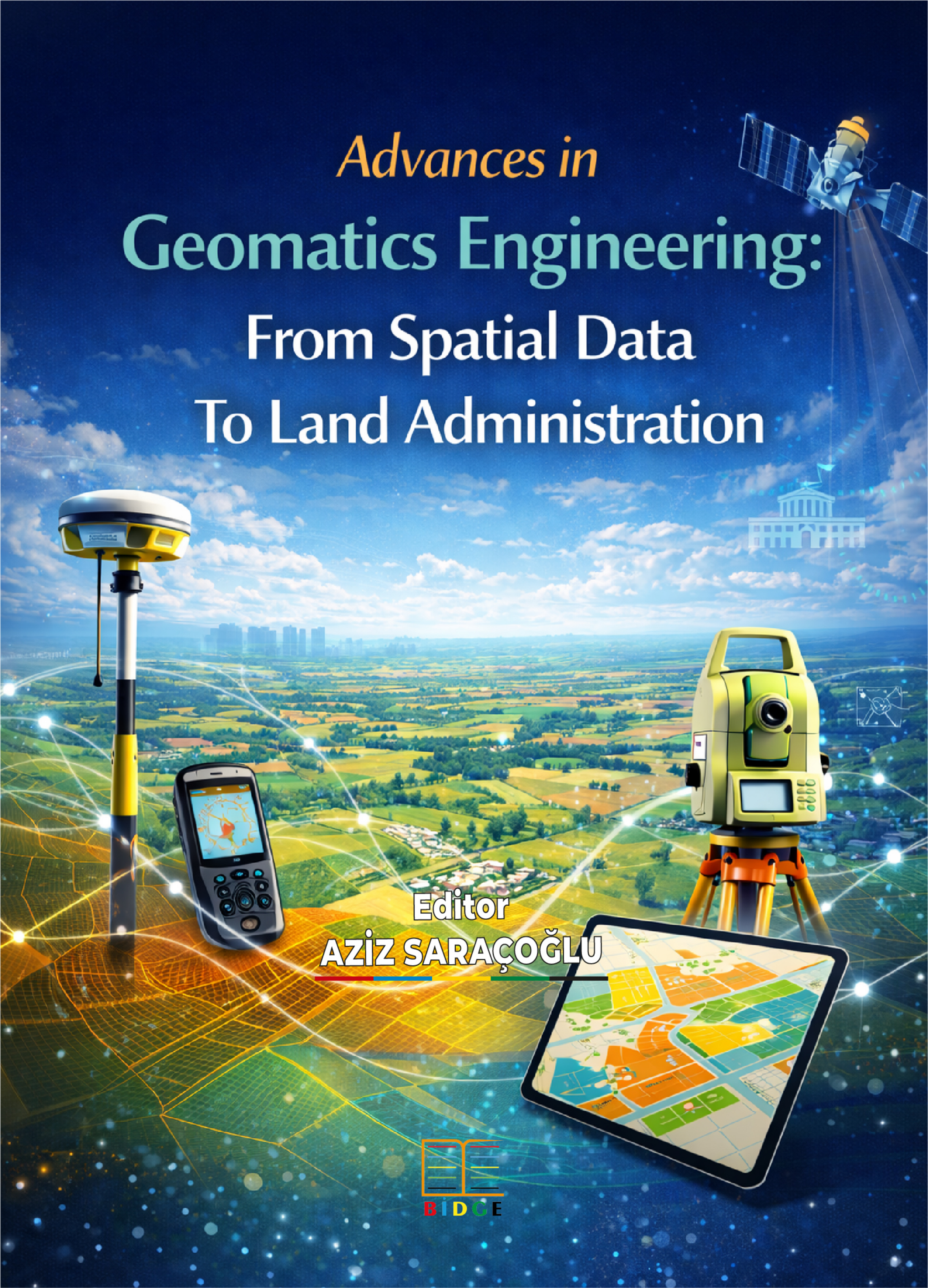
Advances in Geomatics Engineering: From Spatial Data To Land Administration

Editor
AZİZ SARAÇOĞLU



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Advances in Geomatics Engineering: From Spatial Data To Land Administration

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PREFACE

Geomatics Engineering has evolved into a dynamic discipline that bridges the gap between the physical world and digital management. This book, titled **"Advances in Geomatics Engineering: From Spatial Data to Land Administration"** explores this broad spectrum by connecting the technical processes of spatial data production with the administrative mechanisms of land management. It underscores the critical role of the profession not only in capturing precise measurements but also in transforming them into vital legal, economic, and ecological decisions.

Addressing global challenges such as rapid urbanization, rural development, and climate change, this volume presents a comprehensive workflow from raw data to actionable insight. The chapters examine how advanced technologies, including Artificial Intelligence (AI) and Unmanned Aerial Vehicles (UAVs), are utilized alongside remote sensing and cartographic design. These tools are applied across diverse domains, from environmental monitoring and wildlife inventory to real estate valuation and land administration. This structure reflects the data's journey from a technical input to a strategic asset for sustainable planning and policy-making.

I hope this work serves as a valuable reference for academics, researchers, and professionals, inspiring further interdisciplinary studies in the field. I would like to express my sincere gratitude to all the authors for their contributions, the reviewers for their scientific rigor, and the publishing staff for their support in realizing this project.

Sincerely,

Assist. Prof. Dr. AZİZ SARAÇOĞLU

FIRAT UNIVERSITY

İÇİNDEKİLER

CHAPTER 1

MONITORING URBAN OASES: EVALUATING THE THERMAL IMPACT OF GREEN SPACES IN ISTANBUL USING LANDSAT IMAGERY

AZİZ SARAÇOĞLU[1]

Introduction

The 21st century has been defined by two major characteristics: rapid urbanization and the transformation of natural landscapes into impervious surfaces. According to the United Nations, more than half of the global population currently resides in urban areas, a figure projected to reach 68% by 2050 (United Nations Department of Economic and Social Affairs, 2019). This demographic shift has precipitated significant environmental challenges, most notably the Urban Heat Island (UHI) effect. The term "urban heat island effect" (UHI) was first described by Luke Howard and subsequently formalized (Oke, 1982). The UHI effect refers to the phenomenon in which urban areas experience significantly higher temperatures than their rural surroundings. This is due to the retention of heat by built-up materials such as concrete and asphalt, as well as reduced evapotranspiration.

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The intensification of UHI poses severe risks to urban sustainability, including increased energy consumption for cooling, compromised thermal comfort, and heat-related health issues (Santamouris, 2014). Consequently, the mitigation of rising urban temperatures has become a priority for city planners and policymakers. Among the various mitigation strategies that have been developed, Urban Green Spaces (UGS)—including parks, urban forests, and gardens—are recognized as the most effective nature-based solutions. Vegetation plays a pivotal role in regulating the urban microclimate, primarily through two mechanisms: shading surfaces and lowering air temperature via evapotranspiration (Bowler, Buyung-Ali, Knight, & Pullin, 2010). This phenomenon, termed the "Park Cooling Effect" (PCE), gives rise to the formation of localized cool islands that extend beyond the immediate boundaries of the park (Feyisa, Dons, & Meilby, 2014).

The quantification of PCE and the effective monitoring of urban thermal environments have become possible through the use of satellite-based remote sensing, which has emerged as a critical tool in this field. In contrast to conventional in-situ measurements, which are confined to specific locations, thermal remote sensing provides continuous spatiotemporal data (Weng, 2009). The Land Surface Temperature (LST) derived from thermal infrared bands serves as a key indicator for assessing the relationship between land cover and thermal patterns. The spatial configuration of green spaces has been shown to play a crucial role in mitigating surface temperatures (Zhou, Huang, & Cadenasso, 2011), and indices such as the Normalized Difference Vegetation Index (NDVI) have been employed to correlate vegetation density with LST distribution (Yuan & Bauer, 2007) (Guha, Govil, Dey, & Gill, 2018).

Istanbul, a rapidly developing mega-city that serves as a bridge between Europe and Asia, is experiencing significant pressure from urbanization, which has led to substantial changes in land surface temperatures (Balçik, 2014). As the city experiences growth, it is imperative to comprehend the cooling capacity of its existing parks to facilitate effective urban planning that is resilient to climate change. Recent studies have highlighted the strong correlation between land use changes and surface temperature anomalies in urban areas (Sekertekin & Bonafoni, 2020). Furthermore, the launch of Landsat 9 in 2021 offers enhanced radiometric resolution and data continuity, providing new opportunities for monitoring these thermal dynamics with greater precision (Masek et al., 2020)

This chapter presents a case study that analyzes the thermal impact of selected urban green spaces in Istanbul. The objective of this study is to employ the cloud-computing capabilities of Google Earth Engine (GEE) and the most recent Landsat 9 imagery to achieve three primary goals (Gorelick et al, 2017). Firstly, the study seeks to derive LST and NDVI distributions for a period of heightened temperature during the summer months. Secondly, it will statistically compare the thermal characteristics of parks with those of adjacent built-up areas. Thirdly, the study will quantify the intensity of the cooling effect provided by these urban oases.

Study Area and Site Selection

The present study focuses on the metropolitan area of Istanbul, Turkey, a transcontinental megacity characterized by complex topography and a dense, heterogeneous urban landscape. Istanbul's climatic classification, as designated by the Köppen climate system, is that of a transitional Mediterranean climate (designated as Csa and Csb). This climatological classification indicates that the city experiences hot, humid summers and cool, wet winters. This climatic profile renders the city particularly susceptible to the intensification of heat waves, making the evaluation of UHI mitigation strategies during the summer months critical for urban resilience.

In order to analyze the cooling efficiency of vegetation at a micro-scale, two distinct Regions of Interest (ROI) were selected within the densely populated districts of the city. A "pairwise comparison" strategy was adopted to minimize the influence of external climatic variables; each selected Urban Green Space (Park) was paired with an adjacent impervious surface zone (Built-up) of comparable size.

- Sample Area 1 comprises a mature urban park characterized by dense canopy cover and mixed vegetation, juxtaposed with a high-density residential zone consisting of closely packed buildings and asphalt road networks.
- Sample Area 2 is a recreational green complex, including sports facilities and open grass fields, situated adjacent to a structured built-up block.

The delineation of these study sites was conducted manually through the use of high-resolution satellite imagery, ensuring precise demarcation between "green" and "gray" infrastructures. The spatial configuration of these selected areas, which highlights the contrast between the vegetative cover and the impervious built-up environments, is illustrated in Figure 1.

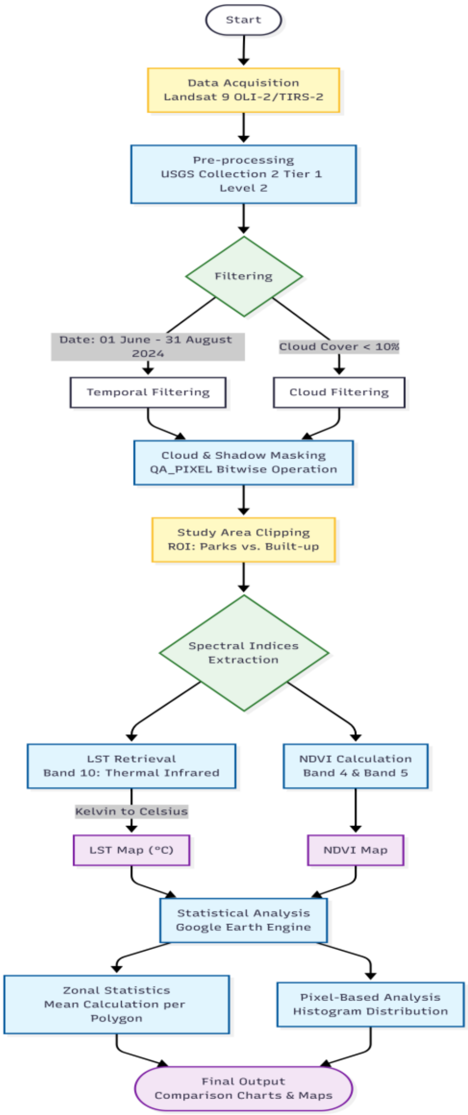
Figure 1 Location of the selected study areas in Istanbul. The red polygons delineate the boundaries of the Urban Green Spaces (Park 1, Park 2) and the adjacent Built-up areas (Built-up 1, Built-up 2) used for the comparative LST and NDVI analysis.

Methodology

This study employed the cloud-computing capabilities of the Google Earth Engine (GEE) platform to process satellite imagery and perform geospatial analyses. GEE was selected for its ability to manage large datasets efficiently without the need for local storage or extensive processing power. The methodological workflow adopted for this study, from data acquisition to the final statistical output, is illustrated in Figure 2.

The geospatial analysis was implemented using the GEE JavaScript Application Programming Interface (API), which provides direct access to the platform's extensive data catalog and high-performance parallel processing capabilities. By leveraging server-side computation, complex operations—ranging from pixel-level cloud masking to zonal statistics—were executed rapidly without the necessity of downloading raw raster data. This cloud-native approach has two primary benefits. First, it significantly reduces the computational time required for processing high-resolution Landsat imagery. Second, it ensures the high reproducibility of the derived results through transparent code execution.

Figure 2 Methodological workflow of the study implemented in Google Earth Engine.



Data Acquisition and Pre-processing

The present study sought to ascertain the correlation between urban green spaces and surface temperature. To this end, Landsat 9 Operational Land Imager 2 (OLI-2) and Thermal Infrared Sensor 2 (TIRS-2) imagery were utilized. The dataset was retrieved from the "USGS Landsat 9 Collection 2 Tier 1 Level 2" archive. The analysis focused on the summer season of 2024 to capture the maximum intensity of the Urban Heat Island (UHI) effect. The image collection was filtered for the period between June 1, 2024, and August 31, 2024. In order to guarantee the integrity of the data, a cloud cover threshold of less than 10% was implemented. Additionally, a pixel-based quality assessment (QA_PIXEL) mask was employed to eliminate cloud and cloud shadow artifacts through the implementation of bitwise operations.

Retrieval of Spectral Indices

Two primary indices were derived from the pre-processed images: The Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) are two key indicators of environmental conditions.

- NDVI Calculation: The Normalized Difference Vegetation Index (NDVI) was calculated to quantify the density and health of vegetation within the study areas using the Near-Infrared (Band 5) and Red (Band 4) bands.
- LST Retrieval: The surface temperature was derived from the thermal band (Band 10). The digital numbers (DN) were rescaled and converted to Celsius (°C) using the scaling factors provided in the USGS product guide.

Statistical Analysis

A zonal statistical approach was adopted to compare the thermal characteristics of the "Park" and "Built-up" classes. The mean values for LST and NDVI were extracted for each polygon. Furthermore, pixel-based histograms were generated to analyze the thermal homogeneity and distribution of pixels within each zone.

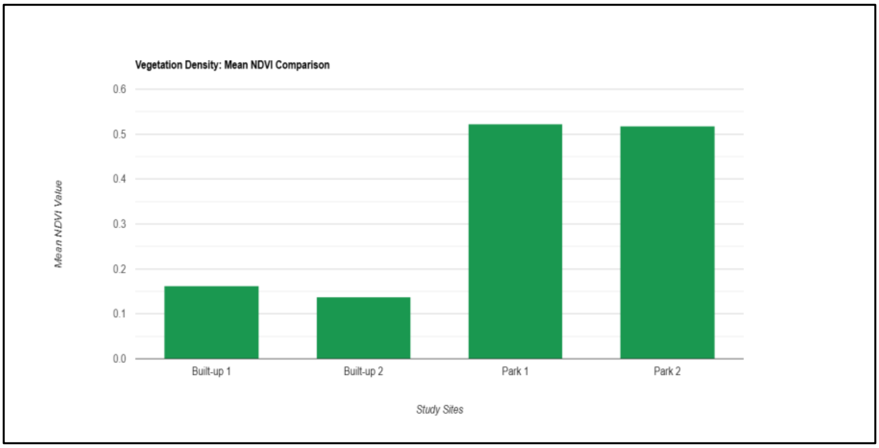
Finally, to rigorously quantify the magnitude of the Park Cooling Effect (PCE), a differential thermal analysis framework was applied. This involved calculating the temperature difference between the paired "green" (park) and "gray" (built-up) samples. By selecting reference built-up sites located in the immediate vicinity of the parks, this study effectively minimized potential biases caused by varying atmospheric conditions or topographic factors that might influence surface temperatures over larger distances. This localized pairwise comparison method ensures that the observed temperature anomalies are primarily attributable to land cover differences.

Results

The analysis of Landsat 9 imagery yielded quantitative evidence regarding the impact of green spaces on urban microclimates. The ensuing discussion will present the findings in terms of vegetation density, surface temperature differences, and pixel distribution characteristics.

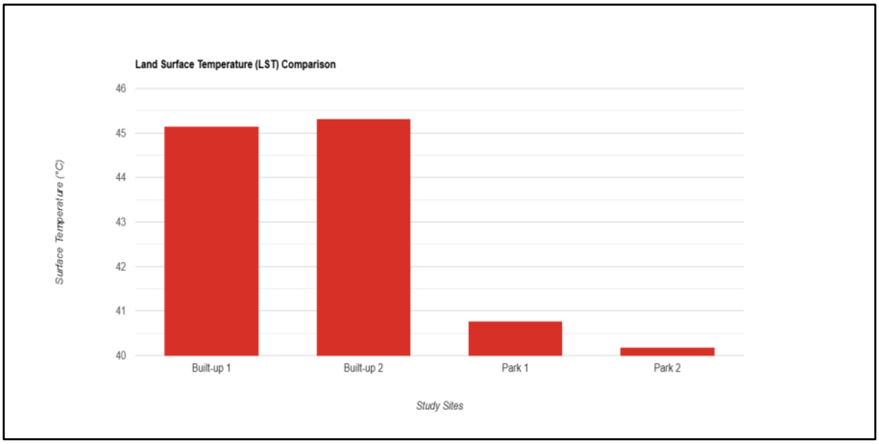
Vegetation Density Analysis (NDVI): The Normalized Difference Vegetation Index (NDVI) results confirmed the distinct land cover characteristics of the selected regions. As demonstrated in Figure 3, the "Park" areas exhibited significantly higher mean NDVI values compared to the "Built-up" areas. Park 1 and Park 2 both exhibited mean NDVI values greater than 0.50, suggesting the presence of robust and substantial vegetation cover. Conversely, the adjacent built-up areas (Built-up 1 and Built-up 2) exhibited mean NDVI values below 0.15, indicative of the predominance of impervious surfaces such as concrete and asphalt. This marked contrast serves to substantiate the selection of study sites and thereby establishes the biophysical foundation for the ensuing thermal comparison.

Figure 3 Comparison of Mean Normalized Difference Vegetation Index (NDVI) values across study sites.



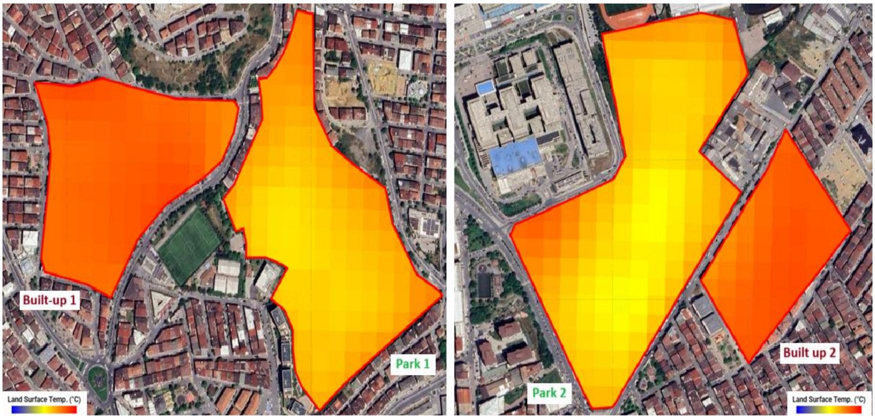
Land Surface Temperature (LST) Variations: The thermal analysis revealed a substantial inverse relationship between vegetation density and surface temperature. The mean Land Surface Temperature (LST) values for each site are presented in Figure 4. The findings suggest that the built-up areas experienced significantly higher temperatures during the study period. The "Built-up 1" and "Built-up 2" records documented mean surface temperatures of approximately 45.1°C and 45.3°C, respectively. Conversely, the green spaces functioned as discrete "cool islands." Park 1 exhibited a mean temperature of 40.8°C, while Park 2 registered an even lower temperature of 40.2°C. Consequently, the study observed a mean temperature difference of approximately 4.5°C to 5.0°C between the parks and their immediate urban surroundings.

Figure 4 Mean Land Surface Temperature (LST) comparison between parks and built-up areas.



Spatial and Pixel-Based Thermal Distribution: To visualize the spatial extent of the cooling effect, the LST distribution was mapped over the study areas (Figure 5). The visual output clearly delineates the boundaries of the parks, which appear as yellow (cooler) zones, contrasting sharply with the surrounding orange and red (hotter) built-up fabrics. This spatial gradient highlights the capacity of the parks to interrupt the continuous heat accumulation of the urban surface.

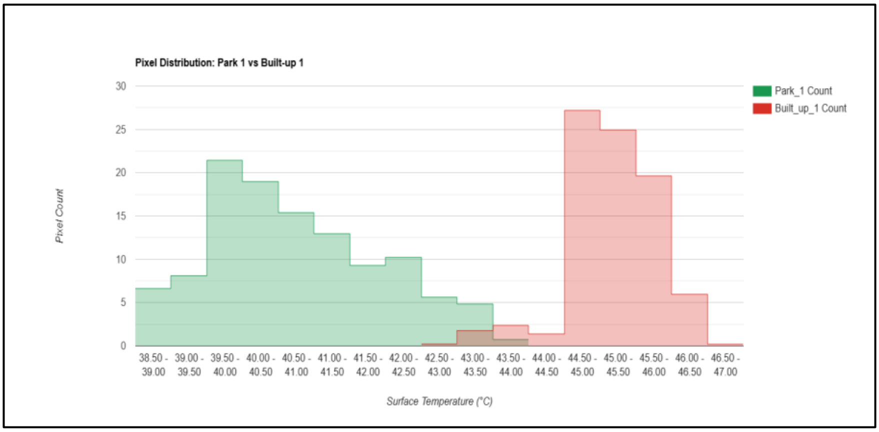
Figure 5 Spatial distribution of Land Surface Temperature (LST) across the selected Regions of Interest (ROI).



In order to comprehend the thermal behavior exhibited by these regions, which extends beyond the confines of simple averages, pixel-based histograms underwent analysis (see Figures 6 and 7). The utilization of histograms serves to elucidate the frequency distribution of temperature values within the polygons.

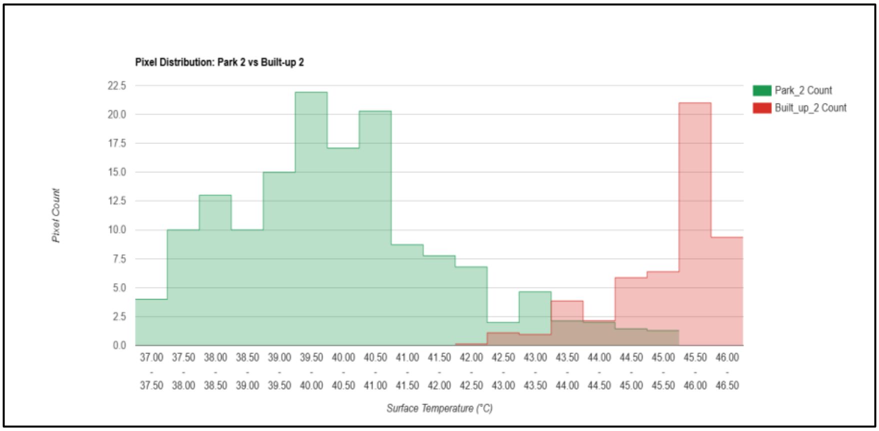
As illustrated in Figure 6, the thermal separation between Park 1 and Built-up 1 is evident. The histogram reveals two distinctly different distributions, with no overlap between them. The park pixels (green) are clustered between 38.5°C and 42.5°C, whereas the built-up pixels (red) form a sharp peak between 44.0°C and 46.0°C. This finding suggests that the park provides a highly homogeneous cooling effect.

Figure 6 Pixel distribution of surface temperatures: Park 1 vs. Built-up 1.



A similar comparison can be made between Figures 7 and 8, which present the results for Park 2 and Built-up 2, respectively. While the built-up area shows a high concentration of pixels greater than 45°C, Park 2 exhibits a slightly wider distribution range (37.0°C - 42.0°C) compared to Park 1. This variation in Park 2 is likely attributable to a heterogeneous landscape composition, potentially comprising open grass fields or sports facilities that possess different thermal properties than dense tree canopies. However, the observed cooling trend remains statistically significant and distinct from the urban fabric.

Figure 7 Pixel distribution of surface temperatures: Park 2 vs. Built-up 2.



Discussion

The findings of this study are consistent with the "Park Cooling Effect" (PCE) phenomenon as described in the extant literature. The robust negative correlation evident between NDVI and LST substantiates the notion that vegetation plays a pivotal role in determining urban surface temperatures. The underlying mechanism responsible for this phenomenon is attributed to two primary factors: evapotranspiration and the shading provided by tree canopies. These factors work in concert to prevent the underlying surfaces from absorbing solar radiation.

The histogram analysis methodically underscores the "buffer capacity" of urban parks. While built-up areas rapidly reach extreme temperatures (exceeding 45°C) due to the high thermal emittance and heat capacity of construction materials, parks maintain a moderated microclimate. The slight variation in the distribution of Park 2 indicates that the type of vegetation may influence the intensity of the cooling effect. Mature trees with broad canopies have been shown to offer superior cooling compared to open grass fields. This suggests that urban park design should prioritize canopy cover for maximum climate resilience.

Conclusion

This chapter presents a case study on the thermal impact of urban green spaces in Istanbul using Landsat 9 data processed via Google Earth Engine. The study successfully quantified the cooling potential of urban parks during the summer months. The findings indicated that urban parks in Istanbul offer a cooling effect of approximately 4-5°C compared to adjacent built-up areas.

The pixel-based analysis further revealed that this cooling effect is consistent and creates a distinct thermal boundary between green and gray infrastructures. These findings underscore the vital role of "urban oases" not only for recreational purposes but also as essential infrastructure for climate change adaptation. In the context of future urban planning in Istanbul, the preservation of existing green spaces and the augmentation of the ratio of dense canopy cover in new park designs are recommended strategies to mitigate the Urban Heat Island effect and enhance the thermal comfort of the city's residents.

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CHAPTER 2

FROM IMAGERY TO INSIGHT: A CONCEPTUAL INTEGRATION OF REMOTE SENSING AND CARTOGRAPHIC DESIGN IN ENVIRONMENTAL MAPPING

OSMAN SAMİ KIRTILOĞLU[1]
MÜGE AĞCA[2]

Introduction

Environmental mapping has become a central component of contemporary geographic research as landscapes undergo rapid transformation due to climate change, urban expansion, land degradation, and hydrological modification. Accurately observing and effectively communicating these changes requires the combined strengths of remote sensing and cartographic design. Remote sensing provides the spectral, spatial, and temporal measurements necessary to describe environmental processes, while cartographic design offers the visual and conceptual structure through which these measurements are interpreted and understood. Integrating these

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perspectives is essential for transforming complex geospatial data into clear, meaningful, and actionable environmental information.

Despite their complementary roles, remote sensing and cartography have often been treated as separate domains in both academic literature and professional practice. Technical studies typically emphasize sensor physics, spectral behavior, and classification algorithms, whereas cartographic research focuses on visual perception, symbolization, scale, and communication. This separation creates a conceptual gap: although remote sensing generates analytically accurate representations of environmental conditions, cartographic design ultimately determines how those representations are perceived, interpreted, and used. Addressing this gap requires a unified framework in which analytical accuracy and perceptual clarity are treated as mutually reinforcing components of a single environmental mapping workflow.

Remote sensing establishes the scientific foundation for environmental monitoring through its capacity to capture multispectral, multi-temporal, and multi-scale observations of the Earth's surface. The interaction between electromagnetic radiation and surface materials produces characteristic spectral signatures that enable the identification of vegetation, soil, water, urban materials, and disturbance patterns (Campbell & Wynne, 2011; Jensen, 2015). Advances in satellite missions such as Landsat and Sentinel, along with UAV-based platforms and cloud computing environments, have further expanded the scope of environmental analysis by enabling consistent long-term monitoring, ultra-high-resolution mapping, and large-scale data processing (Colomina & Molina, 2014; Gorelick et al., 2017; Wulder et al., 2019; Zhu et al., 2019).

However, analytical outputs alone do not ensure meaningful environmental interpretation. Classification results, spectral indices, and change detection products must be translated into cartographically coherent maps before they can effectively support scientific understanding, policy development, or public awareness. Cartographic principles such as symbolization, color management, visual hierarchy, generalization, and scale selection play a critical role in shaping how environmental information is perceived and understood (MacEachren, 2004). Even highly accurate datasets may lead to confusion or misinterpretation if visual design does not reflect the structure, uncertainty, or limitations of the underlying data.

This section advances an integrated perspective in which remote sensing and cartographic design are understood as interconnected phases of a continuous mapping process, spanning data acquisition, analytical modeling, semantic translation, and visual communication. Particular emphasis is placed on issues that often limit the effectiveness of environmental maps, including semantic consistency between analytical results and mapped categories, scale management across different levels of analysis, transparent communication of uncertainty, and user-focused design. By strengthening the connection between data and meaning, this approach enhances the interpretability and credibility of environmental information.

Looking forward, the integration of remote sensing and cartography opens pathways for methodological and conceptual innovation. Emerging directions include the use of machine learning to support adaptive visualization, multi-scale cartographic strategies that respond to varying analytical resolutions, and educational models that bridge technical remote sensing training with design-oriented cartographic thinking. Together, these developments position the integration of remote sensing and cartographic design as a necessary step toward more accurate, accessible, and impactful environmental mapping, capable of supporting research, decision-making, and public engagement in an increasingly complex environmental landscape.

Remote Sensing in Environmental Mapping

Remote sensing has become one of the core methodological foundations of contemporary environmental science. It provides the means to observe, quantify, and model Earth system processes across spatial and temporal scales that are impossible to achieve with field based techniques alone. The rapidly expanding ecosystem of satellite missions, airborne sensors, and unmanned aerial vehicles has shifted environmental analysis from simple descriptive mapping toward more integrated and process oriented interpretations of change. At its scientific core, remote sensing is based on the interaction between electromagnetic radiation and the physical properties of the Earth's surface. Radiometric measurements, originally captured as digital reflectance or radiance values, can be converted into spatial indicators that describe environmental condition and function.

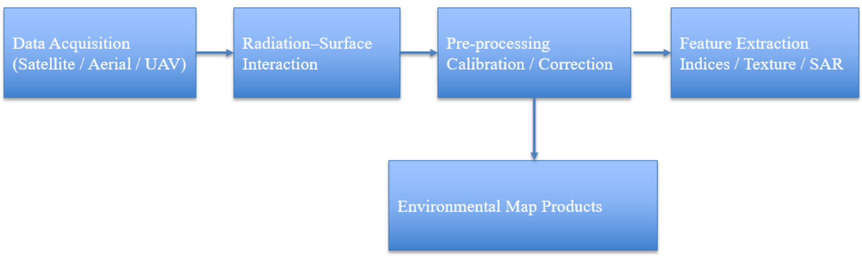
Conceptual Foundations

Remote sensing is grounded in radiative transfer theory, which explains how electromagnetic energy interacts with surface materials. When incoming energy, whether solar or emitted by an active instrument such as Synthetic Aperture Radar, reaches the surface, it is absorbed, scattered, or reflected in ways that reveal the physical and chemical characteristics of soil, vegetation, water, snow, and built structures. These responses form spectral signatures that allow researchers to classify surfaces, retrieve biophysical parameters, and detect change, as described by Jensen. The development of multispectral and hyperspectral technologies has strengthened the ability to isolate these responses and relate them to specific environmental variables.

Data Acquisition and Platform Diversity

Every remote sensing workflow begins with data acquisition. The choice of platform, whether satellite, aircraft, or UAV, determines the spatial, spectral, temporal, and radiometric resolution of the imagery. Long running missions such as Landsat and Sentinel offer globally consistent archives that are essential for long term environmental studies. Commercial high resolution satellites, including the WorldView series, support detailed mapping of urban and infrastructural environments. UAV platforms provide very high resolution data for agricultural, ecological, and geomorphological investigations. Active systems such as LiDAR and Synthetic Aperture Radar further expand the analytical potential by offering three dimensional observations and imaging capabilities that are unaffected by cloud cover, as explained by Campbell and Wynne. A simplified illustration of the remote sensing workflow is shown in Figure 1.

Figure 1. Conceptual Remote Sensing Workflow.



2.3. Pre-processing and Radiometric Harmonization

Before imagery can be used for environmental interpretation, it must undergo several preprocessing steps. These typically include

- Radiometric calibration, which converts digital numbers into physical radiance or reflectance values.
- Atmospheric correction, which removes the influence of atmospheric scattering and absorption to allow comparison across different dates and sensors.

- Geometric rectification and orthorectification, which correct terrain effects and align images to a common spatial reference.
- Co-registration, which ensures precise alignment across multiple dates and is essential for change detection.

Such procedures are necessary for long term environmental monitoring, where small changes may be masked by noise, atmospheric effects, or sensor differences if the data are not properly harmonized.

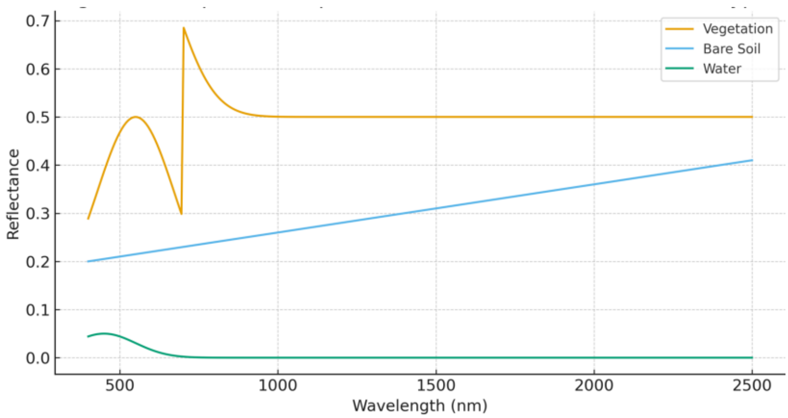
Feature Extraction and Environmental Indicators

After preprocessing, feature extraction techniques convert calibrated imagery into environmental variables. These techniques draw on physical principles as well as modern computational methods. Common approaches include**:**

- Spectral indices, such as NDVI, NDWI, NBR, and EVI, which act as indicators of vegetation condition, moisture availability, burn severity, and hydrological features.
- Spectral unmixing and hyperspectral analysis, which help identify material mixtures within single pixels.
- Textural and structural descriptors that capture canopy arrangement, surface roughness, and spatial patterns.
- Machine learning classifiers, including random forests, support vector machines, and convolutional neural networks, which perform well in complex landscapes, as demonstrated by Belgiu and Drăguţ.
- Backscatter based models and polarimetric SAR, which provide information on surface moisture, biomass, and geomorphological structure.

Figure 2 presents an example of spectral response curves for typical land cover types.

Figure 2. Spectral Response Curves of Common Land Cover Types.



Environmental Applications

Remote sensing supports a wide range of environmental applications. Table 1 provides a comparison of widely used Earth observation satellites relevant to these applications.

Land use and land cover mapping: This is one of the most widely used applications and supports biodiversity research, watershed management, agricultural monitoring, and environmental impact assessment. Advances in machine learning have improved classification performance in complex environments.

Vegetation and ecosystem monitoring: Spectral indices and time series analyses allow detection of drought stress, phenology, biomass accumulation, and disturbances such as wildfire.

Hyperspectral systems can distinguish vegetation at species level in many cases.

Table 1. Comparison of Major Earth Observation Satellites.

Satellite/ Mission	**Operator**	**Spatial Res.**	**Spectral Bands**	**Revisit Time**	**Main Applications**
Landsat-8/9 OLI	USGS/ NASA	15–30 m	9 multispectral + PAN	16 days	Land cover, vegetation, hydrology, change detection
Sentinel-2A/B MSI	ESA	10–20 m	13 multispectral bands	5 days	Agriculture, ecosystem monitoring, coastal studies
PlanetScope	Planet Labs	3–5 m	RGB + NIR	Daily	Precision agriculture, high-frequency land monitoring
MODIS (Terra/Aqua)	NASA	250–1000 m	36 bands	Daily	Climate, fire, phenology, global-scale monitoring
WorldView-3	Maxar	0.31–1.24 m	29 bands incl. SWIR	<1 day	Urban mapping, minerals, detailed land analysis
Sentinel-1 SAR	ESA	5–20 m	C-band radar	6–12 days	Floods, soil moisture, deformation, all-weather monitoring

Hydrological and coastal studies: Remote sensing plays a central role in monitoring water extent, sediment transport, thermal pollution, and wetland transitions. Synthetic Aperture Radar is especially well suited for mapping floods during extreme weather events, as shown by Martinis and colleagues.

Urban environmental assessment: Thermal data help identify areas affected by urban heat islands. Multispectral imagery supports mapping of impervious surfaces, canopy cover, and air quality proxies.

Climate and Earth system monitoring: Sensors such as MODIS provide daily global coverage and support a broad range of environmental analyses including climate modeling, fire detection, and vegetation dynamics.

Limitations, Challenges, and Emerging Directions

Remote sensing remains subject to several limitations. Atmospheric conditions, mixed pixel effects, sensor noise, and scale mismatches continue to create challenges. Persistent cloud cover reduces the usefulness of optical imagery, particularly in tropical and coastal regions. As archives grow, the computational demands of processing high resolution multi sensor time series also increase, which has contributed to the widespread use of cloud based environments such as Google Earth Engine, described by Gorelick and colleagues. Ensuring consistency in preprocessing, calibration, and model interpretation remains essential for producing reliable environmental assessments, as emphasized by Zhu.

Despite these constraints, the overall trajectory of remote sensing is strongly positive. The combination of long term satellite records, high resolution commercial imagery, advanced computational methods, and interdisciplinary research continues to expand its capabilities. When paired with effective cartographic design, remote sensing supports the translation of radiometric information into clear and informative environmental products, thereby turning raw imagery into evidence and actionable environmental knowledge.

Cartographic Design Principles in Thematic Mapping

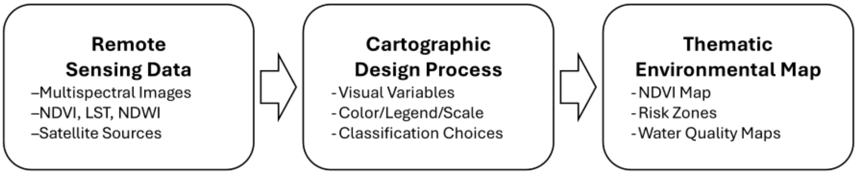
Introduction to Cartographic Design in the Remote Sensing Context

Cartographic design plays a pivotal role in transforming geospatial data into meaningful and interpretable visual products. As satellite sensors generate increasingly complex and high-resolution datasets, the need for effective cartographic communication becomes more urgent, particularly in the domain of environmental monitoring and thematic mapping. Remote sensing provides the raw spectral and spatial data, but it is cartographic design that determines how those data are perceived, understood, and used (Slocum et al., 2009; MacEachren, 1995).

