Gleyce Kelly Dantas Araújo Figueiredo

SOYBEAN YIELD ESTIMATES BASED ON TEMPORALLY STABLE PIXELS USING MODIS/EVI DATA

ESTIMATIVA DE PRODUTIVIDADE DA CULTURA DA SOJA BASEADA NA ESTABILIDADE TEMPORAL DE PIXELS UTILIZANDO DADOS MODIS/EVI

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Abstract

Soybean is one of the main commodities of the Brazilian agricultural market, and is subject to constant speculation in internal and external markets. Timely and accurate yield estimation using remote sensing represents an important advance in the search for objective crop forecasting in Brazil, since it may help government to plan storage and/or acquisition of food, serving as support to food security, decision making and management of natural resources. However, an operating crop yield estimating system is not currently available in the country. The main goal of this study was to propose a methodology to estimate soybean yield at county level, based on spectral data (EVI/MODIS) and historical yield data during 2000/2001 to 2010/2011 cropping season, in Parana state. These data were used to establish the correlation between EVI and soybean yield at pixel level using two approaches: by month (October to April) and by phenological stages (emergence to maturity, emergence to flowering, flowering to maturity, flowering to grain filling), generating two types of correlation maps. It was possible to detect pixels that had the best correlation over the crop cycle and still find the most suitable period to estimate yield. The results showed that the highest correlation was found in the vegetative peak period of the crop for both approaches. Then I compared the performance of correlation maps against crop specific mask to estimate soybean yield. The correlation maps showed meaningful results with RMSE of 0.173 ton/ha while the crop specific mask showed RMSE of 0.294 ton/ha. Then I selected the temporally stable pixels within the correlation maps using the temporal stability technique in order to include only pixels that presented the same temporal development pattern during the crop cycle. The technique was efficient, once selected pure pixels or pixels with some percentage of the crop, so these pixels were used to estimate soybean yield during the eleven years of study; also using the approaches by month and by phenological stages. For the first approach the vegetative peak showed better results and February showed values closest to official data with RMSE of 0.187 ton/ ha, the best performance of the second approach was the period from flowering to maturity, with RMSE of 0.193 ton/ ha and Willmott agreement index of 96% for February and 95.8% for the flowering to maturity period. This methodology showed to be efficient to estimate yield monthly, thereby it is possible to use it as an auxiliary tool in yield forecast.

Key-words: Crop forecasting, EVI, correlation maps, summer crop.

Resumo

A soja é uma das principais commodities do mercado agrícola brasileiro, e está em constante especulação no mercado interno e externo. A estimativa da produtividade com precisão e antecedência utilizando o sensoriamento remoto representa um importante avanço na procura de formas objetivas para previsão de safras no Brasil, uma vez que pode auxiliar a avaliação de rendimento da cultura, servir de apoio à segurança alimentar, ao planejamento econômico e a gestão dos recursos naturais. No entanto, ainda não há no país um sistema operacional para estimar produtividade. O principal objetivo desse estudo foi propor uma metodologia para estimar, por município, a produtividade da soja, baseado em dados espectrais (EVI/MODIS) e dados históricos de rendimento durante os anos safra 2000/2001 a 2010/2011 no estado do Paraná. Esses dados foram utilizados para estabelecer a correlação entre EVI e produtividade da soja por pixel utilizando duas abordagens: por mês (outubro a abril) e por estágios fenológicos (emergência a maturação, emergência a floração, floração a maturação, floração ao enchimento dos grãos), criando-se então dois tipos de mapas de correlação. Com isso foi possível detectar pixels que tinham as melhores correlações ao longo do tempo e ainda encontrar o período mais adequado para estimar a produtividade. Os resultados mostraram que a maior correlação foi encontrada no período de pico vegetativo da cultura para ambas as abordagens. Em seguida comparou-se o desempenho dos mapas de correlação com máscaras de culturas especificas para estimar a produtividade. Os mapas de correlação apresentaram resultados mais significativos, com RMSE de 0.173 ton/ha, enquanto a máscara de cultura específica apresentou RMSE de 0.294 ton/ha. Em seguida selecionamos os pixels temporalmente estáveis dentro dos mapas de correlação por meio da técnica de estabilidade temporal, a fim de incluir somente pixels que apresentassem o mesmo padrão temporal de desenvolvimento durante a safra. A técnica apresentou-se eficiente, selecionando desde pixels puros a pixels com alguma porcentagem da cultura dentro dele, assim, estes pixels foram utilizados para estimar a produtividade da soja durante os onze anos de estudo, também utilizando as abordagens por mês e por fase fenológica. Para a primeira abordagem o período de pico vegetativo apresentou melhor resultado, sendo o mês de fevereiro o que apresentou valores mais próximos aos dados oficiais com RMSE de 0.187 ton/ha, na segunda abordagem o melhor desempenho foi para o período de floração a maturação com RMSE de 0.193 ton/ha e o índice de concordância de Willmott foi de 96% para fevereiro e 95.8% durante a floração e maturação. Esta metodologia mostrou ser eficiente para estimar a

