect of housing prices on urban land prices is stronger than the inverse. Monitoring local market dynamics is necessary, as national averages do not reflect local variations in land acquisition costs (Bratt and Lew 2016).

Nevertheless, it is clear that land prices impact the affordability of housing. Rising land prices lead to a reduction in floor space and the exclusion of lower-income families from acquiring land for housing (Bertaud 2009). Choi et al. (2020) noted that, in metropolitan areas, land availability affects the prices of low-tier houses more than those of high-tier ones. Grimes & Aitken (2010) showed that land price dynamics, along with supply elasticity, influence how the market absorbs demand spikes. Land price trends are also a critical factor in policy decision-making, as they impact housing affordability, as a result of both public support (subsidies, tax incentives etc.) and private development initiatives. Nevertheless, government actions rarely focus on land affordability. Land costs are typically considered part of the total construction costs and left to the developer, rather than being treated as a factor per se. For developers, having fixed land costs in residential construction projects may motivate them to keep housing prices affordable (Bertaud 2010). However, this cannot be expected in a speculative market. Speculative land price growth and real estate bubbles are indeed critical issues, as rising land prices hinder affordable housing. Based on Paccoud et al. (2022) it can be argued that, unless there is an exceptional rise in land prices, the public sector refrains from market regulation because of the political cost and a lack of focus on ensuring housing affordability.

Land costs also affect the feasibility of small rental properties (fewer than ten units), usually owned by homeowners living nearby, as an additional source of income (Mallach 2009). Increasing land costs pose an additional burden on small rental property investors because of increased construction costs, loan debt, and property taxation (Mallach 2009). Mallach (2009) argued that the small rental property sector allows for more affordable rents for lower income tenants. Therefore, increasing land costs will either deter these small investors or drive rents up, making them less affordable. This is critical in countries like Greece, where the private rental sector is limited and the public rental sector almost inexistent. Homeownership in Greece has always been dominant, but rates dropped from ~77% in 2010 to 69.6% in 2023 (Eurostat 2025a). In countries with traditionally high homeownership rates, land acquisition costs have a stronger impact on prospective homeowners because of high demand and supply constraints, especially for young families in urgent need of affordable housing.

Household income increase is a factor driving housing demand up along with land prices (Bertaud 2009), but things are not so simple. In Greece there has been a boom in real estate



prices since 2019, but it would be wrong to assume an increase in income as the main reason. Indeed, the minimum wage rose from ~640€ in 2019 to ~910€ in 2023 (Eurostat 2025b), but the standardised House Price to Income Ratio also increased by ~16% for the same period (Eurostat 2025c), indicating a dramatic spike in housing costs. Overall, 28.5% of Greek people were under housing cost overburden in 2023 (Eurostat 2025d).

The demand for land to build on also depends on the availability of stock that can meet modern needs. Older housing stock, of lower energy performance, may still be on the market at lower prices, but without contributing to housing affordability due to increased maintenance and energy costs. Since increased land costs are passed on to prospective buyers or self-build homeowners, total construction costs must also be considered. In Greece construction costs for new residential buildings rose ~19% from 2020 to 2023 (Eurostat, 2025e), and the Construction Cost Index (CCI) increased by 20.5% from the 2021 baseline (Eurostat, 2025f). Interestingly, the CCI disregards land costs, which typically represent 15-20% of total construction costs. This percentage may increase in the case of single or two-storey houses intended for family homeownership, rather than in apartment buildings. Overall, the increased land cost is a value that homeowners do not typically capitalise on, unlike investors, and is therefore an additional burden in terms of affordability. This is especially true when the increase in land premiums does not align with the actual value increase of the land, for example, due to improved infrastructure in the area.

GIS and Real Estate Analysis

During the last decade there has been an increasing interest in the use of Geographical Information Systems (GIS) in real estate analysis, but the discussion is not new. Back in the 1990s, Thrall and Marks (1993) were theorising on the potential of GIS and spatial reasoning for improving real estate analysis. However, despite a growing body of literature supporting the use of GIS tools and methods in real estate analysis, it remains a niche field in academic research (Reed and Pettit 2019). A main challenge for integrating GIS scientific methods into real estate analysis is data availability, since real estate prices are not always available or accessible, especially in smaller and imperfect markets (Reed and Pettit 2019). Moreover, each property market has its own particularities and spatiotemporal variations, making the generalisability of GIS-based models debatable (Reed and Pettit 2019). Lastly, the applicability and utility of GIS-based models in real estate practice are not self-evident and must be clearly and efficiently explained, accounting for the GIS knowledge and training barriers faced by real estate professionals (Reed and Pettit 2019). Aligned with global research trends, the integration of GIS methods in real estate analysis is still limited in Greece, which can be partly attributed to Greek real estate market issues with data accuracy and availability (Dimopoulos and Moulas 2016).

