

DOI: <https://doi.org/10.5281/zenodo.14231256>

## ADVANCEMENTS IN MATHEMATICAL AND REMOTE SENSING TECHNIQUES FOR ECOLOGICAL MODELLING AND ENVIRONMENTAL IMPACT ASSESSMENT, A SYSTEMATIC REVIEW (2014-2024)

**Shakespear Chiphambo**

[schiphambo@wsu.ac.za](mailto:schiphambo@wsu.ac.za)

Walter Sisulu University, SOUTH AFRICA

### ABSTRACT

Understanding the complex dynamics of ecosystems and evaluating the long-term impacts of human activities is a significant and challenging task. Recent advancements in mathematical modelling have led to the development of more complex and accurate ecological models, which have the potential to revolutionize our understanding of ecosystems. Remote sensing technologies have improved to provide high-resolution data on ecosystem changes, offering unprecedented insights. Data analytics techniques have advanced to handle large and complex environmental datasets, opening up new possibilities for understanding and managing our environment. This paper reviews these and other recent advancements in 39 research papers from 2014 to 2024, highlighting their potential to impact ecological and environmental research profoundly. By integrating these techniques, researchers can enhance predictions of ecological changes and inform more effective conservation strategies, thereby shaping the future of our planet.

**Keywords:** Ecosystems, Mathematical Modelling, Remote Sensing, Data Analytics, Environmental Impact.

### 1. INTRODUCTION

Ecosystems are intricate networks of interactions among living organisms and their physical environment, making it challenging to predict the outcomes of human activities in these systems. Traditional ecological research methods often lack the sophistication to fully understand and predict these interactions (Henderson & Loreau, 2023; Mumby et al., 2014; Strauss, 2014). As human activities such as deforestation, pollution, and climate change continue to impact ecosystems globally, the urgency for advanced mathematical and scientific techniques to understand these complex systems better and assess long-term environmental impacts cannot be overstated (Krapivin et al., 2015; King et al., 2014; O'Neill et al. et al., 2014).

Recent developments in mathematical modelling, remote sensing, and data analytics offer promising new tools for addressing these challenges. Mathematical models have become increasingly sophisticated, incorporating various variables and interactions (Vink et al., 2021; Heymans et al., 2016; Villa et al., 2014). Remote sensing technologies have advanced, providing high-resolution data that can track environmental changes with greater accuracy (Zhao et al., 2020;

Wang et al., 2020; Manfreda et al. et al., 2018). Data analytics, particularly machine learning, has transformed how we interpret large datasets and predict future ecological trends (Zhong et al., 2021; Christin et al., 2019; Thessen, 2016). This implies a need to implement mathematical modelling, remote sensing, and data analytic tools to predict and track environmental changes for the benefit of the human community.

This paper explores the necessity of these advanced techniques, reviews recent advancements, and discusses their application in understanding ecological dynamics and assessing human impacts on the environment.

## **2. LITERATURE REVIEW**

### **2.1 Mathematical Modelling**

Mathematical modelling has seen significant advancements in recent years, providing more detailed and accurate representations of ecological systems. Dynamic systems models, which simulate ecosystem changes over time, have incorporated more complex variables and interactions (Vink et al., 2021; Kéry & Royle, 2020; Liqueste et al., 2016). These models help predict how ecosystems respond to various stressors, such as climate change and habitat loss (Heymans et al., 2016; Yin et al., 2017; Ernakovich et al., 2014).

Network analysis, a method used to study the relationships between different species within an ecosystem, has also advanced. Mantyka-Pringle et al. (2017) highlight network analysis to map species interactions and energy flows, which provides insights into ecosystem stability and resilience. These techniques are crucial for understanding how disruptions in one part of the network can affect the entire ecosystem (Liu et al., 2022; Aarikka-Stenroos & Ritala, 2017; Bairey et al., 2016).

### **2.2 Remote Sensing**

Remote sensing technologies have rapidly evolved, offering new capabilities for monitoring environmental changes. High-resolution satellite imagery and advanced sensors now provide detailed data on land use, vegetation cover, and other critical ecological parameters (Zhao et al., 2020; Wang et al., 2020; Manfreda et al., 2018). These technologies allow researchers to track deforestation, habitat fragmentation, and other changes in real time, providing valuable information for environmental management (Harris et al., 2021; Pajares, 2015; Lu et al., 2014).

Innovations in remote sensing also include using drones and unmanned aerial vehicles (UAVs) for high-resolution, localised monitoring (Mangewa et al., 2019; Deng et al., 2018; Gallacher, 2016). These tools offer fine-scale data that complement satellite observations and enhance human understanding of ecosystem dynamics (Lyu et al., 2022; Bhatnagar et al., 2021; Ivosevic et al., 2015).

