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Development and Evaluation of a Taro Model within the APSIM Plant Modelling Framework

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Abstract: Taro (*Colocasia esculenta* L., Schott) is a culturally and nutritionally important crop in Southeast Asia, Africa, and the Pacific Islands, contributing to food and nutrition security, rural livelihoods, and cultural heritage. Despite its importance, taro has received far less attention in crop modelling compared with cereals, which dominate research due to their central role in global food systems. As a result, models for root and tuber crops remain underdeveloped, and taro is particularly underrepresented. Early attempts to simulate taro growth using APSIM Classic (*v*7.10) were limited by sparse physiological data and a rigid codebase that constrained extensibility. APSIM Next Generation (APSIMX) provides enhanced modelling capability through its Plant Modelling Framework (PMF), but there is no dedicated taro model available yet. This study aimed to develop and evaluate an APSIM taro model capable of simulating growth, yield, and resource use. The model was built within the APSIM's PMF, adapting structural components from the potato model and linking them to APSIM's soil water and nitrogen modules. Key processes included phenology, canopy expansion, root and corm growth, biomass partitioning, and nitrogen uptake. Phenology was parameterised using thermal time targets, canopy development with leaf appearance and branching rules, and biomass accumulation with radiation use efficiency (RUE). Partitioning was dynamically resolved through APSIM's arbitration framework. Model calibration used field data from Samoa (2023–2025), while independent validation was conducted with trials conducted at the Koronivia Research Station (Fiji Ministry of Agriculture) under non-limiting water and nitrogen conditions. Calibration demonstrated strong agreement between observed and simulated corm dry matter ($R^2 = 0.93$; bias = –3.4 g m^{-2}), and validation confirmed robust performance with the Fiji dataset ($R^2 = 0.90$; bias = +33.2 g m^{-2}). These results highlighted the model's ability to reliably capture corm biomass accumulation across contrasting environments. However, weaker performance was observed for leaf area index and aboveground (leaf and stem) biomass, indicating the need to refine canopy representation and partitioning rules. A particular challenge in representing taro growth is its unique branching habit: suckers arise from buds on the corm rather than from above-ground stem nodes, as in potato. This requires a different representation of branching dynamics, competition for assimilates, and partitioning between the mother plant and suckers. Adapting from an existing potato model provided a valuable foundation, enabling rapid assembly of a preliminary taro model structure. However, accurately representing taro's distinctive physiological processes, particularly its branching from the corm rather than from aerial stems, requires extensive parameterisation and testing. This process was constrained by the scarcity of high-quality, in-season datasets spanning diverse environments, planting dates, plant densities, and management regimes, all of which are essential for capturing cultivar × environment × management interactions. Despite these challenges, APSIMX provided the flexibility to integrate diverse processes into a functional taro model. Future development should focus on improving canopy and stem representation, expanding cultivar parameterisation, and explicitly modelling sucker growth. With targeted validation across environments, the APSIM Taro model has the potential to become a robust tool to assist the design of taro-based cropping systems that support sustainable intensification and farming systems' adaptation to climate change.

Keywords: *Root and tuber crops, research priorities, Pacific Countries, food security, climate change, farming systems adaptation*

1. INTRODUCTION

Taro (*Colocasia esculenta* L., Schott) is a vital root crop with deep cultural and nutritional significance in regions such as Southeast Asia, Africa, and the Pacific Islands (Matthews 2010; Lebot and Aradhya, 1991; Ragone 1997; Chandrasekara and Kumar, 2016; Lloyd et al. 2021). Despite its significance as a staple crop in many regions, taro has historically received far less attention in crop modelling compared with grain crops, which dominate the research landscape due to their global cultivation and role in food security (Silva and Giller, 2020). Whist models for cereals are well-developed, there remains a substantial gap in models tailored to root and tuber crops, with taro being notably underrepresented (Boote, 2019). As a result, there has been a lack of robust models to guide decision-making and optimise taro cultivation under varying environmental and management conditions.

