Intelligent Chorems: Towards AI-Augmented Predictive Mapping

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Abstract— ***Chorems are schematic visual constructs designed to synthesize and communicate the spatial structure of territories. While traditionally static and manually designed, recent developments have enabled their animation and partial automation using geographic data. However, their integration with artificial intelligence for dynamic forecasting and exploratory analysis remains underexplored. In this paper, we introduce the concept of intelligent predictive chorems, AI-driven representations that not only reflect current spatial patterns but also anticipate their future evolution. Our methodology combines deep learning for spatio-temporal forecasting with spatial clustering and generalization techniques to construct interpretable geovisual summaries. These predictive chorems are generated automatically and displayed over simplified territorial backdrops, enabling both expert users and non-specialists to grasp complex trends in space and time. Applied to urban mobility data, our approach demonstrates how predictive chorems can serve as powerful tools for scenario exploration, planning, and real-time decision support. The results highlight their potential to bridge the gap between data-driven forecasts and human-centered spatial reasoning—positioning this approach as a promising bridge toward a new generation of intelligent geovisual tools.***

Keywords-component: Intelligent chorems, Deep Learning, Intelligent geovisualization, Automated Cartography, Geographic prediction.

I. INTRODUCTION

In today's data-rich environment, the continuous production of spatio-temporal information from sensors, open data platforms, and urban mobility systems presents both an opportunity and a challenge for understanding territorial dynamics [21, 4, 3]. The mere accumulation of raw data is insufficient; there is a pressing need for intelligent methods capable of synthesizing and revealing trends, explaining spatial phenomena, and most importantly, forecasting their future evolution [33, 7]. Traditional cartographic approaches, especially those involving direct projection of temporal data, often fall short in conveying meaningful insights, particularly when dealing with complex or rapidly changing environments. This has given rise to the field of predictive geovisualization, at the crossroads of artificial intelligence using deep learning, spatial analysis, and schematic cartography [30].

Among various visual synthesis tools, chorems — schematic constructs introduced by Roger Brunet in his seminal work — offer a compelling way to represent the structural organization of space [11]. Originally designed for static and manual use, chorems are increasingly being explored for dynamic applications, aided by automation, animation, and spatial analysis technologies [8, 9, 16]. However, their integration with predictive intelligent frameworks remains limited. Bridging chorems with automated forecasting techniques represents a novel and timely contribution toward creating intelligent, interpretable geovisual tools that facilitate spatial decision-making.

This study introduces a new approach for generating predictive chorematic maps using deep learning models to model and forecast complex spatio-temporal processes. The proposed methodology combines temporal prediction with spatial clustering and cartographic generalization [10], producing visual summaries in the form of chorems that represent not only current spatial patterns but also their anticipated evolution.

Applied to urban mobility data this method captures and forecasts flows over time, enabling a clearer understanding of both regular and emergent spatial dynamics. To the best of our knowledge, this represents the first attempt to integrate deep learning-based spatio-temporal forecasting with chorem-based geovisualization into a unified, automated framework. The goal is twofold: to provide intuitive visual representations, and to offer actionable insights for planners, analysts, and decision-makers through a data-driven, yet human-interpretable, mapping system.

The remainder of this paper is structured as follows. We first review related work in geovisualization, schematic cartography, and AI-based forecasting. We then present the core components of our methodology, followed by an implementation and case study. The paper concludes with a discussion of preliminary results, limitations, and future research directions.

II. BACKGROUND AND STATE OF THE ART

In this section, we briefly discuss related works required to understand our research.

A. Chorems

The concept of the chorem was introduced in the 1980s by French geographer Roger Brunet, as part of his work within the RECLUS research group (Réseau d'étude des changements

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dans les localisations et les unités spatiales). In his foundational work "*La composition des modèles dans l'espace"* [11], he defines chorems as schematic representations of territory, designed to highlight the underlying spatial structures.

