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REVIEW

Enhancing Wetland Restoration through Machine Learning-Based Decision Support Systems

Mejorando la Restauración de Humedales mediante Sistemas de Soporte de Decisiones Basados en Aprendizaje Automático

Fredrick Kayusi[1,2], Petros Chavula[3]

[1]Department of Environmental Studies, Geography & Planning, Maasai Mara University, -861-20500, Narok-Kenya.
[2]Department of Environmental Sciences, Pwani University, 195-80108, Kilifi-Kenya.
[3]Africa Center of Excellency for Climate-Smart Agriculture and Biodiversity Conservation, College of Agriculture and Environmental Sciences, Haramaya University, P. O. Box 138, Dire Dawa, Ethiopia.

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Corresponding author: Fredrick Kayusi

ABSTRACT

Researchers are increasingly employing Machine Learning (ML) and Deep Learning (DL) algorithms to address complex geo-environmental challenges, particularly in predicting risk, susceptibility, and vulnerability to environmental changes. These advanced computational models have shown significant promise in various applications, ranging from natural disaster prediction to environmental monitoring. Despite their growing usage, very few studies have leveraged Machine Learning-Based Decision Support Systems (MLBDSS) to restore the health status of wetland habitats. To our knowledge, there are no comparative analyses between Machine Learning models and traditional Decision Support Systems (DSS) in this specific context. Wetlands play a crucial role in supporting biodiversity, including fish and wildlife populations, while also contributing to improved water quality and providing essential ecosystem services to nearby communities. These services include flood control, carbon sequestration, and water filtration, which are vital for both ecological and human well-being. However, over the past decades, wetland areas, particularly in coastal regions, have faced significant degradation due to anthropogenic pressures, resulting in a substantial reduction of these critical benefits. This ongoing loss poses serious ecological and socio-economic challenges that require immediate and effective intervention. Current wetland assessment and mitigation frameworks often encounter limitations in their practical implementation, despite regulatory advancements aimed at promoting wetland conservation. These shortcomings can lead to delayed project approvals, increased costs, and further loss of valuable ecosystem services. Integrating ML and DSS models into wetland management strategies could provide innovative solutions to overcome these challenges by improving predictive accuracy, optimizing restoration efforts, and enhancing decision-making processes. The development of hybrid models combining ML and DSS approaches may offer a more holistic framework for addressing wetland loss, ultimately contributing to sustainable habitat restoration and conservation efforts.

Keywords: Wetlands; Wetland Restoration; Machine Learning; Deep Learning; Decision Support Systems.

RESUMEN

Los investigadores están empleando cada vez más algoritmos de Aprendizaje Automático (ML, por sus siglas en inglés) y Aprendizaje Profundo (DL, por sus siglas en inglés) para abordar desafíos geoambientales complejos, particularmente en la predicción de riesgos, susceptibilidad y vulnerabilidad ante cambios ambientales. Estos modelos computacionales avanzados han demostrado un potencial significativo en diversas aplicaciones, que vandesde la predicción de desastres naturales hasta el monitoreo ambiental. A pesar de su creciente uso, muy pocos estudios han aprovechado los Sistemas de Soporte de Decisiones Basados en Aprendizaje Automático (MLBDSS, por sus siglas en inglés) para restaurar el estado de salud de los hábitats de humedales. Hasta donde sabemos, no existen análisis comparativos entre modelos de Aprendizaje Automático y los Sistemas de Soporte de Decisiones (DSS, por sus siglas en inglés) tradicionales en este contexto específico. Los humedales desempeñan un papel crucial en el apoyo a la biodiversidad, incluyendo poblaciones de peces y vida silvestre, mientras también contribuyen a mejorar la calidad del agua y brindan servicios ecosistémicos esenciales a las comunidades cercanas. Estos servicios incluyen el control de inundaciones, la captura de carbono y la filtración de agua, los cuales son vitales tanto para el bienestar ecológico como humano. Sin embargo, durante las últimas décadas, las áreas de humedales, particularmente en regiones costeras, han enfrentado una degradación significativa debido a presiones antropogénicas, lo que ha resultado en una reducción sustancial de estos beneficios críticos. Esta pérdida continua plantea serios desafíos ecológicos y socioeconómicos que requieren una intervención inmediata y efectiva. Los marcos actuales de evaluación y mitigación de humedales a menudo encuentran limitaciones en su implementación práctica, a pesar de los avances regulatorios destinados a promover la conservación de humedales. Estas deficiencias pueden llevar a la aprobación tardía de proyectos, mayores costos y una mayor pérdida de valiosos servicios ecosistémicos. La integración de modelos de ML y DSS en las estrategias de gestión de humedales podría proporcionar soluciones innovadoras para superar estos desafíos, mejorando la precisión predictiva, optimizando los esfuerzos de restauración y mejorando los procesos de toma de decisiones. El desarrollo de modelos híbridos que combinen enfoques de ML y DSS podría ofrecer un marco más holístico para abordar la pérdida de humedales, contribuyendo finalmente a la restauración y conservación sostenible de hábitats.