Key driver of the increasing focus on integrating GIS and real estate is the pronounced need for real estate analyses – still overly reliant on assumptions and heuristics – to become more data-driven regarding decision-making and valuation methodologies. This has been amplified by post-2010 systemic shocks in property markets worldwide (Renigier-Bilozor et al. 2018), as well as by criticism of real estate methods lacking standardisation and transparency, such as in real estate appraisal and taxation (Bencure et al. 2019). Reed & Pettit (2019) argue that GIS and real estate integration can be data-driven, thus providing more scientifically robust output. Kobylinska and Cellmer (2016) noted that, regarding price diagnosis and prediction, geostatistical methods are important because of the spatial aspect of real estate transactions and their potential to synergise efficiently with traditional statistics.



Research Aim

The aim of this study is to assess land price shifts and their implications for housing affordability in the Greek city of Volos via GIS-based geostatistical analysis. This pilot study thus contributes to the growing body of literature on spatially informed decision-making, improving land price-monitoring methodologies in property markets. While similar methods have been applied in other international contexts (Chen et al. 2020; Szczepanska et al. 2020), this is the first application of Kriging-based land price modelling in Volos, contributing a local case-study to the wider discourse on geospatial real estate analysis.

Data and Methodology

Study Area and Data Collection

For the purpose of this pilot study, the clearly defined urban core of the Greek city of Volos was selected, with an approximate area of 12.3 km². Volos is a dynamic and varied port city on the eastern coastline of central Greece, including numerous recreational and tourism areas, a university, an industrial zone, and integrated transport infrastructures (a port, a railway, and a national-road hub). For GIS geoprocessing, data on 67 buildable land plots and their sale prices (€/m²) were collected between Q4-2022 and Q1-2023 (Figure 2) from online real estate platforms, after their locations were confirmed via Google Earth using photos posted on the property sale listings. Data collection was cross-sectional, focusing on a specific, short time-period. Sampling was based on availability and accessibility (convenience, non-probabilistic sampling). The sample dataset used in the EBK interpolation ($N=67$) had a *mean* and *median* of 352 €/m² and 298 €/m², respectively, a *range* of 905 €/m², and a *standard deviation* of 205 €/m². The distribution of the data had a positive *skewness* of 1.38 (more low-price land plots and few high-price outliers) and a *kurtosis* of 4.68. Such variability in real estate prices datasets is expected. Similarly, the follow-up land plot locations and prices ($N=38$) used for price monitoring were collected between Q4-2024 and Q1-2025 (Figure 3).

The land property locations and their announced prices¹ were digitised into GIS layers using ArcGIS Pro software, which was also used for geostatistical analysis, modelling, and mapping. During geoprocessing the GGRS87 geographic coordinate system was used, and the raster resolution for all GIS layers was set at 5m (5x5m cells). The following section describes the interpolation method selected for land plot price mapping, the defined model parameters, and the accuracy validation of the EBK output.

Probabilistic Interpolation - Empirical Bayesian Kriging (EBK)

For real estate price modelling, Kriging interpolation methods are often the best choice due to spatial autocorrelation of properties, which is inherently handled in Kriging methods. Also, in cases of small datasets and due to the need to interpolate values in unsampled locations, the use of Kriging methods is suggested (Kuntz and Helbich 2014). Moreover, property prices are often temporally constrained, with missing data or fragmented continuity over time. Kriging methods focus on spatial price modelling without explaining causal relations and are thus not limited by sample size and data inconsistency issues (Kuntz and

¹ In this paper, 'prices' refer to sale prices, unless otherwise stated.