Previous efforts to model taro (e.g. Crimp et al. 2017) have made significant strides in simulating growth and development using the Agricultural Production Systems sIMulator (APSIM, https://www.apsim.info/). However, these efforts were constrained by limited availability of detailed data, preventing full validation and refinement of the model. While APSIM Next Generation (henceforth, APSIMX: Holzworth et al. 2014) introduced significant advancements in crop modelling, a dedicated taro model has not yet been developed within this framework. The lack of specific physiological data and the reliance on generalized parameters from related crops have further hindered the ability to accurately represent taro's unique growth characteristics. The APSIM platform offers powerful tools that are well-suited for overcoming these challenges. With its user-friendly interface, APSIM-NG allows scientists to visually construct and configure crop models using drag-and-drop components (Brown et al. 2014). This version of APSIM also provides a comprehensive suite of features to assist in building, testing, evaluating, and auto-documenting models. However, despite its potential, the absence of detailed data necessary for creating and validating a robust taro model within this advanced framework continues to limit progress in the development of the taro model. To bridge this gap, recent research focused on collecting comprehensive datasets on taro growth and development. These datasets are crucial for refining the model and better reflect the specific characteristics and management needs of taro. The modular design of APSIM, with its flexible Plant Modelling Framework (PMF), facilitates the integration of such datasets into models that are more robust and dependable. This study was conducted to develop a taro model within APSIM using the Plant Modelling Framework.

2. FIELD TRIALS

Field trials were conducted in three Pacific Island locations (Fiji, Vanuatu, and Tonga) between 2012 and 2016 to establish baseline data on taro growth dynamics (Crimp et al. 2017). These experiments provided essential information on canopy development, radiation use efficiency (RUE), biomass allocation, and soil-plant interactions, forming the initial stage for the model parameterisation. Building on this foundation, additional trials were established in Samoa and Fiji between 2023 and 2025. Each field was divided into three blocks (dimensions: 6 m × 3.75 m) to record aspects of crop development including: destructive harvests to measure phenology and biomass partitioning, leaf tip counts to track appearance rates, and branching observations. Biomass of leaves, petioles, stems, roots, and corms was recorded fortnightly, and weeds were removed by hand as needed to avoid competition for resources with the standing crop. At both sites, 100 medium-sized suckers (~25-30 cm long) were planted at 1.50-m × 0.75-m spacing to a depth of 15-20 cm under non-limiting nutrient conditions. The Samoa trials were conducted near Tanumalala in north-western Upolu (planted on 17 October 2024), which is the drier part of the Island, and received ~765 mm of rainfall during the growing period. Daily temperature and radiation data were obtained from NASA database, while daily rainfall inputs were derived from **CHIRPS**, a widely used satellite-station blended precipitation product. Soil characteristics required for model parameterisation including soil bulk density, soil $pH_{1:5}$, electrical conductivity of soil (EC), soil organic matter (SOM) content, crop lower limit (CLL_{15}), and drained upper limit (DUL_{100}) were measured. Soil water content and mineral nitrogen (N) were monitored at intervals throughout the growing season, alongside destructive harvests to track growth and resource uptake. These data formed the calibration dataset, enabling refinement of parameters related to phenology, biomass allocation, and N concentration. The Fiji trial was established at the Koronivia Research Station (Fiji Ministry of Agriculture) and planted on 15 August 2024, received ~3000 mm of rainfall during the crop cycle and was managed under optimal water and nutrient conditions. Weather data were recorded at the Koronivia Research Station. This dataset was used as an independent dataset for model validation, corm yield, leaf area development, and biomass accumulation.

3. MODELLING TARO USING APSIM PMF

APSIM represents a cutting-edge evolution of the original APSIM framework, offering faster runtimes, streamlined model-building, and enhanced documentation (Holzworth et al. 2022). Central to APSIMNG is the PMF, a versatile platform for developing and parameterizing crop models without modifying APSIM's core code. In developing a taro model within APSIM, the PMF's modularity was leveraged to encapsulate taro's unique physiology and growth dynamics. This approach allowed simulating critical crop processes such as canopy

development, RUE, and corm growth, and producing a robust and adaptable model applicable across cultivation systems. The following sections outline the conceptual approach employed to developing the Taro model, detailing how each component was integrated and designed to reflect taro's unique growth dynamics.