Palabras clave: Humedales; Restauración de Humedales; Aprendizaje Automático; Aprendizaje Profundo; Sistemas de Soporte de Decisiones.

INTRODUCTION

Wetlands are among the most important, dynamic and diverse ecosystems worldwide. They provide a wide range of ecosystem services, including freshwater supply, groundwater recharge, soil erosion control, carbon sequestration, climate regulation and hydrological regulation.[1] They are particularly important for the preservation of rare species and biodiversity.[2] Although they make up only 6 % of the Earth's surface, wetlands are considered the most valuable ecosystem as they store approximately 37 % of terrestrial carbon and provide 47 % of total ecosystem services.[3] However, approximately 85 % of wetlands worldwide have disappeared since 1700, and the number is increasing. Therefore, the creation and restoration of wetlands must be promoted.

Wetlands have long been undervalued and, as a result, they have been degraded to an alarming degree necessitating urgency for restoration. In the 1600s, it is believed that the lower 48 states in the United States contained over 220 million acres of wetlands.[4] Over 64 % of the world's wetlands have disappeared since 1900 across the globe. More than half of the world's wetlands have been destroyed since 1970. While wetland protection laws have increased in the last decade, restoration efforts have not been as successful as researchers once thought they would be. In the United States, over 1,000,000 wetland acres have been restored, but nearly 60 % remain in poor to nonfunctional condition. It is not feasible to restore every wetland, so it becomes important to prioritize areas where restoration would most benefit the landscape. Currently, no decision support system exists on the market that incorporates expert knowledge regarding ecosystem attributes while incorporating various landscape data, especially via the use of remote sensing data.

Although great advances have been made in understanding wetland ecology and advances in wetland restoration and creation, the availability of technology and big data to support informed decision-making for wetland creation or restoration is limited [5]. Multiple disciplines, including hydrology, ecology, biology, chemistry, and engineering, must work together to ensure that wetland restoration projects are successful.[6] In this work, a wetland decision support system is presented that enables stakeholders, such as restoration practitioners or developers.[7] Hence, studying wetland restoration under various environmental and climatic conditions using low-cost and high-resolution Earth observation data, hydrological field data and artificial intelligence.

The ecological importance of wetlands has made their restoration a global priority, although disagreements over methods remain. Because they can analyze large ecological data sets, optimize restoration plans, and predict outcomes under changing climatic conditions, machine learning-based decision support systems have the potential to be revolutionary.[8] The European Union (EU) has adopted a biodiversity strategy for 2030 with the aim of increasing the number and quality of wetlands. This approach, which halts degradation and conserves and restores wetlands, is consistent with combating climate change and extreme weather. To enhance wetland restoration, it aims to strengthen wetland ecosystems as carbon sinks and centers of biodiversity, thereby supporting climate change adaptation and mitigation for improved wetland restoration.

As a result, improved wetland restoration significantly advances the UN's Sustainable Development Goals (SDGs), particularly SDG 6 (Clean Water), SDG 15 (Life on Land) and SDG 13 (Climate Action). By improving water resources and ecosystem services through restored wetlands, Agenda 2063, which places a strong emphasis on environmental sustainability, is consistent with the current study for Africa.(9) As essential carbon sinks, wetlands reduce atmospheric carbon and promote biodiversity by providing habitat for a wide range of species. Their restoration secures livelihoods, promotes sustainable agriculture and increases resilience to droughts and floods. Wetland restoration can address pressing environmental issues while promoting ecological health and sustainable development by combining cutting-edge technologies with cooperative international efforts.(10) In the 1990s, wetlands in Africa covered almost 1,2 million square kilometers, but they have since declined dramatically due to infrastructure development, agricultural encroachment and deforestation. In many places today only fragmented wetlands remain, and in some places, losses exceed 30 %. Water management, climate resilience and biodiversity conservation all depend on the restoration of these wetlands. Decision makers can prioritize restoration efforts and predict the impacts of interventions under different climatic conditions by leveraging machine learning (ML), a powerful tool for analyzing historical and current wetland data.(11) By using such technologies, Africa can demonstrate its commitment to the African Union's Agenda 2063, which places great emphasis on environmental sustainability and resilience.