produtividade por mês, assim é possível utilizá-la como ferramenta auxiliar na previsão de produtividade.
Palavras-chave: Previsão de safra, EVI, mapas de correlação, cultura de verão.

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1. Introduction

According to Brazilian Food Supply Agency - Conab (2013) soybean crop production was estimated in 90,224.9 thousand tons in Brazil for the 2013/2014 cropping season. This amount increased 10.7% in Brazilian production and 6.4% of planted area compared to the previous cropping season.

Soybean is an important commodity to Brazil's economy and one of the most important in the world, being one of the primary oilseeds used for animal consumption of soybean meal, and for human consumption of the oil (Goldsmith, 2008). With this demand of grains, it is essential that the country has a system for crop monitoring and production forecasting capable with good accuracy.

Remote sensing techniques and Geographic Information Systems have been used by Brazilian government for the purpose of optimizing the process of agricultural monitoring to make it less subjective. Conab has sought effective methods to improve the crop monitoring and crop area/yield estimates for Brazil, combining these tools with the traditional methodology of survey aiming to estimate crop areas and predict impacts on crop yields (Conab, 2010). Moreover, monitoring agriculture using remote sensing techniques has the advantage over traditional methods of crop forecasting, for example surveys, once it has less subjectivity of information greater flexibility in data acquisition and less cost (Sano et al., 1998).

There are many approaches to monitoring agricultural and forecasting yield. Those based on agro-meteorological parameters, which use meteorological data and soil properties as input data to simulate several process of the crop in a region. This approach reaches reliable results at field level; however, differences in weather conditions and management practices makes this type of model unable to simulate crop development at regional scale (Rudorff and Batista, 1990).

Statistical regression-based methods are commonly used in conjunction with remote sensed data to estimate crop yield (Wall et al., 2008). These are based on empirical relationships between historical yields and reflectance from vegetation indices. The plant development; stress and yield capabilities are expressed in the spectral reflectance from crop canopies and could be quantified using spectral vegetation indices (Labus et al., 2002). Past studies (Maselli and Rembold, 2001; Labus et al., 2002; Kastens et al., 2005; Ren et al., 2008; Becker-Reshef et al., 2010; Mkhabela et al., 2011) have found very good results in estimating grain yield using spectral data and regression analysis.

Vegetation indices (VI) are dimensionless radiometric measurements that indicate the relative abundance and activity of green vegetation, including leaf area index (LAI), percentage of green cover, chlorophyll content, green biomass and absorbed photosynthetically active radiation (APAR) (Jensen, 2006). Most of the VIs are condensed information which can reflect terrestrial vegetation cover and growth condition effectively and economically (Ren et al., 2008). Because of VIs characteristics it is extensively used to monitoring crop growth and yield estimation.

Although widely applied to agricultural monitoring the Normalized Difference Vegetation Index (NDVI) has some limitations such as influences of atmosphere effects and canopy background. In order to reverse these issues the Enhanced Vegetation Index (EVI) was proposed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences (Huete et al., 1999, 2002).

Satellite sensors such as the *Moderate Resolution Imaging Spectroradiometer* (MODIS), aboard Terra and Aqua satellites, with low spatial resolution and high temporal resolution, seems appropriate for monitoring vegetation; it allows the generation of these indices with regularity and promotes monitoring of crops that have high spectral dynamics throughout the production cycle.

Many studies use VI average from their studied area as input data in yield estimate models (Rojas, 2007; Johann, 2012; Moraes, 2012). However, using medium or low spatial resolution images several non-pure pixels can be mapped influencing the crop spectral profile. Thereby, this VI average no longer can represent the crop development. An alternative to this is to select pixels with high correlation with historical yield as carried out by Maselli and Rembold (2001) and Kastens et al. (2005), and thus do not enter outliers values in the estimates.