In thematic cartography, the ultimate goal is not merely to display information but to facilitate spatial reasoning and insight. The effectiveness of this process is governed by how visual variables (e.g., color, size, shape, texture) are used in accordance with human perceptual and cognitive principles (Bertin, 1983; Robinson et al., 1995). This is especially important when dealing with continuous raster data derived from remote sensing, such as vegetation indices, land surface temperature, or turbidity levels. Numerous studies emphasize the importance of integrating cartographic theory into the workflow of remote sensing applications. For example, Brewer and Pickle (2002) demonstrate how cartographic symbolization can influence risk perception in environmental hazard maps. Similarly, Kraak and Ormeling (2020) highlight that poor cartographic decisions—such as inappropriate classification or confusing color schemes—can obscure spatial patterns, mislead interpretation, or introduce unintended bias.

In this section, we explore key design principles that ensure the clarity, usability, and interpretability of thematic maps based on remote sensing data. By aligning cartographic techniques with both data characteristics and user needs, thematic mapping becomes a robust tool not only for visualization but also for environmental decision support. This conceptual workflow is summarized in Figure 3.1, which illustrates the transformation of remote sensing data into thematic maps through cartographic processing stages.

Figure 3. Conceptual flow from satellite-derived data to a thematic environmental map.



Visual Variables in Thematic Map Design

Visual variables are the fundamental graphical elements used in cartographic representation to encode and communicate spatial information. First conceptualized by French cartographer Jacques Bertin in his seminal work Semiology of Graphics (1983), visual variables serve as the building blocks of thematic map design. They determine how data is visually translated into symbols, shapes, colors, and patterns that can be cognitively processed by map users. In thematic mapping, particularly when working with environmental data derived from remote sensing, the thoughtful selection and application of visual variables are essential to ensure both perceptual clarity and semantic accuracy. A well-designed map not only presents data but also supports pattern recognition, comparative analysis, and informed decision-making. Types of visual variables are:

1. Bertin (1983) originally proposed seven visual variables:
2. Position – spatial location on the map (x and y axes)
3. Size – variation in area or length of symbols
4. Shape – differences in symbol form (circle, triangle, etc.)
5. Value – lightness or darkness of a symbol

6. Color hue – qualitative differences in color
7. Orientation – angle or direction of symbol
8. Texture – frequency or pattern density

Subsequent scholars and practitioners have proposed additional variables such as:

- Transparency, especially for layering remote sensing products (MacEachren, 1995)
- Saturation (intensity of color) and focus (sharpness or blur)
- Animation or temporal change, particularly in web-based or interactive mapping (Roth, 2013)

While not all visual variables are suitable for all data types, a typology based on data structure helps guide appropriate use.

Environmental datasets derived from remote sensing often fall into different measurement scales—nominal, ordinal, or quantitative (interval or ratio). Thematic cartographers must align the data structure with the correct visual variables to avoid misinterpretation. Table 2 summarizes the match between visual variables and data types commonly found in environmental mapping. Failure to align visual variables with data types may result in visual bias. For instance, using value or size to represent nominal categories implies a non-existent hierarchy. Conversely, using random hues for a temperature scale undermines the gradient nature of the data. These core visual variables are illustrated in Figure 4, showing how each can be employed in thematic cartography depending on data structure.

In remote sensing, raster layers often represent continuous surfaces (e.g., NDVI, NDWI, turbidity), requiring subtle gradations and perceptually uniform encodings. Here, value (lightness/darkness) and hue (color) are the most frequently used variables. In recent years, there is growing emphasis on using perceptually uniform color schemes, such as those developed by Brewer (1994) or using CIELAB color space, to avoid misrepresenting value gaps.

Additionally, texture becomes relevant when classifying high-resolution satellite images into land use categories. For example, urban areas might be visually distinguishable not only by color but also by repetitive patterns, while vegetation shows smoother texture distributions.

Table 2. Appropriate visual variables for different data types in thematic mapping (adapted from Slocum et al., 2009).

Data Type	**Examples**	**Recommended Visual Variables**
Nominal	Land cover classes, soil types	Color hue, shape
Ordinal	Risk levels, erosion severity	Value, size, texture
Quantitative	NDVI, land surface temperature, chlorophyll-a	Value, size, color saturation

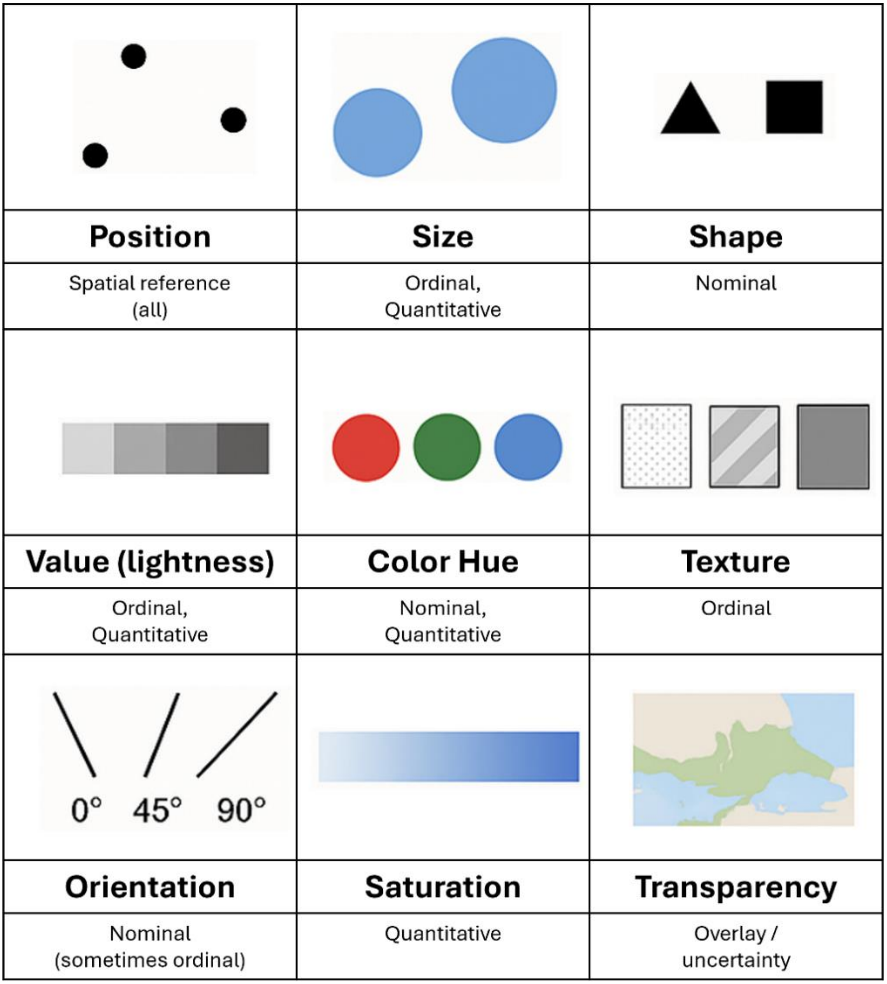
Visual variables should not be evaluated in isolation. Their combined effect shapes the overall visual hierarchy of the map. For example, large symbols in a bold hue will naturally draw more attention, even if the data they represent are less critical. Thus, cartographers must design with perceptual weight in mind to guide map readers toward appropriate focal points. Moreover, attention should be given to color vision deficiency (CVD).

Studies show that approximately 8% of males and 0.5% of females experience some form of CVD (Jenny & Kelso, 2007), making it essential to choose color palettes that remain legible under colorblind conditions. Tools such as ColorBrewer2[3] (Brewer &

[3] https://colorbrewer2.org

Harrower, 2023) and Coblis[4] simulator are widely used to test and correct for this.

Figure 4. Visual variables commonly used in thematic cartography, as introduced by Bertin (1983) and extended in modern cartographic practice.



[4] https://www.color-blindness.com/coblis-color-blindness-simulator/

Color Theory and Perception in Thematic Cartography

Color is one of the most powerful and immediate visual variables in thematic cartography. When applied effectively, color enhances communication, supports visual hierarchy, and aids in the intuitive interpretation of spatial patterns. Conversely, poor color choices can distort data representation, introduce perceptual bias, or confuse the map reader particularly when visualizing complex environmental data derived from remote sensing.

Fundamentals of Color Theory

Color theory in cartography is grounded in both artistic traditions and perceptual psychology. The three primary dimensions of color are:

- Hue: the basic color type (e.g., red, green, blue)
- Value: lightness or darkness of a color (often tied to intensity)
- Saturation: purity or vividness of the color

These dimensions are commonly represented in color models such as RGB, CMYK, and CIELAB. For map design, CIELAB and HSL are particularly useful because they more closely align with human perception. For example, a perceptually uniform change in color value corresponds more naturally with perceived differences in data intensity (Brewer, 1994).

- Sequential, diverging, and qualitative color schemes are three principal types used in thematic mapping:
- Sequential: ordered progression from light to dark (e.g., NDVI)
- Diverging: two contrasting hues diverging from a central midpoint (e.g., change maps)

- Qualitative: distinct hues for unordered categories (e.g., land cover types)

These schemes must be chosen based on the measurement scale of the data, to avoid misinterpretation.

Perception and Visual Accessibility

Human color perception is influenced by context, contrast, and individual differences such as color vision deficiency (CVD). Around 8% of men and 0.5% of women have some form of red-green color blindness (Jenny & Kelso, 2007). Therefore, map color design must account for, color contrast ratios, redundant coding (using labels, textures), colorblind-safe palettes (e.g., ColorBrewer safe schemes). Moreover, color perception is not universal. It varies across cultures, devices (screen vs print), and even lighting conditions. A map that is legible on-screen may be unreadable in grayscale printing.

Color Choices in Remote Sensing-Based Maps

Remote sensing products typically represent continuous surfaces (e.g., vegetation indices, surface temperature, turbidity), which require sequential color gradients. NDVI maps, for instance, often use green-to-brown or green-to-white scales, but not all such choices are perceptually intuitive or semantically neutral. Similarly, false-color composites (e.g., NIR–Red–Green) must be interpreted with care, especially when used in public-facing products. In such cases, post-processing with perceptually balanced palettes improves clarity. To assist in selecting appropriate color schemes for remote sensing-based thematic maps, Table 3 summarizes typical data types, suggested color encodings, and example applications commonly encountered in environmental mapping.

Table 3. Recommended color schemes for remote sensing-derived environmental datasets.

Product	Data Type	Suggested Color Scheme	Example Use
NDVI	Quantitative (0–1)	Sequential (green → brown)	Vegetation health
LST (Land Surface Temp.)	Quantitative	Sequential (blue → red)	Urban heat island
NDWI	Quantitative	Sequential (blue → white)	Water content
Land Cover	Nominal	Qualitative hues	CORINE/Copernicus classifications
Land Change	Diverging	Red ↔ Gray ↔ Green	Urbanization gain/loss

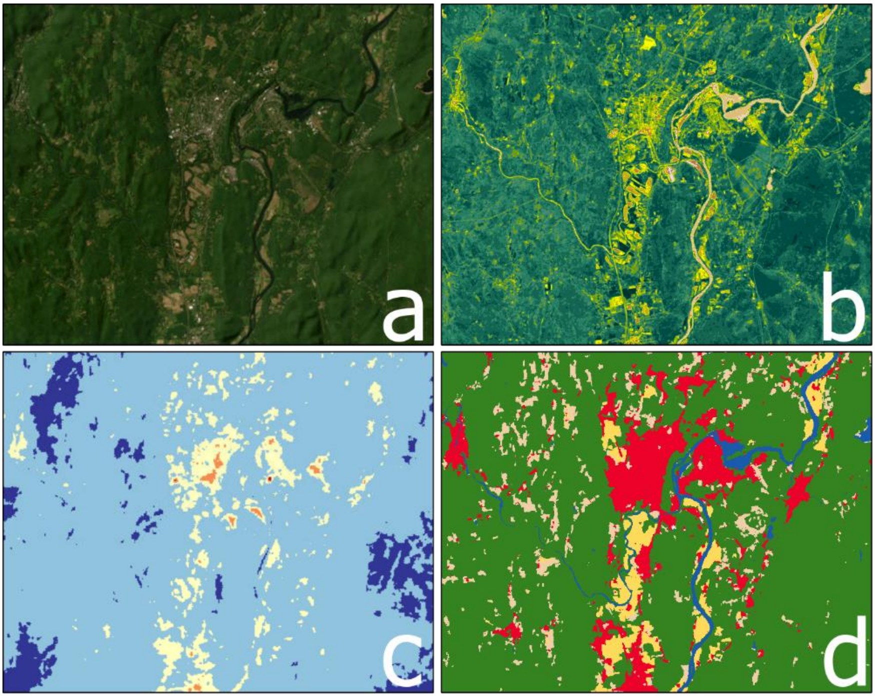
Figure 5 illustrates the visual impact of different color schemes applied to the same dataset. The comparison highlights how perceptual clarity and interpretive accuracy vary across sequential, diverging, and qualitative palettes.

Tools and Best Practices

The use of color in thematic cartography is both an art and a science. While aesthetic preferences influence the visual appeal of a map, ensuring perceptual accuracy and interpretive clarity demands adherence to color theory and user-centered design principles. To this end, cartographers increasingly rely on a suite of specialized tools and frameworks that support perceptually valid, cognitively ergonomic, and accessible color design.

Among the most widely adopted tools is **ColorBrewer2**, a web-based application developed by Cynthia Brewer and colleagues, which offers scientifically tested color palettes tailored for thematic mapping.

Figure 5. Example remote sensing-based thematic maps of the same area (a) via sequential (b:NDVI), diverging (c:LST), and qualitative (d:Land Cover) color schemes.



The tool categorizes palettes into sequential, diverging, and qualitative types, aligning them with appropriate data characteristics (e.g., ordinal, interval, categorical).

It also accounts for reproduction constraints such as colorblind safety, print-friendliness, and projection to monochrome. Another essential tool in inclusive design is the **Coblis Color Blindness Simulator**, which allows map designers to preview how their color schemes appear to users with various forms of color vision deficiency (CVD), including deuteranopia, protanopia, and tritanopia. Incorporating this step into the design workflow ensures that maps remain interpretable to a wider audience without sacrificing thematic fidelity. For more advanced or customized palette generation, tools such as **Adobe Color**[5], **Viz Palette**[6], and **iWantHue**[7] allow users to define color sets based on hue rotation, perceptual distance, or branding requirements. These tools offer integration with digital design environments, supporting both static and web-based mapping platforms.

Beyond simple hue selection, ensuring **perceptual uniformity** in color transitions is essential—particularly for continuous raster datasets such as land surface temperature or vegetation indices. This requirement is addressed by tools and frameworks that operate in *CIELAB (Lab) color space*, which models human color perception more accurately than standard RGB or HSV systems. Visual differences in this space are more consistent with actual perceived differences, allowing smoother gradients and better visual ordering in sequential or diverging ramps. Finally, empirical validation—through expert review, user testing, or automated accessibility checks—forms a critical component of best practices. Professional cartographers routinely test maps under different lighting conditions, screen resolutions, and reproduction scenarios to ensure robustness and clarity.

Common Mistakes and Misrepresentations in Color Application

Despite the availability of advanced design tools and guidelines, color misuse remains one of the most common and consequential sources of cartographic error. In environmental mapping, such errors can obscure patterns, mislead readers, or introduce unintended biases—particularly in policy-making, risk communication, or public awareness campaigns. One of the most problematic practices is the use of **rainbow color ramps** (often default in GIS software) to represent continuous data. While visually

[5] https://color.adobe.com
[6] https://www.susielu.com/data-viz/viz-palette
[7] https://medialab.github.io/iwanthue/

appealing, these ramps are **not perceptually uniform**—meaning that equal changes in data do not result in equal visual differences. For instance, the transition between yellow and green may appear more abrupt than between red and purple, distorting the underlying data distribution. Moreover, rainbow ramps are particularly inaccessible to colorblind users.

Another frequent mistake is the application of **sequential color schemes to nominal data**, which introduces false hierarchies. For example, mapping land use types (e.g., forest, urban, wetland) using a light-to-dark gradient may imply an order that does not exist, misleading viewers about environmental importance or priority. Maps also suffer from **excessive color saturation or high-contrast palettes**, which can induce visual fatigue, especially during prolonged use. This issue is exacerbated in digital interfaces or presentations, where backlit displays enhance brightness and intensity. Furthermore, using too many visually similar hues in qualitative maps—such as multiple shades of blue or green—makes it difficult to distinguish between categories, especially in areas with dense spatial patterns.

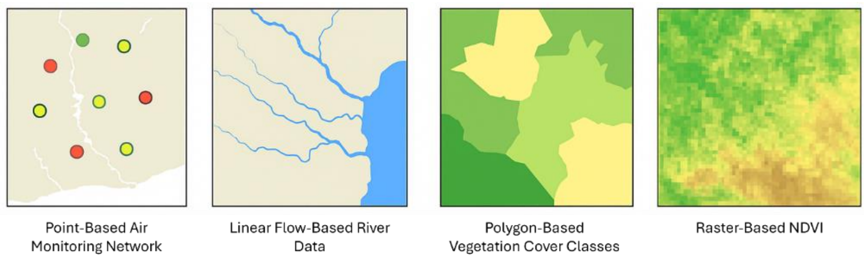
To avoid such pitfalls, cartographers should adhere to several foundational principles: align color scheme with data type (e.g., sequential for ordinal, qualitative for nominal), minimize cognitive load by reducing interpretive effort, and maximize clarity through perceptual ordering and appropriate legend construction. All design choices should be informed by the intended audience, use context (e.g., print vs screen), and sensitivity to perceptual differences. When in doubt, adopting a minimalist approach often yields better outcomes. A well-designed map does not attempt to show everything, but rather conveys the **right information with the right visual tools**, grounded in perceptual science and guided by best practices.

Symbolization Techniques for Environmental Features

Symbolization plays a critical role in translating geospatial data into meaningful visual representations, especially in the context of environmental mapping. Environmental features such as vegetation zones, water bodies, land degradation patterns, or pollution hotspots often exhibit varying geometries and data structures. The challenge lies in transforming these heterogeneous data types into perceptually intuitive and semantically accurate map elements. *Vector data*, depending on their geometry, demand distinct symbolization strategies. Point features, such as meteorological stations or pollution monitoring sites, are typically represented with size- or color-coded circles to convey intensity or class. Linear features such as rivers or fault lines require varying line widths, directional arrows, or flow-based gradients to communicate volume or directionality. Polygonal data, representing regions like land cover zones, protected areas, or erosion extents, often benefit from fill patterns or color hue variations that respect thematic boundaries. *Raster data,* particularly those derived from remote sensing, present continuous spatial variation. For such datasets, visual variables like value (lightness) and hue become essential in representing elevation, vegetation index values, land surface temperature, or water turbidity. It is crucial to align these symbols with both data measurement scale and the cognitive expectations of the user.

A visual comparison of typical symbolization strategies is provided in Figure 6, where point-based, line-based, polygonal, and raster examples are presented side by side to illustrate how symbol selection reinforces data interpretation. Complementing this, Table 4 summarizes symbolization options across data types, indicating optimal visual variables and real-world applications.

Figure 6. Examples of symbolization techniques applied to different types of environmental features.



Cultural interpretations of symbols must also be considered. While green often implies vegetation and blue represents water in many regions, these associations may not hold universally. In international or cross-cultural communication contexts, designers must test for intuitive understanding and avoid over-reliance on assumed semantic conventions.

Table 4. Summary of symbolization strategies for various environmental data types based on geometry, data structure, and intended message.

Feature Type	Geometry	Symbol Type	Visual Variable	Common Application
Air stations	Point	Colored circles	Hue, size	Air quality index
Rivers	Line	Width & arrows	Size, orientation	Streamflow volume
Forest zones	Polygon	Textured fills	Pattern, hue	Habitat delineation
NDVI	Raster	Gradient fill	Value (light–dark)	Vegetation health

Map Layout, Composition, and Visual Hierarchy

Beyond symbology, the spatial organization of map elements determines how effectively a map communicates its message. Map layout refers to the arrangement of the title, map body, legend, scale bar, metadata block, and supporting graphics within a bounded space. When composed strategically, these components guide the reader's eye in a logical and aesthetically balanced flow, establishing what is known as visual hierarchy. At the core of the layout is the map body, the primary spatial frame, typically placed slightly off-center to allow breathing room for the legend and other marginalia. The title must be prominent yet not visually overpowering. Legends should be situated close to the data they describe without occluding important areas. Scale bars, north arrows, and inset maps serve functional purposes and are best positioned where they support orientation without distraction.

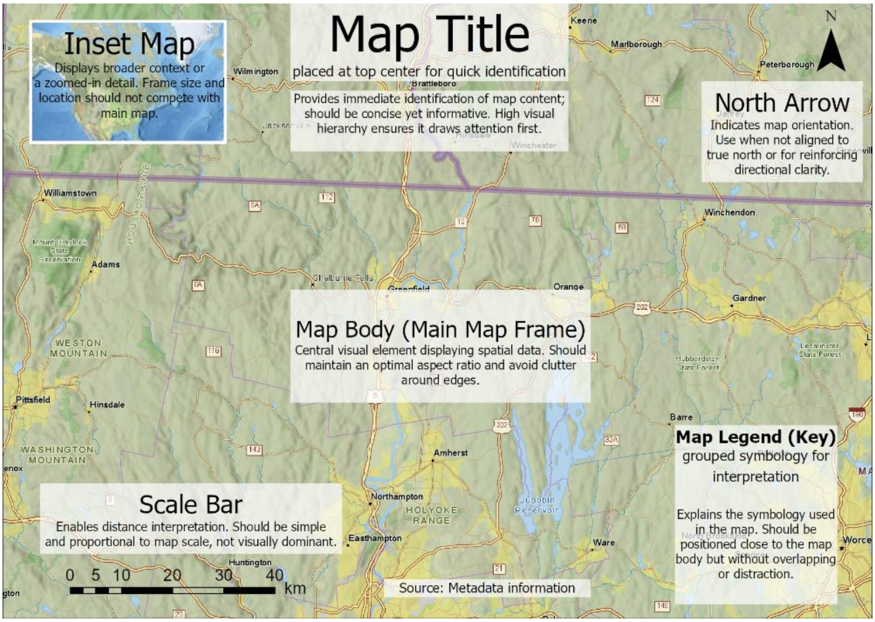
Effective layouts often leverage invisible alignment grids to maintain coherence. Elements aligned along vertical and horizontal axes produce a cleaner, more professional appearance. Additionally, white space, when used judiciously, helps separate clusters of information, reducing cognitive load. Visual hierarchy can be reinforced through size, contrast, and color. Larger elements naturally attract attention, while muted tones can recede to the background. Color choices must also account for readability in both digital and print media. Accessibility is key—designers should test for color vision deficiency compatibility and ensure adequate contrast between foreground and background layers. Figure 7 demonstrates a model layout for environmental thematic maps, identifying zones of emphasis, alignment patterns, and spatial grouping of components. This layout serves as a flexible template adaptable to both static and interactive cartographic products.

Legends, Labels, and Map Typography

If a map's symbology and layout represent its visual language, then legends and labels are its grammar—defining the syntax through which the user reads and interprets the content.

Despite their importance, these elements are often overlooked or added as afterthoughts.

Figure 7. Cartographic layout template highlighting optimal positioning of title, map body, legend, and marginalia, ensuring visual balance and user guidance.



Legends should precisely replicate the symbols used in the map, including their color, size, and line width. They must be organized logically, ideally grouping elements by thematic category. For instance, a legend might separate land use classes, hydrographic features, and anthropogenic hazards into distinct sub-sections. Continuous data legends—such as those for NDVI or land surface temperature—must include value ranges and, if necessary, interpretation guides. Labels serve both locational and informational purposes. They identify geographic features, denote administrative boundaries, or provide explanatory text. Their placement must follow cartographic conventions: rivers are labeled along their flow lines, city names are placed horizontally near the centroid, and labels never appear upside-down. Avoiding clutter is paramount—excessive labeling can obscure key map features and hinder readability.

Typography choices contribute greatly to the map's visual tone. Cartographers are advised to use no more than two font families: typically a sans-serif type for the map body and a serif type for metadata. Font sizes should scale appropriately with the intended display format, with titles large enough to establish dominance, and source notes small but legible. Consistency across font type, size, and weight reinforces professionalism and visual unity. Table 5 outlines best practices in cartographic typography, specifying recommended font types and sizes for each map component. This structured guidance helps ensure that textual elements support rather than distract from the map's core message.

Table 5. Typography guidelines for environmental thematic maps.

Element	**Font Type**	**Size (pt)**	**Style**	**Notes**
Title	Sans-serif	18–24	Bold	Clear and prominent
Labels	Sans-serif	8–12	Regular	Must be legible on screen and print
Legend	Sans-serif	10–12	Regular/Bold	Match symbol color/size
Source/Metadata	Serif	7–9	Italic	Less visually dominant

Other frequent issues include overcrowded layouts, inconsistent symbology across map series, unreadable fonts, and failure to account for users with color vision deficiencies. Maps are often printed or photocopied in grayscale—designers must therefore verify that color differences remain legible without hue information alone. To mitigate these issues, best practices include using perceptually uniform color ramps (e.g., from ColorBrewer), matching classification methods to data distribution (e.g., natural breaks instead of equal intervals), maintaining consistent symbology, and simplifying layouts for clarity. Testing map products with sample users—especially those outside the expert community—can uncover usability issues early.

Integration Strategies: From Data to Design

The integration of remote sensing and cartographic design is a pivotal stage in the production of environmental maps, shaping both their analytical credibility and communicative value. Remote sensing provides quantitative information about Earth's surface, yet these measurements remain abstract until they are given structure and visual form. Cartography, in turn, transforms analytical results into representations that are understandable and useful for a range of audiences. The relationship is therefore not a simple transfer of data but a coordinated process in which analytical, semantic, and visual decisions work together to construct meaning. This section examines how these elements interact and proposes a framework for guiding the transition from remote sensing outputs to clear and effective thematic maps.

Conceptual Framework: Bridging Analytical and Visual Domains

Remote sensing and cartography have traditionally been approached as separate practices: one focused on measurement and modeling, the other on communication and visual reasoning. For environmental mapping, however, these two domains are interdependent. A fully integrated workflow can be understood through three interconnected stages.

The first stage, analytical transformation, encompasses the technical procedures of remote sensing, including data acquisition, radiometric and geometric corrections, spectral index calculation, classification, and other relevant modeling steps. At this point, the outputs reflect physical measurements and algorithmic processes, but they are not yet thematic information.

The second stage, semantic transformation, introduces interpretive structure. Here, analytical values are translated into categories or descriptors that reflect environmental meaning. For example, vegetation index values become classes that signify healthy, moderate, or stressed vegetation. These decisions draw on ecological knowledge, study objectives, and contextual factors such as seasonality.

The final stage, visual transformation, involves the translation of semantic structure into cartographic form. Symbolization choices, color design, scale, generalization, and layout determine how effectively the mapped information will be interpreted by end users. Even the most accurate analysis can lose clarity if the visual design is poorly executed.

Visual Integration: From Analytical Layers to Cartographic Expression

Once analytical results have been prepared and structured semantically, their effectiveness depends heavily on visual presentation. Several design considerations are especially important for environmental mapping.

Symbolization conveys the quantitative or qualitative differences within the data. For remote sensing–derived products, symbolization must reflect the nature of the underlying variable. Vegetation indices typically align with green palettes, while temperature or moisture gradients are better expressed through sequential or diverging schemes. Poor symbolization may imply patterns that do not exist, leading to misinterpretation even when the analysis is correct.

Color design influences how readers perceive relationships within the data. The selection of sequential, diverging, or qualitative palettes must consider perceptual hierarchy and accessibility. Environmental themes often require intuitive connections such as cooler tones to represent lower temperatures or higher moisture levels. Effective color design strengthens the thematic message and supports visual reasoning.

Generalization and density management become essential when working with high-resolution or highly detailed remote sensing data. Excessive detail can obscure spatial patterns or overwhelm the reader. Carefully controlled generalization, whether through smoothing, merging small polygons, or simplifying raster classes, helps maintain legibility without diminishing core environmental information.

Semantic Integration: Translating Remote Sensing Indicators into Thematic Meaning

Semantic integration focuses on ensuring that analytical measurements align with meaningful environmental categories. This step requires careful consideration of classification thresholds, ecological understanding, and thematic consistency. Remote sensing indicators must be interpreted in context. For instance, vegetation index values may vary widely depending on crop species, phenological stage, soil background, or climatic conditions. Class definitions that work in one region may be unsuitable in another.

Accuracy assessment and thematic validation are also part of semantic integration, helping ensure that the defined classes represent real environmental conditions. When analytical values are clearly linked to environmental meaning, the resulting maps serve as reliable tools for evidence-based decision-making.

Integration Workflow: A Conceptual Model

The integration of remote sensing with cartographic design can be summarized as a continuous workflow that connects data acquisition to final map production. Although individual projects may differ in scale and complexity, the underlying logic remains consistent.

The process begins with data acquisition, whether multispectral, hyperspectral, or radar-based, followed by pre-processing, where corrections for geometry, atmosphere, and cloud cover ensure that the imagery is analytically reliable. In the analytical stage, environmental indicators such as vegetation indices, surface moisture metrics, or classification outputs are generated. These results are then organized through semantic structuring, which assigns categories and environmental meaning to the analytical values. The final steps involve cartographic representation, where color choices, symbolization strategies, visual hierarchy, and layout bring the thematic information into a coherent, communicative form. The workflow concludes with the production of the final thematic map, ready for scientific or decision-making purposes.

This conceptual model reinforces the idea that remote sensing and cartography function most effectively when treated as complementary components of a unified process. Analytical accuracy, semantic clarity, and visual design must be coordinated to ensure that environmental information is both reliable and accessible.

Scenarios: Integrated Environmental Mapping

Scenario 1. Vegetation Health Mapping for Agricultural Monitoring

This scenario illustrates how remote sensing observations and cartographic design principles can be combined to support agricultural management. In a typical agricultural region, multispectral Sentinel-2 imagery provides the foundation for assessing vegetation health. After standard preprocessing steps, vegetation indices such as the Normalized Difference Vegetation Index and the Soil Adjusted Vegetation Index are calculated to represent canopy vigor and the degree to which soil background influences the measured signal. These indicators help differentiate between early growth stages, moderately developed vegetation, and fully developed healthy canopies.

To make the outputs easier to interpret, the analytical results are grouped into meaningful vegetation classes. Lower index values often correspond to bare soil or stressed vegetation, midrange values reflect partially developed canopies, and higher values indicate healthy vegetation cover. These classes may vary depending on crop type and the timing of the growing season. The mapped results are then refined through cartographic design choices that emphasize clarity, including the use of intuitive green color schemes, clear parcel boundaries, and the masking of uncertain observations.

When presented within this workflow, the scenario demonstrates how remote sensing and cartography together can assist with irrigation planning, fertilizer scheduling, early detection of stress, and evaluation of spatial variability in crop performance. The example also highlights practical considerations such as cloud contamination, mixed pixels, and seasonal changes in reflectance, which underscore the importance of careful calibration and quality assessment.

Scenario 2. Urban Heat Island Mapping for Climate Adaptation

This scenario describes how thermal remote sensing can be used to support climate adaptation planning in an urban environment. Landsat-8 thermal infrared data provide the necessary information for estimating land surface temperature after radiative transfer calculations, emissivity adjustments, and atmospheric corrections are applied. These temperatures are then linked with indicators of built and vegetated surfaces to help distinguish between natural areas, impervious surfaces, and densely built districts.

Once temperature values are retrieved, they are translated into a set of categories that represent different intensities of the urban heat island effect. Areas with lower temperatures are mapped as low-intensity zones, intermediate values correspond to moderate stress, and higher temperatures identify potential hot spots that may require targeted mitigation measures. The visual expression of these classes is enhanced through the use of a diverging blue to red color scheme and through the inclusion of contextual layers such as land use or population density.

Through this scenario, readers see how thermal remote sensing and cartographic design principles combine to inform practical responses to urban heat. The resulting products help identify locations where tree planting, reflective materials, shading structures, or other cooling strategies may be implemented. At the same time, the scenario draws attention to common limitations, including atmospheric humidity, variations in surface emissivity, and the need for on-the-ground validation to ensure accurate interpretation of temperature patterns.

Discussion and Future Directions

The integration of remote sensing and cartographic design offers a promising framework for producing environmental maps that are analytically robust and visually coherent. The earlier sections demonstrated how environmental understanding emerges when physical measurements, semantic structure, and visual representation operate as a unified workflow. However, this integrated approach is not without limitations, and a number of conceptual, methodological, and technological challenges continue to shape the evolution of environmental mapping. The following discussion outlines these limitations and highlights emerging directions that are likely to influence future research and practice.

Limitations of the Integrated Approach

Although the integration framework strengthens the connection between measurement and interpretation, several constraints remain. Remote sensing datasets vary widely in spatial resolution, spectral properties, temporal frequency, and radiometric quality, which complicates efforts to establish standardized workflows. Differences across sensors often require dataset-specific corrections or calibrations, limiting the transferability of analytical models.

Cartographic decisions introduce an additional layer of complexity. Choices related to classification thresholds, color design, symbolization, and generalization inevitably carry a degree of subjectivity. These decisions can influence how users interpret environmental conditions, even when the underlying analytical results remain unchanged. Moreover, increasingly high-resolution imagery imposes computational demands that may restrict the scalability of integrated workflows, especially for applications involving long-term temporal archives.

Finally, the conceptual model does not apply equally across all environments. Persistent cloud cover, rapidly changing landscapes, heterogeneous land-use patterns, and areas with limited ground-validation data challenge the reliability of both analytical outputs and derived thematic maps. These factors underscore the need for continual refinement of integration strategies and for developing transparency in how uncertainties are communicated to users.

Conceptual and Methodological Challenges

A persistent gap remains between analytical processes and perceptual design. Remote sensing analysis is driven by physical modeling and statistical interpretation, whereas cartographic design draws on cognition, communication theory, and user behavior. Even when analytical results are accurate, poor symbolization or inappropriate classification schemes can distort environmental meaning. This analytical–perceptual disconnect remains one of the central methodological obstacles in the field.

Another limitation concerns issues of scale and generalization. Remote sensing makes it possible to analyze landscapes at increasingly fine spatial resolutions, yet effective cartographic representation often requires simplification or aggregation. Environmental patterns that appear meaningful at one scale may disappear or become misleading at another. Although the integrated workflow outlined earlier provides a conceptual guide, the field still lacks consistent principles for determining how much detail should be preserved or generalized without compromising thematic integrity.

Uncertainty is also an under-addressed aspect of environmental mapping. Atmospheric noise, sensor limitations, classification inaccuracies, and modeling assumptions all contribute to uncertainty in remote sensing outputs. Yet maps often present this information as definitive. Visual strategies for representing uncertainty remain underdeveloped, and their adoption in practice is limited.

Technological Shifts and Their Implications

Rapid technological developments continue to reshape the landscape of remote sensing and cartographic design, opening new possibilities for integration.

Machine learning is expanding beyond classification and feature extraction into areas that directly affect cartographic design.

Emerging techniques can support adaptive color schemes, automated legend creation, dynamic classification thresholds, and real-time visual analytics. The potential to incorporate user behavior and perceptual studies into these models presents a promising direction for developing more responsive visualization tools.

Cloud-based geospatial platforms such as Google Earth Engine enable global-scale analysis and near-real-time monitoring. These environments make it possible to process extensive satellite archives efficiently, but they also introduce new challenges: cartographic design must adapt to vast, temporally continuous datasets, and visual frameworks must scale accordingly to remain coherent and informative.

Advances in immersive technologies—extended reality environments, interactive 3D and 4D mapping, and multimodal interfaces—are also influencing environmental visualization. These systems enable users to experience landscapes in new ways, whether through holographic environmental models, dynamic terrain simulations, or tactile mapping systems designed for accessibility. Their adoption will require new theories of interaction, sensory integration, and visual hierarchy.

User-Centered and Participatory Approaches

While remote sensing and cartography provide powerful analytical and visual tools, effective environmental communication ultimately depends on the needs and abilities of the users. User-centered cartography emphasizes clarity, accessibility, and engagement, and its role in environmental mapping continues to grow.

Future work should prioritize empirical studies that examine how different user groups interpret maps, including assessments of cognitive load, decision-making accuracy, and color-vision accessibility. Designing multi-level interfaces that accommodate scientists, policymakers, and local communities will also enhance the usability of RS-derived products. Participatory mapping, in which stakeholders contribute to classification choices or thematic categories, offers an avenue for incorporating local knowledge and strengthening environmental decision-making. Such approaches are particularly important in contexts involving environmental justice, where cultural perspectives and community experiences influence how spatial information is understood and acted upon.

Integrating Ethics, Uncertainty, and Future Directions in Environmental Mapping

The growing reliance on environmental maps for climate planning, risk assessment, resource management, and public communication has amplified the need for approaches that acknowledge uncertainty, uphold ethical standards, and anticipate future technological and methodological developments. Remote sensing and cartographic design together produce influential representations of environmental conditions, and their integration must therefore be guided by transparency, accountability, and adaptability.

Uncertainty is inherent to all stages of environmental mapping. Sensor noise, atmospheric effects, classification errors, and modeling assumptions all influence the reliability of remote sensing products, yet such uncertainties are rarely communicated clearly in final map representations. Addressing this gap requires visual strategies that convey uncertainty without overwhelming readers, as well as transparent reporting of data sources, methodological assumptions, and potential limitations. Ethical considerations extend further to issues of representation and impact: maps derived from RS data can influence political negotiations, land-use decisions, and the vulnerability of specific communities. Establishing ethical guidelines for environmental cartography—

similar to existing standards in journalism or medical imaging—would help ensure that remote sensing outputs are used responsibly and equitably.

Looking ahead, the integration of remote sensing and cartography will increasingly depend on advanced frameworks that better connect analytical results with thematic and visual meaning. Formalized semantic structures that link RS metrics with cartographic categories could improve consistency across sensors and regions. Developments in adaptive multi-scale cartography may enable maps to adjust their structure, level of detail, and visual form dynamically in response to user needs and data characteristics. At the same time, immersive spatial interfaces and machine learning–supported visualization tools promise new ways of interacting with environmental information. Achieving these advances will require interdisciplinary training that bridges remote sensing, design studies, environmental science, and user-centered visualization.

Ultimately, the future of environmental mapping lies in approaches that integrate physical measurement, thematic interpretation, and perceptual communication into a continuous and coherent workflow. Remote sensing provides unprecedented observational capabilities, but these capabilities reach their full potential only when paired with thoughtful cartographic design and an awareness of ethical responsibility. As technologies evolve and the volume of Earth observation data continues to grow, the integration of analysis and design will become even more essential for producing maps that support scientific inquiry, inform policy decisions, and engage diverse public audiences.

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CHAPTER 3

A GIS PERSPECTİVE ON THE PRODUCTİON PROCESS OF ORİENTEERİNG MAPS: A CAMPUS-SCALE APPLİCATİON

HATİCE CANAN GÜNGÖR[1]

Introduction

Since 2006, orienteering in our country has had its own federation and caters to all age groups in society (Tanrıkulu, 2011:121). Orienteering can also be described as a sport in which participants "play chess while running." In addition to being an outdoor sport that requires navigating through designated control points using a map and compass, orienteering is considered an educational activity that develops spatial perception, wayfinding, and decision-making skills. At its core, it requires map-reading ability. The maps used in orienteering are specialized, highly detailed, user-oriented, and emphasize spatial accuracy. The production process of these maps involves stages such as spatial data collection, classification of the collected data, thematic differentiation, and field verification. In this respect, it bears

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significant similarities to spatial data production processes in Geographic Information Systems (GIS) (Tosun & Gökçe, 2025:107).

GIS is an information technology that transfers all types of location-related data into a digital environment through software, hardware, and human components, ultimately producing maps that can be updated (Çabuk, 2014:42). Steps in map creation, such as the use of satellite imagery, field data collection, thematic classification of spatial elements, and representation on the map, parallel GIS processes including data acquisition, layering, positional accuracy, and spatial representation. Therefore, this study demonstrates that orienteering maps are not merely visual products for sporting purposes, but also constitute spatial data that can be transferred to a GIS environment and analyzed.