East Africa is home to important wetland ecosystems such as the Lake Victoria Basin and the Nile Basin wetlands. Wetlands supported livelihoods through agriculture, fishing and water supply in the 1990s and accounted for about 20 % of the region's land area.(12) However, due to rapid population growth, industrialization and climate variability, wetland coverage today is only about 15 %. The ecological balance has been disrupted, flooding has increased and biodiversity is now at risk due to this loss.(13) By mapping degraded areas, identifying degradation drivers and simulating restoration outcomes, wetland restoration – supported by machine learning-based decision systems – can provide targeted solutions. Improving water security, preserving biodiversity and ensuring sustainable development across the region depend on such interventions. Industrial development, urbanization and agricultural encroachment have caused Uganda's wetlands, which made up 13 percent of the country's land area in the 1990s, to shrink to less than 8 percent today.

This can be explained by Uganda's dependence on wetlands, which are crucial for biodiversity, flood control and water treatment.(14) As of May 2024, the country's population was 45 905 417, representing an average annual growth rate of 20,9 percent since the last census in 2014. The degradation of wetlands could be due to the fact that according to Uganda's National Population and Housing Census (PHC) in 2024, 62,3 % of households were engaged in agriculture, 60,7 % in crop cultivation, 36,7 % in livestock farming and 80,2 % were active in agriculture. As a result of their degradation, vital habitats were lost, flooding increased and water quality deteriorated. By evaluating complex ecological data to guide restoration initiatives,(13,15) ML can revolutionize wetland restoration. For example, predictive models can assess how restoration affects carbon sequestration and flood mitigation, enabling evidence-based policy making.

ML may help restore wetlands with unprecedented accuracy and effectiveness. Large datasets such as ecological parameters, climate models, and satellite imagery can be processed by ML algorithms to identify degraded wetlands and rank restoration projects. These systems are capable of tracking recovery progress in real time, optimizing resource allocation, and predicting the success of various interventions. Wetland restoration projects at local and international levels can significantly contribute to biodiversity conservation, climate change mitigation and sustainable development through the use of such technologies. Future generations can secure environmental and socioeconomic benefits by integrating machine learning into wetland restoration strategies in Uganda and elsewhere.

ML and deep learning (DL) algorithms are increasingly being used by researchers to predict the risk, susceptibility and vulnerability of various geo-environmental challenges. However, to the best of our knowledge, very few studies have used machine learning-based decision support systems (MLBDSS) to restore the health status of wetland habitats, and none have addressed a comparison of ML and DSS models in this regard.

Literature review

Inclusion and Exclusion Criteria for Literature Review

This section outlines the methodology used to identify, select, and review relevant literature for the study titled "Enhancing Wetland Restoration through Machine Learning-Based Decision Support Systems (MLBDSS)." A systematic literature review was conducted to gather existing research on wetland restoration, Machine Learning (ML), Decision Support Systems (DSS), and their combined application in environmental conservation efforts. The inclusion and exclusion criteria were defined to ensure that the review captures high-quality, relevant, and recent studies.

Inclusion Criteria

- Relevance: Studies that focus on wetland restoration, ML algorithms, DSS models, or a combination of these topics.
- Publication Date: Research published between 2010 and 2025 to ensure the inclusion of recent advancements.
- Language: Only studies published in English were considered.
- Peer-Reviewed Articles: Only peer-reviewed journal articles, conference papers, and reputable reports were included.
- Application-Based Studies: Research that provides case studies or practical applications of ML or DSS in environmental restoration projects.

Exclusion Criteria

- Irrelevant Topics: Studies focusing solely on theoretical aspects of ML or DSS without application to environmental conservation.
- Outdated Research: Studies published before 2010, unless they are seminal works.
- Non-Peer-Reviewed Sources: Articles from non-peer-reviewed journals, blogs, or opinion pieces.
- Non-English Publications: Studies published in languages other than English.
- Duplicate Publications: Identical studies published in multiple sources were excluded.