The high spectral dynamic of soybean crop cycle is a valuable characteristic, changing from exposed soil to total vegetal coverage in short time; thus, areas covered by the crop will have the same temporal pattern during the soybean crop cycle. This characteristic can be useful to select soybean pixels. Based on this it is necessary to use a technique that separates targets or fields with the same development. Temporal Stability technique created by Vachaud et al. (1985) is widely applied in soil science to select fields with the same pattern (moisture) during a period.

Therefore, based on temporal changing this technique can help to select soybean pixels, once agricultural crops follow a temporal development pattern.

In this context, the hypothesis of this work was considered: It is possible to estimate soybean yield based on empirical relationship between EVI and yield using pixels that are temporally stable at county level in Paraná State.

1.1. Objectives

The main goal of this study was to develop a methodology to estimate soybean yield using regression analyses and spectral data, at monthly scale and at county level, based on pixel analysis during 2000/2001 to 2010/2011 cropping seasons in Paraná state.

1.2. Specifics objectives

- Establish correlation, at pixel level, between EVI and historical yield;
- Create maps with spatial variation of correlation by month and by soybean phenological stages;
- Select pixels that are temporally stable in each correlation map;
- Estimating crop yield monthly during the growing season;
- Analyze the correlation evolution over soybean cycle.

1.3. Thesis Organization

This thesis is divided into eight chapters, three of them are the results written in the form of scientific papers and the last the main references.

The first part deals with the introduction, in which is described the importance of soybean, the problem encountered in forecasting yield and main techniques used to circumvent this problem, and then we clarify our goals based on the problem.

The second chapter is the literature overview about soybean importance, remote sensing applied to agriculture and yield estimate.

Chapter 3 is the general methodology, which addresses the study area and the main materials used in this study.

From chapter 4 I start to explain the results, this part was written as scientific papers which included: Introduction, material and methods, results and discussion, conclusions and references.

Chapter 4 presents the paper "*Mapping the spatial variation of correlation between EVI and soybean yield*" which analyzed the spatial variation of correlation by monthly and by soybean phenological stages, and from this we created correlation maps.

The paper presented in chapter 5 is "*Using correlation maps to assess soybean yield from EVI data in Paraná state, Brazil*" that tested the correlation maps to assess soybean yield estimation, in additional we compared the soybean yield estimation using the correlation maps and using a crop specific mask.

Chapter 6 presented the paper "*Using Temporal Stability to Estimate Soybean Yield. A case study in Paraná state, Brazil*", that addressed the selection of temporally stable pixel which we used to soybean estimate yield by month and by phenological stages.

Chapter 7 I handle the general conclusions of this thesis.

2. Literature Overview

2.1. The soybean importance

According to Food and Agriculture Organization of the United Nations FAO (2007) the extraordinary expansion of soybean production in the last 10 years has changed global agriculture and impacted strongly on international agricultural commodity markets. This development has been particularly intense in the Mercosur region and Bolivia. According to FAOstat (2013) the United States is the world leader in the production of grain followed by Brazil and Argentina as shows Figure 2.1.

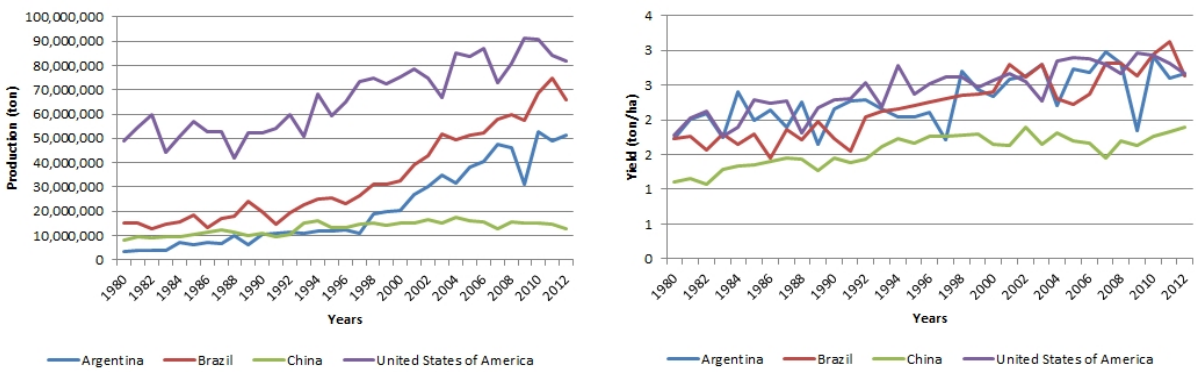

Figure 2.1 Largest producers of soybeans in the world.
Source: FAOstat (2013).