### **2.3 Data Analytics**

The application of data analytics, particularly machine learning and big data techniques, has revolutionised ecological research. Machine learning algorithms can analyse vast datasets to identify patterns, predict trends, and assess ecological impacts with high precision (Zhong et al.,

2021; Christin et al., 2019; Thessen, 2016). These techniques are beneficial for modelling complex interactions and predicting the effects of various stressors on ecosystems (Lucas, 2020; Huntingford et al., 2019).

Big data analytics also allows for integrating diverse data sources, such as satellite imagery, field observations, and environmental data, providing a comprehensive view of ecological systems (Ustin & Middleton, 2021; Ullo & Sinha, 2020; Chi et al., 2016). This holistic approach enhances our ability to understand and manage ecological dynamics in the face of human-induced changes (Sun & Scanlon, 2019; Sharma et al., 2018; Yang et al., 2017).

### 3. METHODOLOGY

This conceptual paper is based on a comprehensive literature review from 2014 to 2024. The methodology involved synthesising findings from peer-reviewed journals, conference papers, and other scholarly sources related to advancements in mathematical modelling, remote sensing, and data analytics. Key sources were selected based on their relevance to the topic and contribution to advancing these techniques in ecological research.

The review focused on identifying recent developments in each area, assessing their applications in understanding ecological dynamics, and evaluating the long-term impacts of human activities. The analysis included theoretical advancements and practical applications, providing a comprehensive overview of how these techniques address current environmental science challenges. To synthesise literature from 2014 to 2024, a desktop review was done in journals, books, and graduates' theses. The literature search was conducted on Google Scholar and the Research Gate. The search for literature to address the title was based on the following criteria:

- Publication dates were considered to range from 2014 to 2024.
- Application: The articles were assessed whether they demonstrate the application of these advancements in ecological modelling or environmental impact assessment.
- Influence: The selection also reviewed the number of citations the article received, as highly cited papers often indicate influential research. The selected articles' citations range from 51 to 1343.
- Results and discussions: The researcher ensured that the results and discussion of every article selected highlight the advancements' significance and practical applications.
- Integration: The articles were assessed whether they integrate mathematical modelling and remote sensing techniques with ecological and environmental impact assessments, often providing a comprehensive view of advancements.

Table 1 below summarises the types of journals searched for this paper's relevant literature.

Source of articles	Number of articles
Journals	32
Books	2
Monographs	1
Systematics review	3
Conference Proceedings	1
<b>Total</b>	<b>39</b>

## 4. DISCUSSION

### 4.1 Enhancements in Mathematical Modelling

Recent advancements in mathematical modelling have provided new tools for understanding complex ecological interactions. Dynamic systems models, which simulate the behaviour of ecosystems over time, have become more sophisticated, incorporating a more comprehensive range of variables and interactions (Vink et al., 2021; Kéry & Royle, 2020; Liqueste et al., 2016). These models help predict how ecosystems respond to various stressors, such as climate change and habitat loss, by simulating different scenarios and assessing their potential impacts (Heymans et al., 2016; Segan et al., 2016; Ernakovich et al., 2014).

Network analysis has also advanced, offering insights into the structure and function of ecological networks. Recent studies have used network analysis to map species interactions and energy flows within ecosystems, providing a better understanding of ecosystem stability and resilience (Mantyka-Pringle et al., 2017; Aarikka-Stenroos & Ritala, 2017). These insights are crucial for identifying key species and interactions that are critical for ecosystem health and for developing strategies to mitigate the impacts of environmental changes (Liu et al., 2022; Yang et al., 2017; O'Neill et al., 2014).

### 4.2 Innovations in Remote Sensing

Advancements in remote sensing technologies have revolutionised the monitoring of environmental changes. High-resolution satellite imagery and advanced sensors provide detailed data on land use, vegetation cover, and other ecological parameters (Ustin & Middleton, 2021; Wang et al., 2020; Manfreda et al., 2018). These technologies enable researchers to track deforestation, habitat fragmentation, and other changes with greater accuracy, providing valuable information for environmental management (Harris et al., 2021; Pajares, 2015; Lu et al., 2014).

Using drones and UAVs has further enhanced remote sensing capabilities, offering high-resolution, localised monitoring that complements satellite observations (Mangewa et al., 2019; Deng et al., 2018; Gallacher, 2016). These tools provide fine-scale data that improves our understanding of ecological dynamics and allows for more precise assessments of environmental changes (Lyu, Li et al., 2022; Bhatnagar et al., 2021; Ivosevic et al., 2015). Integrating drone data with satellite imagery and field observations provides a comprehensive view of ecosystem changes, enabling more effective management and conservation strategies.