Study Method Flowchart

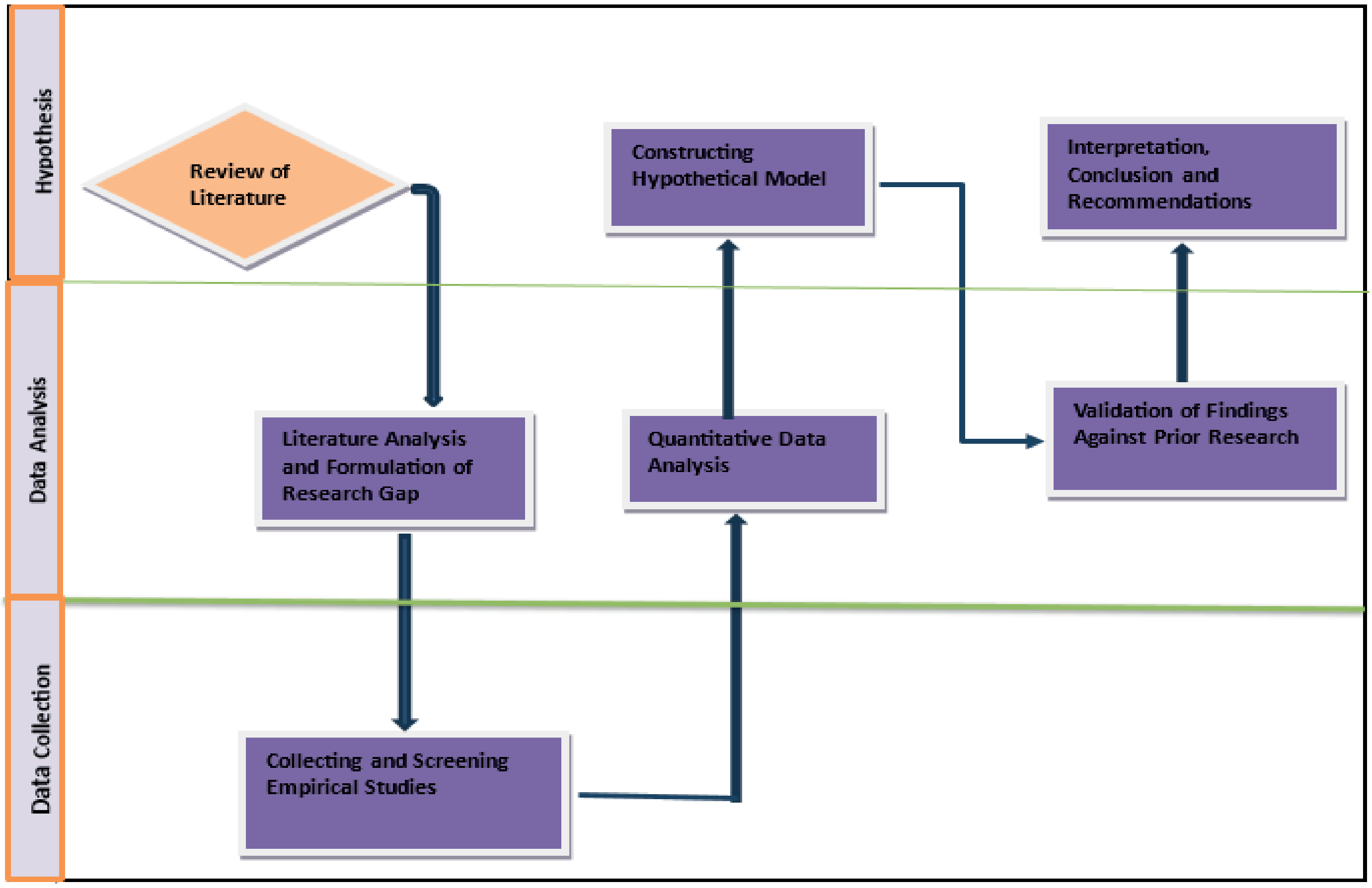

Figure 1. Study methodology flow chart

Table 1. Inclusion and Exclusion Criteria for Literature Review

Criteria	Inclusion	Exclusion
Topic Relevance	Wetland restoration, ML, DSS, environmental projects	Theoretical ML/DSS without practical applications
Publication Date	2010-2025	Pre-2010 (except seminal works)
Language	English	Non-English publications
Peer-Reviewed Sources	Yes	Non-peer-reviewed sources
Application Focus	Case studies, practical applications	Purely theoretical works
Duplicate Publications	Unique studies	Duplicate entries across different sources[16,17,18,19]

This methodology ensures a comprehensive and focused literature review, capturing key studies that explore the potential of integrating ML and DSS to enhance wetland restoration efforts.

