Article

From maps to models: Key concepts in Geographic Information Systems

Yohannes Shifera Daka[1], **Kassaye Hussein**[2], **Ashenafi Yimam**[2]
[1]Department of Forestry, Dambi Dollo University, Dambi Dollo, Ethiopia
[2]School of Geography and Environmental Studies, Haramaya University, Dire Dawa, Ethiopia
E-mail: yohannes.shifera@dadu.edu.et, kassaye.hussien@haramaya.edu.et, asheyimam@gmail.com

Received 2 January 2025; *Accepted 10 February 2025*; *Published online 25 February 2025*; *Published 1 September 2025*

Abstract
Geographic Information Systems (GIS) have dramatically altered the landscape of spatial data analysis, which have allowed practitioners and scholars to gain important insights in a variety of domains, including emergency response, environmental management, and urban planning. Central to the functionality of GIS are two integral components: maps and models. Although maps have historically been used to graphically and statically depict spatial data, GIS models go beyond static representations to turn maps into dynamic, predictive tools. These models help predict and analyze spatial dynamics across time by simulating real-world phenomena. These models allow for simulations of real-world phenomena, aiding in forecasting and analyzing spatial processes over time. This paper explores the evolution of GIS, focusing on the shift from traditional cartographic maps to dynamic models, highlighting how these advancements have revolutionized spatial analysis and influenced real-world applications. An understanding of how GIS is influencing the future of spatial data interpretation is provided by the exploration of the interaction between maps and models.

Keywords advancements; maps; models; predictive tools; static representations.

Computational Ecology and Software
ISSN 2220-721X
URL: http://www.iaees.org/publications/journals/ces/online-version.asp
RSS: http://www.iaees.org/publications/journals/ces/rss.xml
E-mail: ces@iaees.org
Editor-in-Chief: WenJun Zhang
Publisher: International Academy of Ecology and Environmental Sciences

1 Introduction

The management, analysis, and interpretation of spatial data have advanced significantly with the appearance of Geographic Information Systems (GIS). Complex geographical phenomena can be modeled thanks to GIS's ability to integrate diverse datasets. This integration has become a cornerstone of decision-making in various fields such as urban planning, environmental conservation, disaster management, and more. Decision-making in a variety of fields, including urban planning, environmental preservation, disaster management, and more, now relies heavily on this integration (Longley et al., 2015).

The combined usage of maps and models, each with a unique but complementary function, is essential to the development of GIS. In their traditional form, maps show spatial features at a specific point in time and act as visual representations of geographic data. But with the advancement of GIS, these maps have evolved into dynamic, interactive tools that incorporate increasingly complex models that enable the simulation and prediction of spatial events (Keita et al., 2021). Understanding the differences between maps and models is crucial because it shows how GIS has changed from being a tool for representing static data to a potent platform for dynamic analysis.

In GIS, one of the biggest advancements in spatial science is the switch from static maps to dynamic models. By increasing the predictive capacity of geographical data, this change has had significant effects on a various sectors, including environmental management and city planning. GIS models are crucial tools for complicated decision-making because they enable us to simulate spatial processes and forecast future events, in contrast to traditional maps that simply show a snapshot of geographic features (Couclelis, 1997).

2 Key Concepts In GIS: From Maps To Models

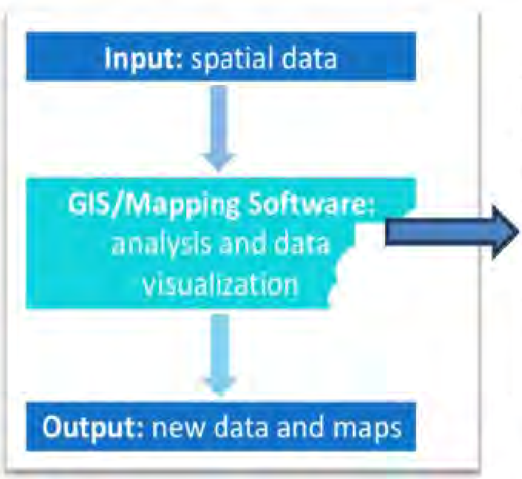
2.1 GIS and spatial data

GIS is a powerful and computerized system designed to collect, store, analyze, query, retrieve, manipulate, present and disseminate spatial or geographic data. Hardware, software, data, procedures, and people are the components of GIS (Bolstad, 2016; Lwin et al., 2020). One of GIS's main advantages is its capacity to integrate spatial and non-spatial data, making complicated analyses possible that would be challenging to accomplish otherwise (Goodchild et al., 2007; Chien et al., 2022). The data used in GIS comes in various formats, including vector and raster data, which are essential for both mapping and modeling processes. This means that transforming spatial data into meaningful analysis through the use of maps and models is one of the key roles of GIS (Longley et al., 2015).

