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An Object Driven Decision Model for Quantifying the Virtual Merkus Pine Tree's Environment Contribution

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Abstract

A tree planted in the wild contributes significantly to nature and its surroundings. Key benefits include biomass production and the strengthening of soil contours. Biomass itself is a tangible output of living organisms, offering both renewable fuel potential and notable economic value. Additionally, the presence of a tree has a considerable effect on soil shear strength, which plays a crucial role in supporting reforestation efforts in deforested areas. The research aims to construct a computational decision model of a virtual Merkus Pine tree to estimate biomass production and evaluate its impact on soil reinforcement as part of the tree's environmental contributions. The model was constructed via two types of methods: an object-oriented approach for technical design and functional-structural plant modeling (FSPM) as a core method to construct a 3D virtual pine tree model. The model is a novel computational decision model operated to visually simulate the growth and development of Merkus Pine, estimate biomass yield, and calculate annual soil shear strength due to the tree's presence. Simulation results indicate that a single Merkus Pine tree can produce up to 242.27 kg of biomass and enhance soil shear strength by approximately 0.88 N by the end of 15 years.

Keywords: Biomass; Soil Shear Strength; Virtual Merkus Pine Tree; Environmental Contribution; Functional-Structural Plant Modeling; Object-Oriented; Computational Decision Model.

1. Introduction

Biomass refers to organic material derived from living organisms, including plants, animals, and their residues. In the energy sector, biomass is a renewable resource, capable of being converted into electricity, heat, or fuel through processes like combustion, fermentation, or chemical conversion [1]. Examples of biomass include wood, agricultural by-products, and energy crops like corn and sugarcane, as well as animal waste. Then, biomass can be academically and practically recognized as a potential clean energy source [2]. As a valuable resource, biomass serves as the raw material for producing chemicals, biomaterials, and biofuels, with significant potential across various industries [3-5].

In addition to its energy applications, biomass is also used to measure the total mass of organisms within ecosystems or individual organisms, such as trees. However, the biomass energy sector faces challenges that require comprehensive development plans based on waste biomass resources and environmental zoning [6]. Therefore, studies assessing biomass are often carried out in environmental research to estimate carbon sequestration in forests or evaluate ecosystem health. Research into standardizing biomass measurement and understanding its positive environmental impacts remains ongoing.

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Also, the presence of organisms such as trees has a significant positive effect on the soil strength around them. This influence is certainly beneficial as a support for reforestation programs aimed at saving deforested areas that are highly vulnerable to natural disasters. The stronger the soil contour in an area, the more it contributes to the safety of the surrounding region from various natural disasters, such as landslides.

On the other hand, in the field of plant computational modelling, the model describes a plant or tree morphologically, physiologically, and statistically. Such models can simulate the growth and development of a tree over time in a three-dimensional (3D) environment, illustrating its impact on the natural surroundings. Numerous researchers have contributed to this area. For instance, Gu et al. [7] developed a model to assess the impact of chemical versus manual topping on radiation interception in machine-harvested cotton in China, offering new management strategies for different planting densities. Similarly, Clarke et al. [8] created a finite element model of Zea mays using CT scan data, representing a pipeline for image stack processing and finite element model development. Additionally, Xin et al. [9] built a 3D model of tomato plants in order to propose a stemwork refinement flow consisting of three processes (i.e., non-replacement resampling, interference branch elimination, and noise deduction). The stemwork phenotype flow in the developed 3D model of tomato plants allows for an automated process in calculating various phenotype characteristics at each stage. The results of this study are imperative in the domain of plant breeding and harvest management. Moreover, Utama & Gunawan [10] constructed a computational model for the Merkus Pine tree to model its development and economic contribution annually.

Then, this study focused on building a computer-generated model of the Merkus pine tree to calculate biomass for individual trees or larger areas, besides the calculation of soil shear strength due to the presence of Merkus pine trees. The model not only simulates the Merkus pine tree growth over time in a 3D environment, but it also predicts the biomass produced and calculates the soil shear strength, whether for a single tree or a forested area. Predictions are provided annually. The model is developed using two methods: object-oriented design and functional-structural plant modeling (FSPM). Since the development or design of the model uses an object-oriented approach, the proposed model is named an object-driven model.

In general, some studies on plant computational modeling have not specifically built a model to make decisions in assessing the contribution of a plant through calculating biomass or soil strengthening for the existence of the plant. Therefore, this study was conducted. This study intends to build a kind of decision model based on plant modeling to assess the contribution of a plant or tree (in this case the pine tree) to the environment in the form of calculating biomass and strengthening the soil. The proposed model, which is an object-based virtual model of Pines Merkus trees capable of simulating biomass calculations in a three-dimensional environment, combining two types of classic main methods (i.e., object-oriented and FSPM), represents the main contribution of this research. Specifically, it contributes to the field of environmental informatics. All components of the model and the results of biomass and soil strength calculation simulations in the three-dimensional environment are presented very clearly in this paper. The paper itself is organized into five sections: introduction, related works, research methodology, results and discussion, and conclusion and future work.

2. Related Works

Numerous researchers have conducted studies in the field of plant and tree modelling with a strong focus on environmental aspects. For instance, Sun et al. [11] developed a general model for wheat plants, aiming to address challenges in simulating the wheat harvesting process using the discrete element method. This model played a key role in optimizing components of wheat harvesting machinery by accurately reflecting the biomechanical properties of wheat, which was essential for simulating harvesting operations.

Yu & Qin [12] proposed an eco-hydrological model for a bioretention system by combining three types of modules (i.e., nitrogen, hydrology, and the plant itself). The developed model was validated with observational data related to plant nitrogen uptake, hydrological performance, and biomass. All of these were implemented in a Canna indica L. plant system in Shenzhen, China. In another study, Urso et al. [13] created a random forest (RF) model to predict things about soil-plant transfer factors based on 10 selected variables (such as plant part, potassium content in soil, and soil and plant types). Only 1,200 out of 3,000 data were usable. This is the most complete dataset with the highest number of accompanying variables.

