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Potential effects of climate change on Brazil's land use policy for renewable energy from sugarcane

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ABSTRACT

Brazil, in its intended nationally determined contribution protocol on the Paris Agreement, set to enhancement the usage of energy from sugarcane. To sustainably meet this goal, the Brazilian government rely on the Sugarcane Agroecological Zoning (SAZ). The SAZ, based on soil, climate, and land use conditions, defines as suitable 63 million hectares (Mha). Such an area would suffice the future demand for sugarcane. However, climate change impacts on the climate conditions necessary to grow sugarcane may promote a mismatch between the SAZ and future suitability. Our goal is to examine the effects of climate change on the SAZ policy. We developed ecological niche models to identify the suitability criteria and generate scenarios under 17 global climate models listed in the IPCC 5 for 2050. An ensemble of the 17 scenarios identifies areas of estimation congruence thus indicating smaller uncertainty regarding the suitability of these areas. Areas of high congruence (above 70% of prediction) encompass 1.53 Mha by 2050, a reduction of 97.5% compared to SAZ. Including areas of high congruence outside of the SAZ increases the suitable area to 7 Mha. The public and private sector in Brazil needs to develop large-scale adaptation strategies such as improving the research cycle of sugarcane varieties and reducing yield gaps by advancing the management of sugarcane fields to propel Brazil into fulfilling its Paris Agreement commitment.

1. Introduction

The evolution of the Brazilian energy matrix has demonstrated a successful shift from oil importer to a world leader in renewable energy. Brazil's main source of renewable energy is sugarcane. Indeed, the sugarcane sector contributes with 17% of Brazil's energy matrix and sugarcane ethanol has replaced almost 42% of Brazilian gasoline needs (EPE, 2016). Sugarcane ethanol has expanded quickly in the early 2000s (Goldemberg, 2007; Granco et al., 2017; Moraes, 2011). From 2004 to 2013, the sugarcane sector invested more than US$ 30 billion, setting up more than 100 mills and expanding the production area from 5.8 million hectares (Mha) to 9 Mha in 2015/16, harvesting 667 million tons of sugarcane, which yielded 33.8 million tons of sugar and 30.2 billion liters of ethanol, resulting in a GDP around 40 billion dollars in 2016 (CONAB, 2016; Unica, 2014). These results make Brazil the main sugar producer and the second largest ethanol producer in the world (Sant'Anna et al., 2016).

In addition to the economic impacts, sugarcane ethanol has been an important instrument in the country's strategy for mitigating greenhouse gas emissions. Due to sugarcane energy, Brazil has avoided emitting more than 300 million tons of CO_2 from fossil fuels since 2003 and converting crop or pastureland to sugarcane may lead to direct impacts on local climate by substantial local cooling effect (Loarie et al., 2011). This success in renewable energy has led the country to commit to a reduction in greenhouse gas (GHG) of 37% by 2025 and 43% by 2030 compared to GHG emission level in 2005 on its intended nationally determined contribution (iNDC) protocol on climate change (UNFCCC, 2015). For the near future, the Brazilian Energy Plan 2024 (PDE 2024) forecasts an increase in production to 44 billion liters of sugarcane ethanol in 9.9 Mha of land (EPE, 2015) representing a demand of 1 Mha of sugarcane over the 2015/2016 area.

However, concerns about environmental impacts and the country's ability to achieve its iNDC committement have incentivized the development of planning policies for the expansion of sugarcane. Among the policies is the Sugarcane Agroecological Zoning (SAZ), a crop zoning established by the Decree No. 6,961/2009 with two main goals: (i) to

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Table 1
Climate and soil conditions to define the SAZ's suitability classes. This classification scheme is adapted from (Manzatto et al., 2009).

		P-Class	R-Class	R-Class	R-Class	S-Class
Suitability conditions	Average air temperature	> 19 °C	> 19 °C	> 19 °C	> 19 °C	> 19 °C
	Annual hydric deficit	< 200 mm	< 200 mm	> 200 and < 400 mm	> 200 and < 400 mm	< 200 mm
	Index for the satisfaction of sugarcane's water necessities	> 0.6	> 0.6	> 0.6	> 0.6	> 0.6
	Risk of frost	< 20%	< 20%	< 20%	< 20%	< 20%
	Soil suitability	high	regular	high	regular	low

guide the industry expansion, and (ii) to act as an active strategy in sparing land in an important environmental biome (Myers et al., 2000; Phalan et al., 2016). The SAZ guides the expansion by describing the areas most suitable for cultivation in terms of soil conditions, slope, climate requirements, and previous land use (Table 1) (Jaiswal et al., 2017; Lucon and Goldemberg, 2010; Manzatto et al., 2009; Zullo et al., 2018). Following this guidelines, the Brazilian government estimates the availability of 63 Mha of land for sugarcane expansion as follow: 18 Mha are classified as the highest suitability potential (P-Class) with good soils and good climate, 41 Mha with regular suitability (R-Class) defined by average soil conditions and good climate conditions, and 4 Mha with low suitability (S-Class), defined by poor soils and good climate conditions (Manzatto et al., 2009). It is important to note that the SAZ offers incentives for farmers that comply with it, such as easy credit and environmental license in order to operate, but it does not force farmers to plant only in the best suitable areas.

The success of agricultural land use zoning as active land sparing strategy is associated with the compliance with the zoning. In other words, if farmers are not convinced that the zoning is mapping the most suitable areas, and the enforcement is low, then farmers may stop following the policy rules (Arima et al., 2014; de Lucena et al., 2009; Niles et al., 2013). Furthermore, another important component of the SAZ requirements is climate, which can become a challenge for a successful implementation of the land use zoning policy.

Studies on the future of agricultural production have cautioned about severe impacts of future climate conditions on agricultural production leading to changes in the distribution of agricultural areas (Jaiswal et al., 2017; Machovina and Feeley, 2013; Pugh et al., 2016; Schlenker and Lobell, 2010), yield loss (Nelson et al., 2014; Pugh et al., 2016; Rosenzweig et al., 2014), and food security (Campbell et al., 2016; Kline et al., 2016). Such negative impacts can undermine the effects of agricultural land-use zoning by affecting the suitability of zoned areas and increasing the possibility of mismatch between the zoning and actual suitability. In the case of sugarcane, current research indicates that climate change poses a threat to sugarcane production due to its relatively low adaptive capacity, high vulnerability to natural hazard, and lack of mitigating strategies (Chandiposha, 2013; de Lucena et al., 2009; Marin et al., 2016; Zhao and Li, 2015). Thus, the Brazilian sugarcane production is not immune to the potential impacts of climate change, in fact, since most sugarcane production in Brazil is rainfed climate change might have significant impacts in sugarcane production (Jaiswal et al., 2017; Marin et al., 2013; Zullo et al., 2018). Still, the SAZ does not present information on potential impacts of climate change on the land suitability of sugarcane, which can have negative consequences for the sugarcane industry and for the environment, such as the establishment of new production site in areas that may not maintain its suitability given climatic change. Indeed, we can ask if the areas defined as suitable by SAZ will remain suitable given climate change. We are especially concerned with the existence of mismatch between current and future suitable areas because the sugarcane ethanol industry is highly specialized and demands large cropland to operate. In the presence of a mismatch, the industry trust in the zoning policy may vanish jeopardizing the sustainability gains from the SAZ policy. Although our research is focused on the case of sugarcane in Brazil, the study of mismatch due to future climate condition is generalizable to other land use policies that are associated with climatic conditions, such as agroecological zoning for palm trees in the rain-forest of the Brazilian Amazon and Indonesia (Harahap et al., 2017; Monteiro de Carvalho et al., 2015) and coffee worldwide (Bunn et al., 2015).