The word *"*chorem*"* derives from the Greek *χώρα* (*chôra*, meaning space, territory, or place and the suffix -*ημα* (-*éma*), which denotes a conceptual object — as in the word *"problem"*. A chorem can thus be understood as a minimal unit of spatial structuring, a kind of molecule of space intended to model territorial forms and dynamics. Originally designed as pedagogical and analytical tools in geography, chorems have gradually been used to formalize complex spatial models. They offer schematic representations of structures such as networks, polarizations, gradients, and centralities [15]. By reducing territorial complexity into simplified graphical forms, chorems facilitate the comparison of territories that exhibit recurring spatial structures—an approach already demonstrated in Roger Brunet's foundational work [11, 15]. Brunet proposed a classification of chorems into seven categories of fundamental spatial structures — such as polarization, networking, gradients, centrality, and hierarchy — each represented by a standardized graphic form (point, line, circle, arrow, network, etc.). These visual forms are associated with territorial meanings, creating a visual grammar that supports the modeling, interpretation, and comparison of spatial systems. Chorems have been widely used in atlases, regional geography studies, territorial planning strategies, and comparative analyses [12, 20].

Thanks to their capacity for simplification, chorems have also become an effective means of visually translating complex geographic concepts. They provide a synthetic graphic language that makes spatial information accessible to a wide range of audiences [26]. This explanatory potential has made them a valuable tool for constructing operational spatial typologies, particularly in the fields of urban planning and territorial development [13].

Over the years, the use of chorems has expanded into various fields of application. In thematic cartography, chorems have enabled the schematization of territorial issues at multiple scales [11, 13, 28]. They have also been incorporated into comparative territorial analyses, where they serve to identify and contrast similar spatial logics [6]. More recently, their potential has been explored in the fields of geomarketing and territorial foresight, where they function as strategic visual tools for planning and decision-making support [6].

In recent years, much work has been carried out about chorems as visual summaries of geographic databases providing a novel definition and classification of chorems, in order both to standardize the construction and use of chorems, and to provide a useful framework computer system [17]. In [16] the authors enhance the role that a chorem map may play in geographic domains, by extending the semantics associated with it through a more expressive visual notation. In particular, by adopting the revisited Schneiderman's mantra, namely "*Overview, zoom and filter, details on demand*" [16], each allow users to acquire information about a single phenomenon by accessing data characterizing it from the underlying database. Cherni et al. [14] have proposed some methodological aspects to automatically extract chorems. In addition, [29] includes chorems as possible methods to represent visually geographic knowledge. Visual summaries based on chorems can be considered as a specific type of thematic map with a higher degree of generalization and abstraction. As previously told, generalization is a cartographic process but not the only existing cartographic process [32].

More recently, [8, 9] involve visualizing sensor data on a map with dynamic updates, often using interactive elements. These visualizations can highlight spatial patterns, temporal trends, and anomalies, and they are used in various applications like smart cities, environmental monitoring, and disaster response.

B. Visual *Analytics and Predictive Geovisualization*

Visual Analytics is an interdisciplinary field situated at the intersection of interactive visualization, data analysis, and artificial intelligence. Its primary goal is to support human analytical reasoning through dynamic, interpretable, and exploratory [1,24]. In spatial contexts, Visual Analytics enables analysts to detect trends, anomalies, and spatial structures within large, complex, and multivariate datasets.

Geovisualization aims at visually representing spatial phenomena for purposes of exploration, analysis, or communication. It becomes intelligent when it incorporates techniques from artificial intelligence, machine learning, or automated data stream processing [27]. These technologies enable the automatic detection of spatial and temporal patterns [22], the adaptive adjustment of cartographic content to user profiles or contexts [2], and enhanced human-computer interaction through the partial automation of analytical tasks. The integration of predictive models such as, neural networks, time series forecasting, or spatio-temporal models, has given rise to predictive visualization, which allows for the cartographic display of future projections (e.g., traffic, pollution, urban dynamics), the combination of forecasts and uncertainty in interactive displays [37] and support for real-time decision-making in contexts such as smart cities or crisis management. The convergence of artificial intelligence, visualization, and GIS paves the way for a new generation of intelligent and predictive geovisualization tools, which leverage deep learning models (e.g., LSTM, GNN) to anticipate spatial dynamics [39], generate adaptive and self-explanatory smart maps, and empower decision-makers with proactive, interpretable, and dynamic spatial analysis environments. By combining exploratory analysis, predictive modeling, and interactive interfaces, visual analytics applied to geography offers powerful perspectives for steering complex territorial systems and facilitating insight-driven decisions [35, 31]. In our work, we build on this philosophy by proposing a geovisual framework based on predictive visual summaries, aiming to make forecasting results more accessible, interpretable, and actionable for decision-makers and urban planners.