In this chapter, the process is discussed from a GIS perspective through an example of an orienteering map produced for a campus area, highlighting the intersections between orienteering maps and GIS.

Orienteering Map Production: Theoretical and Applied Framework

Orienteering maps are specialized maps that represent the competition area in detail and require high legibility and symbolic consistency. The symbol standards, color usage, scale preferences, and object classifications determined by the International Orienteering Federation (IOF) constitute the primary determinants of the map production process. Therefore, orienteering maps are not merely a technical drawing exercise but also entail a selective cartographic generalization process.

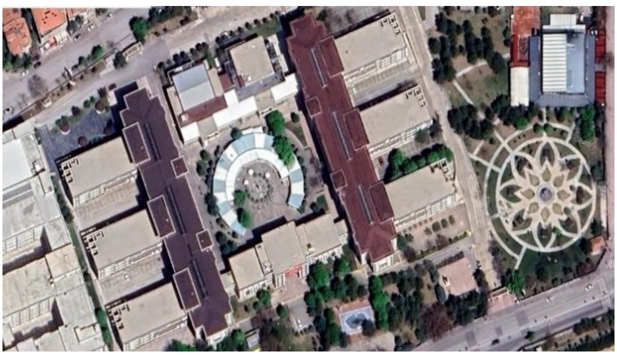
The map production process generally consists of the following stages: Base preparation and preliminary drafting, Fieldwork and on-site verification, Editing and symbolic standardization, Control, revision, and final product stages.

Application Example: Satellite Imagery-Based Map Production Process

The production process of an orienteering map was conducted through multiple stages, including the creation of a digital base using satellite imagery, coordinate transformation, field drafting, and final editing. The process was planned in accordance with the principles of positional accuracy, compliance with standards, and practical validity. At the end of the process, a competition map was prepared as an example of a course.

In the initial stage, SAS Planet software was used to access up-to-date and high-resolution satellite imagery of the study area. Images compiled from different satellite sources were integrated to create a base layer that reflected the general spatial characteristics of the area. This base layer was subsequently used as a visual reference and preliminary assessment tool in the later stages of the mapping process (Figure 1).

Figure 1 Satellite Imagery (Campus Area)

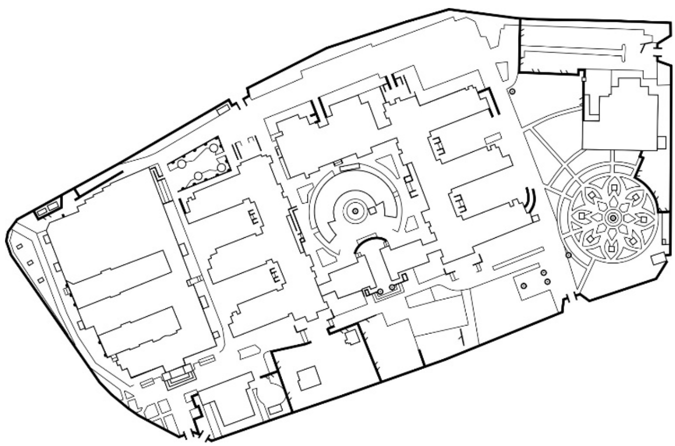


In the satellite imagery of the campus area (Figure 1), key spatial references such as main roads, prominent topographic lines, and natural and artificial land features were identified. These elements were evaluated as guiding reference points for the map production process.

The acquired imagery was processed in the Global Mapper environment and transformed into the UTM coordinate system to ensure positional accuracy. This process provided geographic referencing to the imagery, ensuring that every point marked on the map corresponded accurately to its real-world location (Figure 2). Consequently, a reliable coordinate base was established for subsequent drawing and measurement steps. This also enabled the creation of a dynamic map that can be updated using GIS technology.

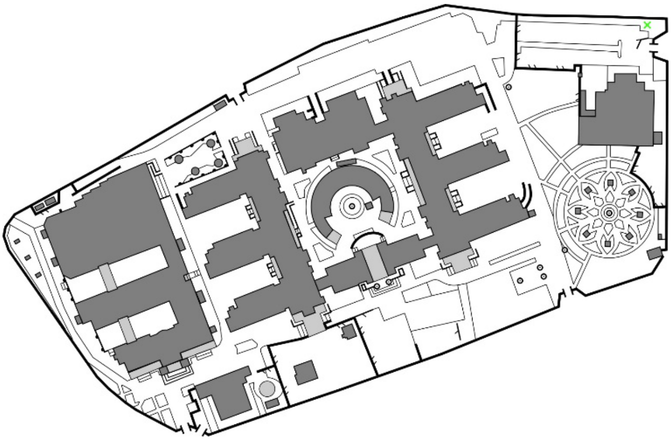
Fieldwork constitutes the most critical stage of the map production process. During this stage, the objects depicted in the preliminary draft were verified on-site, missing elements were observed and added, and incorrect details were corrected. Field drawings were recorded in real-time using tablets, with each spatial feature validated on location. This phase ensured the resolution of uncertainties originating from satellite imagery and finalized the map to accurately reflect actual terrain conditions.

Figure 2. Georeferenced Map



The georeferenced base map was transferred to the OCAD software, where it was designated as the background map for the drawing process (Figure 3). This approach ensured that the mapping work was conducted on a spatially referenced foundation, supporting visual accuracy.

Figure 3. Background Map



Prior to fieldwork, preliminary drafting and assessment were carried out in the digital environment. Road networks, open areas, vegetation density, and topographic features identified from the satellite imagery were marked as drafts, thereby structuring the field process in a planned and goal-oriented manner. The purpose of the preliminary draft was to plan the route to be followed during fieldwork and to establish observation priorities in the terrain. This draft was then transferred to a tablet for field use.

Field mapping was conducted using the Open Orienteering Mapper software through on-site observation. During this stage, the draft lines were compared with actual terrain conditions; missing or erroneous details were corrected, and features not visible in the satellite imagery (such as paths, ground transitions, and vegetation boundaries) were incorporated into the map (Figure 4). In this way, the dataset was enriched and verified using both visual sources and field observations.

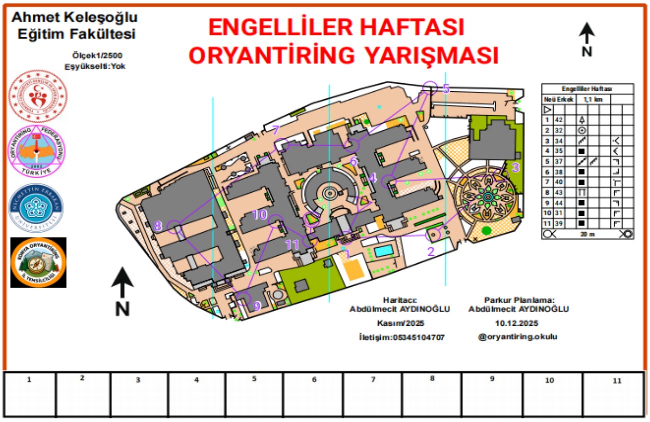
Figure 4. Field Mapping

After the completion of field mapping, the data were transferred back to the computer, and the final editing process was conducted in the OCAD software. Cartographic standards were applied, and the overall integrity of the map was maintained while performing the final adjustments. At this stage, cartographic design criteria such as color balance, symbol selection, legibility, and visual hierarchy were considered. The map thus acquired its final form, suitable for orienteering use (Figure 5).

Figure 5. Orienteering Map

Source: Abdülmecit AYDINOĞLU November/2025 Contact:05345104707

Figure 6. Orienteering Course Map



Source: Abdülmecit Aydınoğlu, November 2025

Contact: +90 534 510 47 07 Course Planning: Abdülmecit Aydınoğlu (@oryantiring.okulu)

The orienteering map used in this study was produced by Abdülmecit Aydınoğlu and has been used with his written permission

Conceptual Evaluation of the Process from a GIS Perspective

GIS, with its data-layer logic, measurability, and spatial comparison capabilities, can provide several potential contributions to orienteering map production. These include layer-based data organization (e.g., roads, natural features, obstacles, control points), distance and area measurements, route comparability, scenario creation for educational purposes, and decision support in course planning processes. Such contributions indicate that GIS can offer a complementary methodological framework for orienteering maps. However, to realize these benefits, future GIS-based applied studies need to be developed.

By presenting the satellite imagery-based orienteering map production process, this study emphasizes that orienteering maps should not be considered merely as tools for sporting purposes, but also as instruments for spatial learning and data generation within a GIS environment.

Conclusion

This study has demonstrated that the orienteering map production process—encompassing data collection, classification, thematic differentiation, field verification, and spatial representation—bears a strong resemblance to GIS data production processes. Due to its measurable and georeferenced structure, the map serves not only for course planning but also as a spatial data product that can be utilized in GIS-based analyses and educational activities.

In conclusion, the study highlights that orienteering maps can be considered a spatial data source that integrates with GIS, providing a significant foundation for enhancing the orienteering–GIS interaction in future research.

For future studies, it is recommended to develop GIS-based data models, integrate mobile field data, and conduct spatial comparisons of different courses.

"We acknowledge that an artificial intelligence tool was used to assist in the English language translation of this chapter."

Kaynakça

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CHAPTER 4

ADVANCED GEOSPATIAL INTELLIGENCE FOR ENVIRONMENTAL RISK ASSESSMENT, REAL ESTATE ANALYTICS, AND SUSTAINABLE SPATIAL PLANNING

ZEYNEL ABİDİN POLAT[1]

Introduction

Environmental risk assessment and spatial planning have undergone a profound transformation over the last two decades, driven by rapid urbanization, accelerating climate change, and increasing socio-economic complexity. Traditional planning and assessment approaches—often based on static datasets, sectoral perspectives, and linear analytical models—are increasingly inadequate for addressing the interconnected nature of environmental hazards, land-use dynamics, and real estate markets (Batty, 2013; Wu & Hobbs, 2002). These challenges demand analytical frameworks capable of integrating heterogeneous spatial data, capturing non-linear interactions, and supporting evidence-based decision-making across multiple spatial and institutional scales.

In this context, geospatial intelligence has emerged as a comprehensive paradigm that extends beyond conventional Geographic Information Systems (GIS). While traditional GIS has

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primarily focused on spatial data management and visualization, geospatial intelligence emphasizes the transformation of spatial data into actionable knowledge through advanced analytics, modeling, and decision-support mechanisms (Longley, Goodchild, Maguire, & Rhind, 2015). By integrating remote sensing, spatial statistics, artificial intelligence, and visual analytics, geospatial intelligence enables a deeper understanding of spatial processes underlying environmental risk, property value formation, and governance performance.

Environmental risks—such as floods, landslides, coastal inundation, and heat stress—are inherently spatial phenomena shaped by interactions between natural processes and human activities. These risks exhibit strong spatial dependence and scale sensitivity, consistent with the foundational principles of spatial analysis (Tobler, 1970; Anselin, 1988). At the same time, real estate markets and land-use systems respond dynamically to environmental risk through shifts in property values, investment behavior, and development patterns. Spatial planning and governance frameworks are therefore required to simultaneously address environmental vulnerability, economic valuation, and regulatory effectiveness.

However, a significant portion of the existing literature treats environmental risk assessment, real estate valuation, and spatial governance as largely independent domains. This fragmentation limits the applicability of research findings for integrated policy formulation and sustainable planning (Openshaw, 1991). Geospatial intelligence provides a unifying analytical framework to bridge this gap by enabling the joint analysis of environmental hazards, exposure patterns, socio-economic vulnerability, and spatial value dynamics within a single spatially explicit system.

Through GIS-based valuation models and spatial econometric techniques, geospatial intelligence incorporates location-specific attributes, neighborhood effects, accessibility measures, and environmental constraints into property value analysis (Anselin, 1988; Malczewski, 1999). Similarly, governance-oriented spatial indicators derived from geospatial analytics enhance transparency and accountability in land administration by revealing spatial inequities, regulatory compliance patterns, and institutional performance variations (Goodchild, 2007).

Another critical contribution of geospatial intelligence lies in its capacity to explicitly address uncertainty. Environmental risk assessments and spatial valuation models are subject to multiple sources of uncertainty, including data quality limitations, modeling assumptions, and future scenario variability. Rather than producing deterministic outputs, geospatial intelligence frameworks emphasize scenario-based analysis, sensitivity assessment, and uncertainty-aware visualization, thereby improving the robustness and credibility of spatial decision-making (Batty, 2013).

From a sustainable planning perspective, the integration of geospatial intelligence into decision-making processes supports resilience-oriented strategies that balance environmental protection, economic development, and social equity. By linking environmental risk assessment with real estate analytics and governance indicators, geospatial intelligence facilitates long-term planning approaches that are adaptive to changing environmental and socio-economic conditions. This integrative capacity is particularly important in rapidly urbanizing regions and environmentally sensitive areas, where competing land-use demands and escalating risks pose significant challenges to conventional planning frameworks.

Against this background, the objective of this chapter is to present a comprehensive geospatial intelligence framework that connects environmental risk assessment, GIS-based real estate analytics, and governance-oriented spatial indicators within a unified analytical structure. The chapter synthesizes conceptual foundations, data requirements, analytical methods, and decision-support applications, highlighting how geospatial intelligence can enhance both scientific rigor and policy relevance in sustainable spatial planning.

Conceptual Foundations of Geospatial Intelligence

Geospatial intelligence is conceptually rooted in the evolution of Geographic Information Science (GIScience) and spatial analysis, yet it represents a qualitative shift from descriptive spatial representation toward knowledge-driven spatial reasoning. While early GIS applications primarily focused on data storage, mapping, and overlay operations, advances in computation, data availability, and analytical methods have expanded the role of spatial technologies into predictive modeling, decision support, and policy-oriented analysis (Longley et al., 2015).

At its core, geospatial intelligence can be defined as the systematic process of transforming spatially referenced data into actionable knowledge through integrated analytical, computational, and visual frameworks. This transformation is achieved by combining spatial data infrastructures with advanced modeling techniques, domain knowledge, and iterative decision-support mechanisms. Unlike conventional GIS workflows, which often follow linear processing chains, geospatial intelligence operates through feedback loops that continuously refine analytical outputs based on new data, model performance, and decision needs.

A foundational principle underlying geospatial intelligence is spatial dependence, which posits that spatial phenomena are not randomly distributed but exhibit structured patterns influenced by proximity and spatial interaction. This principle, formalized through Tobler's First Law of Geography, provides the theoretical basis for spatial autocorrelation analysis, spatial regression, and neighborhood-based modeling approaches (Tobler, 1970; Anselin, 1988). In environmental risk assessment, spatial dependence manifests in clustered hazard patterns, cascading impacts, and scale-sensitive exposure dynamics. In real estate analytics, it explains neighborhood effects, market spillovers, and spatial price gradients.

Another key conceptual pillar of geospatial intelligence is multi-scale thinking. Environmental processes, land-use dynamics, and socio-economic interactions operate simultaneously across multiple spatial and temporal scales. Local-scale phenomena such as parcel-level development decisions are embedded within broader regional, national, and even global systems shaped by climate, policy, and economic forces. Geospatial intelligence frameworks explicitly acknowledge this nested structure by enabling analyses that can be aggregated, disaggregated, and compared across scales, thereby avoiding scale-induced analytical biases (Wu & Hobbs, 2002).

Geospatial intelligence also draws heavily on systems thinking, recognizing spatial systems as complex, adaptive, and non-linear. Environmental risks and land markets do not respond proportionally to external drivers; instead, they exhibit thresholds, feedback mechanisms, and emergent behavior. Traditional linear models often fail to capture these dynamics, whereas geospatial intelligence incorporates spatial econometrics, machine learning, and scenario-based simulations to model such complexity (Batty, 2013). This systems-oriented perspective is particularly valuable for understanding cumulative environmental impacts and long-term planning outcomes.

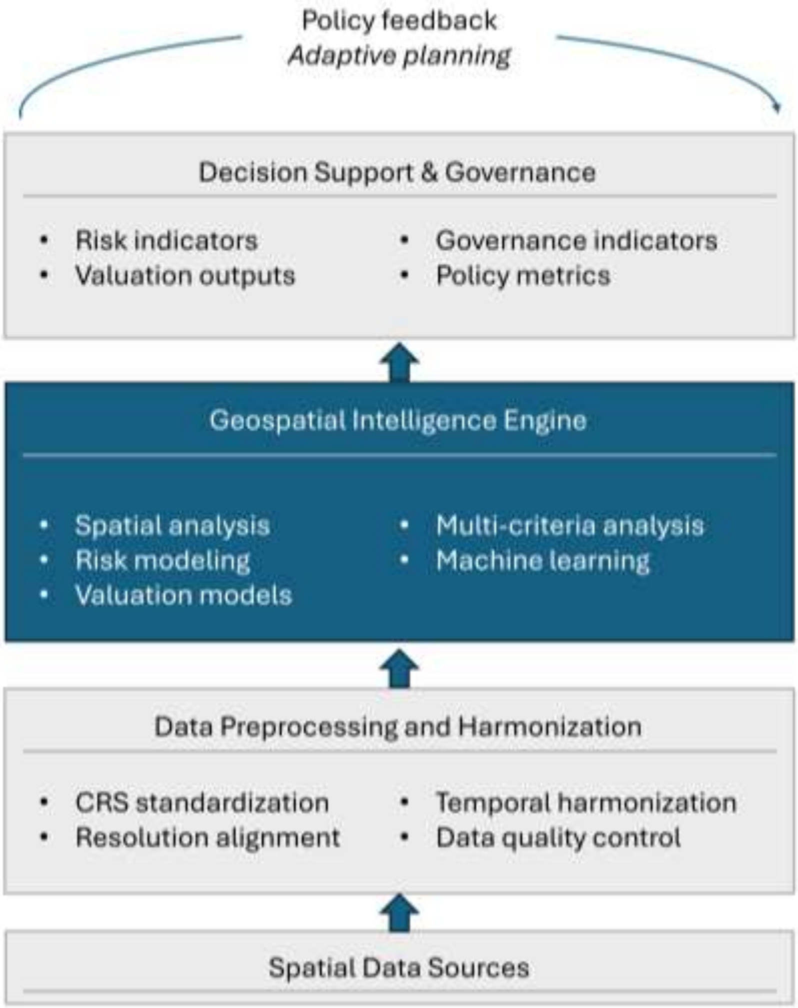
From a governance perspective, geospatial intelligence introduces a shift from reactive, sector-based decision-making toward evidence-based and spatially explicit governance. Spatial indicators derived from geospatial analytics provide measurable, transparent, and comparable metrics that support policy evaluation, regulatory enforcement, and institutional accountability (Goodchild, 2007). By embedding governance considerations directly into spatial analytical frameworks, geospatial intelligence enables planners and decision-makers to assess not only environmental and economic outcomes but also institutional performance and equity implications.

Uncertainty management constitutes another conceptual cornerstone of geospatial intelligence. Spatial data and models are inherently uncertain due to measurement errors, temporal inconsistencies, and simplifications in model structure. Rather than treating uncertainty as a residual problem, geospatial intelligence frameworks explicitly integrate uncertainty analysis through sensitivity testing, scenario comparison, and uncertainty-aware visualization. This approach enhances the credibility of spatial analyses and supports informed decision-making under conditions of incomplete knowledge.

Finally, geospatial intelligence emphasizes the role of visual analytics as a cognitive bridge between complex spatial models and human decision-makers. Visualization is not merely a communication tool but an integral component of spatial reasoning that enables pattern recognition, hypothesis generation, and comparative analysis. Well-designed spatial visualizations support iterative exploration of data and model outputs, fostering more transparent and inclusive planning processes (Openshaw, 1991).

In summary, the conceptual foundations of geospatial intelligence rest on five interrelated principles: spatial dependence, multi-scale analysis, systems thinking, governance integration, and uncertainty-aware decision support. Together, these principles distinguish geospatial intelligence from traditional GIS applications and position it as a robust analytical framework for integrated environmental risk assessment, spatial valuation, and sustainable planning.

Figure 1 illustrates the conceptual architecture of geospatial intelligence and its role in environmental risk assessment and spatial decision support.



Spatial Data Sources and Characteristics

Geospatial intelligence–based environmental risk assessment and spatial planning fundamentally depend on the availability, quality, and integration of diverse spatial datasets. Unlike conventional GIS applications that often rely on a limited number of thematic layers, geospatial intelligence frameworks emphasize heterogeneous, multi-source, and multi-scale spatial data integration to capture the complexity of environmental, socio-economic, and institutional processes (Longley et al., 2015).

Spatial data used in environmental risk assessment and GIS-based real estate analytics can broadly be classified into physical, environmental, socio-economic, infrastructural, and legal–administrative categories. Each category contributes distinct but complementary information to the analytical framework. Physical and environmental datasets characterize natural processes and hazard dynamics, while socio-economic and legal datasets contextualize exposure, vulnerability, and governance conditions. The analytical value of geospatial intelligence emerges not from individual datasets but from their systematic integration within a spatially explicit framework.

A central group of spatial data sources consists of physical environment datasets, including elevation-based representations such as digital elevation models, slope, and aspect layers. These datasets form the backbone of hazard modeling for floods, landslides, and coastal inundation, as well as terrain suitability analyses for land development. Their analytical relevance is strongly influenced by spatial resolution, vertical accuracy, and datum consistency, particularly in risk-sensitive environments where small elevation differences may translate into substantial impact variations (Anselin, 1988).

Land use and land cover datasets represent another critical data category. Derived from satellite imagery, cadastral records, or planning documents, these datasets provide insights into human–environment interactions and regulatory constraints. Zoning plans, impervious surface maps, and land-use classifications enable the identification of development patterns, regulatory compliance, and environmental pressure hotspots. In real estate analytics, land-use data play a key role in explaining spatial variation in property values and development potential.

Infrastructure and accessibility datasets, including road networks, public transport systems, utilities, and public service facilities, are essential for modeling spatial connectivity and service availability. Accessibility metrics derived from these datasets significantly influence both environmental exposure and real estate valuation outcomes. For example, proximity to transportation networks may increase property values while simultaneously amplifying exposure to environmental hazards, illustrating the dual role of infrastructure in spatial risk–value dynamics (Batty, 2013).

Environmental risk assessment further relies on environmental constraint datasets, such as flood hazard zones, coastal setback lines, protected areas, and ecological sensitivity maps. These layers define spatial limitations on land development and directly inform risk mitigation and regulatory enforcement strategies. Within geospatial intelligence frameworks, environmental constraints are often integrated as exclusionary or weighted criteria in multi-criteria decision analysis, linking environmental protection objectives with planning and valuation processes (Malczewski, 1999).

Socio-economic datasets—including population density, income distribution, and property ownership information—are indispensable for assessing exposure and vulnerability. These datasets enable the spatial differentiation of risk impacts across social groups and support equity-oriented planning interventions. In real estate analytics, socio-economic indicators explain demand patterns, market segmentation, and spatial price differentiation, reinforcing the importance of integrating social dimensions into spatial decision-making.

Finally, legal and administrative spatial data, such as parcel boundaries, cadastral records, and ownership information, provide the institutional foundation for spatial analysis. These datasets ensure legal validity, valuation accuracy, and policy relevance, particularly in land administration and governance contexts. Their integration into geospatial intelligence frameworks enhances transparency and accountability by linking spatial analytics with formal regulatory structures (Goodchild, 2007).

The primary spatial data layers commonly employed in GIS-based real estate analysis and environmental risk assessment are summarized in Table 1, illustrating their thematic roles and analytical purposes.

Table 1. Spatial data layers used in GIS-based real estate analysis

Data Category	**Spatial Layer**	**Primary Purpose**
Physical Environment	Digital elevation models, slope, aspect	Terrain suitability, flood and landslide risk assessment
Land Use and Cover	Land-use maps, zoning plans, impervious surfaces	Development control, land suitability, regulatory compliance
Infrastructure	Road networks, utilities, public facilities	Accessibility analysis, service coverage evaluation
Environmental Constraints	Flood zones, coastal setback lines, protected areas	Risk mitigation, environmental compliance
Socio-economic Data	Population density, income levels, property ownership	Market analysis, exposure and vulnerability assessment
Legal and Administrative Data	Parcel boundaries, cadastral data, ownership records	Valuation accuracy, tenure security, planning enforcement

Beyond thematic diversity, a defining characteristic of spatial data in geospatial intelligence is scale dependency. Spatial datasets vary in resolution and extent, and mismatches between data scales can introduce analytical bias if not properly managed. Geospatial intelligence frameworks address this challenge through multi-scale analysis strategies, spatial aggregation and disaggregation techniques, and sensitivity testing across resolutions (Wu & Hobbs, 2002). This ensures that analytical outcomes remain robust and interpretable across planning levels.

In addition, data quality and uncertainty constitute critical considerations in spatial data usage. Measurement errors, temporal inconsistencies, and classification uncertainties are inherent in most spatial datasets, particularly those derived from remote sensing. Geospatial intelligence explicitly incorporates data quality assessment and uncertainty awareness into analytical workflows, reinforcing the credibility of subsequent modeling and decision-support outputs.

In summary, spatial data within geospatial intelligence frameworks are characterized by thematic heterogeneity, scale sensitivity, and uncertainty. Their effective integration forms the empirical foundation for advanced spatial analysis, valuation modeling, and governance-oriented decision support. The following section builds upon this data foundation by examining integrated spatial analysis and valuation methods, highlighting how these datasets are operationalized within geospatial intelligence workflows.

Data Preprocessing and Harmonization

Within geospatial intelligence frameworks, data preprocessing and harmonization constitute a critical analytical stage that directly determines the reliability, interpretability, and policy relevance of spatial analysis outputs. Unlike conventional GIS workflows—where preprocessing is often treated as a technical prerequisite—geospatial intelligence conceptualizes preprocessing as an integral component of spatial reasoning and uncertainty management (Longley et al., 2015).

The heterogeneity of spatial data sources used in environmental risk assessment and GIS-based real estate analytics necessitates systematic harmonization procedures. Spatial datasets commonly differ in coordinate reference systems, spatial resolution, temporal coverage, thematic classification schemes, and data quality. If these discrepancies are not properly addressed, they may introduce bias, distort spatial relationships, and propagate uncertainty throughout analytical workflows.

A fundamental step in spatial data harmonization is coordinate reference system (CRS) standardization. Spatial datasets derived from different sources often employ varying projections and datums, which can lead to positional inconsistencies and misalignment. Ensuring a common CRS is particularly critical in parcel-level analysis, infrastructure accessibility modeling, and hazard mapping, where spatial precision directly influences analytical outcomes. CRS harmonization thus forms the geometric foundation of geospatial intelligence–based analysis.

Spatial resolution alignment represents another key preprocessing challenge. Environmental datasets such as elevation models or satellite-derived land cover maps may be available at fine spatial resolutions, whereas socio-economic or administrative datasets are often aggregated to coarser spatial units. Geospatial intelligence frameworks address this mismatch through resampling, spatial aggregation, and disaggregation techniques, guided by the analytical scale and decision context. Importantly, resolution choices are treated as analytical assumptions rather than neutral technical decisions, and their implications are evaluated through sensitivity analysis (Wu & Hobbs, 2002).

Temporal harmonization is equally critical in dynamic environmental and market analyses. Spatial datasets may represent different observation periods, update cycles, or seasonal conditions. In environmental risk assessment, mismatches between hazard data and exposure data can lead to misleading risk estimates. Geospatial intelligence frameworks therefore emphasize temporal alignment strategies, including time-window selection, temporal interpolation, and scenario-based comparison, to ensure analytical coherence across datasets.

Data quality assessment and error handling are central to preprocessing in geospatial intelligence. Measurement errors, missing values, classification inaccuracies, and outliers are inherent in most spatial datasets, particularly those derived from remote sensing or volunteered geographic information. Rather than eliminating uncertainty, preprocessing aims to identify, document, and manage it. Techniques such as outlier detection, consistency checks, and metadata-based quality screening enhance transparency and support uncertainty-aware modeling (Goodchild, 2007).

The harmonization of thematic classifications and attribute schemas further contributes to analytical consistency. Land-use categories, zoning codes, and socio-economic indicators often vary across data providers and administrative contexts. Geospatial intelligence frameworks promote standardized classification schemes or explicit reclassification rules to ensure comparability. This step is particularly important in multi-criteria decision analysis and valuation modeling, where inconsistent attribute definitions may undermine weighting and aggregation procedures (Malczewski, 1999).

Beyond technical harmonization, geospatial intelligence emphasizes semantic alignment, ensuring that spatial variables represent conceptually compatible phenomena. For example, flood hazard layers derived from different modeling approaches may not be directly comparable without conceptual reconciliation. Semantic harmonization enhances interpretability and reduces the risk of misinformed decision-making.

From an uncertainty perspective, preprocessing and harmonization function as the first line of defense against error propagation. By explicitly documenting preprocessing decisions, resolution trade-offs, and data limitations, geospatial intelligence frameworks enable subsequent sensitivity analysis and scenario evaluation. This transparency is essential for policy-oriented applications, where the credibility of spatial analyses is closely scrutinized.

In summary, data preprocessing and harmonization within geospatial intelligence frameworks extend far beyond routine GIS operations. They represent a structured analytical process that integrates geometric, thematic, temporal, and semantic alignment with uncertainty awareness. By establishing a coherent and transparent data foundation, preprocessing enables robust spatial analysis, reliable valuation modeling, and informed governance-oriented decision support. Building upon this harmonized data structure, the next section examines integrated spatial analysis and valuation methods, focusing on how geospatial intelligence operationalizes data into actionable knowledge.

Integrated Spatial Analysis and Valuation Methods

Within geospatial intelligence frameworks, integrated spatial analysis and valuation represent the stage at which harmonized spatial data are transformed into interpretable indicators, predictive models, and decision-support outputs. Unlike traditional valuation approaches that rely primarily on non-spatial attributes, geospatial intelligence explicitly incorporates spatial relationships, environmental conditions, and regulatory constraints into valuation processes. This integration enables a more realistic representation of land and property markets, particularly in risk-sensitive and rapidly transforming environments.

Integrated spatial analysis is grounded in the recognition that environmental risk, accessibility, land-use regulation, and neighborhood context jointly shape spatial value patterns. Consequently, valuation within geospatial intelligence frameworks is not treated as a purely economic exercise but as a spatially embedded analytical process that reflects interactions between physical, social, and institutional systems (Anselin, 1988). This perspective is especially relevant for sustainable planning, where valuation outcomes directly influence development decisions, investment priorities, and risk governance strategies.

One of the most widely applied approaches in GIS-based valuation is the hedonic pricing model**,** which decomposes property value into constituent attributes, including structural characteristics, locational factors, and environmental qualities. When implemented within a GIS environment, hedonic models benefit from spatially explicit variables such as proximity to services, exposure to environmental hazards, and neighborhood composition. Spatial extensions of hedonic models further address spatial autocorrelation, improving model robustness and interpretability (Anselin, 1988).

Beyond econometric approaches, multi-criteria decision analysis (MCDA) plays a central role in integrated spatial valuation, particularly in land suitability and development prioritization studies. MCDA enables the weighted aggregation of diverse spatial indicators—such as environmental constraints, accessibility measures, and planning regulations—into composite suitability or value indices. Within geospatial intelligence frameworks, MCDA is often combined with expert knowledge, stakeholder input, or data-driven weighting techniques, reinforcing its relevance for policy-oriented decision-making (Malczewski, 1999).

Recent advances in computational capacity have further expanded the valuation toolkit through machine learning–based spatial models**.** These models are capable of capturing complex, non-linear relationships among spatial variables that may be difficult to represent using traditional statistical techniques. In real estate analytics, machine learning approaches support automated mass appraisal, price prediction, and scenario testing, particularly when large and heterogeneous datasets are available. However, geospatial intelligence frameworks emphasize the complementary use of machine learning and interpretable models to balance predictive performance with transparency and policy relevance (Batty, 2013).

Accessibility-based valuation models constitute another important class of integrated spatial analysis methods. These models explicitly quantify the influence of spatial connectivity—such as distance to transportation networks, employment centers, and public services—on property values and development potential. Accessibility metrics derived from network analysis are particularly influential in urban contexts, where transport-oriented development and infrastructure investments shape both market behavior and environmental exposure patterns.

The principal GIS-based valuation methods and their typical application domains within geospatial intelligence frameworks are summarized in Table 2**.** This table highlights how different analytical approaches address distinct aspects of spatial value formation and planning objectives.

Table 2. GIS-based valuation methods and their applications

Valuation Method	**Core Principle**	**Typical Applications**
Hedonic Pricing Models	Decomposition of property value into spatial and non-spatial attributes	Urban housing markets, land price mapping
Spatial Regression Models	Incorporation of spatial autocorrelation effects	Neighborhood influence analysis, market trend detection

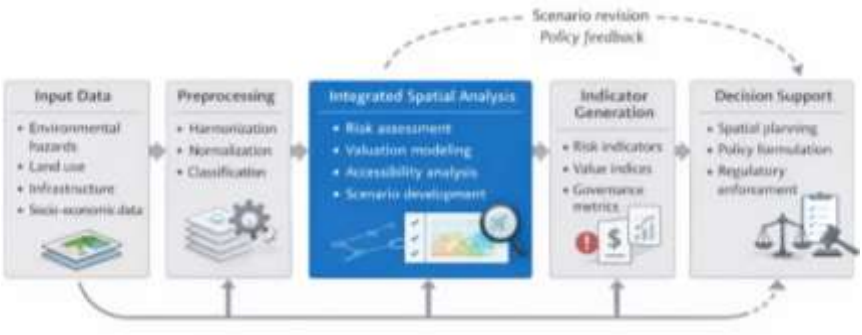
Multi-Criteria Decision Analysis (MCDA)	Weighted integration of multiple spatial indicators	Land suitability, development prioritization
Machine Learning Models	Non-linear modeling of complex spatial relationships	Automated mass appraisal, price prediction
Accessibility-Based Models	Distance and connectivity-based valuation	Transport-oriented development, service proximity analysis

A defining feature of integrated spatial analysis within geospatial intelligence is its scenario-oriented structure. Rather than producing single-point estimates, valuation models are often applied under alternative assumptions regarding environmental risk intensity, regulatory constraints, or infrastructure development. This enables the exploration of potential future value trajectories and supports adaptive planning under uncertainty.

Importantly, integrated valuation within geospatial intelligence also serves a governance function. Spatially explicit valuation outputs reveal how environmental risks and planning decisions are distributed across space and social groups, providing critical input for equity assessment and regulatory evaluation. By linking valuation results with governance-oriented spatial indicators, geospatial intelligence facilitates transparent and accountable decision-making in land administration and spatial planning systems.

In summary, integrated spatial analysis and valuation methods constitute a central operational component of geospatial intelligence. By embedding economic valuation within spatial, environmental, and institutional contexts, these methods enhance the analytical realism and policy relevance of spatial decision-support systems. The next section builds upon this analytical foundation by examining governance-oriented spatial indicators, focusing on how valuation and risk analysis outputs are translated into actionable policy metrics. Figure 2 presents a generalized workflow illustrating integrated spatial analysis and valuation within a geospatial intelligence framework.

Figure 2. Workflow of geospatial intelligence demonstrating the progression from spatial data integration to analysis, indicator generation, and governance-oriented decision support, including iterative feedback for adaptive planning.



Governance-Oriented Spatial Indicators

Within geospatial intelligence frameworks, governance-oriented spatial indicators represent the critical interface between analytical outputs and policy action. While environmental risk models and valuation analyses generate technically robust results, their societal impact ultimately depends on how effectively these results are translated into indicators that can inform planning decisions, regulatory enforcement, and institutional performance evaluation. Geospatial intelligence facilitates this translation by embedding governance considerations directly into spatial analytical workflows.

Spatial indicators derived from geospatial analytics enable decision-makers to move beyond aggregate statistics toward spatially explicit governance assessment. By revealing where risks, values, and regulatory outcomes are concentrated, these indicators support transparency, accountability, and evidence-based policy formulation. This spatial explicitness is particularly important in land administration and spatial planning, where decisions are inherently place-based and distributive in nature (Goodchild, 2007).

A key governance dimension addressed by geospatial intelligence is spatial equity. Accessibility-based indicators derived from spatial analysis reveal disparities in access to public services, infrastructure, and environmental amenities across neighborhoods and social groups. When combined with valuation outputs, these indicators expose inequitable value distributions and potential socio-spatial exclusion patterns, providing a basis for corrective planning interventions (Batty, 2013).

Market transparency constitutes another critical governance objective. Spatial variability in property values, transaction densities, and development intensity can signal speculative behavior, regulatory inconsistencies, or information asymmetries within real estate markets. Geospatial intelligence enables the systematic monitoring of such patterns through spatial price indices and hotspot analyses, enhancing regulatory oversight and market accountability.

Regulatory compliance is also central to governance-oriented spatial analysis. By overlaying zoning regulations, land-use plans, and development permits with observed land-use patterns and valuation outcomes, geospatial intelligence supports the derivation of compliance indicators. These indicators allow planners to identify areas where development deviates from regulatory intent, strengthening enforcement mechanisms and policy evaluation processes (Malczewski, 1999).

Environmental risk governance benefits substantially from spatial indicators that quantify the exposure of assets and populations to hazards. By linking hazard maps with property and infrastructure datasets, geospatial intelligence enables the identification of high-risk value concentrations and critical assets. Such indicators are essential for prioritizing risk mitigation investments, insurance strategies, and disaster preparedness measures.

Beyond regulatory and risk considerations, geospatial intelligence supports the evaluation of institutional performance. Spatial patterns in permit processing times, development approvals, and service provision reveal variations in administrative efficiency and governance capacity. These indicators provide empirical evidence for institutional benchmarking and organizational improvement within planning and land administration systems.

Sustainability-oriented governance indicators further extend the analytical scope of geospatial intelligence. Metrics related to land consumption, development density, and spatial compactness enable the assessment of long-term planning outcomes in relation to sustainability and resilience objectives. By integrating environmental constraints, valuation results, and governance metrics, geospatial intelligence supports holistic evaluations of spatial development trajectories.

The principal governance dimensions and associated indicators commonly derived from spatial real estate analytics within geospatial intelligence frameworks are summarized in Table 3.

Table 3. Governance indicators derived from spatial real estate analytics

Governance Dimension	**Indicator**	**Planning and Policy Relevance**
Spatial Equity	Accessibility to public services	Identification of underserved areas
Market Transparency	Spatial price variability	Detection of speculative behavior

Regulatory Compliance	Zoning conformity index	Enforcement of land-use regulations
Risk Governance	Exposure of assets to environmental hazards	Disaster risk reduction planning
Institutional Performance	Permit processing spatial patterns	Administrative efficiency assessment
Sustainability	Land consumption and density metrics	Compact development and resilience strategies

By structuring analytical outputs around governance-oriented indicators, geospatial intelligence strengthens the connection between scientific analysis and policy implementation. Rather than treating governance as an external consideration, this framework embeds institutional objectives, regulatory constraints, and equity concerns directly into spatial decision-support systems.

In summary, governance-oriented spatial indicators constitute a vital component of geospatial intelligence, enabling the operationalization of environmental risk assessment and valuation results within planning and policy contexts. By enhancing transparency, accountability, and strategic foresight, these indicators support more effective and sustainable spatial governance. The following section builds upon this governance perspective by examining **uncertainty, visualization, and decision support**, focusing on how complex spatial information is communicated and operationalized in practice.

Uncertainty, Visualization, and Decision Support

Uncertainty is an inherent characteristic of environmental risk assessment, spatial valuation, and governance-oriented analysis. It arises from multiple sources, including measurement errors in spatial data, temporal inconsistencies, model assumptions, and the intrinsic variability of environmental and socio-economic systems. Within geospatial intelligence frameworks, uncertainty is not treated as a residual or marginal issue but as a central analytical dimension that must be explicitly acknowledged, analyzed, and communicated to decision-makers.

