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Review

Decision Support Systems in Forestry and Tree-Planting Practices and the Prioritization of Ecosystem Services: A Review

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Abstract: In this study, tree-selection/plantation decision support systems (DSSs) were reviewed and evaluated against essential objectives in the available literature. We verified whether existing DSSs leverage multiple data sources and available online resources such as web interfaces. We compared the existing DSSs, and in this study mainly focused on five main objectives that DSSs can consider in tree selection, including (a) climate resilience, (b) infrastructure/space optimization, (c) agroforestry, (d) ecosystem services, and (e) urban sustainability. The climate resilience of tree species and urban sustainability are relatively rarely taken into account in existing systems, which can be integrated holistically in future DSS tools. Based on this review, deep neural networks (DNNs) are recommended to achieve trade-offs between complex objectives such as maximizing ecosystem services, the climate resilience of tree species, agroforestry conservation, 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 [1]. The importance of planting trees for climate change adaptation and mitigation is increasing, as forests act as carbon sinks [2,3]. This is particularly true in areas with desertification and complex environmental problems that require robust processes that allow the ever-growing human population to benefit from the environment's ecosystem services [4,5]. Furthermore, in many cases, ecosystem services cannot be easily quantified in monetary terms, are taken for granted, and often involve moral and ethical principles [6]. The rapid growth of tree planting and land-use conversion from grassland to forests directly impacts ecosystem services, resulting in increased regulation and service provision [7]. However, further planning is needed to ensure that local environmental concerns and cultural values are internalized and that additional ecosystem services such as timber availability, water quality, biodiversity enrichment, and carbon sequestration are enabled [8].

However, this type of land-use change does not always lead to an improvement in ecosystem services, as grassland biomes are often considered to have potential for forest restoration and planting. Biodiversity and ecosystem services are typically reduced once these grasslands/savannahs are converted, resulting in significant protective measures to plantation strategies, and thus separate ecosystem services need to be identified for forest and grassland biomes [9]. Furthermore, identifying suitable tree species for 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 to adaptation and mitigation strategies for human-caused climate change [10].

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 that influence tree growth and survival. This is because the use of neural networks was proposed three decades ago to solve forest management problems by integrating forest knowledge with artificial intelligence (AI; [11]). AI greatly benefits sustainability and the preservation of ecosystem values, as increasing disruptions in a changing world can only be managed beyond human intelligence [12]. Furthermore, despite the various DSSs and AI systems used, the appointment of appropriate project managers is crucial to the execution and subsequent success of a project [8].

Our study examines various DSSs and compares them based on their objectives and applications. In addition, we provide a literature review focusing on the need for an ecosystem-services-focused DSS and discuss the potential applications of DNNs for these systems.

2. Review of Existing DSS Tools for Tree Selection and Plantations

2.1. Review of the Existing Literature

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) or Geographic Information System (GIS) databases, enabling location-based access to information about the field microenvironment such as soils, climate, elevation, and earlier land/crop use and current conditions, along with multiple management options for optimization [13].

Further efforts to develop a DSS for tree plantations began in the 2000s using a GIS with a focus on street and neighborhood tree plantations, while attempting to address management aspects such as DSS-based strategies to reduce energy, fuel, and pesticides/fertilizers for plantation management [14]. In addition, the focus was also expanded to include aspects such as soil-property-based tree planting, feasibility of the planting area, tree age, species diversity, shade, and canopy cover [15]. It is also important to conduct an existing urban tree cover (UTC) analysis prior to tree-planting decisions, using object-oriented satellite image analysis to identify existing vegetation cover and land-use types [16].

Mitigating a region's hydrological problems also requires selecting appropriate species, prioritizing sites for re-vegetation, and simulating different hydro-climatological conditions annually. These aspects were incorporated into China's bilingual GUI decision support tool for re-vegetation programs, ReVegIH, which could also reduce sediment load release through afforestation modeling [17].

