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Neelesh Yadav , Shrey Rakholia , Reuven Yosef *

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Decision Support Systems in Silvicultural Practices and the Essential Prioritization of Ecosystem Services: A Review

Neelesh Yadav [1], Shrey Rakholia [1] and Reuven Yosef [2,*]

[1] Bioinformatics Center, Forest Research Institute, Dehradun 248006, Uttarakhand, India; NY (ORCiD: https://orcid.org/0000-0002-1539-7296): neelesh_yadav@icfre.org SR (ORCiD: https://orcid.org/0000-0002-2681-3793): rakholias@gmail.com

[2] Ben Gurion University of the Negev, Eilat Campus, P.O. Box 272, Eilat 881020, Israel; RY (ORCiD: https://orcid.org/0000-0003-4331-9866): ryosef60@gmail.com

* Correspondence: RY: ryosef60@gmail.com

Abstract: In this study, tree selection/plantation DSS (Decision Support Systems) were reviewed and assessed based on essential objectives in the available literature. We reviewed existing DSS were using multiple data sources and available online resources such as web interfaces. We compared the existing DSS, focusing primarily on five primary objectives in this study, which DSS may address when it comes to the tree selection including a) Climate resilience, b) Infrastructure/Space Optimization, c) Agroforestry, d) Ecosystem services, e) Urban sustainability. Climate resilience of tree species and urban sustainability is addressed relatively less in existing systems which can be holistically internalized in future DSS tools Based on this review, DNN (Deep Neural Networks) is recommended to address achieving trade-offs between complex objectives such as maximizing ecosystem services, climate resilience of tree species, maintaining Agroforestry, and other benefits.

Keywords: decision support system; climate resilience; ecosystem services; deep neural networks; sustainability

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1. Introduction

The global climate is changing and is predicted to change even faster in the near future (IPCC 2022). The importance of planting trees for climate change adaptation and mitigation is increasing as forests act as carbon sinks (Nunes et al. 2020, Yang 2023). This is particularly true in areas with desertification and complex environmental problems that require sound processes that allow the ever-growing human population to benefit from the ecosystem services of the environment (Poch et al., 2002, Prince and Safriel 2021). Also, in many cases, ecosystem services are not easily quantified monetarily, taken for granted, and often involve moral and ethical principles (Kiker et al. 2009). The rapid growth of tree planting and land use conversion from grassland to forests directly impact ecosystem services, including increased regulation and provision of services (Vihervaara et al. 2012). However, further planning is needed to ensure that local environmental issues and cultural values are internalized, enabling additional ecosystem services such as wood availability, water quality, biodiversity enrichment, and carbon sequestration (Muller and Turner 2007).

However, this type of land use change does not always increase ecosystem services, as grassland biomes are often viewed as having potential for forest restoration and planting, which typically reduces biodiversity and ecosystem services once these grasslands/savannahs are converted, leading to significant conservation measures for forest and grassland biomes, plantation strategies as well as separate ecosystem services need to be identified (Veldman et al. 2015). Furthermore, identifying the suitable tree species for tree adaptability is crucial for future climate scenarios, especially in urban areas, as changing climates lead to the loss of tree species, which can lead to a reduction in ecosystem services such as Urban Heat Island (UHI) mitigation, which can pose a challenge for adaptation and mitigation strategies to human-caused climate change (Lanza and Stone Jr. 2016).

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Using deep neural networks (DNNs), a decision support system (DSS) can be trained to learn from a large dataset of tree data, including information about tree species, climate, soil conditions, and other factors influencing tree growth and survival. This is because using neural networks was proposed three decades ago to solve forest management problems by integrating forest knowledge with artificial intelligence (AI; Kourtz 1990). AI greatly benefits sustainability and preserving ecosystem values, as increasing disruptions in a changing world can only be managed beyond human intelligence (Silvestro et al. 2022). Furthermore, despite the various DSS and AI used, the appointment of appropriate project managers is crucial to the execution and subsequent success of a project (Muller and Turner 2007).

Our study reviews various DSSs and compares them based on their objectives and applications. Furthermore, we provide a literature review focusing on the need for ecosystem service-focused DSS and discuss the potential applications of DNN for these systems.