C. *Research overview*

Despite significant advances in spatio-temporal modeling and geovisualization, existing approaches still face important limitations when it comes to interpreting and communicating complex spatial dynamics. Traditional GIS-based tools and data-driven dashboards often rely on dense, map-heavy visualizations that are not always readable by non-experts and tend to lack semantic abstraction. Moreover, while deep learning models have improved the accuracy of spatio-temporal forecasting, their integration into visual reasoning workflows remains limited. These models are frequently seen as black boxes, providing little intuitive or visual feedback to support human decision-making.

In the field of cartographic schematization, chorems have proven effective for representing territorial structures through a synthetic and interpretable visual grammar. However, they have rarely been combined with real-time data or AI-based forecasting, remaining mostly static and manually designed. Consequently, there is a lack of approaches that can both predict spatial dynamics and represent them through abstract yet intelligible forms, especially for use in planning, crisis management, or urban foresight.

In this paper, we propose a novel framework for Predictive Chorem-Based Geovisualization, which aims to bridge this gap. By combining LSTM-based deep learning [23] for spatio-temporal forecasting with chorematic schematization techniques, we introduce a method that can automatically generate interpretable visual summaries of future spatial patterns. This contribution positions itself at the intersection of AI-driven prediction**,** geographic abstraction, and interactive geovisual tools, offering a new pathway for human-centered spatial intelligence.

III. METHODOLOGY : CHOREMS AND ARTIFICIAL8 INTELLIGENCE – TOWARDS A NEW PREDICTIVE GEOVISUALIZATION

In this section, we present how the challenges outlined above are addressed through our proposed methodology. Our approach is structured as a multi-step pipeline designed to transform raw spatio-temporal data streams into interpretable and predictive chorem-based visualizations. The methodological process unfolds as follows:

A. Case Study: Urban Mobility Forecasting

We applied our predictive geovisualization pipeline to a real-world dataset of bicycle flow measurements collected across the city of Paris[1]. The dataset spans a full 12-month period, from June 2023 to May 2024, and was obtained from a network of urban sensors managed by the city's open data platform. These sensors, installed at various locations across the Paris metropolitan area, continuously record the number of bicycles passing by at hourly intervals (Figure 2).

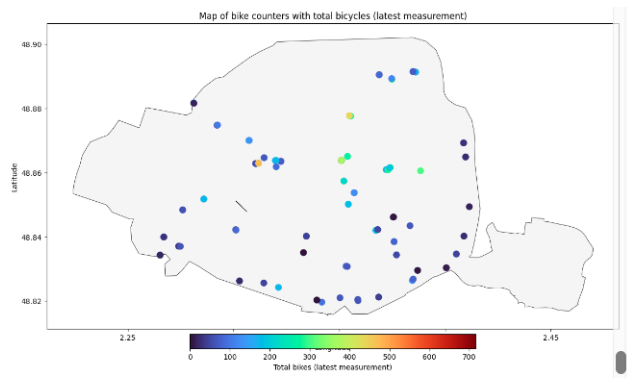

Figure 1. Traditional dot map of the current state of bicycle flows in Paris

B. *Overview of the Architecture*

The proposed approach architecture is organized as a modular processing pipeline designed to transform raw spatio-temporal data into interpretable predictive chorems. As illustrated in the global workflow diagram (Figure 2).

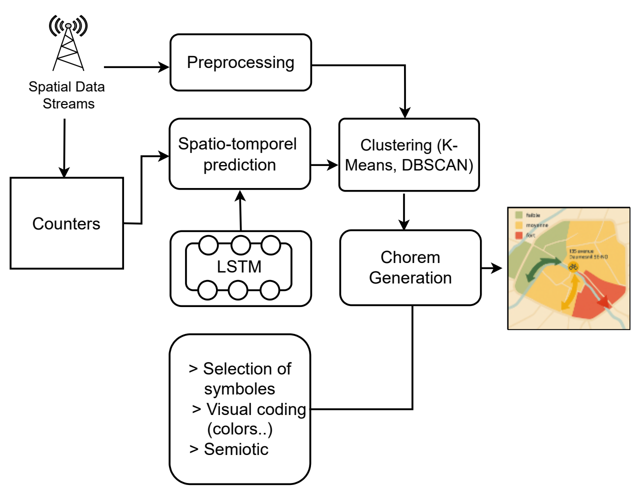

Figure 2. The proposed approach structure.