A multilingual programming (C++ and Fortran)-based DSS known as the Motti Simulator, developed by the Natural Resources Institute Finland (Luke), has also been used for tree selection based on detailed forest stand dynamics and incorporating tree growth and yield models [18]. Additionally, simplified open-source and open-code DSSs such as PT^2 (Prairie and Tree Planting Tool) have allowed users to explore and delineate areas of interest for tree/prairie planting or management using scaled dimensional drawing tools, and then select seeds/woody plants for the various soils with a drop-down menu. This also enabled the selection and calculation of financial costs and long-term management options [19].

Nevertheless, advances in machine learning in recent years have enabled the selection of tree species taking into account climate variability using MaxEnt to determine the suitability and resilience of trees in different climate scenarios. A recent example is the online platform "Which Plant Where" in Australia, which was developed using Python, Django, and PostgreSQL [20]. 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 [21]. In addition, a spatio-temporal urban tree DSS was developed using ensemble CAD and GIS tools. This integrates detailed 3D trees into urban design, allowing the testing of tree placement, species selection, solar exposure, etc. Valuable elements of computational botany and lighting engineering technology make this possible [22].

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 tree databases have been used [23]. In addition, ensemble models that use higher-resolution datasets to infer the potential suitability and realized distribution of tree species through batch generalization are also proposed. This is a boosting method that uses random forest (RF), gradient-booster trees (GBTs), and generalized linear models (GLMs), which are further processed by the meta-learner [24].

2.2. Methods

In this section, reviews and analyses of existing DSSs for tree selection and plantations are reviewed and analyzed using obvious keywords such as 'DSS', 'Decision Support tool', 'Tree selection,', etc., via a Google Scholar search (Figure 1). Keywords such as 'ecosystem services', 'agroforestry', 'urban', 'climate', etc., were also frequently searched for in the literature texts. We compare different DSSs for tree selection/planting based on their objectives, their programming language framework and software (Table 1), and their comparison with the main objectives (Figure 2). Table 1 summarizes DSSs for urban tree plantations, agroforestry, etc., which show prevailing trends of using R and Python tools. This comparison is crucial as it highlights the core concept of tree planting, as the DSS for tree selection/planting is based on a basic structure that includes species, location, and value. Data sources include research articles from Google Scholar, DSS web interfaces, and the gray literature; the practical use of DSS web interfaces was crucial in determining the capabilities and objectives of various DSSs. During the review process, text comparison revealed important patterns and themes in the literature. The DSS findings include recommendations with critical objectives and advocate for advanced techniques such as deep neural networks (DNNs) to improve decision accuracy in tree selection and planting, thereby providing more informed and insightful guidance.