The goal of this research is to analyze the potential impact of climate change on the spatial distribution of suitable areas for sugarcane production by 2050. To address this question, we (i) developed an ecological niche model (ENM) for the current spatial distribution of suitable areas based on the SAZ, and (ii) projected the ENM to 2050 by considering 17 global climate models (GCM) under the representative concentration pathways (RCP) of 4.5 and 8.5 (Thomson et al., 2011, 2010).

2. Materials and methods

2.1. The sugarcane agroecological zoning (SAZ)

The SAZ's goal is to guide the sugarcane expansion while protecting the environment and avoiding negative impact on food security. The mechanism used to achieve this goal is an agroecological zoning that defines areas as suitable, nonsuitable, and not allowed for sugarcane production. The areas suitability is a combination of sugarcane's eco-climatic requirements such as climate, soil, slope, and previous land use. For the climate component many factors are considered such as average air temperature, annual hydric deficit, an index for the satisfaction of sugarcane's water necessities, and risk of frost. Areas that need intense irrigation or that had too much rain were considered unsuitable for sugarcane production. The slope requirement is that areas with slope < 12° can be considered suitable. In addition, the suitability consider soil factors like deficiencies of fertility, water deficits, water excess or lack of oxygen, erosion-prone, restrictions to mechanized harvest, and restrictions to the sugarcane's radicular system development. Although, the SAZ presents the requirements, it does not precise the methodology used to identify such requirements. The combination of the different requirements defines if an area is suitable or nonsuitable. We can group the suitable areas into three suitability classes: (1) highest suitability potential (P-Class) with good soils and good climate; (2) regular suitability (R-Class) defined by average soil conditions and good climate conditions; (3) low suitability (S-Class), defined by poor soils and good climate conditions (Table 1).

Agricultural land use is not considered as a restriction factor; it is important to notice that the Brazilian government has expressed a desire that sugarcane expansion occurs over pastureland, thus reducing direct competition for land with food production from converting cropland (Alkimim et al., 2015; Leal et al., 2013; Walter et al., 2014). Although previous land use is not a restriction in the definition of suitability areas, land cover is a restriction for the SAZ such that natural vegetation cannot be replaced by sugarcane producing areas. To define which areas where covered by natural vegetation, the SAZ uses the land cover classification developed by the PROBIO program (Sano et al., 2008). Although the PROBIO program focus was on biodiversity, it produced maps reflecting the land cover/land use as in 2002 (Sano et al., 2008).

The definition of areas not allowed for sugarcane expansion is a governmental decision to rule out any conversion of natural vegetation and any area in the Amazon, Pantanal, and Alto Paraguay River Basin to preserve these environments (Manzatto et al., 2009). Areas within conservation units and indigenous reserves are also removed from the SAZ (Manzatto et al., 2009). Because the SAZ is focused on the expansion of sugarcane, areas under sugarcane production in 2007 as mapped by the Canasat program (Rudorff et al., 2010) were also removed from the SAZ.

2.2. Ecological niche model for land suitability

Ecological niche model (ENM) is a technique to estimate the potential range of species (Akhter et al., 2017; Broennimann et al., 2012; Guillera-Arroita et al., 2015; Hirzel and Le Lay, 2008; Peterson, 2003; Phillips et al., 2006). An ENM traces the species' ecological niche by relating data on the occurrence of the species with data on other elements of the landscape such as climate, physical environment, human population, land use, among others (Elith and Leathwick, 2009). These models contribute to answering questions related to the distribution of species and predicting distribution shift under a change in the environment (Anderson et al., 2003; Estes et al., 2013; Petitpierre et al., 2016; Silva et al., 2014b). ENM has been used in a broad range of applications, from modeling exotic species (Faleiro et al., 2015; Silva et al., 2015) and pollinators (Silva et al., 2014a) to invasive species (Barney and DiTomaso, 2011; Peterson, 2003; Petitpierre et al., 2016). More recently, ENM started to attract the attention of land change scientists who have used it to model land use suitability (Heumann et al., 2013; Machovina and Feeley, 2013), establish potential of new producing regions (Evans et al., 2010; Trabucco et al., 2010), and land cover change and planning (de Souza and De Marco, 2014; Zhang et al., 2012).

The ENM broad adoption can be attributed to four main factors: the good fit of the models' predictions and potential to transferability (Peterson et al., 2007; Phillips et al., 2008); the user-friendly interface of some ENM software (Elith and Leathwick, 2009; Lozier et al., 2009); the readily available GIS data layers on species records and landscape factors (Elith and Leathwick, 2009; Lozier et al., 2009); and the development of machine learning algorithms and other data-mining techniques (Faleiro et al., 2013; Fourcade et al., 2014). Data dimensionality reduction techniques such as principal component transformation (PCT) are commonly used to improve model estimation (Silva et al., 2014a). ENM has the capability of handling data representing biotic (such as dispersal ability, predation) and abiotic (such as climate and terrain) factors relevant to the study of the potential habitat of a species. Identification of abiotic factors as one of the largest force defining the spatial distribution together with the abundance of GIS layer of climatic and bioclimatic variables stimulated an ENM reliance on abiotic factors (Elith and Leathwick, 2009; Pearson and Dawson, 2003). However, the ENM reliance on abiotic factors has been called out as a source of prediction error (Araújo and Peterson, 2012; Pearson and Dawson, 2003). Researchers have proposed the use of biotic factors, however, the incorporation of these factors is limited by the specificity of each species and lack of data that can be used as a proxy for the biotic factors (Cunningham et al., 2016; Elith and Leathwick, 2009; Lewis et al., 2017).

We recognize the influence of biotic and abiotic factors, however, the approach chosen for this research relies on the abiotic factors affecting the species distribution. The first research goal deals with developing an ENM for sugarcane suitability which is defined in terms of abiotic factors. The second research goal focuses on the projection of the ENM to future climate conditions and analysis of changes in the spatial distribution. Because there is uncertainty regarding future climate, we use an ensemble of the ENM results to examine possible impacts of climate change on land suitability for sugarcane and the SAZ. The aggregation of ENM results under climate scenarios into ensembles aims to identify the uncertainty and high congruence of prediction of the future distribution of suitable areas (Machovina and Feeley, 2013; Ranjitkar et al., 2016; Rosenzweig et al., 2014). The ENM approach allows both to predict changes in climatic suitability and evaluate the uncertainty of this measure derived from the different future climate scenarios (Akhter et al., 2017; Blanchard et al., 2015; Heumann et al., 2013; Machovina and Feeley, 2013).