Surveys, Global Positioning System (GPS) devices, and remote sensing are popular ways to collect spatial data, which form the basis for further analysis (Goodchild, 2007; Liu et al., 2021). Overlay analysis, buffer analysis, and network analysis are among the geographical analysis tasks carried out in GIS; these tasks all depend on accurate spatial data inputs (Couclelis, 1997; Shao et al., 2023). In GIS, the quality of geographic data is crucial since poor or inaccurate data can jeopardize maps and models and produce untrustworthy results (Robinson et al., 1995). Any errors made when gathering or processing data can have a big impact on how maps are interpreted and how accurately models predict outcomes (Albrecht, 2007).

Maps in GIS are often generated directly from this spatial data and then processed and transformed for further analysis.

Table 1 Types of GIS mapping software.



Type	Analysis Power	Examples
Geobrowser	Weak (mainly only to display data)	Google Maps, Google Earth, Apple Maps, Waze, etc.
Web-based	Medium (able to upload additional data, customize display, and perform basic analyses	Carto, ArcGIS Online, Mapbox, Google MyMaps, etc.
Desktop	Strong (installed locally, provides full control of map creation, and perform advanced analyses	ArcGIS Pro QGIS

Source: Longley et al. (2015)

Once map is generated, it is processed and transformed for further analysis. Depending on the model's requirements, this transformation may involve resampling, reprojection, and data normalization. For example, raster data (gridded data) are used to represent continuous phenomena like temperature, elevation, and precipitation. Vector data (points, lines, and polygons), on the other hand represents discrete features like roads, rivers, cities, and boundaries (Longley et al., 2015) (Fig. 1).

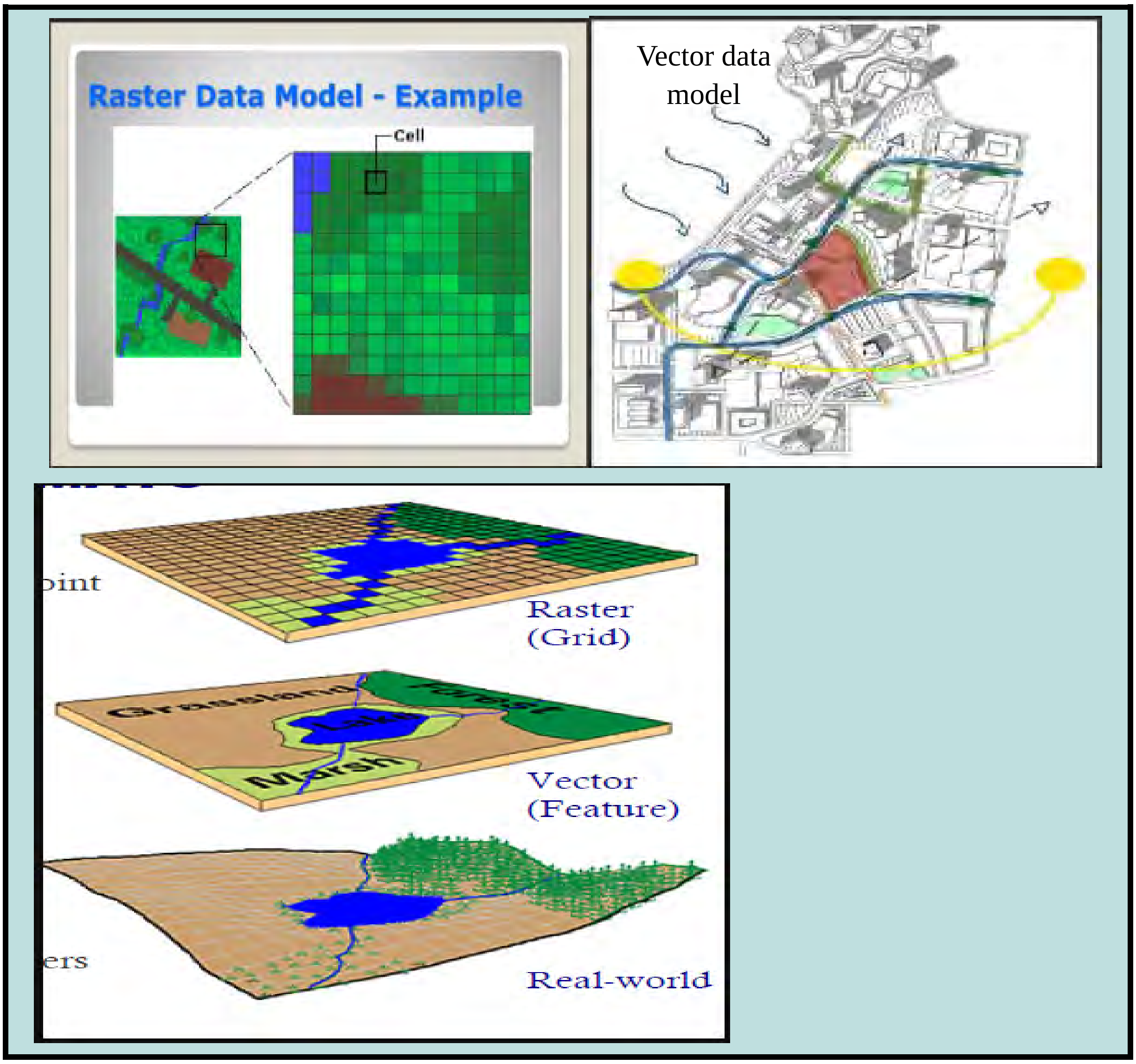


Fig. 1 Raster data model and vector data model.