Helbich 2012). For this pilot study, the Empirical Bayesian Kriging (EBK) method was used. The EBK is an advanced, probabilistic² method combining the advantages of Kriging interpolation with Bayesian statistical principles to improve spatial analysis (Krivoruchko 2012; Krivoruchko and Gribov 2019). A key advantage of the EBK, compared to other Kriging methods, is that it reduces the number of parameters the user has to define, and removes the need to manually customise the semivariogram. In traditional Kriging methods, parameterisation and accuracy of the model depend not only on the quality of the data, but also on the expertise and judgement of the user. Instead, the EBK tool automatically runs multiple simulations, producing a range of semivariograms to help identify the best-fitting model for the case examined. The semivariogram is not fixed or pre-set, like in traditional Kriging methods, but model parameters such as sill, nugget, and range are dynamically adjusted, eventually leading to higher accuracy (Krivoruchko 2012; Krivoruchko and Gribov 2019). Also, the EBK does not assume a semivariogram or stationarity, which is particularly useful when data samples are limited, unevenly distributed, or contain outliers. This is the case with real estate price data in small and imperfect markets, as well as with the dataset used for this study.

The EBK served the aim of this study well, mitigating issues related to the nature of real estate data and ensuring accuracy, even with a smaller, non-uniform sample. The EBK method enhances accessibility by simplifying the parameterisation of the Kriging model. Land plot price modelling using the EBK allowed for control over the interpolation model parameters, providing various indices and graphs to aid in evaluating the model's prediction accuracy and overall performance.

The EBK Model Parameters

Since, as anticipated, the 2022 dataset did not follow a normal distribution, the *empirical* transformation type was applied as the most suitable for normalising this dataset and optimising it before using the data in the Kriging model. For the semivariogram model type, the *exponential detrended* option was selected as it helped optimise the output. This choice aligns with real estate prices, which typically follow spatial trends, gradually increasing/decreasing across different areas. By detrending, the systematic trends of the dataset are removed, improving the efficiency of the Kriging algorithm in capturing local variations.

On other EBK parameters, the *subset size* was set to 20, with an *overlap factor* of 3. Smaller subsets help capture expected local price variations and abrupt pricing changes linked to neighbourhood effects and recent transactions, without overfitting the model. The higher overlap factor improved the continuity and smoothness of the interpolated price surface. For the search parameters, *standard circular* neighbourhood was set up to a radius of ~1230m, allowing for a broader price point search area in case of sampling gaps. The range of 3-8 price points to include was used to simulate the common practice of realtors using the sales comparison method, i.e. searching for comparable properties on sale for valuation purposes. Lastly, the number of *simulations* was set to 200 to ensure a sufficient number of semivariograms were simulated and to optimise the EBK model. It should be noted that the EBK parameters (Figure 1b) were selected via comparative experimentation with various combinations, according to the nature of the data and the study objectives, to geostatistically optimise the price surface output using cross-validation (ArcGIS Pro).

² Interpolation based on probability and uncertainty vs. deterministic methods that assume fixed values and no variability.



Validating the EBK Model

Before using the land plot price surfaces (2022 baseline) with the 2024-2025 dataset, it was necessary to assess the reliability of the interpolated model in terms of accuracy, uncertainty, and overall performance. This was done through the ArcGIS *Cross-validation* tool (Figure 1). One of the key metrics to focus on is the *Average Standard Error* of $\sim 117 \text{ €/m}^2$, representing $\sim 13\%$ of the total variation in the dataset (range of 905). The typical prediction error can be deemed relatively small and acceptable for real estate pricing models, where variations of 15-20% are within the norm, accounting for various prediction and valuation uncertainties. The high variability of the 2022 dataset further supports this conclusion. The $\sim 13\%$ error margin allows the price model to effectively account for uncertainty, which is crucial for reliable price prediction and informed decision-making in real estate analysis.