2. Review of existing DSS tools for tree selection and plantations

One of the earliest DSSs for tree plantations in forestry was developed at the University of Canterbury, a framework-based system coded in Prolog. The focus was on knowledge-based decision support by linking to the Forest management information system (FMIS) database or Geographic Information Systems (GIS), enabling location-based access to information about the field microenvironment such as soils, climate, elevation, and previous land/crop use and current conditions along with multiple management options for optimization (Mason 1996). This section reviews existing DSS on tree selection and plantations using apparent keywords like 'DSS', 'Decision Support tool', 'Tree selection,' etc., as Google Scholar search (Figure 1).

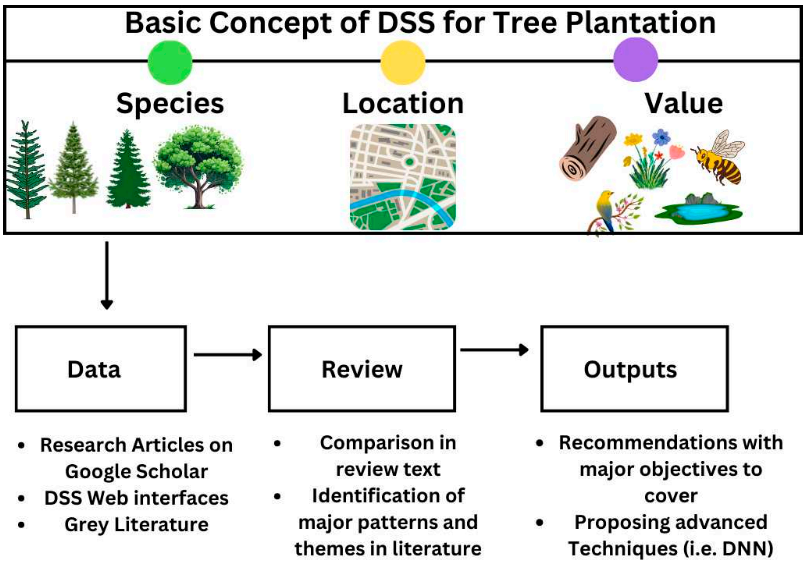

Figure 1. Flow diagram of the purpose of this study emphasizing the key concept and objectives of DSS.

We focus on five primary objectives in this study, which DSS may address when it comes to the tree selection, including a) Climate resilience, b) Infrastructure/Space Optimization, c) Agroforestry, d) Ecosystem services, and e) Urban sustainability (Figure 2).

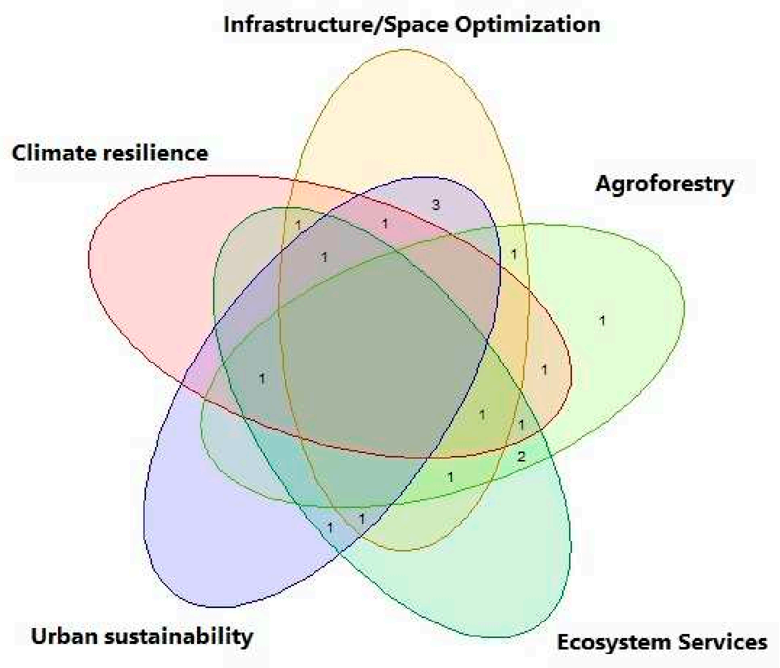

Figure 2. The figure represents Venn diagram of DSS (number represent the number of DSS fitting in the categories) and their major objectives to draw similarities and differences in DSS objectives. Details relevant to this figure are provided in Table 2.