Several researchers have highlighted the potential of machine learning in wetland restoration. The random forest models can be used to predict the success of wetland vegetation recovery and identified soil moisture and hydrological variability as the most critical predictors of restoration outcomes. Similarly, some studies applied support vector machines to assess wetland restoration, emphasizing the importance of nutrient gradients and vegetation composition in driving success. Others have utilized neural networks in spatial-temporal modeling, demonstrating how these tools optimize restoration scenarios by predicting long-term ecological impacts. These studies confirm the efficacy of machine learning in processing complex datasets and identifying key ecological drivers, paving the way for data-driven restoration strategies.

Findings Supporting Machine Learning

Findings from these studies illustrate that machine learning enhances the precision of ecological predictions. For instance, Basher,[20] noted that their random forest model achieved over 90 % accuracy in predicting vegetation recovery. This high level of precision enables managers to design targeted interventions. Dakos et al.[21] found that their models effectively quantified nutrient thresholds critical for species regeneration, providing actionable thresholds for restoration planning. Tramblay et al.[22] demonstrated the utility of integrating spatial and temporal data into neural networks, significantly improving predictions of ecological outcomes compared to conventional methods. Collectively, these findings validate the robustness of machine learning in addressing the multifaceted challenges of wetland restoration.

Authors with Contrasting Findings

Contrary to the above, Ardabili et al.[23] observed limitations in machine learning applications, particularly in wetlands characterized by high spatial and ecological heterogeneity. Their study revealed that the models struggled to achieve consistent accuracy due to data scarcity and variability. Ladi et al.[24] found that in smaller-scale wetlands, traditional statistical models outperformed machine learning algorithms, especially when data quality was limited. These authors argue that machine learning requires extensive, high-quality datasets to deliver reliable results, which may not always be available in all wetland ecosystems. These contrasting findings emphasize the contextual nature of machine learning efficacy, highlighting the need for tailored approaches.

Insights into Challenges and Opportunities

The divergence in findings among authors underscores key challenges in applying machine learning to wetland restoration. Data availability, quality, and model complexity are recurring themes. While robust datasets empower machine learning, ecosystems with limited monitoring often present hurdles. The potential for overfitting and model bias in high-complexity environments is another concern. However, these limitations also present opportunities to advance research. For instance, improving data collection frameworks and integrating diverse data sources can enhance model performance and reliability, addressing gaps identified by authors like.[25]

Synthesis of Similarities and Differences

In conclusion, while many researchers affirm the promise of machine learning in wetland restoration, others highlight its limitations in specific contexts. Studies by Micheli et al.[26], Ley et al.[27], Zhao et al.[28] and Ferreira et al.[30] demonstrate the value of advanced algorithms in predicting restoration outcomes and informing management. However, contrasting perspectives, such as those from Ley et al.[27] and Ardabili et al.[23] caution against over-reliance on machine learning, particularly in data-scarce or small-scale wetlands. Bridging these gaps requires an integrated approach that combines machine learning with improved data infrastructure and tailored methodologies, ensuring that decision support systems are robust and adaptable to diverse ecological contexts.

Machine Learning Techniques in Wetland Restoration

Machine learning techniques present highly motivated potential that can contribute to environmentally sustainable wetland management solutions. Decision Support System (DSSs) based on such techniques can draw from large and diverse data compared to traditional hydrological and ecological models, and can indirectly assist restoration monitoring and conservation management by helping extract information from big data that cannot be automatically processed by already implemented models.[31] The future applications of machine learning techniques seem largely unexplored, which allows opportunities for thought, research, and implementation to subsequent advances in wetland restoration, research, and management.[32]

Considering the increasing number of studies utilizing machine learning for solving environmental, hydrological, and ecological problems, the research question that motivated the present study arises: How many machine learning techniques have been proposed for solving wetland restoration problems? Addressing this question is the aim of the present research. The study aims, through an extensive literature review, to investigate the state of the art of this research topic, and assess and classify the different methods and their uses. The detailed results expose the current use of machine learning techniques for wetland restoration and explain guidelines for the addition of future research aiming at enhancing wetland restoration through decision support systems.

