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"Luiz de Queiroz" College of Agriculture

Sugarcane yield gap in Brazil: a crop modelling approach

Leonardo Amaral Monteiro

Thesis presented to obtain the Doctor degree in Science.
Area: Agricultural Systems Engineering

Piracicaba
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I would like to dedicate this Thesis for my family

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"Your work is going to fill a large part of your life, and the only way to be truly satisfied is to do what you believe is great work. And the only way to do great work is to love what you do. If you haven't found it yet, keep looking. Don't settle. As with all matters of the heart, you'll know when you find it."
(Steve Jobs)

CONTENTS

RESUMO

Quebra de produtividade (*Yield Gap*) da cana de açúcar no Brasil: uma abordagem baseada em modelo de simulação de culturas

Atualmente, a cana de açúcar ocupa uma área de aproximadamente 10 milhões de hectares, revelando um pronunciado avanço dos canaviais para regiões marginais, onde anteriormente predominavam os cultivos de grãos e pastagens. Assim, os objetivos deste estudo foram calibrar e avaliar um modelo de estimativa da produtividade de colmos da cana de açúcar em 12 locais, sob elevado padrão tecnológico e operacional de cultivo; avaliar o desempenho de um sistema de dados meteorológicos em *grid* (NASA/POWER, 1°x1°) para incrementar a densidade espacial de estações meteorológicas no Brasil para serem empregados em modelos de simulação de culturas; e mapear, a produtividade potencial (Yp), a produtividade obtida pelos produtores com elevado nível tecnológico (Ybf) e a produtividade real média (Yavg) de colmos no Brasil, para, posteriormente, determinar a quebra de produtividade da cana de açúcar decorrente do déficit hídrico (YG_{WD}) e do manejo da cultura (YG_{CM}), a fim de indicar estratégias para um cultivo mais sustentável. O modelo agrometeorológico de estimativa apresentou desempenho satisfatório na simulação das produtividades, tanto na fase de calibração como na validação. A produtividade estimada na calibração foi de 81.9 Mg ha^{-1} enquanto que a observada foi 82.3 Mg ha^{-1}. Na validação, a produtividade estimada foi 82,9 Mg ha^{-1} e a observada foi 86,9 Mg ha^{-1}. Esses resultados sugerem a possibilidade do emprego desse modelo para a estimativa da produtividade da cultura da cana-de-açúcar, principalmente em termos de planejamento agrícola em média e grande escalas. O sistema NASA/POWER apresentou desempenho satisfatório em relação às variáveis meteorológicas que controlam a Yp (radiação solar e temperatura do ar). Por outro lado, embora os totais anuais de precipitação tenham sido bastante semelhantes, a precipitação apresentou coeficientes estatísticos apenas razoáveis, principalmente para aplicações em modelos de simulação da produtividade (R^2 = 0,60 e MAPE = 233,4%), sendo sugerido, portanto, o uso de dados dessa variável provenientes de estações pluviométricas locais. Na grande maioria dos locais avaliados o erro percentual da produtividade potencial variou entre ±15%, enquanto que a produtividade atingível foi superestimada em 14% quando esta foi estimada com os dados de precipitação do sistema NASA/POWER. Por outro lado, quando os dados de precipitação foram modificados pelos dados de estações pluviométricas da ANA, houve apenas 5% de superestimativa da produtividade. Por fim, foram geradas 259 estações meteorológicas virtuais com os dados do sistema NASA/POWER e a precipitação das estações pluviométricas da ANA. Posteriormente, os *yield gaps* por efeito do déficit hídrico e do manejo da cultura foram determinados. Os resultados indicaram que o principal fator restritivo da produtividade da cana de açúcar no Brasil é o déficit hídrico (74% do YG total), enquanto que as práticas de manejo da cultura sub-ótimas contribuem com 26% da quebra total. Isso contribuiu para um melhor entendimento dos aspectos que afetam a produção de cana de açúcar em diferentes regiões brasileiras, sendo, portanto, possível se delimitar estratégias, como o uso de cultivares tolerantes à seca, a irrigação e a descompactação dos solos, que tornem a cultura mais resiliente e produção canavieira mais eficiente e sustentável.

Palavras-chave: *Saccharum spp*; Produtividade potencial; Produtividade atingível; Produtividade média; Déficit hídrico; Manejo agrícola; Sustentabilidade

ABSTRACT

Sugarcane yield gap in Brazil: a crop modelling approach

Currently, the cropping area is around 10 million hectares, in which the sugarcane fields are expanding for marginal regions, mainly where grains and pasture were previously cultivated. From that, the objectives of this study were: to calibrate and evaluate a sugarcane yield model using data from 12 fields conducted under high technology field conditions; to evaluate the performance of a gridded system (NASA/POWER) to increase the spatial density of the weather stations in Brazil, to be employed as input data of crop simulation models; to map, in micro-region scale, the potential (Yp), the best farmer's (Ybf) and average actual (Yavg) sugarcane yields in Brazil, in order to determine the sugarcane yield gaps by water deficit (YG_{WD}) and by crop management (YG_{CM}), and to define strategies for a most sustainable sugarcane crop production. The yield model showed a good performance in the yield simulation, during the calibration and validation phases. The estimated yield in the calibration phase was 81.9 Mg ha^{-1} while the observed one was 82.3 Mg ha^{-1}. In the validation phase, the estimated yield was 82.9 Mg ha^{-1} and the observed was 86.9 Mg ha^{-1}. These results suggested that this kind of model can be used for yield estimation, mainly for agricultural planning purposes, at regional and national scales. The NASA/POWER weather data showed a reasonable performance when compared to observed data that control Yp (solar radiation and air temperature). On the other hand, although the annual average rainfall were very similar in all locations evaluated, this variable presented unsatisfactory statistical coefficients (R^2 = 0.60 and MAPE = 233.4%), being suggested, therefore, to replacement of rainfall data from the gridded system by the ones from local rainfall stations (ANA). In the majority of the locations, the percentage errors of Yp were ±15%, while the attainable yield was overestimated by 14% when estimated without replace the rainfall data by the ANA's data. Otherwise, when the rainfall data were modified by the ones from ANA, a better adjustment was obtained, revealing an overestimation of only 5%. Finally, 259 virtual weather stations were generated with NASA/POWER data and rainfall from ANA database to estimate yields. The yield types were spatialized through software ArcGis 9.3® at micro-region level. The yield gaps by water deficit and crop management were determined. It was observed that the sugarcane yield losses in Brazil are mainly caused by water deficit (74% of total yield gap), while 26% was due crop management. These results contribute for a better understanding about the factors that control sugarcane production and, therefore, they can be used to define strategies, such use of drought tolerant cultivars, irrigation, and soil decompaction, to make sugarcane production in Brazil more efficient and sustainable.

Keywords: *Saccharum spp*; Potential yield; Attainable yield; Average yield; Water deficit; Crop management; Sustainability

1 INTRODUCTION

Sugarcane crop is indubitably the main renewable energy source in Brazil, presenting 19.1% of whole primary energy production in the country, while petroleum still represents 41% of total energy sources (BALANÇO ENERGÉTICO NACIONAL - NEB, 2014). During the last four decades, Brazil has been a worldwide leader of sugarcane production. The total area cultivated with sugarcane in 2013 was around 10 million of ha. Other countries with importance for sugarcane production are India, China, Thailand and Pakistan (FAO, 2014). The evolution of Brazilian harvested area and average yield levels are presented in Figure 1.1.

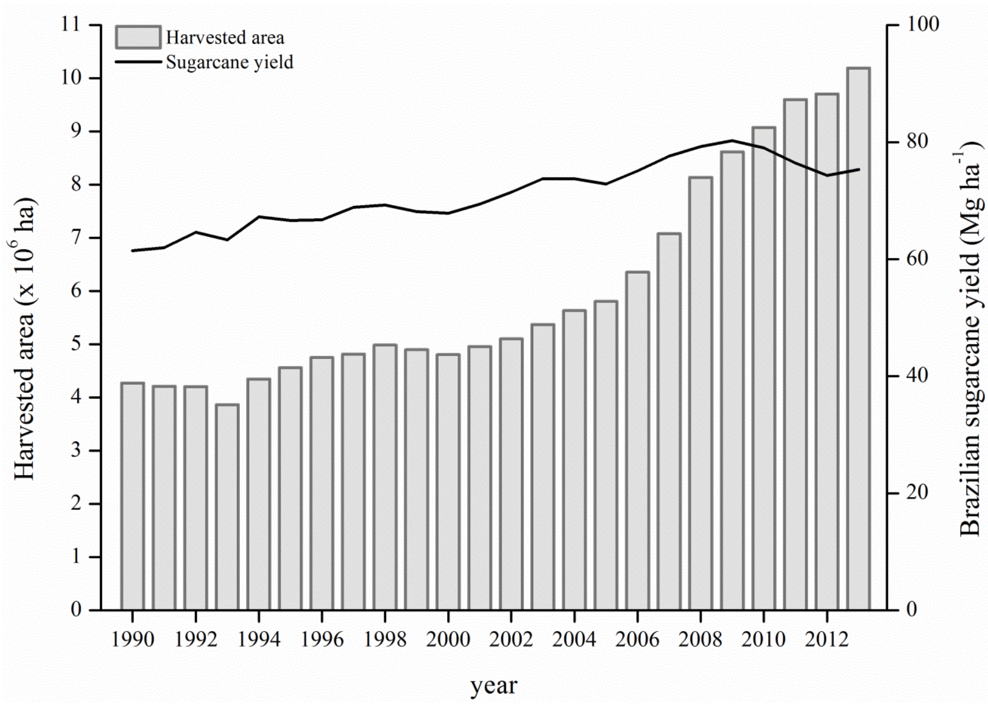

Figure 1.1 - Evolution of the sugarcane yield and harvested area in Brazil
Source: IBGE (2014)

The substantial expansion of sugarcane fields in Brazil started at the beginning of 2000's and was motivated by the high oil prices in the international market and by the introduction of flex-fuel cars in the Brazilian market in 2003 (SAMANEZ et al., 2013). The evolution of the crop is still present and for the growing season of 2014/15 the Brazilian Agricultural Supply Agency (CONAB) estimates an increase of sugarcane area of about 290,000 ha, especially in the regions where grains were previously cultivated, like in central Brazil (CONAB, 2014), and climatic conditions are marginal for this crop.

The evolution of the sugarcane harvested area in Brazil from 1992 to 2012, based on official data from Brazilian Institute of Geography and Statistics (IBGE) (Figure 2), allows to identify the following aspects: a) regions where sugarcane cultivation is becoming more intensive along the years like in northeastern São Paulo; and b) regions where sugarcane is frequently in expansion like in northwestern São Paulo, southern Goiás and northeastern Mato Grosso do Sul. Otherwise, sugarcane fields have been increased also in the north and northeast regions of the country, where irrigation has been required, like in Tocantins (TO) and Bahia (BA) states.

As observed in Figure 1.2, there is a clear expansion of sugarcane areas mainly in central part of Brazil along the last decades, however, the employment of suitable methods to evaluate the impact of weather variability on yield for defining the best potential regions for sugarcane production are still rare.

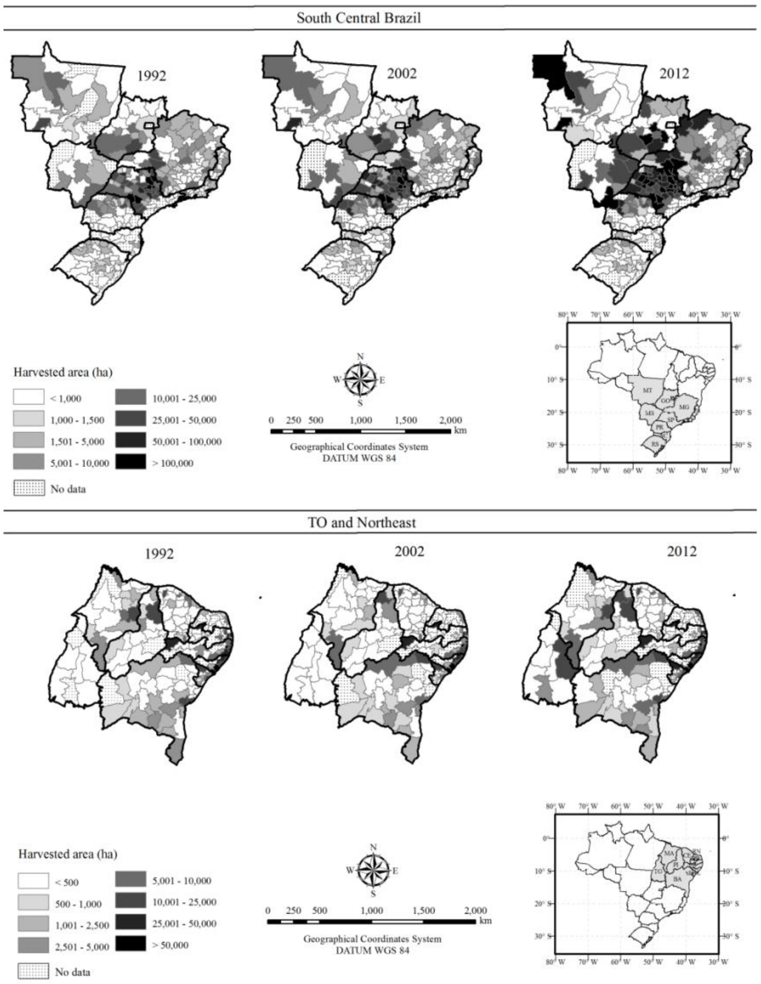

Figure 1.2 - Spatial and temporal variability of sugarcane harvested area in Brazil
Source: IBGE (2014)

Crop simulation models are potential tools which integrate weather, soil, crop genetics and management characteristics, allowing to estimate crop yield and test the interactions among yield factors in a particular system (TSUJI et al., 1998; JONES et al., 2003; WALLACH et al., 2014). These models can also be applied to identify regions with potential for crop production when linked to a geographic information system (GIS), allowing to design strategies for improving yield (FOLBERTH et al., 2012; MONTEIRO; SENTELHAS, 2014).

For suitable use of crop simulation models for agricultural planning purposes, long-term weather data records are required (WHITE et al., 2011). Basically, weather data used as inputs in crop models are: maximum and minimum air temperature, solar radiation and rainfall, while the other variables needed to run the simulations can be derived (WALLACH et al., 2014).

Currently, the access of quality weather datasets is still difficult in many parts of the world. Frequent gaps and measurement errors can be found due mainly to inadequate maintenance of sensors and location of the weather station (HOOGENBOOM, 2000). In addition, this author emphasizes the importance of the dataset to be organized in a standard format in an integrated agrometeorological system and then distributed among users. Indeed, that is the first step to improve the capacity of crop models applications and then generate more confidence on yield forecasting for agricultural activities.

Although in Brazil the spatial density of public conventional weather stations is still low (nearly of 265) (INSTITUTO NACIONAL DE METEOROLOGIA – INMET, 2014), there are some alternatives to increase the potential weather stations for agricultural applications. According to Smith (2000), is of high importance the quality for long-term public datasets with a reasonable spatial density for agricultural optimization and management strategies, which are essential for an efficient and competitive agriculture. Thereby, a suitable alternative to increase the weather stations network is to use gridded databases (WHITE et al., 2011) with satisfactory surface covering, which becomes an useful tool for decision-making systems and planning strategies.

Gridded weather databases (GWD) are systems able to provide observed, interpolated and estimated weather data for agriculture and industry applications. They provides an estimative of long-term data which are based on many sources of data such as satellites, radar imagery, land and ocean surfaces observation, sondes and meteorological ballons (STACKHOUSE, 2010). GWD configures a global coverage in several spatial resolutions (0.5 to 2.5° latitude and longitude grid) and can be employed to filling gaps as well as to create virtual weather stations with long-term weather databases.

With a consistent and long-term weather database is possible to make use of crop simulation models and then determine more efficiently strategies for climatic risk management. In that context, yield gap (YG) calculations has been used as a tool to define the causes of yield break and the agricultural practices to its reductions, such as irrigation, best sowing date, among others (LOBELL et al., 2009).

According to what was previously presented, this study assumes that Brazilian sugarcane sector requires consistent information to improve sustainable production, mainly in the regions to where the crop is expanding, and that the knowledge of sugarcane yield gap in the different regions of the country will help the mitigation of climatic risks by adaption of better crop management practices.

The main objective of this study was to generate sugarcane yield gaps data at national to support sugarcane planning and production and to guide government agencies, agronomists and growers in the adaption mechanisms to improve the efficiency of this crop. For that, the following objectives were addressed:

a) To calibrate and evaluate a crop simulation model to estimate sugarcane yield under operational field conditions;
b) To evaluate the performance of gridded weather database provided by NASA/POWER system when compared to observed data and the impact of its use on sugarcane yield simulations;
c) To estimate sugarcane potential and attainable yield for different Brazilian regions and compare them to the actual data reported by official agencies;
d) Couple the crop simulation model with geographic information system (GIS) for mapping the spatial variability of potential, attainable and actual sugarcane yields in Brazil, and to determine the magnitude of the yield gaps caused by water deficit and crop management.

1.1 Literature Review

1.1.1 General aspects of sugarcane crop

Sugarcane (*Saccharum* spp.) is a crop that belongs to Poaceae botany family. Although the sugarcane origin is not yet clear, the most probable center of origin is southern Asia, more specifically in New Guinea (BARNES, 1964; MOZAMBANI et al., 2006; FIGUEIREDO, 2008).

Sugarcane production is the most ancient economic activity in Brazil. In 1933, was created the Sugar and Alcohol Institute, in order to develop and improve the production. In the beginning of 1970's, due to the first petroleum crisis, Brazilian government launched the "Pro Álcool" program. This program was created to introduce ethanol in the Brazilian energetic matrix, in order to diminish the dependence of the country on fossil fuels (SAMANEZ et al., 2013).

Geographically, sugarcane is cultivated in latitudes ranging between 35° N and S, in humid environments where it is grown mainly under rainfed conditions. When cultivated in sub humid climates, irrigation is required for obtaining satisfactory yield levels (DOORENBOS; KASSAM, 1979).

Sugarcane is classified as a "perennial crop", once the planting is not done every year. The crop remains in the field for five years, in average, sprouting after each harvest (TERAMOTO, 2003). However, this crop can be classified as a "non-perennial crop", since replanting is normally done after five years (SUGUITANI, 2006).

The first cycle after the planting is called "plant cane" (PC). Conceptually, "plant cane" is established by other live cane stalks which contain buds (propagated vegetatively) that will sprout and then generate other plants (JAMES, 2004; SEGATO et al., 2006).

In traditional Brazilian southeastern sugarcane regions, PC is planted at the beginning of the year (January, February and March), and after 15-18 months it is harvested in the next year during the dry season (April to September). There is also the PC planted in September and October, which is harvested after 12 months (PC12). After the first cutting, the next growing cycle is named "ratoon cane" (RC) (CARVALHO, 2009). RC is harvested along the dry season of the year in order to supply mills with raw material for ethanol and sugar production.

The sugarcane is cultivated around the world, under several soil and climate conditions. Table 1.1 presents the cane production, cropping area and yield of the main sugarcane producers around the world. Brazil is the major sugarcane producer, presenting higher harvested area than the other producer countries. The sugarcane yield around the world presents a short range, although some countries such as Australia and South Africa require at least supplementary irrigation to reach acceptable yield levels (INMAN-BAMBER et al., 2012).

Table 1.1 - Overview of the main sugarcane world producers in 2013 and their sugarcane production (10^6 Mg), harvested area (10^6 ha) and average yield (Mg ha^{-1})

Country	Production (10^6 Mg)	Harvested area (10^6 ha)	Average yield (Mg ha^{-1})
Brazil	736.0	9.8	75.1
India	343.7	5.1	67.4
China	124.2	1.8	69.0
Thailand	98.2	1.3	75.5
Pakistan	62.0	1.1	56.4
USA	30.3	0.4	75.7
Australia	24.7	0.3	82.4
South Africa	16.6	0.3	55.3
Total	1800	26.5	70.1

Source: FAO (2014)

In Brazil, almost the totality of sugarcane production is under rainfed system. The state of São Paulo is the main producer, representing around 60% of whole sugarcane production in the country (IBGE, 2014). However, sugarcane fields are expanding to other regions where climate conditions are considered marginal for rainfed crop. As a function of that, efforts have been done and studies being developed in order to increase and encourage the use of irrigation for increasing yield levels, mainly in the drier areas to where the crop is advancing.

1.1.2 Climate and sugarcane production

The sugarcane crop is grown in a large range of environments and therefore under several climates in which the growth, development and production are controlled mainly by solar radiation, air temperature, rainfall, crop evapotranspiration and soil water availability (HUMBERT, 1968; DOORENBOS; KASSAM, 1979). The monitoring of the climatic variables that determining the sugarcane yield is a strategic issue to provide a better understanding of the crop production and then design the decision-making to improve the competitive edge of the sugarcane sector (VAN DEN BERG; SINGELS, 2013).

The water deficit is the most important abiotic stress that controls the capacity of sugarcane fields to achieve high yields. Therefore, the understanding of the water deficit and stalks production relationship configures a key factor to design strategies to reach more suitable yield levels mainly in restricted environments (ROBERTSON et al., 1999).

Furthermore, the development of breeding programs have been supported the obtaining of more adapted sugarcane cultivars allowing the crop expansion in more restrictive environments for sugarcane production. Management practices such as irrigation and employment of cultivars with a moderate drought (INMAN-BAMBER et al., 2012) and thermal tolerance (GREENLAND, 2005; VERÍSSIMO et al., 2012) mainly for frost occurrences can provide a most suitable sugarcane expansion reaching reasonable yield destined for industries. Cardozo and Sentelhas (2013) highlighted that studies to demonstrate the effects of climatic factors on the sugarcane physiological processes are required for a better crop understanding, mainly related to stalks sugar accumulation and crop maturity.

There are many ways to evaluate the relationships between climatic conditions and sugarcane growth, development and production. Currently, field experiments (ROBERTSON et al., 1999; SILVA et al., 2008), remote sensing (RUDORFF et al., 2010) and crop simulation models (KEATING et al., 1999; JONES et al., 2003; SINGELS et al., 2008; MONTEIRO; SENTELHAS, 2014) configure suitable alternatives to evaluate those relationships in a given environment. However, the use of crop simulation models is a powerful tool because they allow to evaluate the crop performance under several climatic scenarios, sowing/planting dates, irrigation and fertilization schedules, and management strategies with a relative low costs (HOOGENBOOM, 2000; JONES et al., 2003). The effects of climatic conditions on crop production also can be evaluated in a spatial scale, when crop simulation models are coupled with geographic information systems (GIS) and then provides information that can be employed for strategic planning and best cultivar recommendation in relation to drought and frost occurrences (CUADRA et al., 2012; MONTEIRO; SENTELHAS, 2014).

1.1.2.1 Solar radiation

Agricultural production is largely controlled by solar radiation (SR). SR is the main source of energy for the earth, controlling several processes since the photosynthesis up to general atmosphere circulation (PEREIRA et al., 2002; MAVI; TUPPER, 2004).

SR is the main agrometeorological factor influencing crop water consumption (ALLEN et al., 1998). Therefore, SR measurement becomes essential for monitoring crop water requirements (evapotranspiration) throughout the growing cycle, as well as for designing irrigation strategies to maximize crop yield.

Sugarcane, which is a C4 plant, have showed maximum photosynthetic efficiency reaching 6% of the total incoming solar energy, while for C3 plants this capacity is approximately 4.6% (ZHU et al., 2008).

Under non limiting conditions, sugarcane biomass accumulation capacity depends on the amount of energy intercepted, which is expressed by radiation use efficiency (RUE, g MJ^{-1}) (ROBERTSON et al., 1996). Monteith (1977) characterized RUE as the ration between total biomass produced and total incident radiation. For sugarcane, RUE is influenced by several factors as cultivar, crop type (plant or ratoon canes), crop age, maturity cycle (early, mid and late) and crop management options (e.g. row spacing, plant population, and nutritional status) (ROBERTSON et al., 1996; PARK et al., 2005a). Due to its high efficiency, C4 crops, such as sugarcane, can reach up to 2 g MJ^{-1} under optimum conditions (MUCHOW et al., 1997).

The biomass accumulation in sugarcane is primarily controlled by the amount of the SR intercepted by the sugarcane canopy and by the rate of photosynthetic efficiency conversion to dry matter (ROBERTSON et al., 1996); however, sugarcane RUE is not constant along the growth cycle (PARK et al., 2005a; DONALDSON et al., 2008; VAN HEERDEN et al., 2010), mainly under water deficit conditions (ROBERTSON et al., 1999). Many of the sugarcane simulation models have been applied RUE approach to simulate biomass accumulation, despite its variation according to crop management, cultivars and cropping systems (irrigated or rainfed) (PARK et al., 2005b; VAN HEERDEN et al., 2010).

1.1.2.2 Air Temperature

Air temperature, as well as solar radiation, is one of the main environmental factors which drive sugarcane growth and development (DILLEWIJN, 1952). Although there are several references in the literature indicating thermal limits for sugarcane growth (FAUCONNIER; BASSEREAU, 1970) it is difficult to define them exactly due to the large range of environmental conditions where the crop is cultivated.

In general, maximum growing rates are reached at temperatures between 30 and 34 °C. On the other hand, under temperatures higher than 35 °C and lower than 20 °C, growing rates decrease significantly (MARIN et al., 2009). According to Liu et al. (1998), the minimum base temperature to simulate the sugarcane phenological development can ranges considerable due the large range of crop varieties and diversity of climatic conditions where it is cultivated. Doorenbos and Kassam (1979) and Barbieri et al. (1979) suggested as minimum base temperature for sugarcane growing and biomass accumulation between 16 and 18 °C. Minimum base temperature for leaf emergence reported by Inman-Bamber (1994) for Australian NCo376 and N12 cultivars was 10 °C. Bacchi and Souza (1978) reported 19 °C as base minimum temperature for Brazilian cultivars. DSSAT/Canegro crop simulation model (INMAN-BAMBER, 1991; SINGELS et al., 2008) simulates the sugarcane growth and development as a function of thermal-time accumulation approach, in which the minimum base temperature for leaves and tillering, respectively, are 10 and 16 °C for the NCo376 sugarcane variety, similar to what is considered by APSIM-Sugarcane (KEATING et al., 1999), which considers 9 °C as the minimum base temperature throughout the sugarcane growing cycle. For some Brazilian sugarcane cultivars, Marin and Jones (2014) found a base minimum temperature of 9.4 °C. These results presented above showed that the minimum air temperature for sugarcane growth and development presents a large range which is strongly dependent of the cultivar and physiological process considered.

Alexander (1973) highlighted the importance of seasonal temperature variation for sugarcane, once under low temperatures before harvest the metabolic activity is reduced and an increase of sucrose accumulation on millable stalks occurs. According to Cardozo and Sentelhas (2013), the reduction of air temperature can induce the sugar accumulation on the stalks, which is important for the producing regions in southern Brazil, mainly in Paraná state, where this is the major environmental stress for ripening process.

Greenland (2005) reported a minimum air temperature for sugarcane plant death around -5 °C. APSIM-Sugarcane model (KEATING et al., 1999) also employee minimum air temperature in which the leaf area index is reduced in 10% for each day with air temperature below 0 °C and lead to death canopy when the temperature achieve -5 °C.

Based on these evidences regarding the effect of low temperatures on sugarcane growth, Monteiro and Sentelhas (2014) suggested a reduction yield frost factor when modeling the sugarcane yield for the state of São Paulo, Brazil, based on the probability of frosts determined by Astolpho et al. (2005).

1.1.2.3 Water responses and requirements

In several regions around the world, sugarcane is grown under rainfed conditions and therefore the water availability becomes a limiting factor for this crop to reach high yield levels (INMAN-BAMBER; SMITH, 2005). It is well known that sugarcane fields require a large amount of water during the growing season. According to Doorenbos and Kassam (1979), the regions for sugarcane production would provide annually water amounts between 1500 to 2500 mm. However, in the main Brazilian regions this amount of water is lower than 1500 mm and the average sugarcane yield is 75.1 Mg ha^{-1} (Table 1.1). Therefore, this highlighted that the rainfall distribution is more important than properly the amount of water along the crop cycle.

In Brazil, sugarcane plantations are mainly cultivated under rainfed condition, which makes the water deficit the main factor to reduce yields. According to Robertson et al. (1999), a higher impact of water deficit (WD) on final stalk yields occurs during the mid-season, when canopy is well established and water requirements are very high. Monteiro and Sentelhas (2014) established a relationship between average sugarcane yield break and water deficit for the state of São Paulo, Brazil, and found a rate of reduction of 11.2 Mg per each 100 mm of water deficit. This result agrees with those obtained by Tilley and Chapman (1999) in Australia, which ranged from 10 to 15 Mg for each 100 mm of water deficit.

Moderate water deficit periods are desirable in the end of the crop cycle because the stress contributes for sugar accumulation in the stalks (ALEXANDER, 1973; CARDOZO; SENTELHAS, 2013). Inman-Bamber (2004) and Scarpari and Beauclair (2004) reported that a water deficit of 140 mm previous to the harvest is enough to achieve a satisfactory sucrose storage in the millable stalks.

The water consumption by sugarcane depends basically of the weather conditions and the phenological phases of the crop. The general sugarcane phenological phases are shown at Figure 1.3.

Other factors affecting sugarcane evapotranspiration are maturity cycle, cultivar, soil physics characteristics and irrigation strategies.

A compilation of sugarcane water consumption or maximum crop evapotranspiration (ETc) reported around the world, for different crop types (plant and ratoon cane) is presented in the Table 1.2.

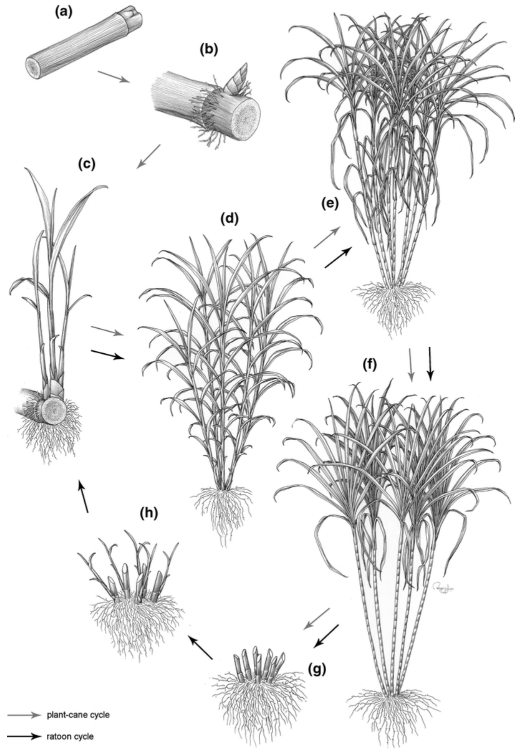

Figure 1.3 - Sugarcane phenological phases and cycles (plant and ratoon). (a) Stalk pieces used in planting; (b) beginning of bud sprouting and rooting; (c) Tillering initiation; (d) Intense tillering; (e) Beginning of maturation; (f) Millable stalks presenting optimum sucrose concentration; (g) Harvesting; (h) ratoon sprouting
Source: Chiavegatti-Gianotto et al. (2011)

Table 1.2 - Water consumption (ETc) of sugarcane crop in different regions around the world

Growing cycle	ETc			Country	Reference
	Min	Avg	Max		
RC	1.9	4.0	6.3	Brazil	Souza et al. (1999)
PC	-	2.7	-	Brazil	Gava et al. (2011)
PC*	-	3.2	-		
RC	-	2.5	-		
RC*	-	3.0	-		
RC	1.2	4.7	7.5	Brazil	da Silva et al. (2012)
2^{nd} and 3^{rd} RC	1.1	4.5	7.8	Brazil	da Silva et al. (2013)
CP	-	3.2	-	Brazil	Silva et al. (2014)
RC	-	3.0	-		
PC*	-	4.0	-	South Africa	Olivier and Singels (2003)
RC	-	2.5	-		
RC	-	2.1	-		
RC	-	5.5	-	Australia	Inman-Bamber and McGlinchey (2003)
RC	-	5.2	-	Swaziland	
RC	2.0	-	6.0	Thailand	Watanabe et al. (2004)
RC	-	8.0	-	Australia	Inman-Bamber and Smith (2005)
RC	-	7.0	-	Swaziland	
PC and 1^{st} RC	0.5	5.0	8.6	USA	Anderson et al. (2015)

PC is plant cane; and RC is ratoon cane

1.1.3 Crop simulation models

Due to high complexity of agricultural systems, the researchers developed simplifications in order to study the behavior of the biological processes, through simulation models (TSUJI et al., 1998; HOOGENBOOM, 2000). Therefore, crop simulation models are a simplification of real systems.

Due the increasing demand for an efficient food production, the identification of regions with high production capacity in order to supply the demands is becoming more and more necessary. For that, crop simulation models have been developed to evaluate crop responses to environmental conditions (MIGLIETTA; BINDI, 1993). So, they have been applied to test the interactions among weather, soil and crop characteristics and estimate crop yield (TSUJI et al., 1998; JONES et al., 2003; WALLACH et al., 2014).

