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ESTIMATION OF BASAL AREA IN COPPICE OAK FORESTS USING GEOSTATISTICAL KRIGING

© CC BY L. Ghahramany[1], M. Pir Bavaghar[2]

[1] University of Kurdistan,
Dr. Hedayat Ghazanfari Center for Research and Development of Northern Zagros
Sanandaj, Iran
e-mail: l.ghahramany@uok.ac.ir; ORCID 0000-0002-3721-8084

[2] University of Kurdistan,
Dr. Hedayat Ghazanfari Center for Research and Development of Northern Zagros
Sanandaj, Iran
e-mail: m.bavaghar@uok.ac.ir; ORCID 0000-0002-4649-6705

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Abstract

Aim. This study evaluates the application of Ordinary Kriging, a geostatistical interpolation method, for estimating basal area index in coppice oak forests of the northern Zagros region, Iran.

Methodology. The research was conducted in a 6,103-hectare coppice oak forest in northern Zagros, Iran, dominated by *Quercusbrantii* alongside other oak species (*Q. infectoria* and *Q. libani*). A systematic-random sampling grid was employed to establish 136 sample plots (0.1 ha each), where diameter at breast height (DBH) was measured for all trees (DBH $\geq$ 5 cm) to calculate basal area. Exploratory data analysis was conducted to assess data normality and spatial trends, while variogram analysis was performed to determine the spatial correlation structure. Ordinary Kriging was then applied to predict basal area across the study area, with prediction accuracy evaluated through leave-one-out cross-validation using statistical metrics including mean absolute error (MAE), root mean square error (RMSE), and their relative values.

Results. The forest exhibited relatively low basal area (14.53 m^2/ha) despite high stem density (350 stems/ha), indicating the dominance of young trees and coppice regeneration. Variogram analysis revealed strong spatial dependence (spatial dependence degree = 99.8%), with an exponential model providing the best fit to the data ($r^2 = 0.676$). Ordinary Kriging yielded accurate spatial predictions (MAE = 1.25 m^2/ha, RMSE = 3.26 m^2/ha), demonstrating its effectiveness for basal area estimation in coppice oak forests.

Research implications. These findings demonstrate that geostatistical methods such as Ordinary Kriging provide a precise and cost-effective alternative to traditional forest inventories, enhancing sustainable forest management practices. The observed strong spatial dependence of basal area confirms its suitability as a regionalized variable, facilitating the development of optimized sampling strategies for future forest assessments. This geostatistical approach has significant potential to improve forest resource assessment, carbon stock estimation, and conservation planning in ecologically important ecosystems such as the Zagros oak forests.

Keywords: Basal area estimation, Coppice forests, Geostatistics, Ordinary Kriging, Spatial interpolation, Zagros Mountains, *Quercusbrantii*

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ОЦЕНКА БАЗАЛЬНОЙ ПЛОЩАДИ ДРЕВОСТОЯ В ПОРОСЛЕВЫХ ДУБРАВАХ С ПРИМЕНЕНИЕМ ГЕОСТАТИСТИЧЕСКОГО МЕТОДА ОБЫКНОВЕННОГО КРИГИНГА

© CC BY Гахрамани Л.[1], Пир Бавагар М.[2]

[1] Университет Курдистана, Научно-исследовательский центр по изучению и развитию лесного хозяйства Северного Загроса имени доктора Хедаята Газанфари
г. Санандадж, Иран
e-mail: l.ghahramany@uok.ac.ir; ORCID 0000-0002-3721-8084

[2] Университет Курдистана, Научно-исследовательский центр по изучению и развитию лесного хозяйства Северного Загроса имени доктора Хедаята Газанфари
г. Санандадж, Иран
e-mail: m.bavaghar@uok.ac.ir; ORCID 0000-0002-4649-6705

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Аннотация

Цель. В данном исследовании оценивается применение обыкновенного кригинга, геостатистического метода интерполяции, для оценки индекса базальной площади древостоя в порослевых дубовых лесах северного региона Загрос, Иран.

Процедура и методы. Исследование проводилось в порослевом дубовом лесу в северном Загросе, Иран, с доминированием *Quercus brantii* наряду с другими видами дуба (*Q. infectoria* и *Q. libani*). Лес занимает площадь около 6103 га, расположен на высоте от 1280 до 2040 м и уклоны варьируются от 0 до 137%. Для закладки 136 пробных площадей (по 0,1 га каждая) применялась систематически-случайная сетка выборки размером 520×520 м. На каждом участке с помощью штангенциркуля измеряли диаметр на высоте груди (DBH) всех деревьев с DBH 5 см и более и рассчитывали прикорневую площадь на гектар для каждого участка на основе собранных данных с целью расчёта базальной площади. Был проведён предварительный анализ данных с целью оценки нормальности данных о базовой площади, выявления отклонений и анализа тенденций, связанных с направлением склона. Вариограммный анализ выполнялся для определения структуры пространственной корреляции. Затем применялся обыкновенный кригинг для прогнозирования базальной площади по всей исследуемой территории, при этом точность прогноза оценивалась посредством перекрёстной проверки с исключением по одному с использованием статистических метрик, включая среднюю абсолютную ошибку (MAE), среднеквадратичную ошибку (RMSE) и их относительные значения.