In addition, Aishwarya & Reddy [14] developed a model for disease detection and grouping using CNN architectures (i.e., Xception, DenseNet169, Inception, and pre-trained on the ImageNet dataset). They applied two non-linear equivalences to the decision counts from the base learners, and the collaborative method produced final predictions for test experiments, evaluated using four metrics: recall, precision, accuracy, and F1-score. Also, in a previous study, Utama & Gunawan [10] constructed an object-oriented model of the Merkus Pine tree, focusing on its above-ground features. This model simulates the growth and expansion of the Merkus Pine tree, encompassing its morphological construction and commercial impact.

Moreover, Fidan et al. [15] conducted a study aimed at looking at the sustainable use of crop residues (especially tomato plants) in producing biomethane. Fidan et al. [15] detailed the effects of various substrate ratios, sulfuric acid pretreatment concentrations, and yeast (Saccharomyces cerevisiae) additions on biogas and biomethane yields under mesophilic conditions (37°C). Then, Behnia et al. [16] conducted a study to evaluate energy consumption in sugarcane production at Salman Farsi Sugarcane Agro-Industry Company in Khuzestan Province, Iran, by comparing the conventional sugarcane cycle and the ratoon cycle. In this case, efficient energy consumption will contribute positively to the environment. Conventional sugarcane showed higher energy input (124,912.32 MJ ha^{-1}) and output (107,530.44 MJ ha^{-1}) compared to ratoon farming (input 80,317.81 MJ ha^{-1} and output 87,586.68 MJ ha^{-1}).

Furthermore, Hu et al. [17] proposed an approach to optimize crop layout, which focused on planting the most suitable crops in a given area. This approach combined multi-objective interval parameter programming, life cycle assessment, highest entropy, and a dynamic land use adaptation and impact model (Dyna-CLUE). The results of the study showed that population intensity, gradient, and average temperature of the coolest area are the major features affecting the supply of rice, corn, and soybean. Torquato et al. [18] applied a variety-exclusive tree canopy development model to 20 commonly planted species in Australia (i.e., Melbourne). The developed model was used to simulate the increase in canopy protection in a newly developed housing area over 30 years (2025–2055). Tree class choices and planting strategies were mimicked under several rain conditions. The aim was to select tree species and planting practices that are currently used. Then, Kang & Kim [19] developed a computational fluid dynamics (CFD) model to assess the impacts of trees planted on overpasses on airflow and thermal comfort in road canyons. The developed model incorporates parameterization schemes for tree obstruction, shading, and evapotranspiration. To methodically evaluate the impact of trees on airflow and temperature in the canyon, various tree heights and locations were considered and simulated at three times of day corresponding to the sun's height in the studied area: morning, noon, and evening.

From the various types of previous research that have been successfully reviewed, not a single study has done the study for the purpose of creating a special decision model based on plant computational modeling that specifically calculates the contribution of a tree species to the environment, including calculating biomes and soil strengthening. The current study makes a significant contribution by proposing an object-driven computational decision model for the Merkus Pine tree to measure its environmental impact, specifically biomass production and the reinforcement of the surrounding soil. By combining the object-oriented method with FSPM, the model produces a virtual representation of the Pine tree (especially Merkus class), both morphologically and physiologically. Additionally, the model is able to mimic the tree's contribution to biomass production and its other environmental benefit, in the form of soil durability reinforcement. This quantitative contribution is important in making decisions regarding the reforestation strategy of deforested forests. That is why the developed model is called a decision model.

The combination of the three elements presented in this paper—the three-dimensional model of the Pines Merkus tree along with its morphological growth, the biomass and soil strength calculation model (as an environmental contribution of the Pines Merkus tree), and the in-depth explanation of the developed model using an object-oriented approach—addresses a research gap that was not covered by previous studies. It is evident that this research makes a significant contribution to the field of science, particularly in the area of environmental informatics.

3. Research Methodology

This study is a continuation of the work conducted by Utama & Gunawan [10]. The model produced from this study is a combination of two types of models. The two models combined are a decision model and a computational plant model. A computational plant (or tree) model is a computer-based model that describes the morphological growth of a tree (in this case a pine tree). The data and information produced are then used to assess (assessment is a type of quantitative decision [20]) the tree's contribution to the surrounding environment. This research was carried out in five stages, as illustrated in Figure 1. It began with understanding the contribution of the Merkus Pine tree to the environment through a literature review, interview, and also observation. Biomass is a common contribution that a tree can provide to help preserve nature and can even be used in the renewable energy industry.

The second stage involved data collection. Interviews, observations, and direct field measurements were conducted. The interviews aimed to review and validate the work of Utama & Gunawan [10]. Experts from the Mangunan Pine Forest Management and the Forest Management Unit Office were interviewed. Observations and direct measurements were conducted in the Mangunan Pine Forest to collect morphological data of the Pine trees. The data that has been successfully collected has become open data, and can be accessed at https://www.doi.org/10.6084/m9.figshare.28423850.

The third stage focused on model design. An object-oriented approach was used for model design [21]. Three types of diagrams were utilized: object, activity, and sequence diagrams. The object diagram detailed the components that needed to be included in the model. The activity diagram, resembling a flowchart, was used to illustrate the algorithm of the developed model, while the sequence diagram visualized the data transfer between the components in the model.

The model construction was carried out using the FSPM method [22] during the fourth stage of the research, executed on a modelling platform called Growth Grammar-related Interactive Modelling Platform (GroIMP) [23]. GroIMP is a modeling platform that supports features like interactivity, rich 3D object arrays, and a data interface. Its standout feature is an integrated modeling language called XL. The primary focus of GroIMP is functional-structural plant modeling. GroIMP is a Windows-based, stand-alone platform. In this fourth stage, a virtual 3D model of the Merkus Pine tree was successfully developed, which is capable of simulating the tree's expansion while also calculating the biomass and soil strength of each tree on an annual basis.

The final stage done in this study is the verification and validation activity of the model that has been successfully created. Model verification and validation are carried out to ensure that the created model is a rationally and practically correct model. The verification and validation process used is adopted from [24]. To answer that the model is academically correct, the components of the model developed must be compared with the theoretical model. If the same, then it has a verification value of 1.00. While the model is said to be practically correct, all data used and calculated data must be the same as the data in the field.