### 4.3 Advances in Data Analytics

Integrating machine learning and big data analytics into ecological research has transformed how we analyse and interpret large datasets. Machine learning algorithms can identify patterns, predict trends and highly assess ecological impacts, offering new insights into complex ecological interactions (Zhong et al., 2021; Christin et al., 2019; Thessen, 2016). These techniques are beneficial for modelling various stressors' effects on ecosystems and predicting future ecological states (Lucas, 2020; Huntingford et al., 2019).

Big data analytics enables the integration of diverse data sources, such as satellite imagery, field observations, and environmental data, providing a comprehensive view of ecological systems (Ullo & Sinha, 2020; Chi et al., 2016). This holistic approach enhances our ability to understand and manage ecological dynamics, allowing for more informed decision-making and better management of environmental resources (Sun & Scanlon, 2019; Sharma et al., 2018; Yang et al., 2017). The application of big data analytics also facilitates real-time monitoring and rapid response to environmental changes, improving the effectiveness of conservation and management efforts.

## 5. RECOMMENDATIONS

To fully leverage the advancements in mathematical modelling, remote sensing, and data analytics, the following recommendations are proposed:

**Integration of Techniques:** Combine mathematical modelling, remote sensing, and data analytics to create comprehensive ecological assessment and management frameworks. Integrating these techniques can provide a more complete understanding of ecosystem dynamics and improve the accuracy of predictions (Vink et al., 2021; Ustin & Middleton, 2021; Christin et al., 2019).

**Enhanced Collaboration:** Foster interdisciplinary collaboration among ecologists, data scientists, and remote sensing experts. Collaborative efforts can enhance the development and application of advanced techniques, leading to more effective solutions for addressing ecological challenges (Gallacher, 2016; Chi et al., 2016).

**Investment in Technology:** Nations must increase funding for research and development of advanced technologies. Supporting the continued advancement of mathematical modelling, remote sensing, and data analytics will improve their accessibility and applicability in ecological research and environmental management (Fulford et al., 2020; Thessen, 2016; Lu et al., 2014).

**Training and Education:** Provide training and education for researchers and practitioners in advanced analytical techniques and technologies. Enhancing the skills and knowledge of those working in ecological and environmental research will improve the effective use of these tools and techniques (Bhatnagar et al., 2021; Yang et al., 2017; Ivosevic et al., 2015).

## 6. CONCLUSION

Integrating advanced mathematical and scientific techniques is essential for unravelling the complex relationships within ecosystems and assessing the long-term impacts of human activities. Recent advancements in mathematical modelling, remote sensing, and data analytics offer powerful tools for enhancing our understanding of ecological dynamics and improving environmental management. By adopting these advanced techniques, researchers can provide more accurate predictions and develop more effective strategies for conservation and sustainability. Continued investment in these technologies and increased collaboration and training will further enhance our ability to address the challenges facing ecosystems and the environment.