Further efforts to develop a DSS for tree plantations began in the 2000s using GIS with a focus on street and neighborhood tree plantations while also attempting to address management aspects such as DSS-based strategies for reducing energy, fuel, and pesticide/fertilizers for plantation management (Randall et al. 2003). In addition, the focus was also expanded to include aspects such as soil property-based tree planting, the feasibility of the planting region, tree age, species diversity, shade, and canopy coverage (Kirnbauer et al. 2009). It is also essential to conduct an existing urban tree cover (UTC) analysis before tree planting decisions, using object-oriented satellite image analysis to identify existing vegetation cover and land use types (McGee III et al. 2012).

Mitigating a region’s hydrological problem also requires selecting suitable species, prioritizing sites for revegetation, and simulating other hydro-climatological conditions annually. These aspects were included in China’s bilingual GUI decision support re-vegetation program’s tool ReVegIH, which also could reduce sediment load release through afforestation modeling (McVicar et al. 2007).

Multi-lingual programming (C++ and Fortran) based DSS, known as Motti Simulator, developed by the Natural Resources Institute Finland (Luke), was also used for tree selection based on detailed forest stand dynamics and incorporating the tree growth and yield models (Saksa et al. 2021). Additionally, simplified open-source and open-code DSS such as PT2 (Prairie and Tree Planting Tool) allowed users to explore and delineate areas of interest for planting or managing trees/prairie using scaled dimensional drawing tools and then selecting seeds/woody plants for the respective soils with a dropdown menu. This also enabled the selection and calculation of financial costs and long-term management options (Tyndall 2021).

Nevertheless, advances in machine learning in recent years have enabled the selection of tree species incorporating climate variability using MaxEnt to determine the suitability and resilience of trees in different climate scenarios. A current example is the online platform “Which Plant Where” in Australia, which was developed using Python, Django and PostgreSQL (Tabassum et al., 2023). In addition, others use tree selection tools developed by the United States Department of Agriculture (USDA) such as the Tree Advisor and the Woody Plant Selection Tool for Multi-functional Purposes, using MySQL and the Drupal framework (Bentrup and Dosskey 2022). Also, Spatio-temporal Urban Tree DSS was developed using ensemble CAD and GIS tools, which integrates detailed 3D trees into

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urban design, which allows testing of tree placement, species selection, solar shade exposure, etc., with valuable elements of computational botany and light engineering technology makes this possible (White and Langenheim 2019).

Although tree planting decision support systems have addressed tree selection ecosystem services such as UHI mitigation, only simple filtering techniques with limited variables that filter the attributes from the tree database have been used (Werbin et al. 2020). In addition, ensemble models that use higher resolution datasets are also proposed to infer the potential suitability and realized distribution of tree species through batch generalization. This is a boosting method where Random Forests (RF), Gradient-booster trees (GBT), and Generalized linear models (GLM) are used, which are used by the meta-learner, i.e., linear regression, can be further processed (Bonannella et al. 2022).

We compare various DSS for tree selection/plantation based on their objectives, programming language framework and software (Table 1) along with their comparison with the primary objectives (Figure 2). Table 1 summarizes DSS in urban tree plantation, agroforestry, etc. revealing a prevalent trend towards utilizing R and Python tools. However, the technologies employed span a broad spectrum, encompassing languages such as C#, C++, .NET, Python, R, and Java, and web development tools like HTML, CSS, and JavaScript. The emphasis on these languages also suggests a shared recognition within the community of their effectiveness in handling data-driven tasks and facilitating interdisciplinary collaboration in environmental decision-making.

Table 1. Comparison of various DSS developed for tree selection/plantation.