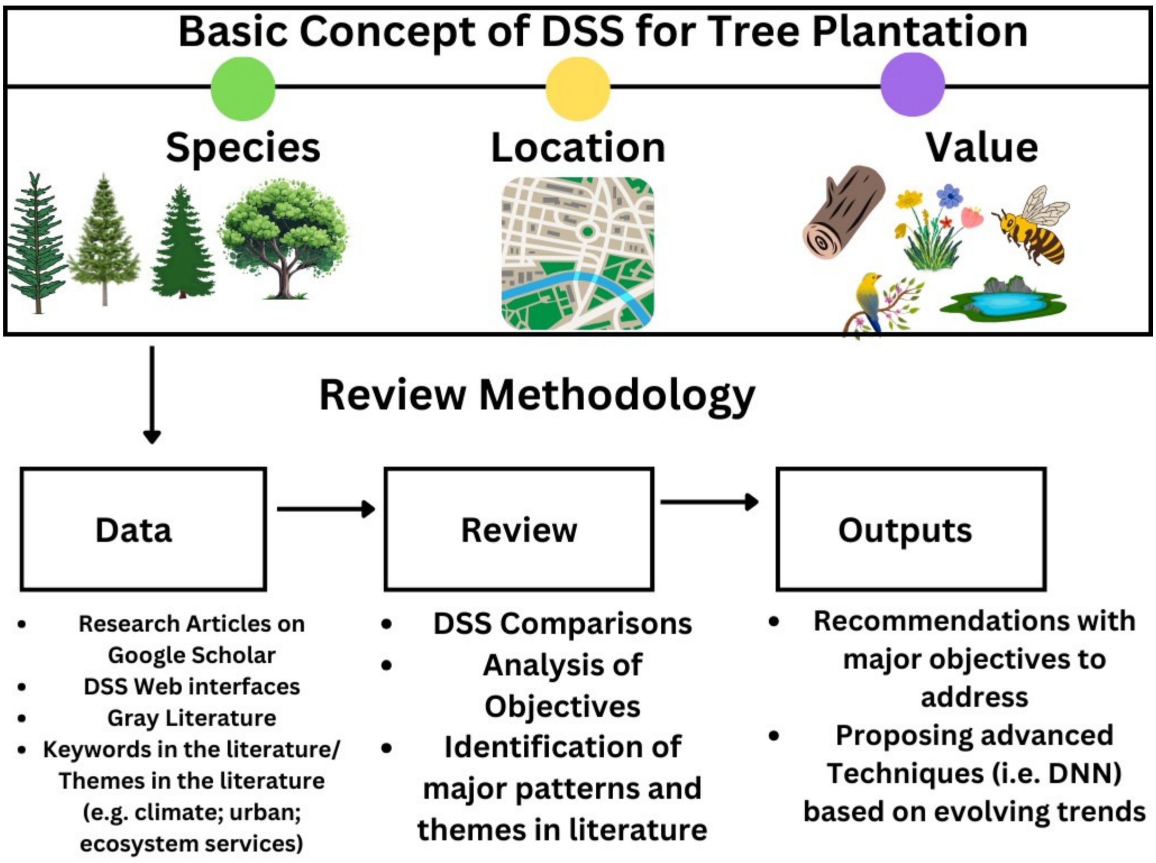

Figure 1. Flow chart of the purpose of this study highlighting the key concepts and objectives of DSSs.

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

	DSS Name (Provisional)	Software/Language/Framework	Objective Type	Reference
1	Knowledge-based DSS	Prolog	Forest plantation DSS	[13]
2	Prototype Decision Support System	SMODT; ArcTrees; Treemodules ∣ Visual Basic Analysis (VBA)	Urban tree plantation suitability	[15]
3	ReVegIH Decision Support Tool	C#, Visual Basic, C++, .NET	Tree species selection with ecohydrological modelling	[17]
4	Prototype Decision Support System (Randall)	ArcView GIS Extension ∣ Avenue	Neighborhood greening	[14]
5	Decision Support Tool—Precision Forestry	HprAnalys, ArcGIS, Motti stand simulator	Tree species selection with stand dynamics	[18]
6	Virginia UTC Assessment Process	ERDAS; ISODATA	Object-oriented classification of urban tree canopy analysis	[16]
7	Right Place, Right Tree—Boston	R packages—shinydashboard; leaflet; tigris; DT	Tree plantation DSS for UHI mitigation	[23]
8	Which Plant Where?	Python; Django; PostgreSQL	Plant selection tool for climate resilience and sustainability	[20]
9	Tree Advisor USDA	MySQL; Drupal	Woody plant selection tool for multifunctional objectives	[21]
10	Plant-Best	R	Plant selection tool for slope protection	[25]
11	Spatio-Temporal Decision Support System for Street Trees	QGIS/ArcGIS; exlevel GrowFX; Autodesk; AutoCAD; ForestPro	Detailed 3D trees for urban design	[22]
12	Florida Agroforestry Decision Support System (FADSS)	Delphi; SQL	Agroforestry planning and tree selection	[26]
13	PT^2 (Prairie and Tree Planting Tool)	HTML; CSS; Javascript	Prairie and tree planting selection and financial cost estimation	[19]
14	Diversity for Restoration (D4R)	JavaScript, Python, and R.	Ecosystem restoration and agroforestry	[27]
15	Citree	PHP; MariaDB server	Tree selection for urban areas in temperate climate	[28]
16	i-tree USDA	Java; Javascript; Python	Multi-module suite for urban tree structures and ecosystem service evaluation	[29]
17	Unique DSS for Agroforestry Systems	R; HTML	Decision support tool for coffee and cocoa agroforestry systems	[30]