Environmental risk models, for instance, depend on assumptions regarding hazard intensity, return periods, and exposure conditions that may vary across space and time. Similarly, GIS-based valuation models are sensitive to data quality, variable selection, and methodological choices. Geospatial intelligence addresses these challenges by adopting **uncertainty-aware analytical strategies**, including sensitivity analysis, scenario comparison, and robustness testing. These strategies enable analysts to identify dominant sources of uncertainty and assess their influence on analytical outcomes (Anselin, 1988; Batty, 2013).

Scenario-based analysis plays a particularly important role in managing uncertainty within geospatial intelligence. Rather than relying on single-point estimates, spatial models are applied under alternative assumptions related to environmental conditions, regulatory frameworks, or infrastructure development pathways. This approach allows planners to explore plausible futures and evaluate the implications of different policy choices under uncertainty. Scenario comparison thus supports adaptive and resilient decision-making, especially in contexts characterized by long-term environmental change and socio-economic transformation.

While uncertainty analysis enhances analytical rigor, its value for decision-making depends on effective communication. Visualization serves as a critical interface between complex spatial analyses and human cognition. Within geospatial intelligence frameworks, visualization is not merely an end-stage presentation tool but an integral component of spatial reasoning and exploratory analysis. Through maps, charts, and interactive visual interfaces, visualization enables users to detect patterns, compare scenarios, and understand spatial relationships that may not be evident from numerical outputs alone (Openshaw, 1991).

Advanced cartographic design principles are essential for conveying uncertainty without oversimplification or misinterpretation. Techniques such as graduated symbols, transparency, fuzzy boundaries, and ensemble mapping allow uncertainty to be visually encoded alongside central estimates. By explicitly representing uncertainty, geospatial intelligence supports more informed and cautious decision-making, reducing the risk of false precision in planning and policy contexts.

Visual analytics further extends the role of visualization by integrating interactive exploration with analytical computation. Decision-makers can dynamically adjust model parameters, weighting schemes, or scenario assumptions and immediately observe the spatial consequences of these changes. This interactive capability enhances transparency and supports participatory decision-making processes by enabling stakeholders to engage directly with spatial evidence (Goodchild, 2007).

In governance contexts, visualization enhances accountability by making spatial inequalities, regulatory outcomes, and risk concentrations visible and interpretable. Maps and dashboards derived from geospatial intelligence frameworks support communication between technical experts, planners, policymakers, and the public. This shared visual language facilitates consensus-building and improves the legitimacy of spatial decisions.

From a decision-support perspective, geospatial intelligence integrates uncertainty analysis and visualization into spatial decision-support systems (SDSS)**.** These systems combine data management, analytical modeling, and visualization within a unified environment, enabling iterative and evidence-based decision-making. By linking analytical outputs with governance indicators and planning objectives, SDSS operationalize geospatial intelligence in real-world policy and planning workflows (Malczewski, 1999).

In summary, uncertainty management, visualization, and decision support are inseparable components of geospatial intelligence. By explicitly addressing uncertainty, leveraging advanced visualization techniques, and embedding analysis within decision-support systems, geospatial intelligence enhances both the robustness and usability of spatial analyses. These capabilities are essential for translating complex environmental risk and valuation assessments into informed, transparent, and accountable spatial decisions. The next section synthesizes these analytical and governance insights by examining applications in sustainable spatial planning, highlighting how geospatial intelligence is operationalized in practice.

Applications in Sustainable Spatial Planning

Geospatial intelligence provides a robust operational framework for translating analytical insights into sustainable spatial planning practices. By integrating environmental risk assessment, spatial valuation, governance indicators, uncertainty analysis, and decision-support mechanisms, geospatial intelligence enables planners to address the multifaceted challenges associated with long-term spatial development. Its application-oriented nature makes it particularly suitable for planning contexts where environmental constraints, economic objectives, and social considerations must be reconciled.

One of the most prominent application domains of geospatial intelligence is environmental risk–informed land-use planning. Spatial analyses that integrate hazard maps, exposure patterns, and vulnerability indicators support the delineation of risk-sensitive zones and the formulation of development restrictions. In flood-prone or coastal areas, for example, geospatial intelligence enables planners to evaluate how alternative zoning regulations influence both environmental risk and property values. This dual perspective facilitates planning strategies that minimize risk while maintaining economic viability (Batty, 2013).

Geospatial intelligence also plays a critical role in urban redevelopment and regeneration processes. In many cities, redevelopment areas are characterized by legacy environmental risks, socio-economic disparities, and fragmented governance structures. By combining spatial valuation models with accessibility analysis and governance indicators, geospatial intelligence supports the identification of priority intervention areas and the assessment of redevelopment impacts across social groups. This capability is essential for promoting equitable and inclusive urban transformation.

In the context of infrastructure and transport-oriented planning, geospatial intelligence enables the assessment of how infrastructure investments affect spatial accessibility, land values, and environmental exposure. Accessibility-based valuation models reveal how proximity to transport corridors or public facilities influences development patterns, while risk indicators highlight potential trade-offs between accessibility gains and increased hazard exposure. Such analyses support more balanced infrastructure planning decisions that align mobility objectives with sustainability and resilience goals (Anselin, 1988).

Climate adaptation and resilience planning represents another critical application area. As climate change alters hazard frequencies and intensities, planners must evaluate the long-term implications of different adaptation strategies. Geospatial intelligence supports scenario-based planning by integrating climate projections, hazard modeling, and spatial valuation under alternative future conditions. This approach enables planners to compare adaptation pathways, prioritize investments, and design flexible strategies that remain effective under uncertainty (Wu & Hobbs, 2002).

Geospatial intelligence further contributes to land administration and regulatory planning by enhancing transparency and evidence-based governance. Spatial indicators derived from valuation and risk analysis enable monitoring of regulatory compliance, detection of informal development, and evaluation of institutional performance. By linking regulatory outcomes with spatial patterns of value and risk, geospatial intelligence strengthens accountability and supports continuous policy evaluation (Goodchild, 2007).

From a sustainability perspective, geospatial intelligence supports the assessment of compactness, land consumption, and spatial efficiency. By integrating land-use data, valuation outcomes, and governance indicators, planners can evaluate whether development trajectories align sustainability objectives such as reduced sprawl, efficient infrastructure use, and equitable access to services. These evaluations provide a spatially explicit basis for aligning local planning decisions with broader sustainability agendas.

Importantly, geospatial intelligence facilitates participatory planning and stakeholder engagement. Through interactive visualization and scenario exploration tools, diverse stakeholders can engage with spatial evidence, explore trade-offs, and contribute to planning processes. This participatory dimension enhances the legitimacy and social acceptance of planning decisions, particularly in contexts involving contested land uses or environmental risks (Openshaw, 1991).

In summary, applications of geospatial intelligence in sustainable spatial planning extend across land-use regulation, urban redevelopment, infrastructure planning, climate adaptation, and governance evaluation. By integrating analytical rigor with practical decision-support capabilities, geospatial intelligence enables planners to design spatial strategies that are resilient, equitable, and responsive to environmental change. The final section synthesizes the chapter's contributions and outlines future research directions and planning implications.

Discussion and Conclusions

This chapter has articulated geospatial intelligence as an integrative analytical framework that bridges environmental risk assessment, GIS-based real estate analytics, and governance-oriented spatial decision-making. By moving beyond traditional, siloed approaches to spatial analysis, geospatial intelligence enables a holistic understanding of how environmental processes, market dynamics, and institutional structures interact across space and scale. The discussion below synthesizes the chapter's key contributions, highlights methodological implications, and outlines directions for future research and practice.

From a conceptual standpoint, the chapter positions geospatial intelligence as an evolution of Geographic Information Science toward **knowledge-driven spatial reasoning**. Unlike conventional GIS applications that emphasize data handling and visualization, geospatial intelligence integrates spatial dependence, multi-scale analysis, systems thinking, and uncertainty awareness into a coherent analytical paradigm (Longley et al., 2015; Batty, 2013). This shift is particularly important for environmental risk assessment and spatial planning, where decisions must account for complex interactions and long-term consequences.

Methodologically, the chapter demonstrates that the analytical strength of geospatial intelligence lies in the integration of heterogeneous spatial data and analytical methods**.** The structured progression from spatial data sources to preprocessing, integrated analysis, valuation, governance indicators, and decision support illustrates how raw spatial data are systematically transformed into policy-relevant knowledge. The inclusion of GIS-based valuation models and governance-oriented indicators highlights the added value of embedding economic and institutional dimensions within spatial analysis, rather than treating them as external considerations (Anselin, 1988; Malczewski, 1999).

A key contribution of this framework is its explicit treatment of uncertainty. Environmental risks, land values, and governance outcomes are inherently uncertain, yet planning decisions often rely on deterministic representations. By emphasizing scenario-based analysis, sensitivity testing, and uncertainty-aware visualization, geospatial intelligence supports more robust and transparent decision-making under uncertainty. This approach reduces the risk of false precision and enhances the credibility of spatial analyses in policy contexts.

The application-focused sections of the chapter illustrate how geospatial intelligence can be operationalized in sustainable spatial planning. Whether applied to risk-informed land-use regulation, urban redevelopment, infrastructure planning, or climate adaptation, geospatial intelligence provides planners with tools to evaluate trade-offs, assess distributive impacts, and align development strategies with sustainability and resilience objectives. Importantly, the integration of governance indicators ensures that analytical outputs remain directly relevant to institutional performance, regulatory compliance, and social equity (Goodchild, 2007).

Despite its strengths, the geospatial intelligence framework is not without limitations. Data availability and quality remain persistent challenges, particularly in contexts where up-to-date, high-resolution, or institutionally reliable spatial data are lacking. Moreover, the increasing use of machine learning and complex modeling techniques raises concerns regarding interpretability and transparency. Addressing these challenges requires continued methodological development, standardization of workflows, and the adoption of explainable modeling approaches that balance analytical sophistication with policy usability.

Future research directions should focus on several key areas. First, the integration of real-time and near-real-time spatial data offers opportunities to enhance the responsiveness of geospatial intelligence–based decision-support systems. Second, advances in participatory GIS and visual analytics can further strengthen stakeholder engagement and democratic governance in spatial planning processes. Finally, deeper integration of governance theory and spatial analytics may improve the evaluation of institutional performance and policy effectiveness across different spatial and administrative contexts.

In conclusion, this chapter demonstrates that geospatial intelligence provides a powerful and flexible framework for addressing the intertwined challenges of environmental risk, spatial valuation, and sustainable planning. By combining analytical rigor with governance relevance and decision-support capability, geospatial intelligence enhances both the scientific foundations and practical effectiveness of spatial planning. As environmental and socio-economic pressures continue to intensify, geospatial intelligence will play an increasingly central role in shaping resilient, equitable, and sustainable spatial futures.

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CHAPTER 5

GeoAI PERSPECTIVES ON SPATIAL DATA ANALYSIS

1. FEVZİ DAŞ[1]

Introduction

The integration of spatial science and artificial intelligence (AI), especially through machine learning and deep learning methods, is known as GeoAI (spatial artificial intelligence). It represents a major shift in how we analyze and interpret spatial data today (Gao, 2021). The growth of this interdisciplinary field comes from several key factors. These include the rise of geospatial big data, improvements in graphics processing units (GPUs), and the computing power from high-performance computing (HPC) systems (Gao, 2021). Spatial artificial intelligence aims to create smart systems that can imitate human perception, spatial reasoning, and the discovery of geographic patterns. It provides scalability that goes beyond the limits of traditional methods (P. Liu & Biljecki, 2022)

Traditional geographic information systems (GIS) approaches often rely on expert knowledge, deductive reasoning, and rule-based (top-down) methods. In contrast, spatial artificial

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intelligence adopts an inductive and data-driven approach where algorithms learn complex patterns and relationships within the data (W. Li & Li, 2020). This shift means moving from a "knowledge-driven" structure in spatial analysis to one where machine learning algorithms scan large data sets and learn features on their own. In particular, deep learning techniques can automatically extract features from unstructured data like satellite images, geospatial (GIS-based) data, and sensor data. This feature extraction process is at the center of the analytic transformation (W. Li & Li, 2020). As a result, it becomes possible to derive meaningful spatial information from raw data without needing predefined rules. This brings many advantages (Güney, 2019).

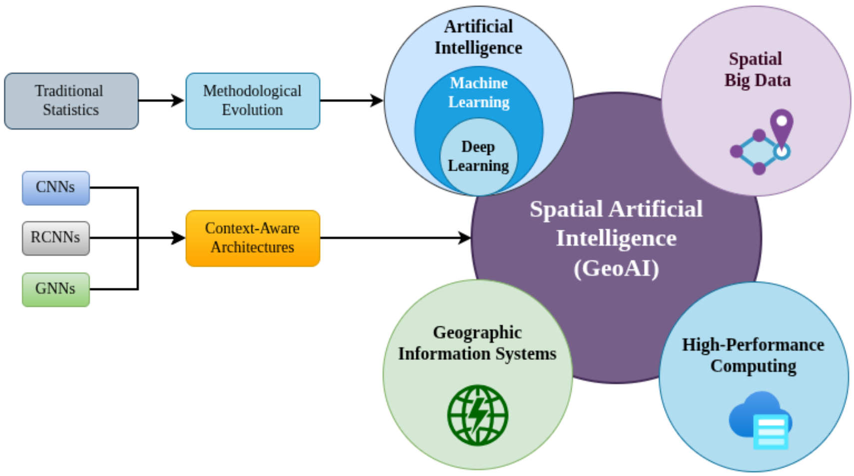
The main factor that sets spatial artificial intelligence apart from general artificial intelligence applications is the unique nature of geographic data. In the literature, this is highlighted by the principle that "spatial is special." (Goodchild, 1992) It requires integrating geographic features like spatial autocorrelation, spatial heterogeneity, and spatial dependency into the architecture and learning processes of artificial intelligence models (Gao, 2021). Location information acts as a key that connects heterogeneous data sets, while geographic domain knowledge improves the contextual accuracy of models. Therefore, spatial artificial intelligence is not just a toolset for processing geographic data. It is also a new methodological framework where spatial principles are combined with computational intelligence.

This field has roots in expert systems from the 1980s and early artificial neural network studies (Gao, 2021). Today, it plays a critical role in solving complex spatial problems across a wide range, from urban planning to epidemiology, disaster management to precision agriculture (Janowicz et al., 2020). In this context, spatial artificial intelligence is described as the fourth paradigm of geographic information science. It expands the boundaries of scientific research with its ability to automatically discover and explain patterns, relationships, or knowledge from data (W. Li & Li, 2020).

Fundamentals of Spatial Artificial Intelligence

Spatial artificial intelligence can be described as an interdisciplinary field that sits at the crossroads of artificial intelligence, spatial big data, high-performance computing, and geographic information systems. Figure 1 presents the core components of spatial artificial intelligence and its connections with related fields.

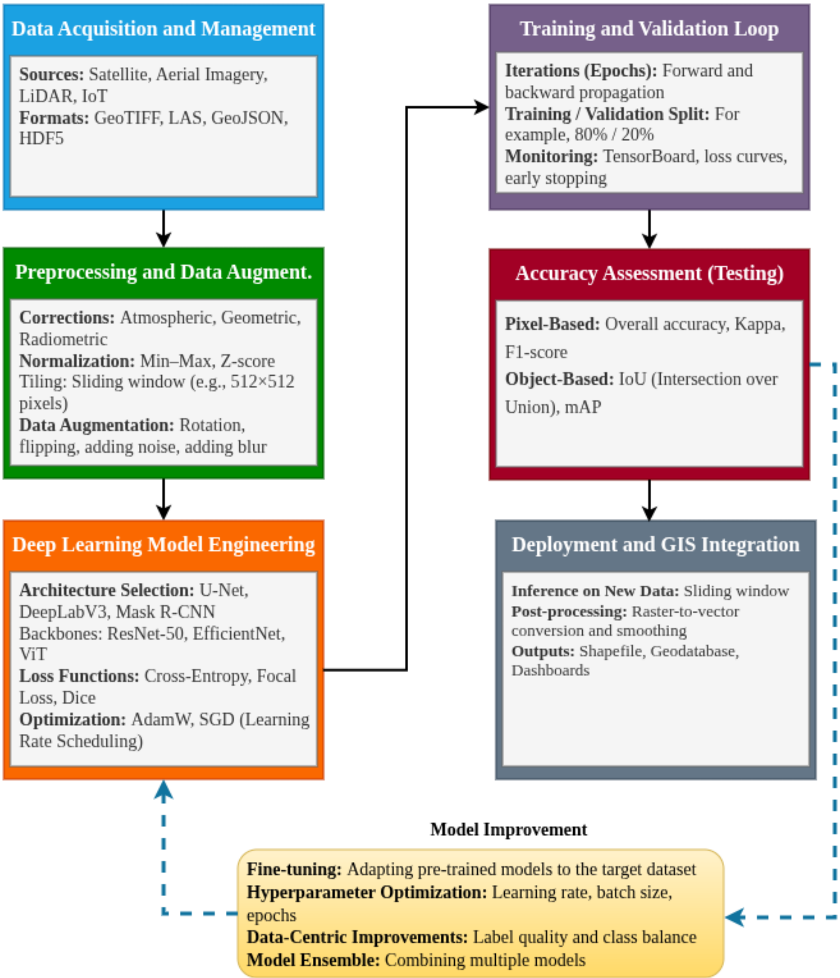
Figure 1 Core components of spatial artificial intelligence and related fields



The methodological base of this field has shifted from traditional statistical approaches to machine learning and deep learning algorithms that automatically detect patterns in data and generate predictions.

Figure 2 outlines the key workflow steps in spatial artificial intelligence. While these steps might differ slightly based on specific applications, they remain consistent across many uses. Like most artificial intelligence processes, this one begins with data collection and management, and it concludes with deployment and integration into geographic information systems.

Figure 2 Spatial artificial intelligence workflow



This section explores the main artificial intelligence architectures applied in spatial artificial intelligence studies, along with how they are tailored to address spatial challenges (Boutayeb et al., 2024) (Pierdicca & Paolanti, 2022).

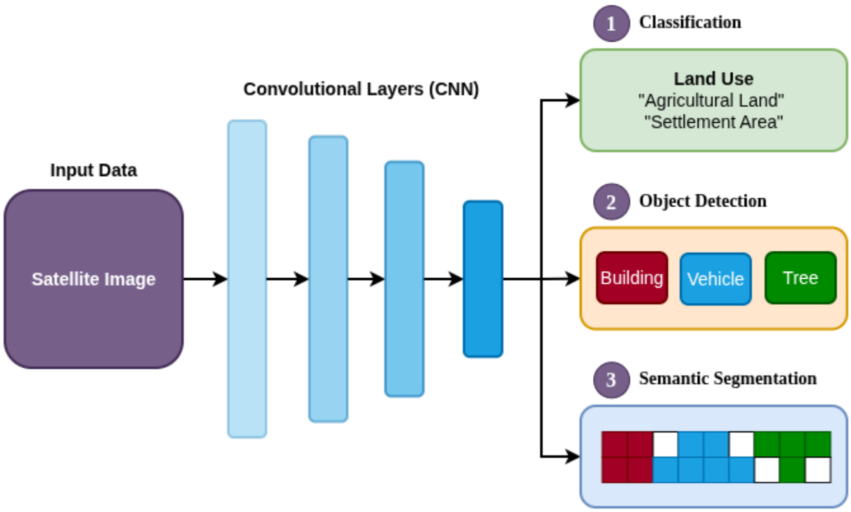
Concepts in Machine Learning and Deep Learning: Machine learning refers to a collection of techniques that enable computers to identify patterns in data without being explicitly programmed for each task and to use those patterns for making predictions (El Naqa & Murphy, 2015). Traditional machine learning algorithms, such as Random Forests and Support Vector Machines, have long been applied to spatial classification and regression tasks. However, they often operate within constrained learning frameworks and depend on manual feature extraction.

Deep learning, on the other hand, stands out as a subset of machine learning with a distinct approach. It draws inspiration from the human brain's operations, aiming to mimic them through artificial neural networks (ANNs). With its multi-layered structure, deep learning can start from raw data and progressively uncover more abstract and intricate features on its own (Boutayeb et al., 2024). This "deep" design has emerged as a key driver in spatial artificial intelligence, particularly for handling vast, unstructured spatial datasets—like satellite imagery or geospatial data—by removing the need for predefined rules (Zhu et al., 2017).

Basic Neural Network Architectures and Their Spatial Applications: In spatial artificial intelligence applications, various deep learning architectures are employed, tailored to the type of data and the specific analysis problem. One prominent example is Convolutional Neural Networks (CNNs) (Purwono et al., 2023). This architecture serves as a foundational model for spatial image analysis and computer vision tasks. CNNs rely on a mathematical operation called "convolution" along with sliding windows to detect local patterns in images, such as edges and textures. It performs exceptionally well in areas like land use classification from remote sensing imagery, object detection (e.g., buildings, roads, vehicles, settlements), and semantic segmentation (Boutayeb et al., 2024).

Figure 3 presents the core concept behind CNNs and many similar deep learning models that operate in a comparable way.

Figure 3 Processing satellite data with convolutional neural networks and resulting outputs



CNNs handle spatial data in a layered manner, progressing from basic features (like pixel values) to more advanced semantic insights (such as object categories).

Another widely adopted deep learning approach in spatial artificial intelligence is Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks. Unlike CNNs, RNN architectures are built to manage sequential data and retain information from prior inputs (LeCun et al., 2015). Standard RNNs, however, struggle with capturing long-term dependencies, which led to the development of LSTMs. In the realm of spatial artificial intelligence, LSTMs are commonly applied to time series analyses (e.g., air pollution forecasting), trajectory mining (e.g., vehicle or human movements), and traffic flow predictions, where temporal relationships are essential, often yielding strong results (M. Li et al., 2019).

Transformer-based models, which incorporate attention mechanisms, represent another important class of deep learning approaches that have gained significant attention. Initially designed for natural language processing (NLP), transformer architectures use "attention mechanisms" to process long-distance relationships in data simultaneously (Devlin et al., 2019). In spatial artificial intelligence, they serve as alternatives or complements to CNNs, particularly through Vision Transformers (ViTs) for tasks like scene classification and object detection in remote sensing images (Dosovitskiy et al., 2020). They also prove effective in spatial time series forecasting and integrating diverse data types (e.g., text and location data).

Generative Adversarial Networks (GANs) are yet another contemporary deep learning model frequently used in spatial artificial intelligence applications. Comprising two competing networks—a generator and a discriminator—GANs are designed to produce realistic data (Goodfellow et al., 2020). In spatial analysis, GANs support tasks such as map style transfer (e.g., converting satellite images into map bases) (Isola et al., 2016), cloud removal (Singh & Komodakis, 2018), and enhancing spatial datasets through data augmentation.

Spatially Explicit Models: General-purpose artificial intelligence models tend to ignore key geographic principles when processing spatial data, such as Tobler's First Law, which states that "things closer together are more related than those farther apart." For this reason, spatial artificial intelligence research focuses on developing "Spatially Explicit Models," where spatial knowledge and principles are directly woven into the model's design (Scheider & Richter, 2023). These models build spatial dependence and spatial heterogeneity right into the learning process. For example, techniques like spatial embedding or spatial representation learning allow geographic coordinates, neighborhood connections, and spatial distance measures to be integrated into the neural network layers (Wu et al., 2020). This approach leads to models that are enhanced with geographic domain knowledge, rather than relying solely on data-driven learning (Janowicz et al., 2020). In fields such as image classification, geographic knowledge graphs, and geographic question-answering systems, spatially explicit models outperform standard machine learning approaches (Chu et al., 2019).

Data Sources and Processing

The success of spatial artificial intelligence research, which arises from the integration of geographic information systems and artificial intelligence, largely depends on the volume, variety, spatial and temporal coverage, and quality of the data employed. Traditional spatial analysis methods typically rely on relatively limited and well-structured datasets, whereas contemporary spatial artificial intelligence research increasingly depends on what is commonly referred to as geospatial big data—a continuously expanding and heterogeneous collection of data sources (Janowicz et al., 2020). The subsections below examine the core data ecosystem that supports spatial artificial intelligence models, as well as the preparation stages these data undergo before being incorporated into analytical processes.

Spatial Big Data

Spatial big data refers to datasets that combine the standard features of big data—such as volume, velocity, and variety—with unique spatial and temporal elements. It is estimated that approximately 80% of all data generated today contain some form of geographic reference (VoPham et al., 2018), and this proportion is expected to increase in the coming years. Within the context of spatial artificial intelligence, these data span a broad spectrum, from the physical characteristics of the Earth's surface to patterns of human mobility. They can generally be examined in three main categories: remote sensing data, human-perspective spatial images, and volunteered geographic information along with social sensing. Before moving on, it helps to clarify the concept of human-perspective spatial images. This term describes images captured from viewpoints easily perceived by the human eye in everyday environments. Data collected by companies such as Google, using vehicle-mounted or pedestrian-based platforms, provide a well-known example of this type of spatial data.

Remote Sensing Data: The most established and fundamental data source that forms the backbone of spatial artificial intelligence applications is remote sensing imagery obtained from satellites and airborne platforms. Publicly accessible satellite missions such as Landsat and Sentinel provide the opportunity to monitor physical changes on the Earth's surface over several decades. This long temporal coverage makes them an essential resource for long-term environmental analysis and change detection studies (Wulder et al., 2012). In particular, multispectral sensors such as Sentinel-2 play a key role in monitoring a wide range of environmental parameters, including vegetation health and water quality (N. Kussul et al., 2017).

In addition, advances in commercial satellite platforms such as WorldView and GeoEye, as well as in unmanned aerial vehicle (UAV) technologies, have increased spatial resolution to the centimeter level (Manuel Núñez et al., 2019). These high-resolution images allow deep learning models to detect and classify objects such as buildings, roads, vehicles, and even trees or poles with high accuracy. However, the use of such data also requires complex preprocessing steps, including the removal of noise caused by atmospheric effects, cloud cover, and seasonal variations.

Human-Perspective Spatial Imagery: As a complement to the "top-down" perspective offered by remote sensing data, human-perspective imagery has emerged in the literature as a new data source that enables the analysis of urban environments from a "human-centric" viewpoint. Panoramic images obtained from platforms such as Google Street View (Anguelov et al., 2010), Baidu Total View, and Mapillary provide information about building facade characteristics, the human perception of urban green spaces, and street conditions at a level of detail that satellites cannot provide.

In contemporary studies, these data are used not only for mapping the physical environment but also for making socioeconomic inferences. For example, in the study by (Gebru et al., 2017), the demographic structure and income levels of neighborhoods were predicted with high accuracy using the makes and models of vehicles detected from human-perspective spatial imagery. Similarly, (Zhang et al., 2018) developed models to measure whether urban areas are perceived as "safe," "lively," or "boring" using these images. This approach creates a unique data domain for spatial artificial intelligence in terms of making the social dimension of urban fabric measurable.

Volunteered Geographic Information and Social Sensing: The widespread adoption of mobile devices and location-based social networks has transformed people into data producers, giving rise to the concept of "social sensing." Geo-tagged text and photographs obtained from platforms such as Twitter (X), Facebook, and Flickr, along with crowdsourced map data like OpenStreetMap (OSM) and high-resolution UAV data such as OpenAerialMap, provide real-time data about human mobility and spatial interactions (VoPham et al., 2018).

These data are particularly critical in fields such as disaster management and epidemiology, where official data sources are inadequate or delayed. For example, trajectory data obtained from mobile phones are widely used to simulate human mobility in disease spread models or to predict traffic flows (Boutayeb et al., 2024). Social media data, on the other hand, add a semantic layer to spatial analyses by helping to understand public response and local conditions during an event.

Data Preparation and Enrichment

The success of spatial artificial intelligence models, particularly deep learning algorithms, is not achieved through the direct use of raw data, but rather through careful processing, labeling, and enrichment of this data. At this point, there are a number of procedures and operations that need to be followed. These are explained below.

Labeling and Training Data Generation: Supervised learning methods require labeled data, accepted as "ground truth," for the model to carry out the learning process. One of the major bottlenecks in spatial artificial intelligence applications is the lack of high-quality training datasets. For example, to train a model that will detect buildings from satellite imagery, thousands of building samples need to be marked on images through manual or semi-automatic methods. As emphasized in the literature by the "Garbage In, Garbage Out" (GIGO) principle, errors or biases in training data directly reduce the model's prediction accuracy and generalization ability (VoPham et al., 2018). Therefore, monitoring labeling quality during the data preparation phase and ensuring that the dataset represents geographic diversity are of critical importance.

Data Fusion and Integration: Solving complex geographic problems is generally not possible with a single data source. Spatial artificial intelligence enables the combination (data fusion) of heterogeneous data sources. Geographic location serves as a common key that links datasets in different formats (image, text, sensor data) to each other (S. Li et al., 2017). For example, in studies where urban functional zones are identified, physical characteristics obtained from remote sensing images are combined with human activity data obtained from social media, allowing both the physical structure and the purpose of use of the area to be modeled simultaneously (Miller & Goodchild, 2015). Similarly, in air quality prediction models, satellite-based aerosol measurements, ground station data, and meteorological data are integrated to obtain predictions with high spatiotemporal resolution. This integration is one of the fundamental methodological approaches that gives spatial artificial intelligence an advantage in understanding the multidimensional nature of spatial events.

Core Spatial Artificial Intelligence Tasks

The increase in the diversity and volume of data sources has made it necessary for the algorithms used to process these data to become more specialized. Spatial artificial intelligence has specialized in certain fundamental tasks by adapting general computer vision and machine learning techniques to the unique structure of geographic data (multi-scale nature, rotation variation, spatial dependency) (Janowicz et al., 2020). From this perspective, spatial artificial intelligence has a more complex and multidimensional structure compared to many existing artificial intelligence tasks. This section examines three fundamental technical operations that enable the transformation of raw spatial data into meaningful information. These are: object detection, semantic segmentation, and spatiotemporal prediction operations.

Object Detection and Extraction: Object detection is the process of identifying and classifying the locations of specific geographic features (buildings, vehicles, ships, aircraft, trees, etc.) within satellite or aerial imagery. Unlike traditional methods, spatial artificial intelligence-based object detection offers high success rates in images with complex backgrounds and different scales. The main purpose in these applications is to define the presence and location of the detected object by drawing a "bounding box" around it.

Two main deep learning architectures stand out in the literature for this task. The first method is called Region-Based Methods. R-CNNs (Region-based Convolutional Neural Networks) and their derivatives, Faster R-CNNs and Mask R-CNNs, first propose potential object regions on the image and then classify these regions (Adegun et al., 2023). While these methods offer high accuracy, they can be costly in terms of processing speed and computational criteria.

Another method that comes to the forefront is Regression-Based Methods. Algorithms such as YOLO (You Only Look Once) (Redmon et al., 2015) and SSD (Single Shot Detector) (W. Liu et al., 2015) directly predict object locations and classes by scanning the image in a single pass. Particularly recent versions like YOLOv8 are preferred in scenarios such as disaster response or traffic monitoring that require real-time detection due to their balance of speed and accuracy.

In spatial artificial intelligence applications, object detection plays a critical role in areas such as detecting illegal constructions in urban planning, tracking ships and aircraft in the defense industry, and identifying and counting tree species in agriculture (Zhu et al., 2017). However, the very small size of objects in satellite images, angular differences resulting from bird's-eye view, and dense object clusters such as adjacent buildings continue to exist as fundamental technical challenges in this field.

Semantic Segmentation and Classification: Unlike object detection, which only identifies the location of objects, semantic segmentation involves assigning each pixel in an image to a specific class (such as road, forest, water, building). This operation is a dense pixel-level classification of the image and provides an "image-to-image" transformation (Long et al., 2014). This method forms the basis for automatic generation of vector data (vectorization).

The most widely used architecture in this field is U-Net and its derivatives, which have an encoder-decoder structure. U-Net shows very high performance in tasks requiring precise boundary detection, such as extracting building footprints and mapping road networks, thanks to its structure that preserves spatial context while extracting image features (down-sampling) and then returns these features to the original image size (up-sampling) (Ronneberger et al., 2015). Additionally, architectures such as DeepLab and SegNet are also widely used in land cover and land use (LULC) classification (Sahana et al., 2022).

Segmentation studies conducted with spatial artificial intelligence provide significant speed and cost advantages over traditional manual digitization methods in environmental analyses such as calculating the proportion of urban green spaces, monitoring water resources, and detecting impervious surfaces (concrete, asphalt).

Spatial Prediction and Time Series Analysis: Spatial artificial intelligence not only describes the current situation but also makes future predictions by learning patterns in spatial and temporal data. This task generally includes processes of predicting values at unknown points (spatial interpolation) and predicting future values (temporal prediction). More detailed information about these concepts and applications is provided below.

Time Series Forecasting can be used in modeling spatially varying data over time, such as traffic flow, air pollution (PM2.5), or disease spread (Y. Li et al., 2017) (Qi et al., 2018). RNNs and especially LSTM networks are widely used in these applications. LSTM models produce more accurate predictions compared to traditional statistical methods by learning long-term dependencies and temporal patterns (such as seasonality) in the data. For example, changes in air quality in a specific area of a city over the next 24 hours can be predicted using spatial artificial intelligence models with historical sensor data and meteorological data.

In spatial prediction and gap-filling applications, deep learning-based generative models (such as GANs) are used to remove cloudy areas in satellite images or predict values in regions without sensor data (Bengio & Neural Information Processing Systems Foundation, 2010). Additionally, Graph Neural Networks (GNNs) directly incorporate spatial dependency into the model in tasks such as traffic speed prediction by modeling spatial neighborhood relationships and network structures (such as road networks).

These methods enable decision-makers to develop preventive strategies in dynamic processes such as modeling the impact of environmental factors in environmental epidemiology and forecasting energy demand in smart cities.

Sectoral Applications and Case Studies

Today, spatial artificial intelligence has moved beyond being a theoretical research area and has become a technology that produces concrete value in solving complex spatial problems and transforms decision support mechanisms (Gao, 2021). This section examines the application areas of spatial artificial intelligence technologies in different sectors such as smart cities, environmental management, public health, and commerce, as well as the methodological transformations they create in these areas, in light of case analyses. This section focuses on the more prominent or commonly used applications. Of course, spatial artificial intelligence has a much broader application area and impact.

Smart Cities and Urban Planning: The smart city concept is based on the integration of Internet of Things (IoT) sensors, big data, and artificial intelligence to increase the efficiency of urban operations. Spatial artificial intelligence optimizes urban planning by providing data analysis-based insights into population dynamics, land use patterns, and infrastructure monitoring processes in this ecosystem (Batty et al., 2012). Unlike traditional methods, spatial artificial intelligence algorithms have the potential to increase efficiency by up to 30% by optimizing resource allocation, infrastructure planning, and traffic management in urban development projects (Janowicz et al., 2020).

Modeling urban mobility is one of the most critical applications in this field. Deep learning architectures such as Graph Convolutional Networks (GCNs) and LSTM models are used for predicting spatiotemporal traffic flows (Yu et al., 2018). For example, hybrid models like T-GCNs have been developed that learn the topological structure of road networks to predict traffic density and congestion in specific areas of a city. Additionally, in specific urban problems such as parking management, studies in the literature have shown that LSTM-based models provide higher accuracy in predicting parking occupancy rates (for example, 99% accuracy and 1.59 RMSE) compared to traditional machine learning methods such as random forest and support vector machines (Yu et al., 2018).

In addition, spatial artificial intelligence plays a critical role in monitoring and mitigating the urban heat island effect. Deep learning models working with the fusion of satellite images and meteorological data can predict temperature variations in urban areas at high resolution and guide strategies such as green roof applications by analyzing the relationship between vegetation and building density. Furthermore, using human-perspective spatial imagery, the perceptual quality of urban green spaces and buildings (safety, liveliness, etc.) can be automatically scored, making urban design decisions data-driven (Darmawan et al., 2025).

Environmental Management and Climate Change: Environmental monitoring and combating climate change are recognized as among the most important issues of recent years. This field is one of the areas where spatial artificial intelligence is most intensively used. Particularly in air pollution modeling, spatial artificial intelligence uses satellite-based Aerosol Optical Depth (AOD) data to overcome the limited spatial coverage of ground stations. Deep neural networks (DNNs) and ensemble learning methods integrate multiple variables such as meteorological data, land use, and traffic density to predict concentrations of pollutants like PM2.5 at high spatiotemporal resolution. These models can model the nonlinear complex structure and spatial autocorrelation of atmospheric processes more successfully than traditional statistical methods (Shoko & Dube, 2024).

In the context of natural disaster management, spatial artificial intelligence has the potential to be used in pre-disaster risk reduction, disaster response, and post-disaster damage assessment phases. For example, CNNs can be used to model the spread of forest fires, predicting the future boundaries of the fire based on variables such as wind speed, topography, and vegetation (Radke et al., 2019). Similarly, highly accurate analyses can be performed even in cloudy weather conditions using Sentinel-1 SAR (Synthetic Aperture Radar) images and U-Net-based segmentation models for flood risk mapping and detecting flood-affected areas. Additionally, damage levels in buildings can be automatically classified using aerial photographs and deep learning algorithms for post-earthquake damage assessment, enabling the guidance of response teams (Shoko & Dube, 2024).

Public Health and Epidemiology: Spatial artificial intelligence has brought a new dimension to epidemiology in monitoring disease spread, assessing environmental impact, and planning health services. Unlike traditional epidemiological methods, spatial artificial intelligence can detect disease outbreaks at near real-time speed using "digital traces" such as social media data, search engine trends, and location data obtained from mobile devices (Salathé et al., 2012). For example, during the COVID-19 pandemic, areas at risk of virus spread were identified and intervention strategies were developed by analyzing human mobility data and spatial interactions (Kraemer et al., 2020).

In environmental epidemiology, spatial artificial intelligence is used to more precisely measure environmental factors (air pollution, noise, lack of green space) to which individuals are exposed. Using human-perspective spatial imagery and deep learning algorithms, factors such as neighborhood-level green space amount (for example, street trees), physical condition of buildings, and urban disorder can be automatically extracted, and the relationship between these factors and health outcomes such as obesity, diabetes, and depression can be examined. For example, in a large-scale cohort study conducted in the United States, tree presence in street images analyzed with deep learning was found to be inversely related to depression incidence (Sahana et al., 2022). Additionally, within the framework of precision medicine and the concept of "geomedicine," the goal is to provide personalized preventive health services by creating environmental risk profiles specific to the places where patients live and work.

Commerce and Retail: The retail sector benefits from spatial artificial intelligence techniques in areas such as market analysis, store location selection, and supply chain optimization. Spatial artificial intelligence is used to identify the most suitable new market areas for a business and increase sales volumes of existing stores by analyzing customer behaviors and demographic characteristics. Beyond traditional location selection models, artificial intelligence-based approaches use data-driven algorithms to model the relationship between customer locations and physical stores (Miller & Goodchild, 2015).

Specialized frameworks developed particularly for retail analysis (such as "GeoAI-Retail") integrate geographic information systems with machine learning in processes such as customer segmentation, competitor analysis, and sales forecasting. These systems increase supply chain efficiency and enable faster responses to customer demands through insights obtained from complex datasets (such as credit card spending, mobile device data, population distribution). Additionally, in areas such as sales forecasting and consumer demand prediction, the purchasing tendencies of potential customers in a specific region and the most profitable locations can be predicted using spatial algorithms (Huff, 1964).