2.3. Modeling framework

To achieve our goals, we developed a modeling framework consisting of three steps. In step (1), we created an ENM representing each suitability class defined in the SAZ using the bioclimatic variables for the current climate conditions. In step (2), we evaluated the ENM using bioclimatic variables from 17 global climate models (GCM) for RCPs of 4.5 and 8.5. This step generates 1020 probability maps (340 for each suitability class; 170 under each RCP), which were analyzed individually and later combined in an ensemble map of predicted suitable areas. In step (3), we conducted a spatial analysis to identify potential mismatch between the current spatial distribution of SAZ suitable areas and the areas predicted by the ensemble map.

For this paper, congruence of prediction is defined as the frequency that each area is predicted as suitable by individual ENM. By following Rosenzweig et al. (2014), we set the threshold for high congruence of model's estimation as a proportion of 70% or more of models predicting the area as suitable. Likewise, the areas with a proportion of prediction inferior to 70% of the models are considered areas of low model congruence, thus nonsuitable for sugarcane production. For this study, areas with low model congruence are considered more susceptible to negative impacts of climate change, while areas with high model congruence are considered less susceptible.

Several approaches are available to implement ENM differing in the algorithm used to predict the species' distribution and results (Duan et al., 2014; Howard et al., 2014; Stockwell and Peterson, 2002; Wisz et al., 2008). We tested the three algorithm most frequently used in the literature in Step (1): (i) Maxent (MXT) (Phillips et al., 2006); (ii) Random Forest (RDF) (Howard et al., 2014); and (iii) Support Vector Machine (SVM) (Drake et al., 2006). The results of each algorithm were evaluated and only the algorithm that produced the best-fitting prediction was used on the next steps of this research. The ENM was performed on R Statistical software, with the packages *dismo* for the MXT algorithm (Hijmans et al., 2017), *randomForest* for the RDF algorithm (Liaw and Wiener, 2002; Svetnik et al., 2003), *kernlab* for the SVM algorithm (Karatzoglou et al., 2004).

2.4. Ecological niche model evaluation

To identify which algorithm generates the ENM that best represents the set of conditions for the SAZ Classes, we perform the True Skilled Statistics (TSS) as the assessment tool (Allouche et al., 2006). This statistic varies from -1 to +1, where negative values and < 0.5 are considered no better than random and where a value closer to +1 is considered excellent. The use of TSS has advantages over other metrics for binary presence-absence predictions of species distribution (Allouche et al., 2006; Garcia et al., 2013). The TSS is a threshold-dependent measure. The receiver-operator curve (ROC) threshold is used in this research. The ROC threshold provides the value in which the model has the same number of omission and commission errors, thus reducing overfitting problems (Duan et al., 2014; Silva et al., 2014b). This is a more precautionary threshold than the least presence training threshold (Faleiro et al., 2015; Silva et al., 2014a).

The evaluation uses a repeated measures ANOVA to test the equality of the TSS means for each algorithm regarding each SAZ Class (Duan et al., 2014; Pearson et al., 2006; Segurado and Araújo, 2004; Silva et al., 2014a). Thus, defining the best algorithm is not only the one with the highest TSS, but it also has the highest TSS over all samples for each SAZ Class.

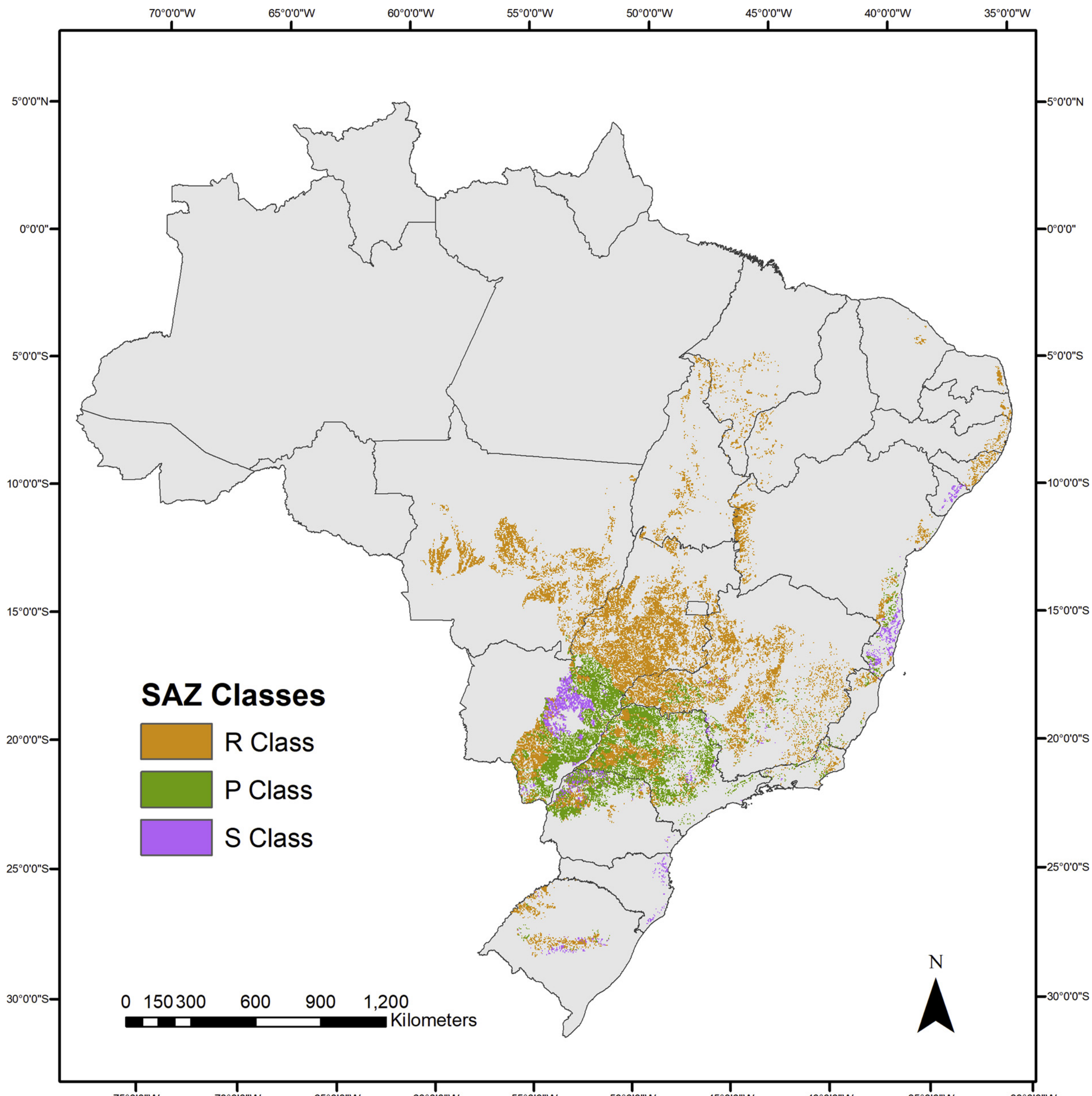

Fig. 1. Representation of the three suitability classes (P – high suitability, R – regular suitability, S – low suitability) defined by the SAZ.