Supervised Learning Techniques

Frequently, restoration projects include collections of samples of the biological or physical features they are trying to influence before the project's implementation, along with extensive baseline data to understand spatial and temporal heterogeneity across the site. Using such geospatially explicit information to understand where the ecological response can be expected, and potentially why these responses vary across a particular site,[33] can be a powerful tool for optimization. Increasingly sophisticated technologies to gather, store, and analyze biophysical data often require greater expertise to harness effectively for management decision-making. Restoration site managers typically do not have sufficient time, experience, or resources to implement and maintain decision support systems. One alternative is the creation of management support systems that apply advanced computer and information technologies to provide a full range of tools to be used on a need-to-know basis by individuals.

The use of predictive models to evaluate the probability of potential negative impacts from constructed actions would be extremely useful but is rarely implemented. Agencies and non-profit organizations, with their multiple obligations, are interested in "best available science" to optimize investment allocations and minimize the time needed for restoration efforts. The ability to provide decision-relevant information on detailed scheduling of site infrastructure improvement before, and revegetation after,[34] habitat reconstruction would greatly enhance the efficiency and effectiveness of wetland restoration projects. Machine learning algorithms have risen to prominence owing to their ability to provide effective predictive models for a wide range of environmental domains; the most commonly applied machine learning algorithms involve supervised learning.

Unsupervised Learning Techniques

Clustering techniques are widely used unsupervised learning methods. Several clustering algorithms produce good results in different cases. For example, K-Means clustering is often used due to its simplicity and efficiency, which create K clusters such that each data point belongs to the closest cluster. Other clustering approaches are hierarchical cluster analysis algorithms that create a tree of clusters, and noise points in the datasets can be handled nicely,[35] but they are harder to understand and not as efficient because of the high computational complexity. Density-Based Spatial Clustering of Applications with Noise does not assume a predefined number of clusters in the dataset, but the user needs to specify two other input variables. BIRCH is mainly used for large datasets due to its efficiency. In our study, we could employ clustering algorithms to identify habitats or to partition animal species into homogeneous groups, which in turn can be used to guide future wetland restoration projects.

Integrating Ecological, Hydrological, and Socio-economic Data

Several ongoing initiatives harvest different types of data through geo-knowledge platforms, web mapping services, and web services that allow the use of open data. Additionally, this research uses a collection of sources to compile datasets specifically for the exigencies of its development. To promote the integration of datasets, it used international classifications when detected and also provided the guidelines to create specific datasets.[14] The water management responsibility demands that models encapsulate quantity and quality water problems on ecological, hydrological, and socio-economic levels. However, their development still tends to focus solely on the availability, reliability, or purpose of the data, which may allow the incorporation of demographic, spatial, and land cover variables into the model. Therefore, nowadays, human population growth their ecological requirements, and the protection of water sources are increasing political issues. Models based on these new urban ecosystems necessarily consider specific elements related to the urban water regime.

The theoretical review paper aims to provide those involved in the development of machine learning-based decision support systems for the water sector with an integrated view of how to use ecological, hydrological, and socio-economic data to enhance the impact of the implemented policies. Examples of methods used in the different disciplines, and also in other fields that could be tested for the integrated model are provided.[36] The main goal is to develop a generic background for the future generation of interdisciplinary decision support systems that can predict and classify the actual ecological status, which is expected to be reached by the stakeholders, and to support the decision-making process in complex urban environments.

Feature Engineering and Selection

Feature selection methods help to reduce a model's complexity and to speed up computation by identifying a subset of variables from a set of variables that result in good predictive accuracy of the model. The process of selecting a subset of relevant features for a model is called feature selection. A feature selection algorithm may work in two ways: filter or wrapper methods. Filter methods consist of scoring and ranking the relevance of each feature, and then choosing those with the highest rank. It can be done quickly, but then a model must be built and evaluated based on the selected features to choose the best subset. Wrapper methods use a predictive model to score a subset of features, but the evaluation of all the possible feature subsets requires building and evaluating many predictive models, making this approach computationally more expensive.

Currently, available feature selection methods become, however, an unacceptable burden when dealing with a large feature set. To solve this issue, lesser feature importance has been simplified through a scoring method that measures the contribution of each feature to model estimation given that all the features are available. Feature scoring is an established part of estimating Random Forest models, as the out-of-the-bag case resampling permits estimating feature importance during model estimation, for example, by evaluating how well the tree grows with and without each particular predictor variable. The mean decrease in accuracy represents for RF the averaged accuracy difference between predictions made on out-of-the-bag cases with and without permuting the value of each feature every time the log of the out-of-the-bag prediction accuracy is computed.