Another important aspect of crop models is that they have been also employed as a complementary tool for classical experimental research, once it is possible to simulate, with reduced costs, several experimental designs and test performance of crop cultivars in a variety of environments and management options, such as fertilization and irrigation schedules (HOOGENBOOM, 2000; JONES et al., 2003).

Currently, crop models can be classified according to the approach employed to describe the crop process and their relationship with the environment as follows: “empirical”, “mechanistic” and “statistical” models (PARK et al., 2005a; RAES et al., 2006). There are also the hybrid crop models, which add physiological processes with empirical equations. Crop simulation models can also be distinguished between “crop-weather analysis model” and “empirical-statistical models” (BAIER, 1979).

Hoogenboom (2000) suggested the following model classification: a) deterministic models, when an exactly calculation or prediction is calculated by stochastic processes and probabilistic results are obtained; b) mechanistic models, when many crop process are described through mathematic equations that determine crop growth and development; and c) functional models, including simplified equations and empirical relations that represent an agricultural system.

1.1.3.1 Sugarcane crop simulation models

Sugarcane yield models have been developed for a large range of purposes since from the basic and investigative research in which aspects related with crop growth, yield and water relations are tested under many environmental field designs (ROBERTSON et al., 1999; INMAN-BAMBER et al., 2012) until operational making systems where crop simulation models can be coupled in a geographic information system (GIS) giving a spatial overview of crop yield in a regional or national scale (MONTEIRO; SENTELHAS, 2014).

The most popular sugarcane simulation models used by the scientific community are Canegro (INMAN-BAMBER, 1991; SINGELS et al., 2008), included on *Decision Support System to Agrotechnology Transfer* (DSSAT), and APSIM-Sugarcane (KEATING et al., 1999), available at *Agricultural Production System Simulator* (APSIM).

Initial efforts were done to develop a sugarcane growth model which had origin in the early of 1970's through the equations to estimate crop photosynthesis and respiration. DSSAT/Canegro was originated in the early of 1970's, by equations related to photosynthesis and respiration suggested by de Wit (1965) and McCree (1970). Canegro was developed by the South African Sugar Association Experiment Station (SASEX) (INMAN-BAMBER, 1991) to evaluate the best sugarcane planting dates to improve the South African mills harvest efficiency. This model simulates the sugarcane growth, development and production in a daily time-step. Basically, the required input data to run the model simulations are weather data (maximum and minimum air temperature, solar radiation and rainfall), detailed soil characteristics (layer depths, soil moisture at field capacity and wilting point, root growth factor, saturated hydraulic conductivity, bulk density, organic carbon and texture characteristics), cultivar characteristics and crop management. Total sugarcane biomass accumulation is driven by the photosynthetic active radiation conversion efficiency (PARCE, g MJ^{-1}), photosynthesis, and respiration approach (INMAN-BAMBER; THOMPSON, 1989). The standard sugarcane cultivar in the model is a South African sugarcane cultivar "NCo376", which suggests a model calibration at the cultivar level for sugarcane performances analysis. Canegro simulates phenological phases based on thermal-time approach, which for NCo376 sugarcane cultivar admits 10 °C as the minimum base temperature for leaves emergence, tillering and canopy expansion. Biomass partitioning above-ground and roots biomass throughout cycle are driven by a non-linear function that is weighted by the solar radiation and air temperature (SINGELS et al., 2008).

The Canegro has been employed under Brazilian conditions for cultivar parameters calibration (MARIN et al., 2011; NASSIF et al., 2012), impact of future climate changes scenarios in the sugarcane yield and water productivity (MARIN et al., 2013), to determine the climatic risk associated with the crop water deficit and the most suitable saving irrigation schedules in the operational sugarcane fields (VIANNA; SENTELHAS, 2014).

The APSIM-Sugarcane is a dynamic simulation model that simulates in a daily time-step the sugarcane growth, development and production as a function of the weather, water and nitrogen conditions. APSIM-Sugarcane was developed from 35 datasets distributed along Australia, Hawaii, South Africa and Swaziland, in order to cover a large range of environments where sugarcane is grown. The five phenological stages (planting, sprouting, emergence, beginning of stalk growth and flowering) (INMAN-BAMBER, 1994; ROBERTSON et al., 1998) are simulated considering a thermal-time approach, in which the minimum base temperature is 9°C, optimum and maximum air temperatures are, respectively, 32 and 45 °C (KEATING et al., 1999). Additionally, if daily minimum air temperature reaches at least 0 °C, the LAI is reduced in a rate of 10% per day, while under minimum air temperature below -5 °C, the plants are death. The sugarcane total biomass production follows the radiation use efficiency (RUE, g MJ^{-1}) approach, and after this biomass is reallocated in stalks and sucrose yields.

APSIM-Sugarcane application in Brazil is recent and has been employed to simulate sugarcane yield under different fertilization (COSTA et al., 2014) and to verify the effect of trash management on yield (MARIN et al., 2014).

Another crop simulation model, derived from agro-ecological zone model, that has been applied successfully to estimate the sugarcane yield is based on the Doorenbos and Kassam (1979) approach. This model has a generic approach, composed by two modules. The first calculates the potential yield (Yp) according to de Wit (1965) approach, in which solar radiation, air temperature and photoperiod control the gross biomass production. Corrections coefficients for leaf area index (C_{LAI}), crop respiration (C_{resp}) and harvest index (C_{HI}) are added in the equation according to the target crop and, therefore, is taken the potential stalk yield in terms of dry biomass production. Finally, to estimate the potential millable stalk yield, the stalk water content (C_{WC}) is added. The second module was designed to estimate the attainable yield (Yatt) by a multiplicative approach, in which the relationship between the relative yield depletion (1 – Yatt/Yp) and the relative crop water deficit (1 – ETa/ETc) is weighted by crop response factor to water deficit factor (ky), applied for each sugarcane phenological phase (MONTEIRO; SENTELHAS, 2014). This model, commonly named as FAO model, can provide a range of applications due the low input data required, mainly in terms of soil characteristics and genotype parameters, which make it of high potential for operational use, for local to national scale, when properly calibrated.

Among the applications of FAO model under Brazilian conditions the main of them are: climate changes impacts on the sugarcane yield in southern Brazil (GOUVÊA et al., 2009); sugarcane crop efficiency (MARIN; CARVALHO, 2012); potential and attainable sugarcane yield zoning and yield gap due to water deficit determination (MONTEIRO; SENTELHAS, 2014).

1.1.4 Use and applications of gridded weather data

Agricultural planning and risk analysis evaluation require access to long-term weather data (BOOTE et al., 1996; SENTELHAS; MONTEIRO, 2009). The same is valid for precise crop yield assessment, which requires high quality weather data, with enough spatial and temporal variability (DE WIT; DIEPEN, 2008).

Many agricultural regions around the world have low spatial density of ground weather stations, which requires, according to Soltani et al. (2000), alternatives for covering these gaps, such as: weather generators, like WGEN (RICHARDSON; WRIGHT, 1984) and SIMMETEO (GENG et al., 1986); and gridded weather datasets, available at websites of different institutions like National Center for Environmental Prediction – Department of Energy (NCEP, http://www.ersl.noaa.gov), Climate Research Unit (CRU, http://badc.nerc.ac.uk/data/cru), WorldClim (http://www.worldclim.org), and Prediction Of Worldwide Energy Resources (NASA/POWER, http://power.larc.nasa.gov).

Typically, these gridded datasets are available at many spatial scales, which can range from 0.5 to 2.5 degree of geographic coordinates covering the entire earth surface. Usually, these data are provided in a daily time step, having all weather variables available.

These gridded weather databases have been employed for national analysis in terms of potential production estimative in food security programs, mainly in developing countries, where ground weather stations are available (FOLBERTH et al., 2012).

White et al. (2011) evaluated the performance of the NASA/POWER system for continental United States and concluded that, even with a relative coarse resolution, the system was able to simulate more accurately the incoming solar radiation when compared to the weather generator WGENR (GARCIA y GARCIA; HOOGENBOOM, 2005). White et al. (2011) also evaluated the air temperature estimated by NASA/POWER and found a high correlation for maximum and minimum air temperatures when compared to observed data.

Van Wart et al. (2013) tested four gridded weather data (NOAA, NCEP/DOE, CRU and NASA/POWER) with different spatial resolutions and evaluated their performance for simulating rice yield in China, maize yield in USA and wheat yield in Germany. The results were compared with the yield estimated with ground weather data. The results indicated a better result when air temperature from NOAA and solar radiation from NASA/POWER were used together.

Bai et al. (2010) evaluated the NASA/POWER system to estimate the maize potential yield in the major agro-ecological zones in China. However low correlations were found between the yield estimated with NASA/POWER data and yield estimated with data from conventional weather stations, the authors recommend to coupled air temperature from ground stations with solar radiation from NASA/POWER to increase the weather stations network in order to estimate maize yield gaps in a national scale in China.

1.1.5 Yield gap analysis

Many approaches have been employed to evaluate the deviations of average yields from potential ones. One of them is the yield gap (YG) analysis, which is the difference between potential (Yp) and average (Yavg) yields (LOBELL et al., 2009; VAN ITTERSUM et al., 2013). The YG determination can be useful to quantify the magnitude of water deficit and/or crop management impacts on food and energy production (LOBELL et al., 2009; LICKER et al., 2010; EGLI; HATFIELD, 2014). Moreover, YG analysis also can guide the choice of the better strategies for increasing food security, both for planning actions and decision-making (VAN WART et al., 2013).

When studying YG, the yield concepts must be well defined in order to understand what YG means. Potential yield (Yp) is a yield from a given crop/cultivar well adapted to the environment, which the growth and development are controlled only by the incoming solar radiation, air temperature, photoperiod, CO_2 atmospheric concentration and crop genetics. In other words, all the other factors, such as nutrition, pests, diseases and weeds control, are effectively controlled (EVANS, 1993; VAN INTTERSUM; RABBINGE, 1997). Yp can be estimated by several ways; however, by crop simulation models is the most appropriated method, once Yp is controlled only by the interaction between the genotype and weather conditions (incoming solar radiation, air temperature and photoperiod). Some studies consider field experimental or maximum yield achieved by farmers as Yp; however they cannot represent Yp for a given region since it is almost impossible to reach a perfect crop management throughout the growth period (LOBELL et al., 2009; VAN INTTERSUM et al., 2013).

Under high technological field conditions, the farmers that achieve the yield plateaus can reach around 75 to 85% of the Yp (CASSMAN et al., 2003). Some exceptions can be found in the literature, such as for irrigated maize in Nebraska, USA, in which the yield reached 90% of the Yp (VAN INTTERSUM et al., 2013) and for wheat in India, where the average yield reached 95% of Yp (BRUINSMA, 2003).

The next yield level is named attainable yield (Yatt), which is limited only by water deficit, being also called as water-limited potential yield (LOBELL et al., 2009). It is the potential yield penalized by the water deficit, and thus influenced by soil water availability, rainfall, crop evapotranspiration, and crop response to water deficit (GRASSINI et al., 2015; SENTELHAS et al., 2015). Attainable yield is considered the rainfed yield under optimum crop management.

Below Yatt, there is the best farmer's yield (Ybf), which is the yield achieved by the best farmers of a given region. These farmers conduced their fields under very controlled crop management and high agro-technology. Finally, the average yield (Yavg) is the ones reached by the average farmers, which the crop management is done under average technology employed in the fields. The Yavg depend also on the factors associated to crop management, such as pest, disease and weed control, and soil preparation and fertilization. In conclusion, the final yield obtained in the field will be the result of the interaction of determining, limiting and reducing factors (SENTELHAS et al., 2015) as presented in Figure 1.4. Based on this figure, YG gap can be caused by water deficit and crop management. Usually, the YG for the main crops around the world have been ranging from 20 to 80% of Yp, which varies according to the cultivar, location, cropping systems (irrigated and rainfed) and crop management (LOBELL et al., 2009).

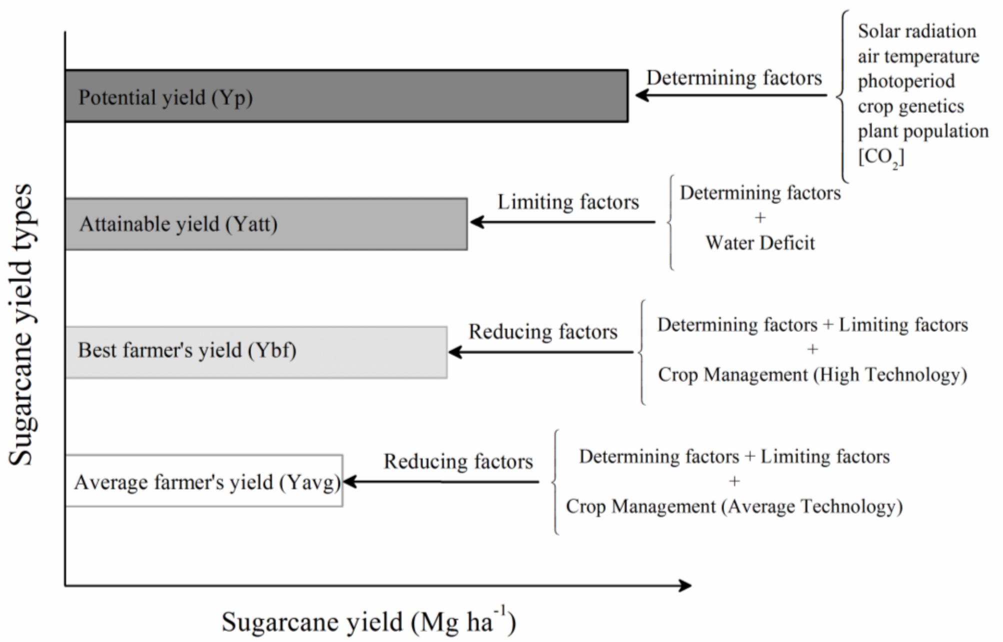

Figure 1.4 - Types of yield and their determining, limiting and reducing factors and yield gaps caused by water deficit and crop management factors
Adapted from Lobell et al. (2009); van Inttersum et al. (2013), and Sentelhas et al. (2015)

Currently, few studies have been developed to investigate and suggest management strategies to decrease the YG in the sugarcane crop production. In South African sugar belt, van den Berg and Singels (2013) employed a process-based crop simulation model to evaluate the sugarcane YG in South Africa. The authors showed that YG can be provoked not only by climatic variability, but also by new pests (mainly sugarcane thrips), inadequate nutrition and crop management.

In Brazil, Monteiro and Sentelhas (2014) employed an agrometeorological model to estimate the potential and attainable yields for the state of São Paulo, in order to determine the YG caused by water deficit, whereas Marin and Carvalho (2012) verified an increase in the sugarcane crop efficiency or a reduction in the YG from the 1990/91 to 2005/06 growing season, which is associated to the improvement in the crop management practices.

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2 CALIBRATION AND VALIDATION OF A SIMPLE AGROMETEOROLOGICAL MODEL TO ESTIMATE SUGARCANE YIELD UNDER OPERATIONAL FIELD CONDITIONS

Abstract

Crop simulation models are important tools employed for evaluating edaphoclimatic and crop management strategies in agriculture, allowing to determine yield and its variability among years and locations through computer systems. The objective of this study was to develop and test a simple sugarcane yield simulation model for operational field conditions in Brazil. The potential yield (Yp) was estimated through solar radiation, photoperiod, and air temperature data, and their relationships with crop physiology. Attainable yield (Yatt) was estimated by penalizing Yp by water deficit, using a multiplicative approach considering the phenological phases and their sensitivity to water deficit, expressed by the crop response factor (ky). The yield data were obtained from 12 sugar mills across the country, considering different climates, soils, crop cycle (plant and ratoon), planting dates, crop systems (rainfed and irrigated) and years, totalizing 206 yield data. Weather data were obtained from the nearest meteorological station of each one of 12 evaluated mills. Soil water holding capacity (SWHC) was determined according to the predominant soil type in each region. Model development and calibration were done using 2/3 of all data and aimed to minimize RMSE and MAPE and maximize R^2 and agreement index (d), all related to harvest index (HI), crop coefficient (kc) and ky adjustments. The validation was done with 1/3 of independent data. In the calibration phase, the estimated cane yield was 81.9 (±22.2) Mg ha^{-1}, while observed cane yield was 82.3 (± 23.9) Mg ha^{-1}, resulting in ME = -0.4 Mg ha^{-1}, RMSE = 13.2 Mg ha^{-1}, MAPE = 12.5%, R^2 = 0.65 and d = 0.70. During the validation phase, similar results were obtained with estimated cane yield of 82.9 (± 27.5) Mg ha^{-1}, while observed was 86.9 (± 30.1) Mg ha^{-1}, resulting in ME = -4.0 Mg ha^{-1}, RMSE = 13.8 Mg ha^{-1}, MAPE = 12.2%, R^2 = 0.79 and d = 0.80. Based on that, the proposed sugarcane yield model was able to capture the yield variability conditioned by weather conditions, crop management practices and crop system type (irrigated and rainfed), allowing its use for operational purposes in computer systems.

Keywords: Sugarcane; Mathematical-physiological crop simulation model; Calibration and validation; Operational data; Potential and attainable yields

2.1 Introduction

Crop simulation models have been applied as a tool for agricultural production assessment, and better understanding of crop responses to different weather, soil and management conditions (TSUJI et al., 1998; JONES et al., 2003; WALLACH et al., 2014).

Crop simulation models can be applied under different spatial scales, from the crop field up to country level, allowing to plan strategies to achieve the most suitable yield plateaus (HOOGENBOOM, 2000). They have been used for testing agricultural options such as performance of new cultivars and their comparison, best sowing dates with lower climatic risks, irrigation schedules and fertilization rates (ASSENG et al., 2013; LEHMANN et al., 2013). For sugarcane, the crop models have been used to support decision-making in order to improve the crop planning and, therefore, to minimize the uncertainties associated with management actions (BOCCA et al., 2015).

There are several crop simulation models developed for sugarcane crop, being DSSAT/CANEGRO (INMAN-BAMBER, 1991; SINGELS; BEZUIDENHOUT, 2002) and APSIM sugarcane (KEATING et al., 1999) the most important. However, these models require several parameters related to genetic, ecotype, cultivar, and management options, which make their use under operational conditions very complex, mainly because of the great variety of cultivars, soils and managements employed by the mills.

Even considering the improvements of technologies, such as processing capacity of computers destined for agricultural simulations, the adoption of process-based models for operational scales is still a challenge (XIONG et al., 2008; BALKOVIC et al., 2013). Such challenge is associated to the fact that crop models are not able to simulate the effects of pests, weeds and diseases on yield (BONDEAU et al., 2007; VAN WART et al., 2013), which become other sources of uncertainties on simulations.

In order to make the use of models simpler, García-Lopez et al. (2014) highlighted the importance of improving methods to estimate crop yields under limited input datasets. Some researchers have indicated reasons for the employment of empirical-based crop models under large scales and planning systems approaches, as describe below:

a) process-based models require a large number of parameters which should be calibrated for specific conditions, increasing the potential of uncertainty and coarse errors when applied in upscaling approaches (CHALLINOR et al., 2009; REIDSMA et al., 2009);

b) processed-based models require a huge set of input data such as long-term weather database at a daily time step, specific soil data with high level of detail for several layers, and specific management factors (sowing/planting date, maturity group, irrigation and plant population), which generally are not available beyond the research stations (RAES et al., 2006; RAMIREZ-VILLEGAS; CHALLINOR, 2012);

c) in the regions with low technological level, the crop model parameters needs to be recalibrated and validated under experimental controlled conditions. However, field experiments are costly and demand labor force for detailed measurements barely available, which increases potential of errors on parameters estimation (JONES et al., 2003; GEERTS; RAES, 2009; FOLBERTH et al., 2012).

Therefore, empirical or mathematical-physiological crop models can be applied as an alternative for evaluations at regional and national levels, since presenting satisfactory results.

In this way, approaches based on the relationship between water deficit and crop yield have shown satisfactory results with enough accuracy to be used for agricultural planning in several regions around the world, where the access to soil and weather databases and local crop parameters calibration are limited (RAES et al., 2006; GARCÍA-LOPEZ et al., 2014).

In the Brazilian agriculture, the crop simulation models, based on simple approaches, have been employed effectively. The reasons for that are associated to limited access to long weather series and to soil profile data. Nevertheless, empirical crop models have been used successfully for agro-climatic zoning (MONTEIRO; SENTELHAS, 2014), technological level evaluation (MONTEIRO et al., 2013), potential impacts of climate change (GOUVÊA et al., 2009; SANTOS; SENTELHAS, 2014), determination of crop efficiency (MARIN; CARVALHO, 2012), evaluation of genotypes tolerance to drought (ANDRIOLLI; SENTELHAS, 2009; BATTISTI; SENTELHAS, 2014), and evaluation of irrigation strategies (GEERTS; RAES, 2009).

Considering the importance of sugarcane crop to the Brazilian agricultural sector and the necessity of a better planning of this crop based on yield estimates at regional and national levels, the objective of this study was to develop and calibrate a simple agrometeorological yield model based on operational sugarcane yield data under irrigated and rainfed conditions, and validate it with independent data in order to evaluate its feasibility for yield estimation in different Brazilian regions.

2.2 Material and Methods

2.2.1 Sugarcane yield model description

The agrometeorological yield model employed to simulate sugarcane yield was developed from the Doorenbos and Kassam (1979) approach and was adapted to operate in a ten-day time step. The model has two modules: one for potential yield (Yp), which is estimated according to de Wit (1965) approach; and another for attainable yield (Yatt), which is estimated by the depletion of yield by the relative crop water deficit (1 – ETa/ETc) of each crop phase, according to crop sensitivity to water stress.

The original approach simulates potential gross production in terms of dry matter (PG, kg DM ha^{-1} $period^{-1}$), which is controlled by incoming solar radiation, air temperature and photoperiod. For agricultural crops, correction coefficients (C_x) are requested to convert PG for the target crop. Considering the difference on PG production under clear and cloudy sky, total potential gross production (PG_{total}) was calculated through the sum of these two conditions (PG_{clear}, PG_{cloudy}, respectively), according to:

$$PG_{total} = PG_{clear} + PG_{cloudy} \tag{1}$$

Furthermore, PG_{clear} and PG_{cloudy} were estimated as a function of average extraterrestrial solar radiation (Qo, MJ m^{-2} $period^{-1}$), effective sunshine hours and photoperiod ratio (n/N), and air temperature (cT_{clear} and cT_{cloudy}), according to:

$$PG_{clear} = (107.2 + 8.604 \times Qo) \times cT_{clear} \times n/N \tag{2}$$

$$PG_{cloudy} = (31.7 + 5.234 \times Qo) \times cT_{cloudy} \times (1 - n/N) \tag{3}$$

where cT_{clear} and cT_{cloudy} are correction coefficients related to photosynthetic efficiency (C4 crops) and influenced by air temperature. Quadratic equations to estimate cT_{clear} and cT_{cloudy} effects can be found in Pereira et al. (2002). For days with average air temperature (Tav) lower than 16.5 ^{o}C, the equations are:

$$cT_{clear} = -9.32 + 0.865 \times Tav - 0.0145 \times Tav^2 \tag{4}$$

$$cT_{cloudy} = -4.16 + 0.4325 \times Tav - 0.00725 \times Tav^2 \tag{5}$$

and for Tav higher or equal to 16.5 °C, they are:

$$cT_{clear} = -4.16 + 0.4325 \times Tav - 0.00725 \times Tav^2 \tag{6}$$

$$cT_{cloudy} = -1.064 + 0.173 \times Tav - 0.0029 \times Tav^2 \tag{7}$$

As mentioned previously, potential yield is calculated in terms of dry matter (Yp_{DM}) through correction coefficients (C_x). These coefficients allow to simulate the effects of leaf area index throughout the crop cycle (C_{LAI}), crop respiration as a function of air temperature (C_{resp}), and harvest index (C_{HI}), according to:

$$Yp_{DM} = \sum_{i=1}^{m} (PG_{total} \times C_{LAI} \times C_{resp} \times C_{HI}) \tag{8}$$

where Yp_{DM} is the potential yield of dry matter (Mg ha^{-1}), Σ is the sum of PG_{total} along the crop cycle, which range between i = 1 until the last day of the cycle (m); C_{LAI} is the leaf area index coefficient, estimated as a function of maximum leaf area index (LAI_{max}) throughout each ten day period; and C_{resp} is equal to 0.6 if average air temperature in each period is lower than 20 °C, or 0.5 if average air temperature is greater than 20°C. C_{LAI} was estimated according to:

$$C_{LAI} = 0.0093 + 0.185 \times LAI_{max} - 0.0175 \times LAI_{max}{}^{2} \quad (LAI \geq 5;\ C_{LAI} = 0.5) \tag{9}$$

Harvest index coefficient (C_{HI}) is given by the ratio between potential millable stalks and total biomass accumulated during the crop cycle. During calibration phase, the harvest index (HI) was determined in order to reach the best statistical coefficients, when comparing estimated and observed yields.

Finally, to convert stalks dry matter yield into fresh matter, a water content coefficient (C_{wc}) was added in the model, to obtain the final potential yield (Yp):

$$C_{wc} = (- 0.01 \times WC) \tag{10}$$

$$Yp = Yp_{DM} \times C_{wc}{}^{-1} \tag{11}$$

where WC is the water content in the stalks, admitted as 80%, as recommended by Monteiro and Sentelhas (2014).

Attainable yield (Yatt) was estimate through a multiplicative model. This model presents a linear relationship between relative yield depletion (1 – Yatt/Yp) and relative crop water deficit (1 – ETa/ETc). This relationship is weighted by the crop response factor to water deficit (ky) of each phenological phase (j), according to:

$$Yatt_n = \prod_{j=1}^{n} \left\{ Yatt_{j-1} \times \left[1 - ky_j \times (1 - ETa/ETc)_j \right] \right\} \qquad (12)$$

where $Yatt_n$ is final attainable yield (Mg ha^{-1}) at the end of crop cycle; Π indicates the productory of equation terms; j represents the crop phenological phases (Table 2.1); $Yatt_{j-1}$ is the yield at the end of the previous phenological phase – in case of first phenological stage, $Yatt_{j-1}$ is equal to Yp; ky_j is the crop response factor; ETa and ETc are the actual and maximum crop evapotranspiration (mm period^{-1}), respectively. Actual crop evapotranspiration (ETa) was estimated based on crop water balance model proposed by Thornthwaite and Mather (1955). ETc was calculated through the product between reference evapotranspiration (ETo) and crop coefficient (kc). ETo was estimated by Penman-Monteith equation (ALLEN et al., 1998):

$$ETo = \frac{0.408 \times \Delta \times Rn + \gamma \times \frac{900}{T + 273} \times U2 \times \Delta e}{\Delta + \gamma \times (1 + 0.34 \times U2)} \qquad (13)$$

where ETo is the reference evapotranspiration (mm d^{-1}); Δ is the slope of vapour pressure curve (kPa °C^{-1}); Rn is net radiation (MJ m^{-2} d^{-1}); γ is psychrometric constant (kPa °C^{-1}); T is average air temperature at 2 m above the ground (°C); U2 is wind speed at 2 m above the ground (m s^{-1}); and Δe is vapour pressure deficit (kPa).

Table 2.1 - Sugarcane phenological phases and their respective duration, in days, for plant and ratoon canes

Phenological phases (j)	Number of days of each phenological phase		
	Plant cane		Ratoon cane
	18 months	12 months	12 months
25% full canopy (1)	40	30	30
25-50% full canopy (2)	40	30	30
50-75% full canopy (3)	20	15	15
75-100% full canopy (4)	50	50	50
100% Full canopy (5)	310	180	180
Senescence (6)	50	30	30
Ripening (7)	30	30	30
Total (days)	540	365	365

Adapted from Monteiro and Sentelhas (2014) and Doorenbos and Kassam (1979)

2.2.1 Operational sugarcane yields

Twelve locations where sugarcane represents an important economic activity were chosen for model calibration and evaluation. Spatial distribution of the operational sugarcane fields is presented in Figure 2.1.

For each operational sugarcane field, weather data (maximum and minimum air temperature, solar radiation and rainfall) were obtained from the nearest meteorological station from the National Institute of Meteorology (INMET). Soil water holding capacity (SWHC) for each location was estimated as a function of each predominant soil type in each location based on the Digitized Soil World Map from FAO (2007) adapted for sugarcane crop, according to Prado (2013). Details of each location such as geographical coordinates, altitude, crop system (irrigated or rainfed), crop type and period are presented in Table 2.2.

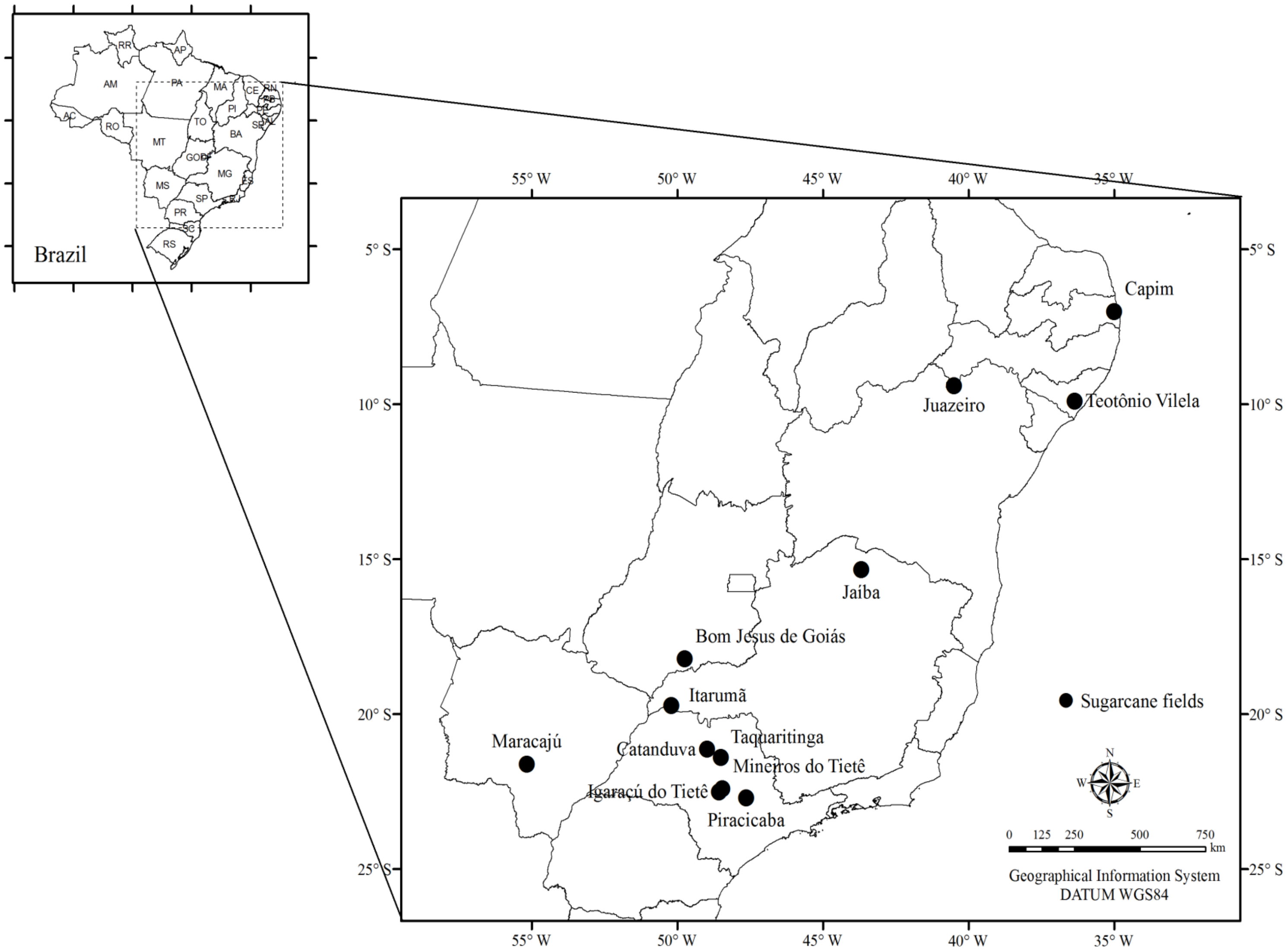

Figure 2.1 - Spatial distribution of operational sugarcane fields in Brazil employed for sugarcane yield model calibration and evaluation

Table 2.2 - Details of the sugarcane operational fields: location; geographical coordinates; altitude; yield levels (TCH, Mg ha^{-1}); soil type; crop system; planting date; crop type; and period used for model calibration and evaluation in different Brazilian regions

Location, state	lat	long	altitude	TCH (Mg ha^{-1})			Soil	Crop	Planting	Crop	Period
	(decimal degrees)		(m)	Avg	Max	Min	type	system	date	cycle	of data
Piracicaba, SP	-22.7	-47.6	546	98	139	55	Ferrasol	R	May to Sep	CP18/RC	2003 to 2011
Igaraçú do Tietê, SP	-22.5	-48.6	498	130	163	90	Nitisol	I	Oct	CP12/RC	2008 to 2012
Mineiros do Tietê, SP	-22.4	-48.5	669	108	130	80	Ferrasol	I	Oct	CP12/RC	2007 to 2012
Taquaritinga, SP	-21.4	-48.5	565	96	140	60	Arenosol	I	June	CP12/RC	2005 to 2010
Catanduva, SP	-21.1	-49.0	293	160	182	107	Nitisol	I	June	CP12/RC	2012
Itarumã, MG	-19.7	-50.2	453	93	104	84	Acrisol	I	June	RC	2002 to 2010
Jaíba, MG	-15.3	-43.7	5	139	180	110	Acrisol	I	June	RC	2010 to 2012
Bom Jesus de Goiás, GO	-18.2	-49.7	619	75	122	38	Ferrasol	I**	Mar to Nov	CP18/CP12/RC	2009 to 2013
Maracajú, MS	-21.6	-55.2	384	84	178	43	Acrisol	R	Mar to Oct	CP18/CP12/RC	2007 to 2012
Capim, PB	-7.01	-35.0	20	42	107	27	Arenosol	I/R	Apr to Dec	CP12/RC	2007 to 2011
Juazeiro, BA	-9.41	-40.5	368	103	146	83	Vertisol	I	April	CP12/RC	2000 to 2012
Teotônio Vilela, AL	-9.90	-36.4	156	103	118	86	Acrisol	I	Feb	CP12/RC	2000 to 2010

lat and long are latitude and longitude; TCH is sugarcane yield in fresh matter, represented by tons of cane per hectare; *Soil classification according to the Digital Soil World Map from FAO (2007). I and R represent, respectively, the irrigated and rainfed crop systems; **saving irrigation which represents an irrigation of 30 mm always when soil available water reached less than 50% of SWHC. CP18 and CP12 represent the cycle of plant cane with 18 and 12 months, respectively; RC is ratoon cane

2.2.2 Model calibration and evaluation

The model was run for each site, considering the following cycles: plant cane of 18 (PC18) and 12 (PC12) months; and ratoon cane (RC) of 12 months. The crop systems corresponded to irrigated and rainfed crops. The parameters related to crop water consumption (kc), crop response to water deficit (ky) and harvest index (HI) were calibrated by "eye fitting" procedure in order to reach the best statistical coefficients, when comparing observed and estimated yields (Figure 2.2).