Challenges, Ethics, and Future Vision

Although spatial artificial intelligence offers revolutionary opportunities in the analysis and interpretation of spatial data, the widespread adoption of this technology brings with it a series of technical, ethical, and operational challenges. The success of models depends not only on algorithmic accuracy but also on data quality, accuracy, currency, computational costs, and social acceptability. This section addresses the fundamental obstacles faced by spatial artificial intelligence, privacy concerns, and future research directions for the discipline. Finally, there is a general assessment regarding our country (Turkey) and specific recommendations for our nation.

Technical Challenges in Data Quality and Generalizability: One of the biggest obstacles in developing spatial artificial intelligence models is the lack of high-quality and labeled training data (ground truth data). Supervised learning algorithms need thousands or sometimes tens of thousands of labeled examples to accurately identify geographic features; however, producing these data is time-consuming and often requires expert knowledge. The lack of labeled data and errors in training sets directly negatively affect model performance. Additionally, integrating heterogeneous data structures from different sensors (satellite, UAV, social media) and making their spatiotemporal resolutions compatible is a significant technical challenge and a serious workload.

Another critical technical issue is giving the model generalization capability. Geographic events are spatially heterogeneous; that is, a model trained in one region (for example, a city in Turkey) may not show the same success in a different geographic context (for example, in a rural area or a different country). While non-spatial artificial intelligence models generally assume that data are independent and identically distributed, autocorrelation and local variations in spatial data often violate this assumption. This situation causes models to experience performance degradation when applied to new regions.

Furthermore, spatial artificial intelligence applications require enormous computational resources, especially when working with high-resolution satellite images and global climate models. Since processing large datasets requires high-performance computing (HPC) infrastructure and GPU hardware, access to these technologies can be costly.

Ethics, Privacy, and Sensitivity of Spatial Data: The biggest obstacle to the social acceptance of spatial artificial intelligence is privacy and ethical concerns. Location data contains sensitive information that can reveal individuals' identities, habits, and health conditions. High-resolution satellite images, human-perspective spatial imagery, and GPS data collected from mobile devices can lead to the tracking of individuals without their consent. Particularly in health research, using patients' home addresses carries the risk of violating personal privacy. To reduce this risk, it is necessary and even essential to conceal individuals' exact locations by adding random noise to the data through techniques such as geomasking.

Another important ethical issue is algorithmic bias. Spatial artificial intelligence models tend to reflect the biases of the data on which they are trained. For example, collecting training data only from developed countries or specific socioeconomic regions can cause the model to make erroneous predictions in disadvantaged areas or among minority groups. Research has shown that clinical artificial intelligence models can produce biased results for socioeconomically disadvantaged groups and deepen health inequalities. Therefore, algorithmic fairness and geographic representativeness of data should be at the center of the model development process.

Explainable Spatial Artificial Intelligence: Deep learning models are generally characterized as "black box" systems whose internal working principles are complex and difficult to understand. For spatial artificial intelligence to be used confidently in critical areas such as public policy, disaster management, or epidemiology, it must be possible to explain why the model made a particular decision or prediction.

Explainable Spatial Artificial Intelligence (GeoXAI) aims to transparently reveal the geographic and environmental factors that affect model predictions. For example, methods such as SHAP (Shapley Additive exPlanations) are used to understand which variables (traffic density, wind direction, land cover, etc.) contribute most to the model in air pollution prediction. This approach increases not only the accuracy of the model but also spatial causality and reliability.

Future Trends such as Digital Twins and Autonomous Systems: The future of spatial artificial intelligence is moving toward deeper integration with digital representations of the physical world. At this point, we encounter the concept of “Digital Twins”. Spatial artificial intelligence plays a central role in creating "Digital Twins," which are dynamic digital copies of cities, buildings, or natural systems. By automatically extracting information from satellite images and sensor data to continuously update these twins, spatial artificial intelligence enables the testing of simulations and "what-if" scenarios in urban planning.

On the other hand, the success of models like GPT in natural language processing has triggered the development of similar "Foundation Models" in the spatial domain. Large-scale models pretrained with diverse datasets, such as Segment Anything Model (SAM) or Prithvi, can be adapted to specific geographic tasks (such as building detection or land cover classification) through fine-tuning with less training data (Jakubik et al., 2023).

Physics-Informed AI is another important concept that stands out in terms of future vision. Future research is focusing on hybrid approaches that integrate physical laws (such as hydrological flow rules or atmospheric dispersion) into artificial intelligence algorithms, rather than models that only learn from data. This approach increases the physical consistency of models, enabling more reliable and generalizable predictions even when data is scarce.

In conclusion, spatial artificial intelligence goes beyond keeping a static record of spatial data and forms the foundation of autonomous systems that perceive the world, analyze it, and predict the future. The success of this technology will depend on balancing technical capabilities with ethical responsibilities and deepening interdisciplinary collaboration. Considering natural disasters and changes such as earthquakes, forest fires, and desertification that frequently occur in our country, it can be clearly seen that spatial artificial intelligence holds very important potential for our nation. Work that can be done in this field has the potential not only to contribute to the literature but primarily to contribute to solving some fundamental problems in our country.

Conclusion

This chapter has discussed the role of spatial artificial intelligence in the analysis and interpretation of spatial data. By combining geographic information systems, remote sensing, big data, and high-performance computing with machine learning and deep learning methods, GeoAI represents a clear shift from traditional rule-based approaches toward data-driven spatial analysis. These methods allow complex spatial patterns and relationships to be identified more efficiently and at larger scales.

The chapter has outlined the main deep learning architectures used in GeoAI and explained how they are adapted to the specific characteristics of geographic data, such as spatial dependence, heterogeneity, and scale. It has also emphasized the importance of diverse data sources and careful data preparation, including labeling and data fusion, for achieving reliable model performance. Key GeoAI tasks—object detection, semantic segmentation, and spatiotemporal prediction—have been shown to support practical applications across a wide range of sectors.

Despite its advantages, the use of spatial artificial intelligence raises important challenges related to data quality, generalization, computational cost, privacy, and ethical concerns. Addressing these issues through explainable models, responsible data practices, and interdisciplinary collaboration is essential for the effective use of GeoAI.

Overall, spatial artificial intelligence offers strong potential both as a research framework and as a decision-support tool. In regions facing rapid urban change, environmental risks, and natural hazards, GeoAI can play a valuable role in improving spatial understanding and supporting informed decision-making.

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CHAPTER 6

APPLICATION OF UNMANNED AERIAL VEHICLE REMOTE SENSING FOR ANATOLIAN WILD SHEEP INVENTORY AND DESIGNING POPULATION MAP

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Introductıon

Nowadays, several techniques have been used in wildlife management. One of these techniques is Remote Sensing. Remote sensing techniques such as Unmanned Aerial Vehicles (UAV), LIDAR, Satellite Imagining, Camera traps, Global Nagivation Satellite System (GNSS) provide significant contributions in areas

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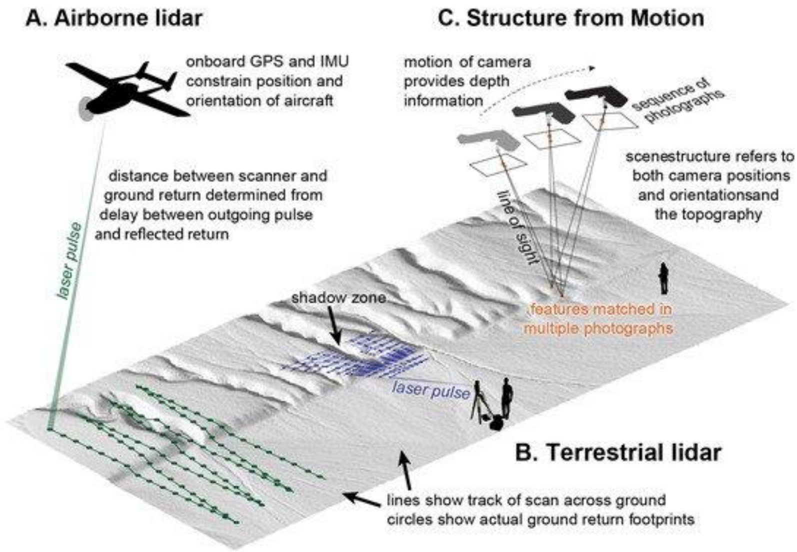
such as wildlife development, biodiversity (Mutlu et al 2018). Remote sensing techniques are more advantageous compared to other techniques due to increasingly threatened wildlife populations, wild animals in remote habitats, and wild animals moving fast (Moll et al 2007, Hebblewhite et al 2010, Dirzo et al 2014 & Tilman et al 2017). Classical geodetic measurement methods are gradually giving way to automatic photogrammetric and laser measurements. Data obtained by terrestrial laser scanning (TLS) and aerial laser scanning (ALS) are used in many scientific fields such as geomorphology, archaeology, ecology, and engineering.

Three-dimensional Digital Surface Models (DSMs) and Digital Terrain Models (DTMs) are created by laser scanning. Laser scanning techniques require expensive equipment and often specialized software. Laser scanners save a lot of time in acquiring, processing, and analyzing data, but these solutions are very expensive. SfM, which is a measurement method that has started to gain popularity in recent years and originates from inexpensive computer vision techniques, is seen as a good alternative for obtaining field data.

This method is based on the same principles as stereoscopic photogrammetry (Wróżyński et all 2017). In the SfM method, 3D structures are created from a series of overlapping frames (Figure 1).

Fıgure 1 A schematic illustration of three methods to produce high resolution digital topography



Reference: Johnson et al 2014

The letters indicate that A is Airborne lidar (light detection and ranging), B is Terrestrial lidar and C is UAV-based structure from Motion (GPS—global positioning system; IMU—inertial measurement unit).

UAVs are a very significant technique in various studies, such as archaeological sites, irrigation systems and cultural heritage (Eisenbeiss et all 2011, Fernández-Hernandez et al 2015 & Sener et al 2018), vegetation monitoring studies to support sensitive agriculture (Berni et al 2009 &Zhang et al 2012), disaster management (Bendea et al 2008, Chou et al 2010 & Ilic et al 2018), and wildlife management. Along with artificial intelligence and minimized thermal imaging systems, UAVs offer wildlife specialists the opportunity to conduct low-cost research in large areas (Watts et al 2010, Watts et al 2012, Gonzalez et al 2015 & Aylak 2021). Therefore, UAV technologies are emerging as powerful tools in wildlife ecology (Anderson et al 2013). UAV technology includes wildlife studies, sampling of microbes in the air, detection of new species, marine organisms and body behaviour research. Additionally, studies include wild species in various habitats, from light savannahs to dense tropical rainforests.

Anatolia has a rich and colourful structure in terms of biodiversity. Anatolian Wild Sheep is part of this wealth. Anatolian Wild Sheep is the largest endemic mammal species found in Turkey and it is an important species due to its biological characteristics and being the ancestor of domestic sheep. Negative impacts on the Anatolian Wild Sheep, which is only found in Turkey in the world, are eliminated and this type is carried to the future with sustainable wildlife management (Republic of Turkey Ministry of Agriculture and Forestry 2021).

The aim of this study is to perform the inventory study of The Anatolian Wild Sheep living in the Bozdag Wildlife Development Area located in the Karatay district of Konya province. Determination of population density and distribution of Anatolian Wild Sheep in the region, habitat restoration, inventory studies, hunting, and wildlife management, etc. will contribute to the studies.

Anatolian Wild Sheep

The Anatolian Wild Sheep is one of the 15 subspecies of the Asian Mouflon (Ovis gmelinii), one of the five wild sheep species in the world. Anatolian Wild Sheep is one of the endemic species in Anatolia, only live in Turkey. With its short feathers, short ears and tail, long and thin legs, Anadolu Wild Sheep (Figure 2), which looks more like deer than sheep, has a great sense of vision, smell and hearing. Anatolian Wild Sheep is a very important species in terms of biological features, being the ancestor of domestic sheep and the biological diversity in Anatolia.

Fıgure 2 Anatolian Wild Sheeps

Reference: Republic of Turkey Ministry of Agriculture and Forestry,2021

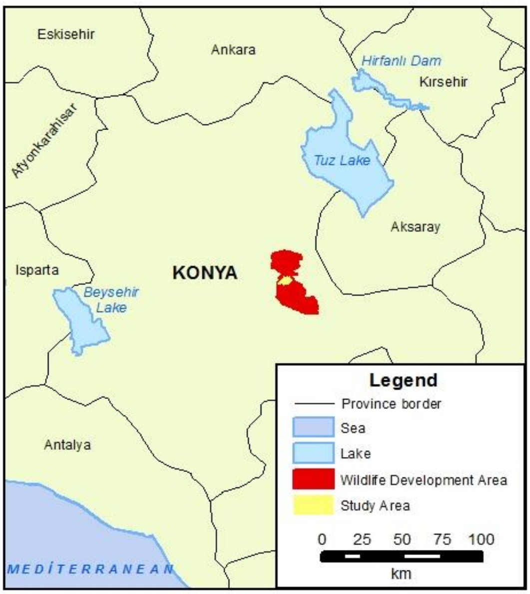
It was first introduced in 1841 by Blyth and in 1856 by Valenciennes, according to the studies in the 1800s; habitats are specified as mountainous regions of Ankara, Eskisehir, Afyon and Konya. The number of Anatolian Wild Sheep faced with the threat of extinction due to overfishing, pressure of some predator species and nutrient shortage dropped below 50 in the 1960s . The habitat of Anatolian Wild Sheep was accepted as the Wild Sheep Protection Area by the Ministry of Agriculture in 1967 in Turkey. Wild Sheep Protection Area covers the borders of Karatay, Selcuklu and Altınekin districts, and on 07.09.2005, an area of 59.296,5 ha was changed and declared as Wildlife Development Area (WDA) with the decision of the Council of Ministers numbered 2005/9453 (Republic of Turkey Ministry of Agriculture and Forestry 2021). It is very important to provide the most suitable living conditions for the Anatolian Wild Sheep and to develop sustainable wildlife management in order to carry this species to the future.

Study Area

As the study area, the area surrounded by a wire fence was determined in the Konya Bozdag Wildlife Development Area (Figure 3). In 1967, the General Directorate of Nature Conservation and National Parks, Konya Branch Directorate of Bozdag Wild

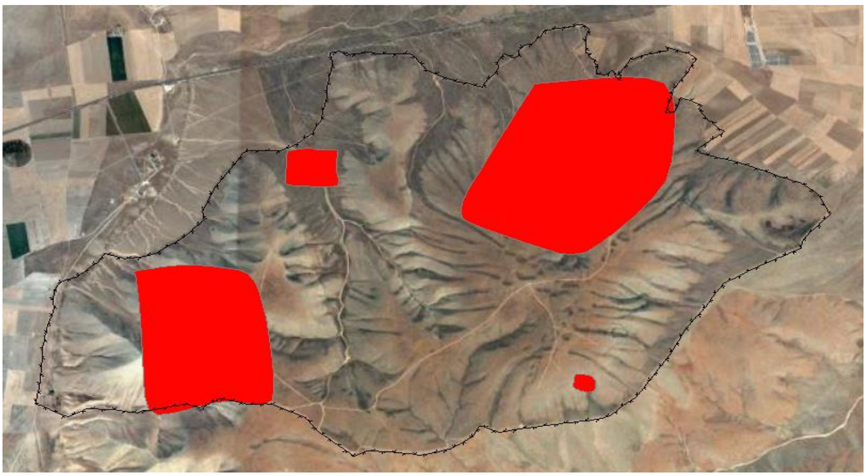
Sheep Protection and Production Area according to a report issued by the Ministry of Agriculture Wild Sheep Protection Area has been declared as. The conservation area covers the borders of Karatay, Selcuklu and Altinekin districts. With the decision of the Council of Ministers, no 2005/9453 dated 07.09.2005, an area of 59.296.5 ha was changed and announced as Wildlife Development Area. During the years 1988-1992, an area of 3429.5 hectares of this area was surrounded by a mesh fence. The study was carried out in this area of 3429.5 ha. There are intense wolves, domestic sheep, dogs and human pressures on the Anatolian Wild Sheep living outside the wire braided area. The terrestrial climate is dominant in the region and there is no other protection status in the area. In addition to Anatolian Wild Sheep in the borders of Wildlife Development Area, wolves, foxes, rabbits, badgers, weasels, eagles, partridges etc. live animals (Republic of Turkey Ministry of Agriculture and Forestry,2021).

Fıgure 3 Konya Bozdag Wildlife Development Area and the study area



In the first part of the study, a preliminary study of an area of 3429.5 hectares was made. The preliminary study consists of examination of current literature and area trips. The preliminary study data was then evaluated and the work plan for the area work was carried out. Before the inventory work we conducted, information was obtained from the personnel working in the development area who knew the area well. A general field survey of the development site was conducted from the monitoring room. According to the information received, four observation areas were determined to be applied to the partial counting technique and studies were carried out in these observation areas (Figure 4). The partial counting technique with air direct observation method was preferred for this study.

Fıgure 4 Observation areas of Anatolian Wild Sheep inventory



Reference: Buğdaycı et al 2019

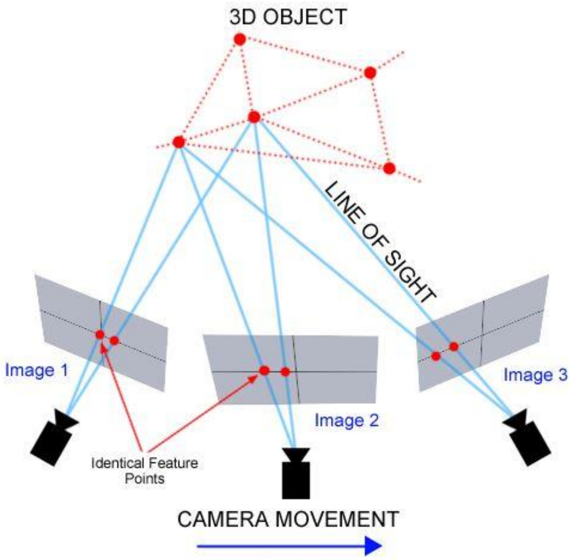
Photogrammetric methods

Today, three-dimensional (3D) modeling with photogrammetric methods is used in many fields. It is possible to create a 3D model from very large areas to very small objects. It is possible to obtain not only visual data but also geometric data from the models. The use of some computer vision techniques, such as " producing 3D models from pictures" and " local features" for positioning, has gained new momentum in the last 20 years. Advances in computer vision lead to the use of different approaches for 3D model production, the most commonly used object being the Motion Object Creation (SfM) method. Since the objective of this method is based on reconstruction, it is used for 3D visualization (Seren et al 2016). SfM is a technique that is rapidly becoming popular in the sciences of the earth sciences and is used to obtain topographic information from digital images (Morgan 2016).

Structure from Motion (SfM). Traditional photogrammetry relies on the concept of combining blocks of aerial images in order to create georeferenced spatial data. Digital terrain models (DTMs or DEMs) were traditionally created using photogrammetric and differential global positioning system (dGPS) data as key components of the process. To process data and improve its quality, most of these techniques still require expensive equipment and professional knowledge.The development of UAV systems with consumer-grade digital cameras allowed for the acquisition of spatial data at a very low cost. Because traditional photogrammetry requires the use of photogrammetric, precalibrated cameras, an alternative processing method was required to stitch, georeference, and orthorectify the acquired imagery. The computer vision community developed such a method: Structure from Motion (SfM) and Multi-View Stereo (MVS), which revolutionized low-cost data acquisition in other environmental applications (Jeziorska et al 2019).

SfM is a ground-breaking, low-cost, and user-friendly photogrammetric approach for working with high-resolution data sets. SfM allows you to create digital models of 3D structures (land, buildings, earth formations, and so on) from a collection of 2D photos (Figure 5).

Figure 5 Principle of Structure-from-Motion (SfM)



This method is used to perceive the 3D environment around people and other living things using 2D pictures created in the eye's retina layer. To construct a geometric model, traditional photogrammetric algorithms require 3D position and orientation information from the camera and ground control points. The model geometry and camera location information are solved automatically and concurrently in the SfM approach. Features must be observed from one image to the next in order to relate them. The properties' path through time is later used to predict the 3D position of the features and camera movement.

In recent years, SfM technique has been used to produce high resolution digital earth model and orthophoto maps by processing images obtained from UAV vehicles through commercial software.

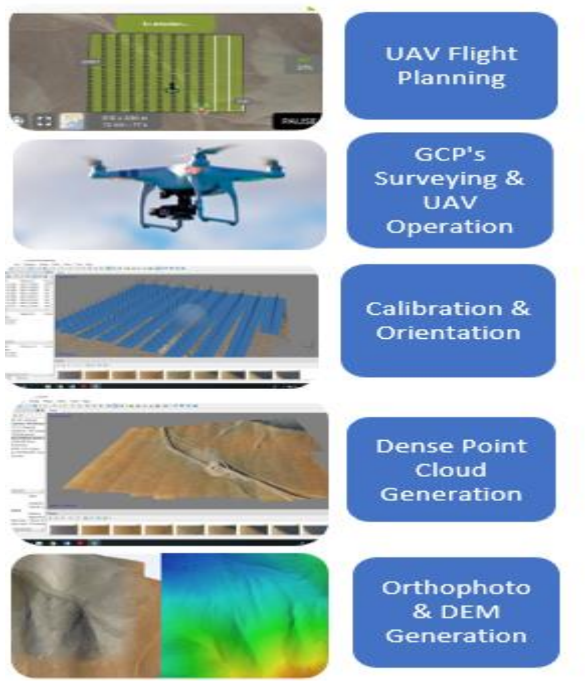
Data Acquisition

In the study, a Toyota 4x4 truck belonging to the 8th Regional Directorate of Agriculture and Forestry for land transportation, a

Nikon binocular to see easily and clearly wild sheep, the Panasonic Lumix GX1 camera was used to photograph the study area.

The images were taken by an UAV platform. The steps of the UAV photogrammetry process are given in Figure 6. For the production of photogrammetric products, it is necessary to plan flight before obtaining the image. UAVs flight planning includes photo scale, rate of transverse and longitudinal overlap, flight height and number of columns.

Fıgure 6 An example UAV image processing workflow



Reference: Buğdaycı et al 2019

After the study area was defined, a flight plan was prepared to obtain all the images of this area. The DJI Phantom 3Pro with 12 MP (4000×3000) resolution camera is used for aerial photography. The maximum service ceiling of the drone above sea level is 6000 m and the communication distance with the remote control is about 5000 m. Vehicle with a weight of 1216 g and a flight time of 25 min depending on weather conditions can reach speeds up to 16 m / s. With GPS receiver, the position accuracy of UAV is ± 1.5 m horizontally and ± 0.5 m vertical. The camera uses a 1 / 2.3eri CMOS sensor and diaphragm f / 2.8, FOV (Field of View) 94º, focal length 20 mm (35 mm equivalent).

During the image data acquisition phase, flight was performed on the predetermined blocks. For all aerial triangulation, 60% of side overlap and 80% of forward overlap were used. Another project parameter, the flying height of UAV above the ground is 100 meters. UAV (DJ Phontom 3 Pro) speed 5 m / sec. is set to. The "Pix4d Capture" mobile software, based on Google Earth, was used to prepare the flight plan and manage the flight. The flight plan was prepared separately for all flights.

In the inventory study, the first and third observation areas were taken by automatic flight. Totally 535 images were taken with the UAV from the study area.

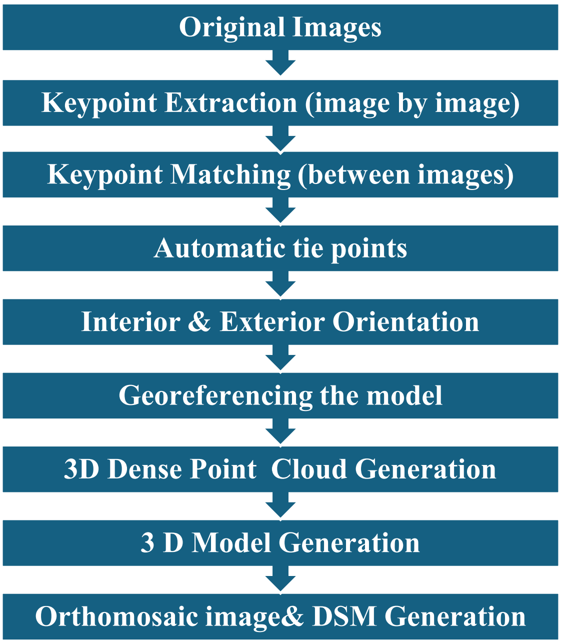
Data Processing

In UAV photogrammetry, image orientation should be performed to produce spatial data and 3D model from images. For a geographic application, data must be georeferenced. There are two common methods for this: direct georeferencing, indirect georeferencing. Although direct georeferencing depends on GPS data, Ground Control Points are used to determine data using indirect technique.

An UAV usually includes its own low cost, lightweight navigation system. However, indirect georeferencing can take full advantage of the use of GPS data recorded during flight and can easily connect to GPS data collected on site. Therefore, the user should decide whether a referenced point cloud should be obtained more quickly. In this study, indirect georeference method is used. For data processing, a Windows 10 (64 bit) operating system workstation with twelve 2.93 GHz central processing units and 16 GB (gigabytes) of internal memory was used.

Agisoft PhotoScan Professional program was used for photogrammetric data production. The processing of the aerial images is started with the loading of the related photos to the program on the workstation. The Photoscan software data processing procedure is shown in Figure 7.

Figure 7 Photoscan Pro software data processing steps



PhotoScan uses automatically selected key points on the image during photo alignment and matching points are used in a randomly selected object space. With this matching process, approximate values are created for the internal and external orientation parameters.

The application will construct a dense point cloud for each pixel (grid) in the future stages using camera parameters based on the anticipated camera location. Its precision and accuracy are comparable to point clouds generated by terrestrial or aerial lidar. The following items can be created with this dense point cloud:

• Orthomosaic mosaic A georeferenced orthophotomap can be created using a variety of mixing modes (for example, assigning a raster color that represents the weighted average value of all pixels from individual images). The output appears to be an aerial image patched together from all of the individual photographs, but it is mathematically correct and can be used as cartographic material.

• A Digital Surface Model (DSM) is made by interpolating the elevation value of raster cells depending on the points within the cell.

• A 3D Mesh is a triangulated irregular network formed by connecting the vertices of a dense point cloud, which may be exported with texture and seen as a colorful 3D model.

For each region, images were evaluated separately and georeferencing was performed by processing the camera coordinates from their navigation. Estimated camera locations were created in the target reference system using dense point cloud, and a digital surface model and orthophoto were created.

By using the orthophotos of the observation areas, sheep can be detected by the naked eye. The number of Anatolian wild sheep determined within the borders of the study area and the sizes of the observation areas are respectively,

1. Observation Area: 40 Anatolian Wild Sheep on 303.458 ha,

2. Observation Area: 21 Anatolian Wild Sheep on 32.701 ha ,

3. Observation Area: 45 Anatolian Wild Sheep on 477.888 ha, and

4. Observation Area: 34 with Anatolian Wild Sheep on 5.636 ha as determined.

The total area of the 4 observation areas scanned in the Wildlife Development Area is 819,675 hectares. The number of Anatolian Wild Sheep in 4 observation areas was determined by looking at the orthophotos one by one (Figure 8). It is concluded that there were 140 Anatolian Wild Sheep in 819.675 ha area.

Fıgure 8 Determination of the number of wild sheep from orthophoto image

Reference: Buğdaycı et al 2019

The calculation includes dividing the number of recorded individuals by the size of the scanned area to obtain a density value. The value obtained by counting is divided by the total observation area and the density is calculated.

According to the count results obtained from the observation areas, the density calculation of the wild sheep was made as follows:

Density (d) = Number of individuals seen / Size of observation areas (ha)

Density (d) = 140 sheep / 819.675 ha

The density of the Anatolian Wild Sheep per hectare was found to be 0.17 with density calculation. The population density obtained as a result of the partial counting technique was interpolated to the fenced area.

Number of sheep = Calculated density value / Working area size (ha)

Number of sheep = 0.17 × 3429.5 ha = 585

The percentage of error rate is 10% in wildlife inventory studies where a partial counting technique is applied (Bilgin 2010).

Margin of Error = Number of Calculated Anatolian Wild Sheep × the percentage of error rate

Margin of Error = 585 × 10% = ± 59

When the margin of error was added, it was concluded that the Anatolian Wild Sheep lived within the range of 526-644 in study area.

Population map of Anatolian Wild Sheep

The calculation of the density values in the observation areas is as follows:

Density (d) = Number of individuals seen / size of the first observation area (ha)

Density (d) = 40 sheep / 303.458 ha = 0.132

Density (d) = Number of individuals seen / size of 2nd observation area (ha)

Density (d) = 21 sheep / 32.701 ha = 0.642

Density (d) = Number of the people seen / size of 3rd observation area (ha)

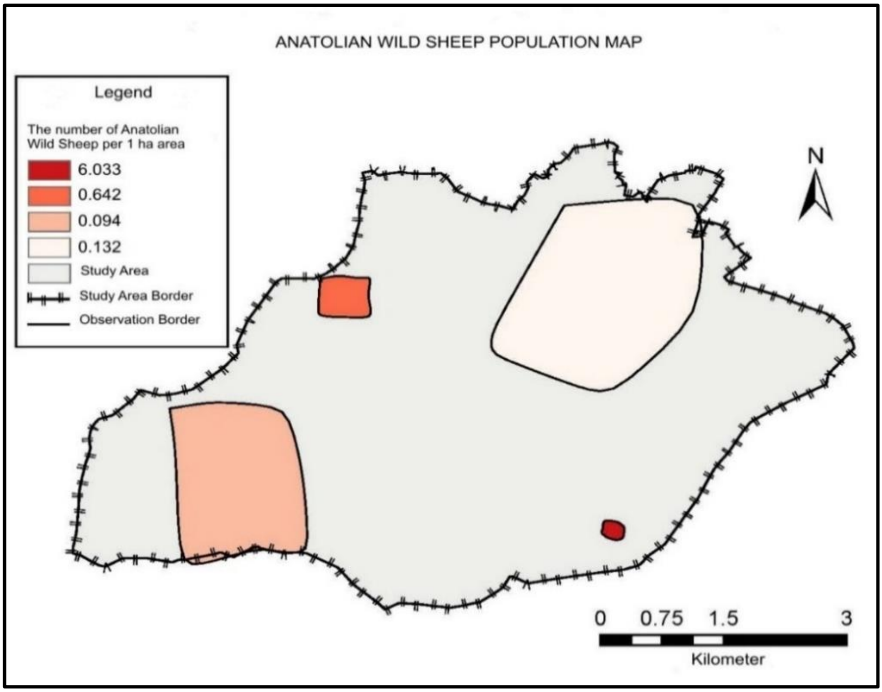
Density (d) = 45 sheep / 477.888 ha = 0.094

Density (d) = Number of individuals seen / 4th size of observation area (ha)

Density (d) = 34 sheep / 5.636 ha = 6.033

The population map was designed according to densities (Figure 9).

Fıgure 9 Population map of Anatolian Wild Sheep



Reference: Buğdaycı et al 2019

Conclusions

As seen at the end of the study, population values were calculated between 0.1 and 6.1 per 1 ha area in the 4 observation areas in the Bozdag Wildlife Development Area. The distribution of Anatolian Wild Sheep in the Wildlife Development Area was shown by a population map. This study shows the transition from classic techniques to UAV technology in wildlife inventory studies, with a determining population density of Anatolian Wild Sheep using UAV.

In the population map produced, less area due to the manual flight in the 2nd and 4th observation areas were scanned. However, the densities are higher in these regions. It is thought that there are more plants for grazing animals in the 2nd and 4th observation areas and these slopes of the hill are shaded due to the measurement in the afternoon hours and the road line leading to the water drinking places may be found in these observation areas. In addition, research on plant density and plant species in these regions will contribute to the research to be carried out within this scope.

The attained inventory results can be used to determine next year's hunting tourism quota within the scope of the General Directorate of Nature Conservation and National Parks and to form a base for the decisions to be taken for the management of the population in general monitor endangered populations. The population map is the basis for the working plans of the inventory studies and the workflow.

The UAV is the appropriate technique for wildlife studies in terms of wildlife and habitats, especially faraway inaccessible areas. But in wildlife studies; the durability and flight speed of the devices is limited, and they cover only small areas. The data storage area in the UAV has the disadvantage of limiting flights to relatively short distances. Although UAVs have such limitations for wildlife studies UAVs to the ecology of some species are so useful.

Due to the large acreage of the Wildlife Development Area, the application of the total counting technique requires considerable time and effort. Sampling methods are preferred to complete the study as quickly as possible by the minimum number of researchers to be able to carry out the inventory study practically and easily.

The Bozdag region is very similar to the Anatolian Wild Sheep in terms of land color. In this type of inventory study, airborne data and body temperatures, and infrared films that determine the location and number of animals, can yield healthy results. But the working area where infrared films will be applied should be a snow covered ground. When these conditions are met, more accurate and sound data can be obtained in the inventory study of Anatolian wild sheep. In other seasons, in the inventory study of Anatolian Wild Sheep, the multispectral air view is more useful because the information is recorded continuously and can be analyzed again after the census. Multispectral images too high spatial resolution provide high levels of detail that allow for distinguishing characteristic differences between species. If there are no cameras with the aforementioned features, the flight height should not be more than 100-150 m. Thermal sensor cameras are especially successful in detecting wild animals living in forest areas. Also; wildlife cannot be disturbed by the sound of the UAV as these cameras can be flown at high altitudes up to 450 m in inventory work. It should be noted that the success rate of the data obtained using a thermal sensor camera will affect the topographic structure and vegetation cover. Furthermore, the use of the UAV to obtain images is easier than on other access platforms (satellite, aircraft, helicopter, etc.). It is very important to know the temporal variation for wildlife management, especially for special species such as Anatolian Wild Sheep. For this reason, inventory studies should be repeated at regular intervals, and inferences should be made for the improvement of wildlife by evaluating the results.

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CHAPTER 7

BALIKESIR - MANYAS – AKÇAOVA VILLAGE LAND CONSOLIDATION PROJECT PARCEL SHAPE ANALYSIS

1. ERMAN BENGİN[1]

Introduction

With the increasing number of human activities on Earth, the demand for land is also constantly rising. This situation changes the natural balance and structure of the soil. In particular, many environmental problems stem from improper land use. Optimizing the use of land and achieving sustainable land management is only possible through effective land use planning. Land use plans are not fully implemented in our country (Gürbüz et al., 2011). To achieve sustainable development and protect the environment, monitoring changes in land management and planning at different time scales is crucial for intervening in events promptly (Kızılelma et al., 2013). Another planning problem in land management is the highly fragmented and scattered structure of agricultural lands in Turkey, which negatively affects the productivity of agricultural activities and rural development (Çay & Acar, 2022; Çay et al., 2025). Many

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parcels lack their own road or direct access to irrigation canals (Sözen & Karataş, 2015). This situation hinders the efficient use of both land and water resources, and also makes it difficult for farmers to carry out their production activities, leading to various social and economic problems (Coelho et al., 2001; Küsek, 2014; Jiang et al., 2022). This fragmented land structure, resulting from the division of agricultural lands through inheritance and sales, not only increases production costs but also reduces the well-being of the rural population (Rusu, 2002; Karataş & Sözen, 2017; Çay & Acar, 2025a).

In countries like Turkey, where agricultural lands are highly fragmented and scattered, the importance of land consolidation becomes even more apparent (Chen et al., 2022; Çay & Acar, 2025b). Fragmented land structure, above all, reduces agricultural productivity (Niroula & Thapa, 2005). As plots become smaller and more numerous, the boundary lines, field roads, irrigation canals, and infrastructure areas between them begin to take up a significant share of the total agricultural land (Liang et al., 2021; Su et al., 2022; Eder, 2024). This means that a portion of the arable land cannot be used effectively. Furthermore, the use of machinery becomes inefficient in scattered and small plots; modern agricultural equipment, such as tractors and combine harvesters, must constantly change plots, resulting in increased fuel and time loss, as well as reduced labor productivity (Yoğunlu, 2013; Bengin & Acar, 2018). Fragmented lands also hinder the efficient provision of infrastructure services because it is challenging to bring irrigation, drainage, and roads to each plot (Niroula & Thapa, 2005). The lack of legal road frontage on many small plots makes it difficult for farmers to access their fields, and limited access to irrigation canals can lead to disputes over water use (Wójcik-Leń et al., 2022). All these reasons negatively affect the yield per unit area in agricultural production and the farmer's income, making land consolidation efforts necessary (Pašakarnis & Maliene, 2010; Zhou et al., 2020; Çay & Sözen, 2023). Land consolidation projects are not limited only to the reorganization of agricultural lands according to modern agricultural management principles; they are also important in terms of improving social services, mobilizing local potentials, and strengthening human resources (Akdeniz et al., 2023; İnam & Akdeniz, 2025; Sözen & Çay, 2025).

Land consolidation projects, which are multi-purpose, costly, and require significant effort, must deliver the intended benefits. Therefore, evaluating the success/benefit performance of land consolidation projects is of great importance (Acar, 2023; Akdeniz & Acar, 2023). In land consolidation projects, the optimum conditions for yield per unit area are directly related to fundamental indicators such as the parcel index (Demetriou et al., 2013). Calculating parcel indices is one of the most fundamental methods used for the technical accuracy and spatial organization of land consolidation studies (Arslan et al., 2021). The consolidation process aims to regulate various criteria, including the reorganization of ownership, parcel size, parcel shape, accessibility, and agricultural productivity (Aslan, 2021). In the regulation of these criteria, analyses such as shape index, fractal index, square pixel scale, and shape factor are scientific indicators that comparatively reveal the parcel characteristics before and after consolidation (Acar & Akdeniz, 2023). These indicators provide quantitative and qualitative data for the optimal execution of modern agricultural practices.

In Turkey, the high average number of plots per agricultural enterprise and the irregular shape of these plots further increase the importance of such indices. Irregular, narrow, and long plots both reduce agricultural productivity and increase the cost of on-field development services. Plot indices numerically reveal the extent to which these expectations are met through land consolidation efforts.

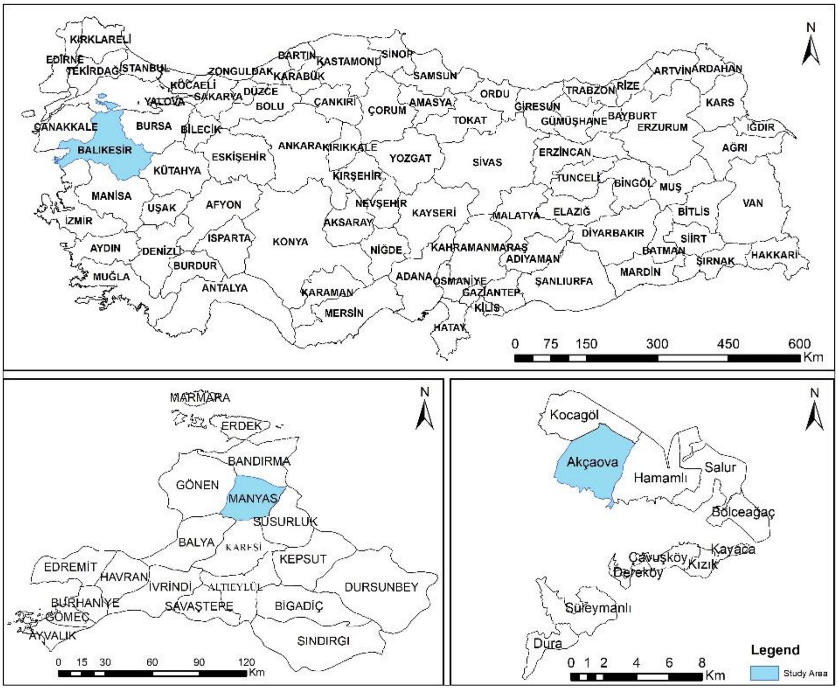
The success of land consolidation projects is now evaluated not only by fundamental indicators such as the consolidation rate, but also in a multidimensional manner with advanced plot indices (Al-Amin et al., 2023). An effective land consolidation project not only increases plot size but also improves the shape and quality of the plots, facilitates the operation of modern agricultural machinery, and ensures integrity in farm size. Therefore, the systematic calculation of plot indices enables both the objective measurement of project quality and the scientific comparison of practices carried out in different fields (Geisse & Hudecová, 2019).