	DSS Name (Provisional)	Software/language/framework	Objective Type	Reference
1	**Knowledge-based DSS**	Prolog	Forest plantations DSS	Mason 1996
2	**Prototype decision support system**	SMODT; ArcTrees; Treemodules | Visual Basic Analysis (VBA)	Urban tree plantation suitability	Kirnbauer et al. 2009
3	**ReVegIH decision support tool**	C#, Visual Basic, C++, .NET	Tree species selection with Ecohydrological modelling	McVicar et al. 2007
4	**Prototype decision support system (Randall)**	ArcView GIS Extension | Avenue	Neighbourhood greening	Randall et al. 2003
5	**Decision Support Tool - Precision Forestry**	HprAnalys, ArcGIS, Motti stand simulator	Tree species selection with stand dynamics	Saksa et al. 2021
6	**Virginia UTC assessment process**	ERDAS; ISODATA	Object-oriented classification Urban Tree Canopy analysis	McGee III et al. 2012
7	**Right Place, Right Tree—Boston**	R packages - *shinydashboard;leaflet;tigris;DT*	Tree plantation DSS for UHI mitigation	Werbin et al. 2020
8	**Which Plant Where?**	Python; Django; PostgreSQL	Plant Selection Tool for climate resilience and sustainability	Tabassum et al. 2023

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9	**Tree Advisor USDA**	MySQL; Drupal	Woody Plant Selection Tool for Multifunctional objectives	Bentrup and Dosskey 2022
10	**Plant-Best**	R	Plant Selection Tool for slope protection	Gonzalez-Ollauri and Mickovski 2017
11	**Spatio-Temporal Decision Support System for Street trees**	QGIS/ArcGIS; exlevel GrowFX; Autodesk; AutoCAD; ForestPro	Detailed 3D trees for Urban Design	White and Langenheim 2018
12	**Florida Agroforestry Decision Support System (FADSS)**	Delphi; SQL	Agroforestry planning and tree selection	Ellis et al. 2000
13	**PT² (Prairie and Tree Planting Tool)**	HTML; CSS; Javascript	Prairie and Tree Planting selection and financial cost estimation	Tyndall 2021
14	**Diversity for Restoration (D4R)**	JavaScript, Python, and R.	Ecosystem Restoration and Agroforestry	Fremout et al. 2021
15	**Citree**	PHP; MariaDB server	Tree selection for urban areas in temperate climate	Vogt et al. 2017
16	**i-tree USDA**	Java; Javascript; Python	Multi-module suite for Urban Tree structures and ecosystem service evaluation	Nowak et al. 2018
17	**Unique DSS for agroforestry systems**	R; HTML	Decision-support tool for coffee and cocoa agroforestry systems	Van der Wolf et al. 2019

This comparison is crucial as it emphasizes the core concept of tree plantation as the DSS for tree selection/plantation operates on a foundational structure encompassing Species, Location, and Value. The data sources include research articles from Google Scholar, DSS web interfaces, and grey literature, as the hands-on use of DSS web interfaces was essential to identify the capabilities and objectives of various DSS. During the review process, textual comparison reveals significant patterns and themes in the literature. The DSS outputs encompass recommendations with critical objectives and advocate advanced techniques like Deep Neural Networks (DNN) to enhance decision-making precision in tree selection and plantation, thereby offering more informed and insightful guidance.

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Moreover, the Venn diagram of DSS comparison reflects how existing DSS have combinations of objectives such as Infrastructure/Space Optimization with urban sustainability. Climate resilience and urban sustainability of trees are addressed least, whereas Infrastructure/Space Optimization and ecosystem services are addressed relatively more in DSS- tools. Nevertheless, the existing DSS addresses all issues at different times as evident from the analysis (Table 2).

Table 2. The DSS reviewed and the relevant objectives they address.

#	DSS	Climate resilience	Infrastructure/Space Optimization	Agroforestry	Ecosystem Services	Urban sustainability
1	Knowledge-based DSS	No	No	Yes	No	No
2	Prototype decision support system	No	Yes	No	No	Yes
3	ReVegIH decision support tool	Yes	No	Yes	No	No
4	Prototype decision support system (Randall)	No	Yes	No	No	Yes
5	Decision Support Tool - Precision Forestry	No	Yes	Yes	No	No
6	Virginia UTC assessment process	No	Yes	No	Yes	Yes
7	Right Place, Right Tree—Boston	No	No	No	Yes	Yes
8	Which Plant Where?	Yes	Yes	No	No	Yes
9	Tree Advisor USDA	No	No	Yes	Yes	No
10	Plant-Best	Yes	Yes	No	Yes	No
11	Spatio-Temporal Decision Support System for Street trees	No	Yes	No	No	Yes
12	Florida Agroforestry Decision Support System (FADSS)	Yes	Yes	Yes	Yes	No
13	PT2 (Prairie and Tree Planting Tool)	No	Yes	Yes	Yes	No
14	Diversity for Restoration (D4R)	Yes	No	Yes	Yes	No
15	Citree	Yes	Yes	No	Yes	Yes
16	i-tree	Yes	No	Yes	Yes	Yes
17	Unique decision-support tool for Cocoa and Coffee	No	No	Yes	Yes	No

