A Dynamic System Model of Climate-Driven Fruiting Occurrence in Smallholder Duku (*Lansium domesticum*) Orchards

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Abstract. Interannual alternation between fruiting and non-fruiting years remains a persistent challenge in tropical perennial fruit-crop systems, particularly in smallholder orchards that are managed as semi-natural stands in Muara Enim District, Sumatera Selatan Province, Indonesia. This study developed a parsimonious climate-driven dynamic system model to simulate annual fruiting occurrence in duku (*Lansium domesticum*) under unmanaged orchard conditions. The model operated at a monthly time step and represented two internal state variables: carbohydrate reserve and seasonal fruit potential. Monthly rainy days were used as the climatic forcing variable, with dry-season conditions regulating flowering induction, and excessive wetness during subsequent reproductive development increasing fruit loss. Temporal calibration and validation were conducted in one core sub-district, followed by spatial testing across additional sub-districts without recalibration, one-at-a-time sensitivity analysis, and ±10% rainy-day perturbation scenarios. The model reproduced alternating fruiting and non-fruiting patterns as an emergent outcome of reserve accumulation, induction thresholds, fruit loss, and post-harvest reset. Spatial validation indicated that one parameter set could be transferred across locations, although local rainfall regimes generated heterogeneous sensitivity to modest climatic perturbation. These findings place duku fruiting within a broader class of perennial fruit systems that respond to climate through delayed, threshold-mediated, and internally buffered processes rather than through direct, linear effects. The proposed framework provides a transparent tool for data-limited regions where reliable yield records are scarce, while supporting comparative risk assessment across heterogeneous smallholder production landscapes.

Keywords: climate-driven phenology; duku; dynamic system model; fruiting occurrence; unmanaged orchards

1 Introduction

Perennial fruit crops often display pronounced interannual variability because reproductive development depends on climatic triggers that interact with stored physiological resources over multiple seasons. This variability is particularly important in tropical production systems, where rainfall timing and intensity can regulate flowering induction, fruit set, and fruit retention. Recent phenology studies have shown that perennial fruit responses to climate are frequently nonlinear and cultivar- or site-specific, especially when chilling, heat, or seasonal water conditions approach biological thresholds [1, 2, 3]. Although duku (Lansium domesticum) is a tropical fruit rather than a temperate dormancy-dependent crop, the same general principle applies: annual production is not simply the result of one climate variable in one year, but emerges from seasonal climatic forcing interacting with internal plant states.

Despite the economic and cultural importance of duku in South Sumatra, previous studies on Lansium domesticum have not yet adequately addressed the mechanisms underlying year-to-year fruiting variability. Existing research has generally focused on botanical description, cultivar or germplasm characterization, fruit quality, propagation, cultivation practices, postharvest handling, or the nutritional and biochemical properties of the fruit. These studies have provided important baseline information, but they have not explicitly examined how seasonal rainfall patterns regulate flowering induction, fruit retention, and fruiting occurrence across years. In particular, there remains limited quantitative evidence on whether duku production failure is associated with rainfall conditions during specific phenological windows, such as the dry-season induction period or the wet-season fruit development period.

This gap is especially important in the community garden systems of South Sumatra Province. Duku trees in this region are commonly grown by smallholders under semi-natural, forest-like, or mixed-garden conditions rather than in intensively managed commercial orchards. Fertilization, pruning, irrigation, canopy manipulation, and crop-load control are generally limited or irregular. As a result, management signals are relatively weak, while climatic variability

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and internal tree condition are likely to exert stronger control over annual fruiting outcomes. However, previous studies on duku have rarely considered this production context explicitly. They have not sufficiently evaluated how unmanaged or low-input community gardens respond to interannual rainfall variability, nor have they developed models capable of distinguishing fruiting and non-fruiting years under data-limited smallholder conditions.

Duku orchards in South Sumatra provide a representative case for examining these dynamics. Trees are commonly grown by smallholders under semi-natural or forest-like conditions, with little fertilization, pruning, irrigation, canopy manipulation, or crop-load control. In such systems, the planted area is relatively stable, and management signals are weak, so yearly production variation is expected to reflect climatic variability and internal tree condition more strongly than deliberate agronomic intervention. Comparable studies of fruit-tree agroforestry and smallholder perennial systems show that tree productivity is shaped by local climate, tree diversity, soil and water conditions, and household-level practices, but climate remains an important driver where external inputs are limited [4, 5].

Most available assessments of tropical fruit production rely on descriptive statistics, correlations between rainfall and yield, or aggregate economic indicators. These approaches are useful for identifying broad associations, but they are limited when fruiting depends on lagged responses and threshold behavior. Studies on Kinnow mandarin, mango, avocado, and native African fruit trees have demonstrated that fruit production and flowering patterns can vary strongly among locations, cultivars, and seasons under different climate regimes [6]. Such evidence suggests that a direct rainfall-yield regression may miss the mechanisms that determine why a population fruits in one year and fails in another.

