Performance of a process-based model for predicting robusta coffee yield at the regional scale in Vietnam

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Abstract

Reliable and timely prediction of robusta coffee (*Coffea canephora* Pierre ex A. Froehner) yield is pivotal to the profitability of the coffee industry worldwide. In this study we assess the performance of a simple process-based model for simulating and predicting robusta coffee yield at the regional scale in Vietnam. The model includes the key processes of coffee growth and development and simulates its response to variation in climate and potential water requirements throughout the growing season. The model was built and evaluated for the major Vietnamese robusta coffee-producing provinces Dak Lak, Dak Nong, Gia Lai, Kon Tum, and Lam Dong, using official provincial coffee yield data and climate station data for the 2001-2014 period, and field data collected during a 10-year (2008-2017) survey. Overall, good agreements were found between the observed and predicted coffee yields. Root mean square error (RMSE) and mean absolute percentage error (MAPE) values ranged from 0.24 to 0.33 t ha^{-1}, and 9% to 14%, respectively. Willmott's index of agreement (WI) was greater than or equal to 0.710 in model evaluation steps for three out of five provinces. The relatively low values of WI were found for provinces with relatively low inter-annual yield variability (i.e. Dak Lak and Dak Nong). Moreover, the model was successfully tested using remote sensing satellite and model-based gridded climate data: MAPE values were ≤ 12% and RMSE were ≤ 0.29 t ha^{-1}. Such evaluation is important for long-term coffee productivity studies in these regions where long-term climate stations data are not readily available. The simple process-based model presented in this study could serve as a basis for developing an integrated seasonal climate-robusta coffee yield forecasting system, which would offer substantial benefits to coffee growers and industry through better supply chain management and preparedness for extreme climate events, and increased profitability.

Keywords: *Coffea canephora*, biophysical model, climate variability, climate risk management

1. Introduction

Coffee is one of the most important agricultural commodities in international trade, playing a crucial role in the economy of several African, American and Asian countries (Lewin et al., 2004; AfDB, 2010; ICO, 2019). The total world production was estimated to more than 150 million 60-kg bags of coffee beans over the past five years, of which 80 to 85% were exported (ICO, 2020). Current coffee bean production is dominated by arabica coffee (*Coffea arabica* L.), which represents roughly 60%; the remaining 40% being for robusta coffee (*C. canephora* Pierre ex A. Froehner) (ICO, 2020). Coffee production is strongly influenced by environmental conditions, and is thus threatened by the increasing variability and changes in climate patterns across several major producing regions worldwide (Bunn et al., 2015; DaMatta et al., 2019). Extreme weather events associated with the El Niño Southern Oscillation (ENSO) (e.g. droughts, frosts, etc.) can influence substantially both arabica and robusta coffee commodity markets (Ubilava, 2012; Cashin et al., 2017; Sephton, 2019). It is therefore vital to develop decision support tools for increasing the preparedness of the various stakeholders of the coffee industry, from smallholder farmers to agribusinesses to governments.

Vietnam is the second largest producer of coffee beans worldwide, with a total coffee production of 1.2 million metric tons on average during 2010-2017 (FAO, 2018), and the first producer in robusta coffee (World Bank, 2004; Marsh, 2007), . The Central Highlands region of Vietnam, which encompasses the major robusta coffee-producing provinces, is among the most drought-prone Vietnamese regions, with considerable crop losses due to drought events being reported during the past two decades (Nguyen, 2005; Vu et al., 2015; ICO, 2019). Seasonal climate forecasts (SCF) have the potential to improve farmers' overall operational management of agricultural production through better decision-making (Hammer et al., 2000; Stone and Meinke, 2005; Meza et al., 2008; Bruno Soares et al., 2018). Indeed, they provide farmers with opportunities to better match management decisions (e.g. sowing windows, sowing area, fertiliser application, harvesting, marketing, etc.) to pending climatic conditions (Hammer et al., 2000; Meinke and Stone, 2005; Parton et al., 2019). A reliable process-based biophysical model, integrated into or coupled to SCF systems, could offer substantial benefits to coffee growers and industry through increased profitability, better supply chain management and preparedness for extreme events such as droughts and floods.

Several studies have dealt with the modelling of the coffee crop, ranging from statistical to process-based approaches (Gutierrez et al., 1998; van Oijen et al., 2010b; Rodríguez et al., 2011; Coltri et al., 2015; Ovalle-Rivera et al., 2020; Vezy et al., 2020). Process-based crop models are developed to understand the weather and nutrient-driven dynamics and constraints of the plant trophic level and facilitate the simulation of interactions between all the constituent processes (e.g. soil, water, plant, management practices, etc.) (Miglietta and Bindi, 1993; Boote et al., 1996; Batchelor et al., 2002; Jones et al., 2016). For example, Rodríguez et al. (2011) developed a model to simulate the growth and development of arabica coffee, which includes refined phenology and physiological processes of the distributed-maturation time tri-trophic population model of Gutierrez et al. (1998). Among the specificities of the Rodríguez et al. (2011)'s model are the incorporation of both the vegetative and the reproductive demands to predict the photosynthetic rate, and incorporation of the dynamics of cohorts of reproductive organs and reserve compartment. van Oijen et al. (2010b) proposed a plot-scale, dynamic model for coffee agroforestry systems (CAF2007) which simulates the processes underlying berry production under shaded or unshaded conditions. The model allows for investigating the impacts on coffee berry production of cultural practices such as pruning, spacing, thinning and fertilising, along with shade tree species management. The CAF2007 was recently modified to improve the calculation of flowering date and the modelling of biennial production patterns, and was tested successfully in in different coffee-growing regions of Nicaragua and Costa Rica (van Oijen et al., 2010b; Ovalle-Rivera et al., 2020). It was also applied in East Africa to investigate the potential impacts of climate change on arabica coffee under various agro-ecological settings and agricultural managements (Rahn et al., 2018). Vezy et al. (2020) incorporated key features of the Rodríguez et al. (2011)'s model (i.e. the plant-scale reproductive phenology formalism) and the CAF2007 model (i.e. canopy temperature-dependent phenology, and the sub-modules for agroforestry system management), along with metamodels structure (Vezy et al., 2018), to develop a plot-scale model, the DynACof model, which simulates various processes, including net primary productivity, growth and yield, in coffee agroforestry systems according to shade tree species and management.

All the aforementioned models were developed initially for arabica coffee and most often have been applied to studies at plant and farm scales. They also involved numerous parameters, 33 in case of the Rodríguez et al. (2011)'s model and more than 100 for the CAF2007 and DynACof models, making their application at larger spatial scales (i.e. regional or provincial scale) very challenging. Furthermore, the few studies that dealt with robusta coffee focused mainly on the impacts of climate change and variability on coffee productivity and distribution (land suitability) (e.g. Davis et al., 2012; Bunn et al., 2015; Craparo et al., 2015). In this study, we aimed at building and evaluating the performance of a simple process-based biophysical model (hereafter referred to as a robusta model) for predicting robusta coffee yield at the regional scale in Vietnam. The model was built based on the main phenological processes represented in the more complex models cited previously (the CAF2007, Rodríguez et al. (2011)'s, and DynACof models), but in a much simpler manner. The model was calibrated and validated using field data collected during a 10-year (2008-2017) survey, and official provincial coffee yield and climate station data for the major robusta coffee-producing provinces in Vietnam. With an overarching goal of developing a process-based model for long-term studies of the impacts of climate variability on coffee yield and productivity at the regional scale, the performance of the robusta model was further assessed using remote sensing satellite and model-based gridded climate data, which are typically used as alternative in these regions when long-term climate stations data are not available.