4. The need for an Ecosystem Services-focused DSS

It is crucial to understand the ecosystem services received from trees during selection and planting, as trees provide various regulatory (carbon sequestration, air pollution reduction) and provisioning (timber, tree crops) services where the non-market values sometimes exceed commercial values and threats such as wildfires and pests must be considered for resilience (Cavender-Bares et al. 2022). Also, models such as the Natural Capital Protocol can be applied to improve agroforestry decision-making and evaluation at the farm level. They describe the connection between a natural capital asset, its condition, the resulting ecosystem services, and the benefits the people derive from those services. Better representation of benefits can also promote the public benefits of agroforestry at the farm level (Marais et al. 2019).

Satellite datasets and IDF (Intensity, Duration and Frequency)-based flood models can provide valuable information about the flooding and waterlogging situation in regions where monsoon and persistent floods occur. The areas affected by flooding and erosion can be identified based on flood depth and flow velocity forecasts for 25-, 50- and 100-year return periods (Quirogaa et al. 2016). Therefore, the selection of tree species adapted to this waterlogging must be assessed based on literature evaluating parameters such as stomatal conductance and net photosynthesis since some tree species show a reduction in these two processes after flooding (Anderson and Pezeshki 2001). In addition, trees such as poplars in riparian zones are very tolerant of flooding because nitrogen metabolism is not affected by flooding compared to species such as Oak and Beech, which are sensitive to successive flooding, and the depth and duration of flooding also need to be taken into account in detailed findings (Kreuzwieser et al. 2002).

It is essential to understand the dynamics of the UHI effect. There are regional and zonal differences, including in urban areas, as although trees are effective in reducing air temperature in areas with high building density, they are ineffective in built-up areas with low building density, and therefore, high-density trees with taller trunks are recommended for built-up areas (Aboelata and Sodoudi 2020). Changes in land use and land cover can influence local surface temperatures. For example, as previously irrigated croplands and forests transform into built-up urban areas over time, this can increase air and land surface temperatures. Conversely, a transition from bare land cover to urban areas could decrease average land surface temperature (LST) for semi-arid regions (Yosef et al. 2022, Sahdev et al. 2023). This highlights the significant influence of both vegetation and urban development on LSTs at the local scale. Vegetation has a cooling effect through transpiration, shading, and rainwater retention.

Similarly, urbanized zones contribute to temperature reduction than regions such as exposed soil or rocky terrains due to their surface properties and materials that promote convection more effectively (Rasul et al. 2017). There is a unique approach to UHI mitigation that consists of creating a regional Heat Vulnerability Index (HVI) that includes socioeconomic (family income, age, building density) and environmental data (e.g., LST, vegetation) to inform decision-making (Johnson et al. 2012), which helps increase urban canopy cover with the most suitable tree species. To mitigate UHI, urban areas need to be categorized as high- and low-density, as land use and availability of trees in cities are limited.

Furthermore, Nature-based solutions (NbS) to air pollution can be implemented zone-wise by involving the plantations. Air pollution-tolerant species such as *Shorea robusta, Ficus religiosa,* and *Mangifera indica* have high tolerance to pollutants and high metal accumulation capacity in industrial areas. Dust removal and deposition are excellent in residential areas in *Azadirachta indica, Dalbergia sissoo*, and *Ficus religiosa* (Menon and Sharma 2021). Slope protection and landslide mitigation tools include Plant-Best, developed in the R statistical programming language (Gonzalez-Ollauri and Mickovski 2017).