3.1 Taro phenology

Taro phenological development was modelled using a thermal time approach. The thermal time accumulates according to cardinal temperatures: no development occurs below 10°C, accumulation is linear between 10–35°C and declines above 35°C until it ceases entirely above 42°C. Taro is typically propagated from a sucker with a small piece of the corm (swollen stem) attached at its base (Lebot, 2009). Thus, seed-based germination models, such as those used for cereals and legumes, are not suitable for modelling the early growth of taro. For the taro model, it was assumed that a sucker consists of a stem (petiole) section and a visible bud, but it lacks roots and leaves and a corm at the time of planting. The apical meristem initiates shoot and leaf development, while root development begins approximately two weeks after planting depending on thermal time accumulation. Taro establishment is influenced by several factors, including sowing depth of sucker, soil temperature, and soil water availability. In the model, early crop development is represented by the emerging phase, which spans from planting to the appearance of visible leaf growth. This phase ends when the sucker establishes a functional root system and visible leaves begin to emerge. The thermal time target for this phase was calculated as the product of the shoot elongation rate (1.35°C days mm^{-1}) and sowing depth, plus a shoot lag of 25°C days. This value marks the end of the establishment phase. Parameter values were adopted from the potato crop model (APSIM2023117347) due to the absence of direct measurements for taro. The thermal time targets for subsequent phases are detailed in Table 1. Each phase has been parameterised by adjusting thermal time accumulation and other growth parameters to reflect the specific growth stages of taro from suckers. The stem population is calculated as the product of plant population and bud number.

Table 1 Input data for the taro phenology for *Uro-ni-vonu* cultivar (GDD is growing degree-days).

Phase	**Description**	**Thermal time (GDD)**
Establishment	Period from planting the sucker until it establishes roots and stabilises in the soil, and appearance of the first leaf	Shoot lag = 25°C $days^{-1}$, Shoot elongation rate (1.35°C days mm^{-1}) 93°C $days^{-1}$
Vegetative growth	Start of rapid growth to corm initiation	2300°C $days^{-1}$
Corm growth	Corm initiation to plateau corm growth	1700°C $days^{-1}$
Senescence	Leaf start to senescence (overlaps corm growth)	500°C $days^{-1}$
Harvest	Removal of corms from the soil	-

3.2 Canopy structure

In APSIM, simple leaf and cohort leaf approaches are two methods for modelling leaf growth and development, each with distinct conceptual frameworks and computational techniques. The simple leaf approach treats the crop canopy as a homogeneous "big leaf". Instead of tracking individual leaves or leaf cohorts, it models the canopy as a single layer, focusing on overall canopy-level processes. In contrast, the cohort leaf approach models leave in groups or "cohorts", allowing for the simulation of individual leaves or groups of leaves based on their position (Brown et al. 2014). The cohort leaf approach was adopted for the simulation of taro canopy development. The number and size of leaves on the primary stem (sucker) is initialized on the day of leaf emergence. Following emergence, the appearance of new leaves on the sucker is predicted from accumulated thermal time and a phyllochron. In this model, canopy development is initialised with a defined initial leaf cohort area (mm^2) assigned to the first leaf cohort, while all subsequent cohorts are set to zero at sowing and expand, progressively, in response to the accumulated thermal time. The model tracks thermal time from sowing to simulate leaf appearance. Each day, the number of leaf tips appearing on the main stem is calculated. This number increases until the final leaf number, measured in-field conditions, is reached. The phyllochron starts at a value of 5°C days for the first leaf and increases to 60°C days for leaves 0 to 25. Leaf appearance stops once this number of leaves has developed, which is specified for the cultivar. The phyllochron values were derived from unpublished leaf appearance measurements.

Once leaves have appeared, their potential size is calculated daily from parameters that describe growth duration, maximum area, lag period, and the senescence phase. The expansion period, during which the green area of an

individual leaf is increased, ranges from 200°C days for the first leaf to 400°C days at leaf 10, and it remains constant at 400°C days for all subsequent leaves. The maximum leaf area, assuming no stress occurs during expansion, increases from 24,600 mm^2 for the first leaf to 300,000 mm^2 at leaf 8. It subsequently declines to 282,160 mm^2 until leaf 16, with a further decrease to 100 mm^2 at leaf 25 (The Authors, unpublished data). The lag period, during which leaves remain at maximum area, is set to a constant value of 1800°C days. The senescence period, during which the green area reduces, is parameterized with a duration of 1600°C days. The canopy development phase ends when the total node number reaches 25.