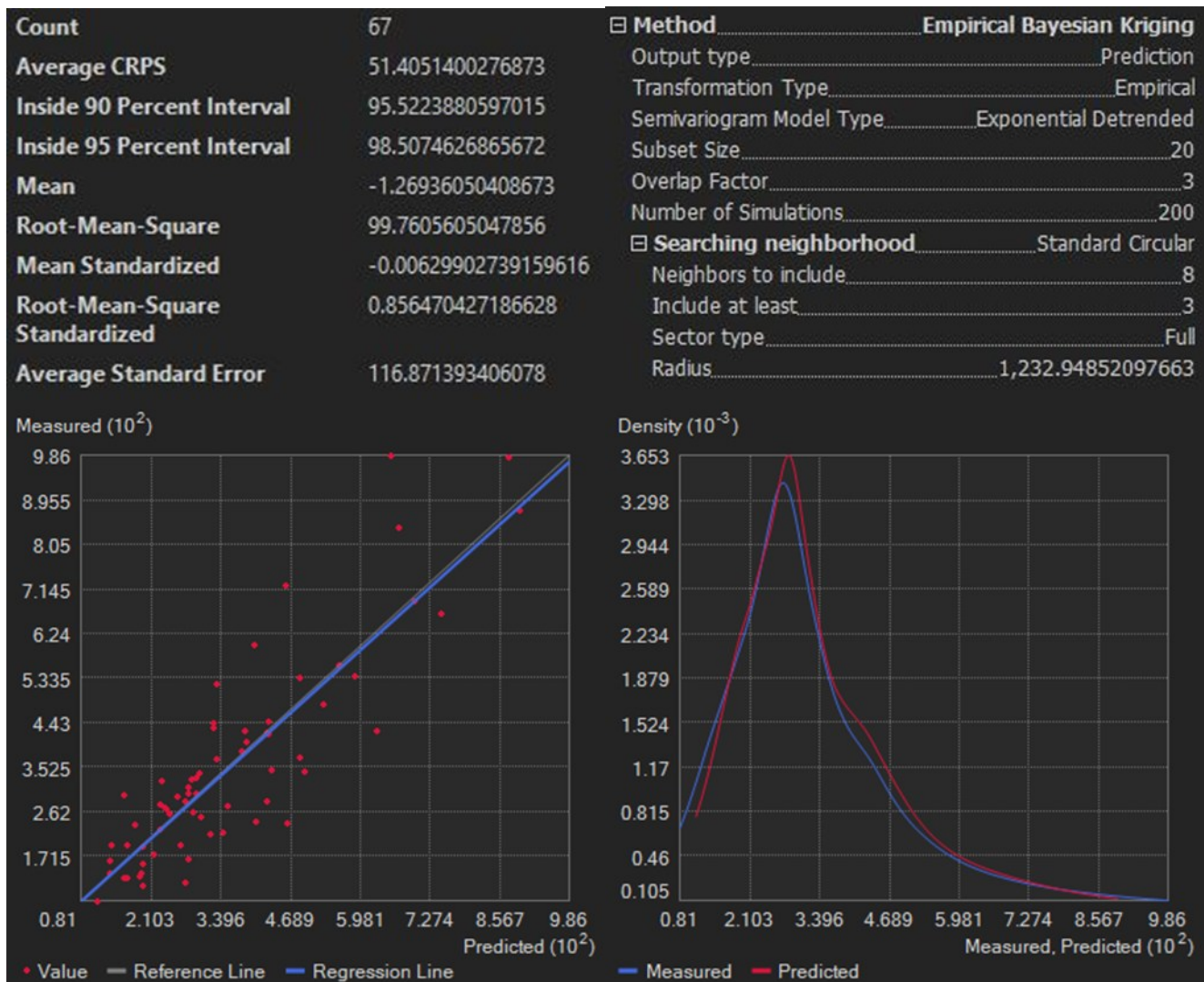
On other metrics, the slightly negatively biased *Mean* of -1.27 indicates that the predictive model tends to slightly underestimate the observed values on average. The *Mean Standardised* error of -0.006 is very close to zero, with the extremely low negative bias being negligible and not affecting the model's reliability. The *Root Mean Square Standardised* error of 0.86, being close to 1, indicates that the model performs efficiently for predictive purposes, with predictions being of similar scale to the observed values and relatively small errors. The 90% and 95% confidence interval indices suggest that the EBK model performs strongly in capturing the spatial trends and the variability of the data, with price predictions for unsampled locations showing increased accuracy.

Furthermore, it is important to assess the fitness of the predictive EBK model using two key graphs. The Predicted vs. Measured values scatter plot (Figure 1c) suggests that the EBK model is overall accurate and refined. There is a slight deviation towards the higher values, where the cone-like pattern of the data also spreads wider as a result of the increased variability in the predictions. This indicates that the model slightly underestimates higher-priced land properties, while for the rest of the price range, the predictions are highly accurate, with the regression line deviating only marginally from the reference line.