The increase in soy Brazil production is stimulated by the demand for animal feed in Europe that imports almost 70% of Brazilian soybean exports (Cavalett and Ortega, 2009). According to Santos (2000) from 1970 to 2000, producing 1.5 million tons on 1.3 million hectares went to 31.7 million tons at 13.5 million hectares, which illustrates the increased productivity the Brazilian soybean crop. Studies performed by the author indicate that during the 90s, increased soybean acreage was on average 1% per year, while production increased 94% during this period.

This production increase is also explained due to introduction of genetically modified soybean in United States and Argentina. Since this introduction, the US grain exportations to Europe fell 9.2 million tons to 6.8 million ton, while Brazilian exportation to Europe increased 3.1 million ton to 6.3 million ton during the same period in 2002 (Greenpeace, 2002).

According to *US Department of Agriculture* - USDA (2011) Brazil strengthened its position as a leading exporter of soybeans and derivatives since the 1990s, with increasing soybean plantings in the Cerrados region and expansion extending into the Legal Amazon region.

The growth rate for Brazil's soybean planted area is projected to average nearly 2.5 percent per year during the coming decade. During the next 10 years, soybean exports are projected to rise about 47 percent.

2.2. The soybean crop in the Brazilian scenario

According to Brazilian Agricultural Research Corporation – Soybean Research Center (Embrapa Soja, 2007), many factors contributed to established soybean as an important crop, first in the southern region of the country and after the Cerrado the central region of Brazil. Some of these factors contributed to the growth of the southern region, highlighting: Similarity between different ecosystems producer countries; establishment of a major industrial park of soybean processing; replacement of animal fats (lard and butter) for healthier vegetable oils consumption human.

For Brazil, the soybean complex has significant economic importance. Besides involving large numbers of agents and organizations linked to various economic sectors, the grain is fundamental in the increment of Gross Domestic Product (GDP); resulting in an average gross value of production of 7.7% per year (Embrapa Soja, 2011).

Soybean cultivation is concentrated in the South and midwest regions of the country. In the last cropping season (2012/2013) Brazilian production reached 81,479.8 thousand tons. Over 38,091.4 thousand tons of the crop is produced in the Midwest region of the country especially in Mato Grosso state, the southern region occupies second place in production with just over 30,025.8 thousand tons produced, followed by the southeast, northeast and north Figure 2.2 shows the Brazilian production and productivity over the country and Figure 2.3 the soybean spatial production (Conab, 2013).

In Paraná state soybeans promoted significant expansion of mechanized plantations, bringing significant technological change, particularly as a result of the management and soil conservation program. The advance of soil conservation, direct sowing, the correction of soil, pest management and the use of genetically improved seeds and supervised by research agencies resulted in significant productivity gains, from averages around 2.1 ton/ha at the beginning of the 90s, to more than 2.9 ton/ha in recent years (Mercante, 2007).

Soybean is the most cultivated specie in terms of area in Paraná state, as well as the largest share in value of production, accounting to 17.2%. Soybean has been a remarkable crop scenario in the state to developing agriculture. Its wide and growing use, should maintain economic importance during the century (Cançado, 2004).

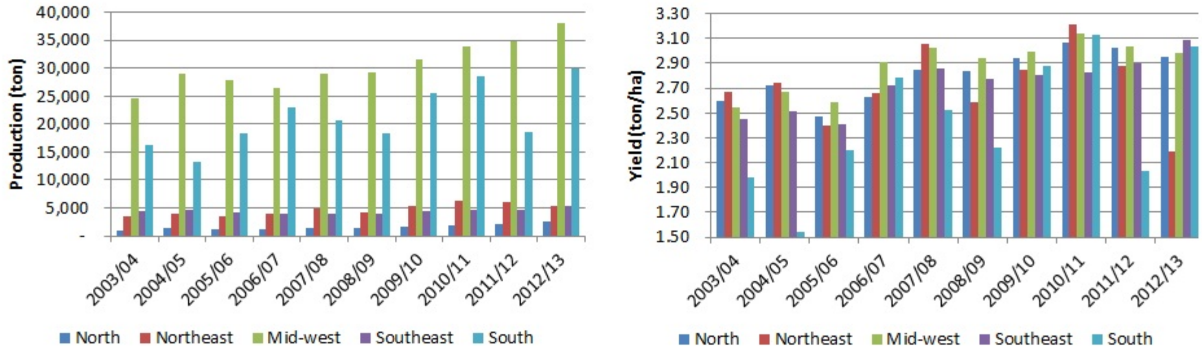

Figure 2.2 Brazilian soybean production and yield
Source: (Conab, 2013).