2.5. Occurrences data set

In the ENM, the potential distribution is based on known occurrences locations of the target species. For our study, areas zoned as suitable are considered as a known occurrence of the species “suitability for sugarcane expansion” that the ENM is defining the distribution range. In other words, the occurrence data set for this research are the areas classified as suitable by the SAZ. The data was acquired in shapefile format from the Brazilian Enterprise of Agricultural Research (EMBRAPA) (available for download at http://geo.cnpma.embrapa.br/projeto_pt.aspx). The original data set was divided into SAZ Classes and converted to a grid format (Fig. 1). The use of gridded data facilitates our modeling approach of ENM. Each SAZ Class was modeled using ENM with the point location represented by the centroid of each cell. After these steps, the P-Class had 724,818 points, R-Class had 1,527,006 points, and S-Class had 160,308 points.

The abundance of points is unusual in the use of ENM (Wisz et al., 2008) and may raise two biases in the models. First, the use of all points can lead to overfitting the model, thus threatening the projection of the model to different climate scenarios (Peterson et al., 2007; Phillips et al., 2008). Second, the abundance of points can lead to spatial autocorrelation as the SAZ criteria are related to physical factors that exhibit spatial dependency (e.g., soil characteristics and climate) (Ettema and Wardle, 2002; Hijmans et al., 2005).

To avoid these biases, we applied a random sampling procedure, which reduces the effects of spatial autocorrelation by imposing a spatial threshold to select data points. The method employed selects occurrence points such that a point is added to the sample only if its distance to any point already present in the sample is larger than 10 km. The procedure first selects a point randomly and then discard those that do not follow the spatial rule (Bini et al., 2009). Using this procedure, we selected 10 random sets for modeling for each SAZ class with 3500 points (except for the S-Class which has only 1000 points due to its smaller observed area). This random sampling procedure has the advantage of avoiding spatial autocorrelation, hence reducing the odds of overfitting by sampling the original data set (Howard et al., 2014). Furthermore, it enables statistical validation of the ENM using repeated measures ANOVA.

Table 2
Bioclimatic variables and the principal component transformation. Individual loadings for each variable and principal component (PC) are showed in each cell. Proportion of variance explained by each and accumulated by PCs, as well as the PC eigenvalues are also presented. The six principal components presented are the environmental factors used by the ENM.

Bioclimatic variables	Principal components					
	PC1	PC2	PC3	PC4	PC5	PC6
Annual Mean Temperature	0.271	−0.229	−0.109	0.006	−0.066	0.072
Mean Diurnal Range	−0.233	−0.097	0.021	−0.429	0.115	0.534
Isothermality	0.208	0.077	0.405	−0.005	−0.196	0.461
Temperature Seasonality	−0.225	0.010	−0.398	0.071	0.267	−0.020
Max Temperature of Warmest Month	0.200	−0.322	−0.305	−0.045	0.156	0.154
Min Temperature of Coldest Month	0.290	−0.126	0.008	0.130	−0.096	−0.023
Temperature Annual Range	−0.253	−0.082	−0.261	−0.223	0.265	0.159
Mean Temperature of Wettest Quarter	0.225	−0.276	−0.256	−0.058	−0.027	0.157
Mean Temperature of Driest Quarter	0.281	−0.160	0.034	0.099	−0.083	0.000
Mean Temperature of Warmest Quarter	0.234	−0.262	−0.285	0.058	0.054	0.065
Mean Temperature of Coldest Quarter	0.283	−0.185	0.021	−0.004	−0.113	0.055
Annual Precipitation	0.263	0.206	0.010	−0.235	0.201	−0.081
Precipitation of Wettest Month	0.256	0.050	0.158	−0.326	0.294	−0.215
Precipitation of Driest Month	0.155	0.429	−0.202	0.097	−0.067	0.359
Precipitation Seasonality	−0.135	−0.303	0.389	−0.180	0.064	0.250
Precipitation of Wettest Quarter	0.258	0.056	0.148	−0.338	0.283	−0.206
Precipitation of Driest Quarter	0.167	0.426	−0.197	0.088	−0.028	0.307
Precipitation of Warmest Quarter	0.102	0.227	−0.256	−0.598	−0.420	−0.140
Precipitation of Coldest Quarter	0.209	0.210	0.111	0.204	0.593	0.122
Proportion explained by each PC	0.578	0.158	0.118	0.060	0.036	0.022
Accumulated variation proportion	0.578	0.736	0.854	0.914	0.950	0.971
PC eigenvalues	10.980	3.005	2.235	1.142	0.679	0.409

2.6. Bioclimatic variables

Three sets of bioclimatic variables were employed to evaluate the effects of climate change on the availability of land suitable for sugarcane expansion. The first set is representative of the current climate conditions which interpolates average climate data for 1960 to 1990 using data from the WorldClim 1.4 (Hijmans et al., 2005). The second set is representative of the future climate conditions under the representative concentration pathway (RCP) 4.5 (average increase of ~1.4 °C), considering 17 global climate models (GCM) (Table 2). While the third set is representative of the future climate conditions under RCP 8.5 (average increase of ~2 °C) for 17 GCM. The 17 GCMs considered are: ACCESS1-0, BCC-CSM1-1, CCSM4, CNRM-CM5, GFDL-CM3, GISS-E2-R, HadGEM2-AO, HadGEM2-CC, HadGEM2-ES, INMCM4, IPSL-CM5A-LR, MIROC-ESM-CHEM, MIROC-ESM, MIROC5, MPI-ESM-LR, MRI-CGCM3, NorESM1-M. Data for both second and third sets came from the CMIP5 (IPCC Fifth Assessment) with downscaling and calibration performed by WorldClim version 1.4 (Hijmans et al., 2005).