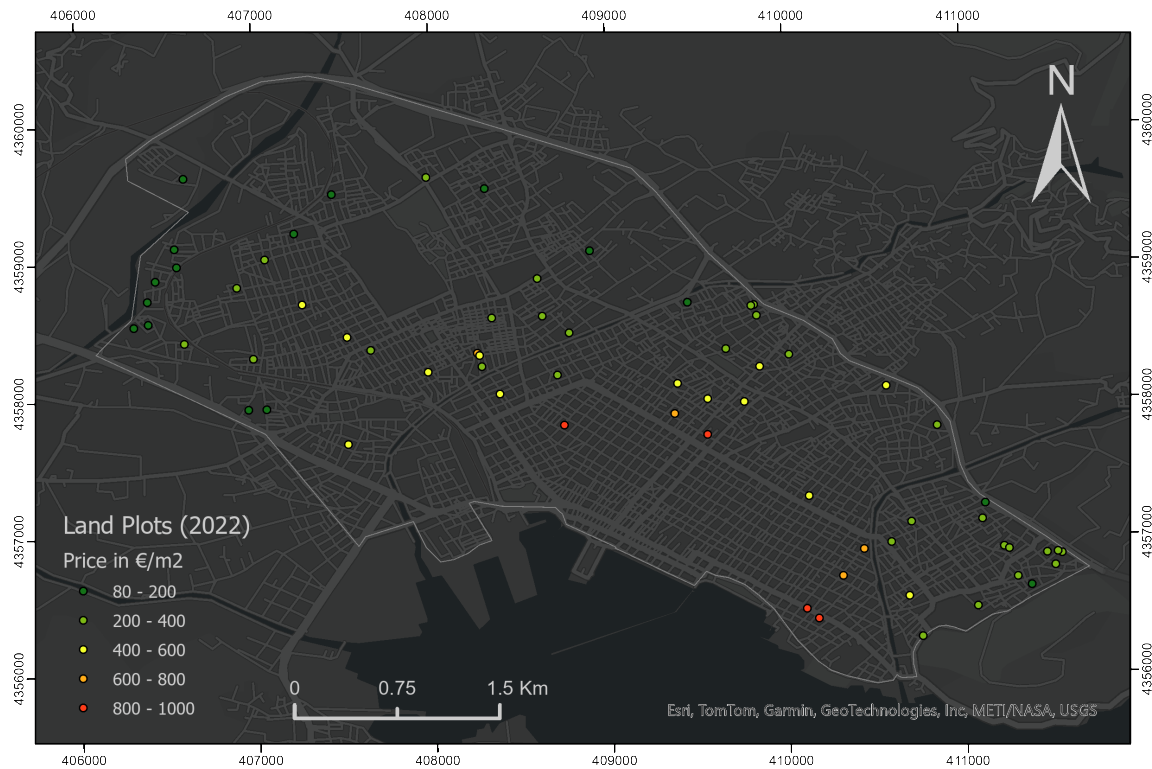
In the Measured vs. Predicted distribution graphs (Figure 1d), the two curves coincide, suggesting that the EBK is not biased in over-sampled areas and effectively represents the entire dataset. This is important considering the dataset was based on available announced land-plot prices on sale and the study area could not be evenly sampled. Despite this, the model accurately captured the distribution of the data, even in under-sampled locations. Overall, the cross-validation profile indicates an accurate and robust EBK model with high predictive accuracy in unsampled locations.