The pipeline is composed of five core stages:

[1] https://opendata.paris.fr/pages/home/

(1) **Data acquisition and preprocessing**, where spatio-temporal data from urban sensors (e.g., bicycle counters, weather APIs) are collected, cleaned, and structured;
(2) **Forecasting** future mobility flows at an hourly resolution based on counting data collected from urban sensors, using Long Short-Term Memory (LSTM) neural networks [27];
(3) **Clustering**, where unsupervised algorithms K-Means2 [34] and DBSCAN (Density-Based Spatial Clustering of Applications with Noise**)** [18], are applied to group sensors with similar behavioral or spatial characteristics;
(4) **Generalization**, in which territorial structures are abstracted and simplified through geometric and semantic generalization; and finally,
(5) **Predictive Chorem Generation**, where these stylized patterns are encoded into visual elements based on chorematic principles to support intuitive geographic interpretation and decision-making.

C. *Spatio-Temporal Forecasting with LSTM*

To anticipate future patterns of urban bicycle mobility, we implemented a Long Short-Term Memory (LSTM) neural network tailored for spatio-temporal sequence forecasting. The forecasting pipeline begins with the preprocessing of time series data collected from urban counting stations. Daily counts are aggregated, missing values interpolated, and all features standardized. Temporal metadata, such as the day of the week, holidays, and season indicators, are encoded and concatenated as auxiliary inputs.

The architecture of the model consists of one or more stacked LSTM layers, followed by a fully connected dense output layer. Each input sequence corresponds to a sliding window of historical observations, typically spanning seven consecutive days (`seq_length = 7`), which are used to predict the value on the eighth day. In its current configuration, the model performs short-term next-step prediction, producing a single output point for each input window (Figure 3).

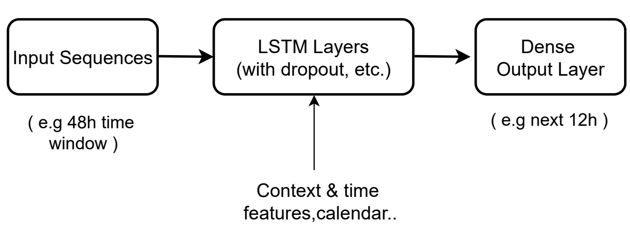

Figure 3. LSTM-based spatio-temporal forecasting pipeline.

This strategy emphasizes immediate trend detection rather than long-term forecasting. Extending the system to multi-step forecasting (e.g., for predicting bicycle flows over a full week or month) remains an important direction for future work.

To ensure robust generalization, we applied time-aware cross-validation strategies, such as training on several months and testing on unseen time intervals. The model's accuracy is assessed using evaluation metrics including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Model hyperparameters, such as the number of layers, hidden units, learning rate, and dropout rate, are optimized through grid search, and early stopping is employed to prevent overfitting.

The LSTM outputs are then forwarded to the clustering module, where predicted flow values are spatially grouped and transformed into symbolic structures via chorematic abstraction. This enables the synthesis of predictive maps that not only anticipate future mobility intensities but also encode them in an interpretable and spatially structured way.

D. *Spatial Generalization and Chorem Generation*

Once the spatio-temporal clusters are defined, we proceed to spatial generalization in order to produce stylized chorem-like regions. This involves several geometric processing steps:

First, a densification step is applied, using small jitter or random displacement to avoid perfect overlaps of clustered points. Then, buffer zones are created around each group of sensors to approximate the spatial influence of each cluster. These buffers are merged using topological union operations to generate contiguous, interpretable regions.

To construct smooth and coherent outlines, we apply Alpha Shape algorithms [19] to extract non-convex hulls around grouped points, followed by geometric simplification to reduce visual noise while preserving spatial structure. The result is a set of chorematic zones — symbolic areas that reflect the spatial organization of predicted flows.

Finally, we enrich each zone with directional arrows whose orientation and thickness encode the predicted flow direction and intensity. These visual elements are grounded in chorem semiotics and enable a schematic but meaningful depiction of territorial dynamics.

IV. PRELIMINARY RESULTS AND DISCUSSION

This section presents the preliminary results of our proposed predictive chorem-based geovisualization framework. The analysis focuses on the effectiveness of LSTM-based forecasting, the spatial clustering outputs, and the visual synthesis of predictive chorems.

We first trained the LSTM model on 80% of the available data, covering 12 months of hourly bike traffic collected from urban sensors in Paris. The remaining 20% was used for testing. The model successfully captured temporal trends, particularly weekday/weekend variations and seasonal fluctuations. The predicted values were then classified into three traffic flow levels (low, medium, high) and aggregated by spatial clusters obtained using DBSCAN and K-Means algorithms.