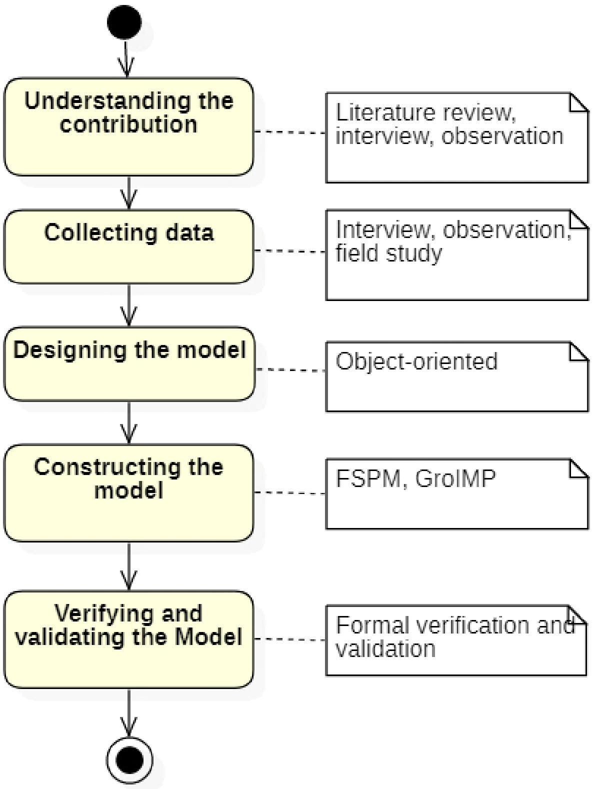

Figure 1. Research Stages and Methods

4. Results and Discussion

The object diagram of the developed model can be seen in Figure 2. The design of this object diagram is an extension of the one created by Utama & Gunawan [10]. Three additional objects in this extended study are the Root, Biomass, and Soil objects. Meanwhile, the MerkusPine object replaces the AboveLandMerkusPine object from the previous study, indicating that the developed model represents a complete Merkus Pine tree, both above and below ground. This affects the biomass calculation, as it now includes both above-ground and below-ground biomass. The Root object is an aggregate object of MerkusPine, meaning that every pine tree inherently has roots. All variables used for biomass calculation are depicted as attributes defined in the Biomass object. Specifically, soil strength is represented via the parameter strength in the Soil object.

As previously explained, biomass consists of both above-ground and below-ground biomass. The above-ground biomass (aboveLandBio) is calculated using the mathematical Equation 1, derived from [25], where stemDia is the diameter of the tree's stem, typically measured 1.3 meters above ground level; and aConst and bConst are constants with values of 0.0936 and 2.4323, respectively. On the other hand, below-ground biomass (belowLandBio) is calculated using Equation 2, where $rtsr$ refers to the root-to-shoot ratio, which has a value of 0.17 [26]. This ratio represents the proportion between root biomass and the above-ground biomass (stem, branches, and leaves). Finally, the total biomass (totalBio) is calculated using Equation 3, which is the sum of the above-ground and below-ground biomass. Then, for calculating the soil strength, the lateral load method on trees is used, as the principle was previously applied by Docker & Hubble [27]. It is assumed that the tree exerts a lateral force on the soil through its root system. The relationship between tree height (using stemLen) and stem diameter (stemDia) as a proxy for root strength is represented by a simple estimation formula in Equation 4, where *st* is the soil strength in Newtons, and c is a constant assumed to be 0.3.