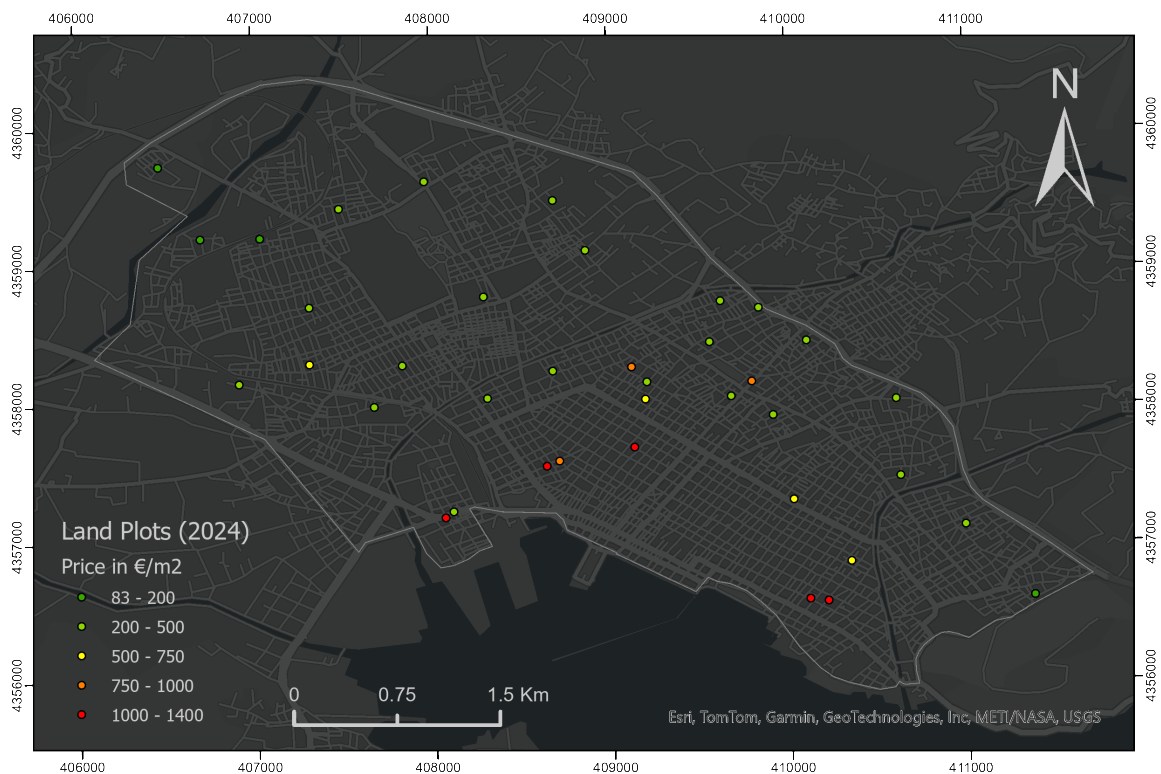
Figure 1: EBK Cross-validation: (a) geostatistical metrics; (b) model parameters; (c) Predicted vs. Measured values scatter plot; (d) Predicted vs. Measured distribution graphs. [from top-left to bottom-right]



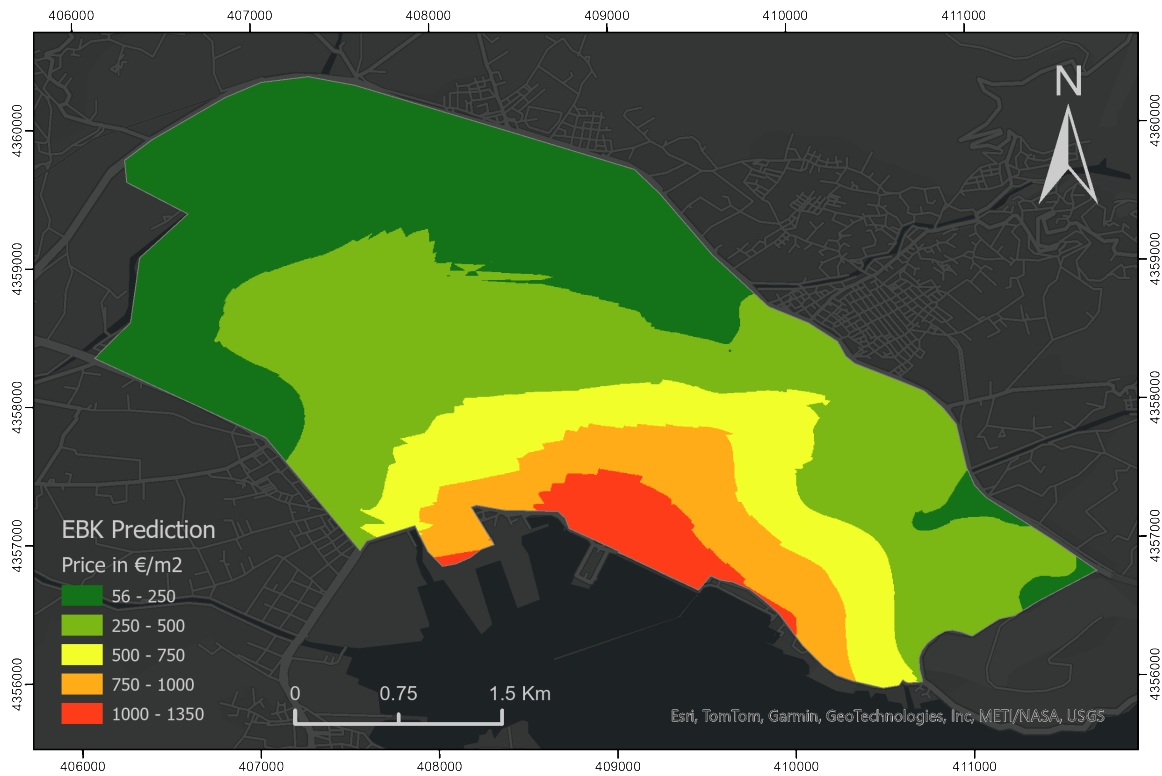
Source: Author.