Both data models have their own file format. The shapefile is the most common vector file format and it is in the form of .shp, .shx, .sbx, .dbf, and .prj, while there are many different raster file extensions, including common image formats. It is in the form of .tiff, .asc, .img, and .jpg (ESRI, 2011).

2.2 GIS maps: Historical context and evolution

Early cartography, when maps were mostly employed to depict geographic spaces and provide a static representation of the world, is where the roots of GIS discovered. Maps have been central to human understanding of geography since ancient civilizations; early attempts to describe the world can be seen in the Babylonian World Map, developed around 600 BCE (Gould, 2014) (Fig. 2).

Fig. 2 Babylonian word map (around 600 BCE).

In essence, early GIS maps in the 1960s and 1970s, were digital maps based on vector-data that made it possible to create layered data that could be digitally stored and queried (Goodchild, 2004). These early maps did have some serious limitations, though: they were static and primarily depicted physical elements; they did not take into consideration spatial relationships or changes over time. They were also unable to forecast future spatial events or examine intricate interconnections (O'Sullivan and Unwin, 2010) (Fig. 3).

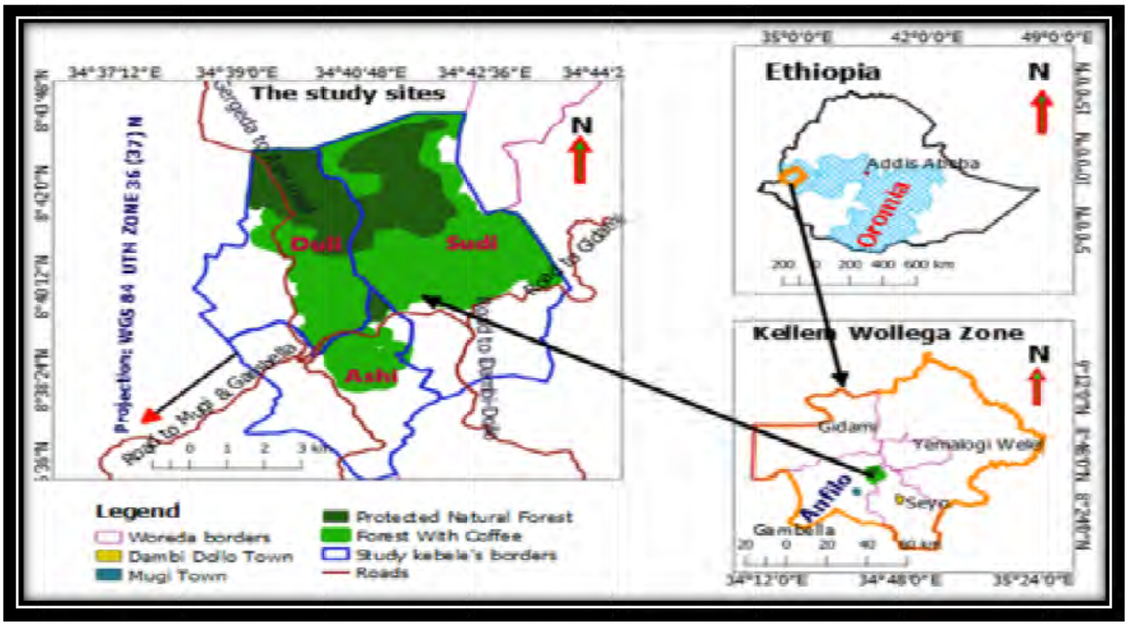


Fig. 3 Visual representation of geographic features through maps (Source: Daka (2022)).

With the advancement of GIS technologies, maps started to play a more dynamic role. Their integration with computational models that could replicate real-world phenomena, such as climatic variability and land-use changes, increased their usefulness for predictive analysis and decision-making (O'Sullivan and Unwin, 2010).

2.3 Transition from maps to models in GIS

The world is in a constant state of flux, and understanding the dynamic processes that shape both the biophysical and human environments is essential to addressing the challenges of today and tomorrow (Batty et al., 2022). Maps, which are static representations of geographical data, have historically been used to convey geographic knowledge (Harris et al., 2021). However, there has been a notable movement toward the use of models, which enable more nuanced, predictive, and dynamic analysis, as the complexity of spatial phenomena and their interactions become increasingly apparent (Dewitt et al., 2021). Advances in Geographic Information Systems technology have enabled this transition, since it has transformed from a tool for merely showing geographic data to a potent system for simulating and forecasting spatial processes over time (Chrisman, 2006; Batty, 2013).