From a qualitative standpoint, the generated maps highlighted recurrent spatial structures such as radial centralities and flow corridors. These features were more difficult to interpret in dense heatmaps. However, several limitations remain: the precision of the predictions depends strongly on the temporal granularity of the training data, and the current visuals lack real-time interactivity or explicit uncertainty representation. The performance of the LSTM model on the test set is in (Table 1).

TABLE I. THE PERFORMANCE OF THE LSTM MODEL

Metrics	Values
RMSE	12.4
MAE	8.7
MAPE	11.3%
Accuracy (Predicted class)	84.6%

To illustrate the outcomes of our predictive pipeline, we developed a chorem-based predictive map of bicycle flows in Paris (Figure 4).

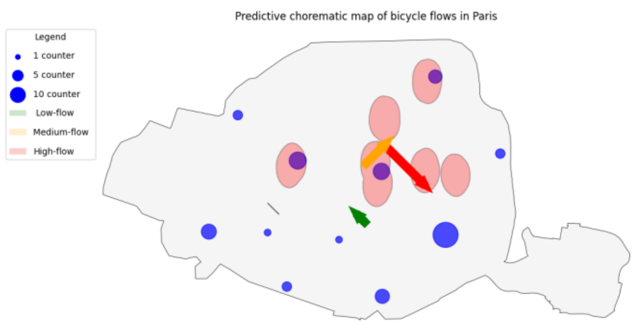

Figure 4. The predictive chorematic map of bicycle flows in Paris

This geovisualization integrates three types of chorems, each tailored for practical use in urban analysis and territorial planning:

- **Geographic chorems**, depicted through points, lines, and polygons, represent the spatial structure of the city and the location of counting stations;
- **Phenomenological chorems**, in the form of colored zoning areas and directional arrows, convey the intensity and dominant direction of predicted bicycle flows;
- **Annotation chorems** highlight strategic zones, anomalies, or noteworthy patterns revealed through data analysis.

Based on the predicted bicycle flow values, counting stations were classified into three categories (low, medium, and high intensity). These categories were then spatialized into zones that abstract the complexity of urban space and reveal structural patterns within the cycling network. Arrows placed at the centroid of each zone indicate the dominant flow direction and relative intensity, while the size of the blue circles reflects the density of counters in each area.

Compared to a traditional dot map (Figure 1), this chorem-based representation offers several major advantages. It simplifies interpretation by aggregating individual stations into coherent zones, highlights strong and weak spatial polarities, and structures the map according to functional logic. This schematic approach enables rapid identification of high-flow corridors and areas where infrastructure adjustments may be necessary.

From a semiological standpoint, the map design draws on the principles of graphic semiology formulated by [5] using color, size, shape, and orientation to encode variables such as flow intensity, direction, and temporal dynamics. This methodological choice ensures a scalable, interpretable, and synthesized representation of complex spatio-temporal phenomena — moving beyond traditional descriptive mapping.

Our approach stands apart from conventional representations like heatmaps [38], glyph-based maps [25] or vector-based flow diagrams [36] which often produce dense, hard-to-read visuals that hinder structural understanding. In contrast, predictive chorems provide a schematic and generalized perspective, focused on dominant spatial structures such as centralities, gradients, and polarizations, thus supporting comparative spatial analysis.

When combined with time-series forecasting models such as LSTMs, chorems become an effective tool for visual forecasting, offering actionable insights for urban planners and decision-makers in dynamic urban contexts. These preliminary results underline the strong potential of predictive chorems as a synthetic, intelligible, and decision-oriented geovisualization method for modeling urban mobility patterns.

V. CONCLUSION AND PERSPECTIVES

This work introduces an innovative approach to predictive geovisualization by combining deep learning techniques with spatial abstraction through predictive chorems. By integrating spatio-temporal forecasting using LSTM neural networks, data clustering, and schematic synthesis, we demonstrated how raw data from urban sensors can be transformed into intelligible and structured maps that support spatial reasoning and strategic planning.

While promising, the current results remain preliminary. Future improvements will focus on enhancing the predictive accuracy of the models, enriching the input data with contextual variables (such as weather or calendar data), and increasing both the readability and interactivity of the generated maps. These developments are crucial to reinforce the operational relevance of predictive chorems in real-world decision-making scenarios.