3.3 Dry matter production

Taro yield predictions are calculated daily from total dry matter (DM) production and its allocation to plant organs. Daily dry matter (DM) production is determined, as in other APSIM modules (Holzworth et al. 2014; Wang et al. 2004), using the radiation use efficiency (RUE) approach and empirical representation of canopy photosynthesis, which converts intercepted radiation into biomass. Each day, when a new leaf tip emerges, a new cohort is added, contributing its area to the total leaf area of the plant. The sum of all the area of the leaves per plant is then used to calculate the Leaf Area Index (LAI), which reflects the proportion of ground area covered by leaves. Subsequently, using the LAI, extinction coefficient, and maximum canopy cover, the model estimates green canopy cover through Beer's law.

$$\text{CoverGreen} = MaxCover \times (1\text{-}e^{-MaxCover \times k \times LAI})$$

where:

- MaxCover represents the upper limit of the proportion of ground area that can be covered by the plant canopy
- e is the exponential function
- k is the extinction coefficient
- LAI is the leaf area index (total leaf area per unit ground area).

An extinction coefficient of 0.54 was used for taro, which is lower than that reported by Crimp et al. (2017).

Based on this approach, the model estimates the fraction of incident solar radiation intercepted by the green parts of the plant as follows:

$$Rad_{int} = CoverGreen \times R_{solar}$$

where:

- R_{solar} is the total incoming global solar radiation
- Rad_{int} is radiation intercepted by the green canopy

The intercepted solar radiation is then converted to DM with a first-degree linear equation that uses the intercepted radiation (R_{int}), and a baseline radiation use efficiency (RUE_{ref}), adjusted by stress and CO_2 modifiers. Taro is particularly sensitive to high vapour pressure deficit due to its large leaves and high stomatal density, which can accelerate water loss and therefore reduce biomass accumulation. In the absence of reliable field data, F_{vpd} was conservatively set at 0.8 to capture this sensitivity of the crop. Nitrogen (Fn) and water (Fw) stresses were calculated as the ratio of actual supply to plant demand, while temperature stress was determined by cardinal temperatures (base, optimum, maximum) that define the crop's response curve. Stresses due to nitrogen, temperature, and vapour pressure deficit are applied according to Liebig's law of the minimum:

$$DM = R_{int} \times RUE_{ref} \times min(F_n, F_t, F_{vpd}) \times F_w \times F_{CO2}$$

where: each factor ranges between 0 (complete stress) and 1 (no stress). Water stress (F_w) is then applied separately, as it acts on potential growth rather than the same processes as temperature or nutrient stresses. The CO_2 modifier (F_{CO2}) adjusts RUE for atmospheric CO_2 concentration, with a baseline value of 1.0 at 350 ppm and increasing as CO_2 levels rise, calculated using the approach of Ludwig and Asseng (2006) and Reyenga (1999). Unlike the stress factors, (F_{CO2}) is generally ≥1, reflecting CO_2 fertilisation effects. These trials were conducted under non limiting water and nutrient conditions; thus, water (Fw) and nitrogen (Fn) stress factors remained near unity throughout the simulations.

3.4 Dry matter allocation

Biomass is distributed to organs according to partitioning coefficients:

$$DM_{organ} = f_{organ} \times DM$$

where: f_{organ} is the allocation fraction for each organ and DM is the total DM produced. The allocation fractions are dynamic, determined through an arbitration process that balances organ demand and phenological stage. This ensures biomass is directed to the appropriate organs while growth remains constrained by nutrient, temperature, water, and CO_2 modifiers (Holzworth et al. 2014). At this stage of model development, no explicit remobilisation factors (e.g. transfer of reserves from stem or petiole to the corm) are included, and biomass partitioning occurs solely through this dynamic arbitration framework. Future refinement should focus on introducing remobilisation pathways to improve simulation of late-season biomass redistribution and corm filling.