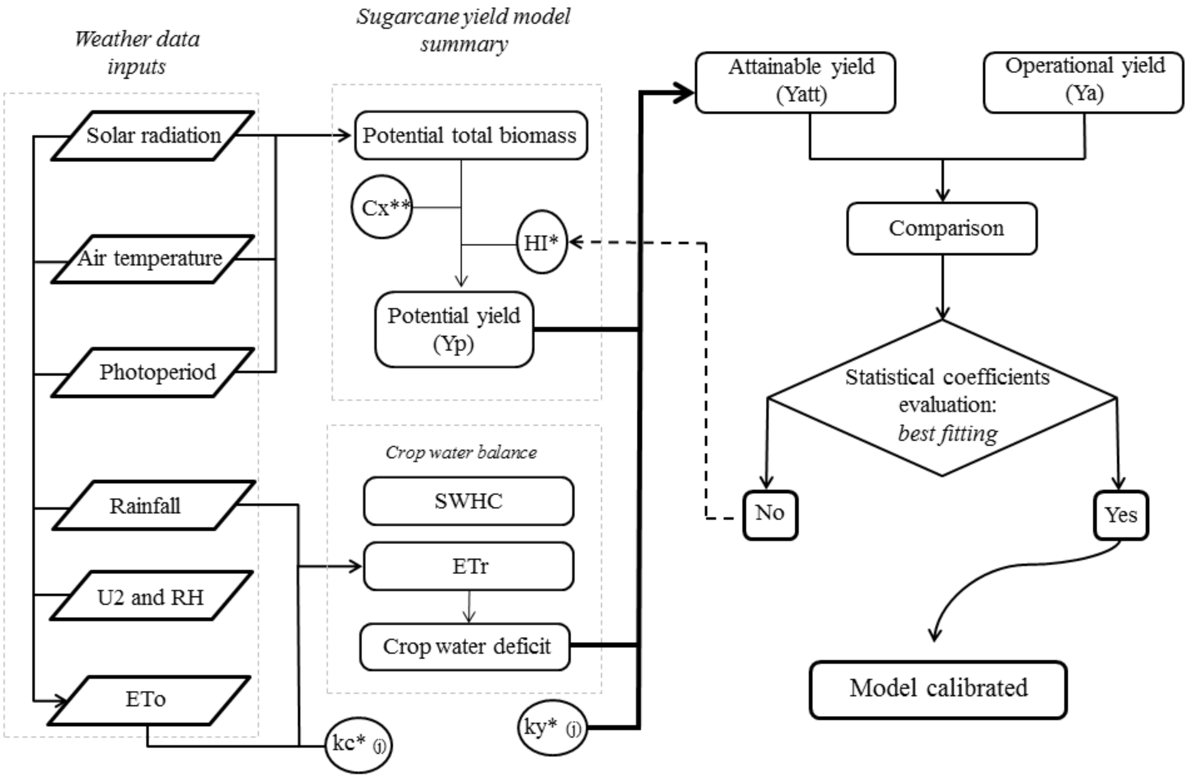

Figure 2.2 - Schematic procedures employed for the sugarcane yield model calibration. *represents the model parameters used for calibration and **are the correction coefficients for the sugarcane total biomass produced

The average harvest index (HI) for sugarcane suggested by Doorenbos and Kassam (1979) ranges from 70 to 80%. For calibration, this parameter was tested for 1% step between 65 and 85%. This process was employed to achieve the minimum root mean square error (RMSE, Mg ha^{-1}), mean error (ME, Mg ha^{-1}) and mean absolute percentage error (MAPE, %) as possible by comparing observed and estimated yields. On the other hand, the calibration intended to maximize the agreement index "d" (WILLMOTT et al., 1985) and the coefficient of determination (R^2) similar to what was done by Xiong et al. (2008) and Marin et al. (2013).

The leaf area indices along the crop cycle (LAI) were those suggested by Monteiro and Sentelhas (2014). The original LAI, kc and ky throughout the growing cycles are presented in Table 2.3. The whole operational yield dataset was composed of 206 yield data. They were randomized and split in three subsets with approximately the same number of samples. For model calibration two sets of data (137) were used, whereas the remained data (69) were used for model validation (Table 2.4).

Table 2.3 - Original parameters employed on the simple agrometeorological model to estimate the sugarcane yield: crop coefficient (kc), crop response factor to water deficit (ky) and leaf index area (LAI) for the different sugarcane phenological phases (j)

Phenological phase (j)	kc*	ky*	IAF**		
			CP18	CP12	RC
25% full canopy (1)	0.40-0.60	0.75	2.5	2.0	2.0
25-50% full canopy (2)	0.75-0.85	0.75	3.0	2.5	2.5
50-75% full canopy (3)	0.90-1.00	0.50	4.5	3.0	3.0
75-100% full canopy (4)	1.00-1.20	0.50	5.0	3.5	3.5
100% Full canopy (5)	1.05-1.30	0.50	6.0	4.5	4.0
Senescence (6)	0.80-1.05	0.50	5.0	4.0	3.5
Ripening (7)	0.60-0.75	0.10	4.5	3.5	3.0

*Sugarcane crop coefficients (kc) and sensitivity water deficit factor (ky) according to Doorenbos and Kassam (1979); **Sugarcane leaf area indices (LAI) for the cycles of plant cane - 18 months (CP18), plant cane - 12 months (CP12) and ratoon cane – 12 months (RC), according to Monteiro and Sentelhas (2014)

Table 2.4 - Number of sugarcane yield data employed for model calibration and validation in different Brazilian regions

Location (state)	Number of data used		Total
	Calibration	Validation	
	Southern		
Piracicaba (SP)	8	3	11
Igaraçú do Tietê (SP)	3	3	6
Mineiros do Tietê (SP)	1	3	4
Taquaritinga (SP)	3	3	6
Catanduva (SP)	1	-	1
Jaíba (MG)	3	1	4
Itarumã (MG)	3	2	5
	Northeastern		
Capim (PB)	10	6	16
Juazeiro (BA)	8	2	11
Teotônio Vilela (AL)	3	3	6
	Central		
Maracajú (MS)	31	14	45
Bom Jesus de Goiás (GO)	63	29	91
Total	137	69	206

2.2.3 Statistical Analysis

For evaluating the performance of the agrometeorological sugarcane yield model, the following statistical indices were used: mean error (ME), root mean square error (RMSE), mean absolute percentage error (MAPE) and agreement index (d), as well as the coefficient of determination (R^2). ME indicates over or under estimation of simulated yields in relation to observed ones; RMSE and MAPE indicate the magnitude of the error, with the first giving the differences in terms of Mg ha^{-1} and the second in percentage. Finally, d, which ranges between 0 to 1, express the general accuracy of the estimates (d = 0, means a total mismatch between simulated and observed yields; whereas d = 1 means a perfect agreement between them), whereas R^2 express the estimates precision. The equations below show how these indices were calculated:

$$ME = \frac{\sum_{i=1}^{n} (Y_{sim(i)} - Y_{obs(i)})}{n} \tag{14}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_{sim(i)} - Y_{obs(i)})^2}{n}} \tag{15}$$

$$MAPE = 100 \times \left| \frac{1}{n} \times \sum_{i=1}^{n} \left(\frac{Y_{sim(i)} - Y_{obs(i)}}{Y_{obs(i)}} \right) \right| \tag{16}$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (Y_{sim(i)} - Y_{obs(i)})^2}{\sum_{i=1}^{n} (\left|Y_{sim(i)} - \overline{Y_{obs}}\right| + \left|Y_{obs(i)} - \overline{Y_{obs}}\right|)^2} \right] \tag{17}$$

where Y_{sim} and Y_{obs} are simulated and observed sugarcane yields, respectively (Mg ha^{-1}); $\overline{Y_{obs}}$ is the average of observed yields; and “i” is the number of yield data used.

2.3 Results and Discussion

2.3.1 Model calibration

The first step for model calibration was to define the best average harvest index (HI) for the data set used in this study, considering different regions, cultivars and harvest seasons. Figures 2.3a and 2.3b shows the variation of RMSE, MAPE, ME, R^2 and d for different HI, ranging from 65 to 85%. The results show a considerably variation of the errors and d index, demonstrating the importance of such parameter for sugarcane yield estimation.

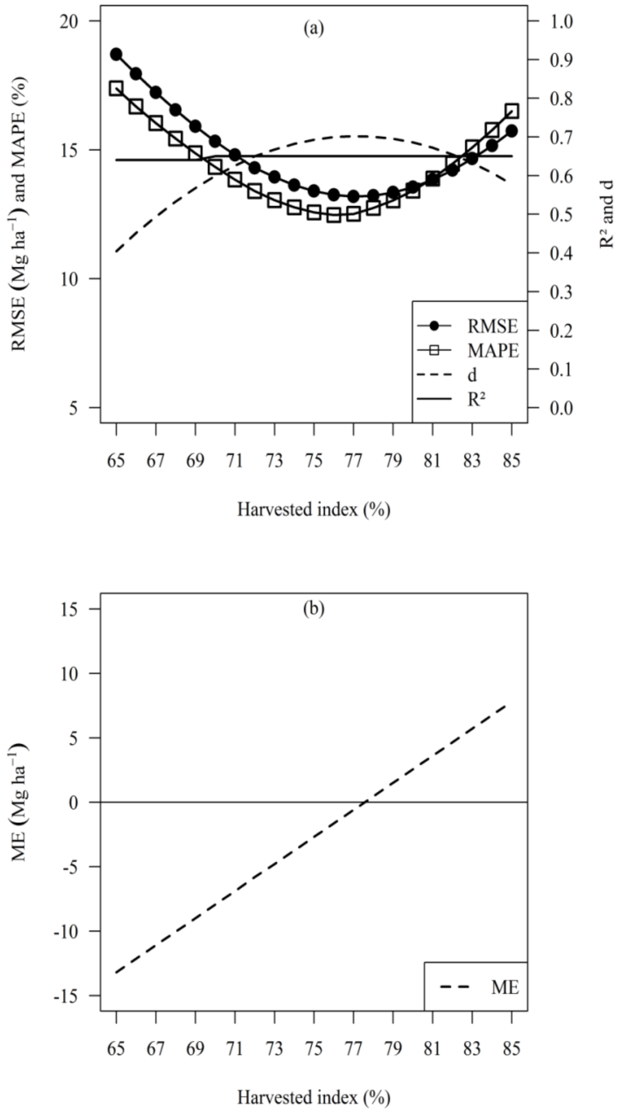

Figure 2.3 - Root mean square error (RMSE), mean absolute percentage error (MAPE), agreement index (d) and coefficient of determination (R^2) (a) and mean error (b) during the calibration phase of sugarcane index

From Figure 2.3 is possible to identify that the harvest index of 77% is the one that resulted in the smallest errors (RMSE = 13.2 Mg ha^{-1}) and highest d index (d = 0.70). This parameter means that for each 100 Mg of sugarcane biomass produced, in average, 77 Mg are of millable stalks which will be used for sugar and ethanol production. According to Robertson et al. (1999), the sugarcane harvest index can range from 65% for rainfed conditions to 83% for well-watered sugarcane fields. The present value obtained by the calibration process is in agreement with this range, since a mix of cultivars, crop systems and harvest time were used.

The crop coefficient (kc) and crop response factor to water deficit (ky) calibration throughout the sugarcane cycle were done by the "eye fitting" procedure, considering the relationship between the observed and simulated yields. The calibrated kc and ky are presented in Table 2.5.

Table 2.5 - Calibrated crop coefficient (kc) and crop response factor to water deficit (ky) for each sugarcane phenological phase

Phenological phase (j)	kc	ky
25% full canopy (1)	0.4	0.7
25-50% full canopy (2)	0.7	0.7
50-75% full canopy (3)	1.0	0.3
75 - 100% full canopy (4)	1.2	0.3
100% full canopy (5)	1.3	0.3
Senescence (6)	1.1	0.3
Ripening (7)	0.8	0.1

These coefficients are very close to those found by Monteiro and Sentelhas (2014) when the calibration of the sugarcane yield model was done for state of São Paulo, Brazil, and using yield data from the surveys conducted by Brazilian governmental agencies such as IBGE and CONAB. The slight differences observed are mainly for ky, which are smaller than those reported by the above mentioned authors. Such differences can be associated with the dataset considered for model calibration, since they are from different climate and soil conditions, cultivars, crop systems (irrigated and rainfed) and crop management employed in the fields across the country.

2.3.2 Performance of the sugarcane yield model

Even being developed with a relative simple approach, the results provided by the agrometeorological yield model proposed in this study, when appropriately calibrated, showed a satisfactory ability to capture the sugarcane yield variability under different climate, soil, crop systems (irrigated and rainfed) and management conditions.

For the calibration phase, the model underestimated yield in average by 2% in relation to observed data (y = 0.98 x) (Figure 2.4a and Table 2.6). The mean error also indicated a slight yield underestimation, with ME = -0.4 Mg ha^{-1}. In terms of magnitude of the errors, the model showed a RMSE of 13.2 Mg ha^{-1}, which corresponds to a MAPE of 12.5% in relation to observed yield. The precision, represented by coefficient of determination, was reasonable (R^2 = 0.65), whereas the accuracy, represented by d index, was good (d = 0.70).

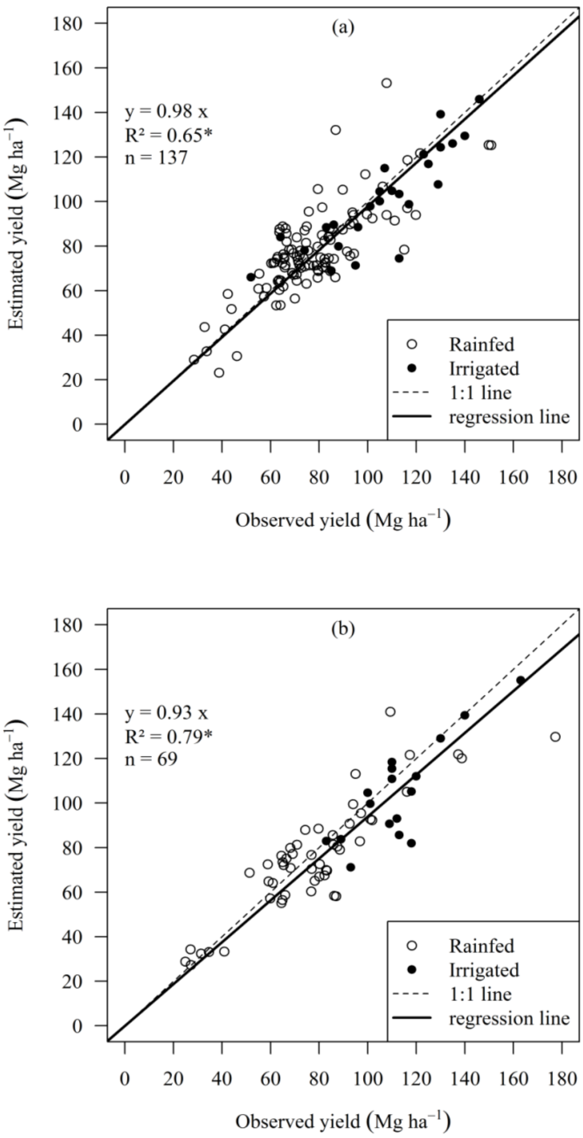

Figure 2.4 – Relationship between observed and simulated yield levels during the calibration (a) and validation (b) phases, considering the proposed agrometeorological yield model. * Significant at 5% of confidence level

During the validation phase, average yield was 86.9 (± 30.1) Mg ha^{-1} for observed data, whereas for simulated data it was 82.9 (± 27.5) Mg ha^{-1}, showing a slight tendency of underestimation, as also observed during the calibration. Such underestimation was, in average, 7%, with ME of -4.0 Mg ha^{-1} (Figure 2.4b and Table 2.6).

Table 2.6 – Observed and estimated average sugarcane yield, mean error (ME), root mean square error (RMSE), absolute percentage error (MAPE), agreement index (d) and coefficient of determination (R^2) for calibration and validation phases of the agrometeorological yield model

Average yields and Statistical indices	Units	Sugarcane yield model performance	
		Calibration	Validation
Observed	Mg ha^{-1}	82.3	86.9
Estimated	Mg ha^{-1}	81.9	82.9
ME	Mg ha^{-1}	-0.4	-4.0
RMSE	Mg ha^{-1}	13.2	13.8
MAPE	%	12.5	12.2
d	-	0.70	0.80
R^2	-	0.65	0.79

Despite the higher ME, the performance of the yield model in terms of error magnitude was very similar. The RMSE was 13.8 Mg ha^{-1} and MAPE = 12.2%. On the other hand, the precision (R^2 = 0.79) and accuracy (d =0.80) were improved. In general words, the sugarcane yield model during the validation phase was able to explain 79% of observed yield variability (Figure 2.4b), with the other 21% probably related to other crop management aspects. Even considering that the results are far from a perfect match, when the performance of the yield model proposed in this study is compared to other studies, becomes clear that it performed very well, as can be observed in Figure 2.4. Tests employing DSSAT/Canegro model in two experimental sites of Australia and South Africa showed that it was able to explain respectively 70 and 83% of observed yield variability (INMAN-BAMBER et al., 1998) which is similar to the present results.

O'Leary (2000) reviewing the performance of APSIM-sugarcane, DSSAT/Canegro and QCANE reported RMSE for fresh stalks biomass of 6.1, 11.1 and 6.4 Mg ha^{-1}, respectively. According to Singels et al. (2008), DSSAT/Canegro presented a relative fresh matter error of around 27.5% and 14.3%, under experimental field conditions in La Mercy and Pangola, both located in South Africa, while Marin and Jones (2014) obtained a MAPE around 18% in five sugarcane field conditions along Brazil. These results show that even with a simple approach, the present model promoted errors of same magnitude of other more complex models, with the advantage of having the same calibration for all 12 locations across the country and less demanding input data.

Under experimental Brazilian field conditions, RMSE of fresh stalks biomass obtained by DSSAT/Canegro ranged from 9.2 to 30 Mg ha^{-1} (NASSIF et al., 2012; MARIN et al., 2013; VIANNA; SENTELHAS, 2015). Otherwise, Oliveira et al. (2012) and Monteiro and Sentelhas (2014) employing the approach proposed by Doorenbos and Kassam (1979) found RMSE around 8.0 and 5.6 Mg ha^{-1} for the states of Minas Gerais and São Paulo, respectively. Results reported by Picoli et al. (2009) when using satellite images associated with a crop yield model presented low coefficient of determination ($R^2 < 0.31$) and RMSE ≈ 20 Mg ha^{-1}. These authors concluded that the satellite techniques should be improved to represent the management strategies better at the field level.

The errors reported in the literature associated to crop yield simulation models are probably due to the following aspects: a) usually studies evaluating the performance of process-based crop models are conducted under experimental conditions and only one cultivar is cultivated; b) the soil where the experiment is installed is often homogeneous; c) there is no variability in terms of climatic conditions; and d) the crop management is close to the perfect, once the crop models cannot simulate directly these effect on yield.

The smaller errors obtained in this study when compared to other studies conducted in Brazil can be associated to the fact that this study used yield data from different sugarcane Brazilian regions (Figure 2.1), which allowed to evaluate different soils, climates, cultivars, crop systems and management conditions.

Although mechanistic crop simulation models use sophisticated tools based on statistical methods for parameters calibration, the errors that they present can also be associated with the large number of parameters required for yield simulations, becoming more difficult to control mainly when there is dependence among them. On the other hand, empirical or mathematical-physiological crop models, which often are based on simple relationships between yield depletion and relative crop water deficit, can provide a similar yield estimates since it is easier to control variations on their parameters. Furthermore, the results presented in this study proved the efficiency of the simple yield estimation model when properly calibrated for many field conditions in terms of climatic and soil characteristics, crop systems (irrigated and rainfed), cultivars and managements, generating acceptable errors and allowing its use for climatic risk analysis.

2.4 Conclusions

1. The calibration of the model parameters, harvest index (HI), crop coefficient (kc) and crop response factor to water deficit (ky), allowed a satisfactory statistical performance of the model when estimated and observed stalks yields were compared;

2. The simple agrometeorological yield model slightly underestimated observed yield, both during the calibration and validation processes; however, it presented a satisfactory performance, mainly for detecting the observed sugarcane yield variability, caused by the combination of different climate and soil conditions, cultivars, crop systems and managements;

3. Due to the acceptable performance of the simple agrometeorological yield model, it can be recommended to estimate yield for different Brazilian locations with reduced input requirement, presenting a high potential for studies associated to crop planning, climatic risks, planting dates recommendation, evaluation of irrigation strategies and yield gap analysis.

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3 ASSESSMENT OF SATELLITE-DERIVED WEATHER DATA SYSTEM (NASA/POWER) FOR SOME BRAZILIAN REGIONS AND THEIR IMPACT ON SUGARCANE YIELD SIMULATIONS

Abstract

Long-term weather series are widely used as input data for crop simulation models. However, in many regions of under-developing and developing countries the access to these data is still restrict, and when available, with significant gaps associated to missing and erroneous data, making them too short to evaluate the impact of climatic variability in the crop production. Therefore, the use of synthetic weather data has been brought as a solution for that, increasing the spatial distributions of weather stations. The NASA/POWER (NP) system provides a completed grid of weather databases in a global coverage of 1° by 1° of geographical coordinates. Even being an important source of climatic data, the virtual weather stations from NP are still not intensively used for studies related to climatic risk analysis for agricultural planning decision making in Brazil. Based on that and considering the necessity of a higher density of weather stations to support the Brazilian agriculture more efficiently, the objectives of this chapter were: a) to compare the weather variables of air temperature, sunshine hours, rainfall and reference evapotranspiration with those provided by INMET; b) to use INMET observed and NP estimated weather data to estimate sugarcane yield by a simple agrometeorological model in order to quantify the errors caused by NP data on yield estimates; and c) to test a combined dataset composed by NP data with rainfall data from ANA in order to see how is the impact caused by the rainfall data on sugarcane yield estimates. The yield model was run for 10 growing seasons (2003 to 2013) considering a cane plant cycle with 12 months. Planting dates were simulated in a ten-day time scale, during all year long, totalizing 36 growing seasons per year. Potential yield (Yp) and attainable yield (Yatt) were simulated with observed and gridded weather datasets, following what was established in the objectives. The statistical errors and indices showed a satisfactory agreement between observed and estimated weather data. When these data were used to estimate Yp high accuracy was observed. For Yatt, the simulations with NP data presented R^2 = 0.70, d = 0.89, RMSE = 24.1 Mg ha^{-1}, ME = 10.8 Mg ha^{-1} and MAPE = 30.4%. Such estimates were improved when NP rainfall data was replaced by local data from ANA, with R^2 increasing to 0.82, d going to 0.96, RMSE of 16.7 Mg ha^{-1}, ME decreasing to 3.8 Mg ha^{-1}, and MAPE to 18.5%. These results suggest that the NP system allows to simulate Yp and Yatt with high accuracy, since with rainfall data from local databases.

Keywords: Crop simulation models; Potential and attainable yield; Gridded weather databases; Climatic variability; Sugarcane

3.1 Introduction

Agricultural planning requires long-term weather data that are usually applied to determine the most appropriated strategies at the regional and national levels by using different agrometeorological techniques, such as simulation models (GARCIA; HOOGENBOOM, 2005; ZHAO et al., 2015). The importance of meteorological variables as input for crop simulation models is unquestionable. The main use of these models is to evaluate the impact of climate variability on crop production, mainly under rainfed conditions, once it is responsible for up to 80% of spatial and inter-annual yield variability (HOOGENBOOM, 2000).

Thereby, the confidence on the yield predictions is strongly dependent on the quality of model’s input, mainly the weather data (MEINKE et al., 1995). Total precipitation and its distribution are the keys to define the success in the crop production mainly under rainfed conditions, however, this variable still is difficult to modelling by climate models, due it high spatial variability (CHALLINOR et al., 2005). The quality of weather data is a source of uncertainty for yield simulations. This aspect is of high relevance for the agricultural lands in expansion, where an efficient planning is required but also where the lack of climatic data is more common (DE WIT; VAN DIEPEN, 2008; FOLBERTH et al., 2012).

Even ground weather stations representing the most common source of meteorological data for agrometeorological studies and, more specifically, for crop modelling applications, usually these datasets are not available for the region of interest or they present missing or erroneous data, making impossible to investigate the climatic risks associated to agricultural activities (HOOGENBOOM, 2000; WHITE et al., 2011; SOLTANI et al., 2000; RAMIREZ-VILLEGAS; CHALLINOR, 2012).

The most common weather variables available in the weather stations are air temperature and rainfall (ABATZOGLOU, 2013). However, only these variables are not enough for running crop simulation models, which also require solar radiation, to estimate potential yield, and relative air humidity and wind speed, to estimate reference and crop evapotranspiration (HOOGENBOOM, 2000; JONES et al., 2003). As a solution for that, prior studies tried to develop empirical relationships to estimate solar radiation and relative air humidity as functions of air temperature and precipitation; however, these methods require local calibration, becoming not useful for large scale analysis (ABATZOGLOU, 2013).

Therefore, the use of synthetic weather data, obtained from weather generators or interpolated gridded systems, can be a suitable alternative to provide complete long-term datasets which can be employed as inputs for the crop simulation models, allowing an assessment of the effects of climatic variability and their impacts on the crop yield (SENTELHAS et al., 2001; BAI et al., 2010; VAN WART et al., 2013a,b), crop management options (SOLTANI; HOOGENBOOM, 2007), crop water requirements (ABABAEI, 2014), and hydrological studies (CARON et al., 2008) in several spatial and temporal scales.

According to Soltani and Hoogenboom (2003), the most used weather generators for agricultural applications are WGEN (RICHARDSON; WRIGHT, 1984), SIMMETEO

(GENG et al., 1986), LARS-WG (SEMENOV et al., 1998), MARKSIM (JONES; THORNTON, 2000), WM2 (MAVROMATIS; HANSEN, 2001), TAMSIM (MEINKE et al., 1995) and CLIGEN (NICKS et al., 1994). On the other hand, these generators require observed records as an initial source of data for statistical methods that use stochastic approaches (QIAN et al., 2011; CARAWAY et al., 2014).

The performance of gridded weather databases (GWD) are systems able to provide observed, interpolated and estimated weather data for different applications (STACKHOUSE, 2010). They can provide long-term data, which are estimated based on several sources of data like satellites and radar images, land and ocean observations, and meteorological probes and balloons (STACKHOUSE, 2010).

Currently, GWD provides an entire global coverage of spatial resolutions that can range from 0.5 to 2.5° (DE WIT; VAN DIEPEN, 2008; STACKHOUSE, 2010), being an important source of data for agricultural researches, mainly for assessment of the climatic variability and risks for crops and for supporting police makers at regional, national and global levels (BAI et al., 2010; WHITE et al., 2011; VAN WART et al., 2013a).

The National Aeronautics and Space Administration (NASA) through the program called Prediction Of Worldwide Energy Resources (POWER) provides a long-term database of climatic data. These databases included gridded weather variables in a daily time-step at global level, with a spatial resolution of 1° x 1° (STACKHOUSE, 2010). Although there are several studies reporting the feasibility of the use of NP datasets for crop simulations in in the United States of America, Europe and Asia (DE WIT; VAN DIEPEN, 2008; BAI et al.; 2010; WHITE et al., 2011; VAN WART et al., 2013a), almost nothing is reported for Brazil. Approaches evaluating the performance of estimated weather databases in Brazilian agriculture are not still common. Indeed, due to uncertainty and different methods to measure/estimate each meteorological variable, the comparison and evaluation of GWD systems with ground weather records is an important step for increasing the confidence on them, in order to have a robust virtual weather data network (STACKHOUSE, 2010).

For sugarcane crop, studies coupling GWD with crop simulation models, in order to evaluate the spatial variability of yield under different climatic conditions, are still rare. In Brazil, the use of GWD is a great opportunity to overcome the restrict access to non-well-distributed public weather databases, making possible to conduct agrometeorological studies. Due to the low spatial density of the ground weather stations in the Brazilian territory and being the GWD a potential tool to increase the weather stations network for agrometeorological research purposes, the objectives of this chapter were:

a) To compare the gridded weather data provided by the NP system with the observed weather data, air temperature, sunshine hours, reference evapotranspiration, and rainfall, from the stations of the National Institute of Meteorology (INMET) and National Weather Agency (ANA);

b) To employee observed and GWD datasets as input in a sugarcane yield simulation model and determine the magnitude of errors for potential and attainable yields;

c) To test a combined dataset to be used for sugarcane yield simulations, in which air temperature, sunshine hours, and reference evapotranspiration were provided by NP system and rainfall records from National Water Agency (ANA), aiming to improve the accuracy of the yield simulations, in comparison with the yield estimated with observed weather variables.

3.2 Material and Methods

3.2.1 Locations selected as sources of weather data

A south-north transect was established to select 20 ground weather stations (GWS) across Brazilian territory in order to compare the observed with gridded weather database (GWD). The variables used for comparison were: air temperature (average, maximum and minimum); sunshine hours; reference evapotranspiration (ETo), estimated by the Penman-Monteith equation (ALLEN et al., 1998); and rainfall. These data were summarized for a ten-day time scale to match with the data required to run the sugarcane yield model for estimating potential (Yp) and attainable (Yatt) yields. The GWS data were obtained from the National Institute of Meteorology (INMET) conventional weather station network, while the GWD were obtained from the same location, based on its geographical coordinates. The spatial distribution of weather stations selected for the present study is presented in Figure 3.1.