2. Materials and methods

2.1 Description of the robusta model

The robusta model is a simplified, process-based biophysical model that simulates the potential growth and development of coffee plants on a daily time step based on weather data (minimum and maximum temperature, solar radiation, and rainfall) and information from the previous growing season (i.e. harvest date and yield). The model is inspired by a prior model by van Oijen et al. (2010b), which was developed to estimate the potential productivity of arabica coffee agroforestry systems. The main output of the robusta model at the end of the simulation period is the yield at the regional scale.

Three main processes are involved during the simulation: (1) radiation interception by leaves according to the Beer-Lambert's law (Swinehart, 1962); (2) conversion of the intercepted radiation into biomass based on the radiation use efficiency (RUE); and (3) accumulation of crop biomass and allocation to the different plant organs according to source-sink rules specific to coffee plants (DaMatta et al., 2007; van Oijen et al., 2010b). An overview of the model is illustrated in Fig. 1. No disease or pest impacts on yield are considered; as such, the predicted yield value corresponds to a potential value. In the following sub-sections, we describe the main equations used for simulating biomass production and assimilates partitioning into the different plant organs.

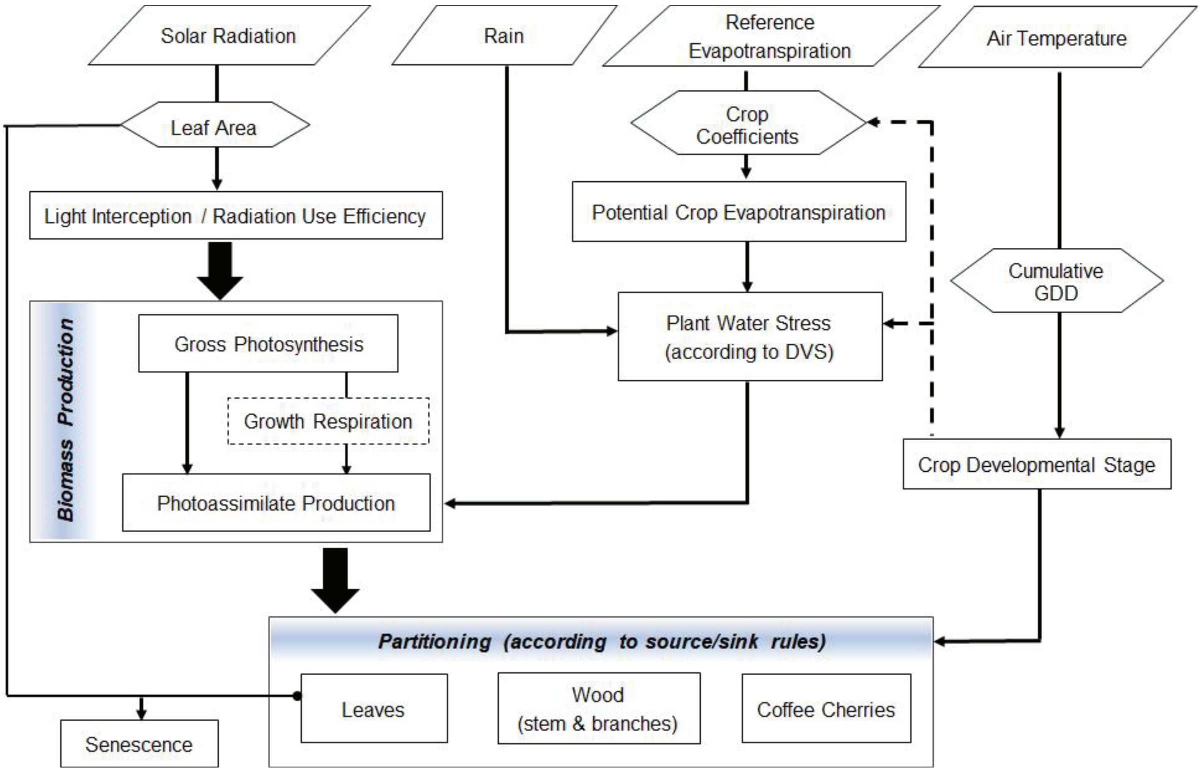

Fig. 1. Schematic representation of the main processes of the robusta coffee model. Abbreviations: GDD: growing degree days; DVS: Crop developmental stage.

2.1.1 Biomass production (active growth)

The phenology of robusta coffee trees includes two stages: the vegetative phase occurring before flowering and the reproductive phase or cherry development between flowering and harvest. Phenology is driven by the accumulation of growing degree-days. The daily biomass production is simulated in two steps. First, the light interception is calculated using the Beer-Lambert law (Eq. 1).

$$PAR_i = E_a \times E_c \times R_g \times (1 - e^{-K \times LAI}) \quad (1)$$

where PAR_i is the intercepted photosynthetic active radiation on day i (MJ m^{-2} d^{-1}); R_g is the daily solar radiation (MJ m^{-2} d^{-1}); Ea, Ec and K refer to the maximum interception efficiency, photosynthetically active fraction of solar radiation, and extinction coefficient, respectively (unitless).

Then, the intercepted solar radiation is converted into biomass, as follows.

$$\Delta Biom = E_b \times PAR_i \times \left(cost_{respi} - Biom_{veg}\right) \times STRESS \quad (2)$$

where $\Delta Biom$ is the daily increment in biomass (g m^{-2}); Eb is the light energy conversion efficiency (g MJ^{-1}); $cost_{respi}$ refers to the respiration cost of vegetative organs (unitless); $Biom_{veg}$ is the vegetative biomass (leaves + wood) already produced; and $STRESS$ is a drought stress factor (unitless).

The drought stress factor is applied to the daily biomass production based on water stress levels (details are provided in Sections 2.1.5 and 2.3).

Prior to flowering, newly produced biomass is allocated as vegetative biomass (wood and leaves). A factor related to pruning is considered during this phase following van Oijen et al. (2010b). The equations are as follows.

$$Biom_{wood} = \left(1 - K_{prn.wood}\right) \times Biom_{wood} \quad (3)$$

$$Biom_{leaves} = \left(1 - K_{prn.leaves}\right) \times Biom_{leaves} \quad (4)$$

where $Biom_{wood}$ and $Biom_{leaves}$ are wood and leaves biomasses, respectively (both expressed in g m^{-2}); $K_{prn.wood}$ and $K_{prn.leaves}$ are the average percentage of pruning of the wood biomass and leaves biomasses, set according to the average cultural practices of pruning (both are unitless).

2.1.2 Biomass partitioning

The onset of flowering was modelled as the first day of the year exceeding a threshold of cumulative growing degree days since robusta coffee farmers in Vietnam do irrigate their crops to break buds' dormancy and enable synchronous flowering events as much as possible. Given fruit production is the strongest carbohydrates sink in coffee (Cannell, 1976, 1985; Vaast et al., 2005; DaMatta et al., 2007; DaMatta et al., 2008), from flowering onwards, the newly produced biomass is allocated in priority to cherry growth (i.e. fruit demand). Fruit demand is related to the number of fruits and is assumed proportional to the wood biomass grown after the last flowering and the potential of fruit growth. It is calculated as follows.

$$BiomFruit_{dem} = UnitFruit_{dem} \times NF \quad (5)$$

where *NF* is the number of fruits (number per m^2) and $UnitFruit_{dem}$ corresponds to the potential of fruit growth. $UnitFruit_{dem}$ follows a sigmoidal function according to Cannell (1985) (Eq. 6). $UnitFruit_{dem}$ and *NF* are calculated as follows.

$$UnitFruit_{dem} = \frac{\Delta(ST_{t-1}; ST_t) \times Kfruit}{1 + e^{-(ST - (TempREC/2)/cFruit)}} \quad (6)$$

$$NF = Fruit_{pot} \times BiomWood_{SLF} \quad (7)$$

where $Fruit_{pot}$ is the maximum number of fruits per kg of newly produced wood (number per kg); $BiomWood_{SLF}$ is the wood biomass grown after the last flowering (g m^{-2}); $\Delta(ST_{t-1}; ST_t)$ is the difference of degree days between time steps *t-1* and *t*; *Kfruit* is the slope of the biomass accumulation in fruit (unitless); *ST* is sum of temperature above the base temperature (°C); *TempREC* is the sum of degree days between flowering and harvest (degree days); and *cFruit* is the maximum fruit biomass (unitless).