Результаты. Лес демонстрировал относительно низкую базальную площадь (14,53 м²/га) несмотря на высокую густоту стволов (350 стволов/га), что указывает на доминирование молодых деревьев и порослевого возобновления. Анализ тенденций данных о базальной площади, связанных с направлением склона, выявил слабые тенденции вдоль осей север-юг и восток-запад, но включение этих тенденций в кригинговую интерполяцию не повысило точность, поэтому они были исключены из карт прогнозирования и оценки ошибок для индекса базальной площади. Вариограммный анализ выявил сильную пространственную зависимость (степень зависимости 99,8%), что позволяет классифицировать индекс базальной площади как регионализированную переменную и подтверждает использование геостатистических методов для эффективного моделирования и прогнозирования. При этом экспоненциальная модель обеспечивала наилучшее соответствие данным ($r^2 = 0,676$). Диапазон влияния индекса базальной площади составляет 1554 м – максимальное расстояние, на котором сохраняется пространственная зависимость между данными, что делает этот диапазон решающим для определения размеров сети выборки. Валидация обычного кригинга для прогнозирования базальной площади продемонстрировала его высокую эффективность: MAE = 1,25 м²/га, MAEr = 8,61%, RMSE = 3,26 м²/га и RMSEr = 22,4%, что позволяет использовать его для создания карт прогнозирования и стандарт-

ных ошибок прогнозирования для базальной площади в порослевых дубовых лесах.
Теоретическая и/или практическая значимость. Полученные результаты демонстрируют, что геостатистические методы, такие как обыкновенный кригинг, обеспечивают точную и экономически эффективную альтернативу традиционным лесным инвентаризациям, тем самым способствуя развитию устойчивых практик лесопользования. Наблюдаемая сильная пространственная зависимость базальной площади подтверждает её пригодность в качестве регионализованной переменной, способствуя разработке оптимизированных стратегий выборочного обследования для будущих лесных оценок. Данный геостатистический подход обладает значительным потенциалом для улучшения оценки лесных ресурсов, определения запасов углерода и планирования природоохранных мероприятий в экологически важных экосистемах, таких как дубовые леса Загроса.

Ключевые слова: анализ семивариограмм, дуб, пространственная изменчивость, оценка структуры леса, горы Загрос, *Quercus brantii*

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INTRODUCTION

Basal area is a fundamental forestry metric that quantifies the cross-sectional area of a tree trunk at breast height, typically measured at 1.3 m above ground level. Expressed in square meters per hectare (m^2/ha), it represents the cumulative area occupied by tree stems within a forest stand, indicating stand density and structural complexity [41; 45].

This measure is instrumental in assessing stand density, forest structure, and biomass, informing sustainable forest management and ecological research. Changes in basal area over time can indicate growth trends, competition levels, and the effects of silvicultural treatments. Additionally, basal area measurements are integral to allometric equations that estimate tree biomass and carbon stocks, facilitating assessments of carbon sequestration and informing climate change mitigation strategies [1; 8; 13; 28; 31; 35].

Traditional forest inventory methods involve ground-based data collection techniques such as fixed-radius plots, variable-radius plots, and transects. While these approaches provide detailed information, they are labour-intensive, time-consuming, and may not adequately capture spatial variability across large or inaccessible areas. Additionally, the reliance on limited sample plots can lead to sampling errors and may not reflect the heterogeneity of complex forest stands [33; 38; 45; 52].

To overcome the limitations of traditional inventory methods – namely, their time-consuming nature and high costs – advanced techniques such as geostatistics are increasingly employed to model spatial patterns of forest attributes, enabling the prediction of variables at unsampled locations through spatial data analysis. Among these techniques, kriging has emerged as a particularly effective tool for forest inventory and monitoring, offering unbiased estimates with minimal variance and quantifiable uncertainty by leveraging spatial autocorrelation – the principle that nearby observations are more similar than those farther apart. This enhances the accuracy of forest attribute estimations, including biomass, basal area, and volume, especially in heterogeneous or uneven-aged stands. Furthermore, kriging's adaptability allows for the integration of auxiliary data sources, such as LiDAR and satellite imagery, thereby refining forest parameter assessments. Its proven effectiveness across various forest types and terrains makes it invaluable for comprehensive forest resource evaluations. By generating continuous surface maps and quantifying estimation errors, kriging supports more nuanced assessments of forest resources, ultimately facilitating sustainable management practices and advancing ecological research [17; 21; 22; 37; 39; 40; 48].

Geostatistical methods, particularly kriging and its variants, have been widely applied to improve forest attribute estimation across diverse ecosystems. In Spain, universal kriging outperformed the area-based approach in predicting structural parameters such as stem density and basal area in Scots pine stands, especially under conditions of spatial autocorrelation [7]. In northern China, regression kriging using Landsat 9 imagery significantly reduced estimation errors for aboveground biomass (AGB) in coniferous forests [27], while a hybrid random forest/co-kriging model showed high reliability in subtropical regions with complex terrain [47]. Similarly, geographically weighted regression kriging improved AGB predictions in heterogeneous Amazonian forests by accounting for spatial variation [9]. In temperate North America, both kriging and co-kriging methods effectively modeled basal area in lodgepole pine forests using field and NDVI data, with co-kriging yielding higher efficiency due to auxiliary variables [10]. However, in highly fragmented Amazonian landscapes, kriging alone struggled to capture biomass extremes, underscoring the importance of additional data integration [43]. At broader scales, the combination of field, LiDAR, and satellite data within geostatistical frameworks enabled accurate national-scale AGB mapping in Mexico [49]. Collectively, these studies highlight the versatility and effectiveness of kriging-based approaches in enhancing the precision and spatial resolution of forest resource assessments when combined with remote sensing and ancillary data. Kriging methods have been successfully applied across Iranian forests for estimating tree density, stand volume, productivity, and health indicators. Studies show Co-kriging outperforms Simple Kriging for tree density estimation [16], while Ordinary Kriging provides more accurate site productivity assessments than IDW [2]. Kriging excels in mapping stand volume [23] and diameter growth, though IDW may be preferable for volume increment.