$$aboveLandBio = aConst \times stemDia^{bConst} \quad (1)$$

$$belowLandBio = rtsr \times aboveLandBio \quad (2)$$

$$totalBio = aboveLandBio + belowLandBio \quad (3)$$

$$st = c \times stemLen \times stemDia \quad (4)$$

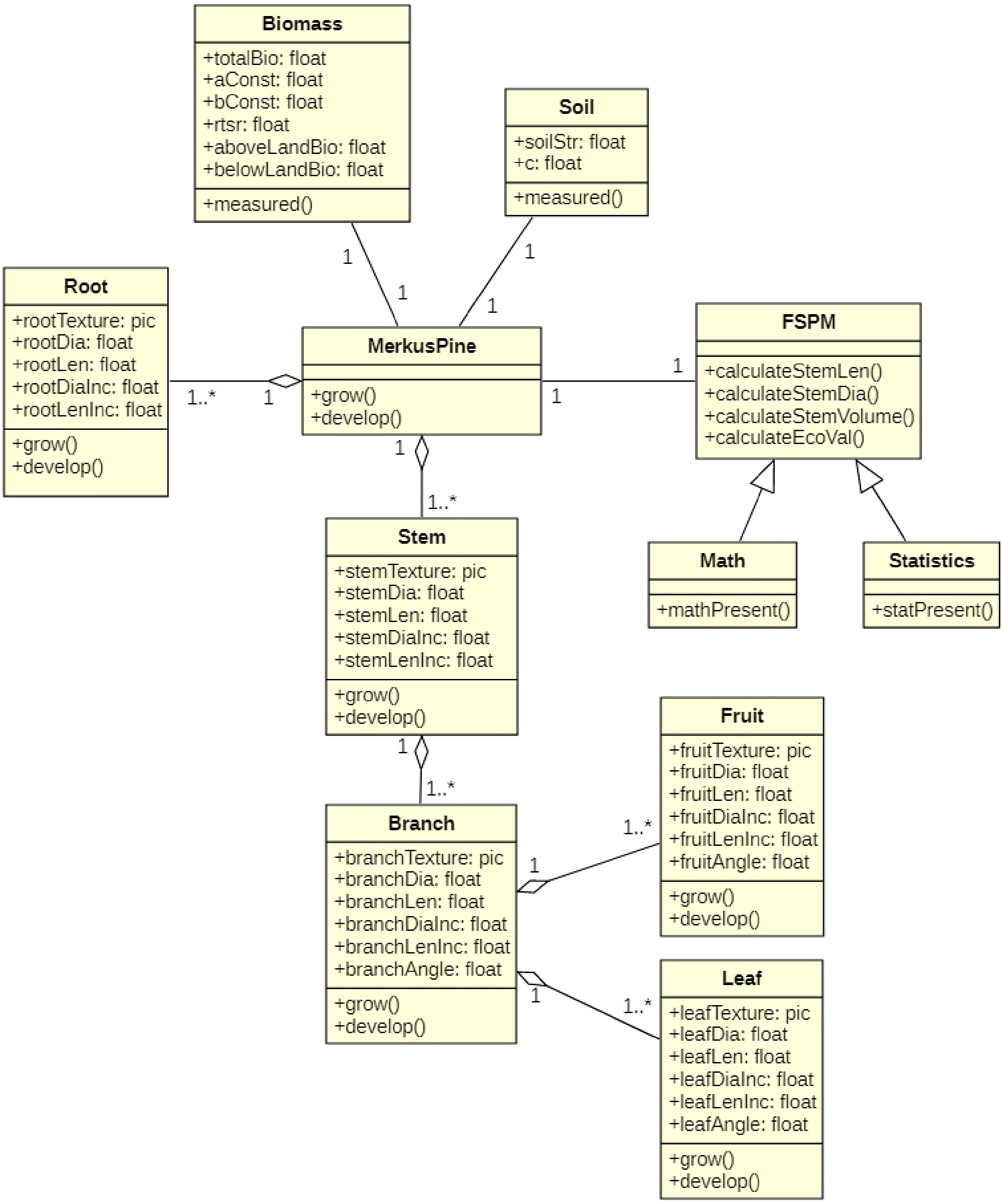

Figure 2. The Object Diagram for the Constructed Model

Furthermore, the calculation of biomass and soil strength for each Merkus Pine tree per year is highly dependent on the growth of its organs. The growth process of the pine tree leading to the total biomass and soil strength value is outlined in the model algorithm shown in Figure 3. All types of biomass and soil strength are calculated annually until the pine tree reaches 15 years of age. The entire process begins by generating variable values, which enable the growth and development of this virtual pine tree. Each year, calculations will be made, including the values of aboveground biomass (aboveLandBio), belowground biomass (belowLandBio), total biomass (totalBio), and soil strength (strength). The first three parameters are attributes of the Biomass object, while the last parameter belongs to the Soil object (refer again to the object diagram in Figure 2). The evolution and increase of the virtual pine tree, including all calculations, will cease when the variable *year* exceeds 15.

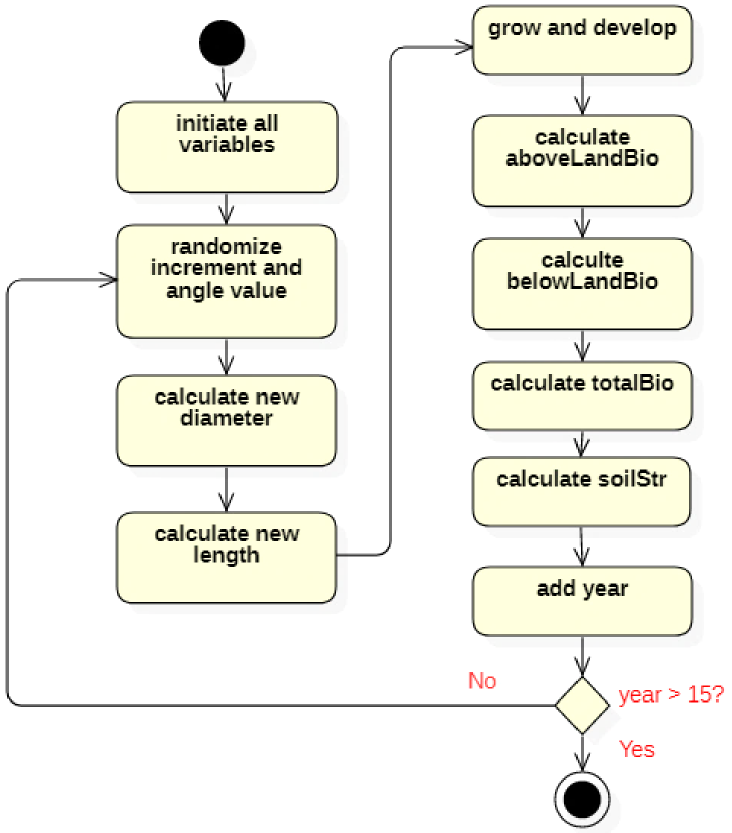

Figure 3. The Algorithm of the Constructed Model

The various parameters exchanged between the objects involved in the model can be seen in the sample sequence diagram in Figure 4, where the evolution of the virtual pine tree culminates in the calculation of different types of biomass (i.e., above-ground, below-ground, and total) and soil strength. In the sequence diagram, there are four types of objects involved, with parameters being transferred from one object to another. An example of this occurs during the progression activities of the virtual pine tree. The four objects involved are MerkusPine, FSPM (as a method object), Biomass, and Soil. When the Grow and Develop activity takes place, the MerkusPine object sends four types of parameter values to the FSPM object: *stemLenInc*, *stemDiaInc*, *rootLenInc*, and *rootDiaInc*. Within the FSPM object, various other parameters are calculated: *stemLen*, *stemDia*, *rootLen*, and *rootDia*, all of which are then sent to the Biomass and Soil objects. Finally, the Biomass object sends three types of parameters—*aboveLandBio*, *belowLandBio*, and *totalBio*. Meanwhile, the Soil object sends the calculation result as *soilStr*. Meanwhile, the 3D representation of the virtual Merkus Pine tree model can be viewed in Figure 5. Figure 5 presents three example images (from running the simulation three times) of the 15-year-old virtual Merkus Pine tree produced by the model. Each time the model is executed, it randomly generates various forms of virtual pine trees. No two trees will have the same shape due to the randomized increments and angles applied each year within a specific range of values.