If the fruit demand is not satisfied by the newly produced biomass, we assumed that a proportion of leaf biomass is remobilized. Although we referred for the assumption to previously reported results on the decline of foliar non-structural carbohydrates and starch in arabica coffee (Chaves et al., 2012; Marias et al., 2017), future research would help elucidate such a remobilization process in case of robusta coffee. The formula of leaf biomass remobilization in the robusta model is as follows.

$$PotRem_{leaf} = K_{rem} \times Biom_{leaves} \quad (8)$$

where $PotRem_{leaf}$ is the potential remobilization of biomass from leaves (g m^{-2}); and K_{rem} is the maximum rate of remobilization (unitless).

2.1.3 Biomass reallocation into leaves and woody parts of the tree (passive growth)

The elaboration of bean yield is based primarily on the determination of the potential number of fruits according to the wood newly formed. Each coffee cherry acts as a priority sink of newly produced assimilates (Vaast et al., 2005; DaMatta et al., 2007). When the fruit demand is satisfied, the newly produced assimilates are reallocated to the vegetative growth. The daily proportion of assimilates ($\Delta Biom_{Veg}$) is thus allocated to leaves ($\Delta Biom_{leaves}$) and wood ($\Delta Biom_{wood}$) as follows.

$$\Delta Biom_{leaves} = \left(\Delta Biom_{Veg} \times L_{percent}\right) - \left(Biom_{leaves} \times T_{sene}\right) - Rem_{leaf} \quad (9)$$

$$\Delta Biom_{wood} = \left(1 - L_{percent}\right) \times \Delta Biom_{Veg} \quad (10)$$

where $\Delta Biom_{leaves}$ and $\Delta Biom_{wood}$ refer to the biomass re-allocated to leaves and wood, respectively (both expressed in g m^{-2}); $L_{percent}$ is a coefficient that accounts for the proportion of leaves biomass in the newly formed biomass (unitless); T_{sene} is the senescence rate of leaves; and Rem_{leaf} is the biomass of leaves that was removed to supply the demand from fruits (g m^{-2}).

2.1.4 Initialization of the wood and leaves biomass at the start of the simulation

We assumed that the coffee tree has already started producing fruits. At the start of each simulation (i.e. date of the harvest in simulation year^{-1}) the above-ground vegetative biomass ($Biom_{Veg}$) is initialized based on the coffee bean yield from the previous season ($Yield_{ref}$).

$$Biom_{Veg} = Biom_{wood} + Biom_{leaves} \tag{11}$$

with $Biom_{wood} = K_{biom} \times Yield_{ref} + I_{biom}$ and $Biom_{leaves} = (LAI \times AP)/SLA$.

where K_{biom} and I_{biom} are two parameters related to the above-ground biomass after the previous harvest (both unitless); SLA is the specific leaf area (m^2 kg^{-1}); AP is the ground surface occupied by each plant (m^{-2}); and LAI is the leaf area index (m^2 m^{-2}).

Given LAI dynamics in coffee trees are strongly influenced by management practices on farms (DaMatta et al., 2007; Silva et al., 2009; Costa et al., 2019), we assumed that the initial wood biomass and LAI values are proportional to the bean yields from the previous season. Thus in this study, we estimated the initial LAI value as $LAI_{init} = K_{LAI} \times Yield_{ref} + I_{LAI}$, where K_{Lai} and I_{Lai}, are two coefficients related to the above-ground biomass and yield after the previous harvest (both unitless).

2.1.5 Water stress factors based on crop water requirements

Water stress can affect coffee growth differently depending on the phenological stage; it is therefore important to consider water stress factors accordingly. To account for crop water requirement (CWR) according to the phenological stages, we considered three main periods (November-December, January-April, and May-October) for characterizing the coffee growth period across the study provinces. CWR is defined here as "the depth of water needed to meet the water loss through evapotranspiration (ET_c) of a disease-free crop, growing in large fields under non-restricting soil conditions including soil water and fertility and achieving full production potential under the given growing environment" (Doorenbos and Pruitt, 1992). The details of the calculations are provided in Section 2.3.

2.2 Study area and data

Data for the five robusta coffee-producing provinces in the Central Highlands region of Vietnam (Dak Lak, Dak Nong, Gia Lai, Kon Tum, and Lam Dong) were used in this study. The Central Highlands is dominated by a humid tropical climate. The total annual rainfall varies between 1800 to 2900 mm. Maximum temperatures are normally above 24°C on average; the average monthly solar radiation across the provinces ranges from 430 to 700 MJ m^{-2}.

Official yield data (2001–2017) sourced from the General Statistics Office of Vietnam (GSOV, 2017), as well as farm data collected during the 2008–2017 surveys (Byrareddy et al., 2019; Byrareddy et al., 2020) were used. Details about the methodology of data collection during the surveys can be found in Byrareddy et al. (2019) and Byrareddy et al. (2020). Coffee yield data from 2005 onwards were considered for Dak Lak and Dak Nong because Dak Nong was officially created in 2004. Thus, Dak Lak data over 2001–2004 used to include those of Dak

Nong. In the calibration and model testing steps, given the absence of official yield data in 2006 for all the provinces, the corresponding missing yield data were replaced by the average of observed yields over the entire period. Note that robusta coffee accounts for 95-96% of the reported coffee production in Vietnam (arabica coffee representing the remaining proportion) (USDA, 2019). Since no detailed information about the annual production of the two coffee varieties were available at the provincial scale from the official statistics, and because robusta is dominant in the Central Highlands (arabica is mainly grown in the northern regions of the country), we attributed the reported yield value in each year to robusta coffee.

Observed daily climate data for the 2000–2014 period and gridded daily climate data for the 2000-2017 period were used in this study. These climate data included maximum and minimum temperatures, solar radiation, and rainfall. The spatial distribution of grids across the study regions is presented in Fig. 2. For each of the study provinces up to four grids were considered based upon the closeness of the centroid of the grid to the robusta cultivation areas (Table 1).

Observed climate data were sourced from the National Centre for Hydro-Meteorological Forecasting of Vietnam (NCHMF, 2014). Gridded data were retrieved from the NASA POWER website (https://power.larc.nasa.gov/). The observed climate data for 2000–2014 were available for Dak Lak, Gia Lai and Lam Dong. They were used for model calibration and first validation. The gridded data were used for further evaluation of the robusta model.