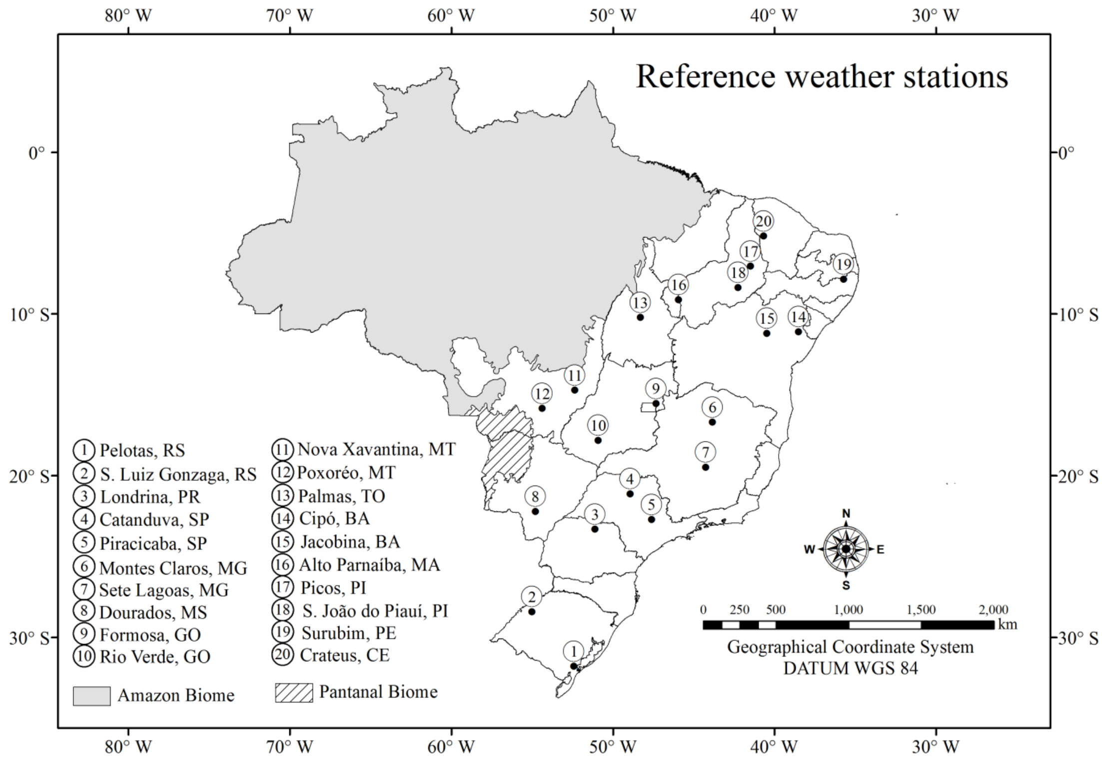

Figure 3.1 - Spatial distribution of controlled weather stations used to comparison of observed and gridded weather datasets

3.2.2 NASA/POWER gridded weather database description

NASA Prediction of Worldwide Energy Resources (NASA/POWER, NP) is a project funded by NASA Langley Research Center in 2003 through Applied Sciences Program (http://appliedsciences.nasa.gov.br/about.php/). Currently, NP provides their databases with applicability in architectural (Sustainable buildings) and agricultural (Agro-climatology) researches. The weather data provided by NP database are interpolated from several sources (ground stations, radar and satellite imagery, and meteorological probes and balloons) and is available in a spatial resolution of 1°, covering an entire global surface (STACKHOUSE, 2010). In the Table 3.1 the weather variables provided by NP database are summarized, with their respective satellite and period of coverage for each weather variable.

Table 3.1 - Detailed information of weather variables provided by satellite-derived NASA/POWER project and their respective temporal coverage

Weather variable*	Satellite**	Temporal coverage
SR	GEWEX SRB 3.0	July 1, 1983 - Dec 31, 2007
	FLASHFlux	Jan 1, 2008 - near present
Tmax, Tmin, Tavg	GEOS-4	July 1, 1983 - Dec 31, 2007
	GEOS-5	Jan 1, 2008 - near present
UR, U10 and Tdew	GEOS-4	July 1, 1983 - Dec 31, 2007
	GEOS-5	Jan 1, 2008 - near present
Precipitation	GPCP	Jan 1, 1997 - near present

*SR = solar radiation (MJ m^{-2} d^{-1}), Tmax = maximum air temperature (°C), Tmin = minimum air temperature (°C), Tavg = average air temperature (°C), RH = average relative humidity (%), U10 = wind speed at 10-m height (m s^{-1}), Tdew = dew point temperature (°C). **Global Energy and Water Exchanges Project Surface Radiation Budget (GEWEX SRB 3.0 – http://eosweb.larc.nasa.gov/project/srb/srb_table); Fast Longwave and Shortwave Radiative Fluxes (FLASHFlux – http://flashflux.larc.nasa.gov/); Goddard Earth Observing System model version 4 and 5 (GEOS-4 and GEOS-5 – http://gmao.gsfc.nasa.gov/), Global Precipitation Climate Project (GPCP – http://precip.gsfc.nasa.gov/)

Radiation data are measure every 3 hours and published at a daily time step at the NP website. SR relative errors (RMSE, %) range between 5 and 41%, with the highest deviations associated with intense clouds cover, mainly in the regions close to the coast or where inclined topography is present (STACKHOUSE, 2010). The reference evapotranspiration was estimated by Penman-Monteith method (ALLEN et al., 1998), which requires net radiation, air temperature, relative humidity (vapor pressure deficit) and wind speed at 2 m above ground. Therefore, as wind speed records are originally available at 10-m height, the wind speed data were corrected to 2 m, considering an adjustment coefficient equal to 0.748, derived from the logarithmic wind profile (ALLEN et al., 1998).

Finally, precipitation was generated by the Global Precipitation Climate Project (GPCP – http://precip.gsfc.nasa.gov/), even considering that this data from NP when compared with observed precipitation data from ground weather stations presented small agreement for daily time-scale (R^2 = 0.25).

3.2.3 Sugarcane yield simulations description

The sugarcane yields were simulated by the model described, calibrated and validated in the Chapter 2. The sugarcane yield model has two modules: the first for potential yield (Yp) simulation, which is driving by solar radiation, air temperature, photoperiod along the crop cycle and genotype characteristics; and the second for attainable yield (Yatt) simulation, based on a multiplicative model considering the relative water deficit and the sensitivity of each phenological phase for this variable (MONTEIRO; SENTELHAS, 2014). All the yield simulations started with the soil water storage (ARM) at the field capacity in order to guaranty that the soil moisture conditions were not restrictive for crop establishment (sprouting and first leaves emission).

As frost occurrence in southern Brazil is frequent (STRECK et al., 2011) and sugarcane is susceptible to this phenomenon (BACCHI, 1982), a frost penalization was introduced in the yield model for high latitude locations of the country. The following criteria were admitted, for each growing period of 12 months, during the 36 planting dates per year: a) if the growing cycle was lower than 185 days due to frost occurrence, there is no millable biomass accumulated and therefore Yp and Yatt becomes zero, due to small sucrose content in the stalks (LIU; BULL, 2001); b) if occurs any other frost event in the growing cycle but with crop cycle larger than 185 days, the biomass is accumulated until the next frost or up to the end of period; c) and if there is no frost occurrence, the biomass is accumulated from begin to final day of crop cycle.

For the simulations a plant cane with a growing season of 12 months was considered. The planting dates were simulated every 10 days, from January 1st to December 21st, totaling 36 cycles per year, during ten years, from 2003 to 2013.

The sugarcane yield simulations were performed with three sources of weather data as the inputs for the crop yield model. In the first, the model was run with the weather data from the National Institute of Meteorology (INMET). In the second, data from NP system was used. In the third, weather data from NP, with exception to rainfall, were used. In this case, NP rainfall data were replaced by observed data from the stations belonging to National Water Agency (ANA).

As extreme minimum air temperature from the INMET and NP system did not agree in a preliminary test, an empirical factor was applied to correct the estimated data, which consistently overestimate this variable. According to this test, all extreme minimum air temperatures from NP in southern Brazil were reduced by 20%. Once fixed, the threshold of temperature in the meteorological screen to represent frost occurrence was 3 °C (GRODSKI et al., 1996).

3.2.4 Weather data and yield simulation statistical analysis

The weather variables (air temperature, effective sunshine hours, reference evapotranspiration and rainfall), and the Yp and Yatt were plotted and then compared through the statistical indices of precision (R^2), accuracy (d) and the respective errors: mean error (ME), root mean square error (RMSE) and mean absolute percentage error (MAPE). The yields, when estimated by the different sources of data, having those estimated with INMET data as reference, and those estimated by NP and combined input data (NP + ANA) also were evaluated by the following statistical coefficients and errors:

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (Y_{G(i)} - Y_{obs(i)})^2}{\sum_{i=1}^{n} (\left|Y_{G(i)} - \overline{Y_{obs}}\right| + \left|Y_{obs(i)} - \overline{Y_{obs}}\right|)^2} \right] \quad (1)$$

$$ME = \frac{\sum_{i=1}^{n} (Y_{G(i)} - Y_{obs(i)})}{n} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_{G(i)} - Y_{obs(i)})^2}{n}} \quad (3)$$

$$MAPE = 100 \times \left| \frac{1}{n} \times \sum_{i=1}^{n} \left(\frac{Y_{G(i)} - Y_{obs(i)}}{Y_{obs(i)}} \right) \right| \quad (4)$$

where i to n are the number of paired data for each site and year, $Y_{G(i)}$ is Yp or Yatt, estimated with gridded weather data from NP, $Y_{obs(i)}$ is Yp or Yatt estimated with observed weather data from INMET, and $\overline{Y_{obs}}$ is the average of yields estimated with observed data from INMET.

3.3 Results and Discussion

3.3.1 Comparison of observed and gridded weather data

3.3.1.1 Comparison of average data

A general comparison of all tested weather variables showed a reasonable agreement between the observed and gridded sources of data, when the records are evaluated in annual time-scale, even for precipitation, that is the variable with highest spatial variability among the ones evaluated. For all variables, when evaluated in that time-scale, the averages are very similar. The annual means are shown in the Table 3.2.

Table 3.2 - Comparison between air temperature (Tavg, Tmax and Tmin), effective sunshine hours (n), reference evapotranspiration (ETo) and rainfall (P) from the National Institute of Meteorology (INMET) (OBS) and NASA/POWER (NP) system, in different locations across Brazil. The standard deviations are between brackets

Location, state	Source	Tavg	Tmax	Tmin	n	ETo	P
		(°C)			(h d^{-1})	(mm $year^{-1}$)	
PAR, MA	OBS	27.1 (1.4)	33.4 (2.1)	20.7 (2.3)	7.6 (2.6)	1783.7 (7.6)	1378.8 (49.1)
	NP	26.0 (1.8)	30.9 (2.7)	21.2 (1.4)	6.9 (2.1)	1530.5 (6.5)	1221 (40.1)
CAT, SP	OBS	23.8 (2.3)	29.4 (2.4)	18.3 (2.5)	6.2 (1.8)	1240 (10.1)	1223.7 (41.0)
	NP	23.5 (3.0)	29.4 (3.1)	18.1 (3.1)	7.0 (1.7)	1326.2 (12.8)	1487.2 (44.7)
CIP, BA	OBS	26.4 (2.1)	32.2 (2.8)	20.7 (1.8)	7.1 (1.9)	1735.8 (10.5)	547.4 (20.6)
	NP	25.1 (1.7)	30.6 (2.4)	21.1 (1.4)	5.9 (1.4)	1619.8 (9.3)	575 (27.4)
CRT, CE	OBS	28.2 (1.4)	33.8 (1.9)	22.7 (1.1)	7.6 (1.8)	1712.6 (6.0)	711.6 (39.0)
	NP	26.4 (2.0)	31.3 (2.7)	21.9 (1.2)	7.0 (1.6)	1646.3 (5.3)	777.8 (35.3)
DOU, MS	OBS	22.9 (3.2)	29.7 (3.4)	17.3 (3.7)	8.1 (1.9)	1434.6 (10.4)	1348 (41.6)
	NP	24.1 (3.4)	30.3 (3.5)	18.6 (3.7)	6.8 (1.6)	1319.2 (14.3)	1556.2 (40.6)
FOR, GO	OBS	23.1 (1.6)	28.4 (1.8)	17.9 (2.0)	7.3 (2.4)	1450.1 (9.6)	1401.6 (51.8)
	NP	23.3 (2.1)	28.8 (2.7)	18.3 (2.2)	7.0 (2.1)	1384.1 (9.5)	1339.3 (43.4)
JAC, BA	OBS	24.9 (2.0)	29.7 (2.6)	20.0 (1.5)	6.9 (1.7)	1630.9 (9.5)	696.4 (31.0)
	NP	24.0 (1.7)	29.9 (2.1)	19.2 (1.5)	6.1 (1.5)	1529.1 (8.7)	537.7 (26.4)
LON, PR	OBS	22.6 (3.2)	28.7 (3.2)	16.5 (3.5)	6.8 (1.8)	1423.9 (13.7)	1594.9 (46.7)
	NP	22.4 (3.2)	28.4 (3.3)	17.2 (3.2)	6.7 (1.7)	1276.1 (14.1)	1575.1 (40.8)
MCL, MG	OBS	23.9 (2.0)	30.0 (2.0)	17.9 (2.6)	7.6 (2.3)	1497.1 (10.4)	1064.5 (48.6)
	NP	23.2 (2.1)	29.2 (2.6)	17.9 (2.1)	7.2 (2.0)	1423.2 (10.2)	1091.1 (44.9)
NXV, MT	OBS	26.3 (1.7)	33.7 (2.1)	19.0 (3.4)	7.0 (2.3)	1723.0 (7.8)	1511 (55.4)
	NP	25.8 (2.1)	31.4 (3.2)	20.7 (1.9)	6.8 (2.1)	1402.5 (10.1)	1649.1 (51.3)
PAL, TO	OBS	28.1 (1.4)	33.8 (2.3)	22.3 (1.2)	6.9 (2.3)	1679.5 (6.8)	1841.6 (57.6)
	NP	27.0 (2.1)	31.9 (3.3)	22.3 (1.4)	6.3 (2.2)	1511.7 (7.3)	1798.3 (49.6)
PEL, RS	OBS	18.7 (4.3)	23.4 (4.5)	14.0 (4.4)	6.8 (2.1)	1207.4 (19.1)	1269.8 (34.6)
	NP	18.4 (4.5)	24.2 (4.9)	13.4 (4.2)	6.8 (2.0)	1112.7 (18.3)	1566.5 (39.8)
PIC, PI	OBS	28.7 (1.7)	34.7 (2.1)	22.7 (1.6)	8.3 (1.8)	1673.7 (6.3)	684.3 (31.9)
	NP	27.1 (1.9)	32.0 (2.6)	22.4 (1.4)	7.2 (1.7)	1604.7 (5.9)	759.9 (31.0)
PIR, SP	OBS	22.3 (2.8)	28.8 (2.7)	15.9 (3.5)	6.7 (1.7)	1232.5 (10.2)	1269.2 (39.3)
	NP	21.8 (2.9)	27.7 (2.9)	16.7 (3.0)	6.8 (1.8)	1307.2 (13.0)	1556.3 (43.2)
POX, MT	OBS	25.9 (1.9)	32.9 (1.9)	18.8 (3.4)	6.2 (2.2)	1590.5 (8.4)	1740.7 (52.8)
	NP	25.5 (2.1)	30.9 (2.8)	20.5 (2.1)	6.2 (2.0)	1368.0 (9.5)	1763.5 (50.0)
RVD, GO	OBS	23.8 (1.7)	30.0 (1.9)	17.6 (2.3)	6.0 (2.4)	1355.2 (10.4)	1640.8 (53.1)
	NP	24.5 (2.4)	30.2 (3.1)	19.3 (2.5)	6.9 (1.9)	1370.6 (11.1)	1567.2 (47.8)
SJP, PI	OBS	28.6 (1.5)	34.2 (2.0)	22.9 (1.3)	8.5 (1.9)	1717.7 (7.7)	640.9 (32.4)
	NP	27.0 (1.8)	32.1 (2.6)	22.1 (1.2)	7.1 (1.8)	1553.6 (6.5)	726.7 (29.0)
SLG, RS	OBS	21.4 (4.5)	27.2 (5.0)	15.5 (4.1)	6.4 (1.9)	1252.9 (17.1)	1803.5 (52.4)
	NP	20.5 (4.7)	27.0 (5.0)	14.8 (4.4)	7.0 (1.9)	1190.8 (17.2)	1879.5 (50.7)
SLS, MG	OBS	22.6 (2.1)	29.0 (1.9)	16.3 (2.9)	7.2 (2.1)	1419.0 (11.3)	1338.4 (53.4)
	NP	22.0 (2.6)	27.7 (2.9)	16.8 (2.8)	7.0 (1.9)	1354.0 (10.9)	1444.3 (48.2)
SUR, PE	OBS	25.1 (1.7)	30.0 (2.4)	20.3 (1.3)	7.7 (1.7)	1856.1 (9.6)	606.1 (22.0)
	NP	24.9 (1.4)	30.0 (2.2)	21.4 (1.1)	6.1 (1.2)	1692.7 (7.6)	805.6 (31.1)

PAR = Alto Parnaíba; CAT = Catanduva; CIP = Cipó; CRT = Crateus; DOU = Dourados; FOR = Formosa; JAC = Jacobina; LON = Londrina; MCL = Montes Claros; NXV = Nova Xavantina; PAL = Palmas; PEL = Pelotas; PIC = Picos; PIR = Piracicaba; POX = Poxoréo; RVD = Rio Verde; SJP = São João do Piauí; SLG = São Luiz Gonzaga; SLS = Sete Lagoas; SUR = Surubim

3.3.1.2 Comparison of data in a ten-day time scale

The comparison between INMET and NP data records were done in a ten-day basis, for 396 observations in each location and weather variable under study, totaled 7920 data. White et al. (2008) highlighted that the NP system can estimate more accurately the air temperature better in a different scale than daily (weekly or bi-weekly) and therefore here we are evaluating the weather variables in the same scale in which the yield model requires the climatic input data (ten-day time scale). The statistical coefficients that resulted from this comparison for 20 locations across a north-south transect in Brazil, firstly for the weather variables responsible by conditioning potential yield (average, maximum and minimum air temperature, and sunshine hours) are presented in Tables 3.3 to 3.6.

Table 3.3 - Statistical indices for the comparison between average air temperature data obtained from the National Institute of Meteorology (INMET) and NASA/POWER system, in different locations across Brazil: coefficient of determination (R^2), agreement index (d), root mean square error (RMSE), mean error (ME), and mean absolute percentage error (MAPE)

Location, state	R^2	d	RMSE (°C)	ME (°C)	MAPE (%)
ALTO PARNAIBA, MA	0.44	0.72	1.8	-1.1	5.7
CATANDUVA, SP	0.76	0.91	1.5	-0.3	5.3
CIPÓ, BA	0.75	0.83	1.7	-1.3	5.2
CRATEUS, CE	0.42	0.63	2.6	-1.9	7.3
DOURADOS, MS	0.80	0.91	2.0	1.2	6.9
FORMOSA, GO	0.46	0.77	1.9	0.2	6.7
JACOBINA, BA	0.65	0.85	1.5	-0.9	4.9
LONDRINA, PR	0.83	0.95	1.3	-0.2	4.7
MONTES CLAROS, MG	0.69	0.88	1.4	-0.7	4.8
NOVA XAV.(XAVANTINA), MT	0.27^{ns}	0.71	2.0	-0.5	6.7
PALMAS, TO	0.60	0.76	1.8	-1.1	5.5
PELOTAS, RS	0.95	0.99	1.0	-0.3	5.0
PICOS, PI	0.53	0.73	2.2	-1.6	6.2
PIRACICABA, SP	0.84	0.95	1.3	-0.5	4.8
POXOREO, MT	0.43	0.80	1.7	-0.4	5.7
RIO VERDE, GO	0.56	0.80	1.9	0.7	5.9
SAO JOAO DO PIAUI, PI	0.50	0.70	2.1	-1.6	6.2
SAO LUIZ GONZAGA, RS	0.94	0.97	1.5	-0.9	6.3
SETE LAGOAS, MG	0.75	0.90	1.5	-0.6	5.5
SURUBIM, PE	0.60	0.87	1.1	-0.3	3.6
Total	0.80	0.94	1.7	-0.6	5.6

^{ns} not significant at 5% of confidence level

The statistical indices related to the comparison of average air temperature from INMET and NP range expressively among the evaluated locations (Table 3.3). In a general evaluation, there was a strong precision (R^2 = 0.80) and accuracy (d = 0.94) between average air temperature from NP and INMET data sources. Considering a locally approach, the coefficient of determination (R^2) ranged from 0.27 in Nova Xavantina, MT, to 0.95 in Pelotas, RS. In a general view, NP showed a better precision in the southern parts of the country (R^2 between 0.76 and 0.95) than in the central and northern parts (R^2 between 0.30 and 0.75). When all locations were evaluated, the R^2 was 0.80, showing that NP data explains about 80% of the variability of the data observed in the INMET weather stations.

Other statistical indices showed that NP data, despite the varying precision, showed a good to excellent accuracy, with d index ranging from 0.63 to 0.99, with a general value of 0.94, which is very high. Considering now the RMSE, it ranged between 1.0 to 2.2 °C with a tendency of underestimation, as shown by ME, which was predominantly negative (-0.6 °C). Finally, the MAPE, error expressed in relative terms, was more stable, ranging between 3.6 and 6.9%, with an average of 5.6%, which can be considered small.

White et al. (2008) found that in continental United States the global Tavg estimated by NP was 0.7 °C cooler than the observed ones. These differences also can be seen in the negative mean errors (ME) for almost every locations evaluated in this study (Table 3.3). For maximum air temperature, the statistical indices for all locations evaluated are presented in the Table 3.4.

The statistical indices related to the comparison of maximum air temperature from INMET and NP range expressively among the evaluated locations (Table 3.4); however with less variation than for average temperature (Table 3.3). The coefficient of determination (R^2) ranged from 0.45 in São João do Piauí, PI, to 0.89 in Pelotas, RS. As observed for average temperature, for maximum air temperature NP showed a better precision in the southern parts of the country (R^2 between 0.60 and 0.89) than in the central and northern parts (R^2 between 0.45 and 0.70).

When all locations were evaluated together, the R^2 was 0.68, showing that NP data was able to explain no more than 68% of the variability of the data observed in the INMET weather stations. All coefficients of determination (R^2) presented significance at 5% of confidence level.

Table 3.4 - Statistical indices for the comparison between maximum air temperature data obtained from the National Institute of Meteorology (INMET) and NASA/POWER system, in different locations across Brazil: coefficient of determination (R^2), agreement index (d), root mean square error (RMSE), mean error (ME), and mean absolute percentage error (MAPE)

Location, state	R^2	d	RMSE (°C)	ME (°C)	MAPE (%)
ALTO PARNAIBA, MA	0.68	0.72	3.0	-2.5	7.8
CATANDUVA, SP	0.57	0.85	2.0	0.1	5.6
CIPÓ, BA	0.61	0.82	2.4	-1.6	5.7
CRATEUS, CE	0.54	0.67	3.2	-2.5	8.1
DOURADOS, MS	0.61	0.87	2.4	0.7	6.5
FORMOSA, GO	0.57	0.81	2.0	0.4	5.5
JACOBINA, BA	0.69	0.90	1.5	0.1	4.0
LONDRINA, PR	0.68	0.91	1.9	-0.3	5.3
MONTES CLAROS, MG	0.61	0.84	1.8	-0.8	5.1
NOVA XAV.(XAVANTINA), MT	0.65	0.72	3.1	-2.3	8.0
PALMAS, TO	0.67	0.78	2.9	-2.0	7.6
PELOTAS, RS	0.89	0.96	1.8	0.8	5.8
PICOS, PI	0.49	0.65	3.4	-2.7	8.4
PIRACICABA, SP	0.64	0.86	2.1	-1.0	6.0
POXOREO, MT	0.56	0.70	2.8	-2.0	7.5
RIO VERDE, GO	0.59	0.82	2.1	0.2	5.5
SAO JOAO DO PIAUI, PI	0.45	0.68	3.0	-2.1	7.1
SAO LUIZ GONZAGA, RS	0.84	0.96	2.1	-0.2	6.1
SETE LAGOAS, MG	0.48	0.76	2.4	-1.2	7.0
SURUBIM, PE	0.60	0.88	1.6	0.1	4.3
Total	0.68	0.90	2.4	-0.9	6.3

Other statistical indices showed that NP data, despite the varying precision, showed a good to excellent accuracy for estimating maximum temperature, with d index ranging from 0.66 to 0.96, with a general value of 0.90, which is very high.

Considering now the RMSE, it ranged between 1.5 to 3.4 °C with average tendency of underestimation, as shown by ME, which was predominantly negative (-0.9 ^{o}C). Finally, the MAPE also varied considerably, between 4.0 and 8.4%, with an average of 6.3%, a little higher than observed for average temperature (MAPE = 5.6%). White et al. (2008), evaluating the performance of NP databases against the weather data observed in stations across the United States of America by the National Weather Service Cooperative Observer Program (COOP), found a R^2 of 0.88 and RMSE of 4.1 °C for maximum air temperature. The most frequent differences for this weather variable when estimated by the NP were around -6 to +3 °C, more pronounced in the western coast. Bai et al. (2010) tested the NP estimates across China and observed a negative mean error (ME) for maximum air temperature in all the weather stations evaluated and the R^2 and RMSE indices were similar to those found in this study. According to the authors, the underestimation of maximum temperature by NP in China can be associated with the very irregular topography in that country. For minimum air temperature, the statistical coefficients are presented in the Table 3.5.

Table 3.5 - Statistical indices for the comparison between minimum air temperature data obtained from the National Institute of Meteorology (INMET) and NASA/POWER (NP) system, in different locations across Brazil: coefficient of determination (R^2), agreement index (d), root mean square error (RMSE), mean error (ME), and mean absolute percentage error (MAPE)

Location, state	R^2	d	RMSE	ME	MAPE
			(°C)		(%)
ALTO PARNAIBA, MA	0.29^{ns}	0.69	2.0	0.5	7.8
CATANDUVA, SP	0.82	0.94	1.4	-0.2	5.9
CIPÓ, BA	0.72	0.90	1.1	0.4	4.2
CRATEUS, CE	0.17^{ns}	0.59	1.9	-0.8	7.0
DOURADOS, MS	0.87	0.94	1.8	1.2	8.7
FORMOSA, GO	0.47	0.80	1.9	0.4	8.4
JACOBINA, BA	0.74	0.87	1.2	-0.8	4.7
LONDRINA, PR	0.88	0.96	1.4	0.7	7.3
MONTES CLAROS, MG	0.75	0.92	1.3	0.2	6.3
NOVA XAV.(XAVANTINA), MT	0.46	0.68	3.1	1.7	14.5
PALMAS, TO	0.34	0.75	1.3	0.1	4.0
PELOTAS, RS	0.96	0.98	1.1	-0.5	6.7
PICOS, PI	0.48	0.82	1.3	-0.3	4.8
PIRACICABA, SP	0.90	0.95	1.4	0.8	7.9
POXOREO, MT	0.62	0.77	2.8	1.8	13.0
RIO VERDE, GO	0.59	0.78	2.4	1.7	10.6
SAO JOAO DO PIAUI, PI	0.39	0.73	1.5	-0.8	5.4
SAO LUIZ GONZAGA, RS	0.95	0.98	1.2	-0.7	7.5
SETE LAGOAS, MG	0.89	0.96	1.1	0.5	5.4
SURUBIM, PE	0.41	0.69	1.5	1.1	5.8
Total	0.81	0.84	1.6	0.	7.3

^{ns} not significant at 5% of confidence level

The coefficient of determination (R^2) ranged from 0.30 in Alto Parnaíba, MA, to 0.96 in Pelotas, RS. As observed for average and maximum temperatures, NP showed a better precision in the southern parts of the country (R^2 between 0.87 and 0.96) than in the central and northern parts (R^2 between 0.30 and 0.75). When all locations were evaluated together, the R^2 was 0.81, showing that NP data was able to explain 81% of the variability of the data observed in the INMET weather stations. The minimum air temperature presented a tendency of overestimation, with only for 7 locations with ME < 0. The average ME was 0.6 ^{o}C, with positive value per location achieving till 1.8 ^{o}C. RMSE ranged from 1.1 to 2.8 ^{o}C, whereas MAPE (7.3%) was higher than for average and maximum temperatures.

The statistical indices related to the comparison of sunshine hours from INMET and NP ranged less than for the temperature (Table 3.6).

Table 3.6 - Statistical indices for the comparison between effective sunshine hours data obtained from the National Institute of Meteorology (INMET) and NASA/POWER (NP) system, in different locations across Brazil: coefficient of determination (R^2), agreement index (d), root mean square error (RMSE), mean error (ME), and mean absolute percentage error (MAPE)

Location, state	R^2	d	RMSE	ME	MAPE
			(h d^{-1})		(%)
ALTO PARNAIBA, MA	0.53	0.83	2.0	-0.7	15.3
CATANDUVA, SP	0.72	0.88	1.3	0.8	21.0
CIPÓ, BA	0.73	0.80	1.6	-1.2	17.4
CRATEUS, CE	0.84	0.92	1.0	-0.7	10.8
DOURADOS, MS	0.57	0.76	1.9	-1.3	18.5
FORMOSA, GO	0.91	0.97	0.8	-0.3	10.3
JACOBINA, BA	0.64	0.84	1.3	-0.8	15.6
LONDRINA, PR	0.85	0.96	0.7	-0.1	9.7
MONTES CLAROS, MG	0.88	0.96	0.9	-0.4	10.0
NOVA XAV.(XAVANTINA), MT	0.87	0.96	0.9	-0.3	11.6
PALMAS, TO	0.87	0.95	1.0	-0.6	11.8
PELOTAS, RS	0.91	0.98	0.6	0.1	8.8
PICOS, PI	0.81	0.86	1.4	-1.2	14.5
PIRACICABA, SP	0.71	0.92	1.0	0.1	12.6
POXOREO, MT	0.80	0.95	1.0	0.1	13.8
RIO VERDE, GO	0.66	0.85	1.7	0.9	39.6
SAO JOAO DO PIAUI, PI	0.85	0.84	1.6	-1.5	17.8
SAO LUIZ GONZAGA, RS	0.89	0.95	0.9	0.6	13.6
SETE LAGOAS, MG	0.87	0.96	0.8	-0.2	11.2
SURUBIM, PE	0.74	0.72	1.8	-1.6	20.8
Total	0.70	0.90	1.3	-0.4	15.2

The coefficient of determination (R^2) ranged from 0.57 in Dourados, MS, to 0.91 in Pelotas, RS. The tendency observed for temperature data, of better estimates in southern Brazil, was not observed for sunshine hours, with the average of 0.70 representing well all the regions evaluated.

Other statistical indices showed that NP data, despite the moderate precision, showed a good to excellent accuracy, with d index ranging from 0.72 to 0.98, with a general value of 0.90, which is high. Considering now the RMSE, it ranged between 0.7 to 2.0 °C with average tendency of underestimation, as shown by ME, which was predominantly negative (-0.4 ^{o}C). Finally, the MAPE varied substantially, between 10.0 and 39.6%, with an average of 15.2%, which can be classified as high.

Part of the discrepancies observed in the sunshine hours can be associated to the fact that this variable was estimated for the NP data by the Ängstron and Prescott method, which apply empirical coefficients, photoperiod, and the relationship between incoming solar radiation and extraterrestrial solar radiation (PEREIRA et al., 2002). As the coefficients "a" and "b" of the Ängstron and Prescott method were not calibrated locally for sunshine hours estimation, errors of more than 1 h can occur, as observed in Table 3.6.

Even with errors of such magnitude, NP system uses to estimate solar radiation with higher accuracy than weather generator, as WGENR (WHITE et al., 2011), which is because this kind of generator is not able to reproduce the empirical distributions of global irradiance, as observed by Hansen (1999). This was also reported by Soltani and Hoogenboom (2003), who observed a weak performance of WGEN in generating solar radiation. These authors recommended improvements in this weather generator for use with crop simulation models and also highlighted that solar radiation from gridded systems, as NP, could be a suitable alternative for agricultural modelling applications.

A general view of the relationship between observed data from INMET and gridded data provided by NP for the period between 2003 and 2013 for each location is presented in the Figure 3.2, for the main variable that affect potential crop yield.

These relationships show that NP data is able to represent the variability observed in the weather stations, mainly for air temperature (Figures 3.2a to c). For sunshine hours (Figure 3.2d), the data express also the observed variability, however with a slightly tendency of overestimation (5.0%).

The rainfall and reference evapotranspiration are the main weather variables to contribute to the water balance and so to regulate the water availability in the soil for crop growth. The comparisons between observed (INMET) and estimated (NASA/POWER) rainfall and reference evapotranspiration are presented in the Tables 3.7 and 3.8.