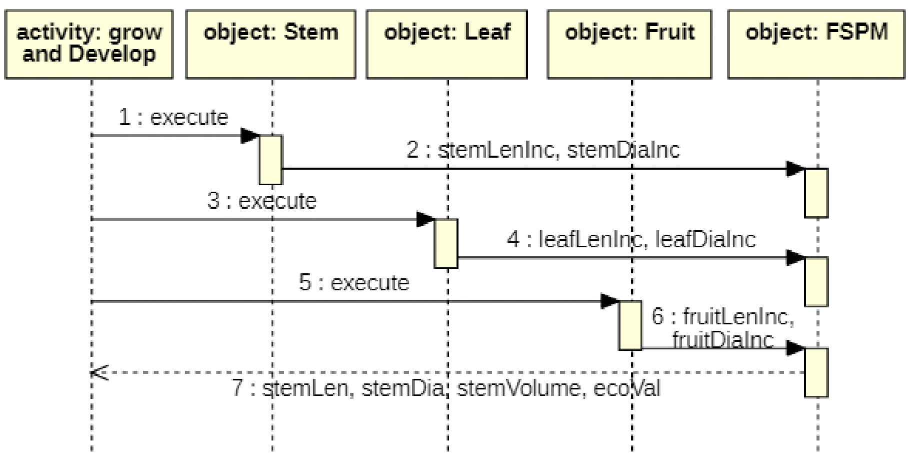

Figure 4. Sequence Diagram for the Constructed Model

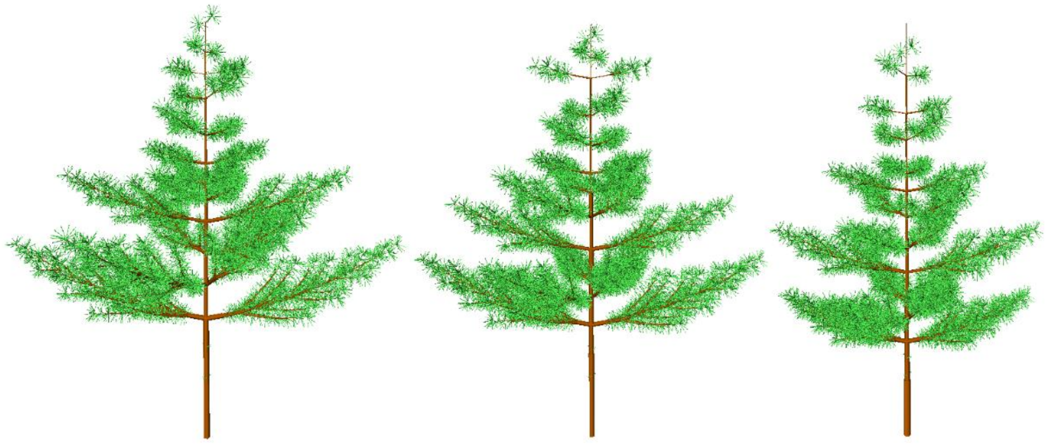

Figure 5. Three Examples of the virtual Merkus Pine Tree

The results of the model simulation for biomass calculation are presented in Figures 6 and 7. Figure 6 illustrates the equation for annual above-ground biomass growth per tree. The derived equation is $y = 0.3849x^{2.2266}$ with an R^2 value of 0.9837, where *y* represents biomass and *x* denotes the year. According to the simulation results, by the end of the 15th year, the highest above-ground biomass was achieved by Pine tree number 1, with a biomass value of 207.06 kg.