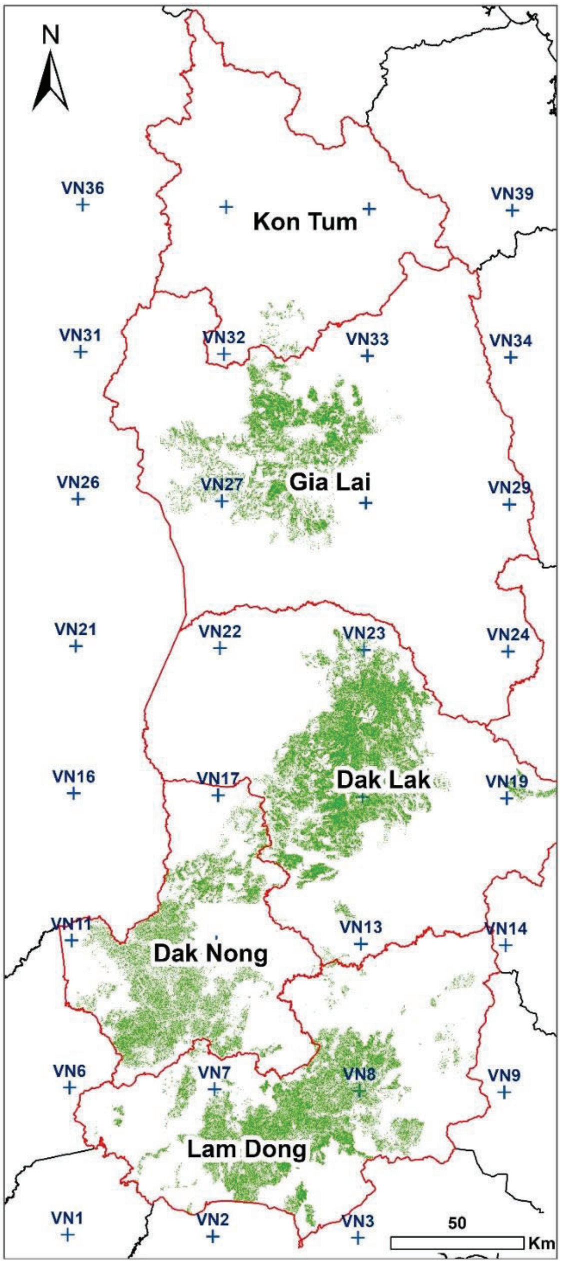

Fig. 2. Map of grid points falling within the boundaries of the study provinces Dak Lak, Dak Nong, Gia Lai, and Lam Dong. Green areas represent coffee crop mask (Source: Ecomtrading Vietnam).

Table 1. Selected grids for each of the study provinces.

	Dak Lak	Dak Nong	Gia Lai	Kon Tum	Lam Dong
Grids	VN13, VN18, VN19, VN23	VN11, VN12	VN27, VN28, VN33	VN32	VN7, VN8

2.3 Calculations of coffee water requirements and determination of coefficients for water stress levels

CWRs were calculated following the formula $\mathrm{CWR} = \mathrm{ET_0} \times \mathrm{K_c}$, where ET_0 is the reference evapotranspiration, and K_c is the crop coefficient. The crop coefficients used for the calculations were retrieved from Amarasinghe et al. (2015) and Byrareddy et al. (2020) (Table 2). CWRs were computed under standard conditions, i.e. disease-free, non-limiting nutrient and soil water conditions, and, as such, corresponds to the potential crop evapotranspiration.

ET_0 was calculated using the Hargreaves and Samani (HS) equation (Hargreaves and Samani, 1985; Hargreaves and Allen, 2003):

$$ET_0 = 0.408 \times 0.0023 \times R_a \times \left(\frac{T_{max}+T_{min}}{2} + 17.8\right) \times (T_{max} - T_{min})^{0.5} \quad (12)$$

where R_a is the extra-terrestrial radiation (MJ m^{-2} day^{-1}); T_{max} and T_{min} are the daily maximum and minimum temperatures, respectively (°C). ET_0 is expressed in mm day^{-1}.

The HS method was chosen because of its simplicity and the variables required. The extra-terrestrial radiation can be calculated for any day and location. Only maximum and minimum temperatures are required. Nonetheless, it should be noted that the HS method can result in ET_0 overestimation in high humidity conditions or ET_0 underestimation when high-speed winds conditions prevail (Allen et al., 1998; Droogers and Allen, 2002).

Table 2. Crop coefficients (K_c) used for the calculations of crop evapotranspiration ET_c. (Source Amarasinghe et al., 2015 and Byrareddy et al., 2020).

Growth period	Month	K_c (unitless)
Harvest / Start of season	November	0.95
	December	0.90
Flower-bud initiation / Blossoming	January	0.90
	February	0.93
	March	0.93
Fruit set	April	0.93
Cherry development	May	0.95
	June	0.95
	July	0.95
	August	0.95
Maturation / Ripening / Harvest	September	0.95
	October	0.95

Depending on the phenological stage and water stress levels (expressed through the number of days with daily rainfall below CWR), different coefficients of biomass reduction were applied (Table 3). The values of these coefficients were derived from information collected during the 2008-2017 surveys (Byrareddy et al., 2020) and expert knowledge (i.e. experienced agronomists and crop physiologists). Expert knowledge was necessary for defining the percentage of daily biomass reduction according to the phenological stage and water stress level under the environmental conditions in Vietnam. We also checked the literature for such relationships in other coffee-producing regions (e.g. Carr, 2001; DaMatta, 2004; Nguyen, 2005; Wang et al., 2015).

Table 3. Rules used for defining the percentage of daily biomass reduction according to the phenological stage and water stress level. The daily biomass reduction coefficient is applied to the newly produced biomass in the model.

Condition	Period	Consecutive days with rainfall < CWR [a] (days)	Daily biomass reduction (%)
A. Harvest and Start of the season			
Normal	November - December	10	0
Dry	November - December	20	5
Very dry	November - December	30	10
B. Flower-bud initiation, blossoming and fruit set			
Normal	January - April	10	0
Dry	January - April	20	15
Very dry	January - April	30	30
C. Cherry development and maturation/ripening			
Normal	May - October	10	0
Dry	May - October	20	10
Very dry	May - October	30	15

[a] : CWR: crop water requirement

2.4 Calibration and validation of the robusta model

2.4.1 Robusta coffee calendar in Vietnam

The robusta coffee calendar in Vietnam can be divided into five periods: the flower-bud initiation and blossoming occurring during January to March; the fruit setting during April; the cherry development during May to August; the maturation stage during September and October; and the ripening/harvest occurring during October to December. These periods are indicative and were used for the modelling purpose. Thus, even though farmers applied irrigation for synchronous blossoming, the actual growth stages and durations may vary across a given province and from one province to another.

2.4.2 Model calibration

Initial parameter values were derived from the CAF2007 model (van Oijen et al., 2010b; Ovalle-Rivera et al., 2020). For the model calibration, the majority of the parameters (Table 4) were varied individually within a range of plausible values. These ranges were based on published studies undertaken across the study regions in Vietnam (e.g. D'haeze et al., 2003; Marsh, 2007) or elsewhere in a robusta coffee-producing country (e.g. Marin et al., 2005; DaMatta et al., 2007; van Oijen et al., 2010b, 2010a; Rodríguez et al., 2011; Ovalle-Rivera et al., 2020), or from field experimental data from the *Centro Agronómico Tropical de Investigación y Enseñanza* (CATIE) research station, Costa Rica. Thus, the calibration was carried by adjusting model parameters so that the predicted yields satisfactorily compared with the official provincial yields. That is, at each variation of a given parameter value, the predicted yields were compared to the observed ones until the best combination, i.e. the model which outputs resulted in fewer errors, was found. The root mean square error (RMSE) and mean absolute percentage error (MAPE) were used as statistical indicators (their respective formulas are provided in Section 2.4.3). Additionally, a visual assessment was also carried out to verify how well the model simulates observed interannual yield variability.

In this study, the calibration of the robusta model was performed using the observed climate and yield data for Lam Dong for the 2001–2014 period. To simulate coffee growth using the robusta model, the start date of each season was set at 1 November of the previous calendar year and the simulations were carried out up to 31 October of the following year. The list of model parameters and their values after calibration is presented in Table 4.

Table 4. Parameters of the robusta model.

