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Climate, altitude, yield, and varieties drive lodging in sugarcane: A random forest approach to predict risk levels on a tropical island

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ABSTRACT

Lodging is a critical factor in reducing sugarcane yields worldwide, mainly due to the selection of highly productive varieties. Understanding the response of yield and lodging to the combined effects of climate, sugarcane traits, and varieties has become a priority under climate change. The aim of this study was to better understand the influence of plant characteristics, climate, and soil conditions on the trade-off between sugarcane yield and lodging on the tropical Reunion Island. Data from a 14-year experimental network run by the eRcane breeding institute were used to build random-forest models to predict sugarcane yield and lodging classes, i.e. <10 %, 10–50 %, >50 % of lodging. Yield and lodging probability were then predicted across the island using climate change projections from 2015 to 2035. Both yield and lodging were highly influenced by the variety and characteristics (height and tillering) and climatic conditions. Areas on the island at high altitudes were subject to high probability of lodging (>50 %), while in areas with high wind speed, the risk of moderate lodging (10–50 %) increased. Overall, conditions or plant characteristics that favor higher yields increased lodging probability. Nevertheless, the correlation between yield and lodging probability varied considerably depending on the variety, highlighting the importance of sugarcane characteristics in resistance to lodging. This study highlights the fact that promoting more productive varieties in recent decades has led to an increase in lodging and identified critical environments on the island prone to increased risk of lodging.

1. Introduction

Understanding the reasons for lodging, or loss of crop erectness, in cropping systems is crucial to develop breeding strategies to reduce the impact of lodging on commercial production systems. Lodging, i.e., when shoots bend over near the ground, occurs in many crops, including rapeseed (Wu et al., 2022), rice, and other cereals (Niu et al., 2022; Zhang et al., 2014). A common consequence of lodging is reduced yield and harvest quality and a slower harvest pace. Improving lodging resistance has significantly contributed to the increase in yields observed in many countries in recent decades (Ookawa et al., 2010; Wang et al., 2023).

Sugarcane (*Saccharum* spp.) is the most important crop for sugar and ethanol production worldwide (Antunes et al., 2019). In terms of biomass, sugarcane is one of the most productive crops (FAO, 2022), and lodging is frequent, reducing both biomass production and cane quality (Berding and Hurney, 2005; Singh et al., 2002; van Heerden et al., 2015). The adverse effects of lodging are a reduction in interception of radiation and in radiation use efficiency, stalk death through smothering, and stalk snapping (Park et al., 2005; Singh et al., 2002; Van Heerden et al., 2010). Additionally, manual harvesting of lodged sugarcanes requires more labor, while mechanical harvesting can snap some stools resulting in gaps in the rows of sugarcane and hence yield losses (Singh et al., 2002).

Lodging typically occurs in high-yielding sugarcane crops (cane weight > 100 Mg ha^{-1}) when wet soil fails to provide adequate support for roots or when the leaf canopy is wet, implying additional weight, and with strong wind (Li et al., 2019; Park et al., 2005; Singh et al., 2002).

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Susceptibility to lodging is known to differ among varieties of sugarcane that produce the same cane yield, suggesting the existence of lodging resistance traits. Previous studies showed that sugarcane lodging increases with stalk height and weight (Berding and Hurney, 2005), while the influence of stalk diameter remains unclear (Berding and Hurney, 2005; Sharma and Khan, 1984). Recent studies also suggest a positive influence of root biomass on resistance to lodging (Jongrungklang et al., 2018), particularly in the upper soil layer (Yang et al., 2020). However, our understanding of these factors is still limited, and further investigation is needed to unravel the complexities of lodging in sugarcane crops.

Despite the importance of lodging for sugarcane production, the exact factors that influence lodging have not yet been deciphered. The use of crop models to simulate lodging processes is still in its infancy (van Heerden et al., 2015) mainly because experiments specifically designed to quantify the effects of lodging on sugarcane productivity are lacking and also because of the practical difficulties involved in conducting such experiments (e.g., Hurney and Berding, 2000; Singh et al., 2002). Moreover, lodging is a random phenomenon associated with extreme daily events such as wind or storms (Christina et al., 2021; Martinez-Vazquez, 2016) and consequently cannot be simply explained by plant growth dynamics in crop models.

Machine-learning algorithms can capture non-linear functional relationships between predictors and dependent variables and as such, offer new opportunities to better understand the lodging phenomenon. Machine learning models have been increasingly used in agronomic studies in the Agriculture 4.0 context (Cravero et al., 2022; Araujo et al., 2023), particularly random forest and support vector machines (Araujo et al., 2023). While machine learning algorithms including random forest have been successfully used to predict sugarcane yield at different geographical scales (dos Santos Luciano et al., 2021; Everingham et al., 2016; Sanches et al., 2019; Hammer et al., 2020), so far, their use for lodging has been limited. Recent studies used satellite imagery (Guan et al., 2022) or RGB images (Modi et al., 2023) to assess sugarcane lodging but these methods have not yet been tested across a wide range of climatic and soil conditions. Using a breeding program with a large dataset where lodging indexes are evaluated should advance our understanding of the lodging phenomenon using machine learning algorithms.

Reunion Island, with its unique blend of very high climatic variability and the regular occurrence of extreme events such as cyclones (Christina et al., 2021), offers an intriguing environment to understand lodging. The altitude of the 23,000 ha of sugarcane that account for approximately 58 % of total agricultural land in Reunion Island (Leung, 2015) ranges from sea level to 1000 m above sea level, resulting in significant variations in temperature and radiation conditions. Reunion Island is also characterized by substantial spatial rainfall variability, thus rainfall can be very low ($<$300 mm yr^{-1}) or high ($>$3000 mm yr^{-1}) depending on the location. The eRcane Institute, a sugarcane breeding research center with 90 years of experience in field selection experiments (Dumont et al., 2022), allowed us to access a large dataset to explore the effect of different cultivars and climates on sugarcane lodging as well as yield.

Given that assessment of lodging is of major importance in guiding breeding selection programs under current and future climate conditions, the main objective of this study was to assess the impact of the varieties of sugarcane and their specific characteristics, together with soil conditions, climate, and geographic locations on lodging probability and sugarcane yield. To this end, we compared different machine learning algorithms and performed a random forest approach to predict yield and lodging using a 14-year dataset belonging to the eRcane Institute breeding program in Reunion Island.