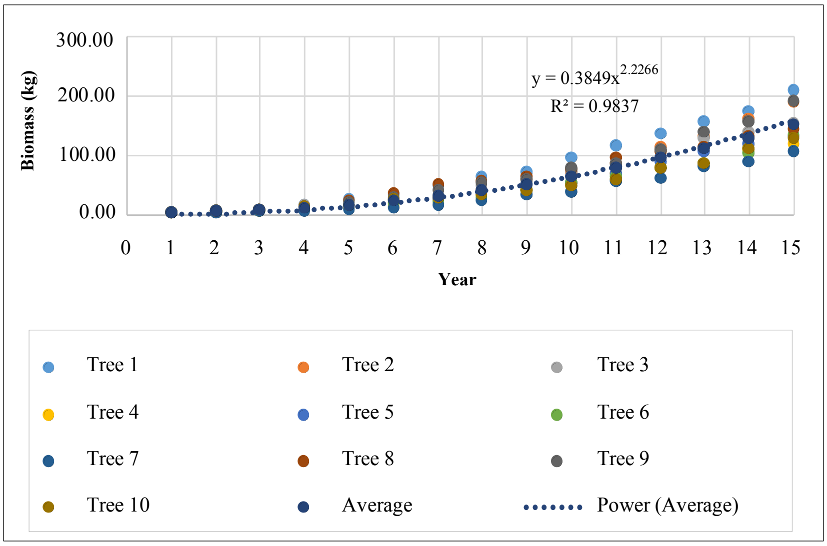

Figure 6. The Annual Above-Ground Biomass for Ten Single Trees

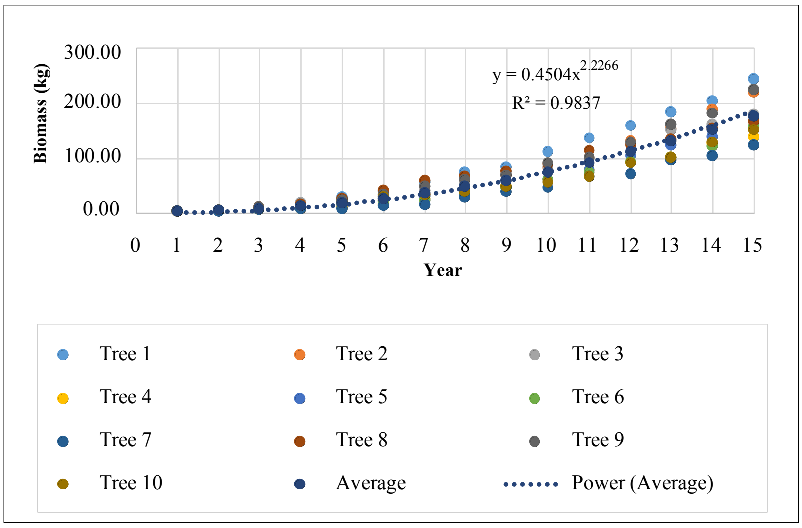

Figure 7. The Annual Total Biomass for Ten Single Trees

The total biomass simulation results are shown in Figure 7, indicating that the total biomass (above and below ground) for the Merkus Pine tree each year can be modeled using the equation $y = 0.4504x^{2.2266}$, also with an *R²* value of 0.9837. In this case, Pine tree number 1 again had the highest total biomass, reaching 242.27 kg in the 15th year. Therefore, the total annual biomass for an area consisting of 10 Pine trees (based on the 10 trees modeled in the simulation) can be calculated using the formula $y = 4.5036x^{2.2266}$, with an *R²* value of 0.9837, as illustrated in Figure 8. The total biomass in the 15th year for these ten Pine trees, according to the simulation, amounts to 1,730.78 kg.

Based on these computational simulation results, it is evident that Pine trees contribute significantly to the environment through continuously increasing biomass production. These findings support the conclusion that Pine trees are an excellent and suitable option for reforesting degraded forests, as they can make a substantial contribution to nature through high biomass yields. The production of 1,730.78 kg of biomass by 10 Pine trees at the end of the 15th year represents a remarkable achievement.

Additionally, based on the average data for diameter and tree height (from the ten simulated trees), soil shear resistance can also be calculated, as demonstrated by Docker & Hubble [27] in developing a model to evaluate the stabilizing effect of riparian vegetation and estimate the influence of tree roots on soil shear strength. The graph in Figure 9 depicts soil strength over the years, considering the force exerted by trees on the soil, which is technically influenced by the area or volume of soil interacting with the root system. Therefore, soil shear resistance is assessed based on the lateral force of the roots on the soil, which increases each year, following a trend line described by the formula $F = 0.0023x^{2.2451}$, with an *R²* value of 0.9834, where *F* represents the soil strength against the pressure exerted by the roots (in Newtons), and *x* denotes the year.

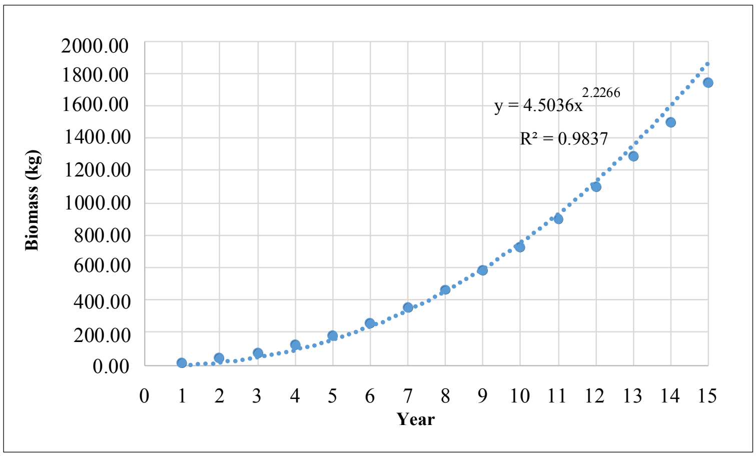

Figure 8. The Annual Total Biomass in One Area Consisting of Ten Trees

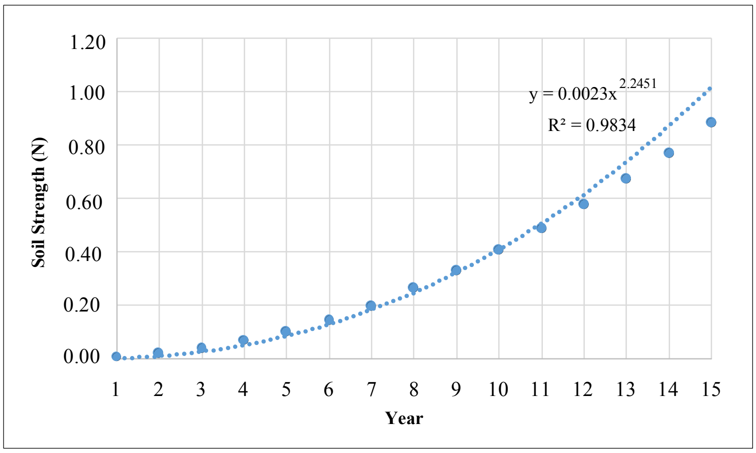

Figure 9. Soil Strength over the Years

The simulation results indicate that the decision to use Pine trees for the reforestation of deforested areas is well-founded. Besides producing significant biomass, these trees progressively strengthen the surrounding soil structure each year. Indeed, the improvement in soil texture develops exponentially, corresponding to the morphological growth of the Pine trees.

Two key factors affirm that the developed decision model is both academically and practically sound: model verification and validation. This decision model builds upon previous research conducted by Utama & Gunawan [10], with all mathematical models used to describe the growth of the Merkus Pine tree derived from [10]. In the model verification process, two crucial components were evaluated: the calculation of tree diameter (used for biomass estimation) and the calculation of soil strength.

Firstly, the mathematical model component used to describe the main stem diameter of the Merkus Pine tree is represented in Code 1, which is the same model employed by Utama & Gunawan [10] and verified using the fundamental code obtained from [28]. Therefore, the model component for tree diameter modeling has a verification value of 1.00. Similarly, the fundamental formula for calculating the increase in soil strength, derived from [27], aligns technically with Code 2. As such, this second component also carries a verification value of 1.00. Consequently, the combined verification value for these two essential model components is 1.00, indicating that the developed decision model is academically valid and consistent with established theories.