Parameter	Description	Unit	Initial value	Range for testing [a]	Value after calibration
E_a	Maximum interception efficiency	-	0.95	n.a. [b]	0.95
E_c	Photosynthetically active fraction of global radiation	-	0.48	n.a.	0.48
E_b	Light energy conversion efficiency	g MJ^{-1}	$16.5\ 10^{-4}$	n.a.	$16.5\ 10^{-4}$
K	Light extinction coefficient	$m^2\ m^{-2}$	0.76	n.a.	0.76
T_{sene}	Senescence rate of leaves	-	$6.4\ 10^{-4}$	n.a.	$6.4\ 10^{-4}$
$cost_{respi}$	Respiration cost of vegetative organs	-	$7.6\ 10^{-5}$	n.a.	$7.6\ 10^{-5}$
Kfruit	Slope of the biomass accumulation in fruits	-	$6.9\ 10^{-4}$	n.a.	$6.9\ 10^{-4}$
K_{rem}	Potential of remobilization of assimilates from leaves to fruits	-	$20.8\ 10^{-4}$	n.a.	$20.8\ 10^{-4}$
$K_{prn.leaves}$	Average percentage of pruning of leaves biomass	-	1.7	n.a.	1.7
cFruit	Maximal fruit biomass	-	327	300-500	400
$Fruit_{pot}$	Maximal number of fruits per kg of newly produced wood	nb kg^{-1}	2000	1000-3000	1300
Tmaxfruit	Maximal rate of biomass allocated to fruits	-	0.55	0.55-0.65	0.61
SLA	Specific leaf area	$m^2\ kg^{-1}$	18	18-27	18
$K_{prn.wood}$	Average percentage of pruning of wood biomass	-	0.28	0.25-0.50	0.33
KLai	Parameter used to initialize LAI at the start of the growth season according to the yield from the previous season		4.5	1.5-7.5	6.20
ILai	Parameter used to initialize LAI at the start of the growth season according to the yield from the previous season		-4.5	-6.5 - -1.5	-2.75
Kbiom	Parameter used to initialize wood biomass at the start of the growth season according to the yield from the previous season	-	4.5	2.5-7.5	4.00
Ibiom	Parameter used to initialize wood biomass at the start of the growth season	-	-4.5	-6.5 - -1.5	-2.65
Kwood	Percentage of newly formed wood in biomass at initialization	-	0.43	0.33-0.48	0.40
$L_{percent}$	percentage of leaves in newly formed biomass	-	0.24	0.20-0.35	0.30
T_0	Base temperature	° C	12	10-15	12
TempREC	Sum of degree-days between flowering and harvest	°C.d	2000	2000-3200	2800
TempFLO	Cumulative degree-days to the onset of flowering	°C.d	1600	1000-2500	1200

[a] : Ranges were based on published studies undertaken across the study regions in Vietnam (e.g., D'haeze et al., 2003; Marsh, 2007) or elsewhere in other robusta coffee-producing countries (e.g., Marin et al., 2005; DaMatta et al., 2007; van Oijen et al., 2010b, 2010a; Rodríguez et al., 2011; Ovalle-Rivera

et al., 2020), or from field experiments from the *Centro Agronómico Tropical de Investigación y Enseñanza* (CATIE) research station.

[b] : not applicable. The default values were from van Oijen et al. (2010b) or field experiments from the CATIE research centre.

2.4.3 Model evaluations

Two model evaluation steps were carried out in this study. First, the model was validated using the observed climate data and official provincial coffee yield data for the 2000–2014 period for Dak Lak and Gia Lai. These data were not used in the calibration step.

The second model evaluation involved the use of gridded climate data. For this performance assessment we hypothesized that the robusta model can achieve a performance similar to that resulting from using climate station data. Since observed climate data are either scarce or not readily available in these coffee-producing regions, freely available satellite and model-based gridded climate data are used as an alternative. Such an evaluation is also justified given the increased reliance on these climate data for studies at larger spatial scales.

Because up to four grids were selected among the grid falling within a given province (Table 1; Fig. 2), we explored two options of gridded climate data aggregation and use within the robusta model. The first option consisted in simulating separately the coffee yield for all the selected grids falling within the province. In such cases the historical provincial yield was used as reference yield for each of the grids; the predicted yield at the province scale was calculated as the average of all grid-level predicted yields. The second option consisted in running the robusta model using the average values of grid-level climate data as inputs, resulting in a unique predicted yield for the province.

2.4.4 Assessment of model performance

Predicted yields were compared against official reported yields to assess the performance of the robusta model. Three statistical indicators were used for this purpose: RMSE, MAPE and the Willmott's index of agreement (WI) (Willmott et al., 2012). Their respective equations are as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}({Y_i}^{m} - {Y_i}^{p})^2} \tag{13}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{{Y_i}^{m} - {Y_i}^{p}}{{Y_i}^{m}}\right| \tag{14}$$

$$WI = 1 - \frac{\sum_{i=1}^{N}|{Y_i}^{m} - {Y_i}^{p}|}{\sum_{i=1}^{N}(|{Y_i}^{p} - \bar{Y}^{m}| + |{Y_i}^{m} - \bar{Y}^{m}|)^2} \tag{15}$$

where N is the number of sample years; ${Y_i}^{m}$ is the *i*th observed value; $\bar{Y}^{m}$ is the mean observed value; and ${Y_i}^{p}$ is the *i*th predicted value.

The RMSE gives the weighted variations in errors (residual) between the predicted and observed yields. MAPE is an accuracy measure of the forecast quality; it is a better index than absolute error measures in comparing model performance among different regions given the likely differences in their average historical yields (Chipanshi et al., 2015). The lesser value of MAPE or RMSE, the better the model performs. WI is a descriptive measure related to the ratio between the model error magnitudes and to the magnitudes of the perfect-model-deviation and observed-deviation (Willmott et al., 2012). WI ranges from -1 to 1. The closer the WI is to 1, the better the model predictions are.

All data and statistical analyses were performed using R version 4.0.0 (R Core Team, 2020). NASA POWER climate data were retrieved using the R package 'nasapower' (Sparks, 2018).

3. Results

3.1 Calibration and validation of the robusta model

The calibration and validation of the robusta model using observed climate data for Lam Dong, Dak Lak and Gia Lai resulted in acceptable model performance overall. The MAPE in the calibration step was 10%, with a RMSE of 0.24 t ha^{-1} and WI = 0.740) (Fig. 3). The validation of the model using independent datasets from the provinces of Dak Lak and Gia Lai showed a slight increase in prediction errors compared to those obtained in the calibration step: RMSE = 0.33 and 0.31 t ha^{-1}, respectively, with corresponding MAPE of 14% and 13% (Fig. 3). The narrow variability of reported coffee yield in Dak Lak (observed yields during 2005–2014 varied generally between 2.1 and 2.5 t ha^{-1}; Fig. 3) could explain the relatively low value of WI (0.184) for this province.