Actionable Insights for Wetland Management

It is time for real co-production of actionable wetland insights across boundaries. We are continuously improving the viability of wetland decision support systems in the real world, with emphasis on modular and plug-and-play professional software products, integrating data from different sources, and applying methods that achieve multidisciplinary integration through soft indicators like perception of place. Our team is focused on decision support systems for climate change-adapted willow carr wetlands and other wetland types, using machine learning.(37) The ultimate aim is that decision support systems can be rapidly transferred and implemented to achieve restoration more quickly, to much higher standards, and at a cheaper cost.

Instead of claiming that we can develop a prediction tool that is capable of accurate ecological predictions for multiple and diverse attributes over broad spatiotemporal scales, what must come first is simply listening to our management partners' wishes. They are capable of accomplishing many pressing decision-making needs with simple analytics, and others with complex computational techniques.(38) None of the several techniques work well for all prediction problems, so there should always remain room for experts with varied talents and the necessity for high-quality data. Depending on the established level of trust, it often represents the more prudent approach to building predictive models that heavily involve training data reflecting the same or similar entities, under the same or similar level of stressors, the same or similar environmental settings, or cyclic patterns of response to a change in a core environmental attribute.

Decision Support Systems Implementation

Decisions in environmental restoration of wetlands are often complex, involve a variety of objectives and outcomes, and have inherent uncertainty in response and future controlling wetland conditions. Adaptive ecosystem restoration and the spatial heterogeneity across wetlands within the landscape pose additional challenges. Decision support tools, such as expert systems, are designed to enhance the effectiveness of wetland restoration and provide transparent decision processes to the end-users such as land managers and policymakers. Comprehensive expert systems could make the best use of machine learning-based models with rich domain-specific knowledge.(39) The application of artificial intelligence technologies such as deep machine learning, deep transfer learning, and complex deep architectures deal with additional complications within wetland restoration decisions.

Artificial intelligence methods have the potential to dynamically improve accuracy upon exposure to more hydrologic and biophysical data. The results of blue carbon along coastal ecosystems as well as the distribution of water quality changes attributed to restoration are land management outcomes often amenable to modeling for decision support. Machine learning models can be employed to solve these learning process tasks. Furthermore, the knowledge transfers that deepen the learning tasks still need to attract more cross-discipline achievements for the sake of human beings, especially applications in the wetland ecosystem restoration below the domain of efficient popularization and recognition.

Challenges Faced in Enhancing Wetland Restoration through Machine Learning-based Decision Support Systems (MLBDSS)

Data Availability and Quality

The availability and quality of ecological data represent one of the main obstacles to the application of machine learning in wetland restoration. Because wetlands are dynamic ecosystems, their complexity can only be fully captured through long-term, high-resolution datasets. However, in many areas, particularly in developing countries, there are gaps or inconsistencies in the data due to a lack of ecological monitoring infrastructure. Missing values, biases, or low spatial and temporal resolution are examples of data quality issues that can affect the performance of machine learning models. Furthermore, when integrating disparate datasets such as hydrological patterns, vegetation metrics, and socioeconomic variables, significant preprocessing effort is often required to harmonize formats and scales. These limitations make it more difficult for ML algorithms to produce accurate predictions, especially in diverse wetland ecosystems with distinct ecological characteristics.

Model Generalizability and Complexity

Ensuring the generalizability of models across different wetland types is a major challenge in ML-based DSS. The ecological roles, hydrological dynamics and degradation drivers of wetlands vary widely, making it difficult to create a model that works for everyone. In such situations, overfitting is a common problem, where models perform well on training data but poorly on unseen data. In addition, due to the complexity of certain machine learning models, such as B. neural networks, problems with interpretability arise. Decision makers often need clear, actionable insights, but complex models can produce results that are difficult to understand or defend. The lack of transparency of these systems can cause those involved to lose trust in them, which would limit their adoption. It is still difficult to develop explainable AI methods and optimize model outputs without sacrificing accuracy.

Integration with Socio-Economic and Policy Contexts

Another important issue is the inclusion of socioeconomic and political factors in ML-based wetland restoration frameworks. Wetland restoration often requires a balance between biological goals and human activities such as infrastructure development, urbanization and agriculture. Rather than focusing exclusively on biophysical parameters, ML models sometimes overlook socioeconomic elements that impact restoration effectiveness, such as financial sources, community participation, and land tenure systems.(37) Furthermore, it could be difficult to organize the collaboration of ecologists, data scientists, and policymakers needed to translate machine learning results into useful policy proposals. This multidisciplinary gap and the lack of easy-to-navigate tools for non-technical stakeholders limit the practical application of ML-based decision support systems in real-world restoration projects. Addressing these challenges requires a more holistic approach that considers environmental, technological and socio-economic perspectives.

