# Chapter 3: Literature Review

Spatio-Temporal Analytics for Ecological Monitoring

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## 3.1 Exhaustive Survey

The literature surrounding spatio-temporal analytics for ecological and environmental monitoring has evolved significantly over the past two decades. The research can be broadly categorized into three distinct eras and technological paradigms: Classical Big Data, Modern Machine Learning, and Emerging Sensor/Quantum-Inspired Trends.

### Classical Big Data and Spatial Statistics

Early approaches to spatio-temporal data primarily relied on adapting classical spatial database management systems (RDBMS) and initial Hadoop frameworks to accommodate massive geographic datasets [1]. Frameworks such as SpatialHadoop and Hadoop-GIS pioneered the use of MapReduce for spatial data processing, while systems like SciDB were built specifically for complex analytics on multi-dimensional array data [2], [3]. Furthermore, foundational spatial design and sampling techniques, such as the Generalized Random Tessellation Stratified (GRTS) design, allowed researchers to monitor non-Gaussian spatio-temporal data effectively, optimizing resources across complex ecosystems like stream networks and wetlands [4], [5]. Traditional geographic information systems (GIS) and remote sensing indices, including NDVI and NDBI, formed the backbone of these classical environmental assessments, enabling the measurement of deforestation, crop productivity, and landscape degradation [6], [7].

### Modern Machine Learning and AI

Recent years have witnessed a paradigm shift toward Deep Learning, distributed in-memory computing, and Bayesian analytics. Spatio-temporal machine learning (ML) models—such as Convolutional LSTMs (ConvLSTM) and Spatio-Temporal Graph Neural Networks (ST-GNNs)—outperform classical models by up to 35% in predictive accuracy when forecasting vegetation health, soil moisture, and flood susceptibility [8], [9]. Scalable probabilistic frameworks like Bayesian Neural Fields (BayesNF) have also emerged, combining the high-capacity function approximation of deep neural networks with hierarchical Bayesian modeling to provide robust uncertainty quantification for climate and public health datasets [10], [11]. At the regional scale, ensemble methods like the CatBoost model and Geographically Weighted Regression (GWR) are being utilized to decode the complex, non-stationary driving factors behind the Remote Sensing Ecological Index (RSEI) in rapidly transforming mining and lake basin areas [12], [13].

### Blockchain, IoT, and Next-Generation Trends

The proliferation of low-cost wireless sensor networks (WSNs) and the Internet of Things (IoT) has introduced Eulerian and Lagrangian data collection techniques that generate continuous streams of spatio-temporal observations [14]. To handle real-time anomaly detection in these dynamic environmental monitoring campaigns (such as water quality or edge-device sensor data), Dynamic Bayesian Networks (DBNs) and automated quality control algorithms are deployed to distinguish true sensor failures from valid ecological anomalies [15], [16]. Researchers are also leveraging two-dimensional wavelet analysis and automated telemetry topology (e.g., the STAMP method) to map wildlife home range drifts and capture multi-scalar landscape patterns without relying entirely on uniform sampling assumptions [17], [18], [19].

## 3.2 Gap Analysis

Despite the proliferation of SCI-indexed research in Big Data spatial analytics, existing literature frequently overlooks the complexities of anisotropic spatial dependency and temporal non-stationarity [20], [21]. Many classical ML models erroneously assume that spatio-temporal data points are independent and identically distributed (i.i.d.), ignoring Tobler's First Law of Geography [22]. While significant advancements have been made in predictive modeling (e.g., ST-GNNs), translating these models into actionable, localized community resilience strategies remains underexplored [23], [24]. Furthermore, while systems exist for discrete spatial event data, continuous environmental domains (like dynamic water quality trends or real-time animal trajectory networks) still lack unified big data infrastructures that inherently integrate secure, immutable edge-computing ledgers and quantum-inspired optimization algorithms [25], [26]. This chapter fills that void by synthesizing advanced predictive Bayesian frameworks with localized socio-ecological metrics.

## 3.3 Theoretical Grounding

Current studies are firmly grounded in advanced spatial statistics and spatial econometrics. Foundational concepts such as Ripley's K-function, Moran's I for spatial autocorrelation, and Markov Random Fields (MRF) form the bedrock of the algorithmic designs reviewed [27], [28]. By utilizing hierarchical dynamic spatio-temporal models and partial differential equations (PDEs) for ecological diffusion [29], [30], modern analytics capture the continuous nature of environmental variables.