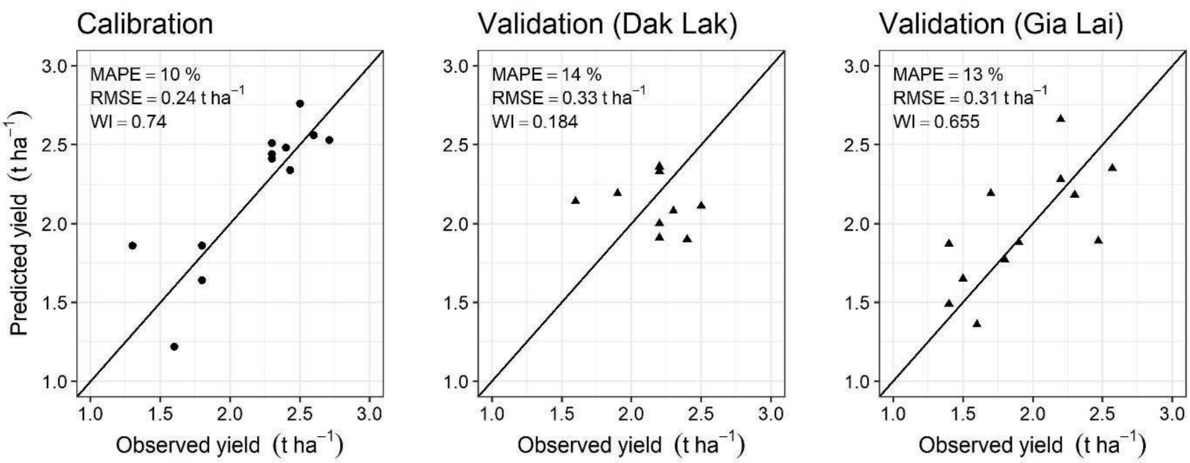

Fig. 3. Performance results of the robusta model during the calibration and validation phases. Data for Lam Dong province were used in the calibration step.

An example of the simulation of wood, leaves and fruit dry matter using the robusta model, along with the daily variation of potential crop water stress for the province Gia Lai, is shown in Fig. 4. In Gia Lai the period spanning mid-November 2009 to May 2010 was generally dry, with the first three months of 2010 recording no rain (Fig. 4B). Such dry weather conditions affected negatively the overall biomass production (wood and leaves), and in lesser proportion fruit setting (fruit setting was at its earlier stages) (Fig. 4A).

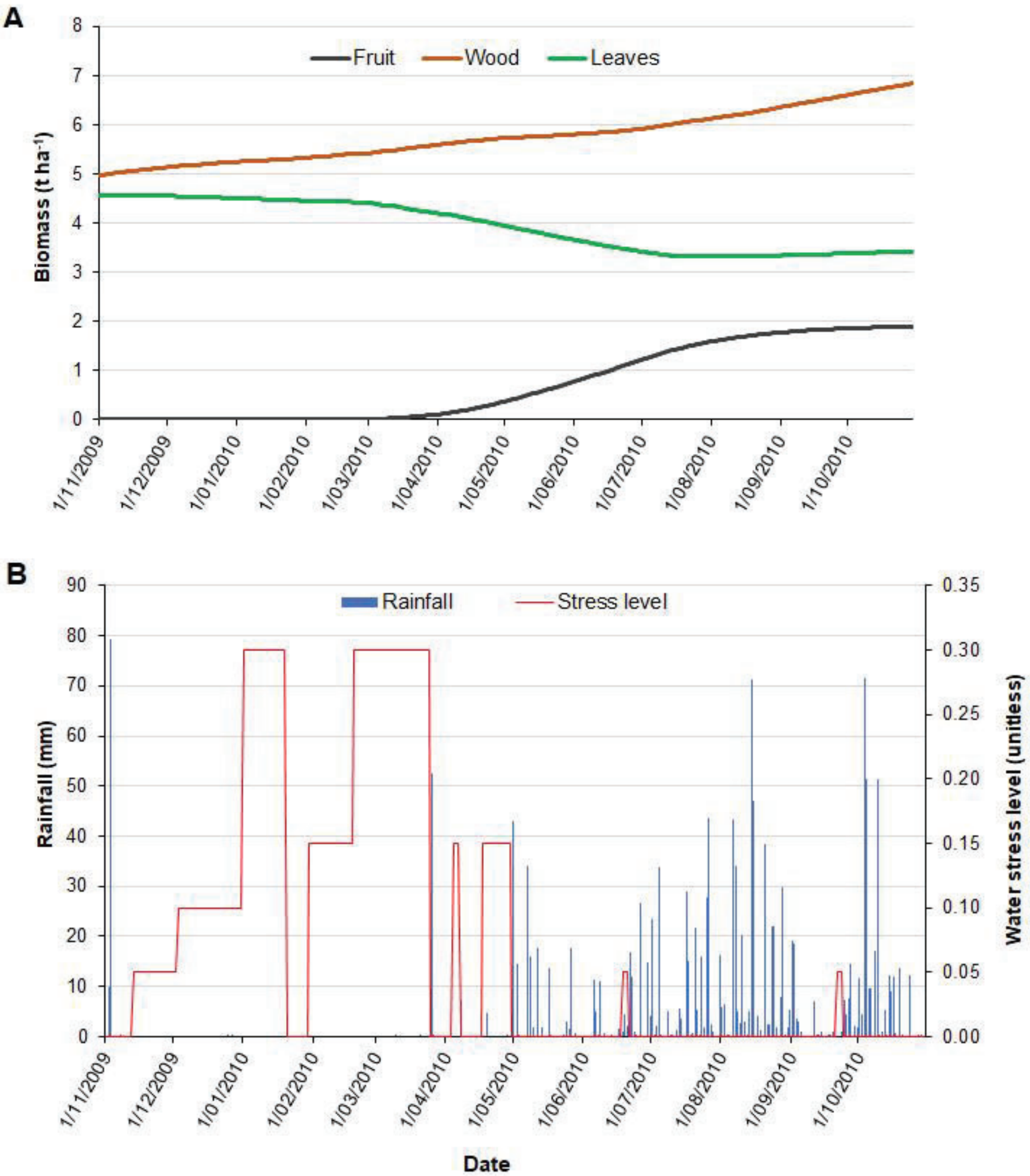

Fig. 4. Simulation of wood, leaves, and fruit dry matters using the robusta model (**A**) and variation of the potential crop water stress (**B**). The example is for the province Gia Lai during the 2009/2010 coffee season.

3.2 Model performance according to the data aggregation methods

Two options of climate data aggregation were tested with the robusta model to further assess the model performance when using gridded climate data.

Running the model under two different options of data aggregation did not result in substantial differences in the outcomes. Overall, the robusta model performed well in both cases, with MAPE ≤ 12% (Table 5). For Dak Lak, Dak Nong, Gia Lai and Lam Dong, similar model performance was obtained for both aggregation methods: 10% (Dak Lak and Gia Lai) and 11% (Lam Dong) prediction errors in both cases of data aggregation, with corresponding RMSE of 0.26 and 0.28 t ha^{-1} (Table 5), though the prediction errors slightly increased for Dak Nong when the average of climate data of the selected grids was considered as model inputs (MAPE from 9% to 10%; Table 5). The relatively highest prediction errors when using gridded climate data were found for Kon Tum where only one grid was considered: MAPE = 12% and RMSE = 0.29 t ha^{-1} (Table 5). In this province particularly, the robusta model tended to underestimate the reported coffee yields (Figs. 5 and 6). For the remainder of provinces, the scatterplots showed fairly good distribution around the 1:1 line (Figs. 5 and 6). The agreements between predicted and observed yields (based on WI values) were higher for Gia Lai, Kon Tum and Lam Dong (WI ≥ 0.700; Table 5), confirming the good capabilities of the robusta model for predicting coffee yield in these provinces. For provinces with relatively low inter-annual yield variability (Dak Lak and Dak Nong; Fig. S1), such agreements between predicted and observed yields were less obvious. WI the error magnitudes in predictions did not capture very well deviations in observed yields (Figs. 5 and 6).

Table 5. Summary of statistical performance indicators (mean absolute percentage error, MAPE, root mean square error, RMSE, and Willmott's index of agreement, WI) of the robusta model run using two methods of gridded climate data aggregation (M.1, M.2).