A central challenge in modeling perennial crops is therefore the representation of internal state variables. For many woody fruit crops, reproductive output is linked to carbohydrate reserves, source–sink balance, and previous crop load. Alternate-bearing research in olive, pistachio, citrus, apple, and date palm consistently indicates that interactions mediate ON and OFF cycles between reproductive demand, vegetative growth, floral bud development, and stored reserves [7, 8]. Process-based perennial crop models similarly emphasize the need to represent phenology, light interception, carbohydrate allocation, reserve remobilization, and yield formation as interacting modules rather than isolated statistical terms [9, 10].

The difficulty is intensified by the form in which production information is commonly available. Regional statistics for perennial crops may report zero production in some years and positive production in others, but the magnitude of positive production can be affected by reporting coverage, market access, harvest completeness, or informal household consumption. A model that attempts to reproduce yield magnitude under these data conditions may create an impression of precision that is not supported by the records. By contrast, a binary occurrence model focuses on a more robust signal: whether fruiting occurred at the population scale.

Dynamic system modeling provides a useful framework for this problem because it explicitly represents stocks, flows, feedbacks, and time delays. In crop and orchard systems, this allows climate forcing to influence internal reserves month by month before annual outcomes are evaluated. The PhenoFlex framework, for example, integrates chill and heat accumulation to predict spring phenology in temperate fruit trees, while APSIM Next Generation has been extended for perennial fruit crops using grapevine as a model plant with modules for phenology, carbohydrate allocation, and yield formation [9, 10]. These models demonstrate the value of biologically interpretable structures even when they are simplified.

For duku, detailed physiological measurements are rarely available, and regional production records may not support precise yield modeling. Under such conditions, it is more appropriate to treat fruiting as an occurrence event: a year either produces fruit or it does not. Event-based representation also avoids overinterpretation of the uncertain yield magnitude and uses the most reliable information from the records. This approach is consistent with the broader movement toward transparent models for data-limited perennial systems, where parsimonious structures can still reveal climate sensitivity, production risk, and threshold responses [12].

The conceptual model developed here assumes that dry-season conditions during June–August promote flowering induction when reserves are sufficient, while excessive wetness during September–November increases fruit loss during reproductive development. Annual fruiting occurrence is then determined during the March–May harvest period. This seasonal logic is compatible with studies showing that consecutive wet days can affect fruit drop and fruit quality, that reproductive loss can remove substantial nutrients after flowering, and that meteorological factors are linked to alternate flowering and yield variation in fruit trees [13, 14].

The objective of this study was to develop and evaluate a climate-driven dynamic system model that simulates fruiting and non-fruiting years of duku in smallholder unmanaged orchards. The model uses monthly rainy days as the climatic forcing variable and two internal state variables—Reserve and FruitPotential—to represent reserve accumulation, flowering induction, fruit loss, and harvest-period classification. Model performance was assessed through temporal calibration and validation at a core sub-district, spatial validation across additional sub-districts without recalibration, sensitivity analysis, and ±10% rainy-day perturbation scenarios. The novelty of the study lies in treating duku fruiting as a threshold-mediated emergent event rather than as a continuous yield response, thereby offering a transferable analytical framework for climate-sensitive perennial fruit systems in data-limited tropical contexts.

2 Methodology

2.1 Study system and observational data

The study focused on duku production in smallholder orchards in Muara Enim District, South Sumatra Province, Indonesia. These orchards are typically unmanaged or minimally managed, meaning that fertilization, pruning, canopy manipulation, irrigation, and systematic pest control are generally absent. This production setting justifies a model structure in which climatic variability is treated as the dominant driver of interannual fruiting variation, while management, soil, and land-use variables are assumed to be stable over the simulation period. Similar assumptions are often required in data-limited perennial fruit systems, where long-term climatic records are more reliable than detailed physiological or management records [4]. Data at the sub-district level for 10 years (2015-2024) was collected from the Agriculture Office and the Central Bureau of Statistics of Muara Enim Regency.

Two types of data were used. The first was the monthly rainy days, locally referred to as rainy days, defined as the number of days with measurable rainfall within each calendar month. Rainy days were selected because they capture seasonal wetness and dryness relevant to flowering induction and fruit development, and are relatively robust compared with point rainfall totals. The second was an annual binary fruiting indicator, where 1 indicated a fruiting year with non-zero production, and 0 indicated a non-fruiting year with zero production. This binary formulation follows the logic of event-based crop modeling, where the main question is whether reproductive output occurs rather than how much yield is produced.

2.2 System boundary and model structure

The system boundary was defined at the orchard-population level within each sub-district. Each sub-district was treated as an aggregate tree population exposed to similar seasonal rainfall conditions. Individual tree variability, market dynamics, pest outbreaks, short-term extreme events, soil heterogeneity, and household decision-making were excluded from the base model. This boundary is consistent with process-based perennial modeling principles, which call for a simplified structure that matches the scale and reliability of available data [9, 10].