Early maps were limited in their capacity to provide deeper analytical insights, as they primarily represent visually geographic features without capturing the temporal dynamics that influence these features (Harris et al., 2021). The appearance of GIS brought a fundamental change. Maps were used as inputs to dynamic models that simulate and forecast spatial processes, rather than being only static representations. As a result, GIS has evolved from a technology primarily used for visualization to one that facilitates both prescriptive and predictive analysis. This shift was driven by the increasing need to understand how geographic systems change over time, which static maps were unable to provide (Batty et al., 2022).

As processing and analysis of large datasets became possible due to advances in computational technology, the transition from static maps to dynamic models started to gain momentum in the 1980s and 1990s (Batty, 2005). These advancements made it possible to depict both the dynamic processes underlying geographic phenomena and spatial aspects. The analysis of spatial processes, the creation of models, and the integration of these models with spatial data became the main focus of Geographic Information Science (GIS) after it became a distinct field in the late 1980s (Chrisman, 2006). This made it possible to develop mathematical and computational representations of actual processes, broadening the use of GIS beyond basic visualization to include more intricate analysis and forecasting (Goodchild, 2007).

In GIS, models are used to depict spatial processes or phenomena in a way that can analyze complex situations or forecast future events. Models can simulate change and provide insights into future situations, in contrast to maps that depict data at a certain moment in time (Gong et al., 2020). This ability to anticipate the future is especially crucial for spatial phenomena like land use change, environmental degradation, urbanization, and catastrophe risk management, because knowing a system's future condition is just as crucial as understanding its present condition. GIS can simulate how systems evolve over time by integrating dynamic processes to the models, providing insightful information for policy & decision-making (Dewitt et al., 2021).

One of the key elements of this transition is the process of data transformation and spatial analysis. In order to use geographic data in models, raw spatial data must be converted into formats that are suitable for modeling, such as raster or vector layers (Smith, 2023). These formats allow for detailed spatial analysis and facilitate the construction of models that predict future outcomes. For example, a land use map, which shows the distribution of different land types in a region, can serve as the input for a model that simulates how future urban development, or zoning changes might affect land use patterns over time (Chen et al., 2020). In this sense, maps supply the data that models use as a basis, while models give the data structure so that better analyses and choices may be made.

Once models are generated, the outputs they provide can be seen on updated maps, which facilitate stakeholder interpretation and application of the findings in practical settings. These outputs, which are frequently displayed as updated or new maps, are used to convey the analysis's findings to a larger audience, which includes the public, policymakers, and decision makers (Jiang et al., 2022). By enabling the integration of spatial analysis with decision making processes, the feedback loop between maps and models improves GIS's ability to handle real-world issues. This procedure aids in making sure that the outcomes of predictive modeling are understandable, applicable, and actionable for those who must take action.

The two main categories of GIS models are prescriptive and predictive models. Predictive models help to foresee changes and get ready for possible future scenarios by predicting future occurrences or situations based on available data. To simulate the effects of many factors, like urbanization or climate change, on biodiversity, land use, or air quality, for example, predictive models are frequently employed (Pei et al., 2020). According to Voinov et al. (2021), prescriptive models, on the other hand, help decision-makers maximize plans for development, conservation, or disaster mitigation by offering suggestions for the optimal course of action under certain circumstances. The two models can address the questions that maps alone cannot answer, especially when they deal with complicated connections between several geographic components or temporal change (Longley et al., 2025).

2.4 Early GIS models and their development

In the early stages of GIS models, the primarily focus was on deterministic models that simulated environmental processes using spatial data. These models simplified complex real-world phenomena to make them calculable in order to reflect the physical world using a limited set of assumptions. Robert Tomlin, whose work in the around 1980s was crucial in forming the area of spatial modeling, was one of the major pioneers in GIS modeling during this time. He developed Cellular Automata model used to simulate urban expansion. In contrast to traditional maps, this model showed how urban areas may grow over time and captured the dynamics of land-use change (Tomlin, 1983; Zhang, 2016).

Other significant individuals and organizations, most notably Howard Fisher and the Environmental Systems Research Institute (ESRI), contributed to Tomlin's work in the 1970s and 1980s. By creating software that would serve as the basis for contemporary GIS technology, Fisher, a pivotal figure in the early development of GIS, significantly advanced spatial analysis. The development of ArcInfo by ESRI, one of the first all-inclusive GIS software programs, revolutionized the industry. ArcInfo made it easier to store, work with, and analyze spatial data, which made it possible to create increasingly complex GIS models. By providing a platform for spatial analysis, these tools made it possible for GIS to evolve from a simple data storage system to a robust framework for modeling geographic and environmental phenomena (ESRI, 2009). Early GIS models were foundational in the evolution of spatial analysis, but they were often limited in scope (Longley et al., 1999).