	M.1 [a]			M.2		
	MAPE (%)	**RMSE (t ha^{-1})**	**WI**	**MAPE (%)**	**RMSE (t ha^{-1})**	**WI**
Dak Lak	10	0.26	0.410	10	0.26	0.407
Dak Nong	9	0.24	0.579	10	0.25	0.558
Gia Lai	10	0.25	0.779	10	0.26	0.771
Kon Tum	12	0.29	0.734	12	0.29	0.734
Lam Dong	11	0.28	0.715	11	0.28	0.709

[a]: in M.1 simulations were performed using grid-level climate data separately. The predicted yield at provincial level is then calculated as the average predicted yield. In M.2 simulations were carried out using the average climate data for all the selected grids falling in the province, resulting in a unique value of predicted yield for the province. Only one grid was considered for Kon Tum (that is, no difference of results is expected).

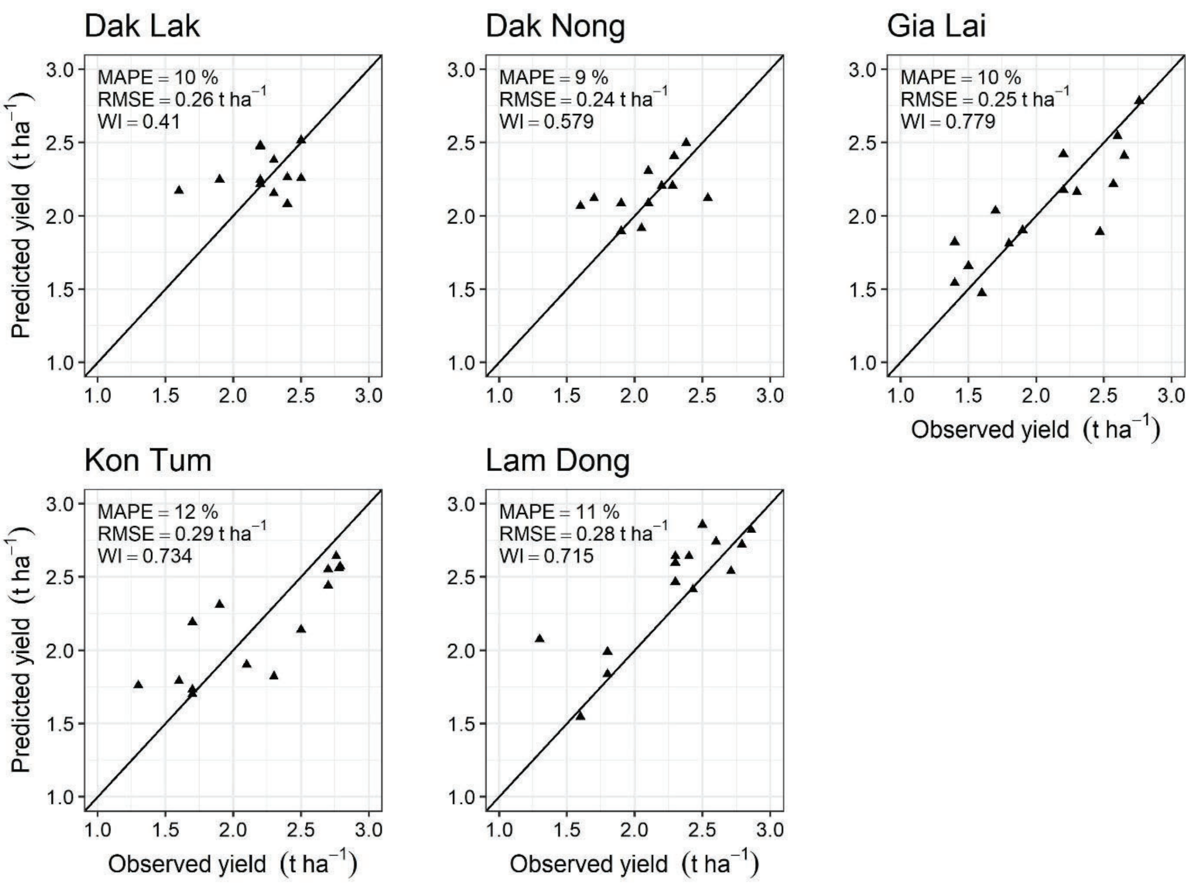

Fig. 5. Scatterplots of observed versus predicted robusta coffee yields from simulations using as inputs the climate data of selected grids separately. The average of grid-level predicted yields for each year was considered as the predicted yield for the province.

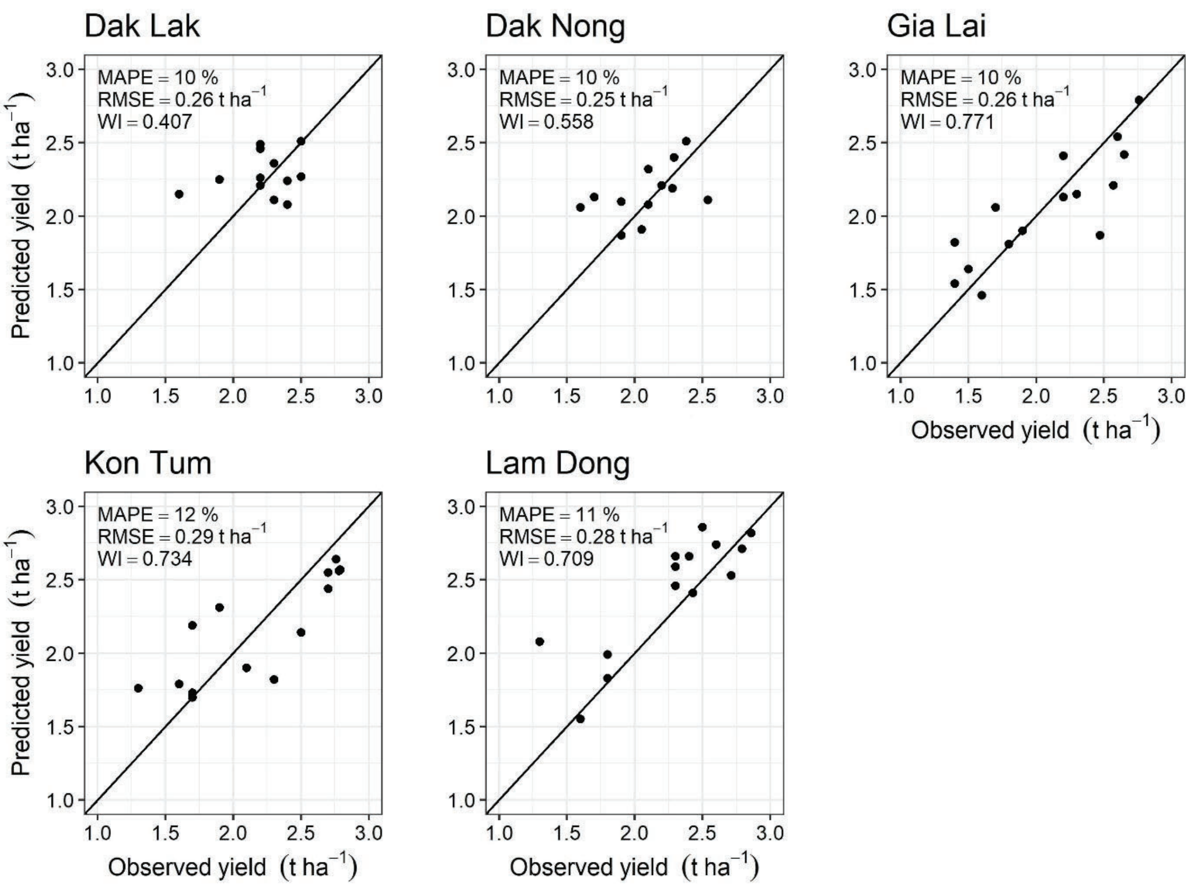

Fig. 6. Scatterplots of observed versus predicted robusta coffee yields from simulations using as inputs the average of climate variables of all selected grids for the province. The simulation resulted in a single predicted value for the province for each season.