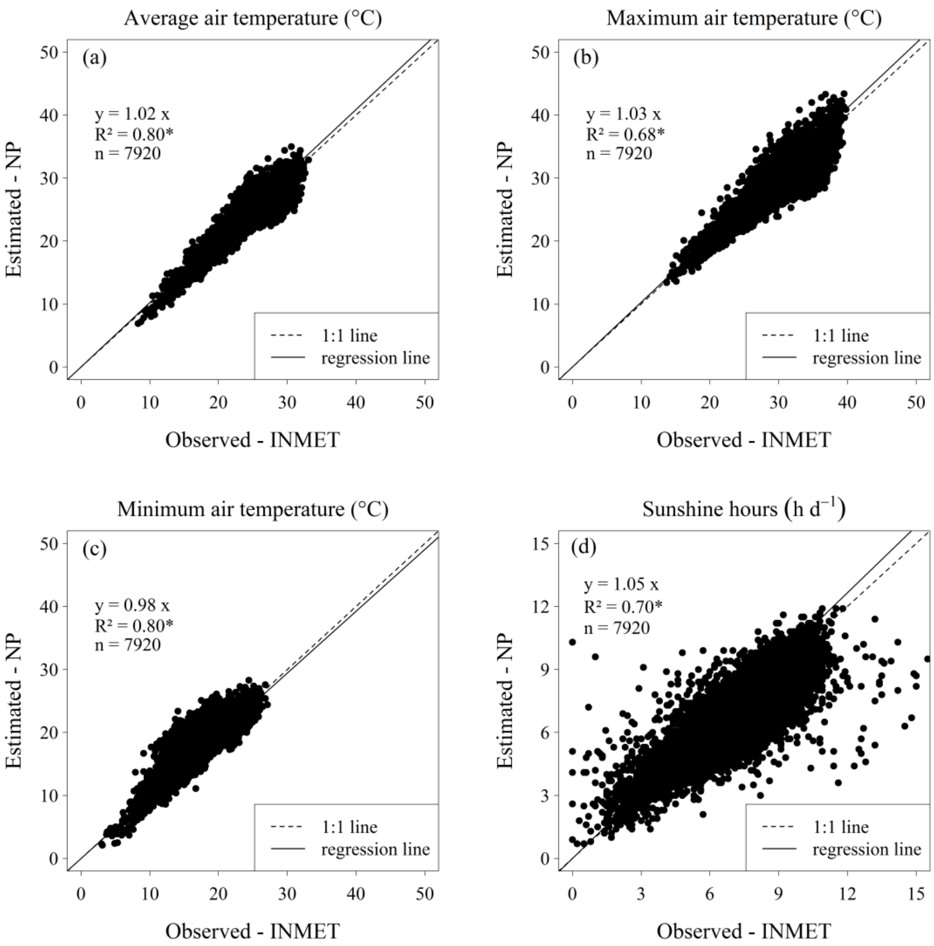

Figure 3.2 - Relationship between the observed (INMET) and gridded (NP, NASA/POWER) weather variables: (a) average air temperature, (b) maximum air temperature, (c) minimum air temperature and (d) sunshine hours for the different locations in Brazil, during the period from 2003 to 2013. *significant at 5% of confidence level

Although coefficient of determination (R^2 = 0.60) , mean error (ME = 1.9 mm ten-day^{-1}) and agreement index (d = 0.88), in general, presented reasonable values for the comparison of rainfall data from INMET and NP, the high RMSE (30.1 mm ten-day^{-1}) and MAPE (233.4%) levels reflect the huge gaps presented by the gridded data (Table 3.7). This kind of performance was already reported by Stackhouse (2010) in the NP documentation, when the rainfall was evaluated from 3 locations in Louisiana (USA) which allows to conclude that rainfall gridded data is not a good option to represent daily events, despite the yearly overall averages are similar (Table 3.2).

Table 3.7 - Statistical indices for the comparison between rainfall data obtained from the National Institute of Meteorology (INMET) and NASA/POWER (NP) system, in different locations across Brazil: coefficient of determination (R^2), agreement index (d), root mean square error (RMSE), mean error (ME), and mean absolute percentage error (MAPE)

Location, state	R^2	d	RMSE	ME	MAPE
			(mm ten-day^{-1})		(%)
ALTO PARNAIBA, MA	0.67	0.89	29.4	-4.4	112.2
CATANDUVA, SP	0.59	0.87	30.3	7.3	235.7
CIPÓ, BA	0.38^{ns}	0.76	23.3	0.8	360.3
CRATEUS, CE	0.72	0.91	23.0	1.8	356.9
DOURADOS, MS	0.55	0.85	30.1	5.8	226.9
FORMOSA, GO	0.64	0.88	31.3	-1.7	168.0
JACOBINA, BA	0.49	0.82	24.2	-4.4	196.4
LONDRINA, PR	0.45	0.81	36.5	-0.6	156.4
MONTES CLAROS, MG	0.71	0.91	26.7	0.7	360.2
NOVA XAV.(XAVANTINA), MT	0.60	0.87	36.5	3.8	204.8
PALMAS, TO	0.54	0.85	39.4	-1.2	104.3
PELOTAS, RS	0.39^{ns}	0.77	33.9	8.2	270.7
PICOS, PI	0.70	0.91	19.0	2.1	268.8
PIRACICABA, SP	0.54	0.84	31.2	8.0	202.1
POXOREO, MT	0.65	0.89	32.2	0.6	98.5
RIO VERDE, GO	0.60	0.88	33.9	-2.0	107.6
SAO JOAO DO PIAUI, PI	0.57	0.86	22.5	2.4	477.6
SAO LUIZ GONZAGA, RS	0.61	0.88	34.8	2.1	210.1
SETE LAGOAS, MG	0.71	0.91	29.3	2.9	347.3
SURUBIM, PE	0.44	0.77	25.2	5.5	290.3
Total	0.60	0.88	30.1	1.9	233.4

^{ns} not significant at 5% of confidence level

Van Wart et al. (2015) evaluated the rainfall data series recorded by NASA/POWER (NP) (1° x 1° grid) and also by Tropical Rainfall Measuring Mission (TRMM) system, which presents a finer grid (2.5 km^2), for eighteen locations around the world, finding very low precision coefficients ($R^2_{NP} < 0.20$ and $R^2_{TRMM} < 0.30$) and high RMSE in a daily time-scale (NP and TRMM ≈ 9.0 mm d^{-1}). When the rainfall for both data sources were analyzed in a bi-weekly time-scale, the precision coefficient and RMSE were slightly improved ($R^2 \approx 0.62$ and RMSE ≈ 35 mm), matching with the magnitude of the results obtained here (Table 3.7), even being evaluated for a shorter time scale (ten-day) (R^2 of 0.60 and RMSE of 30.1 mm).

Therefore, this suggests that local rainfall could provide better results when using crop simulation models, generating more accurate yield estimations.

Table 3.8 - Statistical indices for the comparison between reference evapotranspiration (mm ten-day^{-1}) data obtained from the National Institute of Meteorology (INMET) and NASA/POWER (NP) system, in different locations across Brazil: coefficient of determination (R^2), agreement index (d), root mean square error (RMSE), mean error (ME), and mean absolute percentage error (MAPE)

Location, state	R^2	d	RMSE	ME	MAPE
			(mm ten-day^{-1})		(%)
ALTO PARNAIBA, MA	0.32^{ns}	0.63	10.0	-7.0	15.1
CATANDUVA, SP	0.65	0.88	8.0	2.4	18.2
CIPÓ, BA	0.89	0.94	4.8	-3.2	7.3
CRATEUS, CE	0.52	0.82	4.8	-1.8	8.1
DOURADOS, MS	0.54	0.82	10.1	-3.2	21.0
FORMOSA, GO	0.86	0.95	4.1	-1.8	8.3
JACOBINA, BA	0.85	0.94	4.6	-2.8	8.0
LONDRINA, PR	0.95	0.96	5.2	-4.1	12.8
MONTES CLAROS, MG	0.92	0.97	3.6	-2.1	6.6
NOVA XAV.(XAVANTINA), MT	0.70	0.72	10.6	-8.9	19.9
PALMAS, TO	0.75	0.84	6.0	-4.7	10.6
PELOTAS, RS	0.99	0.99	3.4	-2.6	10.2
PICOS, PI	0.63	0.87	4.5	-1.9	7.7
PIRACICABA, SP	0.83	0.93	6.1	2.1	14.2
POXOREO, MT	0.68	0.8	8.3	-6.2	17.0
RIO VERDE, GO	0.75	0.93	5.8	0.4	11.7
SAO JOAO DO PIAUI, PI	0.66	0.82	6.4	-4.6	10.8
SAO LUIZ GONZAGA, RS	0.98	0.99	3.0	-1.7	8.0
SETE LAGOAS, MG	0.87	0.96	4.5	-1.8	12.9
SURUBIM, PE	0.87	0.89	5.8	-4.5	8.9
Total	0.79	0.93	6.0	-2.9	11.9

^{ns} not significant at 5% of confidence level

For reference evapotranspiration (ETo), the results are quite different from rainfall, with a better agreement between observed (INMET) and estimated (NASA/POWER) data (Table 3.8). Ababaei (2014) evaluating the performance of weather generators for evapotranspiration and irrigation studies in a Province of Iran, detected that these tools also have potential to be employed for hydrological studies in watersheds. The relationship between the observed and estimated rainfall and reference evapotranspiration data are presented in Figure 3.3.

The relationship for rainfall presented in Figure 3.3a shows the high dispersion of data (R^2 = 0.60), with NP underestimating observed data by 13%. It definitely demonstrates that rainfall from NP is not a good option for agroclimatological studies. In the NP documentation (STACKHOUSE, 2010) also is shown an analysis for more than 1000 rainfall stations and their comparison with gridded weather data for daily (R^2 = 0.21 and RMSE = 7.1 mm) and monthly (R^2 = 0.46 and RMSE = 1.72 mm) steps, in which the statistical coefficients were not satisfactory for both time-steps evaluated. Moreover, for both cases the rainfall also was underestimated as shown in Figure 3.3a.

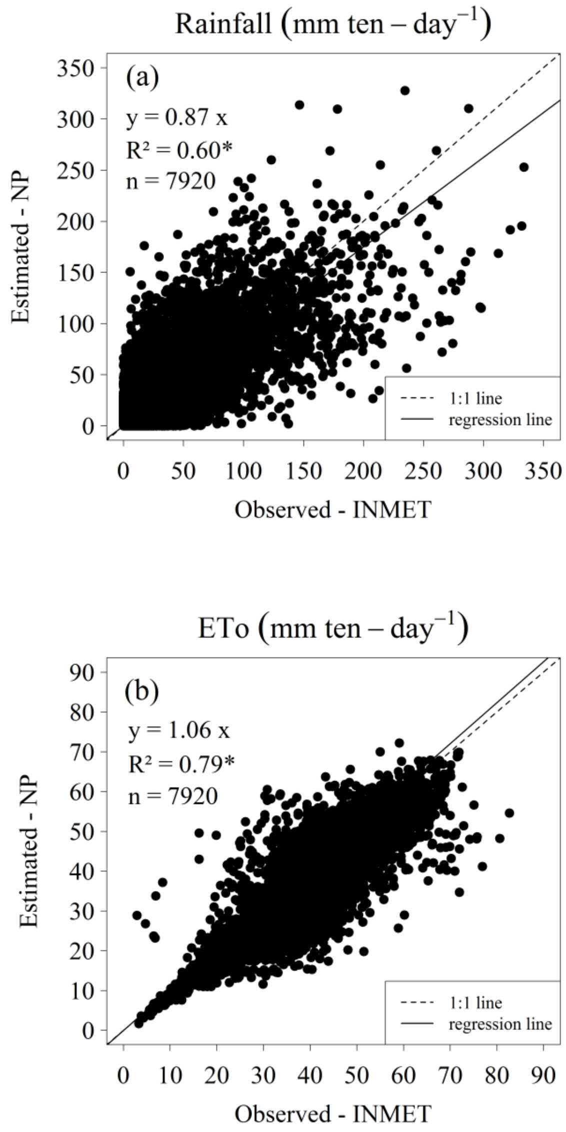

Figure 3.3 - Relationship between the observed (INMET) and gridded (NP, NASA/POWER) rainfall and reference evapotranspiration data for different locations in Brazil, during the period from 2003 to 2013. *significant at 5% of confidence level

It highlights that due the high spatial variability of precipitation data, the use of local rainfall stations is more appropriated to be used for applications in agricultural modelling such are provided by National Water Agency (ANA). On the other hand, ETo when estimated by NP data showed a better agreement with ETo estimated with INMET data, with an overestimation of 6.0% and precision of 79% (R^2 = 0.79), having potential to be employed in crop simulation models for studies at regional and national scales.

3.3.2 Impact of gridded weather data on yield simulations

The sugarcane potential yield was simulated for 36 planting dates, in a ten-day period scale for ten years (2003-2013). The results from this analysis are presented in Figure 3.4 for the estimates with (a) INMET and (b) NP data.

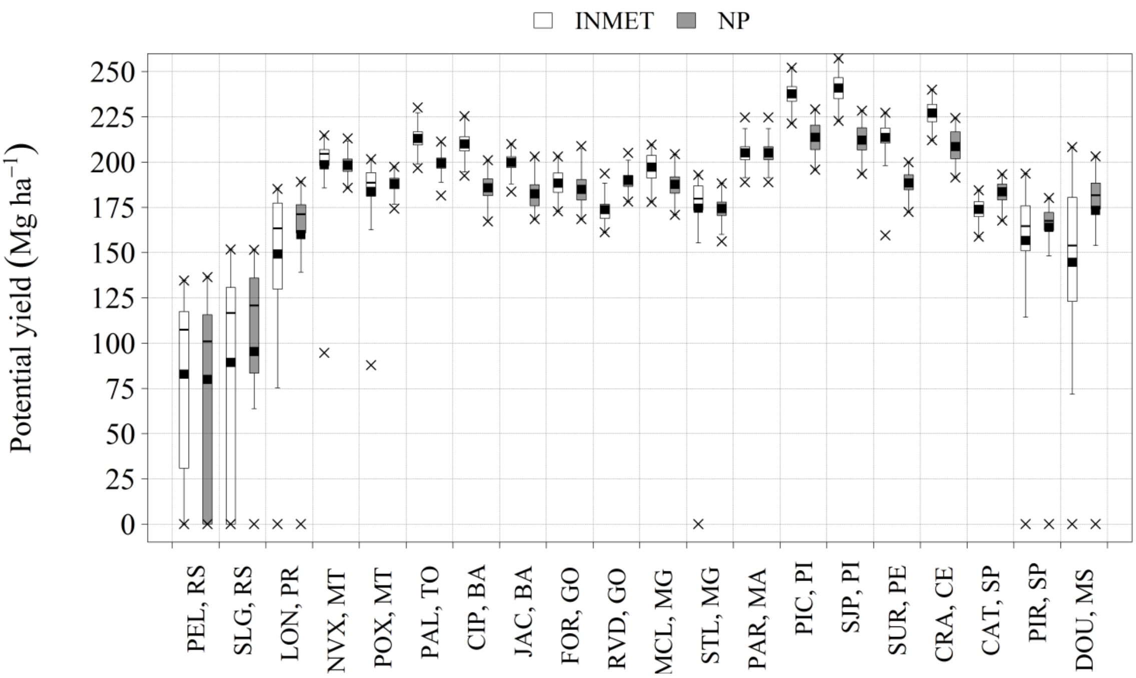

Figure 3.4 - Boxplot for potential yield estimated with weather data from INMET (Observed) and from NASA/POWER (NP, estimated) in different Brazilian locations. PEL = Pelotas; SLG = São Luiz Gonzaga; LON = Londrina; NXV = Nova Xavantina; POX = Poxoréo; PAL = Palmas; CIP = Cipó; JAC = Jacobina; FOR = Formosa; RVD = Rio Verde; MTC = Montes Claros; STL = Sete Lagoas; PAR = Alto Parnaíba; PIC = Picos; SJP = São João do Piauí; SRB = Surubim; CRT = Crateus; CAT = Catanduva; PIR = Piracicaba; and DOU = Dourados

From Figure 3.4, it is clearer observed that for high latitudes the Yp simulations presents higher variability along the year, as in Pelotas and São Luiz Gonzaga, RS, and in Londrina, PR. Such variability is associated to the variations of the meteorological conditions, mainly due to the frosts occurrence as well as to the higher seasonal variation in the photoperiod and solar radiation than in higher latitudes. On the other hand, for the other regions at mid and low latitudes, the potential yield inter-annual variability was very small. The absolute (Yp_{NP} - Yp_{INMET}) and relative ([Yp_{NP} - Yp_{INMET}]/Yp_{INMET}) deviations are presented in the Figure 3.5.

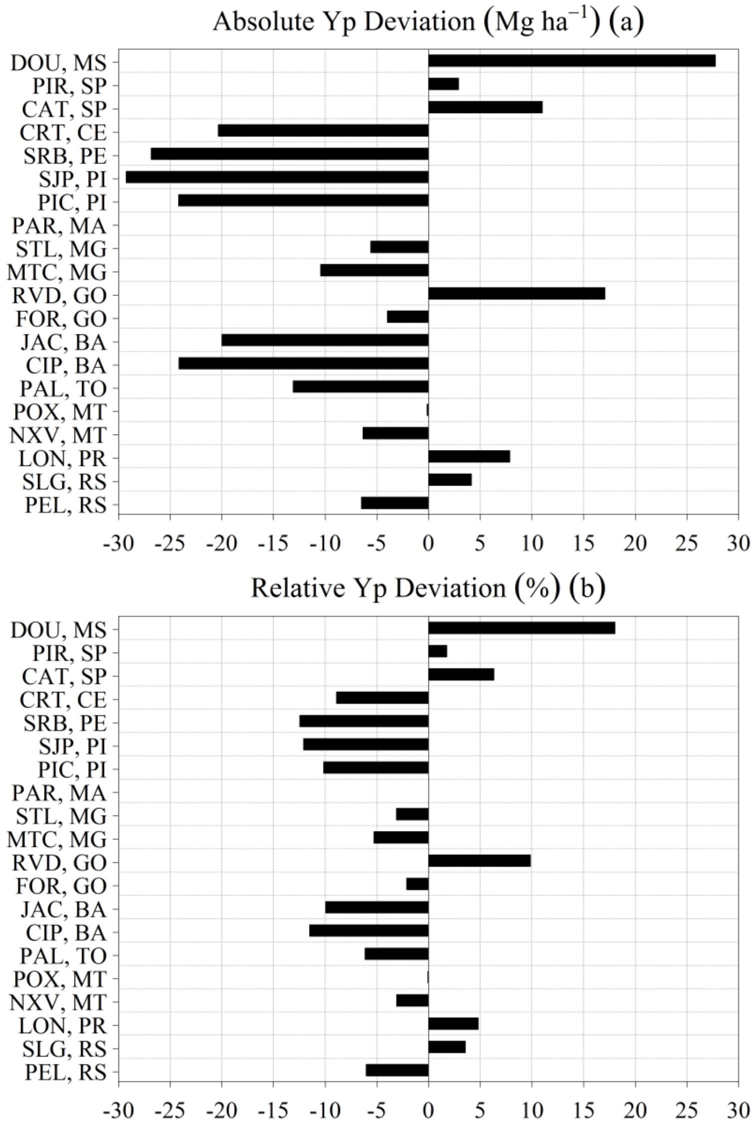

Figure 3.5 - Absolute and relative deviations of potential yield (Yp) in different Brazilian locations. PEL = Pelotas; SLG = São Luiz Gonzaga; LON = Londrina; NXV = Nova Xavantina; POX = Poxoréo; PAL = Palmas; CIP = Cipó; JAC = Jacobina; FOR = Formosa; RVD = Rio Verde; MTC = Montes Claros; STL = Sete Lagoas; PAR = Alto Parnaíba; PIC = Picos; SJP = São João do Piauí; SRB = Surubim; CRT = Crateus; CAT = Catanduva; PIR = Piracicaba; and DOU = Dourados

When comparing the potential yield estimates with data from NP and INMET (Figure 3.5), a huge difference can be observed for some locations. The highest differences when using different sources of data for Yp estimation was for the states of Bahia, Piauí and Pernambuco, with negative differences higher than 20 Mg ha^{-1}, and Paraná state with a positive difference of 20 Mg ha^{-1}. When considering the relative deviation, the highest differences are between 10 and 15%, which for agroclimatological studies can be considered as reasonable. Van Wart et al. (2013a) employing NP database for Yp simulations of rice in

China, maize in USA and wheat in Germany, found errors between 12 and 19%, matching with the results obtained here for sugarcane. Additionally, De Wit and Van Diepen (2008) carried out yield simulations for winter-wheat in Spain, Poland and Belgium, with high confidence when the derived-satellite weather data were employed as model inputs, with errors under potential conditions of the same magnitude found here (up to 15 %), as shown in the Figure 3.5b. As can be seen in Figure 3.3, the main source for Yp differences when using NP data is the sunshine hours (Figure 3.3d), once it has much more data dispersion in relation to INMET data than air temperature data (Figures 3.3a, b and c). However, solar radiation data provided by NP can be a suitable alternative for crop model applications, even when it needs to be converted by sunshine hours through empirical equations (e.g. Ängstrong-Prescott) when this variable is not available (GRASSINI et al., 2015).

According to van Wart et al. (2013a) studies, extremes weather values cannot be well represented by interpolated variables which can cause inconsistences in yield simulations.

For attainable yield, when the simulations were done with observed data, a huge inter-annual yield variability was observed (Figure 3.6), for all locations, promoted basically by the water deficit during crop cycle.

When the Yatt simulations were done with NP data, the variability of same magnitude was also observed (Figure 3.6), showing the same pattern observed when the Yatt estimates were done with observed weather data. The same was also observed when the Yatt simulations were performed with weather data from NP system, but with observed rainfall from the closest ANA pluviometric station (Figure 3.6).

Even considering the similarities in the distribution of the Yatt inter-annual variability, for all evaluated locations, when the differences between Yatt estimated with NP or NP + ANA data with that simulated with observed data (INMET) were computed it was possible to observed a significant reduction in the differences when the combined dataset was used. Such improvement in the performance of the Yatt estimates with combined data can also be seen in Figure 3.7, where is observed a clear improvement of both precision and accuracy.

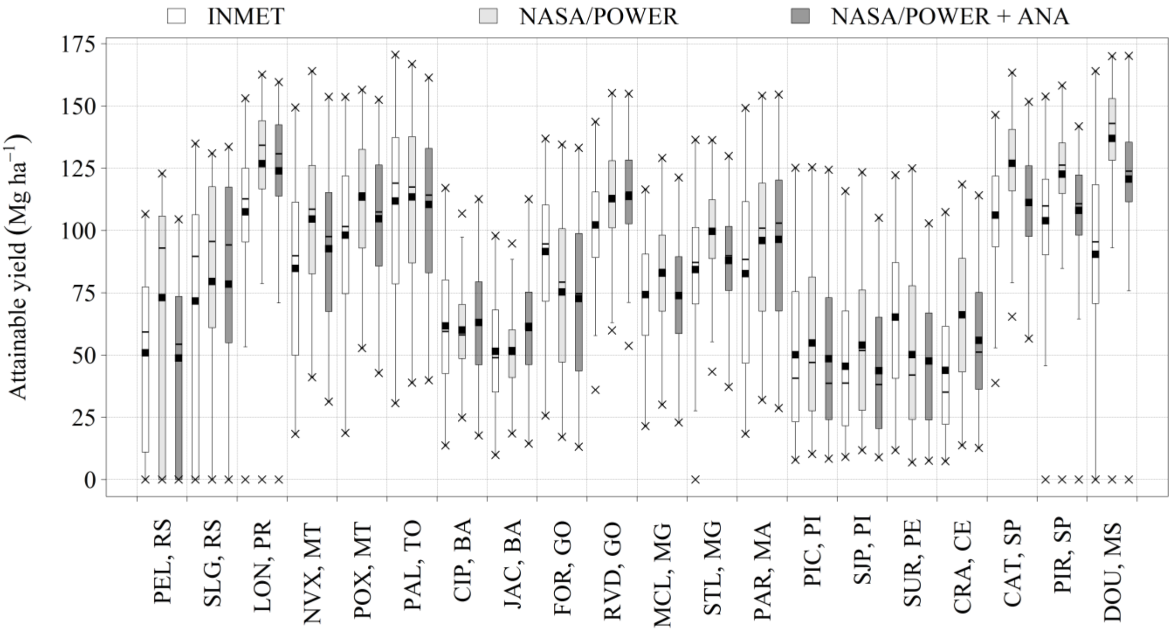

Figure 3.6 - Boxplot for attainable yield estimated with weather data from INMET (Observed), from NASA/POWER (estimated) and NASA/POWER + ANA (combined) in different Brazilian locations. PEL = Pelotas; SLG = São Luiz Gonzaga; LON = Londrina; NXV = Nova Xavantina; POX = Poxoréo; PAL = Palmas; CIP = Cipó; JAC = Jacobina; FOR = Formosa; RVD = Rio Verde; MTC = Montes Claros; STL = Sete Lagoas; PAR = Alto Parnaíba; PIC = Picos; SJP = São João do Piauí; SRB = Surubim; CRT = Crateus; CAT = Catanduva; PIR = Piracicaba; and DOU = Dourados

The statistical analysis when comparing Yatt estimated with NP and with INMET data generated the following indices and errors: R^2 = 0.70; d = 0.89; ME = 10.8 Mg ha^{-1}; RMSE = 24.1 Mg ha^{-1}; and MAPE = 30.4%. On the other hand, when the rainfall data from NASA/POWER was replaced by rainfall data from the closest ANA pluviometric station, and increase in precision, with R^2 = 0.82, and accuracy, with d = 0.96, were observed. Also, all the errors decreased, with ME = 3.8 Mg ha^{-1}, RMSE = 16.7 Mg ha^{-1} and MAPE = 18.5%.

De Wit et al. (2005) investigated the differences of crop yields when considering as yield model input the gridded weather data (50 x 50 km of spatial resolution) and its comparison with ground weather sources in Germany and France. These authors tested the precipitation and solar radiation changes, finding a overestimation of around 9 and 7% when attainable yields were simulated with gridded data for wheat and maize, respectively. These differences can be associated with uncertainties in precipitation from gridded datasets, as can also be seen in Figure 3.7a, where the sugarcane yield was underestimated of 14% (y = 0.86 x) when NP data were employed in the simulations.

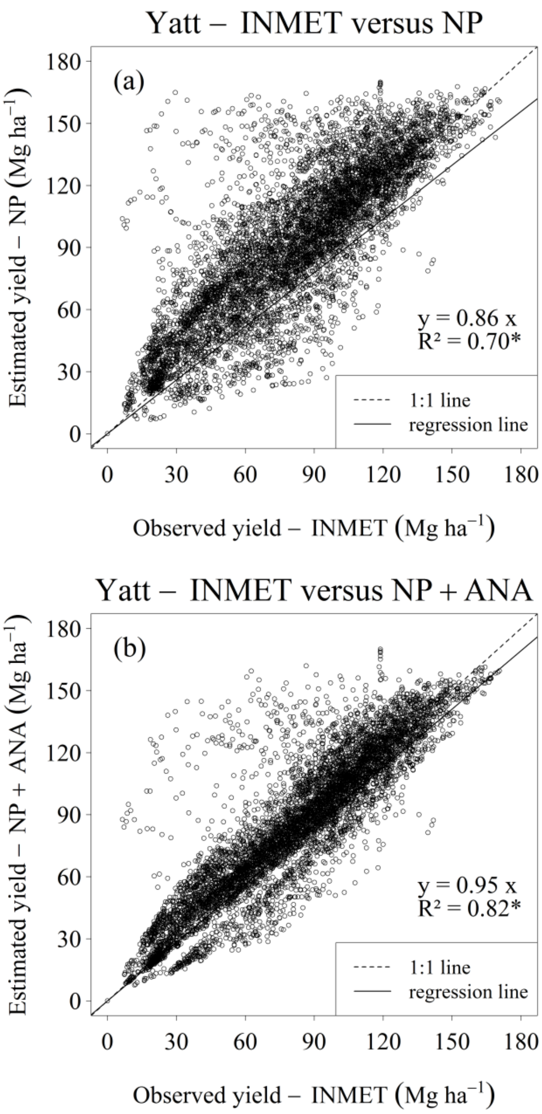

Figure 3.7 - Relationship between sugarcane attainable yields simulated with weather data from: a) INMET and NASA/POWER (NP); and b) INMET and a combined weather dataset (NP + ANA), for different Brazilian regions, for the period between 2003 and 2013

It can configure more one prove that the use of locally precipitation data sets are the most suitable source for rainfall data and confidence climate risk analysis, once the simulated attainable yields presented a good agreement when the precipitation data from NP was replaced by the ones provided by ANA sources (Figure 3.7b).

Van Wart et al. (2013) analyzed the performance of NASA/POWER in to simulate the maize yields in United States, rice in China and wheat in Germany, reporting that the largest discrepancy of estimated Yatt in relation to the observed ones is due water deficit, weighted by precipitation along the growing cycle and also solar radiation. In addition, in which the precision was only 35% of Yatt estimated with controlled weather stations (R^2 = 0.35).

3.4. Conclusions

The results presented in this study allow to conclude that:

1. Even with a relative huge gridded spatial coverage (1° by 1° of latitude and longitude), the weather data generated by the NASA/POWER system showed to be satisfactory to produce air temperature, solar radiation and reference evapotranspiration for Brazilian locations in different regions of the country, being a potential tool to be used to create virtual weather stations and improve the capacity for agricultural analysis in areas with a low weather stations spatial density;

2. The Yp estimated with data from NASA/POWER system presented a reasonable agreement with those estimated with INMET observed data for most assessed locations, presenting, therefore, a high potential to be employed for large scale spatial analysis;

3. The Yatt estimates were improved when NASA/POWER rainfall data were replaced by the rainfall from the closest ANA station. It proves that coupling gridded weather data with local rainfall measurements is the most appropriated way run crop simulation models for large scales analysis.

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4 SUGARCANE YIELD GAP IN BRAZIL: MAGNITUDE, CAUSES AND POSSIBLE STRATEGIES TO ITS MITIGATION

Abstract

Brazil has leading the sugarcane production around the world in the last decades, which is attributed to the suitability of the climates and soils of the country to this crop. However, the current yields are still far from the country´s potentiality, which has compromised the sustainability of the entire production chain of this crop. Such scenario is requiring the use of suitable methods for improving the efficiency of this crop, by identifying the main causes of yield gaps. Based on that, the general objectives of this study were: to determine the sugarcane yield gaps, caused by water deficit and crop management, across the country; to map yields and yield gaps; and, then, to suggest management actions to mitigate them in order to have a sustainable crop production. An agrometeorological yield model was employed to determine the potential (Yp) and best farmer's yield (Ybf) for all production regions in Brazil. The yield model was properly calibrated and evaluated with yield data from twelve sugarcane fields across the country; all conducted under high technology practices, for both rainfed and irrigated crop systems. The model was run for 259 locations, with weather data from NASA/POWER virtual stations for a period of 31 years (1984 to 2013), but with rainfall from National Water Agency (ANA). The Yp and Ybf simulations were done for 30 growing cycles, considering plant and ratoon canes (early, mid and late). The sugarcane final yield was weighted by plant and ratoon canes, according to the seasons suggested in the official agro-climatic zoning. The average observed yields (Yavg) were obtained from the Brazilian Institute of Geography and Statistics (IBGE) for each corresponding micro region across the country, excluding the Pantanal and Amazon biomes. The average Yp in Brazil was 186.5 Mg ha^{-1}, ranging between 68 Mg ha^{-1}, in the South region, to 233 Mg ha^{-1}, in the North region. On average, the Ybf in Brazil was 85.7 Mg ha^{-1}, varying between 61.7 Mg ha^{-1}, in almost all states of Northern region, to 123.3 Mg ha^{-1} in the state of Mato Grosso do Sul. For Yavg, the national range was between 12.7 and 101.1 Mg ha^{-1}, with an average of 54.2 Mg ha^{-1}. Concerning the yield gap, the average total value in Brazil was 123.2 Mg ha^{-1}. The main source for yield losses was the water deficit, which accounted for about 74 % of total losses, while the crop management caused losses of about 26% of the total. These results contribute to better understand which the limitations for sugarcane crop in Brazil are, and, so, which are the main actions to improve yields. Considering that the main source of yield gap for sugarcane is water deficit, irrigation and drought tolerant cultivars are the best strategies for improving yields and making this crop more efficient.

Keywords: Crop simulation model; Potential and best farmer's yields; Yield spatial variability; Crop sustainability

4.1 Introduction

The rapid demand for food and energy has required methods which allow to identify more appropriated regions for an efficient crop production. Due the privileged geographic position (almost all territory in the tropical zone) (Figure 4.1), Brazil has leading the sugarcane world production during the last four decades, presenting a harvested area of around 10 million hectares, being follow by India, China, Thailand and Pakistan with a harvested area of 5.1, 1.8, 1.3 and 1.1 million hectares (FAO, 2014).

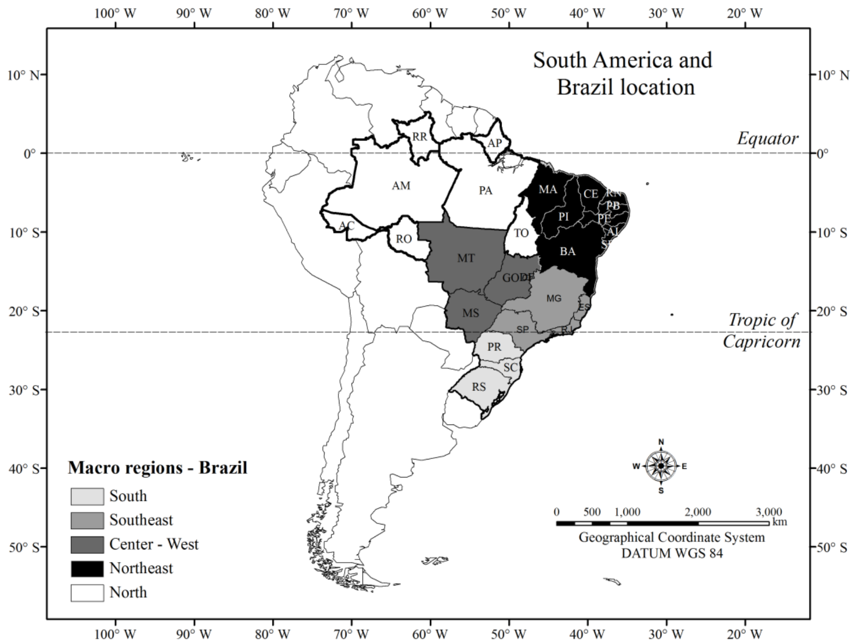

Figure 4.1 – Brazil territory in South America and its macro regions and states

The increasing demand for biofuels, produced in a sustainable way, has requiring an increment in the sugarcane production, considering both area expansion and yield improvement. Among the producers around the world, Brazil is the one that still have areas (around 65 million hectares) for agricultural expansion (IBGE, 2009), mainly into the regions with degraded pasture and marginal lands in relation to climatic conditions (SENTELHAS et al., 2015).