In conclusion, analyses based on parcel indices offer a robust framework that enables a holistic approach to the technical, spatial, and agricultural dimensions of land consolidation. The use of these indices in evaluating consolidation projects both enhances the depth of academic studies and greatly facilitates decision-making for implementing institutions. This study aims to measure the success of land consolidation projects using these indices for the parcels involved.

Material and Methods

The study area is located within the boundaries of Akçaova Village, Manyas District, Balıkesir Province (Figure 1). The Manyas Plain Left Bank Irrigation and Bereketli Pumping Irrigation Project encompasses 11 villages in the Manyas district, covering a total area of approximately 6300 hectares. Akçaova Village, designated as the study area, is one of the largest villages within the project, spanning an area of 1200 hectares.

Figure 1. Akçaova Village Location Map



Land consolidation and field development services in Balıkesir are provided by the 25th Regional Directorate of the General Directorate of State Hydraulic Works, under the Ministry of Agriculture and Forestry. Project data for the study area was obtained from the 25th Regional Directorate. Analyses were performed using LiTop software before consolidation (cadastral situation) and after consolidation (parceling plan). LiCad and ArcGIS software were used to create maps based on the analysis results. Within the scope of the arrangement, analyses were conducted on the geometric shapes of the parcels before and after consolidation, using the shape index, fractal size index, and shape factor criteria. The "Shape Index (SI)" is used to evaluate changes in parcel shape during consolidation projects (McGarigal & Marks, 1995). The SI value takes values in the range of $1 \leq SI \leq \infty$. SI values of 1 and close to 1 indicate that the parcel shapes are close to regular geometric shapes such as squares and rectangles. The SI value, as it moves away from 1, indicates plots with irregular and distorted geometric shapes (Aslan et al., 2007).

The "Fractal Size Index (FD)" is one of the indices used to define plot shapes proportionally (Değirmenci et al., 2017). The FD value takes values in the range of 1≤FD≤2. As the FD value approaches 1, it indicates plots with regular geometric shapes, while values close to 2 indicate irregular and shapeless plots (Gonzalez et al., 2004).

The "Shape Factor (FORM)" index, developed by Russ (2002), takes values in the range of 0≤FORM≤1. When the FORM value of a plot shape approaches 1, it indicates regular geometric shapes, such as rectangles. Values close to 0 indicate plots with irregular and shapeless geometry.

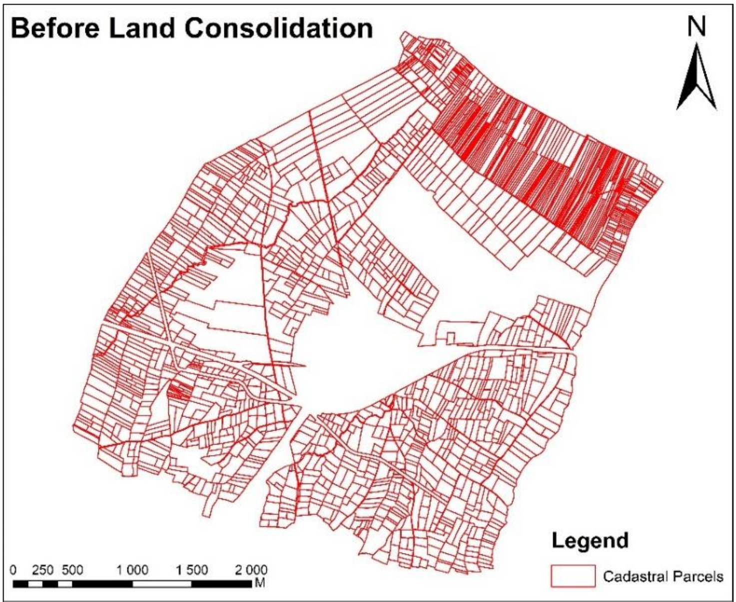
Research Findings and Discussion

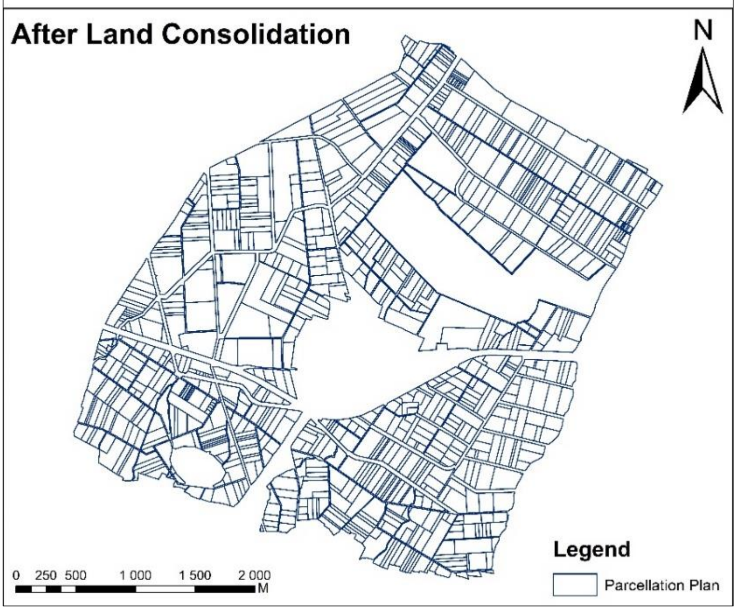
The Akçaova Village land consolidation project includes a total of 1696 parcels. Prior to the project, the total parcel area was 11,987.54 hectares, comprising 1,696 parcels with an average parcel size of 7.07 hectares. After the project, the total parcel area was 11,093.40 decares, comprising 949 parcels with an average parcel size of 11.69 decares (Table 1). It has been observed that through the land consolidation work, the parcel integrity of the farms within the project area has been partially restored, making the area more suitable for agricultural activities. A map showing the pre- and post-project conditions of the project area is given in Figure 2.

Table 1. Kurucuova Village Project Summary

	Before LC	After LC
Parcel Area (da)	**11987.54**	**11093.40**
Number of Parcels	**1696**	**949**
Average Parcel Size (da)	**7.07**	**11.69**

Figure 2 Pre- and Post-Consolidation Situation Map





When the distribution of parcels in the project area is examined according to their parcel sizes, it is observed that the areal density of the parcels falls within the 0-5 decare range both before and after the project (Table 2). Before the project, 1055 parcels, representing 62.21% of the total number of parcels, fell within the 0-5 decare range, whereas after the project, this number decreased to 380 parcels, representing 40.04%. The second most densely populated group, both before and after the project, is the 0-6 decare range. Before the project, there were 431 parcels in the 6-10 decare range, which decreased to 274 parcels after the project was completed. Particularly noteworthy are the parcels in the 11-20 decare, 21-50 decare, and 51-100 decare ranges, where a significant increase in average size is observed after the project. This indicates that a noticeable level of spatial integrity has been achieved in the parcels after consolidation. It is predicted that the increase in average parcel size will lead to increased agricultural production efficiency.

Table 2. Distribution According to Akçaova Village Parcel Sizes

	Before Land Consolidation			**After Land Consolidation**		
Parcel Groups (Da)	**Number of parcels**	**%**	**Average Plot Size (Da)**	**Number of parcels**	**%**	**Average Plot Size (Da)**
0-5	1055	62.21	3.01	380	40.04	3.35
6-10	431	25.41	7.95	274	28.87	8.28
11-20	161	9.49	14.55	189	19.92	15.03
21-50	41	2.42	27.32	87	9.17	28.01
51-100	4	0.24	66.97	15	1.58	62.09
101-500	3	0.18	180.86	3	0.32	122.59
501-1000	0	0.00	0	1	0.11	976.05
1000 >	1	0.06	1108.02	0	0.00	0
Total	**1696**	**100.00**	**7.07**	**949**	**100.00**	**11.69**

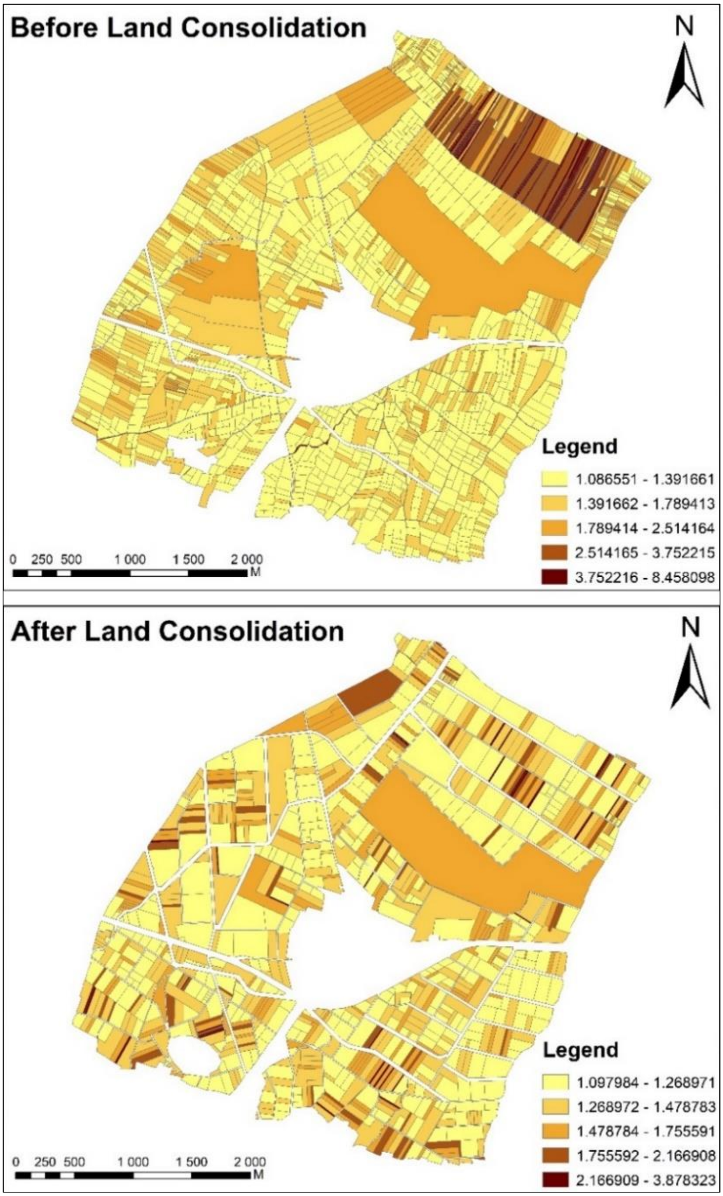
The desired geometric shapes of agricultural lands will increase yield per unit area and reduce agricultural land loss. The regulation of plot shapes will facilitate social acceptance among farm owners and ensure the economic viability and operation of modern agricultural activities. While the geometric shape of plots is among the criteria affecting agricultural mechanization, the most suitable plot shape for agricultural activities should be a rectangle with an aspect ratio between 1/3 and 1/7. In terms of suitability for mechanized farming, which is necessary for modern agricultural activities, the geometric shapes of plots are ranked in the literature as follows: square, trapezoid, irregular, and triangular, after rectangle (Acar & Akdeniz, 2023). In the plot shape analysis conducted in the study area, the number of rectangular plots increased from approximately 38% to 44%, showing a 6% increase. The percentage change in the number of trapezoidal plots remained relatively unchanged. The number of square plots increased by approximately 2%, the number of triangular plots decreased by approximately 6%, and the number of irregular plots decreased by approximately 1%. When the number of trapezoidal plots was evaluated before and after the project, it was found that the number remained the same, with a slight decrease in the number of irregularly shaped plots (Table 3).

Table 3. to Akççaova Village Parcel Shapes

Parcel Shape	**Before Project**		**After Project**	
	Pieces	**%**	**Pieces**	**%**
Triangle	165	9.73	30	3.16
Square	21	1.24	27	2.85
Rectangle	636	37.50	415	43.73
Trapezoid	615	36.26	344	36.25
Shapeless	259	15.27	133	14.01
Total	**1 696**	**100.00**	**949**	**100.00**

According to the shape index value, 82% of the plots were between 1 and 1.79 before the consolidation project. After the project, 86% of the plots were between 1 and 1.76. The value range narrowed after the project, resulting in increased plot density. While 49 plots were between 3.75 and 8.45 before the project, only one plot exceeded 3.75 after the project (Figure 3). This indicates a significant improvement in the geometric shapes of the plots in the consolidation area.

Figure 3. Shape index map



The fractal size index value indicates that 81% of the plots were within the range of 1 to 1.48 before the project, while 92% of the plots fell into the same range after the project. An improvement of approximately 11% is observed in the range closest to the ideal shape form. Regarding plot geometry, 6% of the plots were in the worst range before the project, while 1% were in the same range after the project (Figure 4). This indicates a significant improvement in the geometric shapes of the plots in the remediation area.

The analysis based on the FORM criterion yields results ranging from 0 to 1. A value closer to 1 indicates that the plot shape is suitable for agricultural management and production. FORM maps of the study area, before and after the project, are presented in Figure 5. The FORM value varied between 0.0139 and 0.8470 before the project, and between 0.0664 and 0.8294 after the project. The average FORM value was calculated as 0.5181 before the project, while it was calculated as 0.5505 after the project. It was also determined that there was an improvement in the parcel shapes, as measured by the FORM criterion, after the project.

Figure 4. Fractal size index map

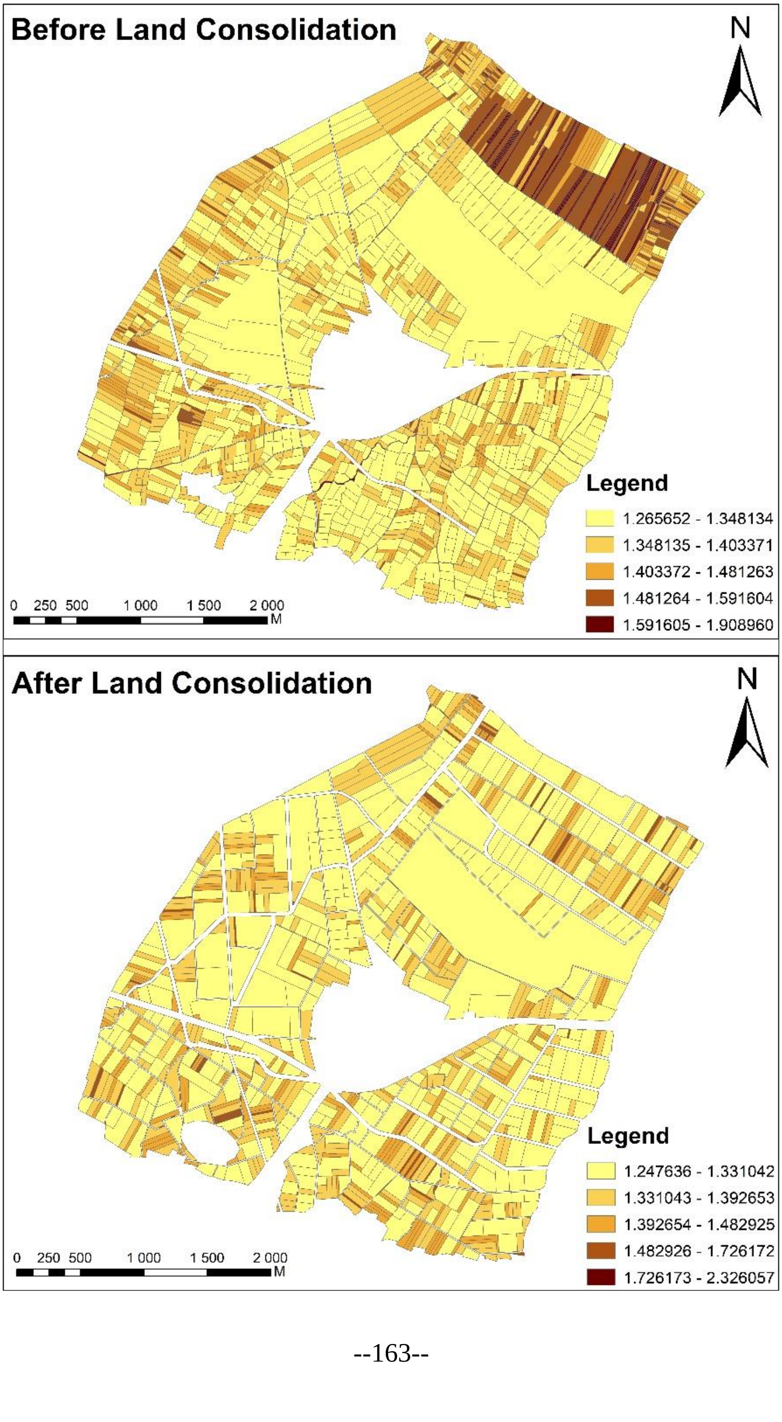


Figure 5. FORM map

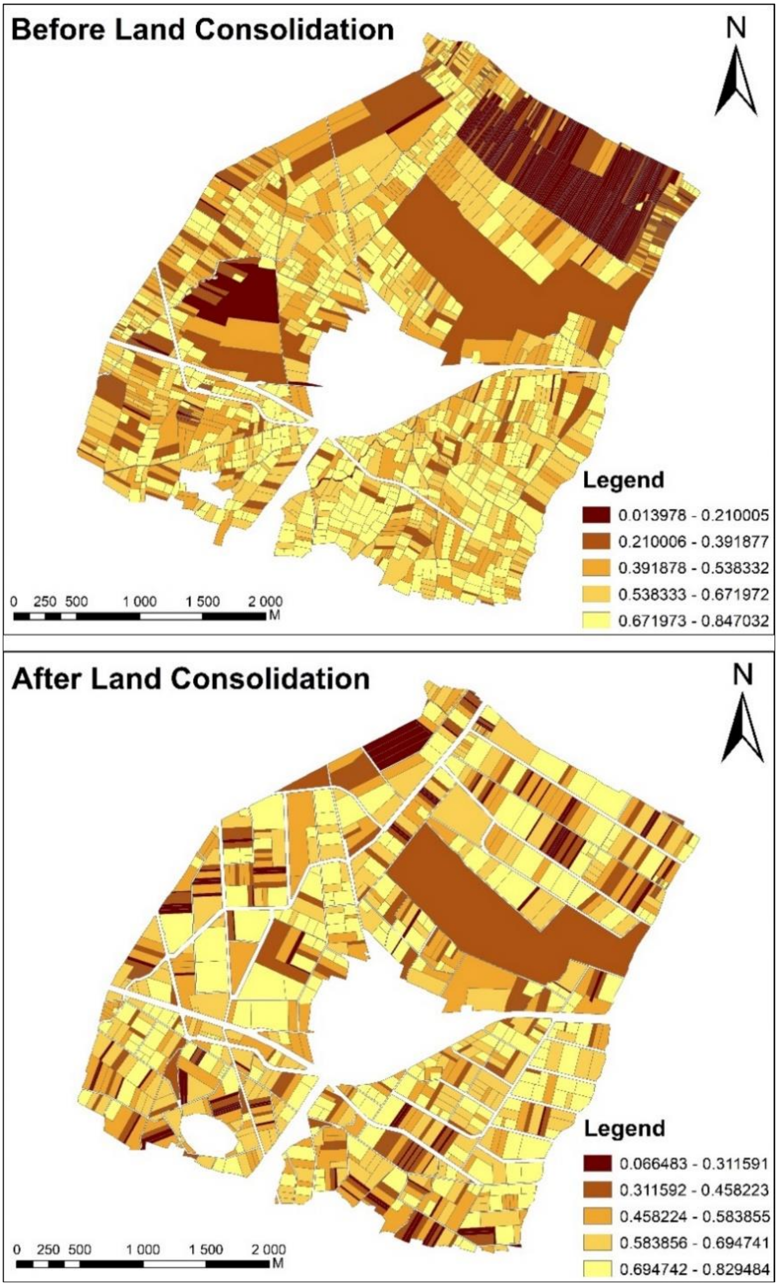


Table 4. Basic descriptive statistical results

		Minimum	Maximum	Average	Median	Standard Deviation	Variance
SI	**Before LC**	1.086551	8.458098	1.587900	1.332074	0.712886	0.508207
	After LC	1.097984	3.878323	1.423024	1.317233	0.322887	0.104256
FORM	**Before LC**	0.013978	0.847032	0.518125	0.563564	0.207685	0.043133
	After LC	0.066483	0.829484	0.550527	0.576335	0.174769	0.030544
FD	**Before LC**	1.265652	1.908960	1.403442	1.373302	0.093835	0.008805
	After LC	1.247636	2.326057	1.368781	1.346418	0.083814	0.007025

Table 4 shows that when comparing the values before and after land consolidation, the SI (Shape Index) indicator shows a significant decrease in irregular parcel shapes, particularly with the maximum value dropping from 8.45 to 3.87. The closer proximity of the mean and median values after consolidation indicates that parcel shapes have become more homogeneous. Furthermore, the significant decrease in standard deviation and variance reveals that parcel shapes have become more regular.

The FORM (Form Factor) indicator shows a narrower minimum and maximum range after consolidation, indicating a more balanced distribution of the form factor. The partial changes in the mean values , from 0.518 to 0.550, and the median values , from 0.563 to 0.576, in Table 4 also indicate an improvement in parcel shapes. The decrease in standard deviation and variance indicates a reduction in shape irregularities, suggesting that parcel geometric shapes have become more suitable for agricultural activities.

Looking at the FD (Fractal Index) indicator, a decrease in variance, in particular, indicates less variation in plot shapes and the formation of more similar, nearly rectangular plot shapes. Based on this indicator, it can be concluded that land consolidation has been successful. Overall, the decrease in maximum values, variance, and standard deviation observed in all indicators shows that plot shapes have become more regular and geometrically suitable for agricultural activities after consolidation. This situation demonstrates that land consolidation is consistent with the expected positive effects on agricultural productivity and the effective use of modern agricultural equipment.

Conclusion

The land consolidation project carried out in Akçaova Village, Manyas District, Balıkesir Province, has resulted in significant improvements, including the elimination of fragmented ownership structures in rural areas, a reduction in agricultural production costs, and an increase in the applicability of modern agricultural techniques. The consolidation rate in the project was calculated as 44.04%. The reduction in the number of parcels from 1,696 before consolidation to 949 after the project, along with the success of parcel consolidation, has also ensured the integrity of the farm. The increase in the average parcel size from 7.07 decares to 11.69 decares indicates that agricultural activities are being carried out more efficiently and that the yield per unit area is more suitable. This shows that the land consolidation efforts have been carried out in accordance with their purpose.

Parcel shape analyses also confirm a significant improvement in spatial quality after the project. The increase in the proportion of rectangular parcels, from approximately 38% to 44%, indicates that a transformation towards the most suitable geometry in terms of maneuverability, fuel consumption, and labor efficiency for modern agricultural machinery has been achieved. The increase in square plots and the decrease in triangular and irregularly shaped plots reveal that the land consolidation process has simplified plot shapes and created a more organized agricultural activity area. However, the inability to eliminate trapezoidal and irregularly shaped plots, the irregularity of village outer boundaries, the necessity of preserving fixed structures within the fields, and the limitations and difficulties in reconstructing existing road and irrigation systems necessitate such plot shapes.

Geometric indicators, such as the shape index, fractal index, and form factor, indicate that plot shapes have become more homogeneous and more suitable for mechanization after the project. The narrowing of the minimum-maximum range and the decrease in the average value of the shape index indicate an increase in regularity in plot shapes. The more balanced distribution of fractal index values after the project indicates that plot shape irregularities have decreased and become more organized. The area available for agricultural activities has increased. The improvement in the form factor shows that the area/perimeter ratio of the plots is approaching a more suitable level for agricultural enterprises. According to the statistical analysis of the criteria used in shape analysis, the shape index criterion gives the best result. Considering the standard deviation, it shows that the geometric shape of the plots has been significantly improved.

These findings, obtained in Akçaova Village, clearly demonstrate that land consolidation should be evaluated not only based on the number and area of plots, but also on plot dimensions, the suitability of the geometric shapes of the plots, and the potential for utilizing modern agricultural tools. In projects that achieve high success rates, the benefits of regulating plot shapes, increasing arable land, reducing production costs, and strengthening farm integrity have been realized mainly in Akçaova Village.

In conclusion, the Akçaova Village land consolidation project is a successful application in terms of strengthening the agricultural production infrastructure, along with the improvements achieved in plot shape, size, and distribution. To increase the project's sustainability, it is essential to conduct more comprehensive analyses of the technical and economic benefits of land consolidation for farmers after consolidation, particularly to undertake additional studies aimed at geometrically correcting the outer boundaries of the village.

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CHAPTER 8

MONITORING PARCEL SHAPE CHANGES AFTER LAND CONSOLIDATION STUDIES: THE CASE OF BUDAKLI VILLAGE, DADAY, KASTAMONU

Musa Nehir SÖZEN[1]

Introduction

The solution to the structural problems encountered in the agricultural sector in our country can be achieved by improving the agricultural structure and optimizing farm sizes (OECD, 2011; Keskin, 2021). In this way, it will also be possible to increase international competitiveness (Camanzi et al., 2003; Beck et al., 2024). Land consolidation (LC) is among the priority applications for improving structural problems in our agricultural sector (Sönmez et al., 2005; Acar & Bengin, 2018). In recent years, LC studies have been carried out widely and intensively in our country (Acar, 2023).

The high degree of spatial fragmentation in agricultural areas is considered one of the most important factors negatively affecting the economic efficiency of agricultural activities (Rahman &

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Rahman, 2009; Manjunatha et al., 2013; Bengin & Acar, 2018). In particular, the unfavorable shapes and sizes of land plots increase production costs, significantly reducing potential income (Gonzalez et al., 2007). Decreased income can lead to migration from rural areas to cities (Ghimire et al., 2021; Erdal et al., 2025). The migration of young people from villages to cities can disrupt the demographic structure in villages, causing long-term social and cultural problems (Smith et al., 2016). In this context, land consolidation practices should be considered not only as a technical engineering activity but also as projects with a social dimension due to the ownership structure and the sense of belonging of landowners (de Vries & Voß, 2018; Demiraslan et al., 2019; Elvestad & Sky, 2019; Acar & Akdeniz, 2023).

Land consolidation projects present a significant challenge in terms of implementation due to their complex technical and social dimensions, which can span extended periods of time (Akdeniz & Acar, 2023). However, after the completion of the projects, it is observed that the crop pattern improves together with existing irrigation projects, the shape of agricultural lands is improved, productivity increases, and property-related problems are partially resolved (Ayrancı, 2004; Oğuz and Bayramoğlu, 2004; Arslan & Tunca, 2013).

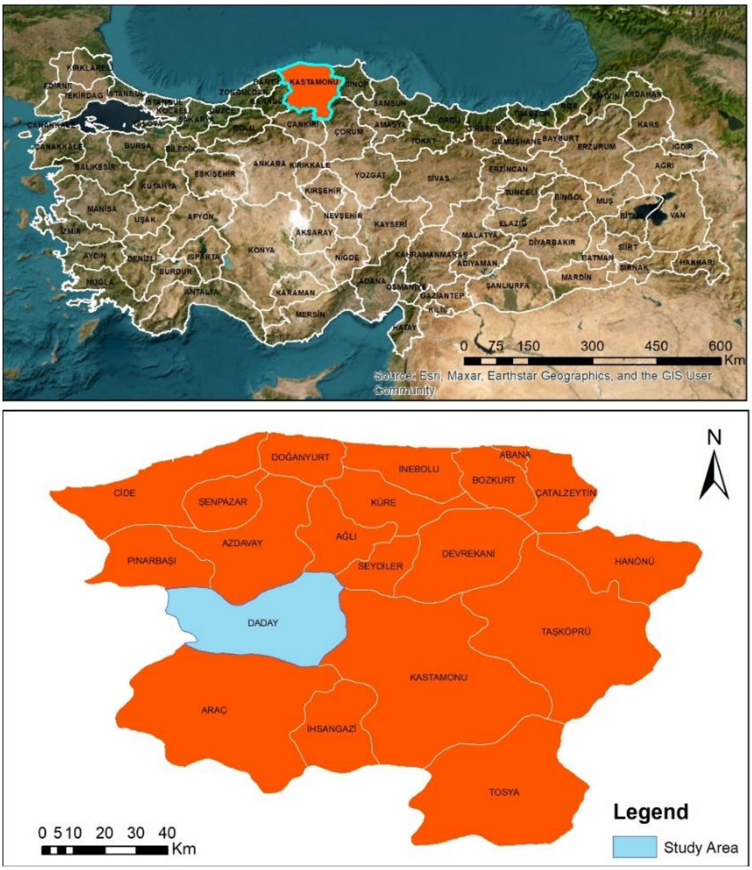
Thanks to land consolidation applications, access to parcels is facilitated through field roads, and it is possible to drain excess water accumulated in the land without harming the crops through drainage channels (Veršinskas et al., 2021). In addition, one of the most significant benefits of land consolidation is that parcel shapes are made more suitable for agricultural activities, enabling production processes on the land to be carried out more effectively and efficiently (Pijanowski, 2014; Al-Amin et al., 2023).

In this study, Budaklı Village in Daday district of Kastamonu province was selected as the case study area. Parcel shape analyses were carried out before and after the application of environmental stabilization (ES) in the study area.

Materials and Methods

In this study, Budaklı Village in the Daday district of Kastamonu Province was selected as the study area. The study area is located approximately 35 km from the center of Kastamonu city and approximately 5 km from the center of Daday district. The 412 parcels within the approximately 232-hectare study area were evaluated within the boundaries of the land consolidation (LC) Project (Figure 1).

Figure 1. Location map of Daday District, Kastamonu Province



This study aims to investigate the effects of land consolidation (LC) applications on parcel shapes in the Budaklı Village sample area of Dayad district, Kastamonu province. In this context, various shape analyses were performed using parcel data before and after LC. The analyses were conducted using various shape indices, selected to quantitatively assess the regularity level, boundary complexity, and suitability for agricultural activities of parcel geometries.

Area and perimeter information for the parcel data used in the study were obtained from digital cadastral maps. All geometric calculations and spatial analyses were performed using Litop 7, ArcGIS 10.5, and NetCAD 8.5 software. To compare parcel structures before and after LC, the analyses were applied using the same methods and parameters.

Shape Index

A shape index was used to determine the level of regularity of plot shapes. The shape index is calculated based on the relationship between the perimeter and area of the plot, revealing the extent to which the plot geometry closely resembles ideal geometric shapes (circle or square). The shape index (SHAPE) is based on a calculation defined by McGarigal and Cushman (FRAGSTATS) that measures shape complexity in an area relative to a square shape with the same area.

Formula:

$$SI = \frac{P}{2\sqrt{\pi A}}$$

Where:

- P represents the parcel perimeter length,
- A represents the parcel area.

An increase in the shape index value indicates that the perimeter of the plot is elongated in relation to its area, and the boundaries have a more irregular and protruding structure; this suggests that the plot geometry exhibits a more irregular and less compact form (McGarigal et al., 2015). Conversely, a shape index value approaching 1 indicates that the plot has a simpler and more compact geometry in terms of perimeter-area relationship, ideally approaching a circular form. According to the FRAGSTATS approach, such low index values correspond to more regular and spatially more efficient units in terms of shape (McGarigal et al., 2015).

Fractal Dimension Index

The fractal magnitude index is an indicator used to measure the complexity and scale-independence of irregularity in plot boundaries (Forman & Godron, 1986; McGarigal et al., 2002).

The fractal index (FD) is a scale-independent spatial metric used to measure the complexity of a plot's boundary geometry. In the FRAGSTATS approach, the fractal index is calculated based on the logarithmic relationship between plot perimeter length and area, as defined by the following equation.

Formula:

$$FD = \frac{2\ln(P)}{\ln(A)}$$

Where:

- P represents the parcel perimeter length,
- A represents the parcel area.

The use of a logarithmic transformation in the formula enables a more objective assessment of boundary complexity by removing scale effects from the perimeter-area relationship (McGarigal et al., 2015). According to FRAGSTATS, the fractal index value theoretically ranges from 1 to 2. A value closer to 1 indicates that the plot boundaries have a more regular, simple, and geometrically straightforward structure; a value closer to 2 indicates that the boundary line exhibits a more indented, protruding, complex, and irregular morphology. In this respect, the fractal index serves as an effective measure for quantitatively expressing the geometric complexity of plot boundaries (McGarigal et al., 2015).

Form Factor

In the FRAGSTATS approach, the shape factor is calculated based on the relationship between plot area and perimeter length. It quantitatively expresses the extent to which the plot geometry approximates the ideal form (McGarigal et al., 2015).

The following equation defines the shape factor:

Formula:

$$FF = \frac{4\pi A}{P^2}$$

Where:

- A represents the parcel area,
- P represents the parcel perimeter length.

In this equation, A represents the area of the plot, and P represents the perimeter of the plot. The coefficient 4π in the formula is determined by referencing the circle, which is considered the ideal geometric shape.

Accordingly, the closer a plot is to a circle, the closer its shape factor value approaches 1. As plot boundaries lengthen and acquire an irregular structure, the perimeter length increases, and the shape factor value decreases (McGarigal et al., 2015).

Square Pixel Scale

Square pixel scaling is a complementary method that allows for the raster-based evaluation of plot shapes (Demetriou et al., 2013). In this method, vector plot geometries are converted into raster format at a specific spatial resolution.

Formula:

$$SPS = \frac{N_p}{A}$$

Where:

- N_p represents the number of pixels representing the parcel,
- A represents the parcel area.

FRAGSTATS works entirely raster-based, and all spatial metrics are calculated from:

Square pixels (cells), constant cell analyses (cell size), and the representation of the area based on the number of pixels.

In the FRAGSTATS 2015 guide:

Area (A) → number of pixels × pixel area

Perimeter (P) → based on pixel segments

Shape, fractal, compactness, etc. → based on pixel representation

Therefore, the term "number of pixels representing the parcel (Np)" is the basic logic of FRAGSTATS (McGarigal ve ark., 2015).

Perimeter–Area Ratio (PARA))

The area-to-perimeter ratio is a measure that reveals the relationship between plot area and perimeter length, and expresses the overall efficiency of plot geometry (Sklenicka, 2006).

$$\mathrm{PARA} = \frac{P}{A}$$

Where:

- P represents the perimeter of the parcel,
- A represents the area of the parcel.

In FRAGSTATS software, the relationship between area and perimeter is evaluated through shape and fractal-based metrics, and criteria based on the perimeter-area ratio, in particular, reveal the complexity of plot geometry (McGarigal et al., 2015). In this study, the area-perimeter ratio (A/P) was used as an indicator supporting the compactness level of plot geometry.

All determined shape indices were calculated separately for pre- and post-land consolidation (TC) plot data, and the results obtained were compared and evaluated. This evaluation quantitatively revealed the effect of land consolidation practices on plot shapes, and changes in plot regularity, boundary complexity, and suitability for agricultural use were analyzed (Sklenicka, 2006; Demetriou et al., 2013).

In this study, multiple shape indices were used in combination to evaluate the effects of TC practices on plot geometry comprehensively. Plot regularity and proximity to ideal geometric shapes were analyzed using the shape index, while the complexity and irregularity level of plot boundaries were assessed using the fractal size index. Additionally, plot compactness and suitability for agricultural mechanization were evaluated through the shape factor. The area-perimeter ratio was considered as an indicator supporting the overall efficiency of plot geometry and the boundary length-area relationship (Gonzalez et al., 2007; Sklenicka, 2006).

In addition, raster-based square pixel scale analyses were used to support the findings obtained with vector-based indices spatially and to evaluate plot boundary geometry from a different perspective. Thus, the changes in plot shapes before and after AT were examined within a multidimensional analysis framework, considering both vector- and raster-based approaches (Demetriou et al., 2013).

Findings

This section presents the effects of land consolidation practices on parcel shapes in the Budaklı Village sample area of the Daday district, Kastamonu Province. In this context, the analysis results regarding shape index, fractal size index, shape factor, square pixel scale, and area-to-perimeter ratio, calculated using parcel geometries before and after LC, are evaluated comparatively. The findings allow for the quantitative demonstration of the effects of land consolidation on parcel regularity, boundary complexity, and suitability for agricultural use. The analysis results are presented through both statistical values and spatial distribution maps, providing a holistic examination of the changes in parcel structure before and after LC.

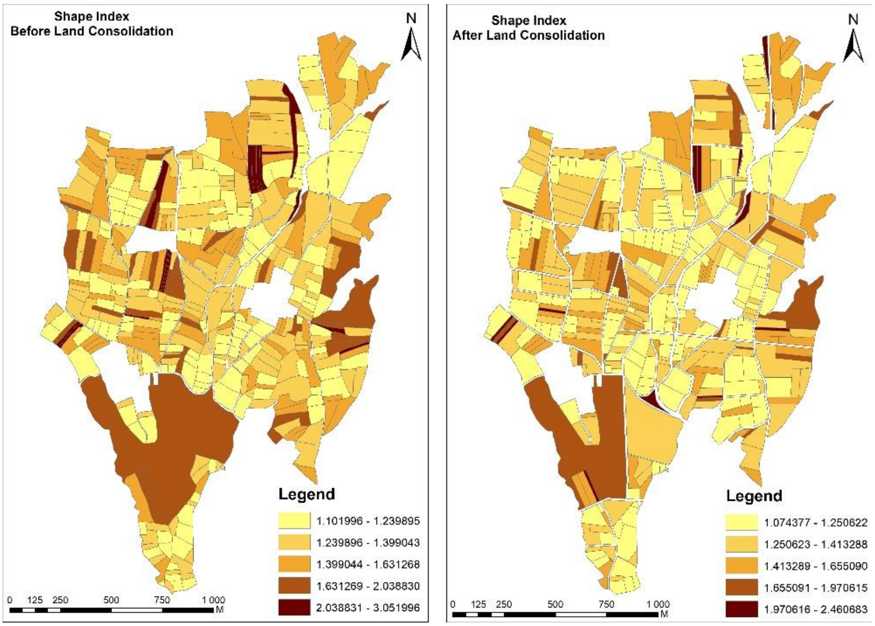
Findings Regarding Parcel Shape Analyses

Descriptive statistics for parcel shape analyses before and after LC are presented in Table 1. Examination of the table shows that LC applications generally have a positive effect on parcel shape characteristics.