The model operated at a monthly time step ($\Delta t = 1$ month). This resolution was chosen to represent seasonal phenological windows while avoiding false precision in daily processes that were not directly observed. Two internal stocks formed the core of the model. Reserve represented the aggregated carbohydrate reserve of the orchard population, increasing through monthly recharge and decreasing through maintenance and fruiting-related depletion. FruitPotential represented the seasonal accumulation of reproductive potential, increasing during successful flowering induction and declining through wet-season loss and harvest release. Carbohydrate-reserve representation is essential because perennial fruiting depends on stored assimilates and source–sink competition, as shown in alternate-bearing and APSIM grapevine studies [7, 8, 9].

The formulation deliberately avoids excessive parameterization. Reserve and FruitPotential are dimensionless state variables, not direct measurements of carbohydrate mass or yield biomass. This choice allows the model to represent relative physiological status while remaining compatible with sparse regional data. In this sense, the model follows the same conceptual logic as larger process-based crop models but reduces the number of measured inputs to the minimum required for testing a mechanistic hypothesis. The model therefore emphasizes interpretability, reproducibility, and portability rather than physiological completeness.

The internal logic of the model is represented in Figure 1, where fruiting occurrence emerges from interactions between rainy-day thresholds, reserve availability, fruit-potential accumulation, and post-harvest reset.

2.3 Seasonal rules and annual classification

Seasonal rules were implemented using threshold-based functions. During June–August, flowering induction occurred when monthly rainy days fell below a dry-season threshold, and Reserve exceeded a minimum level. During September–November, excessive rainfall triggered proportional fruit loss in FruitPotential, representing abortion, fruit-set failure, or reproductive loss under wet conditions. During March–May, annual fruiting occurrence was determined by comparing the maximum FruitPotential reached during the harvest period with a fruiting threshold. If the threshold was exceeded, the year was classified as fruiting; otherwise, it was classified as non-fruiting.

This threshold approach was selected because perennial fruit responses to climate often emerge through abrupt transitions rather than continuous proportional changes. Phenological models for apple, plum, peach, and other fruit species show that climatic requirements are expressed as threshold-like accumulation or limitation processes [3, 11]. Although the present duku model does not represent chill accumulation, it applies the same modeling principle: seasonal climatic signals modify internal states, and annual outcomes emerge when internal states cross classification thresholds.

The seasonal timing of induction, loss, and harvest classification is shown in Figure 2, emphasizing that annual fruiting status is produced by monthly processes distributed across different phenological windows.

2.4 Calibration, validation, sensitivity, and scenarios

Model parameters included dry-season and wet-season rainy-day thresholds, reserve recharge rate, baseline reserve depletion, fruiting-related reserve depletion, fruit-set coefficient, fruit-loss coefficient, and the fruiting classification threshold. Parameter ranges

were selected based on ecological plausibility and exploratory testing rather than direct physiological measurements. Calibration was conducted at one core sub-district using a random search. The available time series was split into training and test sets to evaluate out-of-sample performance.