## 3.4 Summary Table of Analyzed Literature

The following table categorizes the 29 core research papers referenced in this review, outlining their methodologies and key contributions to the domain of spatio-temporal analytics for ecological monitoring.

Table 1: Summary of Reviewed Literature on Spatio-Temporal Analytics

| ID | Author(s) | Year | Title | Key Contribution / Focus |
|---|---|---|---|---|
| 1 | Williams, P. J., et al. | 2017 | Optimal dynamic survey designs for monitoring spreading populations | Fuses statistical models of population spread with dynamic survey designs utilizing ecological diffusion PDEs [31], [32]. |
| 2 | Dereszynski, E. W., & Dietterich, T. G. | 2011 | Spatiotemporal Models for Data-Anomaly Detection in Dynamic Environmental Monitoring Campaigns | Applies Dynamic Bayesian Networks (DBNs) for real-time automated data quality control and sensor anomaly detection [15], [16]. |
| 3 | Jiang, Z. | 2020 | A Survey on Spatial and Spatiotemporal Prediction Methods | Provides a comprehensive taxonomy addressing spatial autocorrelation, spatial heterogeneity, and multi-scale effects [33], [34]. |
| 4 | Alam, M. M., et al. | 2021 | A Survey on Spatio-temporal Data Analytics Systems | Reviews spatial RDBMS, NoSQL databases, and Big Data infrastructures (Hadoop, Spark) for ecological data [1], [35]. |
| 5 | Widodo, Y. E., & Singgalen, Y. A. | 2025 | Strategic Planning for Sustainable Development using Spatio-Temporal Analysis | Assesses the role of spatio-temporal trends to inform sustainable land management and governance [36]. |
| 6 | Crabtree, R., et al. | 2009 | A modeling and spatio-temporal analysis framework for monitoring environmental change using NPP... | Combines satellite data with the NASA-CASA model and spatial autoregression to monitor ecosystem health [37], [38]. |
| 7 | Wikle, C. K., & Royle, J. A. | 2004 | Dynamic Design of Ecological Monitoring Networks for Non-Gaussian Spatio-Temporal Data | Uses extended Kalman filter approximations to design spatially dynamic monitoring networks for non-Gaussian data [4]. |
| 8 | Singgalen, Y. A. | 2024 | Integrating Remote Sensing and Spatial Data for Ecological Sustainability through Spatio-temporal Analysis | Utilizes NDVI, NDBI, and SAVI models to track landscape urbanization and vegetation health [39], [40]. |

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| ID | Author(s) | Year | Title | Key Contribution / Focus |
|---|---|---|---|---|
| 9 | Tariq, N. | 2025 | A Spatio-Temporal AI Framework for Ecosystem Monitoring and Climate-Resilient Community Planning | Proposes the STRMF framework using ConvLSTM and ST-GNN models to predict flood and vegetation stress [23], [41]. |
| 10 | Manjakkal, L., et al. | 2021 | Connected Sensors, Innovative Sensor Deployment and Intelligent Data Analysis for Online Water Quality Monitoring | Reviews IoT buoys, autonomous robots, and AI-based real-time analysis for multi-parametric water monitoring [42], [43]. |
| 11 | Wu, M., et al. | 2023 | Editorial: Coastal environmental and ecological data analysis | Summarizes multivariate statistical analysis and data mining to evaluate coastal eutrophication and biodiversity [44], [45]. |
| 12 | Damalas, A. P. | 2005 | Landscape Ecology of Birds on Mount Leconte, Great Smoky Mountains National Park | Uses Tasseled Cap (T-CAP) indices and PCA to evaluate forest community spatial distribution and avian habitats [46], [47]. |
| 13 | Peterson, E. E., et al. | 2020 | Monitoring through many eyes: Integrating disparate datasets to improve monitoring of the Great Barrier Reef | Integrates crowdsourced citizen-science data with professional remote sensing to map coral reef environments [48], [49]. |
| 14 | Parrott, L., et al. | 2008 | Three-dimensional metrics for the analysis of spatiotemporal data in ecology | Replaces 2D landscape patches with 3D space-time "blobs" to calculate contagion and complexity metrics [50], [51]. |
| 15 | Nelson, T. A. | 2011 | Quantifying Wildlife Home Range Changes | Develops the STAMP method to track polygon topologies and quantify home range shifts using telemetry [52], [53]. |
| 16 | Chen, K., et al. | 2025 | Analysis of spatiotemporal evolution and driving factors of ecological environment quality in the Ili-Balkhash Lake Basin | Employs the Geographic Detector model to interpret RSEI drivers including LST, human impact, and ET [54], [12]. |
| 17 | Chen, L., et al. | 2025 | Spatiotemporal dynamics of ecological quality and its drivers in Shanxi Province and its planned mining areas | Integrates MODIS data, CatBoost, and Geographically Weighted Regression (GWR) for mining area management [13], [55]. |