Many factors influence tree plantations, including the value and placement of trees, particularly in urban areas. This includes public lands, parks and roadsides, and private lands, i.e., residential properties (Kowarik 2023). Kirkpatrick et al. (2012) suggested that small fruit trees are more aesthetic and practical on private lands. About agroforestry, a study found that the management of forests involves significant uncertainty regarding future timber prices, tree growth, and the impact of climate-related changes on tree growth. Since most forest owners prefer to avoid risk and tree growth and timber prices are unpredictable, the study suggests the following implications: longer rotations should be compared to the recommended guidelines. There should be a greater preference for mixed stands than deterministic calculations suggest; the concentration of timber revenues should be less focused on the final harvest, as currently recommended. The consistent retention of multiple timber assortments in the stand is beneficial, indicating the pursuit of more uneven stand structures (Pukkala and Kellomäki 2012).

Therefore, the suitability process must include mixed stands, not just monoculture recommendations. However, this may not be the case for all tree species as agarwood monoculture plantations could also be favorable regarding growth as it is endangered (Nath et al. 2022). Nevertheless, plantation agriculture in tropical countries must be managed based on polyculture systems and not monocultures since the ecosystem services provided by the former are much higher as they include improving biodiversity, pollination, and biological pest control even in the context of small-scale silviculture (Yahya et al. 2017). Hirsch et al. (2023) found species-specific tolerance to

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drought and traffic pollution in urban areas, suggesting using certain tree species along roads and in residential areas.

DSS, such as the FADSS (Florida Agroforestry DSS), addressed economic and environmental services and utilized GIS databases that included vital datasets such as tree attributes, infrastructure, climate, soil, and cropping, including critical levels such as crucial agroforestry management practices (Ellis et al. 2000). It is also essential to include soil datasets such as soil pH, sand content etc., for tree species Species Distribution Models (SDM) as soil variables are strong predictors of habitat suitability (Henderson et al. 2023). The soil datasets are often neglected in many SDMs, so these datasets should be some of the core variables in the decision support system. Finally, recent developments in tree selection DSS include the Diveristy for Restoration (D4R) tool, which allows users to make multi-selections from the menu for restoration objectives, ecosystem services, seeding zones, climate, and other environmental data in decision-making for individual and combined tree species selection (Fremout et al., 2021).

5. Proposed use of DNN in DSS for Tree selection/plantations

In order to improve decision-making in Urban Forestry for sustainable and livable cities, AI has been increasingly used in recent years (Schepers 2023). However, only half of the studies involving the use of AI manage to take into account aspects such as limitations of these methods, including robustness and lack of precision in the absence of some datasets, combined use of discrete and continuous data variables, overfitting, collinearity, etc., (Araújo et al. 2021). The application of AI in forestry can be improved by incorporating XAI (Explainable Artificial Intelligence), LTNL (Learning To Not Learn), and FUL (Feature Unlearning) methods that provide a qualitative and quantitative comparison of model accuracy and add explanations through the use of predefined annotation matrices, i.e., expert knowledge that can improve these deep learning models. Therefore, combining XAI, FUL and expert knowledge can improve the understanding of how the model works instead of simple model results (Cheng et al. 2022).

Furthermore, the use of CNN (Convolutional Neural Networks) is increasing significantly with a large number of applications in agriculture/agroforestry DSS generally based on frameworks such as *Keras, Tensorflow, Tensorflow-Keras, PyTorch, Tensorflow-PyTorch* and *Deeplearning 4j* (Altalak et al. 2022). In addition, the applications of DNN for intelligent geographic data analysis in DSS in agriculture have shown promising results, mainly when BPNN (Back-Propagation Neural Network) based prediction models are used to predict agricultural indicator values (Zeng et al. 2022, Araujo et al. 2023). In addition, DNN-based species distribution models, show better results than traditional models, including DNN created using bootstraps to improve the prediction performance of species distribution. These can be built in the Python environment using the *Scikit-learn* package with bootstrapping aggregation (bagging) performed in the R statistics package *boot* to train the DNN (Rew et al. 2021). Regardless, CNN-based SDMs offer broader advantages, including better learning of non-linear environmental descriptors, compelling distribution predictions of environmental descriptors, and the use of high-dimensional data, enabling improved collection of information about environmental landscapes structured on tensors rather than local values of environmental factors (Deneu et al. 2021). Similarly, the ecosystem service component of a tree plantation DSS can be better understood and improved through these tensors (Unawong et al. 2022), i.e., various functions of multiple vectors, because ecosystem services include multiple services and complex relationships such as the existing environment or land-use can be considered in one vector. The ecosystem services can be considered as multi-linear functions of the vector (Zhang et al. 2023).