Code 1. GroIMP Code for Diameter Increment Calculation

```
if(year!= 15)
 {
     i[diameter] += random(0.0360666667, 0.1592666667);
     totalDiameter = i[diameter];
 }
```

Code 2. GroIMP Code for Soil Strength Calculation

```
F = 0.0023 * Math.pow(x, 2.2451);
```

Next, the model validation process was performed by comparing the results of manual calculations with those generated by the developed model. Across various datasets tested to compare the outcomes of both calculation methods (manual and model-based), identical values were observed, owing to the use of a mathematical model that had already been verified. Therefore, it can be concluded that the developed decision model has a validation value of 1.00. Additionally, the technical data used in the virtual Pine tree growth model were also validated by Utama & Gunawan [10], achieving a validation value of 1.00. These results indicate that the developed decision model is practically sound.

Ultimately, the proposed decision model based on the virtual Merkus Pine tree is both unique and innovative. Building on the research by Utama & Gunawan [10], this model not only simulates the growth of the Merkus Pine tree in a 3D environment but also predicts its biomass production, whether for an individual tree or a group of trees within a specific area. Consequently, the tangible contribution of the Merkus Pine to the environment can be quantitatively forecasted, particularly in terms of biomass production. Furthermore, the developed model can predict or assess the increase in soil strength at any given time due to the presence of Pine trees growing nearby. The outcomes of these computational simulations—both biomass and soil strength improvements—serve as crucial decision-making tools for policymakers, especially in determining whether Pine trees make a significant contribution to environmental sustainability.

In comparison to earlier studies, such as those by Sun et al. [11] through Utama [20], and even Utama & Gunawan [10], which focused on other aspects of plant modeling (e.g., harvesting processes, disease identification, and identifying suitable plant species for specific areas), this study distinguishes itself. Although research conducted by Yu & Qin [12] specifically validated calculations of biomass and nitrogen produced by plants, it did not employ 3D simulation in its implementation. Therefore, this research makes a significant contribution to advancing knowledge, particularly in the field of computational modeling for plants and trees using a 3D simulation approach. Among the ten prior studies, none combined a visual tree growth model (specifically for the Merkus Pine tree) with a time-based simulation of biomass and soil strength. This research successfully fills that research gap.

5. Conclusion

A computational decision model of the virtual Merkus Pine tree has been successfully developed in this study. This model is designed to assist policymakers in gaining a clearer understanding of the contributions of Pinus merkusii trees to the environment. The constructed model is grounded in plant modeling, utilizing morphological growth data to calculate contributions to nature—in this case, estimating biomass production and improvements in soil strength. The model not only simulates the growth of the Merkus Pine over time in a 3D environment but also predicts annual biomass amounts (both above and below ground) for either a single tree or multiple trees within a specific area. According to the simulation results, a single tree reached the highest biomass of 242.27 kg by the end of its 15th year. Additionally, based on the model, a Merkus Pine tree can enhance soil shear strength by approximately 0.88 N in its fifteenth year.

Moreover, through the use of an object-oriented approach, the model's design is highly comprehensible. Three diagrams were utilized in designing the model: object, activity, and sequence diagrams. The object diagram effectively explains the relationships between the model's components, including the organs of the Pine tree. The activity diagram details the algorithm underpinning the developed model, while the sequence diagram illustrates the data flows within the system. These three diagrams ensure that the model's design can be readily understood, even by individuals unfamiliar with computer modeling. As such, this study provides clear insight into how the developed decision model functions.

For future research, fuzzy logic could be employed as the primary method to further refine the model, particularly to reduce bias in calculating the final biomass estimates. Likewise, integrating machine learning (ML) or other data science techniques presents a promising direction, as the combination of functional-structural plant modeling (FSPM) and ML remains largely unexplored. However, a key challenge in developing ML-based models is the requirement for extensive and comprehensive data. While considerable data has already been gathered, it often remains fragmented, necessitating targeted research to compile it systematically. Another significant and challenging area for future study would be to apply this model to various Pine tree species or other types of trees.

6. Declarations

6.1. Author Contributions

Conceptualization, D.N.U.; methodology, D.N.U.; validation, B.A.J.; formal analysis, B.A.J.; investigation, B.A.J.; writing—original draft preparation, D.N.U.; writing—review and editing, D.N.U. and B.A.J. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding and Acknowledgments

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7. References

[1] Ashfaq, M. M., Bilgic Tüzemen, G., & Noor, A. (2024). Exploiting agricultural biomass via thermochemical processes for sustainable hydrogen and bioenergy: A critical review. International Journal of Hydrogen Energy, 84, 1068–1084. doi:10.1016/j.ijhydene.2024.08.295.

[2] Poornima, S., Manikandan, S., Prakash, R., Deena, S. R., Subbaiya, R., Karmegam, N., Kim, W., & Govarthanan, M. (2024). Biofuel and biochemical production through biomass transformation using advanced thermochemical and biochemical processes – A review. Fuel, 372. doi:10.1016/j.fuel.2024.132204.

[3] Watkins, D., Nuruddin, M., Hosur, M., Tcherbi-Narteh, A., & Jeelani, S. (2015). Extraction and characterization of lignin from different biomass resources. Journal of Materials Research and Technology, 4(1), 26–32. doi:10.1016/j.jmrt.2014.10.009.

[4] Halder, P., Kundu, S., Patel, S., Setiawan, A., Atkin, R., Parthasarthy, R., Paz-Ferreiro, J., Surapaneni, A., & Shah, K. (2019). Progress on the pre-treatment of lignocellulosic biomass employing ionic liquids. Renewable and Sustainable Energy Reviews, 105, 268–292. doi:10.1016/j.rser.2019.01.052.

[5] Song, G., Huang, D., Li, A., Li, R., Hu, S., Xu, K., Ren, Q., Han, H., Wang, Y., Su, S., & Xiang, J. (2024). Quick measurement method of three components in lignocellulosic biomass based on kinetic mechanism analysis of PT-TGA. Fuel, 367. doi:10.1016/j.fuel.2024.131521.

[6] Wang, X., Liu, Q., Yang, L., Yang, Q., Li, Y., Yang, Y., Zhou, C., Wang, X., Wang, Y., Gao, G., Liu, W., & Cheng, P. (2024). Perceptions of biomass energy sustainability in policy scenarios of China. Heliyon, 10(17), e37180. doi:10.1016/j.heliyon.2024.e37180.