## REFERENCES

- Aarikka-Stenroos, L., & Ritala, P. (2017). Network management in the era of ecosystems: Systematic review and management framework. *Industrial marketing management*, 67, 23-36. <https://doi.org/10.1016/j.indmarman.2017.08.010>
- Bairey, E., Kelsic, E. & Kishony, R. (2016). High-order species interactions shape ecosystem diversity. *Nat Commun* 7, 12285 (2016). <https://doi.org/10.1038/ncomms12285>
- Bhatnagar, S., Gill, L., Regan, S., Waldren, S., & Ghosh, B. (2021). A nested drone-satellite approach to monitoring the ecological conditions of wetlands. *ISPRS Journal of Photogrammetry and Remote Sensing*, 174, 151–165. <https://doi.org/10.1016/j.isprsjprs.2021.01.012>
- Chi, M., Plaza, A., Benediktsson, J. A., Sun, Z., Shen, J., & Zhu, Y. (2016). Big data for remote sensing: Challenges and opportunities. *Proceedings of the IEEE*, 104(11), 2207-2219. <https://doi.org/10.1109/JPROC.2016.2598228>
- Christin S, Hervet É, Lecomte N. (2019). Applications for deep learning in ecology. *Methods Ecol Evol*. 2019;10:1632–1644. <https://doi.org/10.1111/2041210X.13256>
- Deng, L., Mao, Z., Li, X., Hu, Z., Duan, F., & Yan, Y. (2018). UAV-based multispectral remote sensing for precision agriculture: A comparison between different cameras. *ISPRS journal of photogrammetry and remote sensing*, 146, 124-136. <https://doi.org/10.1016/j.isprsjprs.2018.09.008>
- Ernakovich, J. G., Hopping, K. A., Berdanier, A. B., Simpson, R. T., Kachergis, E. J., Steltzer, H., & Wallenstein, M. D. (2014). Predicted responses of arctic and alpine ecosystems to altered seasonality under climate change. *Global Change Biology*, 20(10), 3256-3269. <https://doi.org/10.1111/gcb.12568>
- Gallacher, D. (2016). Drone applications for environmental management in urban spaces: A review. *International Journal of Sustainable Land Use and Urban Planning*, 3(4).
- Henderson, K., & Loreau, M. (2023). A model of Sustainable Development Goals: Challenges and opportunities in promoting human well-being and environmental sustainability. *Ecological Modelling*, 475, 110164. <https://doi.org/10.1016/j.ecolmodel.2022.110164>
- Heymans, J. J., Coll, M., Link, J. S., Mackinson, S., Steenbeek, J., Walters, C., & Christensen, V. (2016). Best practice in Ecopath with Ecosim food-web models for ecosystem-based management. *Ecological modelling*, 331, 173-184. <https://doi.org/10.1016/j.ecolmodel.2015.12.007>
- Huntingford, C., Jeffers, E. S., Bonsall, M. B., Christensen, H. M., Lees, T., & Yang, H. (2019). Machine learning and artificial intelligence to aid climate change research and preparedness. *Environmental Research Letters*, 14(12), <https://doi.org/10.1088/1748-9326/ab4e55>
- Ivosevic, B., Han, Y. G., Cho, Y., & Kwon, O. (2015). The use of conservation drones in ecology and wildlife research. *Journal of Ecology and Environment*, 38(1), 113-118. <http://dx.doi.org/10.5141/ecoenv.2015.012>
- Kéry, M., & Royle, J. A. (2020). *Applied hierarchical modeling in ecology: Analysis of distribution, abundance and species richness in R and BUGS: Volume 2: Dynamic and advanced models*. Academic Press.



- King, M. F., Renó, V. F., & Novo, E. M. (2014). The concept, dimensions and methods of assessment of human well-being within a socioecological context: a literature review. *Social indicators research*, 116, 681-698. <https://doi.org/10.1016/j.cosust.2015.03.007>
- Krapivin, V. F., Varotsos, C. A., & Soldatov, V. Y. (2015). New ecoinformatics tools in environmental science (Vol. 903). Vienna, Austria:: Springer. Harris, N. L., Gibbs, D. A., Baccini, A., Birdsey, R. A., De Bruin, S., Farina, M., ... & Tyukavina, A. (2021). Global maps of twenty-first-century forest carbon fluxes. *Nature Climate Change*, 11(3), 234-240. <https://doi.org/10.1038/s41558-020-00976-6>
- Liquete, C., Piroddi, C., Macías, D., Druon, J. & Zulian, G. (2016). Ecosystem services sustainability in the Mediterranean Sea: assessment of status and trends using multiple modelling approaches. *Sci Rep* 6, 34162 (2016). <https://doi.org/10.1038/srep34162>
- Liu, X., Li, D., Ma, M., Szymanski, B. K., Stanley, H. E., & Gao, J. (2022). Network resilience. *Physics Reports*, 971, 1-108. <https://doi.org/10.1016/j.physrep.2022.04.002>
- Lu, D., Li, G., & Moran, E. (2014). Current situation and needs of change detection techniques. *International Journal of Image and Data Fusion*, 5(1), 13-38. <https://doi.org/10.1080/19479832.2013.868372>
- Lucas, T. C. (2020). A translucent box: interpretable machine learning in ecology. *Ecological Monographs*, 90(4), e01422.
- Lyu, X., Li, X., Dang, D., Dou, H., Wang, K., & Lou, A. (2022). Unmanned aerial vehicle (UAV) remote sensing in grassland ecosystem monitoring: A systematic review. *Remote Sensing*, 14(5), 1096. <https://doi.org/10.3390/rs14051096>
- Manfreda, S., McCabe, M. F., Miller, P. E., Lucas, R., Pajuelo Madrigal, V., Mallinis, G., ... & Toth, B. (2018). On the use of unmanned aerial systems for environmental monitoring. *Remote sensing*, 10(4), 641. <https://doi.org/10.3390/rs10040641>
- Mangewa, L. J., Ndakidemi, P. A., & Munishi, L. K. (2019). Integrating UAV technology in an ecological monitoring system for community wildlife management areas in Tanzania. *Sustainability*, 11(21), 6116. <https://doi.org/10.3390/su11216116>
- Mantyka-Pringle, C. S., Jardine, T. D., Bradford, L., Bharadwaj, L., Kythreotis, A. P., Fresque-Baxter, J., ... & Lindenschmidt, K. E. (2017). Bridging science and traditional knowledge to assess cumulative impacts of stressors on ecosystem health. *Environment international*, 102, 125-137. <https://doi.org/10.1016/j.envint.2017.02.008>
- Mumby, P. J., Chollett, I., Bozec, Y. M., & Wolff, N. H. (2014). Ecological resilience, robustness and vulnerability: how do these concepts benefit ecosystem management?. *Current Opinion in Environmental Sustainability*, 7, 22-27. <https://doi.org/10.1016/j.cosust.2013.11.021>
- O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., ... & Van Vuuren, D. P. (2014). A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic change*, 122, 387-400. <https://doi.org/10.1007/s10584-013-0905-2>
- Pajares, G. (2015). Overview and current status of remote sensing applications based on unmanned aerial vehicles (UAVs). *Photogrammetric Engineering & Remote Sensing*, 81(4), 281-330. <https://doi.org/10.14358/PERS.81.4.281>