In Zagros forests, Co-kriging effectively assessed oak dieback intensity using auxiliary variables [29], while in Caspian forests, Kriging's accuracy varied with spatial autocorrelation—strong for stem density but weaker for basal area and volume [3]. Long-term monitoring in Mazandaran revealed Kriging's utility in tracking biodiversity changes [23]. Overall, Kriging is a powerful tool for forest management but requires consideration of spatial structure for optimal accuracy [16; 24;29].

Geostatistical methods, particularly Kriging, have been effectively utilized in various forest management applications across Iran, demonstrating their efficiency in estimating forest attributes such as tree density, stand volume, and site productivity. However, their application in the coppice oak forests of western Iran remains limited. A significant challenge in applying geostatistical techniques to these forests is the clumped spatial distribution of trees, a characteristic resulting from traditional silvopastoral management practices. This clustering complicates the modeling of spatial autocorrelation, which is fundamental to the success of geostatistical analyses.

Spanning approximately 5.5 million hectares in western Iran, the Zagros oak forests constitute one of the nation's most ecologically and economically significant ecosystems [25; 42]. Dominated by *Quercusbrantii*Lindl.— a foundational and keystone species – these woodlands support a complex forest structure and host a diverse assemblage of ecologically important companion species, including *Quercusinfectoria*, *Quercuslibani*, *Pistaciaatlantica*Desf., and various species of *Pyrus*, *Amygdalus*, and *Crataegus* [29; 42].

Beyond their ecological significance, the Zagros forests provide considerable economic value to local communities through the supply of diverse non-timber forest products (NTFPs). Medicinal plants, fodder, and edible fruits collected from these woodlands contribute substantially to rural livelihoods [25]. Additional income is generated through ecotourism and traditional practices such as pollarding – locally known as Galazani, the systematic collection of tree foliage for fodder, which further strengthens local economies. Nevertheless, unsustainable harvesting methods continue to threaten the long-term health and sustainability of these forest ecosystems [29].

The ecological services rendered by the Zagros forests are equally vital. Functioning as a major regional carbon sink, these woodlands play a key role in climate change mitigation through substantial carbon sequestration [36]. Their dense vegetation cover also significantly reduces soil erosion relative to adjacent non-forested areas, thereby preserving watershed integrity and minimizing sedimentation in critical water resources [25]. Furthermore, the forests support rich belowground biodiversity, particularly diverse communities of arbuscularmycorrhizal fungi (AMF), including *Glomus* and *Acaulospora* species. These symbiotic fungi enhance soil fertility by improving nutrient cycling, while also boosting the drought tolerance and overall resilience of the dominant oak species [26].

This research aims to evaluate the use of Ordinary Kriging, a geostatistical approach, for estimating the basal area index in coppice oak forests of northern Zagros, Iran, offering a precise method to enhance sustainable management of these ecologically vital ecosystems.

The main research question is: To what extent can Ordinary Kriging accurately estimate the basal area in coppice oak forests of the northern Zagros region?

The findings of this study can significantly enhance the evaluation of forest resources, improve the accuracy of carbon stock assessments, and inform conservation planning efforts, particularly in ecologically sensitive regions such as the Zagros oak forests.

MATERIAL AND METHODS

Study Area

The studied forest, covering approximately 6,103 hectares in the northern Zagros region of western Iran, is located between 45°46'45"E to 45°54'05"E and 35°48'34"N to 35°53'30"N, with elevations ranging from 1,280 to 2,040 m and slopes varying from 0 to 137% (Figure 1). The region receives an average annual rainfall of 647 mm and has an average temperature of 11.4 °C (Kurdistan Meteorological Bureau, 2024). The forest is predominantly coppice (sprout-origin) due to traditional silvopastoral practices, including livestock grazing, pollarding, charcoal production, and the harvesting of non-timber forest products.

Data collection and analysis

A total of 136 circular sample plots, each measuring 0.1 hectares, were established using a systematic-random grid with dimensions of 520×520 m. In this study, the minimum measurable diameter at breast height (DBH, 1.3 m) was set at 5 cm, and trees with a diameter ≥5 cm were included in the calculation of stand basal area. This threshold aligns with the traditional pollarding management practice, in which oak trees are harvested once they reach a 5 cm diameter. Trees with diameters less than 5 cm are considered natural regeneration.

Within each plot, the diameter at breast height (DBH) of all trees with a DBH of 5 cm or greater was measured using a caliper, and the basal area per hectare was calculated for each plot based on the collected data using Equation (1).

$$g_{1.30} = {}^{\pi}/_{4} \times d_{1.30}^{2} \text{ (Equation 1)}$$

Where $g_{1.30}$ is the basal area of an individual tree in the plot (cmI) and $d_{1.30}$ is its diameter at breast height (DBH) in centimeters.

After calculating the basal area (BA) of individual trees with DBH ≥5 cm within each sample plot, the sum of these values yielded the total BA per plot. The plot-level BA was then converted to a per-hectare basis using Equation 2:

$$BA(m^2/ha) = (\sum BAperplot) \times 10 \quad \text{(Equation 2)}$$

In Equation 2, the conversion factor of 10 reflects the fact that each sample plot covers 1,000 m^2. The resulting basal area per hectare values for all sample plots were then used to compute the statistical indices of this parameter.