TensorFlow uses the term "Tensor" to denote the primary data structure used in deep learning algorithms. This "Tensor" represents a multi-dimensional array of numerical values (Singh and Manure 2019). In addition, deep neural networks have been widely used in recent years. This rise in the popularity of deep learning models can be attributed to TensorFlow, an open-source deep learning framework, because this framework provides users with the opportunity to access pre-defined network-trained deep learning classification (and regression) models while allowing customizable training of their personalized or custom datasets (Pally and Samadi 2022).

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The TensorFlow Deep Neural Network (TF-DNN) is used in the Python environment as the primary model of this study because TF-DNN has been applied in GIS studies, which have shown higher spatial prediction accuracy than other techniques such as Random Forests (RF), Support Vector Machine (SVM) and Logistic Regression (LR) (Truong et al. 2023). The TF-DNN can be applied with semi-supervised learning with multivariate multilayer perceptron with training datasets, where the soil, climate, and landscape-environmental layers can be used to determine the land suitability of the plant species in the study, with the results providing continuous better-decision potential when validating through K-fold cross-validation (Bhullar et al. 2023).

For the proper implementation of the TF-DNN, it is essential to use multiple libraries, including *TensorFlow*, *Keras*, *NumPy*, and *Matplotlib*, where *Keras* is used as a backend to build and implement the TF-DNN algorithm as *TensorFlow* acts as a numerical computing library. The *Numpy* library is helpful for many mathematical functions that operate on arrays, and *Matplotlib* is similarly used for visualizing statistical outputs (Osah et al. 2021).

Therefore, the utilization of DNN is essential for improving the precision and efficacy of DSS, contributing to sustainable and well-informed tree selection and plantation strategies in both urban and regional environments.

6. Conclusions

Based on this review, it is essential to consider the focus on increasing climate-resilient tree selection in DSS along with requirements of urban sustainability to maximize ecosystem services in urban environments. Incorporating DNN can also enhance decision-making when multiple ecosystem services and agroforestry benefits are considered, especially when the goal is better predictive modeling capabilities in the context of tree plantations.

Moreover, the primary objectives outlined in the review need to be addressed and incorporated simultaneously, which needs to be included in the reviewed DSS. Applying DNN in future DSS tools will enable the internalization of these challenging objectives, particularly when finding a balance between complex trade-offs such as maximizing ecosystem services, climate resilience of tree species, and maintaining agroforestry benefits.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, S.R., R.Y., and Y.Y.; methodology, Y.Y.; software, S.R.; validation, R.Y., Y.Y.; formal analysis, S.R.; data curation, S.R.; writing—original draft preparation, S.R., R.Y.; writing—review and editing, S.R., R.Y.; visualization, S.R.; supervision, Y.Y.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript." Please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

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Abbreviations

AI Artificial Intelligence; BPNN Back-Propagation Neural Network; CNN Convolutional Neural Networks; DNN Deep Neural Networks; DSS Decision Support System; D4R Diversity for Restoration; FADSS Florida Agroforestry Decision Support System; FMIS Forest Management Information System; FUL Feature Unlearning; GBT Gradient Booster Trees; GIS Geographic Information Systems; GLM Generalized Linear Models; HVI Heat Vulnerability Index; IDF Intensity, Duration and Frequency; IPCC International Panel for Climate Change; LST Land Surface Temperature; LTNL Learning To Not Learn; NbS Nature-based Solutions; RF Random Forests; SDM Species Distribution Modelling; SVM Support Vector Machine; TF-DNN TensorFlow Deep Neural Network; UHI Urban Heat Island; USDA United States Department of Agriculture; UTC Urban Tree Cover; XAI Explainable Artificial Intelligence.

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