We considered the 19 bioclimatic variables (Table 2) derived by WorldClim from climate models at a spatial resolution of 2.5 arc-min (approximately 4 km at the equator) (Hijmans et al., 2005). The bioclimatic variables include several metrics that are closely related to the climatic conditions defined for the SAZ. For instance, air temperature is a SAZ's criterium and there are four bioclimatic variables capturing annual averages, such as annual mean temperature, and temperature annual range, along with 6 variables for seasonal or quarterly averages (Table 2). The annual hydric deficit and the index for sugarcane's water necessity criteria are captured by a combination of the temperature bioclimatic variables mentioned above and precipitation bioclimatic variables such as annual precipitation and precipitation seasonality. Although there are mechanistic methods to obtain the annual hydric deficit, such as the Thornthwaite's method and the Camargo's method (Zullo et al., 2018), the SAZ does not specify the methodology used. For this reason, we decided for using the ENM to find the empirical relation between the SAZ criteria and the bioclimatic variable without defining a functional form. Furthermore, this approach contributes to the literature on the use of ENM for modeling land suitability (de Souza and De Marco, 2014; Evans et al., 2010; Trabucco et al., 2010). A principal components transformation (PCT) was implemented to reduce collinearity among the bioclimatic variables under current climate condition (Jiménez-Valverde et al., 2008; Martins et al., 2015). The PCT generated 19 principal components (PC) from which we selected the first PC until we have > 95% of the variation of the original data set (Table 2). In this case, the first 6 PC accounted for > 97% of the variation, thus they are used as the bioclimatic variables in the ENM. For the future climate ENM, the PCT used is the same as derived from the current conditions data set. By using the same PCT, we are ensuring the comparability of current and future climate ENM by assigning the same weight to the bioclimatic variables in each PC used.

By examining the loading factors presented in Table 2 we can associate each PC with climate conditions. PC1 is representing the influence of temperature during cold and dry periods having the largest loading with bioclimatic variables such as Minimum Temperature of Coldest Month, Mean Temperature of Coldest Quarter, and Mean Temperature of Driest Quarter. PC2 has the largest loading for precipitation during driest month and quarter variables, thus we associate PC2 with dry spell. PC3 indicates strong variation in climate conditions throughout the year with variables Temperature and Precipitation Seasonality. PC4 captures the climate conditions during the warmest and wettest period by the loading with Precipitation of Warmest Quarter, Precipitation of Wettest Quarter, and Precipitation of Wettest Month. PC5 is related to Precipitation of Coldest Quarter, while PC6 capture daily variation in temperature with the largest loading with Mean Diurnal Range and Isothermality. The relationships above also holds for the analysis of ENM under future climate conditions.

3. Results

3.1. The current climate condition ENM

In our modeling framework, step 1 consisted of developing ENM for the suitability classes as defined in the SAZ using the PCs of bioclimatic variables for the current climate conditions data set. We recognized the existence of many algorithms available to implement ENM and tested three algorithm using the TSS (Allouche et al., 2006). Fig. 2 shows TSS

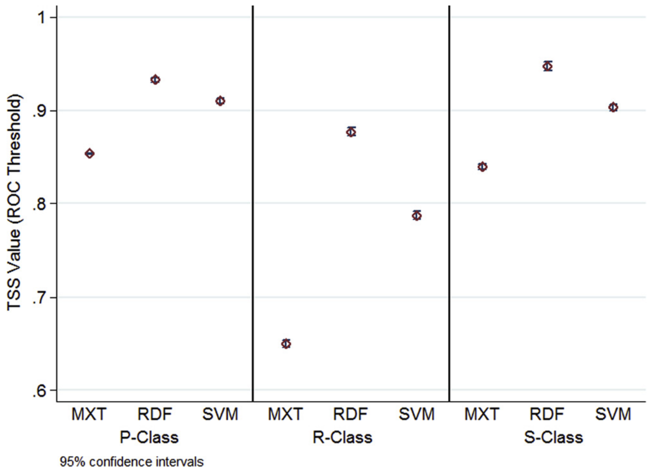

Fig. 2. ANOVA testing of the True Skilled Statistic (TSS) value with receiver-operator curve (ROC) threshold for ENMs developed considering the present climatic conditions with Maxent (MXT), Random Forest (RDF), and Support Vector Machine (SVM) algorithm. Algorithms are compared against each other considering the different SAZ Classes (x-axis), higher value of TSS are preferable to lower values (y-axis). The evaluation used means (mid-points) and 95% confidence intervals (bars).

values for each algorithm and the high scores presented offers support to the use of ENM for modeling land suitability defined by the SAZ. All three algorithms presented a TSS > 0.7, which is considered an excellent fit (Allouche et al., 2006; Garcia et al., 2013); the only exception is the MXT for the SAZ R-Class. The ENM generated using the RDF algorithm (RDF-ENM) had the highest TSS values for all SAZ Classes. Having identified RDF as the best algorithm, we will report the findings obtained using the RDF-ENM.

In step 1, the ENM was developed to identify the areas with climate conditions that were appropriate for each SAZ Class. Because we had 10 random samples for each class when performing the RDF-ENM we obtained 10 prediction maps, which were combined into an ensemble map using the 70% threshold. On the ensemble map (Fig. 3.a – c), we can compare the RDF-ENM results with the SAZ Classes. Areas predicted only by the RDF-ENM are mapped in gray, areas predicted by both RDF-ENM and SAZ are mapped in green, and areas predicted only by the SAZ are mapped in pink. Overall, the models generated satisfactory output. The RDF-ENM for the P-Class produced the most accurate representation of the original data set with 98% of the SAZ areas (Fig. 3.a), while the ensemble for the RDF-ENM S-Class captured 97% of this class area (Fig. 3.c). The ensemble for the RDF-ENM R-Class (Fig. 3.b) estimated 87% of the area defined by the SAZ. A possible explanation for the lower representation of this class is due to the larger area classified as R-Class which covers multiple climatic conditions, thus, creating the potential for many ecological niches and causing the RDF-ENM to underpredict areas.

Whereas the RDF-ENM can successfully predict the areas classified as suitable by the SAZ, the main goal of the ENM is to model the general relationship of climatic conditions and land suitability. Being able to model the general relationship is necessary to project the ENM to future climate conditions. In this approach, we do not incorporate other restrictions on the suitability, such as the prohibition of expansion over natural vegetation and protected areas and the expansion in areas with a slope > 12% because we are assuming they will not change in the future (Manzatto et al., 2009). As a result, the RDF-ENM ensembles overpredicted the range of areas with climatic conditions adequate for the SAZ (illustrated by the presence of gray areas in Fig. 3.a – c).

3.2. Statistical test among ENMs under RCP 4.5 and RCP 8.5

One of our main results is the generation of scenarios of future land suitability using ENM for 17 global climate models under two representative concentration pathways (RCP 4.5 and RCP 8.5). There are significant differences between the RCP 4.5 and RCP 8.5, with the former being an intermediate emissions pathway achieved by implementation of emission reduction policies while the latter RCP is a high emissions pathway assuming no emission reduction policy would be implemented. It is important to highlight that RCP 4.5 assumes that policies and mitigation are in actions (e.g., biofuels use) and mitigation policies will be effective in curbing carbon concentration in the atmosphere (Thomson et al., 2011). Our study considered these differences while modeling sugarcane's land suitability in Brazil in future climate scenarios for 2050.