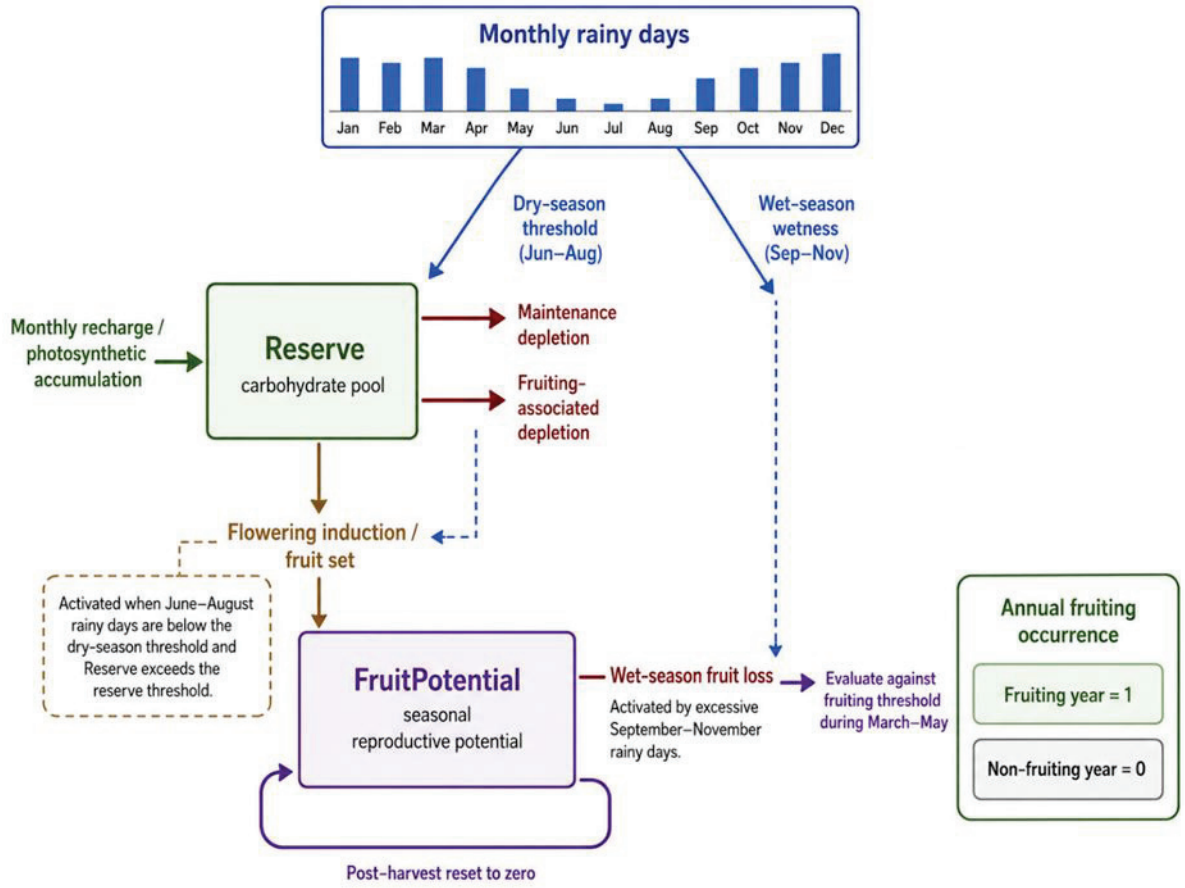

Fig. 1. Stock–flow structure of the climate-driven dynamic model linking monthly rainy days, internal reserve accumulation, fruit potential, fruit loss, harvest release, and annual fruiting classification.

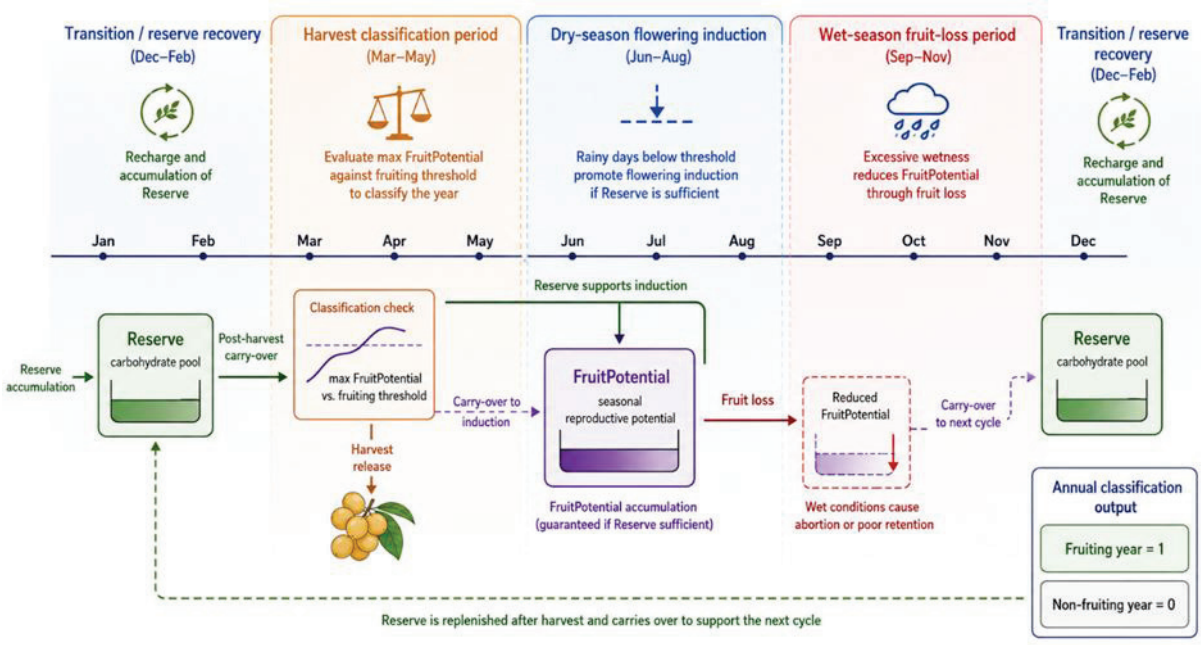

Fig. 2. Monthly seasonal timeline used in the dynamic model, showing dry-season flowering induction, wet-season fruit loss, harvest-period fruiting classification, and post-harvest reset.

The fruiting classification rule was evaluated only after the seasonal sequence had unfolded. This design prevents the model from treating flowering induction as equivalent to harvest success. A year may experience suitable dry conditions for induction but still fail to reach the fruiting threshold if wet-season loss is large or reserve status is insufficient. The model therefore separates induction opportunity, reproductive retention, and harvest-period expression, which is essential for representing tropical fruit systems where flowering does not always translate into production. Model performance was assessed using binary classification metrics: accuracy, precision, recall, and F1-score. These metrics are appropriate because the target variable is an annual fruiting occurrence class. Similar classification-style validation has been used in orchard detection and monitoring contexts, where precision, recall, and F1-score provide complementary measures of predictive reliability. After temporal calibration and validation at the core site, the calibrated parameter set was applied to additional sub-districts without recalibration to test spatial portability. A one-at-a-time sensitivity analysis was performed on key parameters, and a scenario analysis perturbed monthly rainy days by ±10% to assess the effect of modest rainfall shifts on fruiting frequency.