An important advancement in spatial analysis was made in the 1980s with the creation of the Raster model. Geographic phenomena might be represented as a matrix of cells using raster-based GIS, where each cell had a value corresponding to a spatial feature like soil type, temperature, or height (Burrough, 1986). Compared to previous vector-based methods, this innovation significantly improved the management of continuous data. In environmental simulations, where it was necessary to model continuous variables like rainfall or air pollution over wide areas, the raster format proved especially helpful. Additionally, it made it possible to simulate intricate processes like weather patterns and land cover changes over time and paved the way for more advanced models in environmental science, urban planning, and resource management (Jensen, 2007).

Even with these developments, early GIS models had weakness. The incapacity of early GIS models to manage the enormous volumes of data that are now typical in contemporary GIS applications was one of their main problems. Due to early systems' limitations in terms of computational power and data resolution, many models were unable to capture fine-scale geographic information or accurately depict the intricacies of human-environment interactions (Heathcote, 2009). For instance, low-resolution raster models could not capture small-scale spatial variations that were critical for applications in urban planning, where understanding the impact of individual buildings or streets was often crucial. This limitation made it more difficult for GIS to offer precise and useful information for more localized decision making, especially in fields like resource management and urban development (Tobler, 1979).

In response to these challenges, the growing demand for greater accuracy and more complex analyses spurred the development of more advanced GIS models. By the 1990s, GIS had begun to incorporate real-time data and more sophisticated computational algorithms, improving both the accuracy and applicability of models. For example, models were increasingly designed to integrate remote sensing data from satellites and aerial imagery, as well as data collected by sensors embedded in the environment. These advancements allowed GIS to provide more up-to-date and dynamic information, facilitating better decision-making in real-time contexts (Heipke, 2010).

2.5 Recent advances in GIS models

GIS modeling has changed dramatically in recent years in response to the increasing need to understand not just what and where, but also why and how. In order to address fundamental inquiries concerning spatial distributions and patterns, early GIS models mostly concentrated on descriptive analysis (Chen et al., 2008). But given the complexity of today's geographic problems, a move toward more advanced modeling methods that could replicate dynamic processes and offer a better understanding of the fundamental causes of geographic phenomena was required (Heipke, 2010; Batty, 2013).

With the introduction of Agent-Based Models (ABMs) and Geospatial Machine Learning, the incorporation of increasingly intricate procedures into GIS modeling has accelerated in recent years. The study of spatial phenomena has been completely transformed by these models, which provide new ways on both small-scale and large-scale interactions within geographical areas. For instance, ABMs simulate the behaviors and interactions of individual agents that stand in for people, cars, or other objects in a particular setting. An in-depth, micro-level understanding of spatial dynamics is made possible by ABMs (Batty, 2013). This capacity has been especially helpful in fields like urban planning, where it is essential to understand how people behave in response to shifting circumstances (such as transportation or land-use regulations). ABMs have been used in traffic management to model how individual cars or people move through a location, which aids planners in improving road layouts and public transportation systems (Batty et al., 2021).

Furthermore, the more sophisticated tools that allow users to interact with the data in real time have been developed as a result of the growing complexity of GIS models. With the advent of geospatial analytics systems, stakeholders, decision-makers, and the public may now visualize and work with geographic data to make decisions more cooperatively. For instance, local governments can better understand public preferences and concerns by involving citizens in urban planning processes through the use of GIS platforms. Applications of GIS have been extended to a wide range of fields, from disaster management and environmental monitoring to healthcare planning and economic development, thanks to the capacity to model real-world situations and evaluate different solutions prior to their implementation (Zhang et al., 2023).

New opportunities for geographic modeling have been brought about by the recent integration of GIS with state-of-the-art technologies like big data analytics and machine learning. Deep learning algorithms that can analyze enormous volumes of geographic data to find patterns and provide predictions have been made possible by the quick expansion of the amount of geographical data that is now available as well as improvements in processing power (Zhang et al., 2020). For instance, deep learning models have been used to forecast environmental threats like air pollution or flood hazards, predict patterns of urban expansion, and optimize resource allocation for conservation or urban development initiatives. These models are very effective at handling dynamic and changing geographic difficulties because they can both learn from prior data and adapt to new data inputs.

Better algorithms that can manage increasingly complex and varied information are becoming more and more necessary as GIS becomes more integrated with artificial intelligence (AI) and machine learning. Furthermore, it is still crucial to conduct research on how to ensure the ethical use of GIS technology, particularly in delicate fields like urban planning and surveillance (Smith et al., 2023; Li et al., 2024).

Table 2 Some of early and recently developed GIS models with their uses.