Taro exhibits distinct patterns of DM partitioning throughout its growth stages, with biomass allocation shifting among various plant organs as the plant matures. During the initial phase, taro allocates a significant portion of its DM to the development of leaf and petioles. This allocation supports the establishment of a photosynthetically active canopy, essential for energy capture and subsequent growth. Fa'amatuainu and Amosa (2016) observed that leaf and stem DM increased substantially from 35 to 140 days after planting (DAP), indicating a focus on aboveground biomass accumulation during this period. As the plant progresses, there is a notable shift in biomass allocation toward the corm. Goenaga (1995) reported that after approximately 80 DAPs, increases in total dry matter were primarily due to corm and sucker growth, with corm bulking occurring after the attainment of maximal leaf area indices. At later stages of development, the accumulation of dry matter in the corm becomes predominant (Boampong et al. 2020). Fa'amatuainu and Amosa (2016) found that corm dry matter continued to increase up to 175 DAP, while the dry matter in leaf blades and petioles began to decline, indicating a reallocation of resources from the leaves to the corm as the plant approaches maturity.

Crimp et al. (2017) reported on the standing biomass composition of taro at various growth stages, noting distinct shifts in allocation patterns over time. For example, at 43 days after planting (DAP), standing biomass was distributed primarily to stems (40%) and leaves (30%), with roots (20%) and corms (10%) contributing smaller proportions. By 166 DAP, corms accounted for 38% of standing biomass, suckers 30%, while leaves and stems had declined to ~10% and roots to ~3%. At 279 DAP, storage in corms (43%) and suckers (50%) dominated, while leaves (2%), petioles (5%), and roots (nearly 0%) were minimal. These values represent standing biomass proportions, whereas the model requires partitioning fractions of daily growth. Following standard APSIM practice, we used standing biomass trajectories to infer partitioning by plotting organ biomass against total plant biomass to estimate the relative allocation of daily assimilates. This approach allows the observed shifts in standing biomass to inform dynamic partitioning coefficients for daily growth. In APSIM, the allocation of DM into roots, stems, leaves, and storage is determined by the plant's developmental phase and available photosynthate. This process follows the demand and supply principle (Brown et al. 2014), with each organ generates a potential growth demand based on developmental stage, and environmental conditions. Supply of dry matter is generated through photosynthesis and remobilization of stored reserves redistributing previously accumulated dry matter (non-structural components) to meet new growth needs. Arbitration of the dry matter is then calculated based on the supply to total demand ration. When demand exceeds supply, a partitioning or prioritisation system is used.

4. MODEL PERFORMANCE

The model calibration was based on field experiments conducted in Samoa (Figure 1), while model performance was independently evaluated using data from Fiji (Figure 2). Calibration showed that the model captured corm growth with high accuracy (R^2 = 0.93, RMSE = 32.8 g m^{-2}, MAE = 25.5 g m^{-2}, bias = –3.4 g m^{-2}), indicating close agreement between observed and simulated values. In contrast, performance for the aboveground part was weaker: stem biomass showed only moderate agreement (R^2 = 0.44, bias = -24.5 g m^{-2}), leaf biomass was poorly reproduced (R^2 = –5.96, bias = +32.9 g m^{-2}), and aboveground dry matter displayed modest predictive skill (R^2 = 0.28, RMSE = 83.5 g m^{-2}, bias = +28.3 g m^{-2}). Despite these discrepancies, the strong calibration for corm biomass provided a reliable foundation for validation. Validation with the Fiji dataset confirmed that the model maintained strong predictive capacity for corm biomass (R^2 = 0.90, RMSE = 43.4 g m^{-2}, MAE = 40.9 g m^{-2}, bias = +33.2 g m^{-2}), demonstrating consistent performance across environments. However, the same limitations were evident for other components: stem biomass was systematically underpredicted (R^2 = –0.66, bias = –68.0 g m^{-2}), leaf area index was poorly simulated (R^2 = –0.65, bias = –0.14), and aboveground biomass showed limited agreement (R^2 = –0.23, bias = –51.9 g m^{-2}). Overall, the model robustly represented corm accumulation, but it will require refinement of canopy dynamics and dry matter partitioning.