The simplifying assumptions were documented explicitly to clarify interpretation. The model assumes unmanaged orchards, constant planted area, stable biophysical background conditions, climate as the primary driver, seasonal climate control of induction and loss, aggregate population behavior, monthly temporal resolution, binary fruiting outcome, no fruit carry-over after harvest, and time-invariant parameters. These assumptions limit the model's direct application to intensively managed orchards, but they also isolate the climate–reserve mechanism most relevant to the target production system. The core assumptions and their interpretive implications are summarized in Table 1.

Table 1. Core assumptions of the climate-driven dynamic model for duku fruiting occurrence.

Assumption	Interpretive implication
Unmanaged smallholder orchard system	Model behavior mainly reflects climate–reserve interactions rather than active agronomic control.
Constant planted area	Interannual production variation is interpreted as fruiting occurrence, not land-use expansion.
Monthly time step	Seasonal climate signals are represented, while sub-monthly extremes are outside the base model.
Binary fruiting outcome	The model explains fruiting occurrence, not the yield magnitude within fruiting years.
Time-invariant parameters	Long-term structural changes require recalibration or model extension.

3 Results

3.1 Emergent model behavior

The model reproduced alternating fruiting and non-fruiting behavior as an emergent outcome of monthly climatic forcing interacting with internal state variables. Reserve accumulated gradually during non-fruiting periods and declined episodically during fruiting years, reflecting the cost of reproductive activity. Fruit potential increased sharply after successful induction and declined during fruit loss and harvest release. This behavior is consistent with perennial fruit systems in which carbohydrate reserves are depleted during reproductive demand and later replenished through assimilation [8, 9].

Seasonal rainfall signals were reflected in the simulated dynamics. Dry conditions during June–August promoted flowering induction only when the Reserve exceeded its threshold. In contrast, excessive rainfall during September–November reduced accumulated FruitPotential. Annual fruiting occurrence was determined during March–May from the maximum FruitPotential reached during the harvest period. This structure converted monthly processes into annual binary outcomes and reproduced the observed distinction between fruiting and non-fruiting years without requiring continuous yield-magnitude data.

3.2 Temporal calibration and validation

At the core sub-district, the model showed satisfactory temporal performance during both training and testing periods. The training period indicated high accuracy and balanced precision and recall, while the independent testing period remained comparable. The stability of testing performance suggests that the model did not simply memorize calibration years. Instead, the calibrated structure retained predictive skill for years not used in parameter selection. This result supports the use of a parsimonious model in which a small number of interpretable state variables and thresholds capture the timing of fruiting occurrence.

Table 2 summarizes the performance descriptors available from the calibration output. Exact numerical values were reported separately in the calibration file, while the main draft recorded qualitative descriptors. The important result is that testing performance remained robust relative to training performance. Such stability is critical for mechanism-oriented models, because overfitted statistical relationships may perform well during calibration but fail when applied to unseen years or new locations.

The simulated Reserve trajectory also provided a mechanistic explanation for non-fruiting years that occurred after fruiting events. In such years, rainfall conditions alone may appear favorable, but the internal reserve pool may still be below the induction threshold. Conversely, some non-fruiting years allowed Reserve to

recover, creating conditions for subsequent fruiting when the dry-season signal occurred. This behavior illustrates why a single-year rainfall statistic is insufficient to explain annual fruiting occurrence in duku.

3.3 Spatial validation across sub-district

Spatial validation demonstrated that the calibrated parameter set could be transferred to additional sub-districts without recalibration. Performance varied among locations, but most sites remained within acceptable ranges. Some sub-districts showed strong agreement between observed and simulated fruiting sequences, while others showed reduced accuracy in years with marginal climatic conditions. This spatial heterogeneity is expected when local rainfall regimes place systems at different distances from induction and loss thresholds.

The absence of site-specific recalibration is important because it suggests that the model captures general climate–reserve processes rather than only the idiosyncratic behavior of the core site. The result also supports the interpretation that observed spatial variability can emerge solely from differences in rainfall seasonality. Comparable spatial heterogeneity has been reported in fruit-tree climate studies, including habitat suitability modeling, cultivar adaptation studies, and climate-impact assessments for perennial orchards [15].

Table 2. Summary of model performance at the core calibration site.

Period	Accuracy	Precision	Recall	F1-score	Interpretation
Training	High	Balanced	Balanced	Robust	The model reproduced most fruiting and non-fruiting years during calibration.
Testing	Comparable	Stable	Stable	Robust	Out-of-sample behavior remained consistent with training-period performance.