Name of GIS Models	Their uses	Year Developed	Citation
Vector Models	Represents spatial data as points, lines, polygons	1960s	Tomlinson (1967)
Hydrological Models	Models water flow and runoff.	1960s	Dooge (1964)
Fuzzy Logic Models	Incorporates uncertainty into spatial data analysis using fuzzy set theory.	1965s	Zadeh (1965)
Geostatistical Models (Kriging)	Spatial interpolation using autocorrelation.	1970s	Matheron (1963)
Cellular Automata Models	Simulates dynamic land use changes over time.	1970s	White and Engelen (1993)
Land Suitability Models	Assesses land for specific uses.	1980s	McHarg (1969)
Markov Chain Models	Models land use change based on probabilities.	1980s	Clark et al. (1999)
Multi-Criteria Decision Analysis	Land use planning, decision support systems.	1980s	Malczewski (1999)
HEC-RAS Model	River modeling, flood analysis, hydraulic modeling.	1980s	US Army Corps of Engineers (2008)
Generalized Additive Models	Ecological modeling, species distribution, climate change analysis.	1980s	Hastie, Tibshirani (1986)
Multiple Layer Perceptron (MLP)	Classification tasks, environmental monitoring, spatial pattern recognition.	1980s	Rumelhart et al. (1986)
Climate Models (Geospatial)	Models climate system and predictions.	1980s-1990s	IPCC (2001)
SimCity Model	Urban planning, population growth, resource management.	1989s	Maxis (1989)
GWR Model	Spatially varying regression analysis, geographic patterns in data.	1990s	Brunsdon et al. (1996)
Land Transformation Model	Predicts changes in land use and land cover.	1990s	Pontius et al. (2001)

Name of GIS Models	Their uses	Year Developed	Citation
Support Vector Machine	Classifies spatial data using hyperplanes.	1990s	Vapnik (1995)
Raster Models	Analyzes continuous data with grid-based representation.	1990s	Burrough (1986)
Agent-Based Models (ABM)	Models interactions of autonomous agents.	2000-2010s	Liu et al. (2019)
InVEST	Models ecosystem services like carbon, water, biodiversity.	2000s	TEEB (2010)
Space-Time Cube Models	Represents spatio-temporal data in a 3D cube for analyzing patterns over time.	2000s	Kwan (2007)
Random Forest	Classification, prediction of environmental variables, land cover.	2000s	Breiman (2001)
Deep Learning Models	Uses neural networks for complex pattern recognition and classification.	2010s	LeCun et al. (2015).
GeoSOS-ELM Model	Land suitability analysis under climate change scenarios.	2010s	Liu et al. (2016)
DynaClue Model	Urban growth, land use change, dynamic clustering.	2010s	Kamusoko et al. (2013)
LSTM Neural Networks	Predicting spatiotemporal patterns in LU, CC, and urban expansion.	2010s	Li et al. (2020)
Artificial Intelligence for Land Use/Sprawl Modeling	Predicting urban sprawl, modeling land use dynamics.	2010s	Azar et al. (2020).

2.6 Key differences between maps and models

The differences between maps and models are summarized in Table 3.

Table 3 The summarized key differences between a map and a model in GIS.

Aspect	**Map**	**Model**
Definition	A visual representation of spatial data	A simplified, abstract representation of a system or process used for analysis and prediction.
Purpose	Primarily used for visualization and display	Used for analysis, simulations, and decision-making.
Nature	Static, shows a snapshot of data at a specific time	Dynamic, can simulate and predict changes over time.
Representation	Typically shows geographic features like landforms, roads, and boundaries	Represents relationships between different variables and processes (e.g., elevation models, hydrological simulations).
Data Type	Primarily visual; can include data layers like roads, rivers, and political boundaries	Includes quantitative data and mathematical relationships, often incorporating spatial and non-spatial data.
Interactivity	Often static; some maps are interactive in digital formats	Highly interactive, allows for manipulation and simulation of variables.
Examples	Topographic maps, thematic maps, political maps	Climate models, hydrological models, land use change models.
Output	A finished product that communicates information	Often used to generate predictions or results that require further interpretation.
Usage	Primarily for visualization, navigation, and simple spatial analysis	Used for in-depth spatial analysis, forecasting, and planning.
Time Sensitivity	Usually shows a snapshot of data at a particular point in time	Can model changes over time, often with scenarios or future predictions.
Complexity	Generally less complex, straightforward representation of data	More complex, often involves simulations, algorithms, and predictions.

Source: Longley et al. (2015), Chang KT (2015), Bolstad P (2016), ESRI (2024).

3 Conclusions

The move from maps to GIS models signifies a significant change in the way geographic data is studied, used, and represented in a variety of sectors. The "what" and "where" of spatial events are captured by maps, which are static representations; however, GIS models provide dynamic simulations that address the "how" and "why" of geographic processes. GIS can now forecast future trends, model actual situations, and provide a deeper understanding of the intricate relationships between natural and human systems thanks to this transition.