4.1.1 Current sugarcane production in Brazil

After the 2000's, the introduction of flex fuel cars in the Brazilian market promoted an increase in the demand for ethanol and, consequently, for sugarcane production. As a result of that, sugarcane production expanded to new areas, dominating great part of agricultural lands of the center-southern Brazil. For the next growing season (2015/16) is expected a total sugarcane production of around 655 million Mg, which will be destined for sugar (37 million Mg) and ethanol (29 billion of liters) productions (CONAB, 2015). Table 4.1 presents the summary of the sugarcane cropping area during the last growing season (2014/2015), the forecast for the next one (2015/16), the average stalks yield for the last ten years, and the forecasted yield for 2015/16 in all the country.

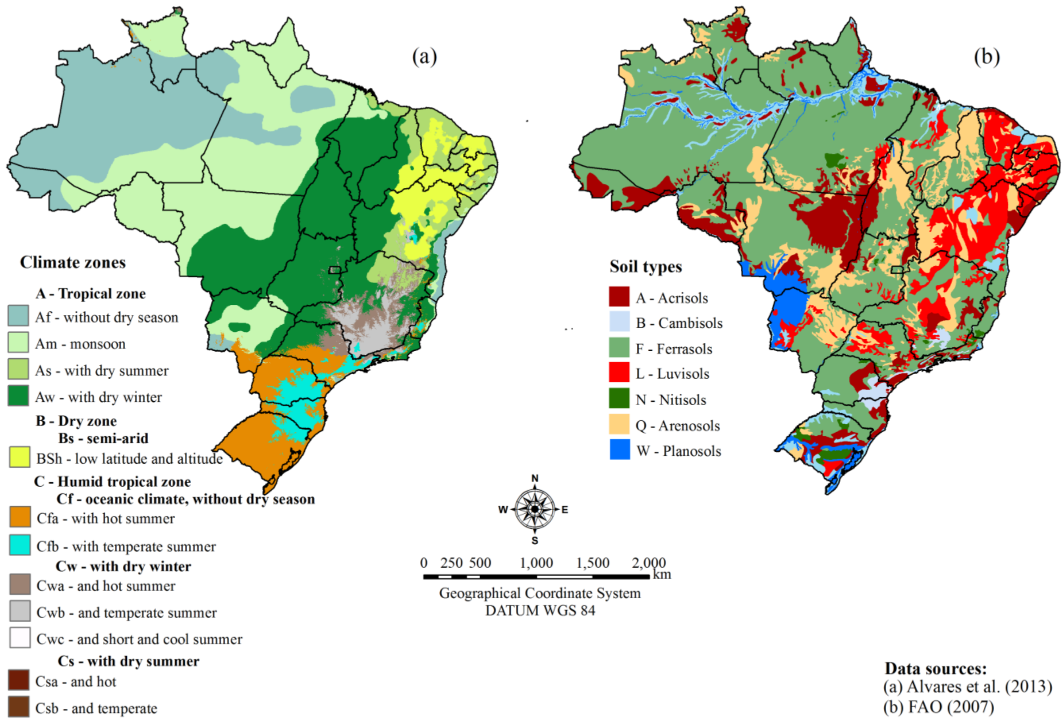

Figure 4.2 – Spatial variability of climates (a) and soils (b) in Brazil, according to Koopen's climate classification (ALVARES et al., 2013) and soil distribution (FAO, 2007)

According to Table 4.1, the sugarcane cropping area in Brazil is going to have a slight increase of 0.73% for the next season (2015/16), but with the yield, in the majority of the regions, presenting a reductions in relation to the average of the last 10 years (CONAB, 2015), which shows that sugarcane yield in Brazil is not following the same tendency of other crops, with significant increments along the years. In addition, the data from Table 4.1 allow to identify a high yield variability among regions, which in part is due to the diversity of climates and soils (Figure 4.2), but also to the different levels of technology used.

Table 4.1 – Summary of sugarcane cropping area, average yield, from 2005/06 to 2014/15, and forecasted yields, for 2015/16, in Brazil

Region, State	Cropping area (10^3 ha)		Stalks yield (Mg ha^{-1})	
	Last year (2014/15)	Forecasted (2015/16)	Average (2005/06 to 2014/15)	Forecasted (2015/16)
Southeast	5,593.1	5,593.2	80.5	74.3
São Paulo, SP	4,685.7	4,687.6	81.9	74.8
Minas Gerais, MG	805.5	807.9	76.6	75.0
Espírito Santo, ES	68.9	64.8	58.9	42.8
Rio de Janeiro, RJ	33.0	32.8	55.3	50.0
Northeast	979.0	1003.2	56.1	58.0
Alagoas, AL	385.3	386.1	60.1	58.8
Pernambuco, PE	260.1	276.3	53.1	55.2
Paraíba, PB	130.6	130.4	49.9	50.5
Bahia, BA	56.0	54.9	66.6	79.6
Rio Grande do Norte, RN	48.2	53.1	48.6	54.3
Sergipe, SE	44.4	45.1	57.3	55.0
Maranhão, MA	38.8	40.4	57.7	67.4
Piauí, PI	13.9	15.2	65.8	68.1
Ceará, CE	1.8	1.8	63.2	76.3
Center-West	1,748.5	1,801.5	73.4	72.9
Goiás, GO	854.2	891.6	75.9	77.0
Mato Grosso do Sul, MS	668.3	682.3	73.9	66.5
Mato Grosso, MT	226.0	227.6	68.8	76.0
South	636.3	621.3	73.8	73.6
Paraná, PR	635.0	620.1	74.7	73.6
Rio Grande do Sul, RS	1.4	1.2	44.8	59.8
North	47.6	51.2	68.0	73.7
Tocantins, TO	27.9	30.2	71.2	75.6
Brazil	9,004.5	9,070.4	75.40	72.10

Source: CONAB (2015)

4.1.2 Yield concepts, approaches and their conditioning factors

The interactions among the genotype (species and cultivar), climatic conditions, and crop management cultivar determine the yield types and, consequently, the yield gap (YG) magnitude.

Potential yield (Yp) is defined as the yield from a genotype well adapted to the environmental conditions where the growth and development are controlled only by the incoming solar radiation, air temperature, photoperiod, atmospheric CO_2 concentration, and crop characteristics, such as plant population (EVANS, 1993; VAN INTTERSUM; RABBINGE, 1997). In addition, Yp is considered as a specific and theoretical yield achieved by a high productivity crop/cultivar without water deficit (limiting factor) throughout the growing cycle, and conducted under optimum crop management, with fertilization and pests/diseases/weeds (reducing factors) effectively controlled (EGLI; HATFIELD, 2014).

There are several approaches to determine Yp. Although Lobell et al. (2009) cited different methods to Yp estimation, such as crop simulation models (CSM), field experiments, and maximum farmer's yield, the first one (CSM) allows to estimate Yp more accurately, once the limiting and reducing yield factors are effectively eliminated from the simulations. Furthermore, even under very controlled experimental fields and high technology for controlling the reducing factors along the crop cycle, is almost impossible to reach and to guaranty that no damage will occur to the plants throughout the growing season (LOBELL et al., 2009; VAN INTTERSUM et al., 2013).

The attainable yield (Yatt) is defined as the yield type achieved by a well-adapted crop/cultivar, in which reducing factors are effectively controlled and the crop growth is conditioning, further than determining factors, by the water deficit intensity along the crop cycle. According to van Inttersum et al. (2013), Yatt is driving, therefore, by determining factors but limited by the water supply, which can be associated mainly with rainfall distribution as well as within soil physics characteristics (texture and structure) and root depth. These factors define the water holding capacity of a given soil, which is directly related to water availability for the crop.

The maximum Yatt for a given region defines the exploitable yield (Yexp), which expresses the maximum ratio between Yatt and Yp, under optimum and high technology management. Usually, Yexp ranges from 75 to 85% of Yp for the major grains around the world (VAN INTTERSUM et al., 2013), although in some experimental fields and very competitive agriculture regions as in U.S. Corn Belt and Southern Asia (NEUMANN et al., 2010) the Yexp are expected to reach 90% of Yp for crops such as maize and rice, respectively.

Finally, the yield achieved by farmers is controlled by all environmental factors associated to factors related to crop and soil management. According to Grassini et al. (2014), the final yield is determined by the interaction of crop, environment and management practices, which vary significantly in both spatial and temporal scales.

Lobell et al. (2009) indicated the most common biophysical and socioeconomic factors that contribute to yield losses in the final farmer's yield are: water stress; high pressure of pests and diseases; sub-optimal planting date; and lack of insurance and credit.

Once crop management is an important aspect for defining the crop yield, the technological level employed by farmers in the field throughout the growing cycle also needs to be considered. Sentelhas et al. (2015) classified the Brazilian soybean farmers according to their technological degree employed in the fields accordingly: Best farmer's yield (Ybf), in which optimum crop management is applied with high response to that specific production environment; and Average farmer's yield (Yavg), when the management employed in the fields is similar to the other farmers in a given region, leading these farmers to lower average annual yields in comparison to more competitive farmers.

Considering that most of sugarcane crop fields in Brazil is conducted under rainfed conditions, the following yield types and their conditionings factors can be considered (Figure 3): potential yield (Yp); attainable yield (Yatt); best farmer's yield (Ybf); and average farmer´s yield (Yavg), with the last one representing what is reported by the surveys conducted by the governmental agencies as Brazilian Institute of Geography and Statistics (IBGE) and Brazilian Food Supply Company (CONAB).

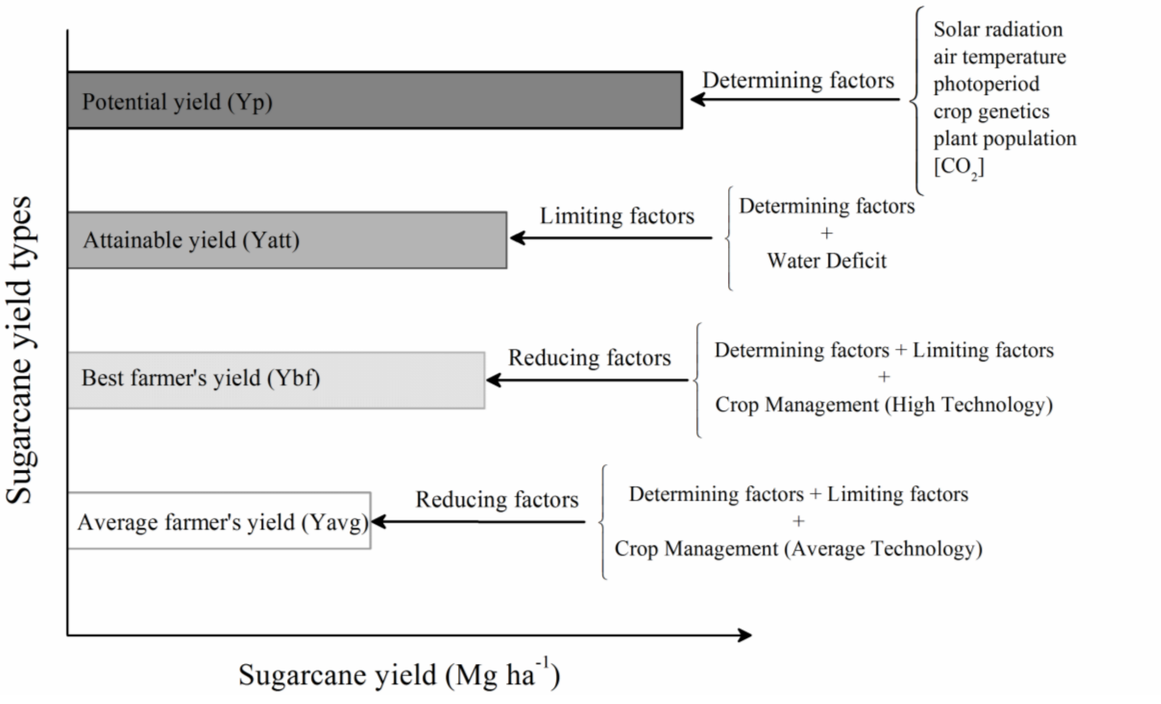

Figure 4.3 – Sugarcane yield types under rainfed conditions and their respective conditioning factors (adapted from LOBELL et al., 2009; VAN INTTERSUM et al., 2013; SENTELHAS et al., 2015)

The comparison between yield types and their conditionings factors lead to the definition of yield gap (YG). According to Neumann et al. (2010), YG is any yield deviation from a potential yield both in irrigated and rainfed crop systems. The difference between the potential yield and the average farmer's yield is the total yield gap (YG_{total}) (CASSMAN et al., 2003). The YG ranges in time and spatial scales (LOBELL et al., 2009; NEUMANN et al., 2010; GRASSINI et al., 2014).

The YG_{total} can be partitioned in terms of yield gap by water deficit (YG_{WD}) and yield gap by crop management (YG_{CM}) (BATHIA et al., 2008; SENTELHAS et al., 2015). The YG_{WD} is the difference between potential (Yp) and attainable yield (Yatt) or best farmer's yield (Ybf). YG_{WD} is controlled by determining factors and water deficit, while the YG_{CM} is obtained through the difference between attainable yield (Yatt) or best farmer's yield (Ybf) and the average farmer's yield (Yavg), which is influenced by all the factors (determining, limiting and reducing) that define the final yield.

The YG_{WD} can be also associated to the potential yield increment for a production system carried out under optimum crop management practices, where the capacity to achieve high yield is driven mainly by the water deficit supply along the crop cycle, as determined by Monteiro and Sentelhas (2014) for sugarcane in the state of São Paulo, Brazil.

On the other hand, YG_{CM} is related, further than determining and limiting factors, by the agricultural practices such as soil fertilization, soil correction and preparation, cultivar and of pests, diseases and weeds control.

Recently, many studies has been focusing on YG analysis for cereal crops (LICKER et al., 2010; GRASSINI et al., 2015; SENTELHAS et al., 2015), although evaluations for major crops in family agriculture (AFFHOLDER et al., 2013), fruits (TEIXEIRA et al., 2008), sunflower (HALL et al., 2013), and cotton and mustard (HEBBAR et al., 2008) also have been developed.

For sugarcane, although the first study about YG was conducted in Australia in 1999 (ROBERTSON et al., 1999), just recently the number of studies about that has substantially increased, with examples for India (RAO, 2012; GOMATHI et al., 2013) and South Africa (VAN DEN BERG; SINGELS, 2013). In Brazil, systematic studies about sugarcane YG, assessing the effects of irrigation and crop management on sugarcane yield, are still not very common, although initial efforts has been done in the traditional sugarcane regions in the state of São Paulo (MARIN; CARVALHO, 2012; MONTEIRO; SENTELHAS, 2014).

4.1.3 Objectives

Considering the necessity of making Brazilian sugarcane production more sustainable and profitable by reducing this crop yield gaps, the objectives of this study were: a) to determine the spatial variability of the sugarcane yield in Brazil; b) to determine the sugarcane yield gap due to water deficit and to crop management in all producing regions of the country; c) to compare the sugarcane yield gap from this study with that presented by the Global Yield Gap Atlas (www.yieldgap.org/); and d) to propose strategies to reduce these gaps in order to promote a more sustainable sugarcane production in the country.

4.2 Material and Methods

4.2.1 Weather and soil data

The sugarcane yield simulations carried out in this study were performed for a period of 30 years (1984 to 2013), covering 30 sugarcane growing seasons. The weather variables employed as inputs in the sugarcane yield model were: solar radiation (SR, MJ m^{-2} d^{-1}); effective sunshine hours (n, h d^{-1}); maximum, minimum and average air temperature (Tmax, Tmin and Tavg, °C); photoperiod (N, h d^{-1}); rainfall (mm d^{-1}); wind speed at 10-m height (U10, m s^{-1}); average relative humidity (RH, %); and reference evapotranspiration (ETo, mm d^{-1}).

A grid composed by 259 virtual weather stations (VWS) (Figure 4.4) plotted as a function of geographic coordinates (latitude and longitude) was generated, excluding the Amazon and Pantanal biomes, which are not eligible for agricultural expansion and sugarcane production by environmental laws.

A computational routine was developed in R language code (R CORE TEAM, 2014) in order to collect the daily weather inputs referent to each VWS provided by NASA/POWER system (STACKHOUSE, 2010). The rainfall data from the gridded platform were replaced by those from National Water Agency (ANA) database, available for each location. Wind speed (U10) data were adjusted for 2-m height (U2) through the wind profile equation, which resulted in a correction factor (f = 0.748), as suggested by Allen et al. (1998). The reference evapotranspiration (ETo), was estimated according to Penman-Monteith method (ALLEN et al., 1998). All dataset were adjusted to a 10-day time scale to be applied as inputs in the sugarcane yield model.

The crop water balance was calculated according to Thornthwaite and Mather (1955) method. Soil physics characteristics, mainly associated to texture, structure, porosity and depth (LACLAU; LACLAU, 2009; PRADO, 2014) were considered to determine the soil water holding capacity (SWHC).

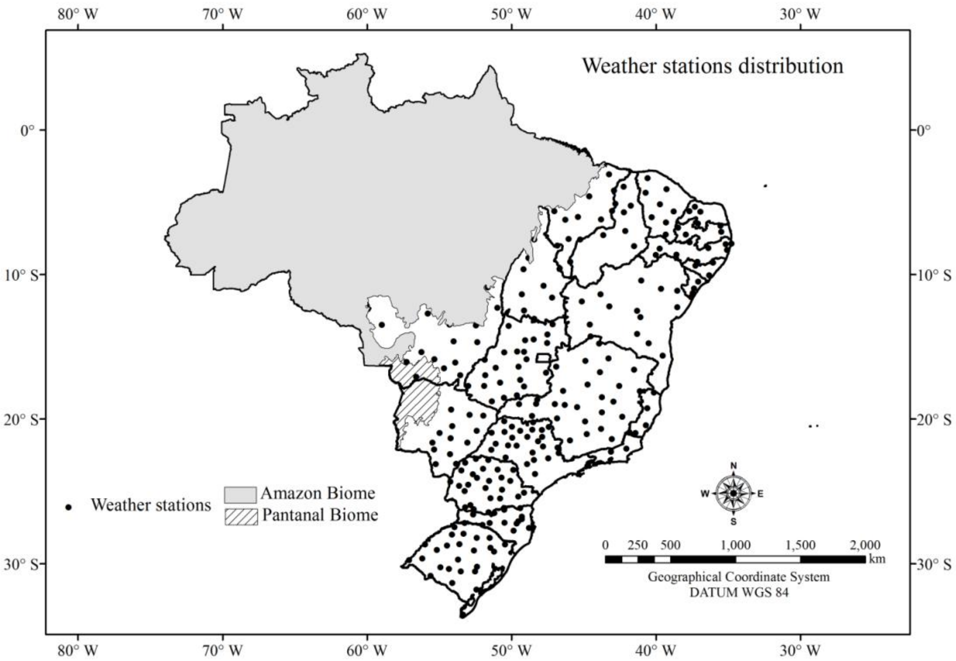

Figure 4.4 – Spatial distribution of the weather stations in Brazil, used in the present study

The Digital Soil World Map (DSWM) (FAO, 2007) was used to define the SWHC in each location. The procedures performed to determine the SWHC for each location are presented in the Figure 4.5.

The sugarcane root system depth was assumed as 1 m, according to what was defined by Laclau and Laclau (2009) for Center-Southern Brazil. A similar procedure was employed by van Inttersum et al. (2013) to determine the soil types for yield gap evaluation in large spatial scales.

The crop water balance was calculated having as inputs the SWHC, rainfall and crop evapotranspiration (ETc), which was obtained by the product between ETo and crop coefficient (kc). Table 4.2 presents the kc values for each sugarcane crop phases. The main output of the crop water balance was the relative water deficit (1 – ETa/ETc), where ETa is the actual crop evapotranspiration (ETa ≤ ETc).

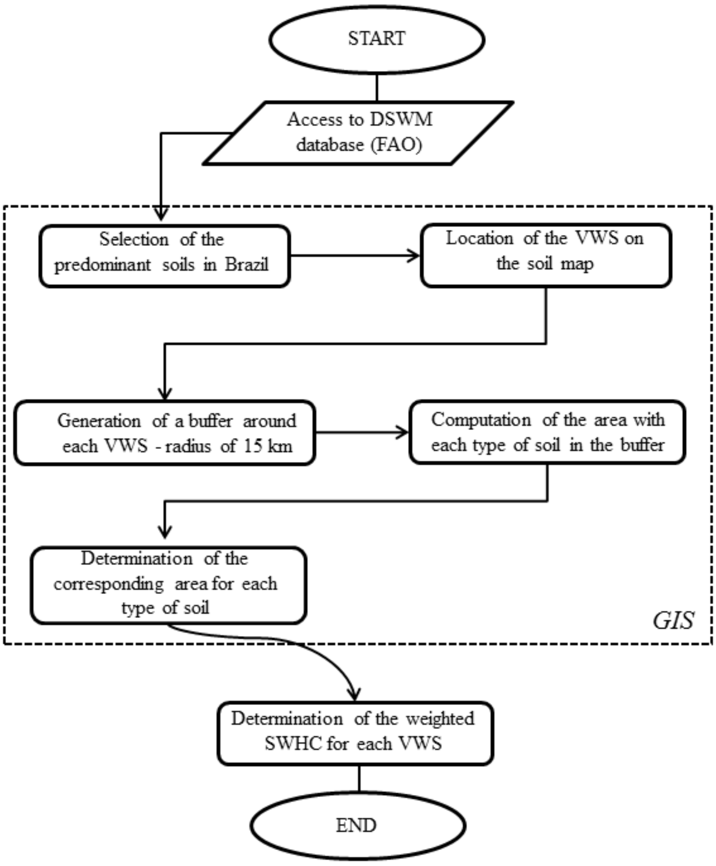

Figure 4.5 – Procedures to define the weighted soil water holding capacity (SWHC) for each virtual weather station (VWS), as a function of the physical characteristics each soil according to the Digital Soil World Map (DSWM) (FAO, 2007)

Table 4.2 – Calibrated crop coefficient (kc) and sensitivity water deficit factor (ky) for each sugarcane phenological phase

Phenological phase (j)	kc	ky
25% full canopy (1)	0.4	0.7
25-50% full canopy (2)	0.7	0.7
50-75% full canopy (3)	1.0	0.3
75-100% full canopy (4)	1.2	0.3
100% full canopy (5)	1.3	0.3
Scenescence (6)	1.1	0.3
Ripening (7)	0.8	0.1

4.2.2 Operational yield data and yield model description

Operational sugarcane yields were collected from twelve mills across Brazil located in traditional and non-traditional areas, with very responsive cultivars to the environment. All fields were conducted under optimum crop management practices, mainly for soil preparation, correction and fertilization, and control of pests, diseases and weeds. The fields were conducted under irrigated and rainfed crop systems. Therefore, in this study we are considering that the operational sugarcane yield was obtained under high technology, defining that as the best farmer's yield (Ybf).

The agrometeorological yield model was adapted from Doorenbos and Kassam (1979) method. The model has two modules, where the first one is used to calculate the Yp, basically as a function of determining factors (incoming solar radiation, air temperature and photoperiod) to calculate the potential gross photosynthesis (PG, kg DM ha^{-1} d^{-1}), added by correction factors to the physiological characteristics of the target crop. The attainable yield (Yatt), here considered as the best farmer's yield (Ybf), was estimated through a multiplicative approach, penalizing the Yp by the relative crop water deficit (1 – ETa/ETc) during all the sugarcane phases (DOORENBOS; KASSAM, 1979; MONTEIRO; SENTELHAS, 2014), being weighted by the corresponding crop response factors (ky) for each crop phase (Table 4.2).

Previous analysis showed that the agrometeorological yield model had a very good performance in the both crop systems (irrigated and rainfed) in comparison with the observed yields during the calibration and validation phases (Figure 4.6), proved by the following statistical indices: coefficient of determination (R^2) between 0.65 and 0.79; Willmott agreement index (d) between 0.70 and 0.80; and root mean square error (RMSE) between 13.2 and 13.8 Mg ha^{-1}, respectively during the calibration and validation phases.

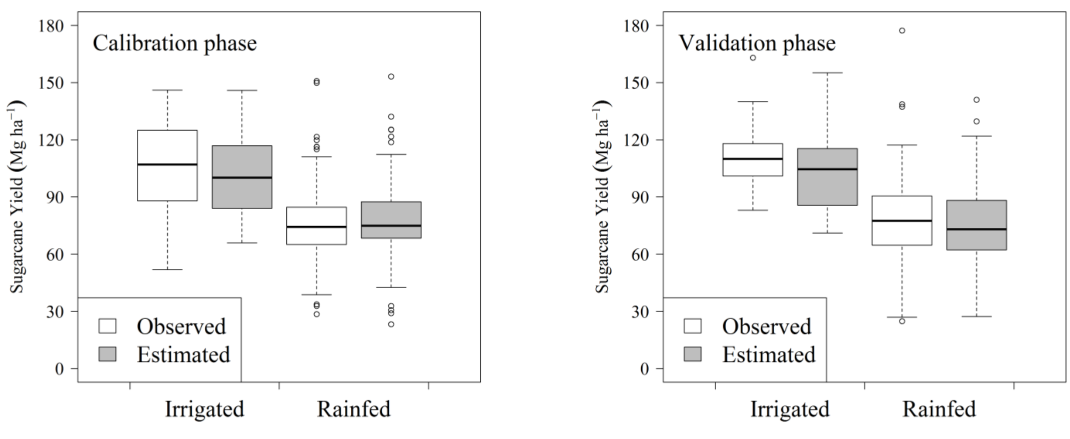

Figure 4.6 – Sugarcane yield variability during the calibration (left) and validation (right) of the agrometeorological yield model, under irrigated and rainfed crop systems

4.2.3 Potential and Best Farmer's yield simulation

The potential and the best farmer's yield were simulated during 30 growing seasons, from 1984 to 2013, considering the planting date (for plant canes) and cane cycles (for ratoon canes) simulated for each ten-days periods during all year long, totalizing 1080 simulations for each location. The median (p = 50%) value was chosen to represents the sugarcane planting or cycle in each period of the year. The sugarcane total cycle was considered as the average of five years (cuts), where the first year represented the plant cane (first year, 20% of cropping area) and the reminders as ratoon cane (80% of cropping area).

The estimated yields were weighted according to the planting and harvesting dates suggested for each macro region (Figure 4.1), available in the literature and in the official agro-climatic zoning of Brazil (EMBRAPA, 2015).

4.2.4 Average observed yield data

Average observed sugarcane yield (Yavg) were taken from Brazilian Institute of Geography and Statistics (IBGE) for each Brazilian micro region from 1990 to 2012 (23 years). Actually, were considered the micro regions with, at least, the last 10 years with sugarcane yield records. A technological trend was identified in these data and it was removed, once the yield model did not consider this effect along the growing seasons. The trend removal procedure was the same presented by Heinemann and Sentelhas (2011), which is exemplified in Figure 4.7 for the micro region of Piracicaba, SP.

4.2.5 Yield Gap determination

The total yield gap (YG_{total}) was determined by the difference between potential (Yp) and actual (Yavg) yields. The YG_{total} fraction caused by water deficit was calculated by the difference between Yp and Ybf, while the YG caused by deficiencies in crop management (YG_{CM}) was calculated by the difference between Ybf and Yavg.

4.2.6 Yield and yield gap mapping

Firstly, were downloaded the terrain elevation images from American National Agency (NASA) through the *Shuttle Radar Topography Mission* (SRTM) (http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp) corresponding to the Brazilian territory. Originally, these images have a GEOTIFF (16 bits) format, with a spatial resolution of 90 m and DATUM WGS84. All the image processing was done in the software *ArcGis®9.3* where an ongoing surface containing the average elevation for each pixel was estimated (raster image).

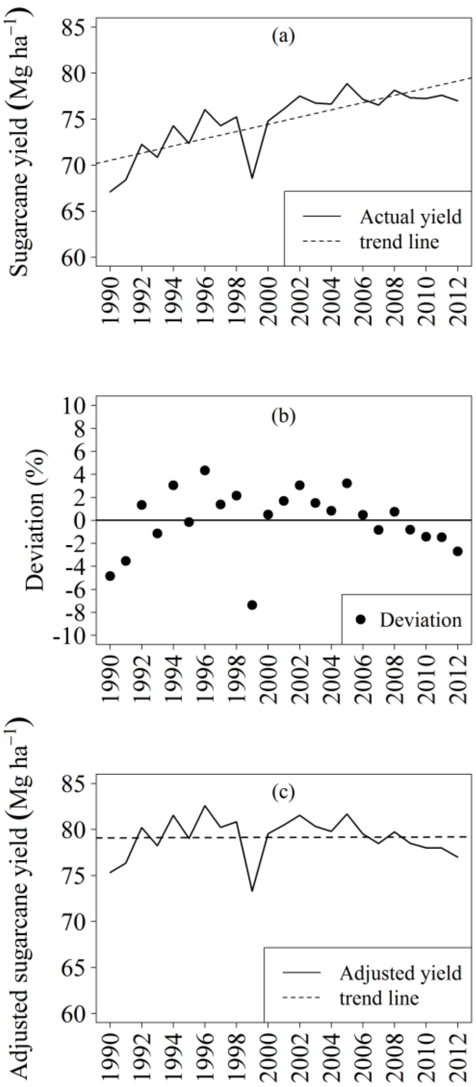

Figure 4.7 – Sugarcane observed yield data from IBGE, with the corresponding technological trend (a), the deviation from the regression values (b), and final sugarcane adjusted yield, used for yield gap determination (c)

As the analysis in this study were simulated regarding a national spatial scale, and Brazil presents the total area of about 8.1 million of square kilometers, the raster image was re-sampled for a spatial resolution of 900 m, allowing to improve the image processing. Even decreasing ten times the spatial resolution in each direction, the weather variables and yields were processed for 11.5 million pixels. Even considering this simplification, this study still has a very high spatial resolution, considering the continental dimensions of the country.

The estimated potential yield (Yp), annual average rainfall (P) and annual average reference evapotranspiration (ETo) were spatialized through a multiple regression linear models as a function of geographic coordinates (latitude (Φ) and longitude (λ)) and altitude (ξ), that were derived from the raster image, and their respective coupled combination (ALVARES et al., 2013).

For spatializing the average annual water deficit (WD) the same dependent variables were use, but with rainfall also added in the model. Finally, the annual average air temperature (Tair) was estimated according to the models proposed also by Alvares et al. (2013). In these cases, the map error corresponding to each estimative deviation (ε) was generated by kriging interpolation and, then, added to the values from the regression model. The generic equation employed for spatial estimates was:

$$V = \sum a + b\phi + c\lambda + d\xi + e\phi\lambda + f\phi\xi + g\lambda\xi + h\phi^2 + i\lambda^2 + j\xi^2 + \varepsilon \tag{1}$$

where: V is the dependent variable to be estimated (Yp, P or ETo); "a" is the linear coefficient; "b" until "j" are the equation coefficients corresponding to each one of the independent variables; and ε is the residual error. The final raster images for Yp and climatic variables were obtained by the sum between the estimates and errors, according to Yamada and Sentelhas (2014).

The best farmer's yield (Ybf) map was obtained by the interpolation procedure called "co-kriging", having SWHC as a co-variable to improve interpolation accuracy. The adjusted average yield (Yavg) map was obtained by weighting the yields and their respective areas, determining a unique value for each micro region.

All the final raster related to yields (Yp and Ybf) and climatic variables (Tair, P and WD) were processed in the GIS to obtain the mean value for each micro region, according to the following steps: "*ArcToolBox – Spatial analyst Tools – Zonal – Zonal Statistics*". Additionally, the YG types were calculated by the difference between the respective Yp, Ybf and Yavg layers for each micro region.

4.2.7 A case study - similarities and divergences between sugarcane YG approaches in Brazil

Two approaches to estimate the sugarcane YG in Brazil were compared. The first approach considered the data published by the Global Yield Gap Atlas (GYGA, www.yieldgap.org/), in which the sugarcane yield gap was determined with the DSSAT/Canegro model, calibrated for Brazilian sugarcane cultivars. The second approach was the one proposed in this study. For both procedures, the final YGs were obtained with a similar way.