Exploratory data analysis was conducted using to assess the normality of basal area data, identify outliers, and analyze trends related to slope direction. The spatial structure of the basal area index was analyzed by constructing and plotting semi-variograms using GS+ software, with variogram parameters determined to assess spatial patterns. Additionally, the isotropy or anisotropy (directional variability) of the basal area index was evaluated by generating and analyzing surface variograms. The degree of spatial dependence (DSD) was calculated using equation 3:

$$DSD = \left(\frac{Sill - Nuggeteffect}{Sill}\right) \times 100 \text{ (Equation 3)}$$

where: Sill represents the total variance of the data and nugget effect is the variance at zero distance.

The spatial dependence degree (SDD) was categorized based on the thresholds proposed by [14; 18]: Weak structure: SDD < 25%; Average structure: 25% ≤ SDD ≤ 75%; Strong structure: SDD > 75%.

Ordinary Kriging interpolation was used to generate prediction and prediction standard error maps for the basal area index, based on data from 136 georeferenced sample plots. The accuracy of Ordinary Kriging estimates was evaluated through cross-validation using statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), relative MAE (MAEr), and relative RMSE (RMSEr), calculated with Equations (4) to (7) [15].

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\left|\mathrm{z}(\mathrm{X_i}) - \hat{\mathrm{z}}(\mathrm{X_i})\right| \quad \text{(Equation 4)}$$

$$\mathrm{MAEr} = \frac{\mathrm{MAE}}{\overline{\mathrm{Z}}(\mathrm{X_i})} \times 100 \quad \text{(Equation 5)}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}[\mathrm{z}(\mathrm{X_i}) - \hat{\mathrm{z}}(\mathrm{X_i})]^2} \quad \text{(Equation 6)}$$

$$\mathrm{RMSEr} = \frac{\mathrm{RMSE}}{\overline{\mathrm{Z}}(\mathrm{X_i})} \times 100 \quad \text{(Equation 7)}$$

where: N is the number of sample plots, $\hat{z}(X_i)$ is the predicted basal area, and $Z(X_i)$ refers to the observed basal area.

Software Tools

Descriptive statistics and data normality tests were performed in R. Spatial trend analysis of density indices was carried out in ArcGIS 10.8. GS+ 5 was used to generate semivariograms and analyze the spatial structure of stand density. Geostatistical analyses – including trend assessment and Ordinary Kriging interpolation – were executed in ArcGIS 10.8 via the Geostatistical Analyst extension's Geostatistical Wizard. Finally, to evaluate model accuracy, we applied leave-one-out cross-validation in ArcGIS 10.8, comparing the predicted values for each of the 136 sample plots against the corresponding field-measured values and calculating error statistics (MAE, MAEr, RMSE, and RMSEr). In this method, each sample is used once as a test case, while the remaining samples constitute the training set for model generation.

RESULTS AND DISCUSSION

Data analysis from sample plots indicates that the mean basal area is 14.53 m² per hectare. Despite a relatively high tree density of 350 stems per hectare, the low basal area suggests a predominance of young trees and root/stem sprouts with small diameters in the structural composition of the studied forest (Table 2). These findings are consistent with previous research conducted in the same region, which reported similar stand structures characterized by high stem density and low basal area due to the abundance of juvenile trees and root sprouts [19].

A trend analysis of basal area data related to slope directionrevealed weak trends along the north-south and east-west axes (Figure 2), but incorporating these trends into Kriging interpolation did not enhance accuracy, so they were excluded from the prediction and error estimation maps for the basal area index.

The variogram analysis for basal area, as presented in Table 1, indicated that the exponential model provided the best fit, supported by a coefficient of determination ($r^2 = 0.676$) and a low residual sum of squares (RSS = 0.0129), explaining approximately 68% of the variability in basal area. The moderate RI value suggests that while the model captures a significant portion of the spatial variability, there remains unexplained variance, possibly due to factors not accounted for in the model or inherent randomness in the system. The choice of the exponential model is particularly appropriate when the spatial autocorrelation decreases gradually with distance, a common scenario in forest stands where environmental factors and biological interactions influence tree growth over space. In summary, the application of the exponential variogram model in this context is supported by both the statistical metrics obtained and corroborating studies in similar forest settings, reinforcing its validity for analyzing spatial patterns in basal area. This outcome aligns with findings from other studies that have employed exponential variogram models to characterize spatial variability in forest attributes [32; 46].

The basal area displayed isotropic behavior, as indicated by an anisotropy ratio of less than 2 (Table 1) and confirmed by the symmetrical surface variogram in Figure 3, leading to the use of an omnidirectional variogram for geostatistical modeling of the basal area index (Figure 4).

The basal area index shows a spatial dependence degree (SDD) of 99.8%, indicating very strong spatial dependence and classifying it as a regionalized variable, which validates the use of geostatistical methods for effective modeling and prediction [6; 18].

The range of influence for the basal area index was determined to be 1,413 m, indicating the maximum spatial extent over which significant spatial dependence exists among observations. Beyond this threshold, spatial autocorrelation diminishes and the basal area values become effectively independent. In geostatistics, the range parameter derived from the variogram is a critical measure, as it defines the distance beyond which spatial correlation between sampling points becomes negligible. This metric plays a fundamental role in the design of an efficient sampling network by guiding the optimal spacing between sample plots to accurately capture spatial variability [5; 12; 20].

The nugget effect for the basal area was found to be very small (0.001), indicating that only a minimal portion of the total variance is attributable to unexplained factors such as measurement error or microscale variability. This low nugget value reflects high spatial continuity and suggests that the exponential variogram model effectively captures the underlying spatial structure of the data.