Key concepts such as modeling, data representation, spatial analysis, and geoprocessing have broadened the use of GIS and enabled it to offer powerful tools for decision making that go beyond simple mapping. While geoprocessing techniques allow the manipulation and analysis of spatial data to serve a variety of applications, spatial analysis allows GIS models to uncover hidden patterns and correlations that are not visible in typical maps.

Furthermore, as big data, cloud computing, and machine learning develop further, they expand the potential of GIS models, enabling them to process enormous volumes of data instantly and increase prediction accuracy. These developments also make it easier for non-experts to interact with geographical data and make defensible decisions by enabling the creation of more interactive and user-friendly GIS platforms.

In the future, geographical analysis will probably undergo a revolution thanks to the incorporation of artificial intelligence (AI) into GIS, which will allow models to automatically adjust to new data inputs and continuously enhance their predictions. Applications across a wide range of industries, including precision agriculture, smart cities, healthcare, and crisis management, will become possible as a result. The transition from static maps to dynamic, predictive models signifies a paradigm shift in our comprehension, interpretation, and interaction with geographic data, in addition to a technological advancement.

In summary, the transition of GIS from maps to models reflects the increasing need for more sophisticated instruments to deal with challenging geographical issues. GIS will become an essential tool for the future as its technology develops further since it has the ability to improve societal results, sustainable development, and decision-making.

Acknowledgment

The authors acknowledged Haramaya University for supporting us through full internet access.

References

Albrecht J. 2007. Spatial Data Quality: From Conceptualization to Implementation. Springer

Azar E, et al. 2020. A review of AI methods for modeling urban sprawl. Environmental Modelling & Software, 131: 104798

Batty M. 2013.The New Science of Cities. MIT Press, USA

Batty M, Xie Y, Zhao D, Chen L. 2022. Geospatial Modeling and Analysis for Urban Planning and Disaster Management. Springer

Bender S, Wang R, Zhang K, Liu P. 2021. Exploring Geospatial Data Visualization and Interpretation. Springer

Bolstad P. 2016. GIS Fundamentals: A First Text on Geographic Information Systems. Xan Edu

Brunsdon C, et al. 1996. Geographically weighted regression: A method for exploring spatial nonstationarity. Geographical Analysis, 28(4): 281-298

Burrough PA. 1986. Principles of Geographic Information Systems for Land Resources Assessment.Oxford

University Press, UK

Chang KT. 2014. Introduction to Geographic Information Systems. McGraw-Hill, USA

Chen Y, Lu H, Li J, Xia J. 2020. Effects of land use cover change on carbon emissions and ecosystem services in Chengyu urban agglomeration, China. Stochastic Environmental Research and Risk Assessment, 34(8): 1197-1215. https://doi.org/10.1007/s00477-020-01847-3

Chrisman N. 2006. Charting the Unknown: How Computer Mapping at Harvard Became GIS. Redland, ESRI

Clark J, Evans T, Anderson D, Walker P. 1999. Land use change modelling and environmental management: A framework for linking research and policy. Environmental Modelling & Software, 14(3): 245-264. https://doi.org/10.1016/S1364-8152(98)00088-2

Couclelis H. 1997. From cellular automata to urban models: New principles for model development and implementation. Environment and Planning B: Planning and Design, 24(2): 165-174

Crampton JW. 2011. Mapping: A Critical Introduction to Cartography and GIS. John Wiley & Sons, USA

Dewitt B, Thompson R, Martin J, Williams L. 2021. Advancements in GIS-Based Decision Making for Environmental Management. Springer

Dooge JCI. 1964. A general theory of the hydrological cycle. Journal of Hydrology, 2(4): 221-228

Feng Y, Wang R, Tong X, Shafizadeh-Moghadam H. 2019. How much can temporally stationary factors explain cellular automata-based simulations of past and future urban growth? Computers, Environment and Urban Systems, 76: 150-162

Fischer MM, Scholten HJ, Unwin D. 2019. Geographic information systems, spatial data analysis and spatial modelling: An introduction. In: Spatial Analytical Perspectives on GIS. 3-20, Routledge, USA

Gong P, Zhang J, Li X, Wu Z. 2020. GIS Modeling for Urban Development and Environmental Management. Springer

Goodchild MF. 2004. GIS and Science: The Development of GIS. Wiley, USA

Goodchild MF, Brunsdon C, Harris R. 2007. Geographic Information Science and Technology. Wiley. USA

Gould P. 2014. The History of Maps in Geography. Oxford University Press, UK

Harris P, Patel R, Singh A, Zhao L. 2021.Geospatial Technologies for Urban Planning and Disaster Risk Management. Springer

Hastie T, Tibshirani R. 1986. Generalized Additive Models. Statistical Science, 1(3): 297-318

Heathcote R. 2009. Geographic Information Systems and Environmental Management. Wiley, USA

Heipke C. 2010. Crowdsourcing and Remote Sensing: Models for Environmental Change. Springer