2. Material and methods

2.1. Experimental network

The experimental network comprised seven sugarcane breeding trials performed at seven experimental stations distributed across Reunion Island between 2008 and 2022 (the year the experiment began varied with the station: see Table 1, Fig. A1). The network of trials was part of a varietal development program conducted by eRcane in Reunion Island (Dumont et al., 2022), which consisted of replicated trials of the sequential process of clonal selection in the successive selection stages of the breeding program. Three types of replicated trials were performed at each experimental station, corresponding to the 3rd, 4th, or 5th stage of the selection program (Dumont et al., 2022). The 3rd stage usually evaluated 120 varieties planted in plots comprising two rows (15 m^2) with two repetitions, while the 4th and 5th stages evaluated respectively, around 30 and 25 varieties planted in plots comprising three rows (45 m^2) with three or four repetitions. The first two types of trials were conducted over three cropping years, and the last type over four cropping years. All the trials were fertilized to reach non-limiting nutrient conditions according to the Serdaf recommendations (Versini et al., 2018). Trials at ES, GL, and LM stations were irrigated to limit water stress as their locations are representative of irrigated areas for growers (approximately 5 mm d^{-1} in ES, 2.5 mm d^{-1} in GL, and compensatory irrigation in LM). All the interrows in the sugarcane trials were 1.5 m wide. The experimental network totaled 226 trials with 7751 varieties under selection and 9 commercial varieties.

2.2. Field measurements

Field measurements included sugarcane yield (fresh stalk weight) and visual assessment indices for lodging, height, tillering, and stalk diameter (Table 2). In each trial, after around 12 months of growth, sugarcane yield was measured by harvesting the whole plot. Lodging, height, diameter, and tillering were visually assessed in each plot one month before harvesting the second ratoon crop. The complete dataset with lodging, tillering, diameter, and height indices comprised 26,433 observations, while the dataset with commercial varieties comprised 2020 observations.

2.3. Soil and meteorological data from each station used for model calibration

Soil data from each experimental station included available soil water capacity (AWC) obtained from a detailed map of AWC covering the whole island (Christina et al., 2021). Daily meteorological data during the crop cycles were obtained from the Meteor web application developed by CIRAD (https://smartis.re/METEOR). This application interpolates climatic data at each requested location using daily climatic data measured by the large-scale meteorological station network from CIRAD, Méteo-France, and BRGM (Christina et al., 2021). The wind speed data we used were not interpolated from the application, rather data were obtained from the meteorological station located closest to each experimental station. For each trial, mean variables (potential evapotranspiration, ETP; global radiation, Rg; mean temperature, Tmean) and total variables (total rainfall, RF; total wind speed, WSp) were calculated between two harvest dates. A water deficit index (WD) was calculated as the ratio between total rainfall and evapotranspiration between two harvest dates.

2.4. Soil and meteorological data for prediction over Reunion Island

As wind speed data were not available for all sugarcane fields on Reunion Island, climatic data from the BRIO project were used for model predictions. Within the framework of the BRIO project, Méteo-France has carried out high spatial resolution climate projections in the

Table 1
Site characteristics: station (Stat.), latitude (Lat.), longitude (Long.), altitude (Alt.), soil available water content (AWC), mean temperature (Tmean), mean total rainfall (RF), mean wind speed (WSp), beginning and ending year of the experiment.

Station	Lat.	Long.	Alt. (m)	AWC (mm)	Tmean (°C)	RF (mm y^{-1})	WSp (km d^{-1})	Beginning year	Ending year
ES	−21.27	55.38	8	150	24.3	783	133	2008	2022
GL	−21.27	55.40	32	110	24.0	631	163	2012	2022
LM	−20.91	55.53	78	100	24.1	1511	230	2008	2022
MC	−20.98	55.61	407	50	21.1	3917	28	2010	2022
SB	−21.06	55.72	40	30	23.6	3339	180	2008	2022
SP	−21.36	55.73	160	20	23.3	4391	123	2008	2022
VB	−21.08	55.29	705	110	20.1	978	61	2008	2022

Table 2
Sugarcane visual indices in the breeding trial network.

Qualitative variable	Stations	Class	Description
Lodging (Lodg, %)	ES, GL, LM, MC, SB, SP, VB	Lodg0	Lodging <10 %
		Lodg10	10 % < Lodging < 50 %
		Lodg50	Lodging > 50 %
Height (H, cm) of the plant	MC[a], SP[a]	H0	Very short (H < 100)
		H1	Short (100 ≤ H < 150)
		H2	Moderate (150 ≤ H < 200)
		H3	High (200 ≤ H < 250)
		H4	Very High (H ≥ 250)
	ES[b], GL[b], LM[b], SB[b], VB[b]	H0	Very short (H < 150)
		H1	Short (150 ≤ H < 200)
		H2	Moderate (200 ≤ H < 250)
		H3	High (250 ≤ H < 300)
		H4	Very High (H ≥ 300)
Tillering (T, stalk number.m^{-1})	ES, GL, LM, MC, SB, SP, VB	Till0	Low (T < 7)
		Till1	Moderate (7 ≤ T < 14)
		Till2	High (14 ≤ T < 20)
		Till3	Very high (T ≥ 20)
Diameter (D, mm) of stalks	ES, GL, LM, MC, SB, SP, VB	D0	Low (D < 20)
		D1	Moderate (20 ≤ D < 30)
		D2	High (D ≥ 30)

[a] low yield potential.
[b] high yield potential.

Southwest Indian Ocean according to the main scenarios of socio-economic development and adaptation and mitigation strategies (Leroux et al., 2021). These simulations used the CMIP5 model of the National Center for Climate Research (CNRM) and three climatic scenarios (RCP2.6, RCP4.5, and RCP8.5). Climatic data, available from the Meteor web application, covering the 2015–2035 period were used to have a range of climatic conditions (temperature, rainfall, etc) similar to the conditions at the experimental stations that were used to train the model. Daily climatic data were available at a resolution of 3 ×3 km (i.e. one grid cell). An average soil water capacity was calculated for each grid cell based on the ASW map (Christina et al., 2021).