4.3 Results and Discussion

4.3.1 Climate mapping

The performance of linear models employed to spatialize the climatic variables and Yp showed to be suitable for the purposes of this study, with a very high R^2 for the majority of them (> 0.90). Only for rainfall, with R^2 = 0.57, the dispersion was greater but still with enough ability to show the spatial variability of this variable. This technique is useful for agricultural planning, mainly for providing information for locations where meteorological data are scarce or missing (YAMADA; SENTELHAS, 2014). The Yp mapping will be discussed in the next section.

Table 4.3 presents the linear regression model coefficients employed for mapping the variables, considering the geographical coordinates (latitude and longitude), elevation and their combination.

The spatial variability of annual average air temperature in Brazil is presented in Figure 4.8. It is clear a south-north thermal gradient going from 16 to 18 °C in the South to 26 until 28 °C in the North-Northeast. This temperature map shows a restriction for sugarcane growth and development in most of southern Brazil, where low air temperatures associated with frost events occur. The use of resistant cane cultivars (mainly with early maturation cycle) configures a way to achieve reasonable yields in this region, as reported by Veríssimo et al. (2012) for the state of Rio Grande do Sul.

Rainfall (P), reference evapotranspiration (ETo), and water deficit (WD) are variables that should be considered for a suitable sugarcane planning, both at regional and national scales. Basically, the integration of P (Figure 4.9) and ETo (Figure 4.10) defines the water availability of a given region and, therefore, the conditions for growing rainfed crops, such as sugarcane (INMAN-BAMBER; SMITH, 2005), as well as for defining the regions where irrigation is required. On average, the WD in Brazilian Northeast ranges from 600 to 1100 mm $year^{-1}$ (Figure 4.11), while in the states of Southeast, a traditional sugarcane producing region, the WD ranges from 200 mm in southern São Paulo to 800 mm in the north of Minas Gerais. These results prove that sugarcane in Northeast region must be irrigated in order to present higher yields. Field experiments conducted by Andrade Júnior et al. (2012), in the state of Piauí, showed that sugarcane plantations under full irrigation can achieve 200 Mg ha^{-1}.

Table 4.3 – Linear regression model coefficients used for spatializing annual average air temperature (Tavg), total rainfall, total reference evapotranspiration (ETo), total water deficit (WD) and average potential yield (Yp); and their respective precision, represented by the coefficient of determination (R^2)

V	Linear regression model coefficients											R^2
	a	b	c	d	e	f**	g****	h	i	j****	k	
	-	(Φ)	(λ)	(ξ)	($\Phi\,\lambda$)	($\Phi\,\xi$)	($\lambda\,\xi$)	(Φ^2)	(λ^2)	(ξ^2)	-	
Tavg	5.1	-	-0.9	-9.6**	3.2**	-	-0.9	-0.016	-9.5***	-	-	0.93
Rainfall	131.5^{ns}	-173.3	20.4^{ns}	-3.6	-5.5	-1.1^{ns}	-650.0	2.730	1.3	38.0	-	0.57
ETo	3055.8	51.2	42.5^{ns}	0.1	1.1	-0.7	72.0	-0.611	0.2	3.5^{ns}	-	0.94
WD	3538.6	59.8	78.4	0.1^{ns}	0.4^{ns}	0.4^{ns}	5.0^{ns}	0.616	0.7	-1.3^{ns}	-0.37	0.96
Yp	-49.8^{ns}	10.2	-13.9	0.1	0.4	0.2	19.0	-0.343	-0.2	-1.2^{ns}	-	0.91

Φ and λ are, respectively, latitude and longitude (in decimal degrees); ξ is altitude (in meters); a to k are the regression model coefficients. ^{ns} is not significant at 5% of confidence level; ** times 10^{-2}; *** times 10^{-3}; and **** times 10^{-4}

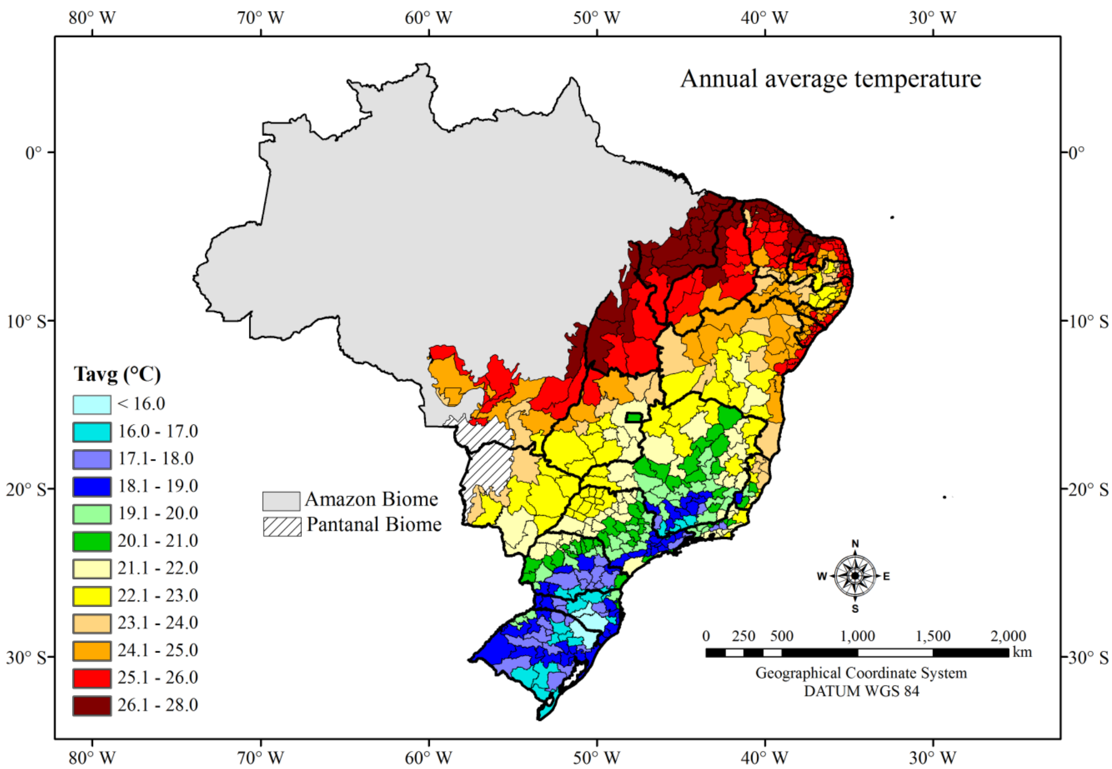

Figure 4.8 – Annual average air temperature in the Brazilian micro regions considered in the present study

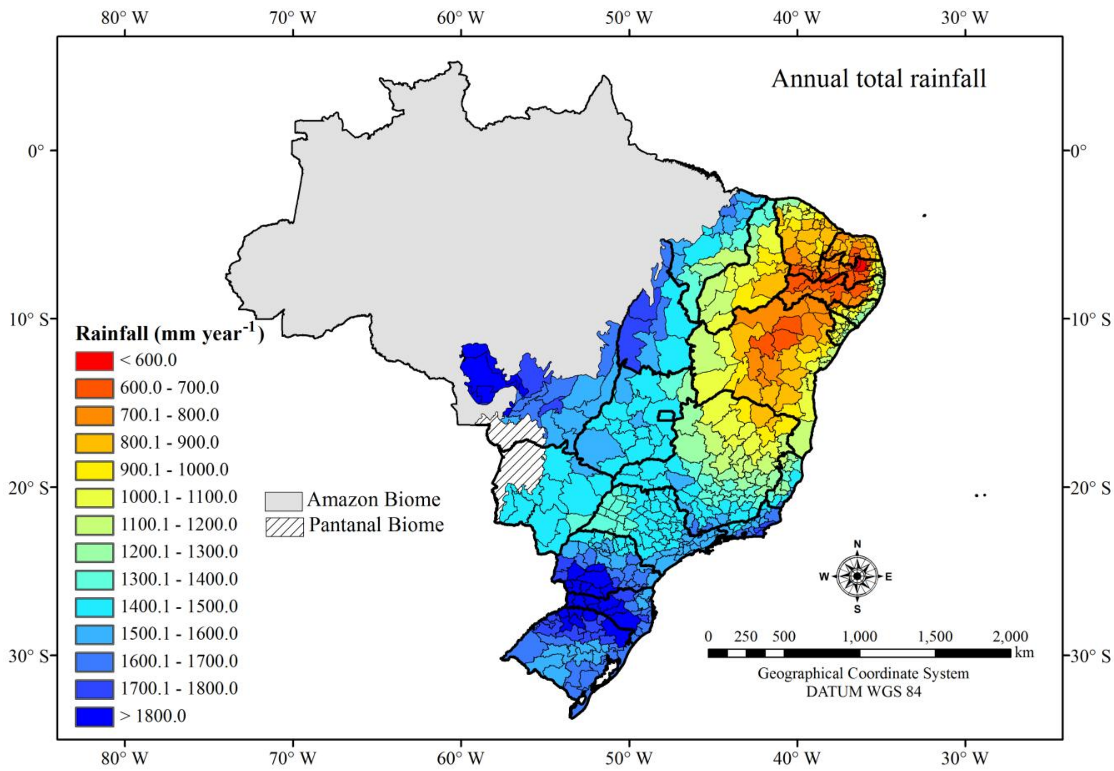

Figure 4.9 – Average annual total rainfall in the Brazilian micro regions considered in the present study

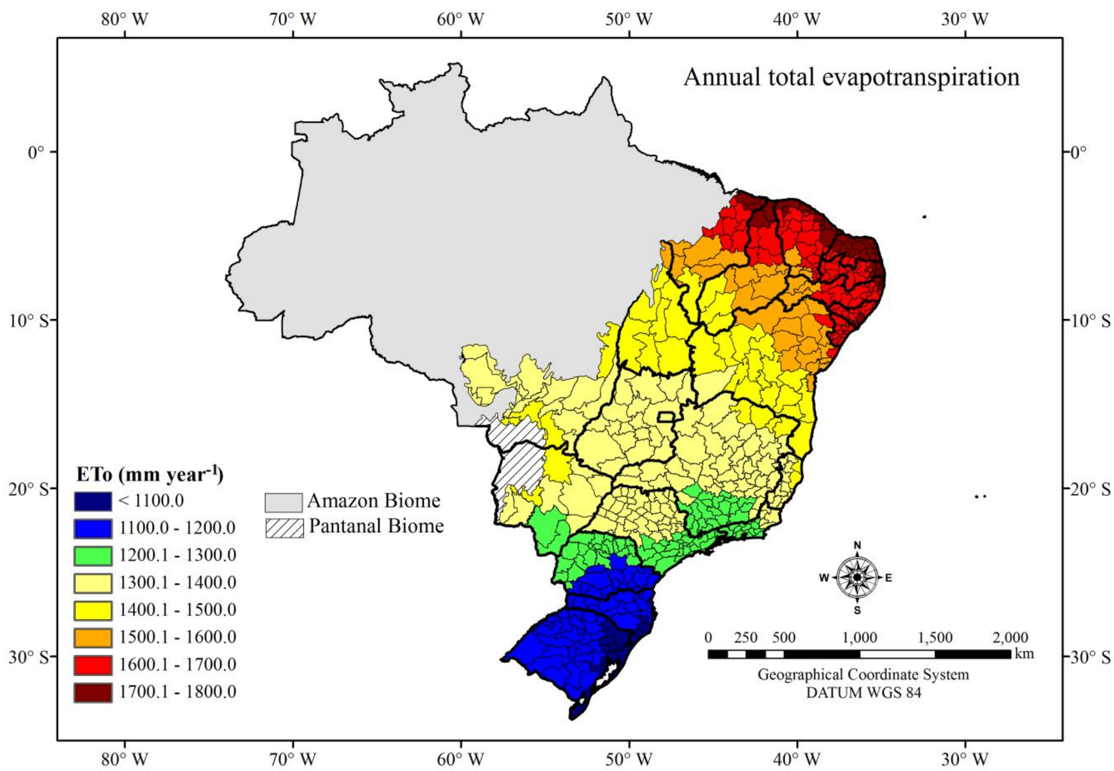

Figure 4.10 – Average annual total reference evapotranspiration in the Brazilian micro regions considered in the present study

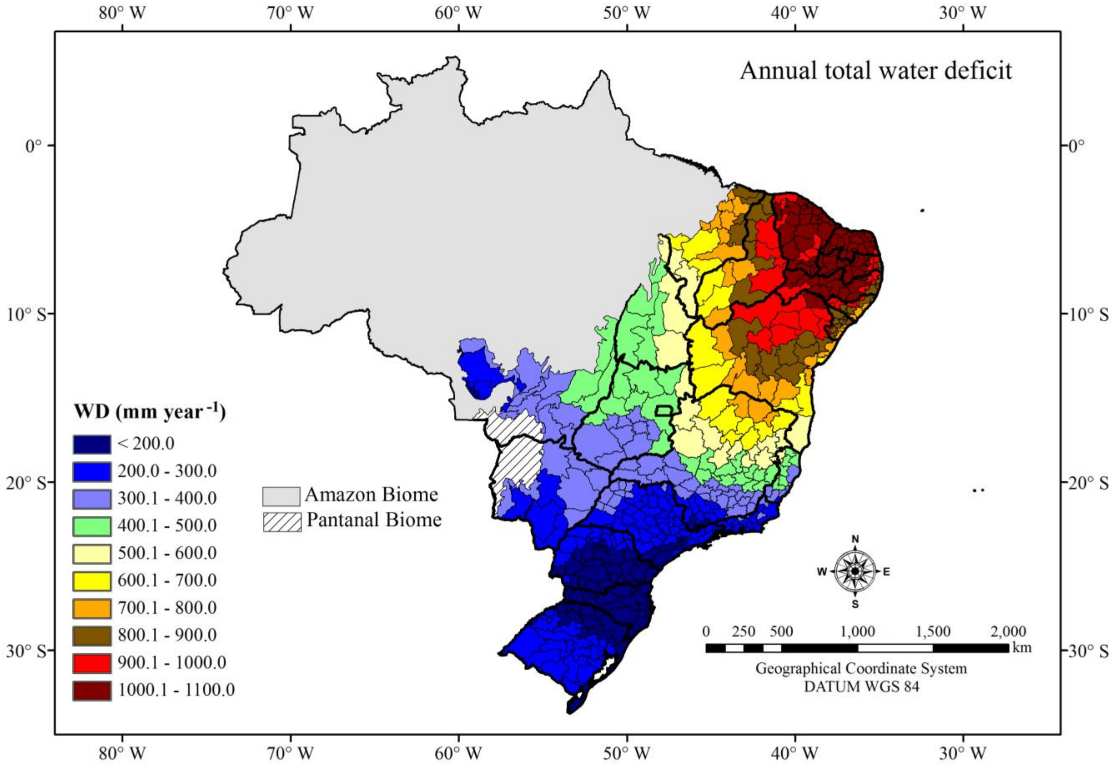

Figure 4.11 – Average annual total water deficit in the Brazilian micro regions considered in the present study

4.3.2 National yields and yield gap assessment

The sugarcane yields, potential (Yp), best farmer's (Ybf) and average (Yavg), showed a huge variation among Brazilian regions, which was mainly caused by differences of climates and soils (Figure 4.2). The estimated sugarcane yields for the main producing regions are presented in Table 4.3.

4.3.3 Potential yield (Yp)

The whole average Yp in Brazil was 186.4 Mg ha^{-1} with a coefficient of variation of 18.4% among locations evaluated (Table 4.3). The highest Yp was found in the Northeast region. In Pernambuco and Paraíba, the average Yp was respectively 225.0 and 219.8 Mg ha^{-1}, with CV ranging between 2.0 and 3.1%. On the other hand, the lowest average Yp was observed in the state of Rio Grande do Sul (Yp = 110.0 Mg ha^{-1}; CV = 18.7%).

Table 4.3 – Sugarcane potential (Yp), best farmer's (Ybf) and average (Yavg) yields in Brazil in the producing macro regions and their respective states

Region, State	Yield types (Mg ha^{-1})											
	Yp				Ybf				Yavg*			
	Max	Avg	Min	CV**	Max	Avg	Min	CV**	Max	Avg	Min	CV**
Southeast	210.5	168.4	122.1	12.0	115.2	88.8	61.7	13.3	101.1	66.6	22.4	28.8
São Paulo, SP	179.2	154.9	126.4	7.8	115.2	100.7	78.5	6.6	97.4	78.6	28.1	18.0
Minas Gerais, MG	210.5	177.8	126.4	9.7	115.2	82.9	61.7	12.1	101.1	64.3	22.5	29.7
Espírito Santo, ES	187.3	156.4	138.8	7.7	102.0	91.9	78.1	5.5	77.2	55.2	26.6	25.0
Rio de Janeiro, RJ	147.5	133.6	122.1	4.8	102.0	95.4	87.2	3.6	74.1	48.2	22.4	27.6
Northeast	232.7	215.3	184.0	3.9	102.1	71.4	61.7	12.7	101.1	47.7	19.1	36.7
Alagoas, AL	228.4	212.6	204.0	2.3	82.6	78.2	61.7	6.1	69.7	63.1	41.0	9.4
Pernambuco, PE	232.7	225.0	211.2	2.0	82.6	66.9	61.7	10.2	90.1	34.4	21.9	33.5
Paraíba, PB	232.7	219.8	200.1	3.1	74.9	64.6	61.7	7.1	68.3	36.9	21.8	30.1
Bahia, BA	224.0	212.8	184.0	4.2	100.8	70.1	61.7	10.5	101.1	51.8	21.9	32.5
Rio Grande do Norte, RN	226.0	206.5	199.3	2.4	63.1	61.7	61.7	0.4	68.3	50.8	26.9	31.8
Sergipe, SE	221.4	208.9	202.8	1.9	86.0	80.9	72.3	4.1	69.2	64.3	32.3	5.5
Maranhão, MA	224.2	216.3	201.4	3.4	102.1	84.6	71.2	6.5	94.4	52.9	19.1	47.1
Piauí, PI	230.3	217.5	202.4	2.3	92.1	72.1	61.7	8.8	90.1	41.4	21.9	28.4
Ceará, CE	230.3	216.2	198.9	3.9	74.9	62.6	61.7	4.3	61.3	42.6	25.6	18.1
Center-West	216.5	191.8	162.6	7.0	123.3	98.3	73.6	9.0	97.4	55.8	16.0	44.6
Goiás, GO	216.5	199.6	171.7	5.3	108.5	93.9	73.6	5.0	91.8	61.9	21.7	43.7
Mato Grosso do Sul, MS	195.1	177.8	166.3	3.1	123.3	105.7	89.1	11.2	97.4	65.1	37.6	30.4
Mato Grosso, MT	213.8	195.0	162.6	6.0	115.2	97.0	89.7	4.4	91.8	42.1	16.0	46.8
South	171.0	127.5	68.5	20.9	115.7	85.9	74.9	13.4	95.3	44.7	11.2	30.8
Paraná, PR	171.0	154.4	117.8	7.4	115.7	96.3	74.9	14.1	95.3	64.2	29.7	28.6
Rio Grande do Sul, RS	147.4	110.0	68.5	18.7	91.5	81.0	74.9	5.2	62.8	34.7	12.7	33.0
North	221.6	216.1	208.5	0.9	115.2	104.3	78.9	6.3	83.0	51.8	22.6	37.4
Tocantins, TO	221.6	216.1	208.5	0.9	115.2	104.3	78.9	6.3	83.0	51.8	22.6	37.4
Brazil	232.7	186.4	68.5	18.4	123.3	85.7	61.7	17.6	101.1	54.2	11.2	40.5

* Average sugarcane yield from IBGE (2014); ** coefficient of variation among locations of the same state, region or country for the average values (%)

In the traditional sugarcane regions in the Southeast region, the average Yp was 168.4 Mg ha^{-1} (CV = 12.0%). In the states of São Paulo and Minas Gerais, the average Yp was respectively 154.9 Mg ha^{-1} (CV = 7.8%) and 177.8 Mg ha^{-1} (CV = 9.7%). On the other hand, in the regions that can be considered as in expansion for the sugarcane crop, in the Center-West region and in in the state of Tocantins, the average Yp ranged between 191.8 and 216.1 Mg ha^{-1} (Table 4.3). These regions also presented the lowest coefficient of variation, between 0.9 and 7.0%, showing less spatial variability of the weather conditions along the year, mainly in terms of photoperiod, air temperature and solar radiation, which are the determining yield factors (Figure 4.3).

Although is not common in Brazil field experiments to evaluate sugarcane potential yield, Andrade Junior et al. (2012) obtained in an irrigated sugarcane field under optimal conditions, in Teresina, state of Piauí, 207.0 Mg ha^{-1}, which is very similar to the results from Table 4.3, where is presented an average potential yield of 217.5 Mg ha^{-1} for the state of Piauí (Table 4.3). This highlights the satisfactory performance of the agrometeorological yield model used in the present study.

In the South region of Brazil, the average Yp was 127.5 Mg ha^{-1} with the highest coefficient of variation among locations (CV = 20.9%) (Table 4.3). It is associated to the large spatial variability of weather conditions among the locations of this region, where there is a huge gradient of temperature from the north of Paraná state, with average annual temperature of 21 ^{o}C, to the south of Rio Grande do Sul state, with less than 17 ^{o}C (Figure 4.8). The low temperature mainly in the state of Rio Grande do Sul reveals also the occurrence of frequent frosts, restricting the growing conditions to the sugarcane crop in the majority of the planting dates.

The spatial variability of average Yp in Brazil is shown in the Figure 12. Eight zones of Yp can be identified, ranging from less than 100 Mg ha^{-1} in the extreme south, where the crop yield is limited by the lower solar radiation, air temperature and photoperiod conditions during the winter, to more than 220 Mg ha^{-1} in the interior of Northeast region, where the predominance of clear sky conditions along the year and the constancy of the climatic determining factor lead to very intense growth of the crop. When the conditions to the state of São Paulo, the most traditional sugarcane producer state, is analyzed, the Yp ranges between 140 and 180 Mg ha^{-1}, which is in agreement with the study of Monteiro and Sentelhas (2014), that found Yp ranging between 140 and 200 Mg ha^{-1}. The slight differences observed between these two studies are associated to the differences in the spatial resolution of the maps, once these authors used a spatial resolution of almost 1ha, whereas in the present study the Yp was averaged for the micro-region. Another, possible difference is related to the simulation procedures that were much more detailed in the present study, with sugarcane being planting every month and ratoon cane harvested during all months of the harvest season, which was not the case in the Monteiro and Sentelhas (2014)'s study.

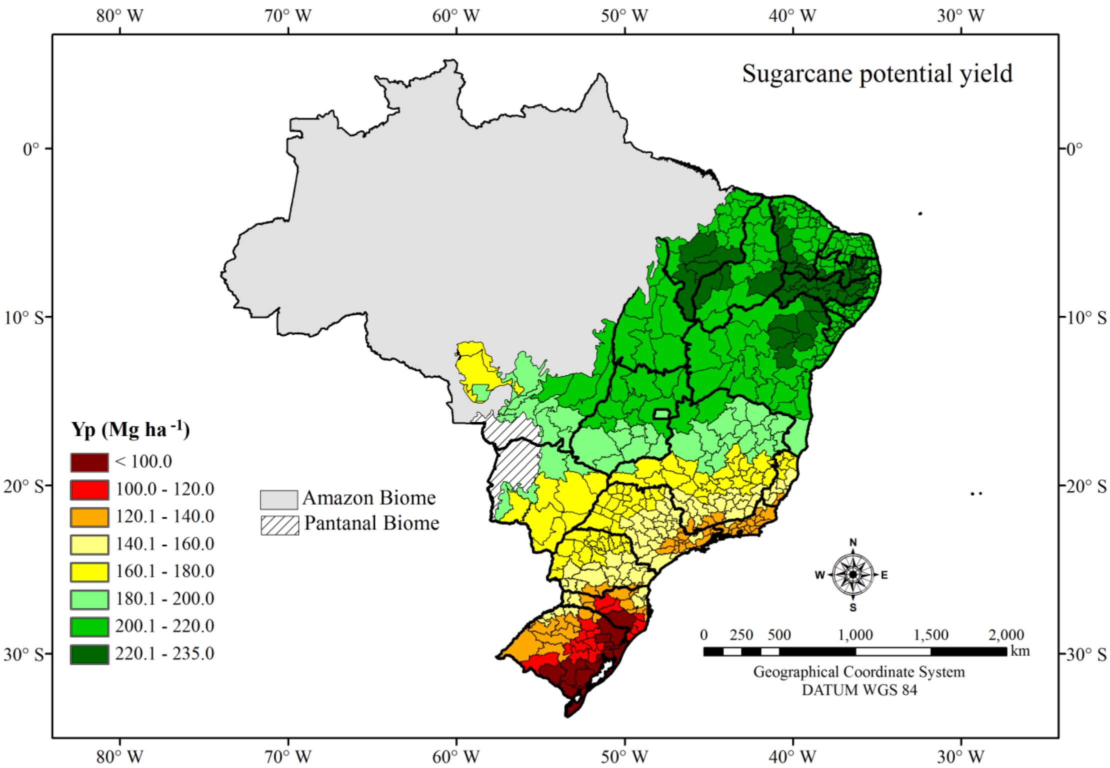

Figure 4.12 – Average sugarcane potential yield in Brazil, in a micro region level

4.3.4 Best farmer's yield (Ybf)

The Brazilian best farmer's yield (Ybf), which is achieved when high technology crop management is applied in a rainfed crop, is presented in Table 4.3 and Figure 4.13. From these data is possible to observe that Ybf varies considerably among the Brazilian macro-regions, what is mainly influenced by the soil water availability, showing a strong relationship with the rainfall, crop evapotranspiration and water deficit along the sugarcane cycle. On average, the Ybf in Brazil is 85.7 Mg ha^{-1} (CV = 17.6%), varying between 61.7 Mg ha^{-1} in the state of Rio Grande do Norte and 105.7 Mg ha^{-1} in the state of Mato Grosso do Sul (Table 4.3).

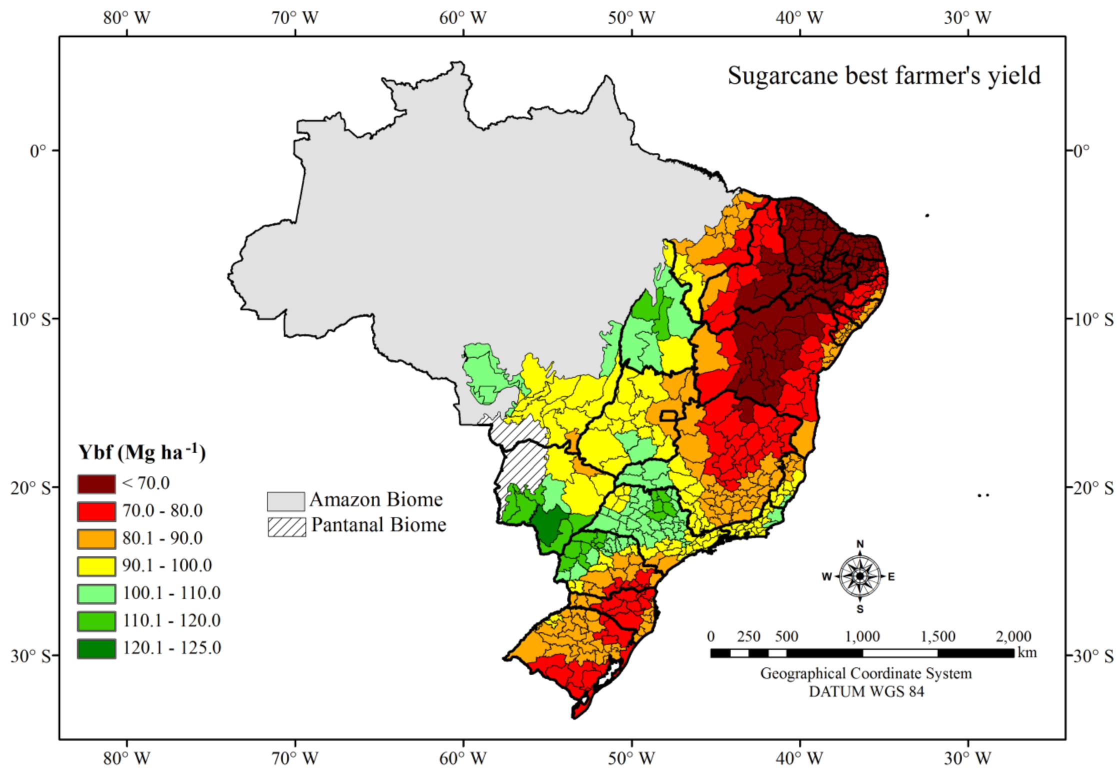

Figure 4.13 – Average sugarcane best farmer's yield in Brazil, in a micro region level

In the Southeast region (Table 4.3), the average Ybf was 88.8 Mg ha^{-1} (CV = 13.3%), with the state of São Paulo presenting the highest average Ybf of 100.7 Mg ha^{-1} (CV = 6.6%), whereas the lowest average Ybf was observed in the state of Minas Gerais, with 82.9 Mg ha^{-1} (CV = 12.1%), which is due to the contribution of the lower yields observed in the center-north of this state (Figure 4.13).

Northeast region presented the lowest Ybf (71.4 Mg ha^{-1}, CV = 12.7%), although on the coast of this region, in the states of Sergipe and Alagoas, and in the south of Maranhão and west of Bahia, the yields were higher than the average for region. This can be explained by the better rainfall amount and distribution in these areas (Figure 4.9) in relation to the interior of the region, where predominates the semi-arid climate (ALVARES et al., 2013).

On the other hand, in the South region, the average yield was 85.9 Mg ha^{-1} (CV = 13.4%). In the northwest of Paraná the yields reached more than 100.0 Mg ha^{-1} (Figure 4.14), which can be attributed to the climate conditions, but also to the very good soils characteristics of the region, such as natural fertility, organic matter and depth for sugarcane roots growth (ZOLIN et al., 2011; PAULINO et al., 2011). On the other hand, in the state of Rio Grande do Sul the average Ybf was 81.0 Mg ha^{-1} with CV = 5.2%. This result differs from those obtained by Veríssimo et al. (2012) in 18 different production environments in the state of Rio Grande do Sul. These authors reported an average yield of 100 Mg ha^{-1}, but obtained only for plant cane and with the planting dates in a specific period to avoid frosts during the first stages of the crop. This is an important strategy in Rio Grande do Sul, where the frosts occur with high frequency; however it make difficult to plan the harvest season, since it would be concentrated in few months of the year. So, for the South region more studies are required to evaluate the performance of early genotypes with faster growing cycle to do not be affected by frost occurrences and guaranty a satisfactory cane production (STRECK et al., 2010).

The Figure 4.13 is shown the spatial variability of average Ybf in Brazil, which clearly shows potentiality of sugarcane production under rainfed conditions but with high technology. The highest Ybf values are observed in northwestern Paraná, center-south of Mato Grosso do Sul, great part of São Paulo, western Minas Gerais (Triângulo Mineiro), southern Goiás, Tocantins and small parts of Rio de Janeiro, Espírito Santo and Mato Gosso. On the other side, the lowest Ybf values are in the Brazilian semi-arid region, including the center of Bahia, east of Piauí, west of Pernambuco and Paraíba, and all Ceará and Rio Grande do Norte states.

4.3.5 Average actual yield (Yavg)

In relation to the average actual sugarcane yields (Yavg), based on the observed yields reported by IBGE, the spatial variability presented in Figure 4.14 shows a considerable divergence when compared to the Ybf. The differences observed are mainly caused by the diversity of crop managements in the different producing regions.

Table 4.3 shows the average Yavg values for all Brazilian regions and their respective states. On average, the sugarcane actual yield in Brazil was 54.2 Mg ha^{-1} although the huge range observed among regions, with a CV of 40.5%. This variation occurs according to the degree of management employed by the farmers, such as irrigation, adapted sugarcane cultivars, soil management and fertilization, and pests, diseases and weeds control. The Yavg variations were not regular in the same region. As well as among regions, the Yavg varied considerably in the same region, with the CV ranging from 28.8% in the Southeast to 44.6% in the Center-West region. Even in the same state, Yavg varied a lot, with the CV ranging from 5.5% in Sergipe to more than 40% in the states of Maranhão, Goiás and Mato Grosso. Considering the Yavg per micro-region (Figure 4.14), the state of São Paulo has almost all micro regions with Yavg higher than 80.0 Mg ha^{-1}, while in the state of Minas Gerais the yields were higher than 60 Mg ha^{-1} only in some micro-regions of Triângulo Mineiro and also in the north of this state, probably where the irrigation is used for obtaining satisfactory stalks yield.