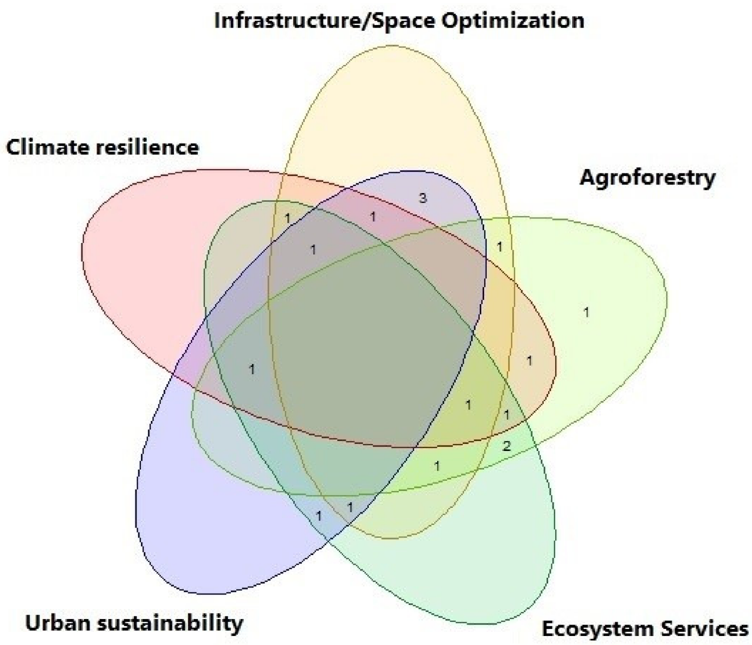

Figure 2. A Venn diagram of DSSs (the number represents the number of DSSs that fit into the categories) and their main goals to show similarities and differences in DSS goals. Details can be found in Table 2. Numbers in the VENN diagram ellipses represent the number of DSS fitting the categories.

Table 2. The DSS reviews and the relevant objectives they address. CR = climate resilience, I/SO = infrastructure/space optimization, AF = agroforestry, ES = ecosystem services, US = urban sustainability.

#	DSS	CR	I/SO	AF	ES	US	Ecosystem Services
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	Air quality; flood mitigation; UHI mitigation
7	Right Place, Right Tree—Boston	No	No	No	Yes	Yes	UHI mitigation
8	Which Plant Where?	Yes	Yes	No	No	Yes	-
9	Tree Advisor USDA	No	No	Yes	Yes	No	Extensive ecosystem services
10	Plant-Best	Yes	Yes	No	Yes	No	Slope protection (landslide prevention)
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	Runoff reduction; erosion control; timber provisioning, etc.
13	PT^2 (Prairie and Tree Planting Tool)	No	Yes	Yes	Yes	No	Biodiversity (wildlife and pollinator habitat); water quality
14	Diversity for Restoration (D4R)	Yes	No	Yes	Yes	No	Extensive ecosystem services
15	Citree	Yes	Yes	No	Yes	Yes	Air quality; bird feeding; provisioning (honey and edibles)
16	i-tree	Yes	No	Yes	Yes	Yes	Air quality; runoff reduction; Carbon sequestration; Cooling effect, etc.
17	Unique Decision Support Tool for Cocoa and Coffee	No	No	Yes	Yes	No	Microclimate buffering; soil fertility; pest/weed suppression; provisioning (timber, food and fuelwood), etc.

Furthermore, in this study, we focus on five main objectives that DSSs can consider in tree selection, including (a) climate resilience, (b) infrastructure/space optimization, (c) agroforestry, (d) ecosystem services, and (e) urban sustainability (Figure 2). The goal of infrastructure/space optimization has been addressed by some DSSs mentioned above (Table 1), and includes aspects such as tree selection to optimize shading, infrastructure constraints, tree placement, spatial considerations, etc. [15,19,20,22].