Hinton GE. 1986. Learning representations by back-propagating errors. Nature, 323(6088): 533-536. https://doi.org/10.1038/323533a0

Imran M, Khan S, Ahmed R, Singh P. 2023. GIS Modeling for Disaster Risk and Mgt. Springer

IPCC. 2001. Climate Change 2001: The Scientific Basis. Intergovernmental Panel on Climate Change, Switzerland

Jensen JR. 2007. Remote Sensing of Vegetation: Remote Sensing of the Environment: An Earth Resource Perspective. Pearson Prentice Hall, Upper Saddle River, NJ, USA

Jiang X, Li B, Zhao H, Zhang Q, Song X, Zhang H. 2021. Examining the spatial simulation and land-use reorganization mechanism of agricultural suburban settlements using a cellular-automata and agent-based model: Six settlements in China. Land Use Policy, 120: 106304

Jokar Arsanjani J, Mooney SM, Nijkamp P. 2013. GIS for Spatial Data Analysis and Decision-Making. Springer

Kamusoko C, et al. 2013. Urban growth modelling using DynaClue: A case study of Harare, Zimbabwe. Computers, Environment and Urban Systems, 39(1): 40-49

Keita L, Sow MA, Diop M. 2021. Advanced GIS Modeling Techniques for Spatial Analysis. Springer
Li, X, et al. 2020. Modeling land use/land cover change in urban areas using LSTM and GIS data. Geocarto International, 35(2): 163-175
Li, X, Wang Y, Zhang L, Sun L. 2024. AI and machine learning in GIS: Challenges and opportunities for complex data handling. Geoinformatics Journal, 41(2): 85-99. https://doi.org/10.1016/j.geoj.2024.01.004
Liu S, Chen H, Zhao L. 2021. Geospatial Data & Models in GIS for Urban & Environmental Anal. Springer
Liu W, et al. 2019. Agent-based models for urban planning: A review of applications in GIS and spatial planning. Environmental Modelling and Software, 119: 18-32
Longley PA, Goodchild, MF, Maguire DJ, Rhind DW. 2015. Geographical Information Systems and Science (4th ed). Wiley, USA
Lwin KK, Aung WM, Myint T. 2020. Spatial Data Collection and Analysis for GIS Applications. Springer
MacEachren AM. 1995. How Maps Work: Representation, Visualization, and Design. Guilford Press, USA
Matheron G. 1963. Principles of geostatistics. Economic Geology, 58(8): 1246-1266
McHarg IL. 1969. Design with Nature. The Natural History Press, USA
Miller HJ, Long JA, Brown D C. 2020. Spatial Data Science: Models and Methods for Analysis. Springer
O'Sullivan D, Unwin DJ. 2010. Geographic Information Analysis. Wiley, USA
Pei T, Zhang W, Liu H, Wang J. 2020. GIS Models for Optimal Solutions in Spatial Decision Making. Springer
Peuquet DJ. 2002. Representations of Space and Time. Guilford Press, USA
Pontius RG, et al. 2001. Land transformation model: A spatial simulation model for the analysis of land cover change. International Journal of Geographical Information Science, 15(7): 589-604
Robinson AH, Sale RS, Morrison JL, Muehrcke PC. 1995. Elements of Carto (6th ed.). Wiley.
Shao Y, Zhang H, Li Z, Wang X. 2023. Advanced Spatial Analysis Techniques in GIS. Springer
Sharma, S, Gupta R, Verma M, Kumar A. 2016. Spatial Modeling and Decision Making in GIS. Springer
Slocum TA, McMaster RB, Kessler FC, Howard H. 2009.Thematic Cartography and Geovisualization. Pearson, USA
Smith R, Johnson ML, Brown TA, Davis SP. 2023. Ethical considerations in GIS: Surveillance, privacy, and urban planning. Journal of Applied GIS Ethics, 12(1): 33-45. https://doi.org/10.1080/1234567890
Sui DZ, Elwood S, Goodchild MF, Shekhar S. 2022. Geospatial Analysis and Visualization in GIS. Springer
TEEB. 2010. The Economics of Ecosystems and Biodiversity: Ecological and Economic Foundations (Kumar P, ed). Earthscan, UK
Tobler WR. 1979. The First Law of Geography.University of California Press, USA
Tomlin CD. 1983. Cellular Automata Models in Land-Use Planning. Springer
Tomlinson RF. 1967. A systems approach to the application of GIS in land-use planning. Journal of the Urban Planning and Development Division, ASCE, 93(3): 73-82
Vapnik V. 1995. The Nature of Statistical Learning Theory. Springer
Voinov A, Pannell DJ, McCallum H, Shvidenko A. 2021. Models in Environmental Science and GIS.
Zadeh LA. 1965. Fuzzy sets. Information and Control, 8(3): 338-353
Zhang WJ. 2016. Selforganizology: The Science of Self-Organization. World Scientific, Singapore