**Figure 2: GIS-based price mapping: baseline land plot prices (2022)**

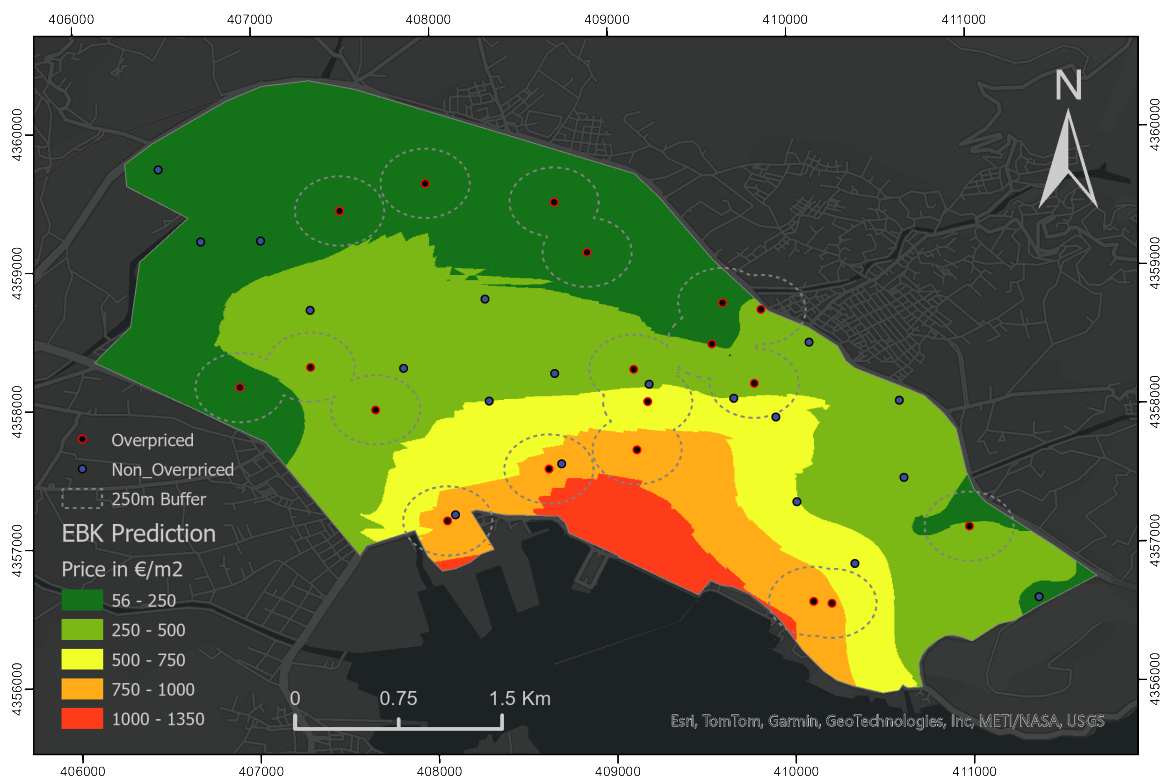
Source: Author.

Figure 3: GIS-based price mapping: comparison land plot prices (2024)

Source: Author.

**Figure 4: GIS-based price mapping: EBK model land plot price-zones**

Source: Author.

Figure 5: GIS-based price mapping: land plot price assessment map

Source: Author.