According to Webster and Oliver [50], a negligible nugget effect implies that the majority of spatial variation is accounted for by the structured component of the variogram, thereby enhancing the precision and reliability of spatial predictions. Similarly, Goovaerts [20] highlights that a small nugget effect is indicative of strong spatial autocorrelation, demonstrating that the spatial variability is well-organized and predictable – an essential attribute for robust spatial interpolation and modeling.

The sill value of 0.4, determined through variogram analysis (Table 1), indicates the level at which the semivariance reaches stability, signifying the distance beyond which spatial dependence among observations becomes negligible. In geostatistics, the sill represents the total variance of the variable when spatial autocorrelation ceases, thereby quantifying the overall variability in the absence of spatial structure. The observed sill value of 0.4 for the basal area index suggests a moderate level of total variance, beyond which spatial correlation is minimal and data points can be considered spatially independent. This information is vital for guiding the design of sampling networks and for improving the understanding of the spatial structure of basal area in the study region.

A higher sill value reflects greater variability within the dataset, whereas a lower sill indicates greater homogeneity. As a key parameter in variogram modeling, the sill defines the plateau reached by the semivariogram and serves as a measure of the spatial range of correlation. Precise estimation of the sill is crucial for effective spatial interpolation and modeling, as it delineates the extent to which spatial dependence influences the variable of interest [34; 44].

Table 1 / Таблица 1

Result of variogram analysis for basal area / Результат анализа вариограммы для базальной области

Fitted model	(Co)	(C)	Co + C	A0 (m)	SDD(%)	Ar	r^2	RSS
Exponential	0.001	0.400	0.401	1,413	99.8	1.6	0.676	0.0129
Spherical	0.279	0.280	0.559	9,110	50.1	1.6	0.289	0.271
Gaussian	0.323	0.486	0.809	12,464	60.1	1.6	0.179	0.0312

Symbols:

Co – nugget effect;
C – Structural variance;
Co + C – sill;
A0 – range of spatial dependence;
SDD – Spatial dependence degree according to Ganawa et al. (2003);
Ar – Anisotropy ratio;
r^2 – coefficient of determination;
RSS – residual sum of squares

Source: compiled by the authors

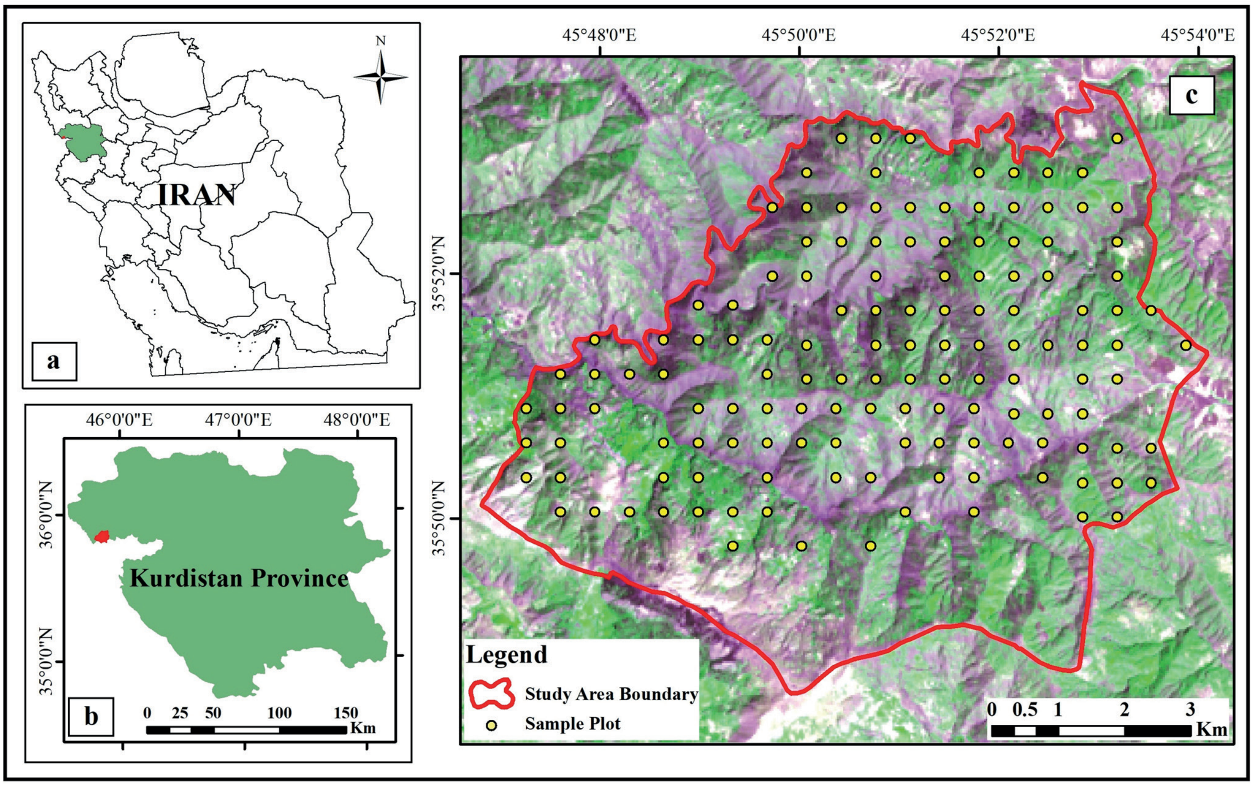

Fig. 1 / Рис. 1. Location of the study area in Iran (a), Kurdistan Province (b), and sample plot’s locations within the study area (c) (Satellite Image from Landsat 8 (RGB 453)) / Местоположение исследуемого района в Иране (a), провинции Курдистан (b) и местоположения участка для отбора проб в пределах исследуемого района (c) (спутниковое изображение с Landsat 8 (RGB 453))