After the models ran for each RCP, we performed a statistical test on the difference of the mean of the models' results (Table 3). The

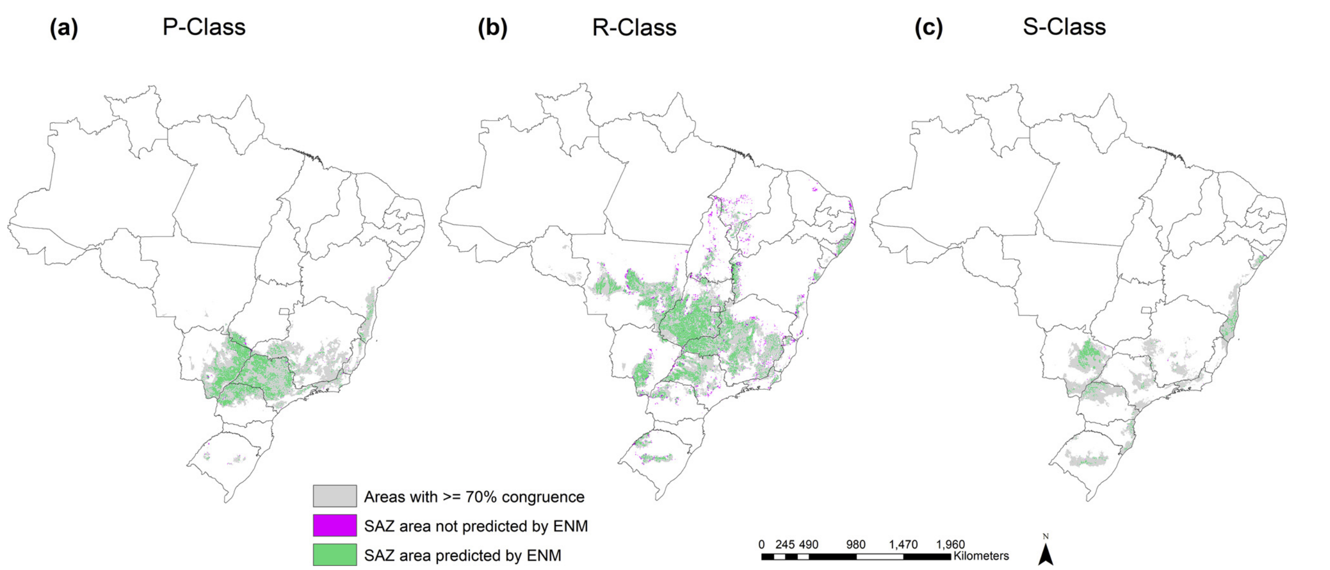

Fig. 3. Ensemble map of the RDF-ENM for each SAZ Class under current climate conditions. The ensemble map uses a threshold of 70% of congruence to indicate areas predicted (gray color). SAZ areas are overlaid, areas in agreement with the ensemble map are green and areas of disagreement are pink. The output from RDF-ENM is classified considering the ROC threshold (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 3
Results for the two-sample *t*-test with unequal variances using Satterthwaite's degrees of freedom test on RDF-ENM outputs under RCP 4.5 and 8.5.

a) The two-sample t-test for the RDF-ENM P-Class under RCP 4.5 and RCP 8.5

Group	Obs	Mean	Std. Err.	Std. Dev.	95% Conf. Interval	
P-Class RCP 4.5	170	4041.647	281.035	3664.252	3486.855	4596.439
P-Class RCP 8.5	170	3367.212	206.961	2698.438	2958.650	3775.773
Combined	340	3704.429	175.211	3230.737	3359.791	4049.068
Diff		674.435	349.018		−12.303	1361.174
Ha: diff ! = 0	Pr(|T| > |t|) = 0.0542					

b) The two-sample t-test for the RDF-ENM R-Class under RCP 4.5 and RCP 8.5

Group	Obs	Mean	Std. Err.	Std. Dev.	95% Conf. Interval	
R-Class RCP 4.5	170	13874.020	613.004	7992.594	12663.890	15084.150
R-Class RCP 8.5	170	12307.580	605.365	7892.988	11112.530	13502.630
Combined	340	13090.800	432.229	7969.915	12240.610	13940.990
Diff		1566.435	861.534		−128.209	3261.079
Ha: diff ! = 0	Pr(|T| > |t|) = 0.0699					

c) The two-sample t-test for the RDF-ENM S-Class under RCP 4.5 and RCP 8.5

Group	Obs	Mean	Std. Err.	Std. Dev.	95% Conf. Interval	
S-Class RCP 4.5	170	1534.924	160.443	2091.921	1218.193	1851.654
S-Class RCP 8.5	170	1371.682	127.297	1659.745	1120.386	1622.979
Combined	340	1453.303	102.349	1887.222	1251.984	1654.622
Diff		163.241	204.808		−239.693	566.175
Ha: diff ! = 0	Pr(|T| > |t|) = 0.4260					

statistical test employed was the two-sample *t*-test with unequal variances with Satterthwaite's degrees of freedom in the STATA 14 I/C software. The *t*-test found no evidence that the results considering RCP 4.5 and RCP 8.5 are different for P-Class and for R-Class with 10% statistical significance (Table 3a and b respectively). A different result was found for the S-Class, which the *t*-test found evidence that the GCM-ENM results are different under RCP 4.5 and RCP 8.5, indicating that both results are significant (Table 3.c). However, both RCP 4.5 and RCP 8.5 ENM results present the trend of area reduction for the S-Class. Based on the *t*-test, the trend area reduction, and the theoretical assumptions of the RCPs, we decided to report the results under RCP 4.5 in the main text. The results under RCP 8.5 are available upon request to the authors.

3.3. The future climate condition ENM

Fig. 4 presents the ensemble results for future sugarcane suitability for areas zoned by the SAZ. We found that only 1.53 Mha out of 63 Mha estimated by the SAZ have a high congruence of prediction, thus considered as suitable by 2050 (Fig. 4). These results are indicative of a potential mismatch of the areas zoned as suitable by the SAZ land use policy and future climate conditions.

The ensemble maps indicate that even areas with the best suitability may be threatened by climate change. By mid-century, the RDF-ENM ensemble predicts only 0.9 Mha for the P-Class out of 18 Mha zoned by the SAZ. Interestingly, this class is concentrated in the center-south of Brazil, a traditional sugarcane producing region. Moreover, the impacts of climate change are even greater for the R-Class with areas predicted to 0.6 Mha by the RDF-ENM (out of 41 Mha), and for the S-Class with only 0.03 Mha (out of 4 Mha). If we assume that Brazil will meet the PDE 2024 with an allocation of 10 Mha to sugarcane – an expansion of 1 Mha over the 2015/16 harvest – and considering only the areas allowed by the SAZ, and consistently predicted on the climate change scenarios, then after meeting the PDE 2024, Brazil would have only 0.53 Mha to expand for the next 25 years.