**Table 1: EBK land plot price predictions and standard errors, compared with 2024 land plot sale prices (N=38) at the sampled locations**

ID	EBK PRED ^a (€/m ²)	EBK SE ^b (€/m ²)	Min (€/m ²)	Max (€/m ²)	Price ^c (€/m ²)	Range Check	Pricing Check
1	801	148	653	949	1321	Out	Over
2	249	72	177	320	341	Out	Over
3	503	88	415	591	436	In	Fair
4	500	73	427	573	474	In	Fair
5	257	60	197	317	323	Out	Over
6	324	110	214	434	350	In	Fair
7	284	41	243	325	476	Out	Over
8	329	94	235	422	287	In	Fair
9	190	79	111	270	248	In	Over
10	186	34	152	220	288	Out	Over
11	186	65	120	251	237	In	Over
12	892	239	653	1131	1000	In	Fair
13	387	86	300	473	424	In	Fair
14	324	93	231	418	568	Out	Over
15	578	144	433	722	490	In	Fair
16	406	93	313	499	871	Out	Over
17	426	54	372	480	480	In	Fair
18	178	40	138	219	127	Out	Under
19	691	121	571	812	577	In	Fair
20	881	170	711	1051	1290	Out	Over
21	511	104	407	614	521	In	Fair
22	880	333	546	1213	1236	Out	Over
23	812	194	618	1006	1370	Out	Over
24	852	221	631	1074	1091	Out	Over
25	860	315	546	1175	394	Out	Under
26	401	114	287	515	487	In	Over
27	413	76	337	489	380	In	Fair
28	196	73	122	269	426	Out	Over
29	446	78	368	524	947	Out	Over
30	140	90	50	229	216	In	Over
31	75	38	36	113	83	In	Fair
32	145	39	106	184	128	In	Fair
33	196	53	143	249	461	Out	Over
34	284	72	213	356	255	In	Fair
35	184	33	150	217	186	In	Fair
36	589	126	463	716	714	In	Over
37	487	104	383	591	456	In	Fair
38	399	77	322	476	409	In	Fair
a: Prices predicted by the EBK model (using 2022 prices as baseline) at the exact points where the 2024 land plots were sampled b: The standard error of the EBK model in the corresponding locations that were used to form the range (min - max) of the prediction c: Prices of the 2024 sample used to assess land plot price dynamics							

Source: Author.



Empirical Results and Discussion

After the EBK model had been validated, the price surfaces were generated and paired with the 2024 land plot prices dataset to assess current price trends in the study area (Figures 3-5). Table 1 shows the land plot price predictions generated with the EBK model, using the 2022 price dataset, at the exact locations where the 2024 points were sampled. The Standard Error (SE) was used to set the min-max range of the predictive model, since the geostatistical robustness had already been validated. In other words, the SE was used to express the expected variation in the EBK prediction model.

According to the EBK model predictions and standard error (2022 baseline), out of 38 land plots (2024) assessed 19 were overpriced, 17 had a price within the $\pm 20\%$ of the prediction, and 2 were underpriced (Table 1)³. However, this does not suffice to determine whether there is an issue with these overpriced properties regarding housing affordability and urban planning. It is necessary to identify their positions relative to the price-zones generated by adjusting the EBK model interpolation output. The land plot and price-zones map (Figure 5) shows that overpriced land plots can be found in all price-zones. However, there is little need to focus on land properties within the very high price-zones (near the city centre), since land uses there are less about housing and more about commerce, and land plots have higher building ratios. Instead, it is useful to locate overpriced land plots within medium- to low-priced zones (Figure 5). In these zones, there is a clustering of overpriced land plots⁴ that risk pushing these price-zones higher, when compared to the 2022 baseline.

Conclusion

Several key conclusions can be drawn from this study. The cost of land acquisition, as a critical factor of housing affordability, can be effectively monitored through geostatistics and price mapping, even in smaller markets with limited data such as the Greek city of Volos. GIS-based analysis reveals that rising real estate prices have pushed up land costs, especially in previously affordable areas of the city, having significant implications for local housing affordability. Rising land plot prices and the impact on housing affordability are issues being observed in many cities worldwide. Therefore, the findings for the city of Volos are relevant to the international discussion and research on housing and social equity.

The methodological approach used in this study can be applied in international contexts and adapted to local spatial and temporal dynamics. The insights gained from this study are also valuable to readers outside Greece who are interested in GIS-based geostatistical analysis of real estate pricing trends in smaller and less-studied areas, where real estate price data are limited. Future research on comparable cities will contribute further towards refining the applicability of such methods in international contexts.

³ Labelled as 'Over', 'Fair' and 'Under' respectively for the pricing check in Table 1.

⁴ See the land plot price points with IDs: 2, 7, 9-11, 28, 30, and 33 in Table 1 and Figure 5.



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