Source: compiled by the authors

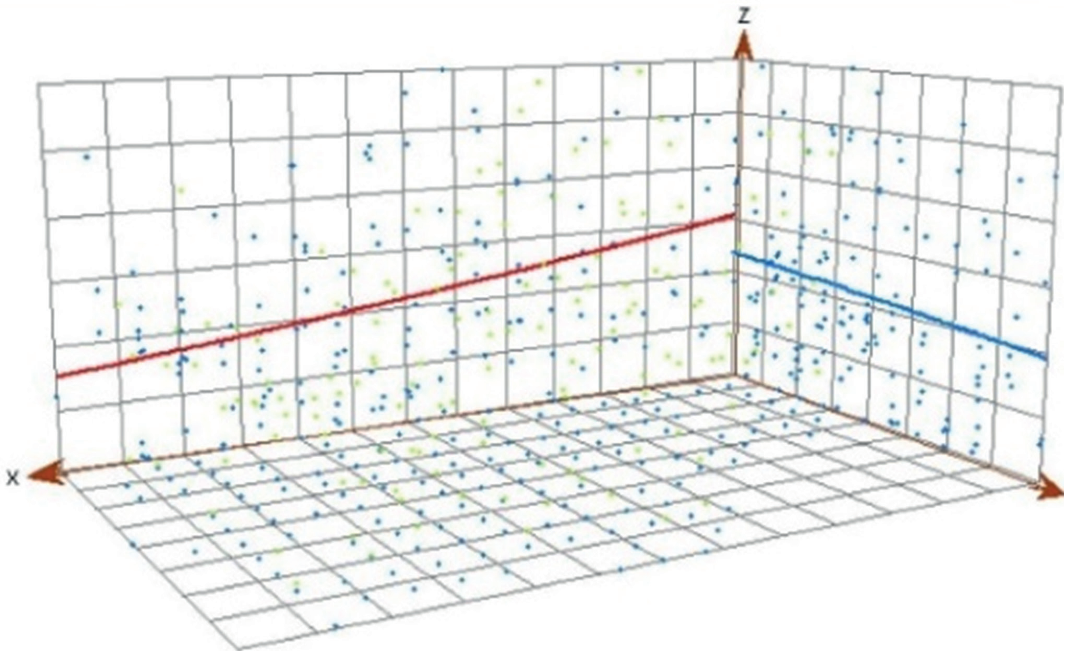

Fig. 2 / Fig. 2. Spatial trends in basal area field data across the study area in the west-east (X) and the north-south (Y) directions. The Z-axis represents the values of the examined basal area / Пространственные тренды полевых данных базальной площади по исследуемой площади в направлениях запад-восток (X) и север-юг (Y). Ось Z представляет значения исследуемой базальной площади

Source: compiled by the authors

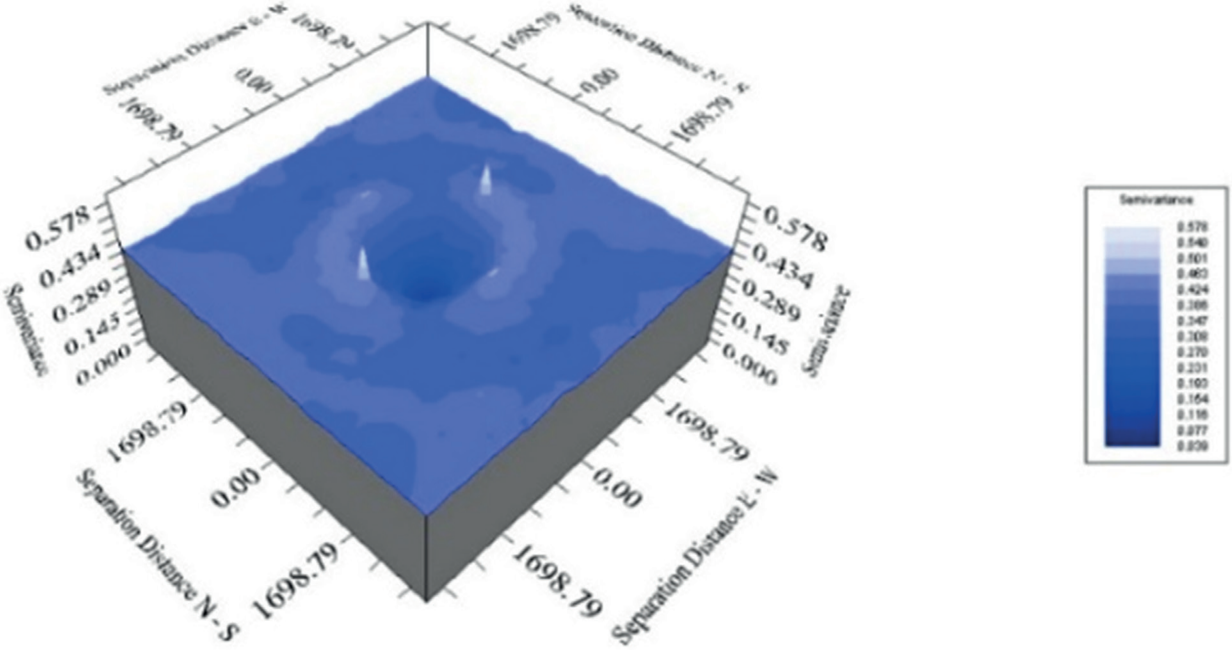

Fig. 3 / Рис. 3. Surface variogram maps in the west-east (W-E) and north-south (N-S) directions, calculated for tree basal area / Карты вариограмм поверхности в направлениях запад-восток (W-E) и север-юг (N-S), рассчитанные для площади основания деревьев