In terms of shape index (SI), the average SI value was 1.381 in the pre-LC period, while it decreased to 1.357 in the post-AT period. Similarly, the median SI value decreased from 1.303 to

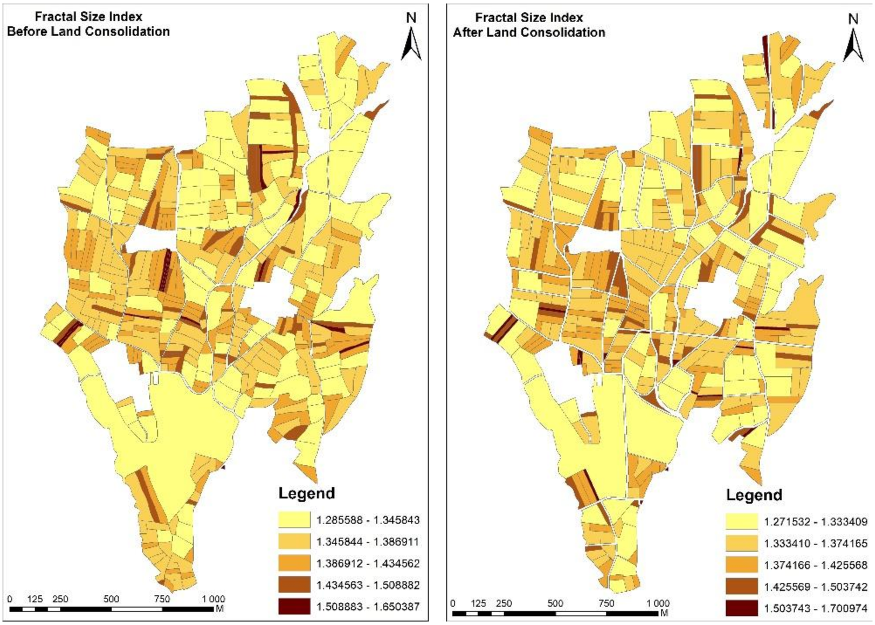
1.277. This decrease in SI values indicates that parcel shapes became more regular and closer to ideal geometric shapes after LC. Furthermore, the decrease in the maximum SI value from 3.052 to 2.461 reveals a reduction in the number of excessively irregular parcels. The decreases in standard deviation and variance values indicate a reduction in the differences between plot shapes (Figure 2).

Figure 2. Parcel shape index before and after AT.



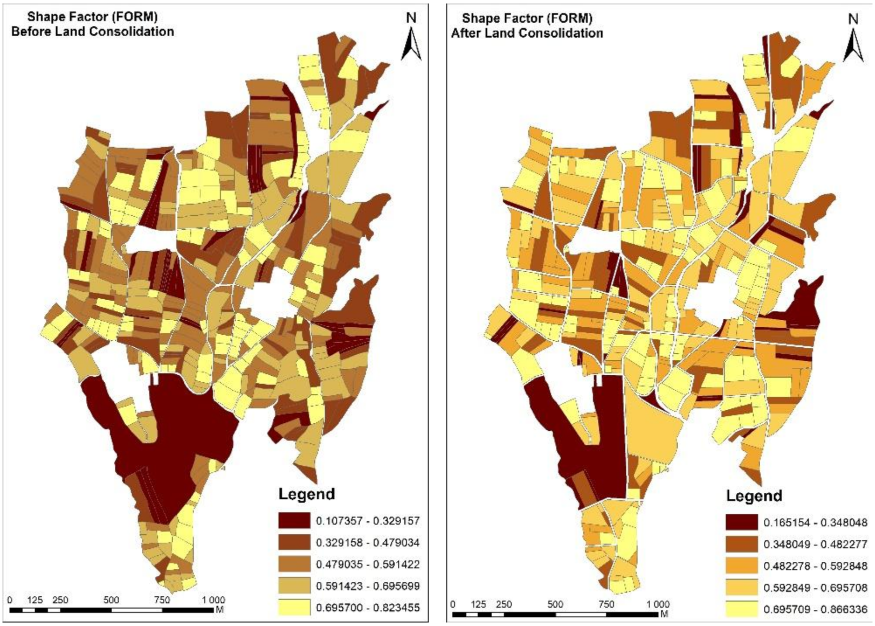
When the fractal size index results are examined, it is seen that the mean values before and after AT are 1.385 and 1.384, respectively. Although the change in mean values is limited, the decrease in the median FD value from 1.376 to 1.370 and the decrease in the minimum FD value indicate that the plot boundaries have generally acquired a simpler structure. However, the increase in the maximum FD value from 1.651 to 1.701 reveals that boundary complexity persists in some plots. The increase in standard deviation shows that the FD values exhibit a more heterogeneous distribution after AT (Figure 3)

Figure 3. Fractal size index before and after AT.



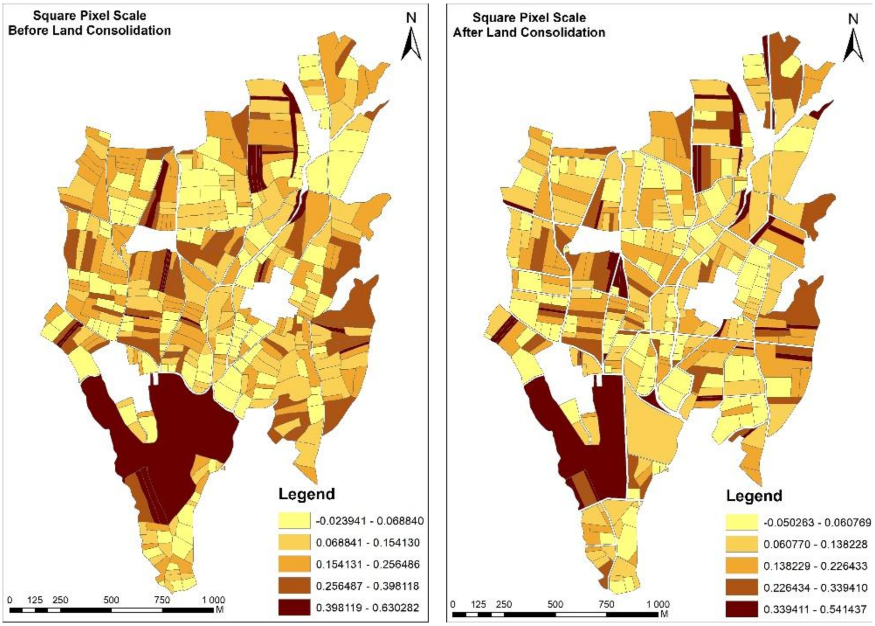
When the shape factor (Form) values are examined, it is seen that the average value increased from 0.568 before LC to 0.581 after LC. The median value also increased from 0.589 to 0.613. This increase indicates that plot compactness and geometric suitability for agricultural activities improved after the application of LC. The increase in the maximum Form value also reveals that some plots approached more ideal shapes. The decrease in standard deviation and variance values indicates that the plot's compactness shows a more balanced distribution (Figure 4).

Figure 4. Shape Factor before and after LC.



When the findings regarding the square pixel scale (SqP) were evaluated, it was determined that the average SqP value decreased from 0.159 before LC to 0.148 after LC. The decreases in median and maximum values indicate that the plot boundaries became more regular in raster representation and that geometric simplicity increased. In addition, the decrease in standard deviation and variance values reveals that the plot shapes exhibit a more homogeneous structure in the post-AT period (Figure 5).

Figure 5. Square Pixel Scale before and after AT.



Overall, the findings quantitatively demonstrate that land consolidation practices have resulted in more regular, compact, and suitable parcel shapes for agricultural activities. In particular, the results regarding the shape index and shape factor clearly show the positive impact of land consolidation practices on parcel geometry.

Table 1 shows a general trend of improvement in parcel shape characteristics after land consolidation. The decrease in the mean and median values of the shape index (SI) in the post-project period indicates that the parcels have become more regular and geometrically more suitable. While there is no significant change in the mean values of the fractal size index (FD), the decrease in the minimum and median values indicates that the parcel boundaries have generally become simpler.

The increase in the mean and median values of the shape factor (Form) after the project reveals that the compactness of the parcels has increased, and they have gained a more suitable structure for agricultural use. The decrease in the mean, median, and maximum values of the square pixel scale (SqP) indicates that the parcel boundaries exhibit a more regular and homogeneous structure in raster representation. Overall, the results show that after land consolidation, parcel shapes achieve a more balanced distribution in terms of both regularity and integrity.

Table 1. Basic descriptive statistics results before and after LC.

Pre-Project				
	SI	**FD**	**Form**	**SqP**
Minimum	1.101996	1.285588	0.107357	-0.02394
Maksimum	3.051996	1.650387	0.823455	0.630282
Average	1.381262	1.385296	0.567832	0.15909
Median	1.303316	1.375576	0.588709	0.134224
Standard Deviation	0.27313	0.055516	0.154017	0.125924
Variance	0.0746	0.003082	0.023721	0.015857
Post-Project				
	SI	**FD**	**Form**	**SqP**
Minimum	1.074377	1.271532	0.165154	-0.05026
Maksimum	2.460683	1.700974	0.866336	0.541437
Average	1.357404	1.38355	0.581389	0.148073
Median	1.276855	1.369932	0.613362	0.116282
Standard Deviation	0.238481	0.062589	0.150285	0.120279
Variance	0.056873	0.003917	0.022586	0.014467

Results

This study, which evaluated parcel shape analyses before and after land consolidation in Budaklı Village, concluded that consolidation generally improved parcel geometry. The decreases in shape index and fractal dimension values in the post-project period indicate that parcels have become more regular and compact. Conversely, the increase in average and median shape factor values reveals that parcel shapes have become more suitable for agricultural mechanization. When square pixel scale and area-perimeter ratio statistics are considered together, it is understood that excessively irregular parcels decreased and shape variability narrowed after the project. The findings demonstrate that land consolidation provides significant gains not only in terms of property and infrastructure regulation but also in terms of parcel shape, which directly affects agricultural production efficiency.

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CHAPTER 9

QUANTITATIVE ASSESSMENT OF AGRICULTURAL LAND LOSS IN LAND CONSOLIDATION PROJECTS: THE CASE OF KÜÇÜKKAVAK VILLAGE

ÖMER ACAR[1]

Introduction

Land, considered a fundamental resource for human survival and development, is limited and therefore unable to meet the demand of the growing population (Denizdurduran et al., 2017; Sezgin & Varol, 2012; İkiz, 2020; Xu et al., 2022). Particularly since the 1900s, the advent of modern agriculture and the rise in industrialization have led to soil pollution and structural degradation (Tomar, 2009; Kul et al., 2021; Türkmenler, 2022). To prevent these problems, land consolidation projects can be implemented, which have far-reaching effects such as taking soil conservation measures (Koul & Taak, 2018), carrying out reclamation works (Ghazaryan et al., 2024), increasing agricultural production efficiency (Martinho, 2020), developing modern agriculture (Singh, 2024), reducing ecological risks (Xu et al., 2022; Ghazaryan et al., 2024), supporting rural

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development (Zhang et al., 2014; Çay & Sözen, 2022), and being used as a fundamental tool in agricultural management (Taszakowski et al., 2017; Çay et al., 2025).

Land consolidation can be defined as the planned reorganization of property structure in rural areas to create larger and more productive land parcels (Lerman & Shagaida, 2007; Pašakarnis & Maliene, 2010; Acar & Bengin, 2018; Duong & Kim, 2022; Sözen & Çay, 2025). It has been observed that an increase in the number of parcels leads to a decrease in land and labor productivity for various reasons (Lerman & Cimpoieş, 2006; Leń, 2018). Currently, land consolidation efforts are among the integrated projects used in the implementation of rural and regional development policies (Crecente et al., 2002; van den Brink and Molema, 2008).

Land consolidation projects, considered one of the most important tools of modern land management policies, are of great importance in terms of increasing production, reducing operating costs, and making parcels suitable for agriculture by combining them and regulating their shapes (Bengin & Acar, 2018; Çay & Sözen, 2023). One of the primary objectives of consolidation projects is to eliminate fragmented and scattered parcels, ensuring that each agricultural parcel has adequate access, thereby eliminating the phenomenon of inaccessible parcels (Küsek, 2014; Veršinskas et al., 2021). Unaccessible parcels are properties that do not have direct frontage to a public road or field road network, and can only be accessed through de facto passage via neighboring parcels. Especially in agricultural lands where mechanization is widespread, the inability of production tools to reach the parcel results in both low productivity and a loss of time and energy. However, de facto passages across neighboring parcels can lead to legal disputes in the long run, thereby increasing social tensions in rural areas. This situation renders many agricultural lands unusable, particularly for agricultural activities (Yang et al., 2023; Saygılı & Çakmak, 2024).

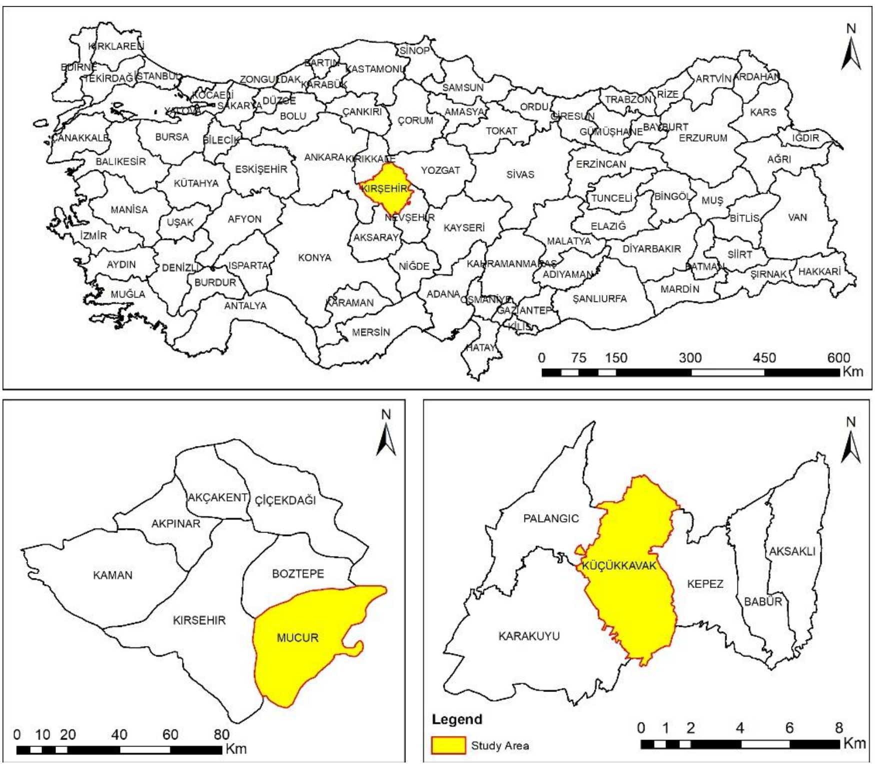
Illegal parcels, frequently encountered in rural areas before land consolidation, hinder the efficient conduct of agricultural activities, increase operating costs, and reduce the economic value of property rights. One of the main aims of land consolidation projects is to eliminate or make functional such parcels. Therefore, the planning and establishment of right-of-way are necessary tools for addressing illegal parcels (Papoušek, 2011; Louwsma et al., 2022). The right of way is considered a limited fundamental right that allows the owner of an illegal parcel to use their land without affecting the essence of the property right. The location, width, continuity, and compatibility of the right-of-way with agricultural mechanization directly affect the economic value and land-use efficiency of the plot. Therefore, in project evaluations, it should be considered not only whether the right of way is defined on paper, but also whether it is actually functional in the field (Brussaard & Grossman, 1992; Yang et al., 2023).

This study examines the status of unauthorized parcels, the reduction rate, the consolidation rate, parcel shapes, and indicators of agricultural land loss before and after land consolidation projects. Comparing pre-consolidation cadastral data with the new parceling situation after consolidation, it is observed that, particularly regarding unauthorized parcels, there are no longer any unauthorized parcels; they have become accessible parcels with legally granted access rights. Similarly, access to irrigation facilities has increased, parcel shapes have been regulated, and agricultural land loss has been reduced. Prior to land consolidation, agricultural land loss occurred in parcels without roads due to the need for access rights through other parcels. This situation causes tension among parcel owners over time and creates unused portions of agricultural land in neighboring parcels. The primary objective of this study is to determine the amount of agricultural land lost due to the road network area required for access to unauthorized parcels before consolidation.

Materials and Methods

The General Directorate of Agricultural Reform of the Ministry of Food, Agriculture, and Livestock implemented the Kırşehir Province Mucur District Land Consolidation and Land Improvement Project. Project data for the study area was obtained from the General Directorate of State Hydraulic Works of the Ministry of Agriculture and Forestry. The land consolidation project in Mucur District was conducted in the villages of Aksaklı, Babur, Karakuyu, Kepez, Küçükkavak, and Palangıç. The work carried out in Küçükkavak Village was included in the evaluation (Figure 1).

Figure 1 Küçükkavak Village Location Map



Based on the obtained digital data, the situation before and after land consolidation, the distribution according to parcel sizes, the geometric shapes of the parcels, parcels without road frontage, the calculation of agricultural land loss due to access to parcels without road frontage, and the areas unusable due to the perimeter length of the parcels were identified. LiCAD, LiTOP, and ArcGIS software were used in the evaluation of the data and the creation of thematic maps.

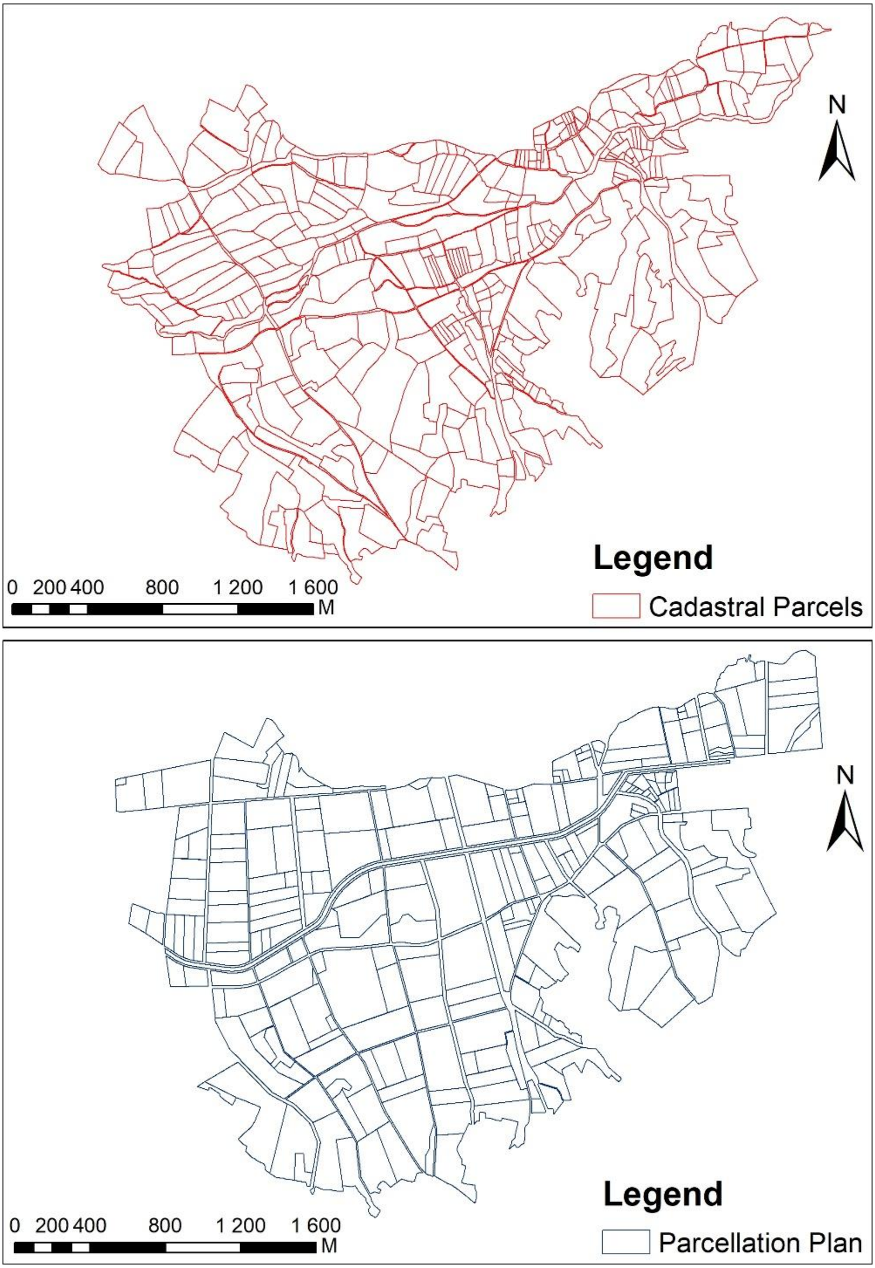
Findings and Discussion

Within the scope of the Küçükkavak Village land consolidation project, a total of 374 parcels were included in the arrangement. Prior to the project, the total parcel area included in the arrangement was 555.11 hectares, with an average parcel size of 14.84 decares. After the project, the total parcel area was calculated to be 520.96 hectares, comprising 264 parcels, with an average parcel size of 19.73 decares (Table 1). The pre- and post-project situation map of the project area is given in Figure 2.

Table 1. Küçükkavak Village Project Summary

	Before LC	**After LC**
Parcel Area (ha)	555.11	520.96
Number of Parcels	374	264
Average Parcel Size (da)	14.84	19.73

Figure 2 Pre- and Post-Consolidation Situation Map



When the distribution of plots in the project area is examined according to plot size, it is observed that the areal density of the plots was in the 0-5 decare range prior to the project. After the project, the density was distributed approximately equally in the 0-5, 11-20, and 21-50 decare ranges at a rate of approximately 25% (Table 2). When comparing the pre- and post-project periods, a decrease of approximately 13% was observed in the 0-5 decare range, while an increase of approximately 10% was observed in the 21-50 decare range. It is anticipated that the increase in average plot size will enhance agricultural production efficiency.

Table 2 Distribution According to Küçükkavak Village Parcel Sizes

	Before LC			After LC		
Parcel Groups (Da)	**Number of parcels**	**%**	**Average Plot Size (Da)**	**Number of parcels**	**%**	**Average Plot Size (Da)**
0 - 5	140	37.43	3.16	64	24.24	2.83
6 - 10	54	14.44	8.49	43	16.29	8.38
11 - 20	102	27.27	15.15	68	25.76	15.26
21 - 50	63	16.84	31.51	70	26.52	33.16
51 - 100	13	3.48	69.63	17	6.44	63.72
101 - 500	2	0.53	107.35	2	0.76	112.98
Total	**374**	**100**	**14.84**	**264**	**100**	**19.73**

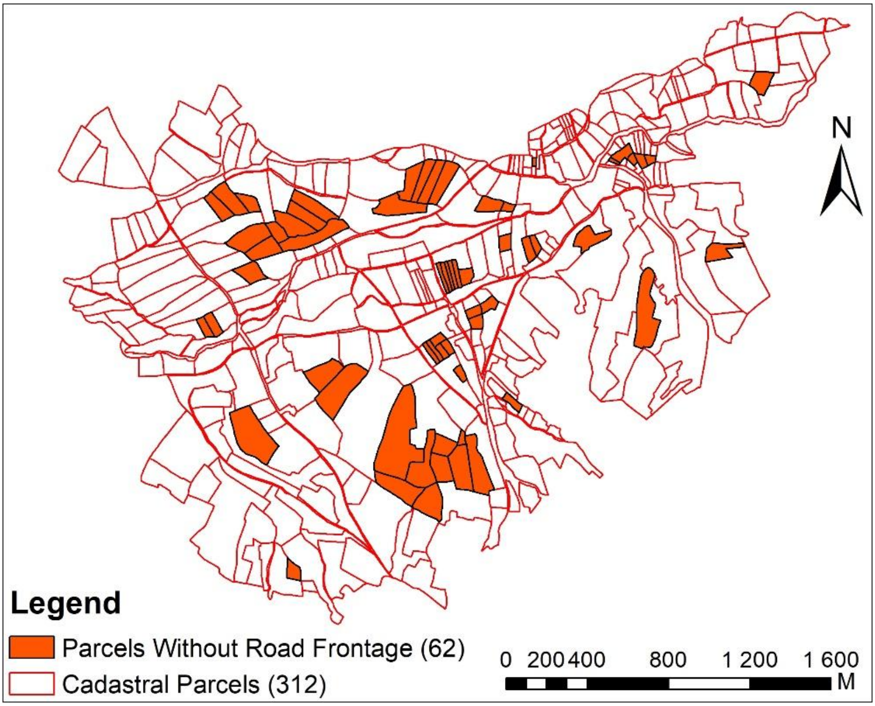
The geometric shape of plots is among the criteria affecting agricultural mechanization. According to studies, the ideal plot geometry for agricultural production should be rectangular. In the literature, plot geometric shapes are ranked according to their suitability for mechanized farming, with rectangles being the most suitable, followed by squares, trapezoids, irregular shapes, and triangles (Acar & Akdeniz, 2023). In the geometric shape analysis of the plots in the study area, the number of rectangular plots increased from approximately 8% to 28%, representing a 20% increase. The number of trapezoidal plots increased by approximately 11%. Square plots were previously absent, but now constitute approximately 2% of the total plots. The number of triangular plots, the least common geometric shape before the project, increased by approximately 1%. The number of irregular plots decreased from 67% before the project to 34% after the project, indicating the most significant change in geometric shape (Table 3).

Table 3. Küçükkavak Village Parcel Shapes

	Before LC		**After LC**	
Parcel Shape	**Pieces**	**%**	**Pieces**	**%**
Triangle	6	1.60	9	3.41
Square	0	0.00	4	1.51
Rectangle	29	7.75	75	28.41
Trapezoid	90	24.06	86	32.58
Shapeless	249	66.58	90	34.09
Total	**374**	**100.00**	**264**	**100.00**

When the road accessibility status of the parcels in the study area is examined, it is seen that 312 parcels have road frontage. In comparison, the remaining 62 parcels provide access through other parcels (Figure 3).

Figure 3. Parcels Without Road Frontage



Prior to the project, plots without road access were accessed via other plots. This resulted in unused agricultural land along the plot boundaries. Road planning was carried out along the plot boundaries by determining the shortest route within the project area. The Supreme Court's 14th Civil Chamber's decision dated April 2, 2007, numbered 2007/3534, stated that a right of way should be granted with a width not exceeding 3 meters. Accordingly, the areas of the planned roads in the project area were calculated, and the agricultural land loss due to the inadequate road access network was determined. The total road area planned for the 62 plots without road access, via the shortest route through the neighboring plot, was calculated as 14.40 decares. After the project, all plots gained access to the road network, thus making this land available for agricultural use.

Due to the limitations of agricultural machinery in approaching and turning at plot boundaries, agricultural production is not feasible in certain areas. These areas are considered agricultural land loss. According to the studies conducted, at least 50 cm of the parcel boundaries are unusable for agricultural use (Akdeniz & Temizel, 2018). To calculate the loss of agricultural land in the parcels formed before and after consolidation in the project area, arable land was calculated by creating internal areas within the parcels. The difference between the arable land and the total parcel area was used to calculate the loss of agricultural land. As a result of the analysis and calculations carried out in the study area, the loss of agricultural land, which was 218,839.10 m2 before the project, decreased to 80,050.27 m2 after the project. The land consolidation project resulted in a 63% reduction in the loss of agricultural land.

Table 4 Loss of Agricultural Land

	Total Area (m^2)	**Arable Area (m^2)**	**Loss of Agricultural Land (m^2)**
Before LC	5551076.89	5332237.79	218839.10
After LC	5209634.03	5129583.76	80050.27

In land consolidation projects, a proportional reduction is made from all parcels subject to regulation to provide space for standard facilities created within the project scope. The consolidation legislation stipulates that up to 10% of the reduction can be made free of charge. In the study area, the reduction rate was calculated as 6.5772%, and this percentage reduction was applied to all parcels included in the regulation.

The consolidation rate is used as a success criterion in evaluating consolidation projects. In the project area, 374 parcels were included in the regulation prior to consolidation, and the project was completed with 264 parcels after consolidation. A consolidation rate of 29.41% was achieved in the project area, and registration procedures were completed.

Conclusion

Land consolidation projects enable the regulation and improvement of plots in agricultural production areas. Following a successful consolidation effort, savings are achieved in every aspect that affects agricultural production costs. Production costs determine the market price of the product; lower costs lead to lower market prices, thus increasing competitiveness. The increase in average plot size in the study area will benefit those engaged in agricultural production following consolidation. Increased plot size is expected to result in savings in time, labor, and fuel.

In the analysis of plot shapes, the number of irregularly shaped plots decreased by approximately 33%, and the number of rectangular plots, considered the most ideal shape for agricultural production, increased by approximately 20%. Although efforts are made to improve the geometric shape of the plots, the presence of irregularly shaped blocks is inevitable if adjustments are not made at the outer boundaries of the village. The irregular shape of the blocks also affects the shape of the plot.

When considered as agricultural land loss, the loss due to road access networks has been mitigated, and the land has been reclaimed for agricultural use. In addition, there are significant gains in reducing losses at parcel boundaries. The larger the geometric shape of the parcels, the less agricultural land will be lost at the parcel boundaries. In the study conducted in the project area, approximately 15 hectares of unusable land, due to both road and parcel boundaries, have been brought back into agricultural use.

Overall, when evaluating the land consolidation project in the project area, it is evident that significant improvements have been made compared to the pre-project period. The better the consolidation efforts and their benefits are explained to the agricultural businesses operating in the project area, the higher the project's success rate will be.

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CHAPTER 10

TECHNICAL ANALYSIS OF THE KONYA-BEYŞEHIR-KURUCUOVA VILLAGE LAND CONSOLIDATION PROJECT

1. ERMAN BENGİN[1]

Introduction

In recent years, population growth has increased anthropogenic pressure on natural resources. This pressure manifests itself particularly in the form of land use for purposes other than agriculture, driven by the need for shelter and food. This unplanned change in land use patterns creates deep and difficult-to-repair marks on nature (Kızılelma et al., 2013). While there are many methods to minimize these degradations, land consolidation efforts are undertaken to protect existing agricultural lands and obtain higher yields per unit area.

In Turkey, land consolidation has undergone various policy periods throughout its historical development and has gained a systematic application area since the 1960s (Küsek, 2014; Albayrak, 2019). The fact that the initial studies were carried out by the General Directorate of Soil and Water in conjunction with irrigation projects

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made consolidation an integral part of large-scale agricultural infrastructure investments (Acar & Bengin, 2018). Following the 1980s, the legal framework established by Law No. 3083 expanded land consolidation beyond irrigation areas to encompass broader rural planning processes. In the 2000s, land consolidation became a central component of modern agricultural policies, and with the enactment of Law No. 5403 on Soil Protection and Land Use, it became a strategic application at the national level (Küsek, 2014; Yıldız & Karalar, 2021).

Due to advancements in technology, spatial analysis tools have gained rapid momentum in recent years, enabling them to produce highly accurate results in a short time. One of these spatial analysis tools is remote sensing techniques, which are more economical and faster than traditional methods in terms of collecting information at different temporal and spatial scales (Kızılelma & Karabulut, 2017). Today, land consolidation projects in Turkey are implemented with significantly higher technical accuracy than in previous periods, supported by Geographic Information Systems (GIS), remote sensing techniques, high-resolution satellite imagery, precision agriculture data, and advanced geometric analysis methods (Köseoğlu & Gündoğdu, 2004).

Land consolidation is a rural planning application with a strong technical dimension and involving different disciplines, aiming to improve the physical, spatial, and ownership structure of agricultural production areas (Geisse & Hudecová, 2019; Çay & Sözen, 2023; Çay & Acar, 2025; Sözen & Çay, 2025). Nowadays, land consolidation efforts have evolved from simply enlarging or merging parcels to become a collaborative field involving multiple disciplines, such as agriculture, engineering, geography, law, and rural sociology. Land consolidation, which aims to ensure the sustainable use of agricultural land, increase production efficiency, and strengthen rural infrastructure, is considered an indispensable component of modern agricultural policies (Akdeniz et al., 2022; Akdeniz et al., 2023).

One of the most fundamental problems in agricultural production areas is the land structure, consisting of small, irregularly shaped, and scattered parcels resulting from divisions through inheritance and the historical fragmentation of property (Sözen & Karataş, 2015; Akdeniz & Acar, 2023). This situation negatively affects agricultural production processes both economically and spatially (Karataş & Sözen, 2017). Producing on small and irregularly shaped parcels results in significant losses in the efficiency of agricultural machinery, leading to increased time, labor, fuel, and energy consumption. Furthermore, parcels with small and irregular boundaries create an obstacle, especially for modern agricultural practices, and further increase the loss of agricultural yield (Acar & Akdeniz, 2023; Çay et al., 2025).

One of the primary objectives of land consolidation practices is to increase parcel sizes and create a land structure suitable for larger-scale economic enterprises (Korthals Altes & Bong Im, 2011; Çay & Acar, 2022). However, the modern consolidation approach requires a series of technical analyses that go beyond parcel size. Indicators such as consolidation rate, interruption rate, and agricultural land loss are key parameters used to measure the technical success level of projects. Through these indicators, changes before and after consolidation can be compared; the evaluations obtained can be clearly presented (Yoğunlu, 2013; Boztoprak et al., 2015; Kuzu & Değirmenci, 2022).

Parcel shapes play a crucial role, especially in agricultural activities (Demetriou et al., 2013). Regular geometric parcels both facilitate planting processes and make machinery movement easier, saving time and fuel (Kwinta & Gniadek, 2017). Conversely, irregular or narrow, elongated forms reduce agricultural productivity, leading to increased boundary losses and loss of agricultural land (Akdeniz & Temizel, 2018).

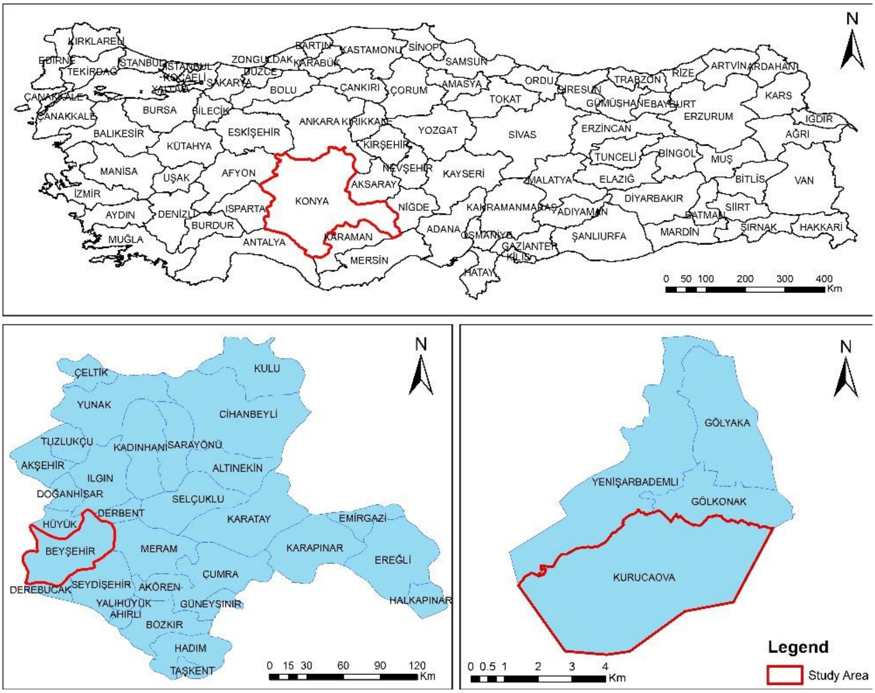
The deduction rate, on the other hand, is the percentage expression of the total share taken from properties for the area needed for roads, canals, drainage lines, communal use areas, and social facilities in the land consolidation process. Ensuring that the deduction is compliant with regulations and balanced directly affects social acceptance and stakeholder satisfaction for the project (Tunalı & Dağdelen, 2018). Similarly, agricultural land loss is a crucial parameter, particularly in assessing areas that are unproductive due to their proximity to boundaries. Considering the inefficiency of a narrow but effective buffer zone of 50 cm along parcel boundaries, the importance of land consolidation in terms of geometric improvement becomes even more apparent (Akdeniz & Temizel, 2018).

Evaluating indicators such as parcel size, consolidation rate, parcel shape, deduction rate, and agricultural land loss is crucial in assessing the performance of land consolidation practices and providing a scientific basis for future planning. This study focuses on these indicators and technically examines the spatial impacts of land consolidation, aiming to contribute to sustainable agricultural practices in rural areas.

Material and Methods

This study utilized the numerical and attribute data from the land consolidation and field development services project in Kurucuova village, which is part of the Isparta Yenişarbademli Martyr Hüseyin Gökhan Eriç Dam Irrigation LC and FDS Project. The project area encompasses three villages within the borders of Yenişarbademli District, Isparta Province, and one village within the borders of Beyşehir District, Konya Province (Figure 1).

Figure 1. Kurucuova Village Location Map



The completed land consolidation project was undertaken by the 18th Regional Directorate of the General Directorate of State Hydraulic Works within the Ministry of Agriculture and Forestry. Data for the land consolidation and field development services project in the Beyşehir district of Konya province was obtained from the 18th Regional Directorate. Analyses were conducted using LiTop software before (cadastral situation) and after (parceling plan) consolidation. LiCad and ArcGIS software were used to create the maps based on the analysis results. Within the scope of the project, the shapes of the parcels before and after consolidation, ownership status, average land size, agricultural land loss, interruption rate in the project area, and consolidation rate were examined.

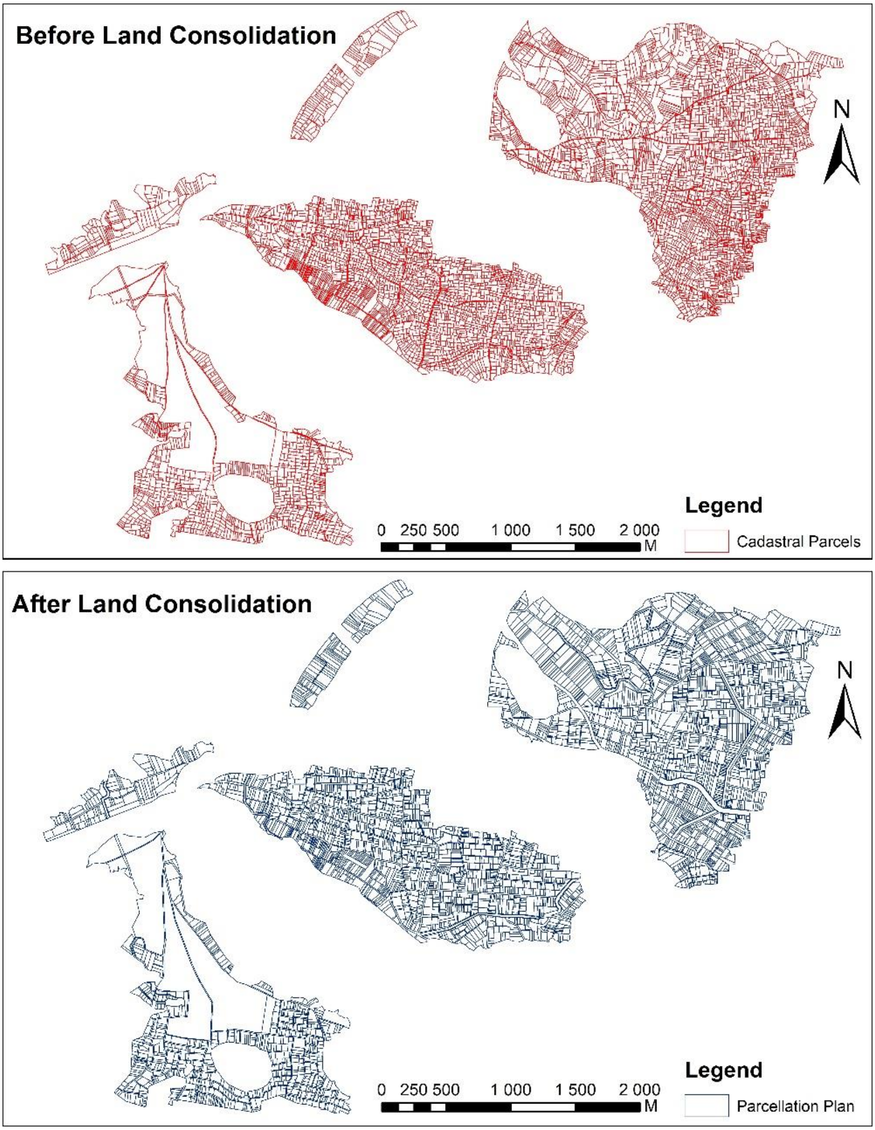
Research Findings and Discussion

The Kurucuova village land consolidation project includes a total of 2111 parcels. Prior to the project, the total parcel area was calculated to be 7,433.74 hectares, comprising 7,266 parcels with an average parcel size of 1.02 hectares. After the project, the total parcel area was calculated to be 6,816.71 hectares, comprising 4,286 parcels with an average parcel size of 1.59 hectares (Table 1). The pre- and post-project situation map of the project area is given in Figure 2.