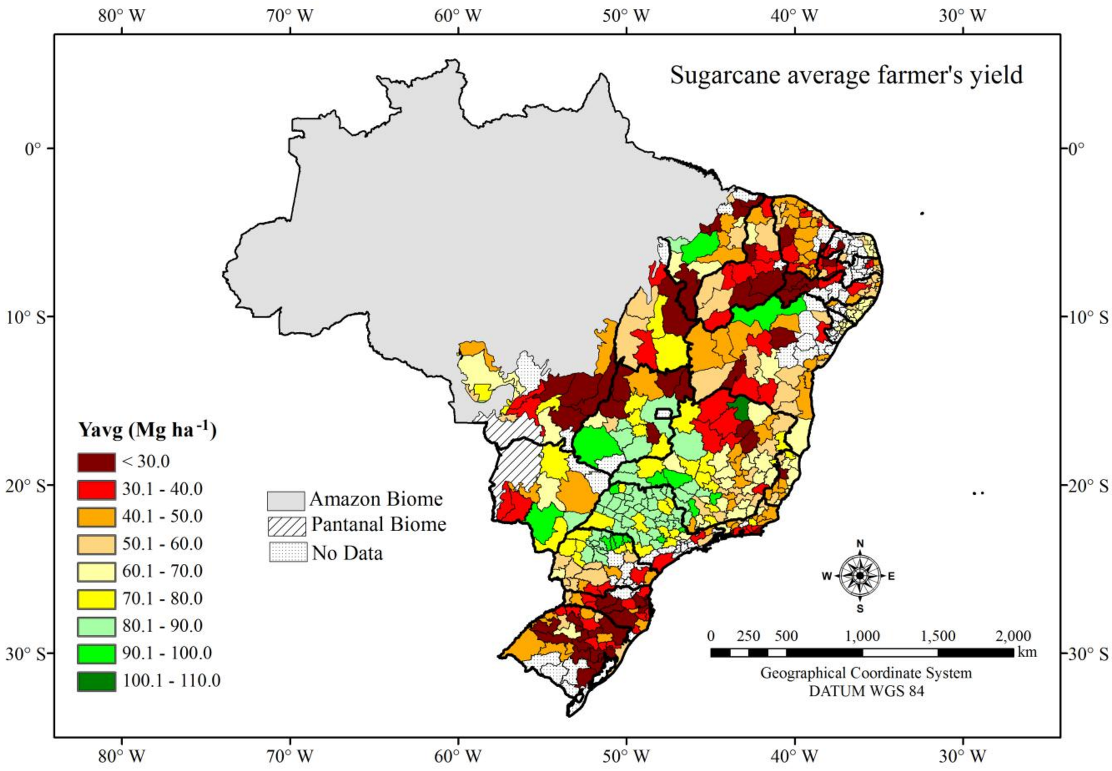

Figure 4.14 – Average sugarcane actual yield in Brazil, in a micro region level

4.3.6 Yield gap assessment

Table 4.4 presents the sugarcane yield gaps caused by water deficit and crop management for all macro regions in Brazil. In the majority of the states the water deficit is the main cause of YG. The only two exceptions are for the states of Rio Grande do Sul (YG_{WD} = 36% of YG_{total}) and Rio de Janeiro (YG_{WD} = 44.6% of YG_{total}). The total sugarcane yield gap (YG_{Total}) (Table 4.4 and Figure 4.15), was, on average, 133.2 Mg ha^{-1}, in which 75.6% (~ 101 Mg ha^{-1}) of yield losses is due to water deficit, while 24.4% (~ 32 Mg ha^{-1}) is due to sub-optimal crop management practices, such as soil fertilization, pests, diseases and weeds control, planting failure, soil compaction, among others.

Table 4.4 – Average sugarcane yield gaps by water deficit (YG_{WD}) and crop management (YG_{CM}), total yield gaps (YG_{total}) and their percentual partitioning, in the Brazilian macro regions and their respective states

Region, State	Yield Gap (Mg ha^{-1})						Average Total YG	Relative Yield Gap	
	YG_{WD}			YG_{CM}				YG_{WD}	YG_{CM}
	Max	Avg	Min	Max	Avg	Min	(Mg ha^{-1})	(%)	
Southeast	146.9	79.6	25.0	72.0	22.0	0.0	102.8	77.4	22.6
São Paulo, SP	81.5	54.3	29.8	70.8	22.9	0.0	78.5	69.1	30.9
Minas Gerais, MG	146.9	94.9	32.1	63.2	18.7	0.0	113.5	83.5	16.5
Espírito Santo, ES	109.2	64.5	31.7	67.8	36.7	7.0	101.2	63.7	36.3
Rio de Janeiro, RJ	57.8	38.2	25.0	72.0	47.1	14.5	85.7	44.6	55.4
Northeast	168.6	143.9	101.9	76.7	24.2	0.0	167.4	85.9	14.1
Alagoas, AL	162.5	134.4	121.4	37.3	16.3	8.3	149.3	90.0	10.0
Pernambuco, PE	168.6	158.2	126.4	48.3	32.9	0.0	190.7	82.9	17.1
Paraíba, PB	167.4	155.2	138.3	42.8	27.8	0.0	179.3	86.6	13.4
Bahia, BA	162.3	142.7	101.9	71.8	18.3	0.0	159.9	89.3	10.7
Rio Grande do Norte, RN	164.4	144.7	137.7	39.9	11.0	0.0	156.4	92.6	7.4
Sergipe, SE	149.1	128.0	117.1	46.9	18.7	6.8	141.5	90.5	9.5
Maranhão, MA	147.0	131.7	115.9	76.7	31.9	0.0	164.5	80.0	20.0
Piauí, PI	168.6	145.4	121.1	68.1	30.8	0.0	175.9	82.7	17.3
Ceará, CE	168.6	153.6	129.4	38.8	20.1	0.4	174.8	87.8	12.2
Center-West	134.7	93.5	48.0	85.9	42.9	0.0	136.4	68.6	31.4
Goiás, GO	134.7	105.7	73.0	81.7	31.7	0.0	138.3	76.4	23.6
Mato Grosso do Sul, MS	102.2	72.1	48.0	84.9	42.4	0.0	112.3	64.2	35.8
Mato Grosso, MT	117.5	98.0	60.6	85.9	54.9	0.0	153.1	64.0	36.0
South	74.1	41.6	0.0	65.9	43.2	0.0	86.5	48.1	51.9
Paraná, PR	74.1	58.0	42.9	60.3	34.8	0.0	91.3	63.6	36.4
Rio Grande do Sul, RS	58.7	29.0	0.0	65.9	47.8	19.8	80.5	36.0	64.0
North	140.2	111.7	96.3	85.9	52.9	1.4	164.3	67.9	32.0
Tocantins, TO	140.2	111.7	96.3	85.9	52.9	1.4	164.3	68.0	32.0
Brazil	168.6	100.8	0.0	85.9	32.4	0.0	133.2	75.6	24.4

The Northeast region, as the driest one in Brazil (Figure 4.11), presents the lowest observed yields (Table 4.3, Figure 4.14). However, high sugarcane yields can be observed in some of the micro-regions, which are due to the employment of irrigation and high technology, such as in Petrolina, PE, Juazeiro, BA, and Grajaú, MA (ANDRADE JUNIOR et al., 2012; TEODORO et al., 2015). In Juazeiro, north of Bahia, Petrolina, east of Pernambuco, and Balsas, center of Maranhão, where the WD are around 650 and 950 mm (Figure 4.11), the average sugarcane yields are above 90 Mg ha^{-1} (Figure 4.14). It can be proved when evaluating studies in Brazilian Northeast region, where sugarcane fields conducted with high technology and under irrigation showed stalks yield increase of more than 100% in relation to the rainfed ones (DA SILVA et al., 2013). It also highlights that water deficit configures the most critical factor to reach high yields in northeast Brazil, while solar radiation and air temperature do not limit that (Figure 4.12).

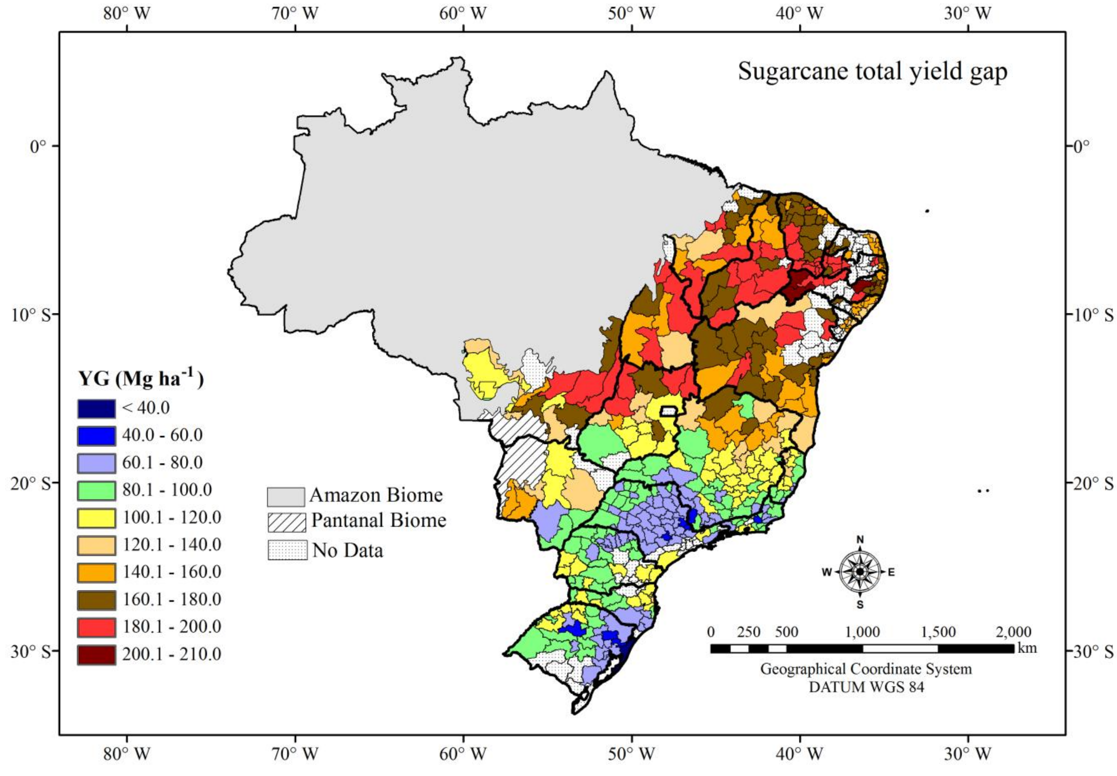

Figure 4.15 – Spatial variability of total sugarcane yield gap in Brazil

In the Northeast region the highest YG_{total} (~167 Mg ha^{-1}) was found (Table 4.4 and Figure 4.15). In this case, the water deficit was responsible for approximately 86% of the total yield break or 143.9 Mg ha^{-1} (Table 4.4 and Figure 4.16).

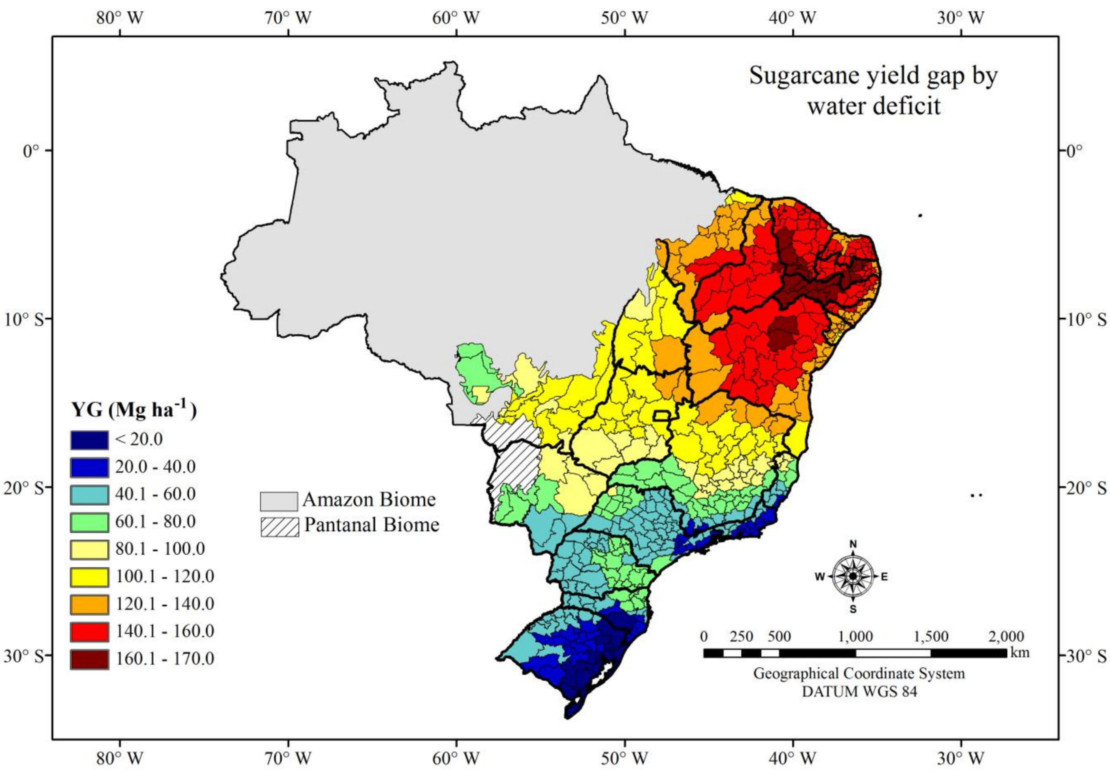

Figure 4.16 – Spatial variability of sugarcane yield gap due to water deficit in Brazil

Nevertheless, under appropriated crop management, mainly associated to irrigation, and with very responsive sugarcane cultivars, in northern Bahia and center of Maranhão, the YG_{total} is mainly driven by the water deficit (Figure 4.16), with YG_{total} around 140 and 126 Mg ha^{-1}, respectively (Figure 4.15), being the crop management close to perfect (Figure 4.16). Similar results were found by Oliveira et al. (2011) studying the effect of irrigation on sugarcane cultivars under very good crop management practices. These authors, found a sugarcane yield increment with irrigation up to 165 Mg ha^{-1} in state of Pernambuco, which represents an increase of 185% on the stalks yields.

In Southeast region, the average YG_{total} is around 103 Mg ha^{-1}, being 77.4% caused by water deficit and the other 22.6% by crop management (Table 4.4 and Figures 4.15, 4.16 and 4.17).

In the state of São Paulo, the YG_{CM} in many regions is 20 Mg ha^{-1} (Table 4.4 and Figure 4.16) while the YG_{WD} ranges between 40 Mg ha^{-1}, in traditional sugarcane micro regions, and 100 Mg ha^{-1}, in the new expanding regions. These results make evident that the most suitable region for sugarcane irrigation is in the north of São Paulo state. Similar results were found by Monteiro and Sentelhas (2014) when evaluating potential and attainable sugarcane yields. Marin and Carvalho (2012) also analyzed the YG in the state of São Paulo, but focusing on crop efficiency. These authors found an average YG_{CM}, along 1990/91 to 2005/06 growing seasons, decreasing from 58 to 42%, as a result of better crop management practices along those years.

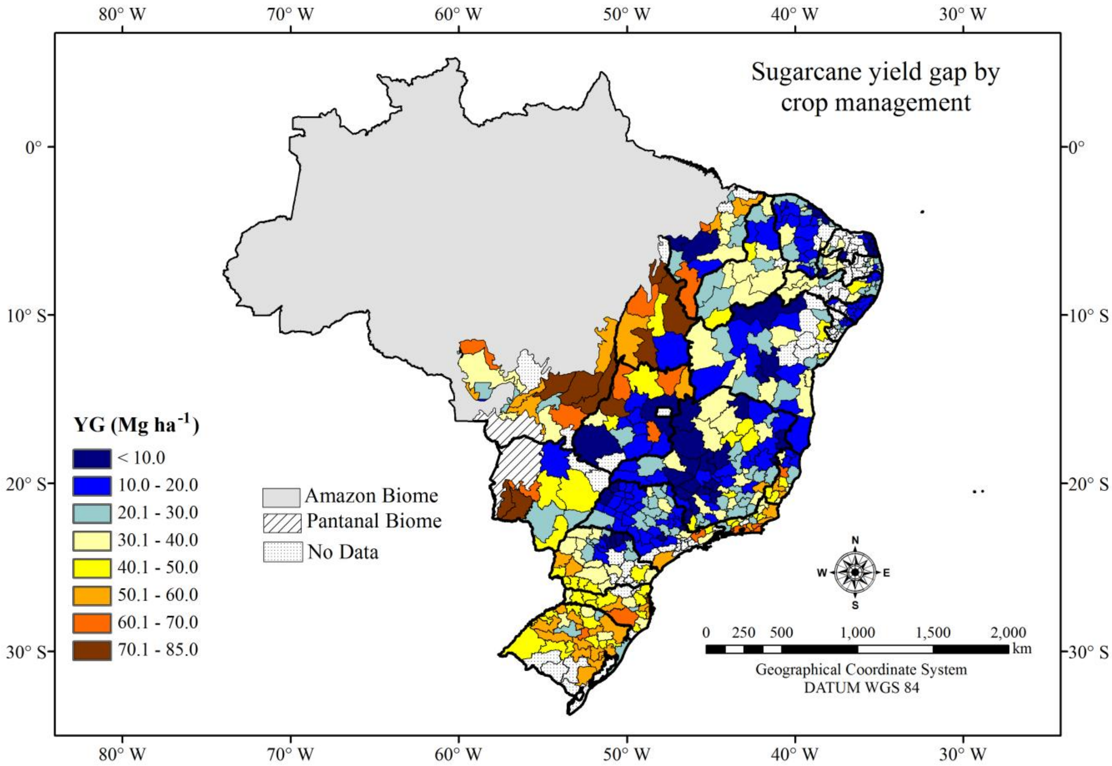

Figure 4.17 – Spatial variability of the sugarcane yield gap due to crop management in Brazil

A recent study concerning sugarcane YG in South African Sugar Belt (VAN DEN BERG; SINGELS, 2013) indicated that the main sources for YG in this region is caused by sub-optimal management operations such as inadequate harvesting time, fertilizing and replanting, as well as socioeconomic conditions. According to these authors, the sugarcane yield gap due to crop management is higher at small farms, with YG_{CM} = 53%, whereas at larger farms YG_{CM} = 23%. These results are similar to what was found in Brazil, where YG_{CM} varied between 7 and 64%. In tropical India, sugarcane yield gap was mainly associated to the crop cycle (plant and ratoon), in which yield declined about 50 Mg ha^{-1} (20-25%) due to the poor capacity of buds to sprout during the winter (GOMATHI et al., 2013).

YG analysis has also been used to determine the impact on the economic activities, where the total YG was around 68% (RAO, 2012). According to Naidu and Hunsigi (2003), in the Indian province of Karnataka, the YG by crop management ranged between 4 and 42 Mg ha^{-1}, which was associated to the climate characteristics of each zone and soil fertilization levels. In partially irrigated field experiments conducted in Australia, YG varied according to the crop phase when the after deficit was imposed (ROBERTSON et al., 1999).

4.3.7 Yield gap study case: similarities and divergences of methodologies and their results

The sugarcane YG analysis provided by the Global Yield Gap Atlas (GYGA - www.yieldgap.org) were done considering long-term daily weather data of maximum and minimum air temperature, and rainfall from at least 15 years. Here are evaluated the results from 17 weather stations provided by Brazilian Institute of Meteorology (INMET). The solar radiation was estimated by Bristow-Campbell (1984) method. In the sugarcane water balance, a maximum root system depth of 2 m was considered for all locations. The yield simulations were performed through the crop simulation model DSSAT/Canegro (INMAN-BAMBER, 1991), included in DSSAT v 4.5 (JONES et al., 2003; SINGELS et al., 2008). Three ratoon maturity cycles were simulated, being early (March), mid (August) and late (November) sugarcane. The final yields were obtained by weighting crop cycles for both potential (Yp) and attainable (Yatt) yields.

The yield simulations for cane plant were not performed. The YG_{WD} were simulated along the long-term data, while the YG_{CM} were calculated as the average along the five years (2006-2010), disregarding the sugarcane technological trends. The yield and YG from GYGA and obtained in this study are presented, respectively, in Figures 4.18 and 4.19.

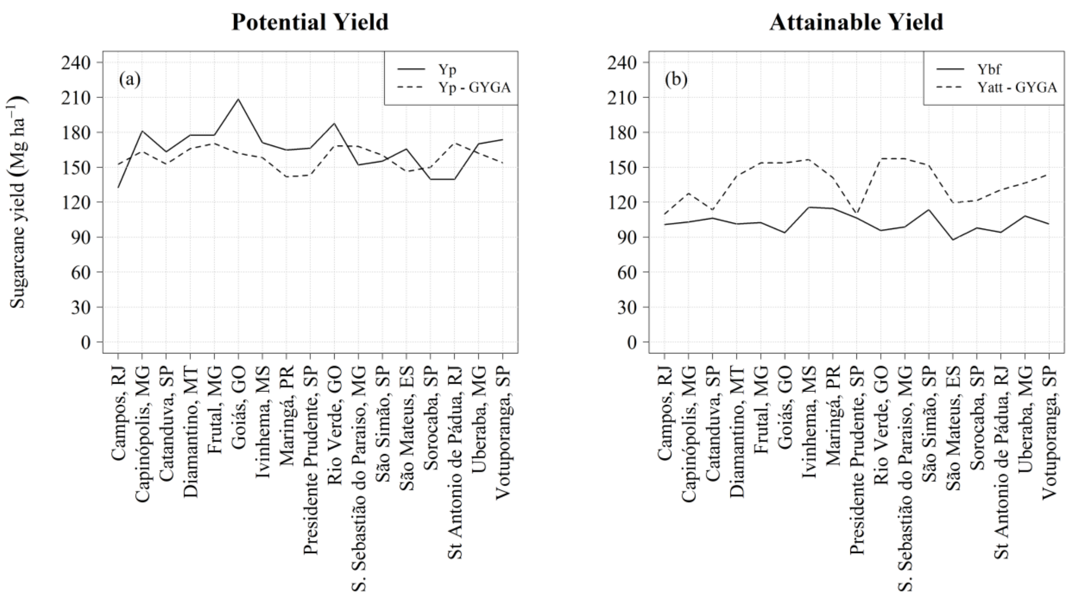

Figure 4.18 – Potential - Yp (a) and attainable - Yatt (b) yields for 17 Brazilian locations, considering GYGA and the present study approaches

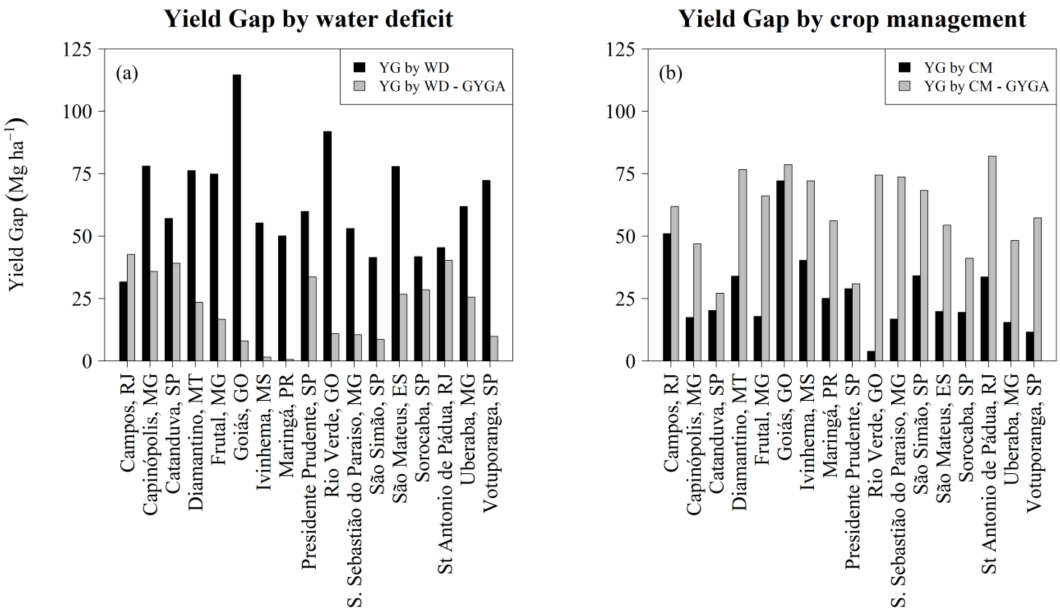

Figure 4.19 – Yield gap by water deficit (a) and crop management (b) for 17 Brazilian locations, considering GYGA and the present study approaches

The potential yields estimated by the both approaches were quite similar for all locations, averaging 166.2 Mg ha^{-1} by the present approach and 158.3 Mg ha^{-1} by GYGA approach, which represents a percentage difference of only 5% (Figure 4.18a). On the other hand, the differences between Yatt, from GYGA, and Ybf, from this study, were expressively different. Ybf averaged 102.5 Mg ha^{-1} while Yatt from the GYGA was 136.8 Mg ha^{-1}, representing a difference of about 25% (Figure 4.18b). The main reason for the difference between Yatt and Ybf is the distinct approaches used to determine them. While the present study used the Yp and Ybf weighted for plant and ratoon canes, the GYGA project used only ratoon cane, but with the DSSAT-Canegro model calibrated for plant cane. Probably, this is why the Yatt results are higher than those obtained in this study.

Focusing on the yield gaps, the average YG_{total} provided by GYGA project and those from the present study are very similar, with YG_{total} of 81 and 91 Mg ha^{-1}, respectively. However, when the YG is partitioned in the YG caused by water deficit (YG_{WD}) and by crop management (YG_{CM}) (Figures 4.19 and 4.20), the results from the GYGA project are very different from the present study. The YG_{WD} from GYGA represents, on average, 33% of yield losses, while the results of this study showed that 81.5% of yield losses are due to water deficit in the same locations in Center-Southern Brazil (Figure 4.20). Therefore, while GYGA project suggests that the management applied in the fields are the main source for sugarcane yield losses, our results considered that the water deficit is the main problem for yield break in the sugarcane fields, which sounds more realistic when data from other studies around the world are analyzed (VAN DEN BERG; SINGELS, 2013; GOMATHI et al., 2013).

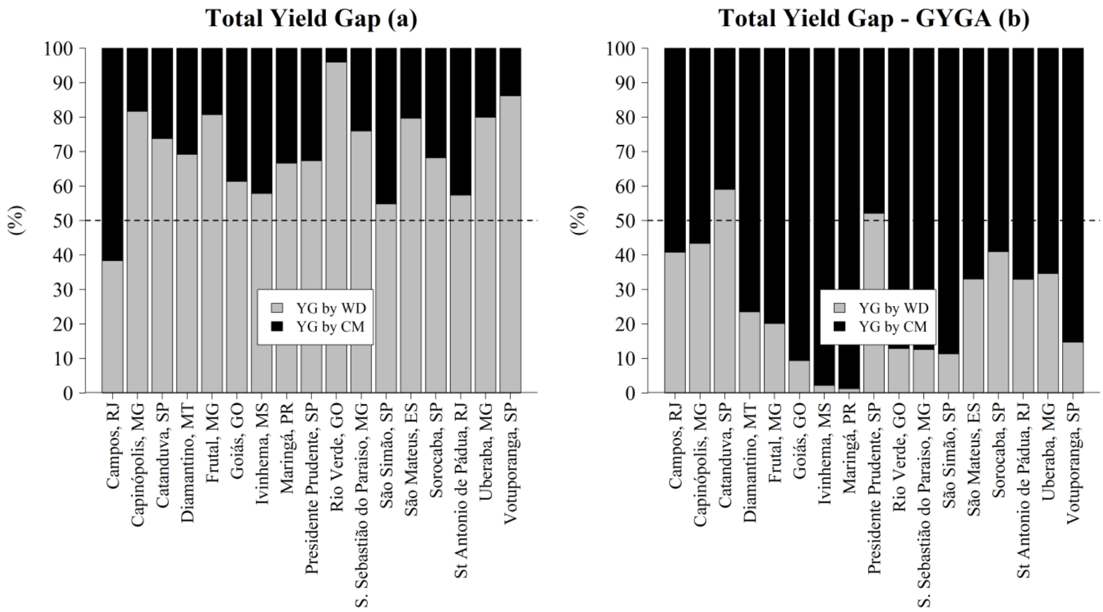

Figure 4.20 – Total yield gaps for 17 Brazilian locations and their respective sources, caused by water deficit and crop management, considering the present study (a) and the GYGA project (b)

4.3.8 Possible solutions to mitigate the sugarcane YG in Brazil

4.3.8.1 Sugarcane cultivars drought tolerant

The Brazilian sugarcane has been expanding to warmer and drier climates, and therefore the occurrence of longer periods with severe water deficits has becoming more and more frequent. In order to reduce the impact of that on sugarcane yield, the introduction of drought tolerant cultivars is a crucial aspect. According to Medeiros et al. (2013), the use of drought tolerant cultivars can substantially avoid the sugarcane yield decline in fields under rainfed cropping systems. These authors tested the performance of two sugarcane cultivars (RB86-7515 and RB96-2962) submitted to water stress during the initial development and concluded that although both cultivars presented damages by water stress, the cultivar RB96-2962 showed a faster recovering after a short stress period. In another study, Machado et al. (2009) evaluated the biometric and physiological responses of two sugarcane cultivars (IACSP94-2094 and IACSP96-2042) to water deficit during different phenological phases. According to these authors, cultivar IACSP94-2094 presented a higher tolerance to drought, once its biomass production and the average plants´ height did not change substantially when under water deficit, even with a reduction on the leaf gas exchanges.

In state of Texas (USA), eighty sugarcane genotypes were evaluated in terms of drought tolerance during a period of 90 days of water stress. Although the yields of all cultivars were affected by those conditions, some of them did not presented significance reduction, which make them potential cultivars for drier regions or to breeding programs aiming drought tolerance (SILVA et al., 2014).

4.3.8.2 Irrigation

The results presented in this study showed that is possible to increase the sugarcane yields in Brazil mainly by the employment of irrigation, since the main yield gap cause is the water deficit.

In Brazil, the majority of sugarcane fields are conducted under rainfed cropping systems, although recent studies have proved the benefits of irrigation to the yield increment (GAVA et al., 2011; SILVA et al., 2014), mainly in the expansion areas (CAMPOS et al., 2014). It can be reinforced by the fact that in Australia about 60% of sugarcane fields are irrigated (INMAN-BAMBER, 2004).

Concerning the crop expansion to marginal regions, where the rainfall distribution is less favorable to sugarcane crop, resulting in a higher water deficit along the year, the employment of full or complementary irrigation is required for achieve profitable sugarcane yields. In a study done in the state of Paraíba, where different levels of water supply were tested, the results showed that irrigation allowed a substantial sugarcane yield increment, with yields achieving about 140 Mg ha^{-1} (da SILVA et al., 2013).

Even in traditional sugarcane regions, where the irrigation is not a common practice, studies conducted in the region of Jaú, state of São Paulo, with drip irrigation during two crop cycles (plant and ratoon) showed a significant increase of yield stalks and sugar production of about 25% (GAVA et al., 2011), showing the potential of this practice to improve yields.

4.3.8.3 Soil compaction and mechanization in sugarcane

Currently, the use of mechanization for sugarcane field operations has been frequent, mainly for planting and harvesting (de SOUZA et al., 2014). This uncontrollable machinery traffic during the growing cycle has leading to the increase the soil compaction (de SOUZA et al., 2012), limiting root growth and, therefore, the water uptake (CHEONG et al., 2009) and, consequently sugarcane yield.

In a study carried out in Pradópolis, state of São Paulo, de Souza et al. (2014) tested the effect of management options in terms of traffic control, highlighting that the sugarcane yield presented a yield increment between 19% and 21%, when machinery operations were better planed. Souza et al. (2015) also concluded that suitable machinery traffic planning can improve the root system, with increments on root biomass up to 44%, which can be associated to a more efficient water and nutrients uptake when compared with fields without traffic control. When traffic control is not considered and soil compaction occurs, the use of sub soilers can provide reasonable results, improving root growth in depth (BAQUERO et al., 2012).

4.4 Conclusions

The results obtained in this study allow to conclude that:

1. The use of the yield model coupled with the geographic information systems allowed to generate detailed information for Brazilian sugarcane planning, in which the spatialized sugarcane yield types (potential, best farmer and actual) were estimated in a reliable way, even in locations where the weather data are scarce or missing;

2. The sugarcane yield gaps obtained in this study were properly determined in all regions evaluated. Is allows to define better strategies to improve the sugarcane yield levels in Brazil, such as regions more responsive to employment of irrigation, like in the Northeast and Center-West regions. On the other hand, the YG estimates also allowed to highlight that the Brazilian sugarcane yields is not substantially affected by crop management, but mainly by water deficit, showing that irrigation could be an important strategy to improve yield levels;

3. There were differences in the main sources of sugarcane yield gap, when evaluating the approach employed in the present study and that of GYGA project. While the results from this study showed that the main source of yield losses in the Brazilian sugarcane fields is the water deficit (YG_{WD}), in the GYGA project it is basically due to suboptimal crop management, even where the sugarcane is presenting a substantial expansion and the climatic characteristics, mainly in terms of water deficit and air temperature are higher than those found in traditional cane regions;

4. Among the management options to improve sugarcane yields across the Brazilian regions, drought tolerant cultivars, irrigation and soil decompaction are those that can contribute for a most suitable and sustainable crop production.

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