- Segan, D. B., Murray, K. A., & Watson, J. E. (2016). A global assessment of current and future biodiversity vulnerability to habitat loss–climate change interactions. *Global Ecology and Conservation*, 5, 12-21. <https://doi.org/10.1016/j.gecco.2015.11.002>
- Sharma, R., Kamble, S. S., & Gunasekaran, A. (2018). Big GIS analytics framework for agriculture supply chains: A literature review identifying the current trends and future perspectives. *Computers and Electronics in Agriculture*, 155, 103-120. <https://doi.org/10.1016/j.compag.2018.10.001>
- Strauss, S. Y. (2014). Ecological and evolutionary responses in complex communities: implications for invasions and eco-evolutionary feedbacks. *Oikos*, 123(3), 257-266.
- Sun, A. Y., & Scanlon, B. R. (2019). How can Big Data and machine learning benefit environment and water management: A survey of methods, applications, and future directions. *Environmental Research Letters*, 14(7), 073001. <https://doi.org/10.1088/1748-9326/ab1b7d>
- Thessen A (2016) Adoption of Machine Learning Techniques in Ecology and Earth Science. One Ecosystem 1: e8621. <https://doi.org/10.3897/oneeco.1.e8621>
- Ullo, S. L., & Sinha, G. R. (2020). Advances in smart environment monitoring systems using IoT and sensors. *Sensors*, 20(11), 3113.
- Ustin, S. L., & Middleton, E. M. (2021). Current and near-term advances in Earth observation for ecological applications. *Ecological Processes*, 10(1), 1. <https://doi.org/10.1186/s13717-020-00255-4>
- Villa, F., Bagstad, K. J., Voigt, B., Johnson, G. W., Portela, R., Honzák, M., & Batker, D. (2014). A methodology for adaptable and robust ecosystem services assessment. *PloS one*, 9(3), e91001.
- Vink, J., Koskela-Huotari, K., Tronvoll, B., Edvardsson, B., & Wetter-Edman, K. (2021). Service ecosystem design: Propositions, process model, and future research agenda. *Journal of Service Research*, 24(2), 168-186.
- Wang, M., Zhang, H., Sun, W., Li, S., Wang, F., & Yang, G. (2020). A coarse-to-fine deep learning based land use change detection method for high-resolution remote sensing images. *Remote Sensing*, 12(12), 1933. <https://doi.org/10.3390/rs12121933>
- Yang, C., Huang, Q., Li, Z., Liu, K. & Hu, F. (2017) Big Data and cloud computing: innovation opportunities and challenges, *International Journal of Digital Earth*, 10:1, 13-53, <https://doi.org/10.1080/17538947.2016.1239771>
- Zhao, Q.; Yu, L.; Du, Z.; Peng, D.; Hao, P.; Zhang, Y.; Gong, P. (2022). An Overview of the Applications of Earth Observation Satellite Data: Impacts and Future Trends. *Remote Sens.* 2022, 14, 1863. <https://doi.org/10.3390/rs14081863>
- Zhong, S., Zhang, K., Bagheri, M., Burken, J. G., Gu, A., Li, B., ... & Zhang, H. (2021). Machine learning: new ideas and tools in environmental science and engineering. *Environmental science & technology*, 55(19), 12741-12754. <https://doi.org/10.1021/acs.est.1c01339>