Table 1. Kurucuova Village Project Summary

	Before LC	**After LC**
Parcel Area (da)	7433.74	6816.71
Number of Parcels	7266	4286
Average Parcel Size (da)	1.02	1.59

Figure 2 Pre- and Post-Consolidation Situation Map



When the distribution of plots in the project area is examined according to plot size, the areal density of plots before and after the project is in the range of 0-5 decares (Table 2). Increases in the average size of the areal groups of plots have been observed. It is predicted that the increase in average plot size will increase agricultural production efficiency.

Table 2. Distribution According to Kurucuova Village Parcel Sizes

	Before Land Consolidation			After Land Consolidation		
Parcel Groups (Da)	**Number of parcels**	**%**	**Average Plot Size (Da)**	**Number of parcels**	**%**	**Average Plot Size (Da)**
0 - 5	7218	99.34	0.87	4219	98.44	1.31
6 - 10	29	0.40	7.68	48	1.12	7.60
11 - 20	11	0.15	14.54	11	0.26	15.17
21 - 50	5	0.07	27.52	5	0.12	27.64
51 - 100	0	0.00	0.00	0	0.00	0.00
101 - 500	3	0.04	199.56	3	0.07	208.60
Total	**7266**	**100.00**	**1.02**	**4286**	**100.00**	**1.59**

While the geometric shape of plots is among the criteria affecting agricultural mechanization, the ideal plot geometry for agricultural production is rectangular, with an aspect ratio between 1/3 and 1/7. In the literature, after rectangles, squares, trapezoids, irregularly shaped plots, and triangles are ranked in terms of suitability for mechanized farming according to their geometric shapes (Acar & Akdeniz, 2023). Plot shape analysis conducted in the study area shows an 11% increase in the number of rectangular plots, from approximately 32% to 43%. The number of trapezoidal plots increased by approximately 2%. The number of square plots decreased by approximately 1%, the number of triangular plots decreased by approximately 2%, and the number of irregularly shaped plots decreased by approximately 9%. A slight increase in the number of square plots was observed when comparing the pre- and post-project evaluations (Table 3).

Table 3. to Kurucuova Village Parcel Shapes

Parcel Shape	Before Project		After Project	
	Pieces	%	Pieces	%
Triangle	330	4.54	94	2.19
Square	224	3.08	83	1.94
Rectangle	2346	32.29	1853	43.23
Trapezoid	2920	40.19	1795	41.88
Shapeless	1446	19.90	461	10.76
Total	**7266**	**100.00**	**4286**	**100.00**

In agricultural production, plowing activities cannot be carried out at the parcel boundaries while machinery is in operation. Due to both the boundary stones at the parcel boundaries and the maneuverability of the machinery, areas become unusable for agricultural use. These areas are considered agricultural land loss. Studies have shown that at least 50 cm of the parcel boundaries are unusable for agricultural use. To calculate agricultural land loss in the parcels formed before and after land consolidation in the project area, the arable land area was calculated by creating internal areas within the parcels. The difference between the arable land area and the total parcel area was used to calculate the agricultural land loss. As a result of the analysis and calculations carried out in the study area, the agricultural land loss, which was 466,971.68 m^2 before the project, decreased to 366,590.21 m^2 after the project. The land consolidation project resulted in a 21% reduction in agricultural land loss.

Table 4. Kururova Village Agricultural Area Loss

	Total Area (m^2)	Total Arable Area (m^2)	Loss of Agricultural Land (m^2)
Before LC	7438890.74	6971919.06	466971.68
After LC	6816761.72	6450171.51	366590.21

In land consolidation projects, a proportional reduction is made from all parcels subject to regulation to provide space for standard facilities created within the project scope. The consolidation legislation stipulates that up to 10% of the reduction can be made free of charge (Acar, 2023). Within the scope of the regulation implemented in the study area, the reduction rate was calculated to be 8.4698%, and this rate was applied to all parcels included in the regulation.

The consolidation rate is used in evaluating the success criteria of consolidation projects. In the project area, 7266 parcels were included in the regulation before it was implemented, and the number was reduced to 4286 parcels after the regulation was completed. A consolidation rate of 41.01% was achieved in the project area, and registration procedures were completed.

Conclusion

Land consolidation projects enable spatial changes on a parcel basis in agricultural production areas. Arrangements are made not only in the location of the parcels but also in their shape and size. In agricultural areas, the geometric shape of the parcels is considered a key criterion in determining production costs, from plowing to harvesting. It is known that labor and fuel costs are lowest in parcels with the most ideal geometry for agricultural production. The transformation of agricultural production areas into larger parcels reduces loss at parcel boundaries and increases arable land. These arrangements strengthen the transportation network in agricultural areas and contribute to crop patterns and productivity by including irrigation and drainage systems. In this context, evaluating the contribution of consolidation projects to agricultural production and conducting post-project research is crucial.

In the study area, compared to the pre-project period, the number of triangular, trapezoidal, and irregularly shaped parcels has decreased. In contrast, the number of rectangular and square-shaped parcels has increased. The rectangular shape, which showed the most significant increase, is considered the most suitable shape for agricultural production. While triangular parcel shapes have not entirely disappeared, they have shown a decreasing trend in increasing agricultural production. The inability to fully correct the parcel geometry stems from reasons such as the irregular geometric structure of the outer boundaries of the neighborhood and the difficulty in linearly constructing fixed structures, roads, and irrigation systems on the landowners' properties. Studies show that boundary correction for the outer boundary of the project area will significantly contribute to improving parcel geometries.

In the project implemented in Kurucuova village, a land consolidation rate of 41.01% has been achieved. Scattered and fragmented lands belonging to the same farm have been brought together and consolidated, which has also had an impact on the geometric shapes. The average parcel size in the project area has increased from 1.02 decares to 1.59 decares, representing an increase of approximately 55%. By consolidating parcels, the total parcel boundary length is reduced, and the usable area for agricultural production is increased.

Based on the analyses conducted, the Kurucuova land consolidation and field development services project has been successful. It is predicted that the implemented changes will yield positive benefits when comparing the pre- and post-project situations. While the contribution of land consolidation projects to reducing agricultural production costs is immediately apparent, the benefits in production efficiency may take some time to materialize. Providing farmers with more detailed information during the interview phase in the project area and explaining the benefits and opportunities that land consolidation will offer them in more detail will contribute to increasing the project's success rate.

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CHAPTER 11

A TECHNICAL EVALUATION OF THE REAL ESTATE APPRAISAL LICENSING SYSTEM: AN EMPIRICAL ANALYSIS BASED ON ENGINEERING-ORIENTED EXPERT OPINIONS

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Introduction

Real estate appraisal is a multidisciplinary engineering activity that requires a holistic evaluation of technical, legal, and economic components and entails a high level of professional

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responsibility (Ertaş, 2019; Kayalık & Polat, 2023b; Pagourtzi et al., 2003; Polat, 2019; Polat & Alkan, 2021; Sakınç & Coşkun, 2018). These analyses are conducted by considering a wide range of factors, including the physical, environmental, and legal status of the property, as well as economic and demographic characteristics; market analysis; intended use of the property; future potential; liquidity and marketability; and risk return profile. Accordingly, property value is assessed using three fundamental valuation approaches namely the cost, market, and income approaches (Kayalık & Polat, 2023a; Yomralıoğlu, 2000; Yomralıoğlu et al., 2011). This framework has been defined in the literature as a multi-criteria engineering application (Pak et al., 2023). The field plays a critical role in both public- and private-sector processes, particularly in expropriation practices, zoning and land readjustment applications, urban transformation projects, mortgage-based financing systems, and investment analyses (Candaş, 2012; Köktürk & Köktürk, 2015). Ensuring that valuation practices are grounded in an objective, scientific, and technical basis is indispensable for safeguarding public interest and for the fair protection of property rights.

In Türkiye, the authority to conduct real estate appraisal is granted through a licensing system regulated by the Capital Markets Board (CMB) (SPL, 2025). Within this framework, candidates are required to pass examinations consisting of four modules and to fulfill a minimum of three years of professional experience before becoming eligible for licensure. Licensed appraisers operate within the organizational structure of the Turkish Association of Licensed Valuers (TDUB) (TDUB, 2025b). While this system establishes the legal and institutional framework of the profession, it also gives rise to significant debates regarding application requirements, examination content, the distribution of professional backgrounds, and fee schedules.

Recent studies indicate that the current system does not fully reflect professional competence and has led to dissatisfaction among practitioners from different disciplinary backgrounds in practice (Polat & Alkan, 2021; Sakınç & Coşkun, 2018). In particular, professionals with an engineering background emphasize that their technical expertise is largely overlooked, that the examination system predominantly focuses on legal and financial content, and that no specific differentiation or advantage is provided for candidates with technical training. In addition, concerns have been raised regarding minimum fee schedules remaining below prevailing market conditions, inadequacies in professional supervision, and the limited level of institutional affiliation within the profession (Erdem, 2018; Erdem, 2023).

This study aims to evaluate the real estate appraisal licensing system implemented in Türkiye from a technical perspective. Accordingly, the examination structure, application requirements, fee policies, balance among professional groups, and the level of professional affiliation are analyzed through a survey conducted with 132 licensed appraisal experts. The findings reveal the strengths and weaknesses of the current system in terms of technical competence and provide a basis for recommendations aimed at restructuring the licensing framework.

Institutional and Legal Framework

The regulation of real estate appraisal activities on a legal basis, the establishment of professional standards, and the authorization of experts are of critical importance for ensuring sustainability within an institutional framework (Tanrıvermiş & Aliefendioğlu, 2019). In Türkiye, this framework is shaped by the CMB and the TDUB (Çete, 2008; SPK, 2025; SPL, 2025; TDUB, 2023). While the CMB is responsible for defining the legal regulations governing appraisal activities and the licensing process, TDUB is tasked with overseeing professional practices, ensuring institutional representation of appraisers, and supporting sectoral development.

The effectiveness of the licensing system depends not only on the examination structure but also on the holistic functioning of various institutional components, including application requirements, experience criteria, the distribution of professional backgrounds, membership structures, and service fee schedules. However, these components are interpreted differently by various professional groups in practice, and certain aspects of the system are considered inadequate or open to debate, particularly by experts with a technical background. Therefore, a detailed examination of the existing legal and institutional framework is a fundamental prerequisite for addressing the system from a technical competence perspective.

CMB Licensing System

In Türkiye, individuals seeking to specialize in the field of real estate appraisal are subject to a licensing process administered by the CMB (SPL, 2025). This system is structured within the scope of Capital Markets Law No. 6362 (Lawmaker, 2012) and aims to ensure that appraisal services are conducted in a reliable and transparent manner from the perspective of capital markets (Ertaş, 2019). The licensing process is based on various competency components, including professional knowledge, experience, ethical compliance, and legal awareness.

To become a licensed real estate appraiser authorized by the CMB, candidates are required to first sit for examinations consisting of four modules. These modules are structured under the titles "Principles of Real Estate Appraisal," "Limited Scope Capital Markets Legislation and Professional Rules," "Construction and Real Estate Accounting," and "Real Estate Legislation." The examinations are administered in a written test format (TDKDER, 2023). To be deemed successful, candidates must achieve a minimum score of 50% in each module and an overall average score of at least 60% across all modules. However, the fact that the examination content is largely based on financial and legal components has led to criticism, particularly from technical and engineering-based professional groups.

Candidates who successfully complete the examination stage are required to have at least three years of professional experience in the appraisal sector in order to be eligible to apply for licensure. This experience requirement covers employment histories in both the private sector and public institutions; however, such experience must be documented through official institutional records. In addition, candidates' criminal records, disciplinary histories, and ethical compliance are also taken into consideration during the application process.

Individuals who become eligible for licensure may operate by obtaining membership in TDUB and may provide services to institutions and organizations recognized by the CMB by preparing appraisal reports. The title of licensed real estate appraiser confers a legal status that enables regular supervision of professional activities and ensures the validity of appraisal reports. However, the overall process remains open to debate in terms of the clarity of application requirements, the balance of examination content, and the extent to which professional training is adequately taken into account; accordingly, the degree to which the system reflects technical expertise constitutes one of the main focal points of this study.

TDUB and the Professional Authorization Structure

TDUB was established in 2009 with authorization from the CMB and commenced its operations after acquiring legal personality in 2011. The primary objective of the Union is to supervise licensed appraisers and appraisal companies in professional, ethical, and institutional terms, to ensure standardization within the sector, and to foster public trust. Within this framework, TDUB maintains a dual membership structure encompassing both individual licensed appraisers and licensed appraisal firms. TDUB undertakes multidimensional responsibilities, including member admission, maintenance of professional affiliation, ethical oversight mechanisms, standardization of appraisal report templates, determination of minimum fee schedules, and the organization of professional development activities. Members are obliged to participate in continuing professional education at specified intervals, comply with disciplinary rules, and transparently document their professional activities through activity reports. However, the applicability and enforcement capacity of these mechanisms are occasionally questioned, and criticisms have been raised regarding the insufficient effectiveness of professional supervision in practice.

The professional authorization process has a limited impact due to TDUB's structurally passive position. The fact that only formal criteria are examined during the membership process of appraisers contributes to a weak sense of professional affiliation. Moreover, the incompatibility of the minimum fee schedule determined by TDUB with prevailing market conditions creates uncertainty regarding income security among appraisers and renders the institution's authority open to debate. From the perspective of institutional representation, it is frequently emphasized that TDUB's administrative structure and policy-making processes should be transformed into a more participatory and interdisciplinary framework. Views asserting that engineering-based professional groups (e.g., geodesy, geomatics, and urban planning) are not adequately represented within TDUB constitute an integral part of the critical perspective underpinning this study.

In conclusion, while TDUB’s current authorization structure positions it as an important actor in strengthening the institutional representation, professional development, and sectoral standing of licensed real estate appraisers, it nevertheless requires structural reforms and a more inclusive representation system in practice.

Application Requirements and Examination Structure

Candidates seeking to obtain a real estate appraisal license are required to meet the conditions set forth by the CMB. These conditions primarily include the successful completion of a licensing examination consisting of four modules and at least three years of active professional experience in the real estate appraisal sector. The application process also encompasses general requirements such as graduation from a higher education institution, the absence of a criminal record, and ethical compliance. The examination modules are structured under the titles “Principles of Real Estate Appraisal”, “Limited Scope Capital Markets Legislation and Professional Rules”, “Construction and Real Estate Accounting” and “Real Estate Legislation”. Each module is administered using a multiple-choice test format and candidates are required to achieve a minimum score of 50% in each module and an overall average score of at least 60% across all modules. Overall, this structure is predominantly based on finance- and law-oriented knowledge domains. Criticisms are widespread regarding the inadequacy of the examination scope for candidates with technical and engineering backgrounds.

The three-year experience requirement considered during the application process is limited to experience obtained exclusively within appraisal firms or relevant public institutions. However, a lack of clarity regarding how such experience should be documented and which activities qualify as valid experience leads to ambiguity in practice and contributes to perceptions of inequality among applicants. For instance, land-based and project-oriented activities performed by certain professional groups are not recognized as appraisal experience, whereas greater flexibility appears to be afforded to specific disciplines. Furthermore, the content and format of the examinations may include questions that do not align with professional practice for engineering-based disciplines, and candidates' technical knowledge and analytical capabilities are not adequately assessed. This situation gives rise to criticisms that the licensing system relies primarily on theoretical knowledge and fails to reflect real-world applications. In particular, individuals specialized in technical fields such as GIS, cartography, land use, and spatial analysis appear to be insufficiently represented within the system.

In conclusion, although the application requirements and examination system provide a standardized structure, they are subject to criticism for being designed in a manner that is insensitive to the needs of technical disciplines and professional diversity. In this respect, the system requires a more balanced and inclusive restructuring grounded in the principle of technical competence.

Minimum Fee Schedule, Professional Affiliation and Supervision

The ability of licensed real estate appraisers to sustain their professional activities depends not only on technical competence and legal status but also on the holistic operation of structural factors such as institutional affiliation, income security, and supervisory mechanisms. Within this context, the minimum fee schedule determined annually by TDUB (TDUB, 2025a) aims to maintain sectoral balance by ensuring fair compensation for appraisers' labor while preventing unfair competition among institutions.

However, field studies indicate that this fee schedule is not aligned with market realities and is often disregarded in the free market. Price competition among appraisal service providers frequently leads to bids being offered below the minimum fee levels; this situation reduces appraisers' income levels and adversely affects professional satisfaction. A substantial proportion of appraisers report that the fee schedule lacks binding force and that TDUB has been unable to establish an effective enforcement mechanism in this regard.

From the perspective of professional affiliation, although TDUB membership is technically mandatory, the sense of institutional commitment and professional solidarity among appraisers remains limited. The membership system largely operates within a formal framework, while interactive processes such as training, representation, and participation are not sufficiently institutionalized. In particular, appraisers from engineering disciplines report being disadvantaged in terms of involvement in TDUB's governance processes and participation in decision-making mechanisms. Supervisory mechanisms are similarly criticized, as an effective oversight framework ensuring the content quality of appraisal reports, methodological adequacy, and compliance with ethical standards is perceived to be lacking. The complaint mechanisms provided by TDUB often have limited impact, and institutional sanctions are rarely enforced. This situation undermines both the integrity of the system and the sustainability of professional standards. In this context, rendering the minimum fee schedule legally binding, strengthening TDUB's capacity for professional representation, and establishing effective supervisory processes are identified as priority requirements for achieving a fair, sustainable, and technically competence-based system.

Methodology

In this study, quantitative data collection and descriptive analysis methods were employed to evaluate the real estate appraisal licensing system implemented in Türkiye in terms of technical competence. The primary focus of the research is to reveal licensed appraisers' experiences with the current system, their levels of satisfaction, and their views regarding potential restructuring. A structured questionnaire was used as the data collection instrument. The survey consists of closed-ended, multiple-choice, and rating-based (Likert-type) questions and includes a total of 26 main items. The question set was organized under five main themes addressing different dimensions of the appraisal system: "Examination system and content", "Application requirements and experience criteria", "Professional group representation and perceptions of technical competence", "Minimum fee schedule and income satisfaction" and "Institutional affiliation and evaluations of TDUB."

The questionnaire was first evaluated in terms of content validity by two academic experts in the field and one licensed real estate appraiser. Following this review, the survey was finalized on an online platform (Google Forms), and the data collection process was initiated in October 2024. The participant group was determined through random sampling based on the lists of licensed appraisers published by the CMB and TDUB. The survey was fully completed by 132 licensed real estate appraisers who are actively working in the sector and represent various engineering-based disciplines. An evaluation of the responses revealed participants' satisfaction levels as well as certain demands for restructuring the existing system. The findings were supported by quantitative results and presented through graphs and tables to enhance visual interpretation. The research methodology questions the current structure of the licensing system from the perspective of engineering-based professional expertise and provides a quantitative foundation conducive to generating policy-oriented recommendations. In this respect, the study aims to fill a gap in the literature by offering a technically grounded evaluation of the licensing system based on empirical quantitative data.

Findings

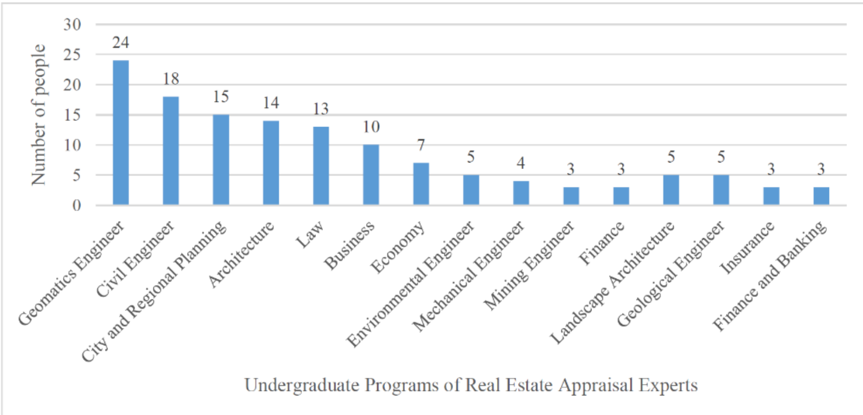
This section presents the findings obtained from the views of licensed professionals regarding the real estate appraisal licensing system implemented in Türkiye, organized under thematic headings. The questionnaire, completed by 132 experts participating in the study, was designed to evaluate various components of the system. During the analysis process, each theme was interpreted using descriptive statistics, percentage distributions, and illustrative statements. The findings are presented under seven main headings: participant profile, examination structure, application criteria, professional representation, income satisfaction, institutional affiliation, and proposals for systemic improvement. This structure enables a comprehensive analysis of the strengths and weaknesses of the appraisal system based on technical competence.

Professional and Demographic Profile of the Participants

The professional and demographic characteristics of the 132 licensed appraisal experts who participated in the study constitute an important basis for the analysis of opinions regarding the licensing system. In terms of gender distribution, approximately two-thirds of the participants are male, while the remaining proportion consists of female experts. With respect to age profile, the vast majority of participants fall within the 30–45 age range, indicating that an active and professionally experienced group of experts was included in the study.

When educational attainment is examined, the majority of participants hold a bachelor’s degree, while a portion have completed graduate education at the master’s or doctoral level. In terms of length of professional experience in the appraisal sector, more than half of the participants have five years or more of experience, indicating that the evaluations are supported by substantial practical sectoral knowledge. The distribution across professional disciplines reveals that the study is grounded in an engineering-oriented perspective. The largest proportion of participants are graduates of geomatics engineering programs, followed by other disciplines such as urban and regional planning, civil engineering, and architecture (Figure 1).

Figure 1 Distribution of participants' undergraduate programs



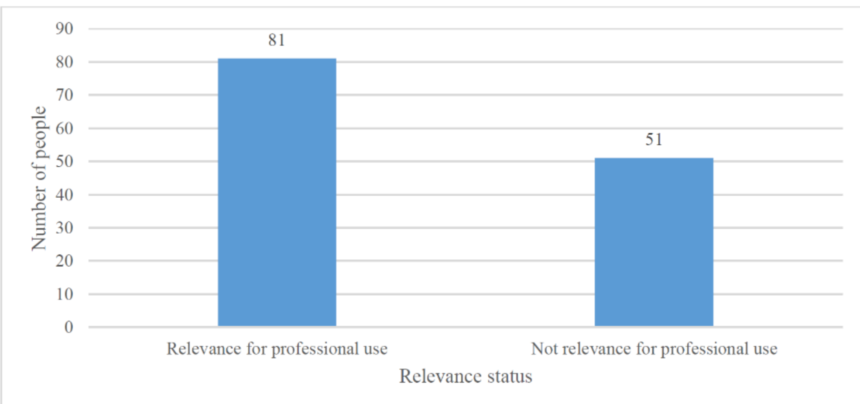
It was observed that experts from various engineering and social science disciplines also contributed to the study. In terms of the distribution of participants by type of employing institution, appraisal firms operating in the private sector constitute the majority, while independent appraisers and those working in public institutions also represent a certain proportion. This composition indicates that the research findings reflect sectoral diversity and variations in practice. In conclusion, the participating experts consist of experienced individuals from technical disciplines who are actively working in the sector, demonstrating that the opinions obtained were gathered from a sample appropriate and reliable for evaluating the system based on technical competence.

Evaluations of the Examination System and Content

According to the study findings, the four-module examination system applied in the licensing process is considered by the vast majority of participants to be inconsistent with professional practice. Criticisms primarily focus on the exam content being heavily based on legal and financial knowledge, while technical and engineering knowledge is insufficiently assessed. A significant portion of participants indicated that the exams do not cover areas requiring technical expertise and, therefore, do not provide a fair evaluation environment for experts from technical disciplines.

Engineering-based experts in particular indicated that the examination structure is inadequate due to the absence of practical assessments and the predominance of questions not directly linked to professional practice. Approximately two-thirds of the participants emphasized that topics such as spatial analysis, surveying techniques, map literacy, and field-based application knowledge are missing from the exam modules. Furthermore, it was noted that a question structure based solely on theoretical knowledge is insufficient for measuring the application-oriented competencies required in the sector. In this context, there is a strong expectation for the examination system to be updated and differentiated according to discipline. Participants' overall evaluations of the examination system are presented in Figure 2.

Figure 2 Participants' views on the professional relevance of exam questions

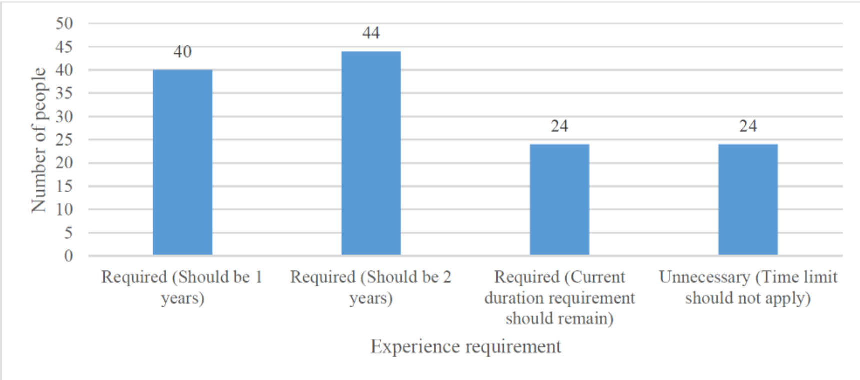


Opinions on Application Requirements and Experience Criteria

The three-year professional experience requirement in the licensing application process has been questioned by participants in terms of both scope and implementation. According to the feedback, the current definition of experience does not adequately reflect technical expertise and professional output, being primarily evaluated based on tenure at specific institutions. This situation weakens the perceived fairness of the application process.

Participants, particularly those from engineering-based professional groups, indicated that technical knowledge and field experience are overlooked and that project-based work in public or private sector settings is not systematically evaluated. In addition, there is a shared view among participants that the application documentation process is bureaucratic and lacks standardization. Uncertainty regarding which activities are considered as qualifying experience reinforces the perception of inequality among applicants. Within this context, there is a strong tendency for the current experience requirement to be redefined in a more flexible and competence-based manner. Participants' evaluations on this issue are presented in Figure 3.

Figure 3 Distribution of participants' opinions on the three-year experience requirement



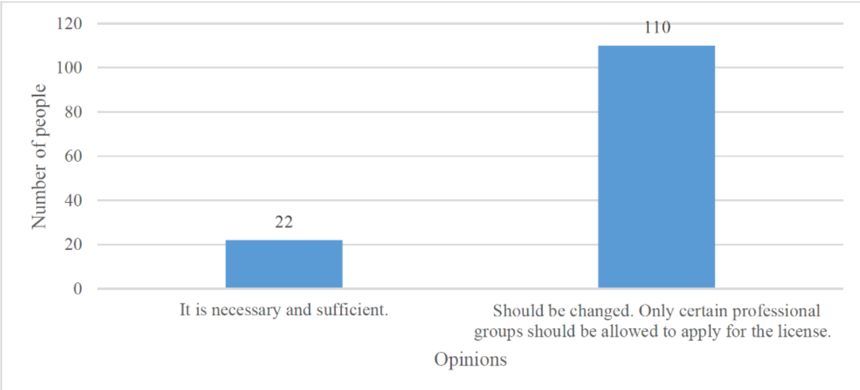
Interdisciplinary Representation and Perception of Technical Adequacy

The research findings reveal a pronounced imbalance in the licensing system regarding representation and perceived fairness across different professional disciplines. The majority of participants indicated that the system does not adequately reflect the competencies of technical disciplines and provides a more advantageous structure for professions with a social science background.

The main reasons for this situation include the exclusion of technically demanding areas from the exam content, the limited recognition of professional activities based on technical practice within the application criteria, and the insufficient inclusion of engineering-based professional groups in institutional representation processes. Technical experts strongly emphasized that the appraisal process is fundamentally an area of expertise grounded in engineering and spatial analysis.

A significant portion of participants indicated that, in order to enhance the quality of appraisal services, technical competence should be made a more central element and the system should be structured in a more balanced way across professional groups. Participants' evaluations regarding perceived representation and advantage distribution across professional groups are presented in Figure 4.

Figure 4 Participants' opinions on the requirement to graduate from any four-year undergraduate program



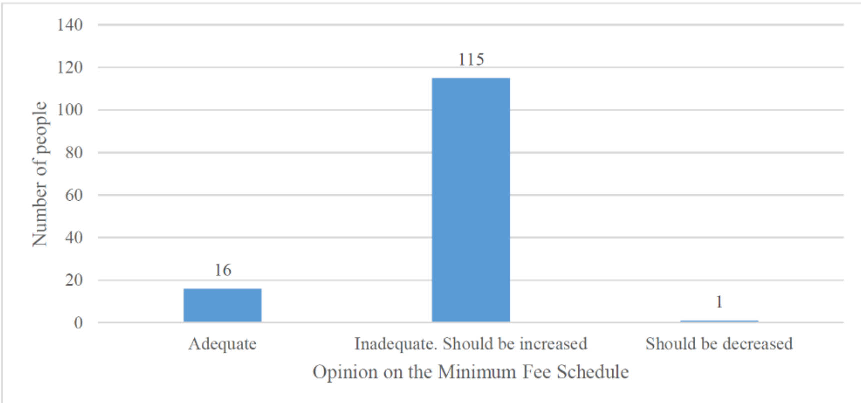
Minimum Fee Schedule and Income Satisfaction

One of the most important factors affecting the professional satisfaction of licensed real estate appraisal experts is the income earned in return for their services and whether this income is established on a fair sectoral basis. The 'Minimum Fee Schedule' published annually by TDUB (TDUB, 2025a) aims to standardize service delivery in the sector and prevent unfair competition. However, the research findings indicate that this objective is largely not achieved in practice.

81% of participants stated that the minimum fee schedule set by TDUB falls significantly below market conditions and is not practically applied. Evaluations on this issue are presented in Figure 5. Experts operating in the private sector, in particular, indicated that due to the non-binding nature of the fee schedule, they are often forced to provide services at lower rates under market pressure. This situation both reduces professional income levels and reinforces the perception of unfairness among experts.

Only 12% of participants indicated that the current fee schedule is adequate, while 87% stated that it is insufficient. Additionally, some participants emphasized that most of the institutions and organizations receiving appraisal services do not consider this schedule, with price competition being the determining factor in service procurement. This situation weakens experts' expectations of income security and negatively affects professional affiliation.

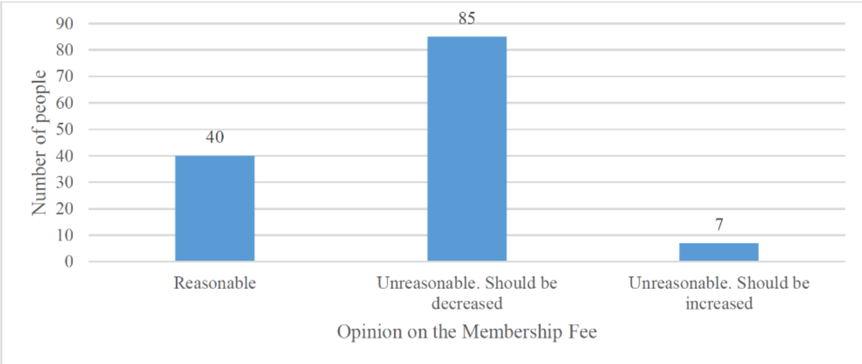
Figure 5 Participants' opinions on the adequacy of the minimum fee schedule set by TDUB



Professional Affiliation, Membership and Institutional Relationship Assessment

The study also examined participants' levels of professional affiliation and their perceptions of TDUB. The findings reveal that a significant portion of licensed appraisal experts have low satisfaction with institutional representation, in-service professional development, and membership processes. Sixty-four percent of participants indicated that TDUB membership is perceived merely as a legal requirement, while 71% stated that membership does not provide a tangible professional benefit. Evaluations regarding TDUB membership fees are presented in Figure 6.

Figure 6 Participants' opinions on the annual TDUB membership fee



59% of participants believe that TDUB does not adequately protect the interests of appraisal experts in the sector, while 66% think that certain professional groups are disproportionately represented in the Union's management structure. Experts from technical disciplines, in particular, indicated that they do not have sufficient influence in institutional decision-making processes, which hinders the development of technical approaches.

In terms of institutional affiliation, 53% of participants found the training and informational activities organized by TDUB to be inadequate, while 47% indicated that access to these activities is limited. Furthermore, opinions suggest that principles such as transparency, equality, and interaction are not sufficiently implemented in the membership process. In this context, institutional bonds remain weak, with individual orientations prevailing over professional unity and solidarity.

In the qualitative data analysis, it was noted that TDUB has limited sectoral visibility, does not act proactively in policy development processes, and its interaction with members mostly remains at the level of emails and document circulation. This situation hinders the strengthening of professional organization and weakens the institutional infrastructure of the system.

In conclusion, the evaluations regarding TDUB point to numerous areas needing improvement in terms of professional representation, oversight capacity, and communication mechanisms. Establishing a transparent and participatory institutional structure in which technical professional groups are more effectively represented would directly contribute to strengthening the licensed appraisal system.

Overall Satisfaction with the System and Recommendations for Restructuring

In the study, participants were asked to evaluate the overall adequacy of the real estate appraisal licensing system, and the findings indicate that the system is only moderately accepted among technical experts. Only 19% of participants rated the current system as “successful” or “very successful”, whereas 58% considered it “inadequate” or “in need of significant revision”. The key criticisms emerging from the qualitative responses include the following:

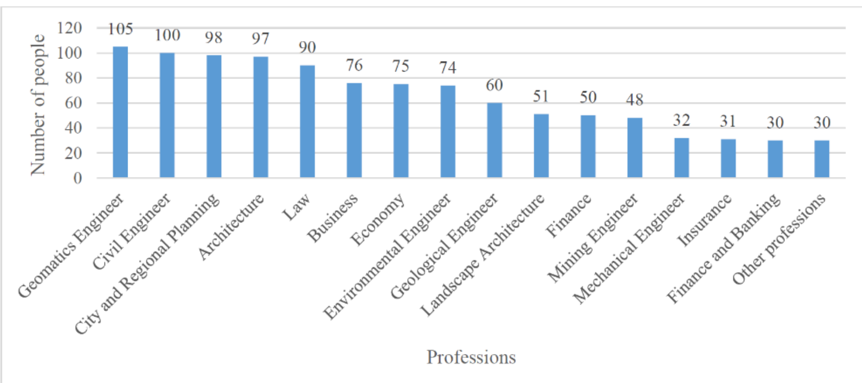
- The exam system fails to adequately assess technical knowledge,
- Representation of engineering-based professional groups is limited,
- The enforceability of the minimum fee schedule is weak,
- TDUB’s institutional capacity and influence are insufficient,
- Professional affiliation among licensed appraisers remains weak.

In response to these issues, participants have proposed various restructuring recommendations. The most frequently mentioned recommendations are as follows:

- Differentiation of the examination system according to professional disciplines (e.g., technical, legal, financial sub-modules),
- Inclusion of case-based and practical assessments focused on technical applications,
- Recognition of engineering-based valuation activities in the licensing application process,
- Transformation of TDUB into a more participatory, pluralistic, and representation-oriented organization,
- Making the minimum fee schedule legally binding and developing effective monitoring mechanisms.

Overall, the majority of participants believe that the current system does not reflect technical competence, overlooks engineering-based expertise, and fails to meet contemporary professional needs. Opinions regarding professional recommendations are presented in Figure 7. In this context, it emerges that the licensing system should be redesigned not merely as an authorization mechanism but also in terms of professional quality, ethical integrity, and sectoral sustainability.

Figure 7 Proposed professional groups for the four-year bachelor's degree requirement



Discussion

This study evaluated the real estate appraisal licensing system in Türkiye from a technical competency perspective, with a particular focus on the experiences, satisfaction levels, and reform demands of engineering-based professionals. The findings indicate that technical training is insufficiently considered across multiple components of the system, leading to various issues in both practical implementation and professional equity.

Firstly, the examination system, as also criticized in the literature (Polat & Alkan, 2021; Sakınç & Coşkun, 2018), is insufficient in measuring technical knowledge and largely relies on financial and legal content. This structure results in the exclusion of technical expertise from the system in fields that require a balance of practical and theoretical skills. The recommendations proposed in this study (e.g., case-based assessments, separation of technical modules, and discipline-specific exam content) are consistent with international examples (RICS, 2022). Criticisms regarding the application criteria indicate that not only the duration but also the quality of experience should be considered. Technical expertise involving fieldwork, spatial analyses, or project-based public service activities not being recognized in the licensing process causes qualified engineers to remain outside the licensed system. This issue represents not only individual dissatisfaction but also a loss of systemic capacity.

Another significant finding is the perceived weakness of TDUB's professional representation. Participants indicated that TDUB functions primarily as a formal structure, provides insufficient support for in-profession training, and lacks adequate representation of technical disciplines in management. This situation contradicts the "organizational belonging" function of professional associations discussed in the literature. From an economic sustainability perspective, the minimum fee schedule published by

TDUB often fails to align with market realities, creating income insecurity and directly affecting the quality of valuation activities. This finding highlights that, in practice, free-market dynamics tend to overshadow professional standards within the sector.

In conclusion, the findings of this study indicate that the licensing system should be restructured not only within a legal and institutional framework but also based on technical competence, professional representation, and economic balance. Strengthening the integration of engineering-based expertise into the system will enhance professional quality and support the sectoral sustainability of the licensing framework.

Conclusion and Recommendations

This study examined the real estate licensing system in Türkiye from the perspective of technical competence, focusing on how it operates for engineering-based professionals. Through a survey of 132 actively practicing licensed valuers, systematic issues were identified across several areas, including exam structure, application criteria, inter-professional representation, income satisfaction, and institutional affiliation. The key findings of the research can be summarized as follows:

- The exam system is primarily based on legal and financial knowledge and is insufficient in covering areas of technical competence.
- The professional experience of individuals with an engineering background is not adequately recognized in the licensing process, leading to representation issues within the system.
- The minimum fee schedule is largely disregarded by the market, resulting in uncertainty regarding income security for valuers.

- Membership in TDUB is perceived by most experts as an obligation rather than a professional benefit, with low levels of occupational affiliation and institutional representation.

In light of these findings, the following recommendations can be made to policymakers, professional organizations, and regulatory bodies:

- The examination system should be restructured: A discipline-based modular exam system should be developed, with technical, legal, and financial modules separated and exam content diversified according to areas of expertise.
- Experience criteria should be made more flexible and clearly defined: Professionally technical activities (e.g., field applications, spatial analyses, project-based engineering work) should be recognized as valid for license applications.
- TDUB's representation and participation structure should be reviewed: The representation of engineering-based professions within the Union should be increased, and more inclusive mechanisms should be established in training, supervision, and policy-making processes.
- The minimum fee schedule should be granted legal enforceability: Market participants must comply with this schedule, ensured through supervision and sanctions, thereby securing professional remuneration with institutional safeguards.
- Education and communication mechanisms should be developed to strengthen institutional affiliation: Regular in-service trainings, professional meetings, and interactive sharing platforms should be encouraged for TDUB members.

In conclusion, this study demonstrates that the licensing system should be restructured not merely as an examination and authorization tool, but also with regard to professional quality, technical competence, and sectoral balance. Enhancing the visibility and influence of technical expertise within the system will improve not only individual satisfaction but also the overall accuracy and reliability of the real estate valuation framework.

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GEÇİCİ KAPAK

Kapak tasarımı devam ediyor.