4. Discussion

4.1 The robusta model as a tool for investigating the impacts of climate variability on coffee production

Coffee yields in Dak Lak, Dak Nong, Gia Lai, Kon Tum, and Lam Dong, have seen a sharp increase over the past 10 years, compared to their levels in the early 2000s (Fig. S1). Such change can be explained by a combination of factors including infrastructure investment in irrigation and strong reliance on irrigation in coffee farms, the affordability of fertilizer, and the increasing adoption of new management techniques (i.e. grafting) in provinces such as Lam Dong (Marsh, 2007; Byrareddy et al., 2019; Byrareddy et al., 2020). The Central Highlands is a drought-prone region (Nguyen, 2005; Vu et al., 2015). Given the projected changes in climate patterns in Vietnam (IPCC, 2014), which could potentially affect negatively agricultural productions and the livelihoods of millions of farmers, it is important to investigate the impacts of climate variability on yield and production for crops like robusta coffee. The robusta model is specifically designed to simulate and predict robusta coffee potential yield at the regional scale. It involves the main growth and development processes altered by climate. In this study, results show that the model was able to predict satisfactorily the robusta coffee yield for Dak Lak, Dak Nong, Gia Lai, Kon Tum, and Lam Dong. Thus, the robusta model provides a solid basis for assessing the impacts of rainfall or temperature variability on coffee yields at the provincial level and can be an important tool for regional impacts studies in Vietnam or other coffee-growing regions or countries.

With the characterization of water stress days throughout the coffee season and the likely impacts these stresses can have on biomass production and yield, one can simulate the potential water required to alleviate the stress and improve crop performance. Such a feature can be strengthened to explore the potential impact of irrigation on coffee yield; this will require, nevertheless, further research work to make the model suitable for such tasks.

It is expected to develop a complete integrated SCF-robusta coffee yield forecasting system, which will use categorical indicators of climate drivers (e.g. Oceanic Niño index, Southern Oscillation Index, Tropical Pacific sea surface temperatures.) and simulated coffee yields to provide probabilistic yield forecasts. This will allow for examining probabilistic yield anomalies (likelihood of exceeding the long-term median or average) associated with the prevailing climate pattern in the year of forecast throughout the coffee season at the provincial scale.

4.3 Limitations and future directions

In spite of the encouraging performance of the robusta model, some limitations were found in this study that indicates a need for further research. There were no detailed data about the annual productions of robusta coffee from the official statistics used in this study. The reported yields included production data of both robusta and arabica coffees. Even though robusta coffee production is largely dominant (approximately 95-96% of the total production; USDA, 2019), we did not derive its production from the reported statistics to avoid any additional uncertainties in the modelling approach. Detailed robusta coffee yield/production information could potentially be sourced from local coffee industry stakeholders such as agricultural commodities trading companies or the Vietnam Coffee and Cocoa Association (VICOFA). The availability of such data would help further assess the performance and improve the robusta model.

The model does not simulate the response of coffee growth to fertilizer rates. Byrareddy et al. (2019) showed that fertilizer management practices were largely homogenous between years at each of the surveyed farms in Dak Lak, Dak Nong, Gia Lai and Lam Dong. One can assume that the reported official yield at the regional scale reflects, at least partly, such fertilizer use. Long-term experimental studies involving wider ranges of fertilizer rates across the study provinces are needed to provide further insights into the impacts of varying fertilizer rates on robusta coffee yields and enable the inclusion of such aspects in the model. With the aim of keeping the structure of the model as simple as possible, neither pests and diseases impacts, nor soil nitrogen processes were considered. The integration of such aspects can also be explored further to reduce prediction errors and broaden the capabilities of the model, or to explore this model where fertilization practices are not so homogeneous.

The alternation of years with high and low bean production, known as biennial growth, was not considered in our model. At the provincial scale such biennial pattern is masked since coffee-growing areas encompass a range of farms with different ages of trees and pruning practices. Moreover, the biennial production cycle could potentially be off-set by irrigation as this is a typical management practice in robusta coffee farms in Vietnam (Byrareddy et al., 2020). Assessing the biennial production cycle at the regional scale in Vietnam using satellite remote sensing data (Bernardes et al., 2012) and implementing such patterns within the robusta model can be investigated in future research.

Given the difficulty of determining accurate LAI values, we used modelled empirical coefficient values based on the yield of the previous season. Because of the exhaustiveness of methods proposed, and the fact destructive sampling of trees is often required (Costa et al., 2019), the determination of LAI in coffee farms can be challenging. Coltri et al. (2015) proposed an empirical relationship for calculating the above-ground biomass and LAI in arabica coffee using simple field measurements and agrometeorological data in Brazil. Although substantial seasonal variations were found in their study, their approach can be investigated in the case of Vietnam and help define more accurately the initial values of the aboveground biomass and LAI in the model. Remotely sensed LAI data at the start of the season (or at critical phenological stages) can be explored as an alternative as well.

The effect of canopy architecture and heterogeneity on light interception and photosynthesis was not considered in the robusta model. Canopy architecture influences light interception and distribution, transpiration, and the whole-plant gas exchange in coffee (Melke and Fetene, 2014; Rodrigues et al., 2016; Charbonnier et al., 2017). A good understanding of the relationships between canopy architecture and light interception or the effects of cultural practices on irradiance interception and canopy photosynthesis in robusta coffee farms in Vietnam would help improve the overall model accuracy. Given the variability of cropping techniques (e.g. pruning) and environmental conditions, which can affect coffee crown architecture and canopy photosynthesis (DaMatta, 2004; DaMatta et al., 2007), investigating such relationships remains an interesting open question for future research.

In this study, the definition of parameter and coefficient values (Table 2) was based on expert knowledge and empirical relationships. Although the model parameters were varied within the reported plausible ranges, a reparameterization, along with updated coefficient values for water stress, may be required for using the robusta model in different environments (i.e. a different country). Nevertheless, the modelling approach used in this study could be readily adapted to a different robusta coffee-producing region, providing the relevant data are available.

5. Conclusions

We presented a dynamic, biophysical model – the robusta model – which processes climate data and information from the previous coffee season to simulate robusta coffee growth and predict yields at the regional scale. Evaluating the performance of the robusta model indicated good agreements between predicted and official reported coffee yields for the five major coffee-producing in Vietnam. The model presented in this paper is one of the first to deal with robusta coffee yield at the regional scale. It was kept simple because of the lack of quantitative information at the regional scale to build a parameter-rich model. The simplicity of the model does not imply that it could not be responsive to the key climate factors driving coffee growth and development. The robusta model was designed as such to be ultimately used within a SCF-crop production forecasting system to support decision making throughout the robusta coffee supply chain while managing climate risks. Despite the satisfactory model performance obtained for most of the Vietnamese coffee-producing provinces, there are aspects that need to be addressed for future improvements of the present robusta model for its application in different coffee-producing regions or countries, which will require long-term datasets on the phenological processes targeted.

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CRediT authorship contribution statement

Louis Kouadio: Conceptualization, Methodology, Software, Data Curation, Validation, Formal analysis, Writing - Original Draft. **Philippe Tixier**: Conceptualization, Methodology, Software, Writing - Review & Editing. **Vivekananda Byrareddy**: Methodology, Investigation, Data Curation, Writing - Review & Editing. **Torben Marcussen**: Software, Data Curation, Writing - Review & Editing. **Shahbaz Mushtaq**: Project administration, Writing -

Review & Editing. **Bruno Rapidel**: Conceptualization, Methodology, Writing - Review & Editing. **Roger Stone**: Funding acquisition, Project administration, Writing - Review & Editing.

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