[7] Gu, S., Sun, S., Wang, X., Wang, S., Yang, M., Li, J., Maimaiti, P., van der Werf, W., Evers, J. B., & Zhang, L. (2024). Optimizing radiation capture in machine-harvested cotton: A functional-structural plant modelling approach to chemical vs. manual topping strategies. Field Crops Research, 317. doi:10.1016/j.fcr.2024.109553.

[8] Clarke, S. S. B., Benzecry, A., Bokros, N., DeBolt, S., Robertson, D. J., & Stubbs, C. J. (2024). A custom pipeline for building computational models of plant tissue. European Journal of Agronomy, 161. doi:10.1016/j.eja.2024.127356.

[9] Xin, B., Smoleňová, K., Bartholomeus, H., & Kootstra, G. (2024). An automatic 3D tomato plant stemwork phenotyping pipeline at internode level based on tree quantitative structural modelling algorithm. Computers and Electronics in Agriculture, 227(2), 109607. doi:10.1016/j.compag.2024.109607.

[10] Utama, D. N., & Gunawan, I. (2023). An Object Driven Model of Above-Land Merkus Pine Tree for Quantifying the Commercial Contribution with Functional-Structural Plant Modeling. IEEE Access, 11, 138675–138686. doi:10.1109/ACCESS.2023.3338719.

[11] Sun, K., Yu, J., Zhao, J., Liang, L., Wang, Y., & Yu, Y. (2023). A DEM-based general modeling method and experimental verification for wheat plants in the mature period. Computers and Electronics in Agriculture, 214. doi:10.1016/j.compag.2023.108283.

[12] Yu, S., & Qin, H. (2023). Modeling the effects of plant uptake dynamics on nitrogen removal of a bioretention system. Water Research, 247. doi:10.1016/j.watres.2023.120763.

[13] Urso, L., Petermann, E., Gnädinger, F., & Hartmann, P. (2023). Use of random forest algorithm for predictive modelling of transfer factor soil-plant for radiocaesium: A feasibility study. Journal of Environmental Radioactivity, 270. doi:10.1016/j.jenvrad.2023.107309.

[14] Aishwarya, M. P., & Reddy, P. (2023). Ensemble of CNN models for classification of groundnut plant leaf disease detection. Smart Agricultural Technology, 6. doi:10.1016/j.atech.2023.100362.

[15] Fidan, B., Bodur, F. G., Öztep, G., Güngören-Madenoğlu, T., Kabay, N., & Baba, A. (2025). Comparison of conventional and machine learning models for kinetic modelling of biomethane production from pretreated tomato plant residues. Industrial Crops and Products, 223. doi:10.1016/j.indcrop.2024.120235.

[16] Behnia, M., Ghahderijani, M., Kaab, A., & Behnia, M. (2025). Evaluation of sustainable energy use in sugarcane production: A holistic model from planting to harvest and life cycle assessment. Environmental and Sustainability Indicators, 26. doi:10.1016/j.indic.2025.100617.

[17] Hu, M., Tang, H., Yu, Q., & Wu, W. (2025). A new approach for spatial optimization of crop planting structure to balance economic and environmental benefits. Sustainable Production and Consumption, 53, 109–124. doi:10.1016/j.spc.2024.12.003.

[18] Torquato, P. R., Szota, C., Hahs, A. K., Arndt, S. K., & Livesley, S. J. (2025). Insufficient space: Prioritizing large tree species and planting designs still fail to meet urban forest canopy targets. Landscape and Urban Planning, 256. doi:10.1016/j.landurbplan.2024.105287.

[19] Kang, G., & Kim, J. J. (2025). How to plant trees on an elevated road to improve thermal comfort in a street canyon. Sustainable Cities and Society, 121. doi:10.1016/j.scs.2025.106207.

[20] Utama, D. N. (2021). Fuzzy logic for decision support models, equipped with case study applications. Penerbit Garudhawaca, Yogyakarta, Indonesia.

[21] Halpin, T., & Morgan, T. (2024). Data Modeling in UML. Information Modeling and Relational Databases, 347–399. doi:10.1016/b978-0-443-23790-4.00001-3.

[22] Mitsanis, C., Hurst, W., & Tekinerdogan, B. (2024). A 3D functional plant modelling framework for agricultural digital twins. Computers and Electronics in Agriculture, 218. doi:10.1016/j.compag.2024.108733.

[23] Hemmerling, R., Evers, J. B., Smoleňová, K., Buck-Sorlin, G., & Kurth, W. (2013). Extension of the GroIMP modelling platform to allow easy specification of differential equations describing biological processes within plant models. Computers and Electronics in Agriculture, 92, 1–8. doi:10.1016/j.compag.2012.12.007.

[24] Doostali, S., Babamir, S. M., & Javani, M. (2023). Using a process algebra interface for verification and validation of UML statecharts. Computer Standards and Interfaces, 86. doi:10.1016/j.csi.2023.103739.

[25] Siregar, C. A. (2007). Biomass estimation in pine plantation forests (Pinus Merkusii Jungh et de Vriese) and soil carbon conservation in Ciaten, West Java. Journal of Forest Research and Nature Conservation, 4(3), 251-266. doi:10.20886/jphka.2007.4.3.251-266.

[26] Sanquetta, C. R., Corte, A. P., & da Silva, F. (2011). Biomass expansion factor and root-to-shoot ratio for Pinus in Brazil. Carbon Balance and Management, 6(1), 6. doi:10.1186/1750-0680-6-6.

[27] Docker, B. B., & Hubble, T. C. T. (2008). Quantifying root-reinforcement of river bank soils by four Australian tree species. Geomorphology, 100(3–4), 401–418. doi:10.1016/j.geomorph.2008.01.009.

[28] Zhang, Y., Henke, M., Buck-Sorlin, G. H., Li, Y., Xu, H., Liu, X., & Li, T. (2021). Estimating canopy leaf physiology of tomato plants grown in a solar greenhouse: Evidence from simulations of light and thermal microclimate using a Functional-Structural Plant Model. Agricultural and Forest Meteorology, 307. doi:10.1016/j.agrformet.2021.108494.