Climate resilience was also addressed in some DSSs, covering aspects such as drought tolerance, heat resistance, resilience of trees, etc., to extreme events in different climate change scenarios [20,25–28]. In addition, the main DSSs aimed at agroforestry include DSS Nos. 9, 12, 13, 14, and 17, which also more or less internalize ecosystem services, since the relevant literature contains the term 'ecosystem services' and a range of ecosystem services are explicitly mentioned (Table 1). The specific ecosystem services are listed in the Section 2.2 (Table 2). Many DSSs are specifically focused on urban sustainability related to tree planting, including DSS Nos. 2, 6, 7, 8, 15 and 16, as these DSSs even emphasized the word 'urban' and subsequently sustainability in urban areas in their published articles (Table 1). DSSs specifically targeted at forestry were very rare, as DSSs generally referred to agroforestry, mainly because farmers and planters were key stakeholders rather than stand-alone forestry applications. However, the stand-alone forestry DSSs also included DSS Nos. 1 and 5, which also highlighted the term 'forestry' in the literature, particularly in the article abstracts (Table 1). Therefore, the independent forestry objective was not taken into account in this analysis.

In addition, the Venn diagram of DSS comparisons reflects how existing DSSs have combinations and commonalities of objectives, such as infrastructure/space optimization with urban sustainability, which are described in the Section 2.3.

2.3. Results

Table 1 summarizes the DSSs focusing on urban tree plantations, agroforestry, etc., and shows a prevailing trend of using R and Python tools. However, the technologies used span a wide range and include languages such as C#, C++, .NET, Python, R, and Java, as well as web development tools such as HTML, CSS, and JavaScript. The emphasis on these languages suggests a shared recognition within the community of their effectiveness in tackling data-driven tasks and facilitating interdisciplinary collaboration in environmental decision making [29,30].

Since DSSs have historically paid the least attention to the goal of climate resilience, it is important to focus on climate-tolerant planting strategies by increasing the functional diversity of trees, as this ensures the maintenance of ecosystem services by preventing tree death [31]. Interestingly, the trade-offs between climate resilience and ecosystem services are particularly embedded in the concept of climate adaptation, as in this context the focus on the use of regulating ecosystem services is important [32].

According to the Venn diagram, the commonalities in the system in terms of the goals they address include infrastructure/space optimization and urban sustainability (n = 6), followed by ecosystem services and agroforestry (n = 6; Figure 2). This shows that existing DSS developers in particular have placed emphasis on spatial optimization in tree selection in urban areas, as well as maximizing ecosystem services in agroforestry ecosystems. Furthermore, climate resilience and the urban sustainability of trees are the least considered, while infrastructure/space optimization and ecosystem services are relatively more considered in many DSS tools (Figure 2). Nevertheless, the existing DSSs address all issues at different times, but not comprehensively. This is evident from the analysis (Table 2).

DSSs aimed at urban sustainability often includes the regulation of ecosystem services such as UHI mitigation (or cooling effect) and air quality. Other regulating ecosystem services such as water quality, runoff reduction, and pollination were also included. In addition, some existing DSSs have extensively addressed a wide range of ecosystem services, for example, DSS Nos. 9, 14, 15, and 17. Provision services are also included, such as in DSS Nos. 12, 13, 15, 17, etc., which include wood and non-timber forest products. Some supporting ecosystem services such as soil fertility were also included (Table 2).

3. 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 services (timber, tree crops). Non-market values sometimes exceed commercial values and threats, such as forest fires and pests, and this must be taken into account for resilience [33]. Additionally, 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, its condition, the resulting ecosystem services, and the benefits that people derive from these services. Better benefit representation can also promote the public benefits of agroforestry at the farm level [34].

One of the most important ecosystem services is flood protection, which can be improved by riparian forests as part of agroforestry (e.g., riparian buffers), providing the same benefits at almost 30% of the cost compared to an engineered protection structure, as shown in a study in Germany [35]. Satellite datasets and IDF-based (Intensity, Duration and Frequency) flood models can provide valuable information about the flooding and water logging situation in regions experiencing monsoons and persistent floods. The areas affected by flooding and erosion can be identified using flood depth and flow velocity forecasts for 25-, 50- and 100-year return periods [36]. Therefore, the selection of tree species adapted to this water logging must be assessed based on the literature that evaluates parameters such as stomatal conductance and net photosynthesis, since some tree species show a reduction in these two processes after flooding [37]. 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 must also be taken into account in detail [38].