2.5. Comparing models for lodging and yield prediction

First, we compared different prediction models for lodging class and yield using the commercial variety dataset, including the variety, soil, and climatic variables as explanatory variables (scale variables). We used the caret R package (Kuhn, 2008) to compare the following models: Random Forest (RF, "ranger" function, Wright and Ziegler, 2017), Multi-Layer Perceptron neural network (MLP, "monmlp" function, Cannon, 2017), Support Vector Machine (SVM, "svmRadial" function, Karatzoglou et al., 2004), K-Nearest Neighbors (KNN, "knn" function, Schliep and Hechenbichler, 2016), and Gradient Boosting Machine (GBM, "gbm" function, Ridgeway and Developers, 2024). We used a double 10-fold cross-validation procedure to calibrate the parameters of each model using the caret package's "train" function: mtry parameter in RF, the number of layers and the number of neurons per layer in MLP, the C and sigma parameters in SVM, the K parameter in KNN, the number of trees and interaction depth in GBM. As the lodging class was unbalanced due to over-representation of the Lodg0 class, and not all the models were allowed to weight observations in the calibration procedure, we duplicated the observed data to balance the number of observations in each class in this model comparison. The lodging classes predicted by the models were compared based on the accuracy, sensitivity, specificity, and precision of each class. The model yields' predictions were compared based on mean absolute percentage error (MAPE), root mean square error (RMSE), and R^2. The random forest model performed the best (Table 3) and was chosen for the rest of the study.

2.6. Calibration and validation of the random forest models

In this study, we used the random forest approach to predict yield and the lodging class probability with the ranger R package. All quantitative explanatory variables were scaled prior to model calibration. For all models, we used a double 10-fold cross-validation procedure to calibrate the mtry parameter (number of variables to split in each node of each tree) and for validation (see pseudocode in supplementary materials, caret R package). The number of trees was set at 5000. For the validation of lodging, an out-of-bag prediction error (OOB, %) and a confusion matrix were calculated and averaged over the ten folds. Accuracy, sensitivity, specificity, and model precision were also calculated. Considering sugarcane yield, a relative root mean square error was calculated between predicted and observed values (rRMSE, %) over the ten folds, and the MAPE and R2. The importance of the variables for model prediction was calculated with the Gini index. As lodging data were not balanced, with around three times more Lodg0 sugarcane than others, the model calibration was weighted by the proportion of lodging in each category.

A first type of random forest was built to assess the impact of sugarcane traits and climate on sugarcane lodging and yield using the whole dataset (26,433 observations). This model included the climatic variables (RF, Tmean, ETP, Wsp, WD, and Rg), the altitude and the soil AWC, and different plant traits including height, tillering, and stalk diameter (Table A1). Finally, a second type of random forest was built using the dataset with the commercial varieties (2020 observations), including the variety, the soil and climatic variables as explanatory variables (RF_Var).

2.7. Yield and lodging prediction over Reunion Island

Soil and meteorological data covering Reunion Island at a 3×3 km scale were used for model prediction (BRIO project, Section 2.4) for the 2015–2035 period. Predictions were performed for the three climatic models and harvest dates each month from July to November (corresponding to the current harvest period of sugarcane on the island). In

Table 3
Comparison of model performance based on lodging class and yield prediction in the commercial variety dataset using duplicated observations to balance out the observations among the lodging classes (n = 4083 observations).

Variable	Indicator	Class	RF	MLP	SVM	KNN	GBM
Lodging	Accuracy	All	0.780	0.715	0.767	0.776	0.771
	Sensitivity	Lodg0	0.744	0.705	0.739	0.738	0.753
		Lodg10	0.736	0.636	0.713	0.735	0.707
		Lodg50	0.860	0.803	0.857	0.856	0.851
	Specificity	Lodg0	0.951	0.908	0.942	0.951	0.930
		Lodg10	0.842	0.834	0.842	0.839	0.851
		Lodg50	0.877	0.831	0.871	0.875	0.874
	Precision	Lodg0	0.885	0.796	0.865	0.883	0.845
		Lodg10	0.701	0.658	0.694	0.700	0.705
		Lodg50	0.778	0.704	0.768	0.774	0.772
Yield	MAPE	All	0.156	0.170	0.159	0.156	0.158
	RMSE	All	20.0	22.6	22.4	20.7	20.1
	R2	All	0.687	0.603	0.608	0.666	0.685

each location, predictions were performed for all combinations of height and tillering class (RF_HT model) or variety (RF_Var). The models were re-fitted for prediction over the whole dataset using the best mtry parameter identified during the calibration. The random forest output was the probability of being in each lodging class among the 5000 trees built.

2.8. Data analysis

All analyses were performed with R4.2 (R Development Core Team, 2023). Data were manipulated using the dplyr package. Visual representations were performed with the ggplot2, ggpointdensity, ggpubr, and raster packages. To facilitate visualization, smooth conditional means based on loess regressions were plotted in some figures. A principal component analysis with a rotation method (varimax, hereafter termed rotated component analysis), was performed using the principal function to assess the impact of climatic variables on yield and lodging probability.

3. Results

3.1. Selection and validation of random forest models

The whole dataset was used to select the sugarcane traits required to predict yield and lodging. The models with the lowest rRMSE for yield and OOB prediction error for lodging included all three traits: height, tillering, and diameter, and models that included only height and tillering (Table A2, A3). As both models presented similar rRMSE and OOB, using diameter did not improve model accuracy and so the RF_HT model was retained. The RF_HT model rRMSE for sugarcane yield was 22.4 %, while the model OOB for lodging was 43.0 % (Table 4, Fig. 1a, b). In the RF_HT model, respectively, 58 %, 52 %, and 59 % of Lodg0, Lodg10, and Lodg50 lodging classes were accurately predicted. The model calibrated on the commercial varieties presented similar prediction quality for yield (rRMSE = 22.2 %) but higher prediction quality for lodging (OOB = 31.0 %, Fig. 1c, d, Table 4). In the RF_Var model, respectively, 74 %, 52 %, and 67 % of Lodg0, Lodg10, and Lodg50 lodging classes were accurately predicted.

Sugarcane characteristics (height and tillering or variety) were the main factors that explained lodging class prediction before climate and soil variables (Fig. 1e, g). Climatic variables had similar Gini indexes, except for Alt and AWC whose Gini values were lower. Height, tillering, and variety were also main factors explaining yield, but the impact of climatic factors was stronger (Fig. 1f, h). Note that some climatic variables were correlated (Fig. A2), impacting the Gini index of each explanatory variable.

Table 4
Performance of the random forest model depending on the explanatory variables for lodging class and yield predictions: model including climatic component, height, and tillering (RF_HT, n = 26,433 observations), and model including individual climatic variables and commercial sugarcane variety (RF_Var, n = 2020 observations).