In the event this scenario is confirmed, an alternative path is the expansion of the sugarcane industry to areas outside of the SAZ. We examined this possibility by expanding the sugarcane land to locations

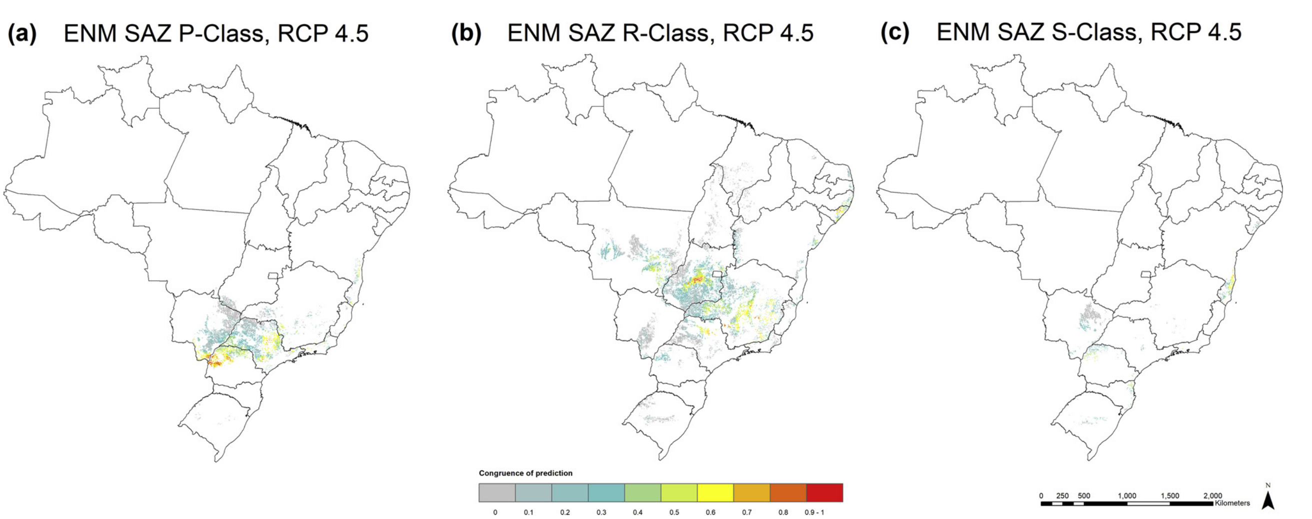

Fig. 4. Sugarcane Agroecological Zoning associated with the ensemble of future distribution of suitable areas for 2050. (a) to (c) are the ensembles of the ENM for each suitability class developed using the 17 GCM under RCP 4.5. Colder colors show low congruence of prediction while warmer colors show high congruence of prediction.

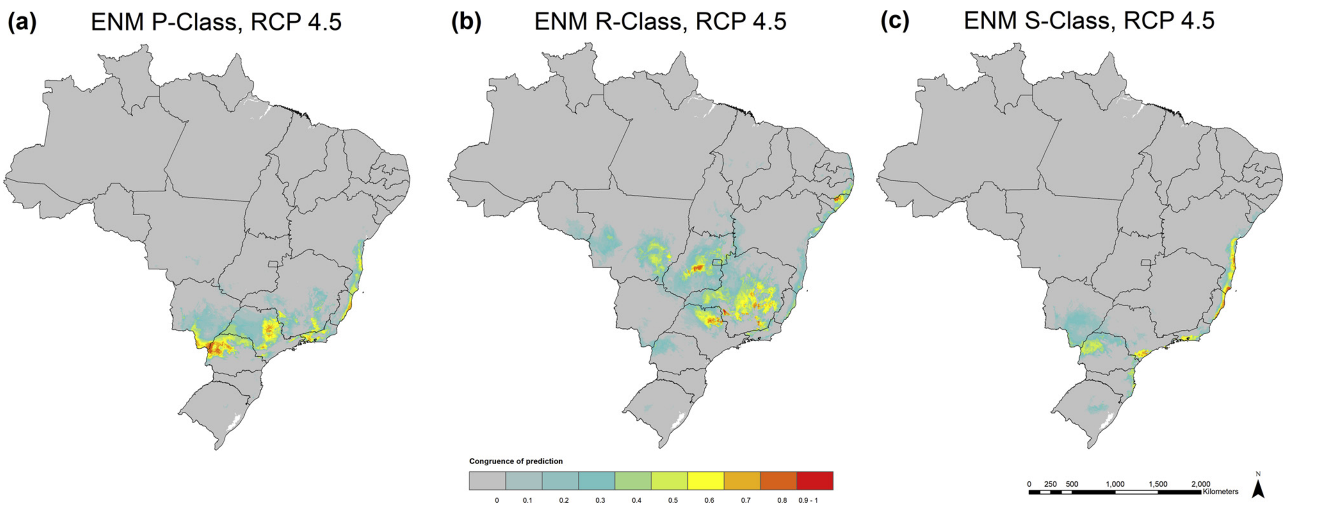

Fig. 5. The probability of future distribution of areas with climatic conditions comparable to the suitability classes developed for the SAZ for 2050. (a) to (c) are the ensembles of the ENM for each suitability class developed using the 17 GCM under RCP 4.5. Colder colors show low congruence of prediction while warmer colors show high congruence of prediction.

not included in the SAZ and consistently predicted as suitable by 2050. The amount of area meeting the criteria rises to 7 Mha (Fig. 5), 1.53 Mha inside the SAZ and 5.47 Mha outside. This enlarged area would be enough to supply the PDE 2024 and future demands. More specifically, Brazil would have 3.2, 2.6, and 1.2 Mha for sugarcane in suitability conditions estimated by the RDF-ENM for the P, R, and S-Classes, respectively. It is important to note that this scenario only considers climate conditions, and it does not incorporate other criteria from the SAZ. Hence, this result should be taken as an unrestricted scenario, whereas the incorporation of other criteria may reduce the amount of area suitable available by 2050.

4. Discussion and conclusion

This paper examined the potential effects of mid-century climate change scenarios to the spatial distribution of zoned areas regarding the Sugarcane Agroecological Zoning. Our models use machine-learning algorithm to establish and project empirical relationship among bioclimatic variables and suitability for sugarcane production. Although not mechanistic as previous research (Jaiswal et al., 2017; Zullo et al., 2018), this approach has the flexibility to identify ecological niche conditions similar to the original SAZ dataset while allowing for analysis of future climate conditions.

When Brazil associated its iNDC with the increase usage of renewable energy provided by sugarcane, it was building upon the promise of 63 Mha zoned by the SAZ and expected abundance of ethanol production due to land availability and expected low prices for the consumers. Traditionally, the sugarcane industry has responded to increase in demand by expanding production area, later followed by improvement of agricultural and industrial processes (Furtado et al., 2011; Goldemberg et al., 2003). The SAZ reinforced this approach of land-expansion first by appointing 63 Mha to sugarcane production during the peak of the expansion boom (Granco et al., 2018; Silva and Peixinho, 2012).