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| ID | Author(s) | Year | Title | Key Contribution / Focus |
|---|---|---|---|---|
| 18 | Saad, F., et al. | 2024 | Scalable Spatiotemporal Prediction with Bayesian Neural Fields | Introduces BayesNF, combining deep learning with hierarchical Bayesian inference for continuous space-time forecasting [56]. |
| 19 | Baratchi, M., et al. | 2013 | Sensing Solutions for Collecting Spatio-Temporal Data for Wildlife Monitoring Applications: A Review | Reviews Eulerian and Lagrangian WSN solutions (RFID, acoustic, radar) for fine-grained animal tracking [57], [14]. |
| 20 | Dobbie, M. J., et al. | 2008 | Sparse sampling: Spatial design for monitoring stream networks | Synthesizes model-based and probability-based spatial sampling designs for complex aquatic populations [5], [58]. |
| 21 | Albani, M. | 2001 | Spatial Analysis in a Successional Perspective: A Boreal Mixedwood Landscape in Northeastern British Columbia | Evaluates DEMs and satellite RS to map topographic gradients and succession in boreal forest landscapes [59], [60]. |
| 22 | Teisseire, M. | 2016 | Spatio-Temporal Data Mining: From Big Data to Patterns | Examines trajectory mining, spatial co-locations, and sequential pattern mining for environmental big data [61], [62]. |
| 23 | Darmawan, S., et al. | 2016 | Spatio-temporal Deforestation Measurement using Automatic... | Applies Fuzzy C-Means and K-Means clustering on MODIS EVI data to temporally track deforestation [63], [7]. |
| 24 | Shekhar, S., et al. | 2015 | Spatiotemporal Data Mining: A Computational Perspective | Reviews statistical foundations for spatial outliers, tele-coupling, predictive modeling, and hotspots [64], [65]. |
| 25 | Yang, Y., & Gulbahar, Y. | 2025 | Spatiotemporal Modeling of Water Quality Trends in a Coastal Wildlife Refuge... | Uses time series decomposition and ANOVA to map local stressors driving DO and pH fluctuations [66], [67]. |
| 26 | Héas, P., & Datcu, M. | 2005 | Modeling Trajectory of Dynamic Clusters in Image Time-Series for Spatio-Temporal Reasoning | Creates semantic labeling of satellite image time-series via Bayesian hierarchical models and graphs [68], [69]. |

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| ID | Author(s) | Year | Title | Key Contribution / Focus |
|---|---|---|---|---|
| 27 | Anthony, J. A. M. | 2004 | Wavelet Analysis: Linking Multi-scalar Pattern Detection to Ecological Monitoring | Compares 1D and 2D wavelet transforms to Fourier spectra and semivariograms for non-stationary ecological data [19], [70]. |
| 28 | Ceccarelli, T., et al. | 2005 | An Application of Advanced Spatio-Temporal Formalisms to Behavioural Ecology | Integrates MADS conceptual schemas and MuTA-CLP logic programming with commercial GIS for animal mobility [71], [72]. |
| 29 | Radeva, K. | 2018 | Aspects and Perspective of Interim Ecological Monitoring Application on Ecosystems by Means of Remote Sensing | Promotes interim high-resolution satellite imagery for real-time wetland monitoring and biodiversity tracking [73], [74]. |