3.4 Sensitivity analysis

Sensitivity analysis identified the dry-season rainy-day threshold and reserve-related parameters as the most influential components of the model. Changes in the dry-season threshold altered whether induction occurred during June–August, while changes in reserve recharge altered the rate of recovery after fruiting. These parameters produced the largest deviations in F1-score from the baseline simulation. Fruit-loss and final classification thresholds had smaller effects within the tested ranges, although they remained important for years near the fruiting boundary. Spatial results also indicated that model errors were not randomly distributed in conceptual terms. Mismatches were most likely when rainy-day values were close to the dry-season or wet-season thresholds. Under these conditions, small errors in rainfall observations, local microclimate, or unmodeled management can push the simulated system across the classification boundary. This pattern is consistent with threshold-controlled systems, where uncertainty is amplified near transition points.

The sensitivity pattern indicates that the model is primarily governed by upstream processes that determine whether reproductive potential can be initiated. Once induction occurs, downstream fruit loss and harvest classification modify the outcome but do not dominate the full temporal sequence. This result is consistent with perennial crop studies in which early phenological or source–sink conditions strongly influence later reproductive outcomes. It also confirms that the representation of reserve recovery is critical for simulating repeated fruiting and non-fruiting cycles.
The relative influence of model parameters is shown in Figure 3, indicating that fruiting classification is most sensitive to dry-season induction and reserve-recovery processes.

3.5 Rainy-day perturbation scenarios

Scenario analysis revealed nonlinear, location-specific responses to a modest rainfall perturbation. A ±10% change in monthly rainy days altered the proportion of fruiting years by up to 0.20 in the most sensitive sub-district. In contrast, several locations showed no change under either the −10% or +10% scenarios. These contrasting responses indicate that the model does not impose a uniform climate effect across all locations. Instead, response strength depends on whether baseline rainfall conditions place the orchard population near or far from critical thresholds.

This threshold behavior has practical implications for production risk. A small rainfall shift may strongly affect fruiting in locations where dry-season induction or wet-season loss is close to a threshold, while the same perturbation may have little effect where the baseline climate remains safely within a fruiting or non-fruiting regime. Similar nonlinear climate responses have been reported in fruit-tree phenology and climate-adaptation studies, where warming, water stress, or changing rainfall can produce cultivar- and location-specific outcomes rather than uniform trends [2, 12]. The response classes and their mechanistic interpretations are summarized in Table 3.

4 Discussion

4.1 Mechanistic interpretation

The results indicate that duku fruiting occurrence can be explained as an emergent property of interactions between seasonal rainfall and internal reserves. Fruiting is not modeled as a direct linear response to rainfall totals. Instead, rainfall affects induction and loss processes during defined phenological windows, while Reserve controls whether the population has sufficient internal capacity to respond. This mechanism accounts for abrupt transitions between fruiting and non-fruiting years and for delayed effects of previous seasons.

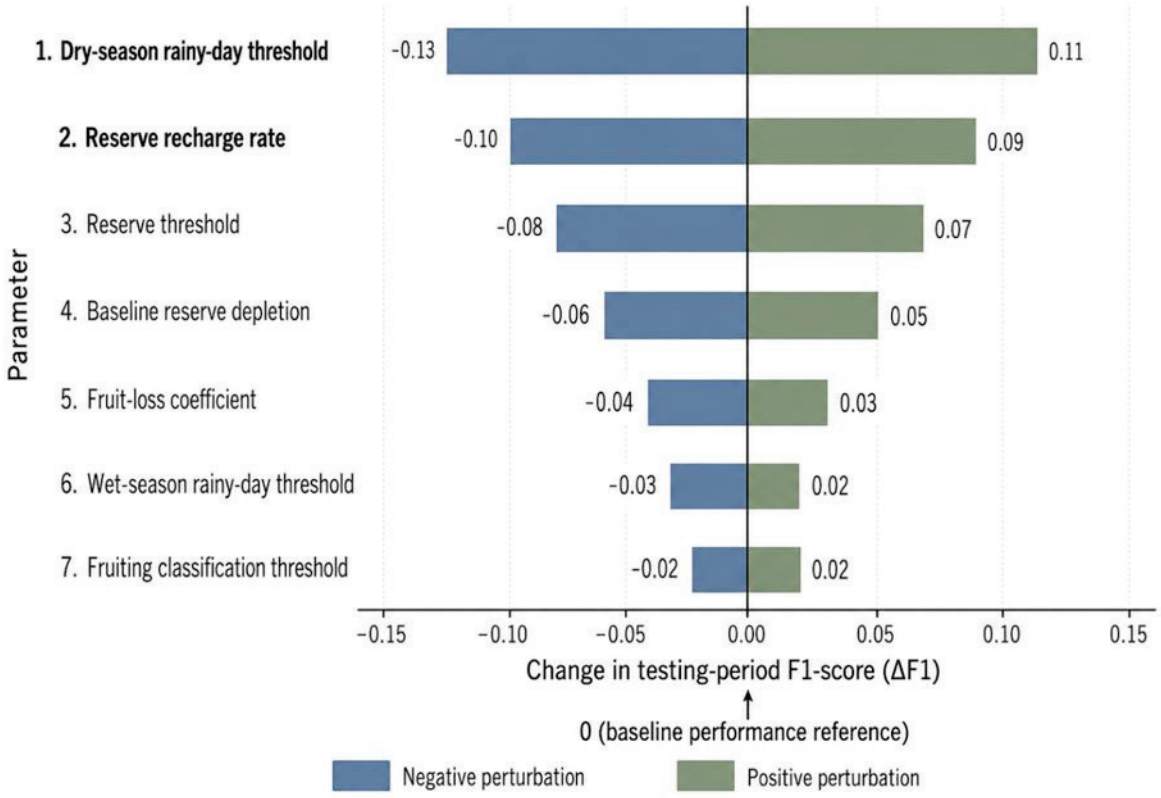

Fig. 3. One-at-a-time sensitivity analysis of key model parameters based on deviations from baseline fruiting-classification performance.