This strategy can be considered a success to stimulating investments and the establishment of more than 100 mills with a large portion of the sugarcane industry expansion taking place in the center-south of Brazil, especially in the states of Minas Gerais, São Paulo, Mato Grosso do Sul and Goiás, which enclosed ~70% of all SAZ areas (Granco et al., 2017; Shikida, 2013; Unica, 2014). It is important to mention that the sugarcane expansion to Goiás, Mato Grosso do Sul, and Minas Gerais was incentivized by low land prices, proximity to São Paulo, and municipality and state-level fiscal incentives (Bergtold et al., 2017; Sant'Anna et al., 2016; Silva and Miziara, 2011; Silva and Peixinho, 2012; Spera et al., 2017). The political and fiscal supports have been justified by the economic development that the sugarcane industry may bring to rural counties. Recent studies have found a positive socio-economic development of the counties hosting the industry and also an indirect positive effect on the GDP per capita of the neighboring counties due to industrial employment and dynamism of local and regional economic activities (Gilio and Moraes, 2016; Moraes et al., 2016).

However, these positives effects are associated with the success of the industry which on itself is not guaranteed. In recent year, more than 79 mills applied for judicial restructuration or bankruptcy between 2008 and 2015 (Batista, 2016; Santos et al., 2016) which represents a severe loss of capital. Nevertheless, the negative consequences of mills closure have many other aspects than the loss of capital or investments. For instance, from 2008 to 2016 there has been a lay-over of 40% of workers in the center-south region (Center for Advanced Studies on Applied Economics (CEPEA), 2018), and news showing lines of unemployed workers, closure of business, and even riots and violence accumulate in the region (Batista, 2016; Globo Rural, 2013; Santos et al., 2016). The leadership of the sector has pointed out the main reasons to be the high production cost due to climatic conditions and low economic margins due to governmental intervention in the fuel market (Globo Rural, 2013).

The mismatch between the expectation of the growing conditions as set by the SAZ and the potential future conditions may harm the industry long-term success. In an extreme scenario that loss of suitability equals crop-failure, Brazil would face challenging times – there would be almost no increase in ethanol production due to lack of area for expansion but the demand would continuous to increase, resulting in lack of fuel and high ethanol prices. This situation would resemble the supply-crisis of the end-1980s which almost destroyed the consumers' trust in the ethanol fuel and industry (Soccol et al., 2005), although the reasons behind each supply-crisis are different.

The use of 17 GCMs and the ensemble analysis represents an additional step to incorporate climate uncertainty into sugarcane's potential to supply green energy to Brazil and the world. The ensemble presents a treatment of uncertainty that is comprehensive and cautionary. It is comprehensive because accounts for 17 GCM present in the IPCC 5, and cautionary because establishes a 70% threshold for high-congruence (Rosenzweig et al., 2014). In our future climate conditions models, we identify a potential for a severe reduction of areas with climatic conditions suitable for sugarcane production. When considering the PCs used to model the SAZ's suitability classes, bioclimatic variables related to temperature and precipitation during cold and dry month/quarter had major loading factors in 4 out 6 PCs. Low precipitation during driest quarter might prompt the use of irrigation while low temperature and precipitation can promote frost. Zullo et al. (2018) identified the increase of areas where irrigation is recommended and risk of frost under future climate conditions. In our models, such areas would not be classified as suitable because the SAZ excludes areas where irrigation is recommend (Manzatto et al., 2009). Our models also corroborate the findings of a south-north gradient of climate conditions for sugarcane (Jaiswal et al., 2017). While Jaiswal and collaborators estimated sugarcane yields, we are analyzing the climatic conditions to sustain the SAZ suitability guidance. Therefore, our model is limited to the empirical relationship among bioclimatic variables and the areas zoned by the SAZ (Fig. 1), and by sugarcane production technology. With this information, the industry can plan adaptation strategies that will lead to long-term success.

Although Brazil is a leader in sugarcane development technology with 500+ new varieties developed over the last decades, it is important to highlight that a maximum of six new varieties are released each year to the market (BNDES and CGEE, 2008; Melo and Poppe, 2014). The option to not follow an expansion strategy supported by high-technological investments is explained by the costly and lengthy development process which runs close to U$50 million and between 10–15 years of experimental clone testing resulting in a low number of new varieties (Barbosa et al., 2012; Ming et al., 2010; Raboin et al., 2008). The financial and temporal costs are even higher for the development of genetic-modified varieties. To test new varieties of sugarcane the industry needs the approval of three governmental agencies that have distinct requirements and unclear protocols, an arrangement that discourages investments in the sector.

Another obstacle to the adoption of new varieties is the sugarcane field renewal process. As a semi-perennial crop, sugarcane field renewal (planting of new varieties) is done in approximately 15–18% of the planted area, requiring about five to six years for complete variety change (Centro de Cana, 2018). Therefore, today's development of new varieties would only be available by the end of Brazil's intended protocol in 2030 and at least another five years to replace the old varieties. In addition, sugarcane producers can be considered more traditional and resistant to invest in a new variety that will be in the field for 7–8 years when compared with farmers that produce annual crops like soybeans. Thus, efforts to mitigate the negative impacts will involve a combination of public and private efforts not only in the development of more productive, drought and disease resistant varieties but also in the development of new management practices and investment in irrigation infrastructure (Jaiswal et al., 2017; Leal et al., 2013; Marin et al., 2016, 2013; Zullo et al., 2018).

The ENM implemented in this research are useful models to understand the potential mismatch of present and future suitability and to start a discussion on the need to invest in technology and management to adapt the sugarcane industry to climate change. The information presented here represents a first step in the treatment of this uncertainty by dealing with 17 GCMs and presenting a large-scale result that calls attention to the strategy of area-expansion instead of a strategy of closing yield-gaps, sugarcane variety development, and management. For the information generated by ENM to have practical applications in guiding the development of new sugarcane varieties, more research is needed on isolating the uncertainty of each bioclimatic variable and GCM in the definition of suitability, as well as, updating the base knowledge used to develop the SAZ. The effect of technological advancements in agricultural production are remarkable and should be incorporated when analyzing longer time-period.

Even though we focus on the SAZ policy, the modeling framework and findings concerning land use and climate change policy presented in this research are applicable to other cases worldwide. The incorporation of climate change scenarios into land use policy is not a common practice yet (Lobell et al., 2008), but current research is proving that it is a pressing need (Berry et al., 2006; Jaiswal et al., 2017; Machovina and Feeley, 2013; Olesen and Bindi, 2002; Rosenzweig et al., 2014; Schlenker and Lobell, 2010; Zullo et al., 2018). Indeed, agricultural land use zoning may suffer from a lack of adaptive capability given the institutional processes needed to establish and/or update land use policies (Pettersson and Keskitalo, 2013).

Brazil has achieved an exceptional development in its energy matrix and the SAZ represents an active land use policy contributing to the sustainability of the sugarcane industry. However, the SAZ is only one step in the roadmap of decarbonization (Rockström et al., 2017). Brazil's long-term intended contribution (iNDC) protocol and the goal of becoming a renewable energy leader will require resilient actions from both the public and private sectors in the short-term to overcome the negative impacts of future climate change. The cost of failure is to lose the trust of the sugarcane industry in the land use policy, thus increasing the pressure to expand to areas outside of the SAZ what jeopardizes the zoning efforts to sustain food security and biodiversity conservation, and Brazil's iNDC goals.

Declarations of interest

None.

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