Variable	Indicator	Class	RF_HT	RF_Var
Lodging	OOB	All	0.430	0.310
	Accuracy	All	0.570	0.690
	Sensitivity	Lodg0	0.589	0.741
		Lodg10	0.520	0.521
		Lodg50	0.592	0.673
	Specificity	Lodg0	0.834	0.839
		Lodg10	0.763	0.823
		Lodg50	0.781	0.868
	Precision	Lodg0	0.834	0.905
		Lodg10	0.364	0.407
		Lodg50	0.410	0.448
Yield	MAPE	All	0.193	0.214
	rRMSE	All	0.224	0.222
	R2	All	0.626	0.548

3.2. Yield and lodging response to sugarcane traits and varieties

Sugarcane traits that are favorable for sugarcane yield were also associated with higher lodging in the varieties in the selection trials (Fig. 2a, b, d, e). Average yield across different climate conditions ranged from 65 to 120 Mg ha^{-1}, depending on the height and tillering classes. The lowest yields were observed for low height (H0) and low tillering (Till0) classes, and yield gradually increased with the increase in height and in the tillering class. Similarly, the probability for sugarcane to remain erect (i.e. not lodge, Lodg0 class) decreased gradually with height class up to H2, and then sharply for height classes H3 and H4 (Fig. 2d). The probability of being in Lodg0 class increased with tillering classes, and the probability of highly lodged sugarcane (Lodg50) decreased in the highest tillering classes (Fig. 2e).

The commercial sugarcane varieties influenced sugarcane yield and lodging (Fig. 2c, f). The average sugarcane yield across the island was around 98 Mg ha^{-1} in old varieties (R570, R577) and increased in recent varieties up to around 115 Mg ha^{-1} in R584, R585, R586, and R587. Intermediate varieties (R579, R582, R583) yielded around 106 Mg ha^{-1}. R570, R577, and R579 had the highest probability of being in the Lodg0 class, and this probability decreased in more recent varieties (Fig. 2f). On average, across the island, R583, R585, and R586 had the highest probability of being in the Lodg50 class.

3.3. Yield and lodging response to climate over Reunion Island

Predicted yield and lodging class, averaged across varieties for the 2015–2025 period, varied depending on where the crop was grown on

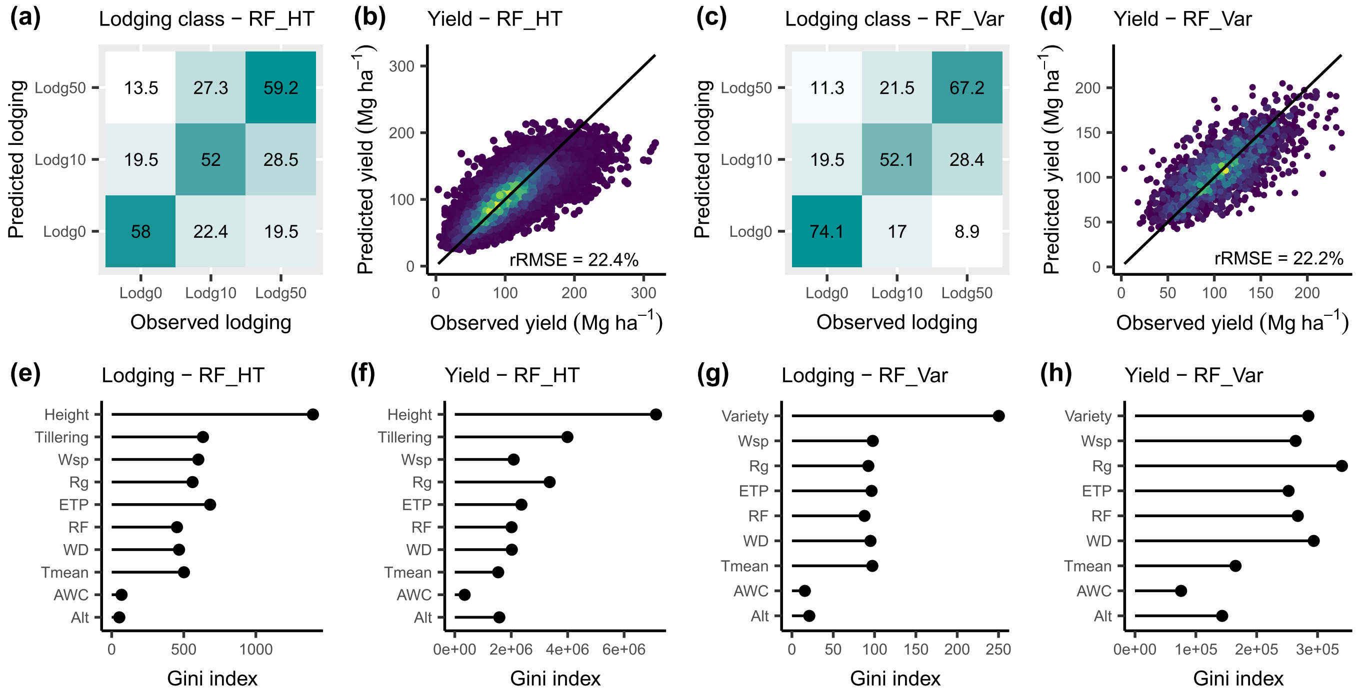

Fig. 1. Sugarcane lodging and yield accuracy in the validation datasets (a, b, c, d) and the relative importance of each variable (Gini index, e, f, g, h) depending on the model concerned, RF_HT (with height and tillering) and RF_Var (with variety). The confusion matrix in (a, c) indicates the percentage of observed classes in the different simulated classes (sum in row). A gradient of color indicating point density was added in the observed vs predicted yield in (b, d). Climatic and soil variables included evapotranspiration (ETP), wind speed (Wsp), global radiation (Rg), water deficit (WD), rainfall (RF), mean temperature (Tmean), altitude (Alt), and soil available water content (AWC).