It is important to understand the dynamics of the UHI effect. There are regional and zonal differences, including in urban areas, because 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 [39]. 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 lead to increases in air and land surface temperatures (LSTs). Conversely, a transition from bare land cover to urban areas could reduce the average LST for semi-arid regions [40,41]. This highlights the significant influence of both vegetation and urban development on LSTs at the local scale. The vegetation has a cooling effect through transpiration, shading, and rainwater retention.

Similarly, urbanized zones contribute more to temperature reduction than regions with exposed ground or rocky terrain due to their surface properties and materials that promote convection more effectively [42]. There is a unique approach to UHI mitigation that involves creating a regional Heat Vulnerability Index (HVI) that incorporates socioeconomic (family income, age, building density) and environmental data (e.g., LST, vegetation) for decision making [43], which helps to increase urban tree canopy cover with the most suitable tree species. To mitigate UHI, urban areas need to be divided into high- and low-density areas because land use and tree availability are limited in cities.

Furthermore, nature-based solutions (NbSs) to air pollution can be implemented zone-wise by involving 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* [44]. Tools for slope protection and landslide mitigation include Plant-Best, which was developed in the statistical programming language R [25].

Many factors influence tree plantation, including the value and placement of trees, particularly in urban areas. This includes public lands, parks, and roadsides, as well as private land, i.e., residential properties [45]. Kirkpatrick et al. [46] suggested that small fruit trees on private property were more aesthetically pleasing and practical. A study on agroforestry 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. Because most forest owners prefer to avoid risk and tree growth and timber prices are unpredictable, the study suggests the following implication: longer rotations should be compared to recommended guidelines. There may 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 inventory is advantageous, which indicates that more uneven stand structures should be pursued [47].

Therefore, the suitability process must include mixed stands and not just monoculture recommendations. However, this may not be the case for all tree species as agarwood monoculture plantations could also be favorable in terms of growth, as they are endangered [48]. Nevertheless, plantation agriculture in tropical countries must be managed on the basis of polyculture systems and not monocultures since the ecosystem services provided by the former are much better, as they include the improvement of biodiversity, pollination, and biological pest control even in the context of small-scale silviculture [49].

Hirsch et al. [50] found species-specific tolerance to drought and traffic pollution in urban areas, suggesting the use of certain tree species along roads and in residential areas.

DSSs such as the FADSS (Florida Agroforestry DSS) dealt with economic and environmental services and used GIS databases that contained important datasets on tree attributes, infrastructure, climate, soil, and cropping, including critical levels such as key agroforestry management practices [26]. It is also important to include soil datasets on soil pH, sand content, etc., for tree species distribution models (SDMs) as soil variables are strong predictors of habitat suitability [51]. Soil datasets are often neglected in many SDMs, so these datasets should be some of the core variables in decision support systems. Finally, recent developments in tree selection DSSs include the Diversity for Restoration (D4R) tool, which allows users to make multiple selections from a menu for restoration objectives, ecosystem services, seeding zones, climate, and other environmental data on decision-making for individual and combined tree species selection [27].

Therefore, by incorporating rich ecosystem services, DSS tools are enriched with more data-driven and knowledge-driven capabilities, introducing complexities in these systems that can then be addressed and improved through the implementation of DNNs, as explained in the following section.

4. Proposed Use of DNN in DSS for Tree Selection/Plantation

In order to improve decision making in urban forestry for sustainable and livable cities, AI has been increasingly used as part of smart technology in recent years [52]. However, only half of the studies using AI manage to take into account aspects such as the limitations of methods, including robustness and lack of precision in some datasets, the combined use of discrete and continuous data variables, overfitting, collinearity, etc. [53]. The application of AI in forestry can be improved by incorporating the XAI (Explainable Artificial Intelligence), LTNL (Learning To Not Learn), and FUL (Feature Unlearning) methods which allow the qualitative and quantitative comparison of model accuracy and explanations through the use of predefined annotation matrices, i.e., expert knowledge that can improve these deep learning models. Therefore, the combination of XAI, FUL, and expert knowledge can improve the understanding of how the model works, instead of only obtaining simple model results [54].