Policy Recommendations

An opportunity also exists to support decision-making through tool development. Specifically, machine learning provides a unique opportunity to develop decision support systems that can provide real-time or near-real-time decision support to wetland managers. Using continuously updated machine learning models,(38) various decision support systems could quickly respond to changes in climate, encroachment, or any unexpected event that could harm newly established vegetation. Given recent advancements, it is possible for machine learning-based decision support tools to be developed that are flexible enough to immediately tailor actions to site-specific challenges. Such tools are not in existence today, but future work would serve the creation of such tools well through the expanded creation of monitoring data, fine-tuning models with additional site-specific data, and close collaboration with land management partners during restoration efforts.

In addition to in situ decision support, these tools could also provide the backbone for global greenhouse gas accounting, greenhouse gas offset registries, as well as potential rewards for enacted changes. In this case, widespread wetland restoration efforts could have the fortuitous co-benefit of producing substantial benefits for no-gateway green infrastructure solutions, helping absorb carbon and supporting critical habitat in the few decades needed to transition from fossil fuels to a regenerative future.(40) Cross-application of best management practices for long-term maintenance might also be possible between low-impact design and SITES.

CONCLUSION

Restoring large regional areas of wetlands can have significant cultural, social, and ecological benefits. However, investing in restoration projects at this scale is a resource-limiting activity. Identifying the highest priority sites for restoration should enhance the ability to achieve the best conservation outcomes and reintroduce lost wetland function. A well-designed decision support system can provide timely and consistent site assessments and screening for projects that provide the greatest benefits. Machine learning systems are perfect candidate tools for site prioritization. In this work, a machine learning decision support system has been developed to prioritize project locations for restoration based on wetland benefits. The system was trained using the six highest national priority wetland attributes and determined to be the major drivers of wetland benefits in the watershed; twelve local wetland attributes; global data sets with 48 wetland attributes; and the universal hydro index. When mapped, machine learning priority areas are generally consistent with current restoration project locations and have ecological and economic implications that warrant careful consideration.

Future wetland attribute training will conclude after extensive wetland sampling and characterizing, with the machine learning model programmed to handle more robust and complex logic. Pending the availability of the required data, a possible next step could be to apply a cluster analysis before machine learning to overcome the volume limitations associated with big data. Additional attribute data could be included in the training as training sites throughout the region are assessed. If a probability metric is not included as an output from processing, water-provided restoration priority sites could be promoted. Results will then be shared with landowners and crafted into a prioritization tool to provide incentives for lower-priority landowners. With the assistance of stakeholders, perhaps a layered approach to ownership and partnerships can be developed leading to larger contiguous restored tracts and better-functioning wetlands. The machine learning model will then be used for iterative feedback in our decision support system for superfine tuning. In addition to precipitation, our initial use case, there is potential to train models to classify wetland categories as beneficial, all wetlands, or excluded through manipulating thresholds and attribute priorities. A wetland classification, when applied in reverse, could be a powerful national wetland inventory update method, effectively crowdsourcing these areas. Extending the idea of an algorithm designed to search for valuable wetland attributes, our decision support system could be used as a spatial decision support system for students learning to monitor and identify wetland services or for activities associated with field data derived from remote sensing. Finally, the results of this work can be applied at the national level targeting restoration activities at the most deserving of the millions of irrigated crop fields in the watersheds of the United States.

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AUTHORSHIP CONTRIBUTION
Conceptualization: Fredrick Kayusi, Petros Chavula.
Data curation: Fredrick Kayusi, Petros Chavula.
Formal analysis: Fredrick Kayusi, Petros Chavula.
Research: Fredrick Kayusi, Petros Chavula.
Methodology: Fredrick Kayusi.
Project management: Fredrick Kayusi, Petros Chavula.
Resources: Fredrick Kayusi.
Software: Fredrick Kayusi, Petros Chavula.
Supervision: Petros Chavula.
Validation: Fredrick Kayusi, Petros Chavula.
Display: Fredrick Kayusi, Petros Chavula.
Drafting - original draft: Fredrick Kayusi.
Writing - proofreading and editing: Fredrick Kayusi, Petros Chavula.