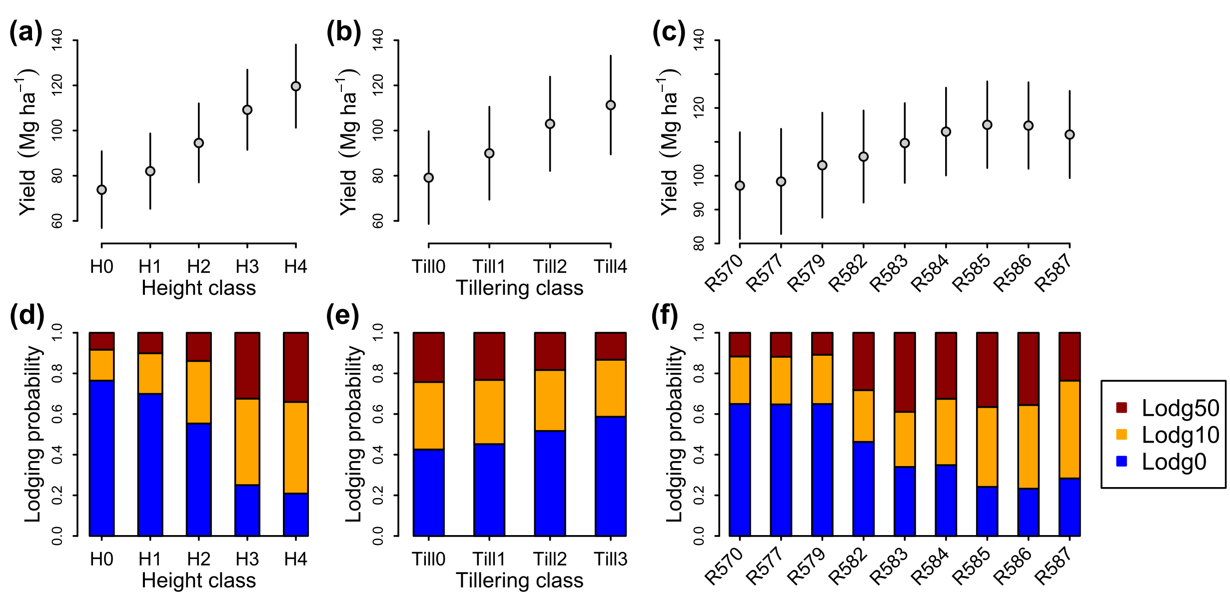

Fig. 2. Difference in yield (a, b, c) and lodging class probability (d, e, f) depending on the sugarcane height class (a, d), tillering class (b, e), and for commercial varieties (c, d). Mean and standard deviation across climates are represented for yield. The mean probability of being in a lodging class (Lodg0, Lodg10, and Lodg50) across climate is represented for lodging. Response to height and tillering was predicted with the RF_HT model, while response to variety was predicted with the RF_Var model.

Reunion Island (Fig. 3a). The highest sugarcane yields were predicted in the eastern and south-western part of the island at low altitudes (near the coast), with yields ranging from 120 to 130 Mg ha^{-1}. The lowest yields were predicted at high altitudes (Fig. 3b), with yields decreasing to 90 Mg ha^{-1}.

The probability of being in Lodg0 class during the 2015–2025 period was less than 0.4 in the western part at high altitudes, as well as well as in the southern and eastern parts at low altitudes, on average, across varieties (Fig. 3d). The highest Lodg10 probabilities were found in the north-eastern and south-western parts of the island at low altitude (Fig. 3e) in areas where the highest wind speeds were also observed (Fig. 3b). Areas with Lodg50 probabilities > 0.3 were all located at high altitudes with a few additional areas in the west at low altitude (Fig. 3e). Additionally, many low altitude areas in the eastern part of the island presented Lodg50 probabilities ranging from 0.25 to 0.3, in contrast to low altitude areas in the western or southern areas that presented lower

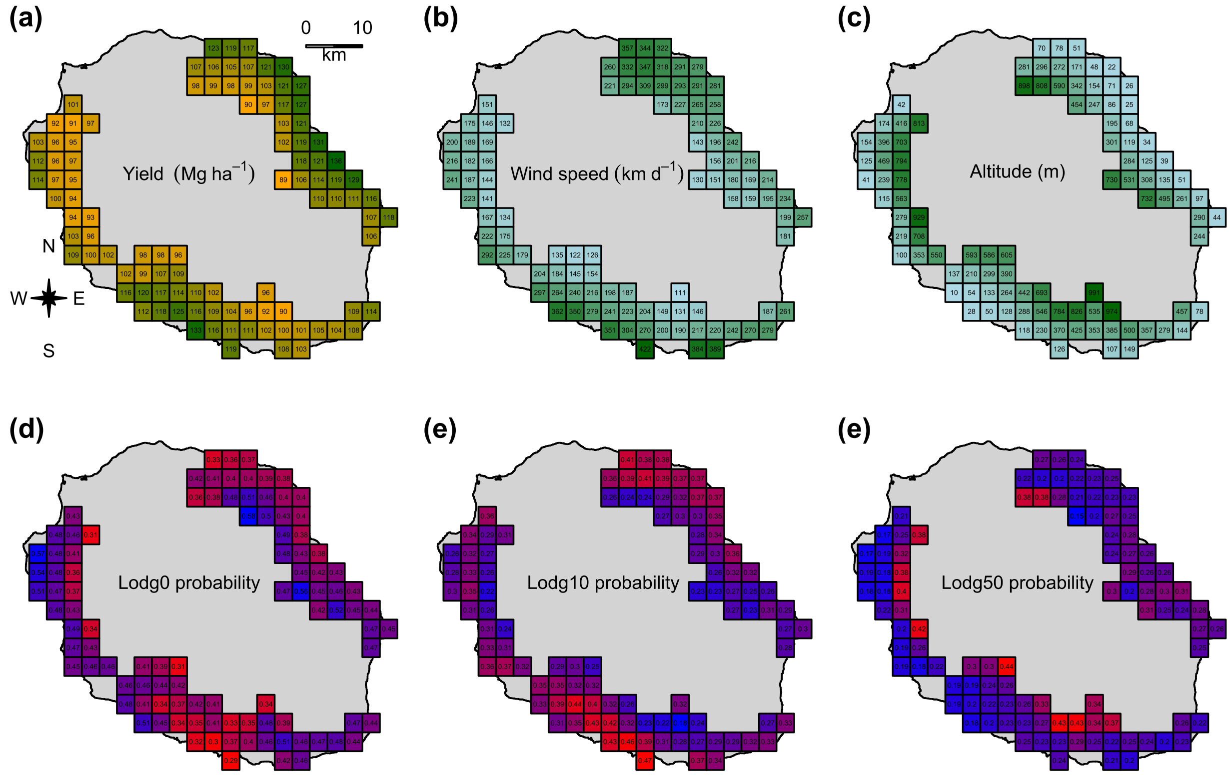

Fig. 3. Average sugarcane yield (a) and lodging class probability (d-e) across Reunion Island sugarcane fields predicted by the random forest model (RF_Var). Average wind speed (b) and altitude (c) across the island are presented to illustrate climate variability. Yield and lodging class probability were averaged over the 2015–2035 period in the three climatic models. A gradient of color was added to each map to distinguish low and high values. For yield (a), orange indicates low values, and green indicates high values. For wind speed (b) and altitude (c), light blue indicates low values and green high values. For Lodg0, red indicates low values, and blue indicates high values. For Lodg10 and Lodg50, blue indicates low values and red high values.