In addition, the use of CNNs (convolutional neural networks) is increasing significantly with a large number of applications in agriculture/agroforestry DSSs generally based on frameworks such as *Keras*, *Tensorflow*, *Tensorflow-Keras*, *PyTorch*, *Tensorflow-PyTorch*, and *Deeplearning 4j* [55]. In addition, the applications of DNNs for intelligent geographic data analysis in DSSs in agriculture have shown promising results, especially when Back-Propagation Neural Network (BPNN)-based prediction models are used to predict agricultural indicator values [56,57]. In addition, DNN-based species distribution models show better results than traditional models, including DNNs built 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 [58]. 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 an improved collection of information about environmental landscapes structured on tensors, rather than local values of environmental factors [59]. Likewise, the ecosystem service component of a tree plantation DSS can be better understood and improved through these tensors [60], i.e., different functions of multiple vectors (as ecosystem services include multiple services and complex relationships, such as between the existing environment and land use) can be considered in one vector. Ecosystem services can be viewed as multi-linear functions of the vector [61].

As explained in the Section 2.3, a trend of DSS frameworks over the years is towards the use of scripting and data analysis languages such as R and Python (Table 1). This trend now also brings with it the possibility of using deep neural networks to solve complexities and improve automation processes, as DNNs can be developed with R [62] and Python much more extensively [63–66].

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 [67]. In addition, deep neural networks have been widely used in recent years. This rise in popularity of deep learning models is due to TensorFlow, an open-source deep learning framework, as this framework offers users the ability to rely on pre-defined, network-trained deep learning classification (and regression) models while enabling the customizable training of their personalized or custom datasets [68].

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 that have shown higher spatial prediction accuracy than other techniques such as random forest (RF), support vector machines (SVMs), and logistic regression (LR) [69]. The TF-DNN can be applied with semi-supervised learning with a 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 continuously better decision-making potential when validated through K-fold cross-validation [70].

For the proper implementation of the TF-DNN, it is important to use multiple libraries, including *TensorFlow*, *Keras*, *NumPy*, and *Matplotlib*. *Keras* is used as a backend to build and implement the TF-DNN algorithm, while *TensorFlow* acts as a numerical computing library. The *Numpy* library is useful for many mathematical functions that operate on arrays, and *Matplotlib* is similarly used to visualize statistical outputs [71].

Therefore, the use of DNNs is crucial for improving the precision and effectiveness of DSSs and contributes to sustainable and informed tree selection and plantation strategies in both urban and regional environments.

5. Conclusions

This study not only highlights existing DSSs developed for the purpose of tree selection and plantation, but also highlights the evolving trends and goals that DSSs address. It outlines various goals that are commonly addressed in the existing literature and notes the lack of a comprehensive DSS that takes into account all of these goals as well as future challenges such as climate resilience and sustainable urban spaces.

Based on this review, it is important to focus on increasing the selection of climate-resilient trees in DSSs, along with urban sustainability requirements, to maximize ecosystem services in urban environments. Given the evolving trend of using scripting and data analysis languages such as R and Python, incorporating DNNs can also improve decision making when considering multiple ecosystem services and the benefits of agroforestry, especially when the goal is better predictive modeling capabilities in the context of tree plantation.

In addition, the main objectives set out in this review must be addressed simultaneously and taken into account and included in the reviewed DSSs. The application of DNNs in future DSS tools will enable the internalization of these challenging goals, especially when it comes to finding a balance between complex trade-offs such as maximizing ecosystem services, the climate resilience of tree species, and maintaining the benefits of agroforestry. This study will provide future DSS developers with an important comparison to address some of the objectives not previously considered in DSSs. The future implementation of DNNs will improve decision making under challenging climate change conditions and the resilience of ecosystem services.

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Abbreviations

AI, Artificial Intelligence; BPNN, Back-Propagation Neural Network; CNNs, Convolutional Neural Networks; DNNs, 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; GBTs, Gradient Booster Trees; GISs, Geographic Information Systems; GLMs, 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; NbSs, 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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