Source: compiled by the authors

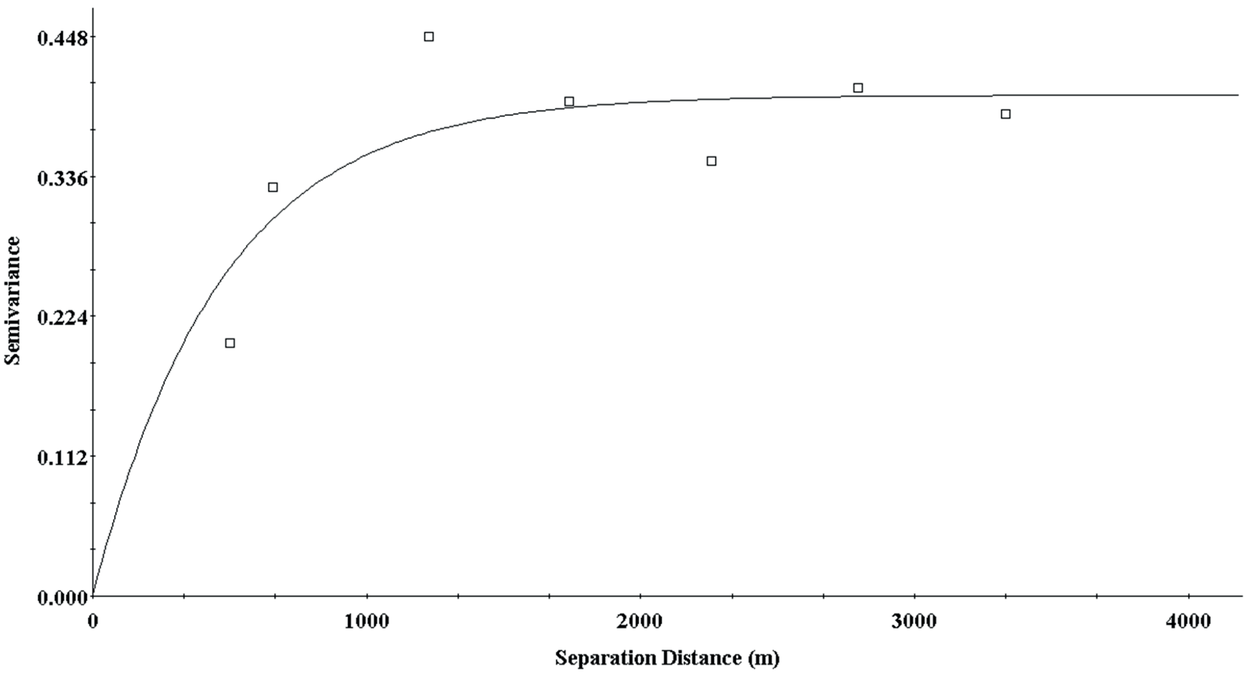

Fig. 4 / Рис. 4. Best-fit isotropic semivariogram models (with search neighborhood=5) of basal area / Наиболее подходящие изотропные семивариограммные модели (с поисковой окрестностью = 5) базальной площади