Lodg50 probabilities.

AWC and climatic variables were gathered in four climatic components representing 93 % of data variance (Fig. 4a, 37 %, 26 %, 17 %, and 13 % for RC1, RC2, RC3, and RC4, respectively). RC1 was mainly explained by Tmean and altitude, RC2 by total RF and WD, RC3 by wind speed, and RC4 by soil AWC. Sugarcane yield was mainly positively correlated with RC1 (R = 0.57) and to a lesser extent with RC3 (R = 0.27, Fig. 4). Despite being less explained by climatic variables, Lodg0 probability was positively correlated with RC2 (R=0.24), and negatively correlated with RC3 (R=-0.27). Lodg10 probability also increased with RC1 (R=0.4=, but contrary to Lodg0, it decreased with RC2 (R=-0.24) and increased with RC3 (R=0.36). Finally, Lodg50 was mainly correlated with RC1 (R = −0.54) but poorly explained by the other climatic components. The RC4 component was poorly correlated with both yield and lodging variables.

3.4. Relation between yield and lodging probability

Considering all the commercial varieties, predicted sugarcane yield was linearly correlated with Lodg0 probability ($R^2 = 0.247$), Lodg10 ($R^2 = 0.155$), and to a lesser extent with Lodg50 ($R^2 = 0.104$, Fig. 5). Nonetheless, the percentage of variance in Lodging probability explained by yield depended on the commercial variety. Lodg0 and Lodg10 were highly correlated with yield in R570, R577, and R579 ($R^2 > 0.2$, Fig. 5a, b), with a decrease in Lodg0 and an increase in Lodg10 with yield (Fig. 5d, e). On the contrary, lodging probability was not correlated with yield in R582, R583, and R584 for all lodging classes ($R^2 < 0.02$). Lodg10 was correlated with yield in the three last varieties, R585, R586, and R587 ($0.15 < R^2 < 0.2$), but while Lodg50 was correlated with yield in R585 and R586, this was not the case in R587.

4. Discussion

4.1. Modeling accuracy and limits

Machine-learning algorithms are being increasingly used to predict lodging from satellite images in sugarcane cropping systems (Guan et al., 2022) as well as in other crops (Zhang et al., 2020). However to date, this approach has never been applied to predict sugarcane lodging in the field based on climatic data or plant traits. Even in other crops, such an approach is still recent, with a few attempts made to link plant traits and lodging (e.g. in wheat, Rabieyan et al., 2023). In Rabieyan et al. (2023), lodging prediction was not classified but based on a lodging scare index. These authors compared different machine learning algorithms and, like in our study, found that the random forest algorithm performed best. On the other hand, using random forest to predict yield is much more frequent, both in sugarcane (dos Santos Luciano et al., 2021) and other crops (Cheng et al., 2022). The yield prediction accuracy in our study was in the same order of magnitude as that previously reported in the literature on sugarcane (Canata et al., 2021; dos Santos Luciano et al., 2021; Everingham et al., 2016; Hammer et al., 2020; Sanches et al., 2019). Among the commonly used algorithms (Araujo et al., 2023), artificial neural network (MLP in our case) performed more weakly in our study. However, it is worth noting that other neural network algorithms such as Long Short-Term Memory may offer promising avenues for future studies with sequential observations. LSTM's ability to handle sequential variables could be particularly useful in the case of lodging, a process that can result from a succession of extreme climatic events and is closely linked to the previous status of the cropping system (sugarcane biomass, saturated soils, etc).

However, even though the prediction quality of our model was deemed sufficient to assess trends in our study, the prediction of lodging