The integration of more advanced AI models, such as spatio-temporal transformers or graph neural networks (GNNs), presents another promising avenue to improve both the accuracy of forecasts and the expressiveness of spatial representations.

In summary, this research lays the groundwork for a new generation of predictive, structured, and user-centered geovisualization at the intersection of artificial intelligence, cartography, and decision support.

REFERENCES

[1] 1 A. Ain, A.R Zamir, S. Savarese, A. Saxena, Structural-RNN: “Deep Learning on Spatio-Temporal Graphs”,

Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp.5308–5317. https://doi.org/10.1109/CVPR.2016.574.

[2] G. Andrienko, N.Andrienko, " Exploratory Analysis of Spatial and Temporal Data: A Systematic Approach" , Berlin: Springer-Verlag, 2006, https://doi.org/10.1007/3-540-31190-4.

[3] N. Andrienko, G. Andrienko, " Visual analytics of movement: An overview of methods", tools and procedures, 2013, Information visualization, vol. 12(1),pp. 3-24.

[4] M. Batty, K. W. ,F. Axhausen, Giannotti , A. Pozdnoukhov,A. Bazzani, M. Wachowicz, Y. Portugali, " Smart cities of the future", The European Physical Journal Special Topics, 2014, vol. *214*, pp.481-518.

[5] J. Bertin, " Semiology of Graphics: Diagrams, Networks", Maps. Madison: University of Wisconsin Press, 1983, Original work published in 1967.

[6] P. Bonnin, J.P. Cheylan, J, " Les chorèmes, un outil d'analyse spatiale pour la comparaison de territoires", In S. Lardon, P. Maurel, & S. Piveteau (Eds.), La modélisation graphique des structures spatiales : les chorèmes, 2002, pp. 95–110, Clermont-Ferrand : INRA SAD.

[7] Z. Bouattou, H. Belbachir, R. Laurini, "Automatic generation of an interactive, real time, web-based maps from sensor-based geographic databases", In 22nd International Conference on Distributed Multimedia Systems, 2016, November, pp. 98-104.

[8] Z. Bouattou, R. Laurini, H. Belbachir, "Animated chorem-based summaries of geographic data streams from sensors in real time", Journal of Visual Languages & Computing, 2017, vol. *41*, pp.54-69.

[9] Z. Bouattou,H. Belbachir, R. Laurini, R. " Multi-agent system approach for improved real-time visual summaries of geographical data streams, International Journal of Intelligent Systems Technologies and Applications, 2018, 17(3), pp. 255-271.

[10] K.E. Brassel, R. Weibel, " A review and conceptual framework of automated map generalization", International Journal of Geographical Information System, 1988, vol.2(3), pp.229-244.

[11] R. Brunet, "La Carte-Modèle et les chorèmes", Mappemonde, vol.46, 1986, pp. 2-6.

[12] R. Brunet, "La carte, mode d'emploi", 1987.

[13] R. Brunet, "Les mots de la géographie : dictionnaire critique." Montpellier : Reclus / La Documentation française, 1990.

[14] I. Cherni,S. Faiz, R. Laurini, R, M. Warghi, " ChoreMAP: extracting and displaying visual database summaries tool", 2015, ThinkMind eKNOW.

[15] J.P. Cheylan, T. Libourel, C. Mende, " Graphical Modelling for Geographic Explanation" Spatial Information Theory A Theoretical Basis for GIS. Proceedings, International Conference COSIT '97, Laurel Highlands, Pennsylvania, USA, October 1997, vol 15.18, pp. 473-483.

[16] D. De Chiara, V. Del Fatto,R. Laurini, M. Sebillo, G. Vitiello, "A chorem-based approach for visually analyzing spatial data", Journal of Visual Languages & Computing, 2011, vol. *22*(3), pp.173-193.

[17] V. Del Fatto, R. Laurini, K. Lopez, M. Sebillo, G. Vitiello, "A chorem–based method for visualizing evolutionary scenarios", Inf. Visual, 2008, Vol. 7 (3)

[18] M. Ester,H.P. Kriegel, J. Sander, X. Xu, " A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise", In Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD '96), 1996, pp. 226–231. AAAI Press.

[19] T. Etherington, " Mapping uncertain spatial object extents from point samples using fuzzy alpha-shapes", Journal of Spatial Information Science, 2023 , vol. 26, pp. 1–22. arxiv.org+15

[20] R. Ferras , "Les modèles d'organisation de l'espace", Armand Colin, 1992.