Source: compiled by the authors

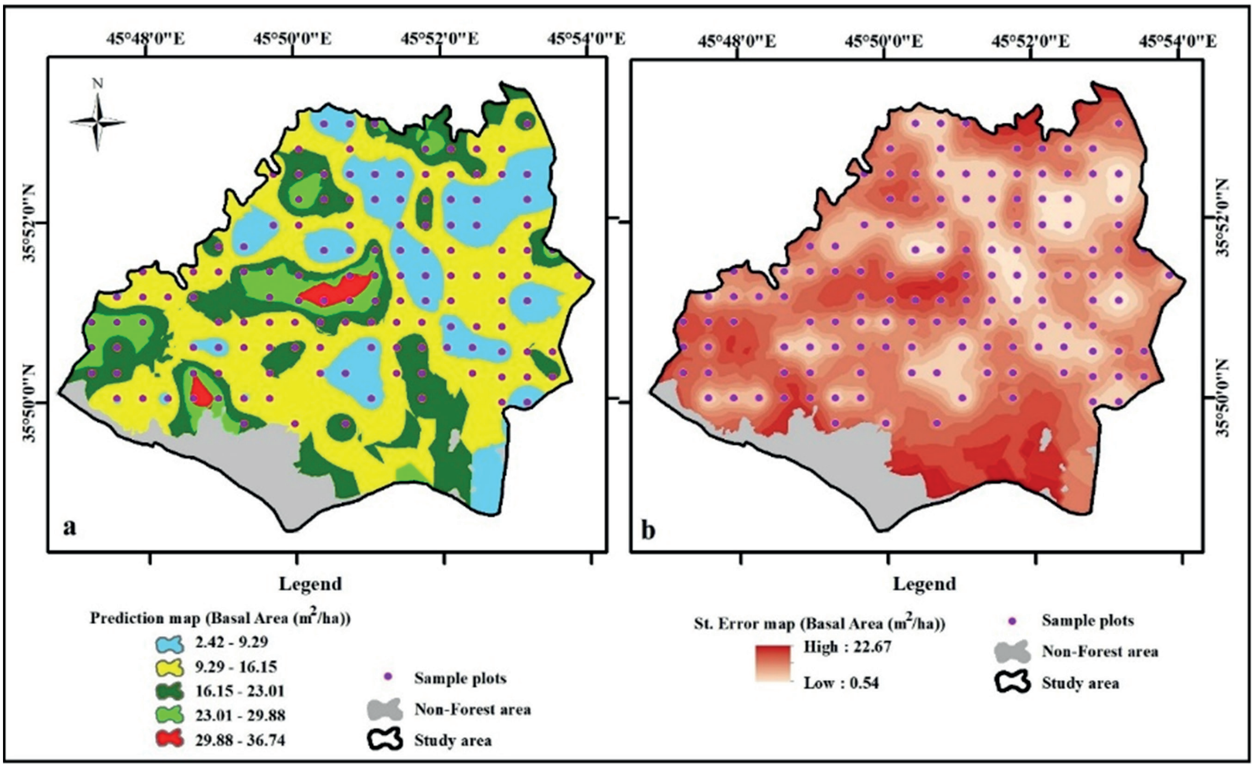

Fig. 5 / Рис. 5. Prediction map (a) and prediction standard error map (b) of basal area for the study area / Прогнозная карта (a) и стандартная карта ошибок прогнозирования (b) базальной области для исследуемой области

Source: compiled by the authors

The validation of ordinary kriging for predicting basal area demonstrated its strong performance, with MAE = 1.25 m²/ha, MAEr = 8.61%, RMSE = 3.26 m²/ha, and RMSEr = 22.4%, leading to its use in generating prediction and prediction standard error maps for basal area, as shown in Figure 5.

The ordinary kriging method provided basal area estimates very close to field-measured values, with an estimation error of 9.9%, matching the field sampling error and confirming the reliability of geostatistical estimates (Table 2).

Ordinary kriging has been proven effective in estimating forest characteristics such as stand volume, basal area, tree density, tree height, Forest canopy height,and canopy cover, making it a reliable and accurate tool for gathering forest structure data and supporting effective forest management [3; 4; 11; 16; 30; 33; 48; 51].

Table 2 / Таблица 2

Summary statistics of basal area index at field sample plots and estimated using the ordinary kriging interpolation method / Сводная статистика индекса базальной площади на участках полевых выборок и оценка с использованием метода обычной интерполяции кригинга

Estimation method	n	Mean	SD	Min	Max	CV (%)	CS	CK	E (%)
Georeferenced sampling	136	14.53	8.5	2.39	35.84	58.5	0.61	-0.46	9.9
Ordinary Kriging	136	14.52	8.36	2.40	35.8	57.6	0.61	-0.46	9.9

Symbols:

n –Sample Size;
SD –Standard deviation;
CV – Coefficient of variation;
CS – Coefficient of asymmetry;
CK – Coefficient of kurtosis;
E – Error of estimate

Source: compiled by the authors

CONCLUSION

This study demonstrates that Ordinary Kriging is an effective geostatistical method for estimating basal area in coppice oak forests of northern Zagros, Iran. The results revealed strong spatial dependence (SDD = 99.8%) in basal area distribution, with the exponential variogram model providing reliable predictions (MAE = 1.25 m^2/ha, RMSE = 3.26 m^2/ha). The minimal nugget effect (0.001) and high model accuracy confirm the robustness of this approach for spatial forest assessment. Based on the variogram range of 1,413 m, a sampling interval of approximately 700 m is recommended. This spacing balances the need to capture spatial autocorrelation effectively while providing sufficient resolution for detailed spatial analysis. Adjustments to this spacing may be necessary based on specific study objectives, terrain complexity, and resource availability.

The findings highlight the potential of geostatistical techniques to overcome limitations of traditional forest inventories, offering a cost-effective and precise tool for sustainable forest management. By enabling accurate mapping of basal area, this method supports improved biomass estimation, carbon storage assessment, and conservation planning in ecologically vital oak ecosystems. Future research could expand applications to other forest attributes and regions, further validating the utility of geostatistical approaches in forestry.

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INFORMATION ABOUT THE AUTHORS

Ghahramany L. (Sanandaj, Iran) – Assoc. Prof., Department of Forestry, Faculty of Natural Resources, University of Kurdistan and Dr. Hedayat Ghazanfari Center for Research and Development of Northern Zagros Forestry;
e-mail: l.ghahramany@uok.ac.ir; ORCID 0000-0002-3721-8084

PirBavaghar M. (Sanandaj, Iran) – Assoc. Prof., Department of Forestry, Faculty of Natural Resources, University of Kurdistan and Dr. Hedayat Ghazanfari Center for Research and Development of Northern Zagros Forestry;
e-mail: m.bavaghar@uok.ac.ir; ORCID 0000-0002-4649-6705

ИНФОРМАЦИЯ ОБ АВТОРАХ

Гахрамани Л. (г. Санандадж, Иран) – доцент кафедры лесного хозяйства факультета природных ресурсов Университета Курдистана и Научно-исследовательского центра по изучению и развитию лесного хозяйства Северного Загроса имени доктора Хедаята Газанфари;
e-mail: l.ghahramany@uok.ac.ir; ORCID: 0000-0002-3721-8084

*Пир Бавагар М***.** (г. Санандадж, Иран) – доцент кафедры лесного хозяйства факультета природных ресурсов Университета Курдистана и Научно-исследовательского центра по изучению и развитию лесного хозяйства Северного Загроса имени доктора Хедаята Газанфари;
e-mail: m.bavaghar@uok.ac.ir; ORCID 0000-0002-4649-6705