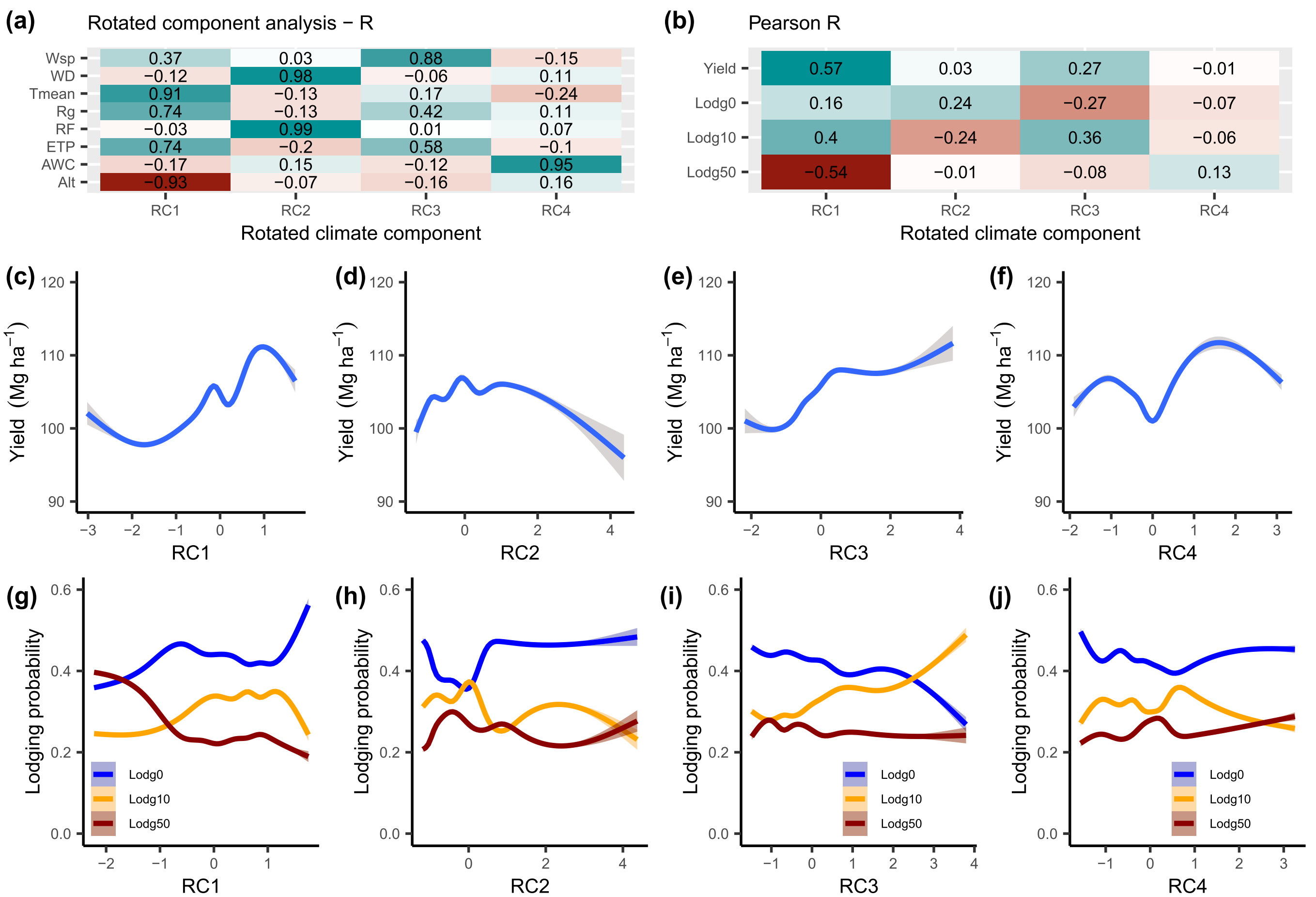

Fig. 4. Relation between yield and lodging class probability and climatic variables. Climatic variables are summarized in four principal rotated climatic components (RC1, RC2, RC3, RC4). (a) summarizes the correlation between climatic variables and principal components; (b) represents the Pearson correlation (R) between yield, lodging class probability, and the four principal components. The changes in average yield (c-f) and lodging probability (g-j) with principal climatic components were smoothed using a loess function. Lodging probabilities and yield were predicted using the RF_Var model.

using random forest models based on climate and varieties can still be significantly improved. Two sources of uncertainty in our approach may have limited our predictive capabilities. On the one hand, the lodging class, that was estimated visually, although appropriate for such a large-scale experimental network, may have prevented a thorough evaluation of sugarcane sensitivity to climatic fluctuations. However, new rapid and original methods for estimating lodging in the field have emerged in recent years in sugarcane, such as those based on infrared (Ma et al., 2024), RGB image (Modi et al., 2023), or satellite image analyses (Guan et al., 2022). These methods could be used in experimental trials to improve lodging prediction. On the other hand, uncertainty in our prediction may arise from the explanatory variables used in our approach. Although monthly climatic variables have successfully predicted yield (dos Santos Luciano et al., 2021), in our study, using monthly rather than annual variables did not improve lodging or yield predictions (data not shown). One possible explanation is that in our climate data, areas with the most extreme peaks of rain or wind were also the areas with the highest annual rainfall and the most wind. In pursuit of parsimony, we thus retained the annual variables. We also explored the use of soil depth as an explanatory variable. However, we ultimately decided to leave it out because it was highly correlated with our available water capacity in the experimental stations (and data were not available for the whole island). Nevertheless, recent research on lodging suggests the importance of examining the underground compartment. For instance, recent studies highlighted the importance of root development in lodging resistance, even if stalk height and weight remained the main determining factors (Jongrungklang et al., 2018; Viaud, 2023; Yang et al., 2020). Consequently, we would expect to find different lodging resistance among sugarcane varieties with different root characteristics, as already observed in other annual crops (Zhang et al., 2022). Additionally, sugarcane root development is now known to be highly variable depending on soil conditions (Chevalier et al., 2023), and future research should thus investigate the effect of soil on lodging sensitivity.

4.2. A trade-off between sugarcane yield and lodging

Overall, the environmental conditions or plant characteristics that are favorable for yield in sugarcane are also favorable for lodging, as illustrated by our study and by previous studies (Li et al., 2019; Van Heerden et al., 2010). This finding also applies to other annual crops (Xue et al., 2017). Previous studies have highlighted the crucial effect of sugarcane stem weight and height on lodging susceptibility (Berding and Hurney, 2005; Jongrungklang et al., 2018), similar to our study. Since the harvested organ in sugarcane is the stem, this trait is also strongly correlated with yield. As in our study, the effect of diameter on lodging is less clear (Berding and Hurney, 2005) and likely overlaps the tillering effect. Strong tillering is often associated with thinner stems (Bonnett, 2013) and potentially slightly less susceptibility to lodging, as our results for severe lodging suggest. The sensitivity of lodging to strong winds, which our study confirmed, has already been documented in the literature (Singh et al., 2002). However, contrary to expectations, heavy rainfall (up to 8000 mm y^{-1} in our predictions) did not increase lodging. This lack of response could be because, under our conditions, very heavy