Table 3. Interpretation of ±10% rainy-day perturbation scenarios.

Response class	Observed behavior	Mechanistic interpretation
Most sensitive sub-district	Fruiting frequency changed by up to 0.20 relative to baseline.	The baseline rainfall regime placed the system near the induction or loss thresholds.
Most stable sub-district	Fruiting frequency did not change under −10% or +10% rainy-day scenarios.	Baseline rainfall regime was far from critical thresholds.
All locations	Responses were heterogeneous and nonlinear.	Climate sensitivity depended on proximity to the threshold rather than on a uniform rainfall effect.

The Reserve stock functions as a memory variable. When fruiting occurs, reserves are depleted, and the probability of immediate subsequent fruiting may decline unless recharge is sufficient. When non-fruiting occurs, reserves can accumulate, increasing the probability that favorable dry-season conditions will trigger induction in a later year. This interpretation parallels mechanisms of alternate bearing in olive, pistachio, citrus, apple, and other woody fruit crops, in which reproductive load influences return bloom through resource depletion, floral bud processes, and vegetative growth dynamics [7, 8].

4.2 Spatial heterogeneity and threshold control

Spatial validation and scenario analysis show that climate sensitivity differs among sub-districts because each location occupies a different position relative to model thresholds. Sensitive locations are near transition zones where a small change in rainy-day frequency can switch annual classification. Stable locations are farther from thresholds and therefore maintain the same fruiting frequency under modest perturbation. This explains why the same regional rainfall change may create strong production risk in one area but little observable effect in another.

The result has methodological significance. A linear model would likely estimate an average rainfall effect, obscuring the fact that risk is concentrated near

thresholds. The dynamic model, in contrast, identifies the conditions under which small climate changes can trigger large changes in outcomes. This insight aligns with the broader orchard modeling literature, which recommends process-based models for evaluating climate sensitivity because they can represent phenological thresholds, feedbacks, and nonlinear interactions among climate, physiology, and management [10, 11, 15].

This interpretation is particularly useful for explaining why historical records can show irregular alternation rather than a strict biennial sequence. The model does not impose an ON–OFF pattern. Instead, alternation emerges only when the combination of reserve depletion, reserve recovery, induction opportunity, and wet-season loss generates such a sequence. Therefore, irregular fruiting cycles are not treated as noise, but as expected outcomes of a dynamic system exposed to variable seasonal rainfall.

Scenario responses are shown in Figure 4, indicating that modest rainy-day perturbations can alter fruiting frequency in threshold-sensitive locations, while leaving stable locations unchanged.