[21] M. F. Goodchild, "Citizens as sensors: the world of volunteered geography", GeoJournal, 2007, vol.69, pp.211-221.

[22] M.F. Goodchild, M. Yuan, T.J. Cova, " Towards a general theory of geographic representation in GIS", International Journal of Geographical Information Science, 2007,vol. 21(3), pp. 239–260. https://doi.org/10.1080/13658810600965271.

[23] S. Hochreiter,J.Schmidhuber,"*Long Short-Term Memory*" Neural Computation, 1997, vol. 9(8), pp. 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735.

[24] D. A. Keim, G. Andrienko, J.D. Fekete, C. Görg, J. Kohlhammer, G. Melancon, "Visual Analytics: Definition, Process, and Challenges", Information Visualization, Springer, 2008, pp. 154–175.

[25] D.A. Keim, HP. Kriegel, " Visualization Techniques for Mining Large Databases: A Comparison", IEEE Transactions on Knowledge and Data Engineering, 2002, vol. 8(6),pp.923–938. https://doi.org/10.1109/69.553161.

[26] M.J. Kraak, A. MacEachren, " Visualization for exploration of spatial data", International Journal of Geographical Information Science, 1999, vol. 13(4), pp. 285-287.

[27] M.J. Kraak, " Geovisualization illustrated", ISPRS journal of photogrammetry and remote sensing, 2003,vol. *57*(5-6), pp.390-399.

[28] S. Lardon, J. Brossier, V. Piveteau, " Territoires, modèles de dynamique et outils de représentation", In J. Brossier, V. Piveteau & S. Lardon (Eds.), Territoires agricoles et développement territorial, 2001, pp. 53–77, INRA Éditions.

[29] R. Laurini, "A conceptual framework for geographic knowledge engineering, Journal of Visual Languages & Computing, 2014, vol. *25*(1),pp. 2-19.

[30] R. Laurini, R.M. Donolo, "Computer-Assisted Visual Reasoning for Territorial Intelligence", Journal of Visual Languages & Computing, 2022, vol. 2,pp. 1-11.

[31] P. Luo, C. Chen,S. Gao, X. Zhang, D. Majok Chol,Z.Yang, Z., & L. Meng, "Understanding of the predictability and uncertainty in population distributions empowered by visual analytics", International Journal of Geographical Information Science, 2025, vol. 39(3), pp. 675-705.

[32] A.M. MacEachren, M.J. Kraak, "Exploratory cartographic visualization: advancing the agenda", Computers & Geosciences, vol 23(4), 1997, 335-343.

[33] A.M. MacEachren, M.J. Kraak, "Research challenges in geovisualization", Cartography and geographic information science, 2001, vol.28(1), pp.3-12.

[34] 11 J. MacQueen, " Some Methods for Classification and Analysis of Multivariate Observations", In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 1967,Vol. 1, pp. 281–297. University of California Press.

[35] 31 S.D. Nagappan, S. M. Daud, " Machine Learning Predictors for Sustainable Urban Planning ", International Journal of Advanced Computer Science and Applications, 2021, vol. 12(7), pp.772–780. https://doi.org/10.14569/IJACSA.2021.0120787

[36] 7 D. Phan, L. Xiao,R. Yeh, P. Hanrahan, T. Winograd, **"** Flow Map Layout", IEEE Symposium on Information Visualization (InfoVis 2005), *2005,pp.219–224.* https://doi.org/10.1109/INFVIS.2005.1532143

[37] 13 J. Sanyal, S. Zhang, G. Bhattacharya, P. Amburn, R. Moorhead, " A User Study to Compare Four Uncertainty Visualization Methods for 1D and 2D Datasets", IEEE Transactions on Visualization and Computer Graphics, 2009, vol. 15(6), pp. 1209–1218. https://doi.org/10.1109/TVCG.2009.114.

[38] 16 L.Wilkinson,M.Friendly, "The History of the Cluster Heat Map", The American Statistician, 2009, vol. 63(2), pp.179–184. https://doi.org/10.1198/tas.2009.0033.

[39] 14 J. Zhang,Y.Zheng, D. Qi, " Deep Spatio-Temporal Residual Networks for Citywide Crowd Flows Prediction ", Proceedings of the AAAI Conference on Artificial Intelligence, 2017, vol. 31(1). https://doi.org/10.1609/aaai.v31i1.11299.