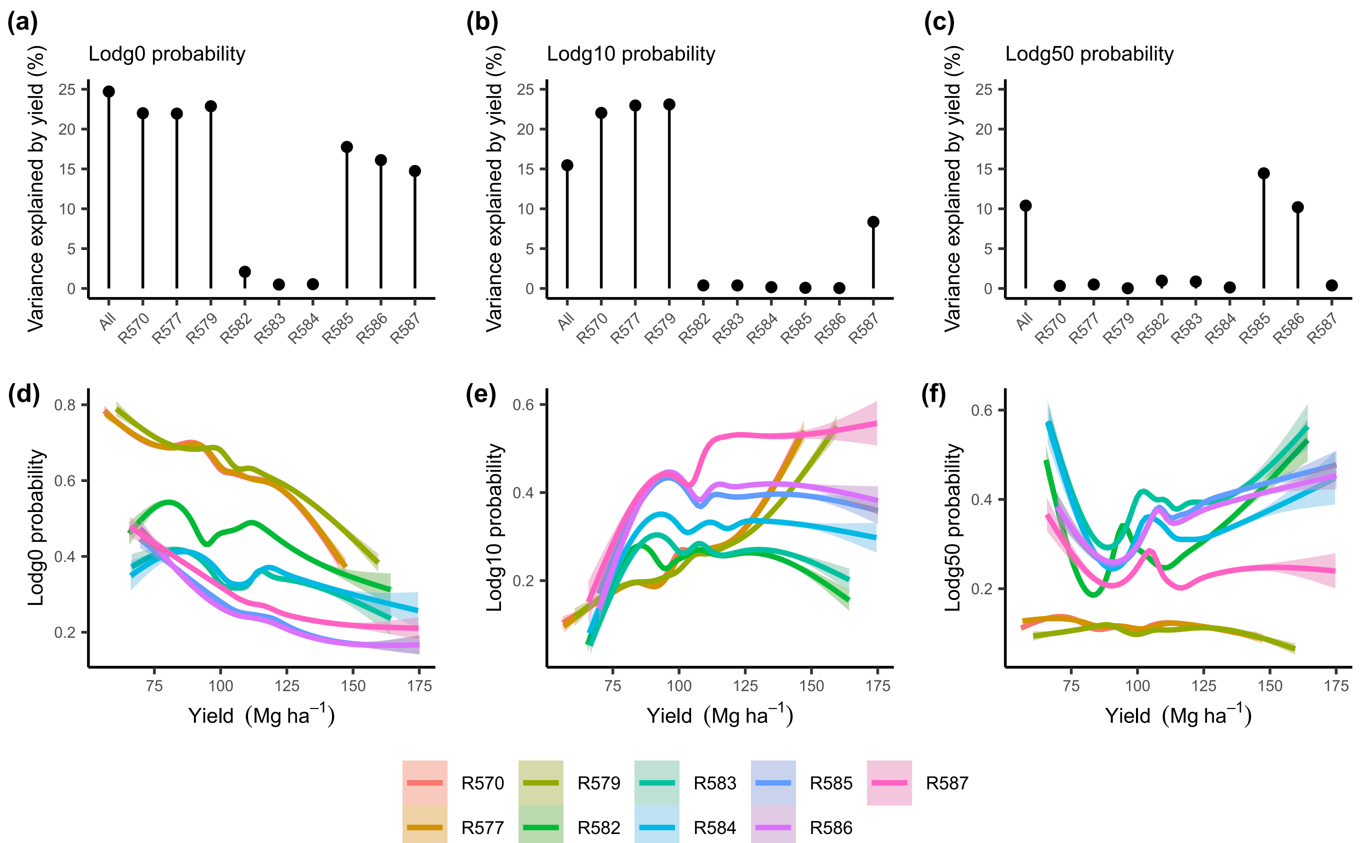

Fig. 5. Percentage of variance of Lodg0 (a), Lodg10 (b), and Lodg50 (c) probability explained by sugarcane yield considering all varieties (All) or for each individual commercial variety (R^2 linear index). (d-f) represent the difference in Lodg0, Lodg10, and Lodg50 probabilities with yield for each commercial variety (non-linear loess function). Lodging probabilities and yield were predicted using the RF_Var model.

rainfall also reduced yields.

In Reunion Island, variety selection perfectly illustrates the preference for selecting new varieties based on yield, thus leading to the selection of varieties that are increasingly susceptible to lodging in recent years. The older varieties R570 (created in 1978), R577 (1987), and R579 (1993) had a much lower probability of lodging than the more recent highly productive varieties (R586, 2013), even if the most recent (R587, 2016) presented reduced susceptibility to high lodging. However, the yield-lodging trade-off may vary depending on the varieties, as in our study, not all varieties exhibited the same yield-lodging correlation. For example, the probability of not lodging remains relatively stable up to 120 Mg ha^{-1} in some varieties, whereas in others, the probability decreases linearly with yield. This finding should encourage the search for lodging resistance traits in sugarcane varieties (Jongrungklang et al., 2018), while retaining yield as an objective.

4.3. Implications for sugarcane management in Reunion Island

The trade-off between lodging and sugarcane yield is critical on tropical islands like Reunion Island due to the regular occurrence of extreme climate events like storms and cyclones (Christina et al., 2021). Other sugarcane producing countries, such as tropical islands, are also subject to extreme winds (e.g. in the Philippines, Stromberg et al., 2011). Like in other areas in the world (Field et al., 2012), on Reunion Island, the intensity of these events is likely to increase in the coming decades (Thompson et al., 2021). In our study, different areas are particularly sensitive to the risk of heavy lodging: the upper reaches of the island and areas subject to strong winds in the east and south, and varieties that are adapted to these conditions should be sought.

Among the varieties studied, three, R577, R583, and R586, were selected in particular for high-altitude areas in recent years. While R577 was shown to be almost insensitive to lodging even at high altitudes, R583 is very likely to lodge in the very same areas (Fig. A3). Such a difference in sensitivity is due to the high height classes of R583 (mainly H3 and H4) compared to R577 (mainly H1 and H2). On the contrary, the more recent R586 showed less probability of heavy lodging in these areas than R583 despite being in the same height classes (H3 and H4). This difference could result in more tillers in R586 (mainly Till2 and Till3) than in R583 (mainly Till2). Consequently, future breeding of varieties with increasing tillers should be sought for cultivation in these areas.

The varieties frequently present in the breeding trials located in the island's eastern and southern windward areas included R579, R582, R585, and R587. Among these varieties growing in windward areas, susceptibility to lodging was mainly observed in R582 and R585, while the more recent variety, R587, was less susceptible to high lodging rates (Fig. A4). All varieties exhibited a similar tillering class (mainly Till2), but their heights differed. While R585 was mainly in classes H3 and H4, R587 was slightly smaller (in classes H2 and H3) but produced similar yields, which may explain its lower susceptibility to lodging. However, this variety is nonetheless subject to moderate lodging. The search for productive varieties with reduced height may consequently be a promising avenue for these windy areas in the future.

5. Conclusions

Our study highlights the significant influence of sugarcane traits and climatic conditions on sugarcane yield and lodging and their strong correlation in the tropical conditions found in Reunion Island. Sugarcane characteristics such as height, tillering, and variety, along with environmental factors, notably altitude and wind speed, play pivotal roles in determining lodging probability. Our findings reveal that regions at higher altitudes are more susceptible to high lodging. At the same time, environments characterized by higher wind speeds increased the risk of moderate lodging on the island. Despite a global trend wherein conditions or traits conducive to higher yields concurrently increase lodging probability, the correlation between yield and lodging probability varies with the sugarcane variety, highlighting the nuanced interplay between plant traits and lodging resistance and the possibility of selecting varieties that are both high-yielding and resistant to lodging. By defining critical environments on the island that are prone to increased risk of lodging, our results underline the need to prioritize varieties of sugarcane that are resilient to lodging, thus ensuring sustainable yields under changing climatic conditions. These insights are not only relevant for Reunion Island but also apply to other sugarcane producing countries with similar climatic conditions, particularly tropical islands susceptible to high winds.

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Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2024.127381.

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