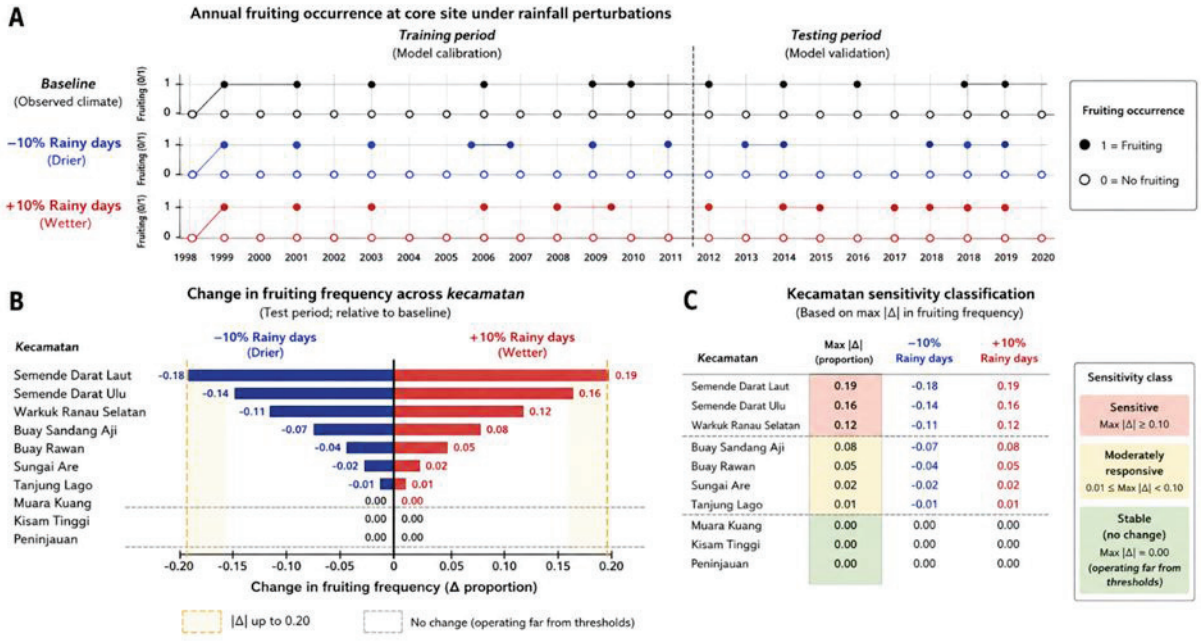

Fig. 4. Simulated fruiting occurrence and fruiting-frequency changes under baseline and ±10% rainy-day perturbation scenarios across the sub-district.

4.3 Relevance to unmanaged and smallholder orchards

The study is intentionally focused on unmanaged or minimally managed smallholder orchards. In such systems, climate-driven processes are more visible because fertilization, pruning, irrigation, and crop-load management do not strongly modify tree response. This does not imply that management is unimportant. Rather, the model provides a baseline for understanding climate–physiology interactions before adding management complexity. Fruit-tree agroforestry studies show that perennial systems can provide important livelihood and ecosystem benefits, but their productivity is shaped by both ecological processes and human decisions [5].

The model also clarifies why adaptation cannot be inferred from annual rainfall totals alone. Two locations with similar annual rainfall may differ in the number of dry-season rainy days, wet-season persistence, and the timing of rainfall relative to reproductive stages. The modeled response, therefore, depends on seasonal distribution, not merely total precipitation. This distinction is important for tropical fruit systems because climate change may alter rainfall seasonality, dry-spell frequency, and wet-season persistence without producing a simple monotonic change in annual totals.

The framework may therefore support comparative risk assessment across smallholder landscapes. Locations with high sensitivity to rainy-day perturbation may require closer monitoring, adaptation planning, or future management intervention. In contrast, stable locations may represent relatively robust production zones. Such information is useful for extension planning, especially where yield records are incomplete, but fruiting occurrence can be reconstructed from local production statistics.

4.4 Scope, limitations, and future development

Several limitations should be recognized. Monthly rainy days were used as the sole climatic forcing variable, so rainfall intensity, dry spell duration, extreme events, temperature, humidity, and radiation were not explicitly modeled. The model also treats each sub-district as an aggregate tree population, which smooths individual tree variability. Parameters were held constant over time, so long-term physiological changes,

land-use transitions, disease pressure, and management shifts were outside the model's boundary.

Future work should test the model against updated datasets, incorporate additional climate variables, and compare binary fruiting occurrence with yield magnitude, where reliable yield data become available. The structure could also be extended by adding management modules for pruning, fertilization, irrigation, or canopy manipulation. Such an extension would follow the path of more detailed perennial crop models, which gradually integrate phenology, canopy development, water relations, carbohydrate allocation, and yield components. Even in its current simplified form, however, the model provides a transparent mechanism-oriented tool for understanding climate-sensitive fruiting in tropical perennial systems.

The use of binary occurrence rather than yield magnitude should also be considered a strength, given the available data. Many regional fruit statistics are affected by reporting inconsistencies, informal marketing channels, and variable harvest completeness. A binary fruiting indicator reduces the effect of uncertain yield magnitudes while preserving the biological signal of reproductive success. Once more reliable orchard-level yield data are available, the model can be extended by replacing the final classification rule with a yield formation function while retaining the same internal Reserve and seasonal climate structure.

5 Conclusion

This study developed a parsimonious climate-driven dynamic system model to simulate fruiting and non-fruiting years in smallholder, unmanaged duku orchards. By representing Reserve and FruitPotential as internal state variables, the model reproduced annual fruiting occurrence as a threshold-mediated outcome of reserve accumulation, dry-season induction, wet-season fruit loss, and harvest-period classification. Temporal validation showed that the model retained predictive skill beyond the calibration period, while spatial validation demonstrated that the calibrated parameter set could be transferred across sub-districts without recalibration. Sensitivity and rainy-day perturbation analyses further revealed that some locations were highly responsive to ±10% rainfall-day changes, whereas others remained stable because they operated far from critical thresholds. These findings confirm that duku fruiting is better understood as a delayed, internally buffered climate response than as a direct, linear function of rainfall. The model contributes to perennial fruit-crop modeling by offering a transparent occurrence-based framework suitable for data-limited tropical contexts. It also provides a practical basis for identifying locations where production risk may increase under modest shifts in rainfall seasonality. Future work should incorporate additional climatic variables, more detailed orchard observations, and management modules to extend the model from mechanism explanation to operational climate-risk assessment and decision support.

Acknowledgment: This publication was funded by the Indonesian Endowment Fund for Education (LPDP) on behalf of the Indonesian Ministry of Higher Education, Science and Technology and managed under the EQUITY Program (Contract Numbers 0011/UN9/SK.BUK.HT/2025 and 0042/UN9.R/SK.SU/2026).

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