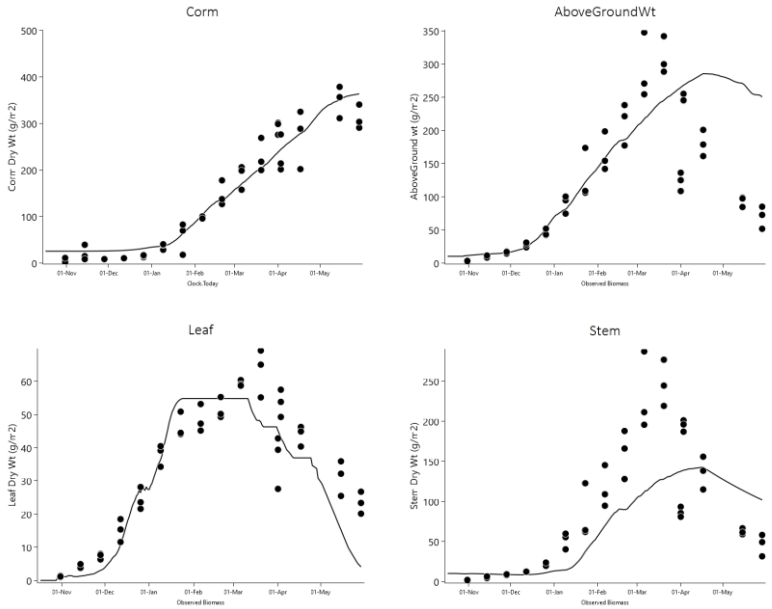

Figure 1. Model calibration for corm and above ground biomass for the *Uro-ni-Vonu* variety grown in Samoa. The circles represent observations while the lines indicate the simulated values.

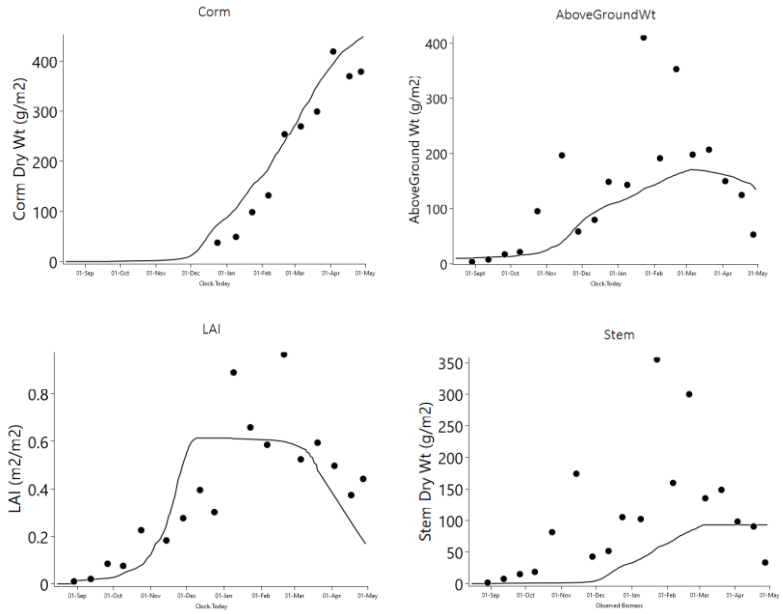

Figure 2. Model evaluation for corm and above ground biomass for the *Uro-ni-Vonu* variety grown in Koronivia Research Station, Fiji. The circles represent observations while the lines indicate the simulated values.

5. CONCLUSIONS AND FUTURE RESEARCH REQUIREMENTS FOR IMPROVING THE APSIM-TARO MODULE

The APSIM Taro model, shows promising performance particularly in simulating corm biomass. However, its evaluation has, so far, been limited to non-stress conditions within a single growing season, leaving its robustness under contrasting environments untested. The current version of the model also requires the final leaf number from each trial as an input, restricting its use in fully predictive applications. Nevertheless, the APSIM PMF framework provides a solid basis for further refinement. Priorities for future development of the model include improving both canopy and stem biomass representation, broadening cultivar parameterisation, and explicitly modelling sucker growth. Broader validation across environments and stress scenarios will be essential to building confidence in the model's predictions and enhancing its value as a tool to assist the design of tropical farming systems in the context of sustainable intensification and climate change adaptation.

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