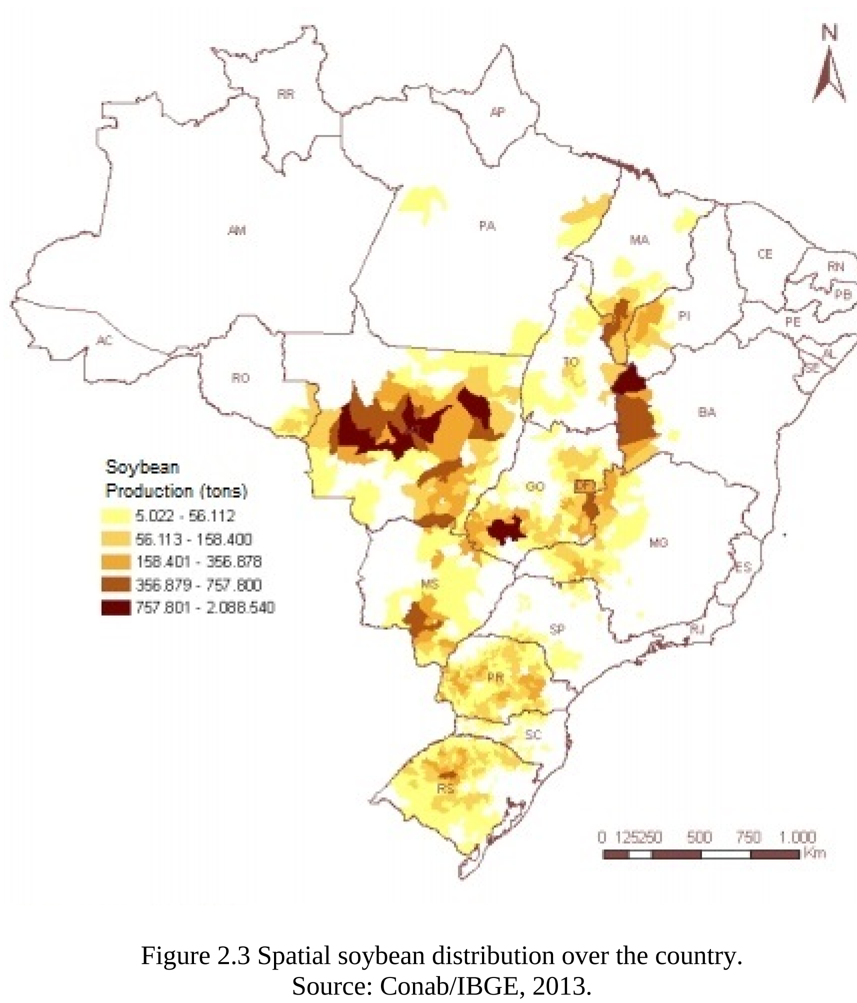

Figure 2.3 Spatial soybean distribution over the country.
Source: Conab/IBGE, 2013.

2.3. Soybean crop cycle characteristics

Farmers who understand how a soybean plant grows and develops can establish their field practices to maximize the genetic potential of the varieties grown. Management practices that may influence crop growth include seedbed preparation, variety selection, planting rate, planting depth, row width, pest management (diseases, insects and weeds), fertilization and harvesting (Mcwilliams et al., 1999).

Growth and development of soybean are measured by the amount of accumulated dry mass (dry matter) on the plant. With the exception of water, dry mass consists of everything that is in the plant, including carbohydrates, proteins, lipids and mineral nutrients (Borkert et al., 1994).

The soybean cycle has two main phases: the vegetative stage (V) and reproductive stage (R). The vegetative phase is beginning with the birth of the seedling and after the opening of the first flower, initiating the reproductive period that ends with the maturity of the plant (Kandel, 2010). Figure 2.4 shows the vegetative and reproductive stages of the soybean.

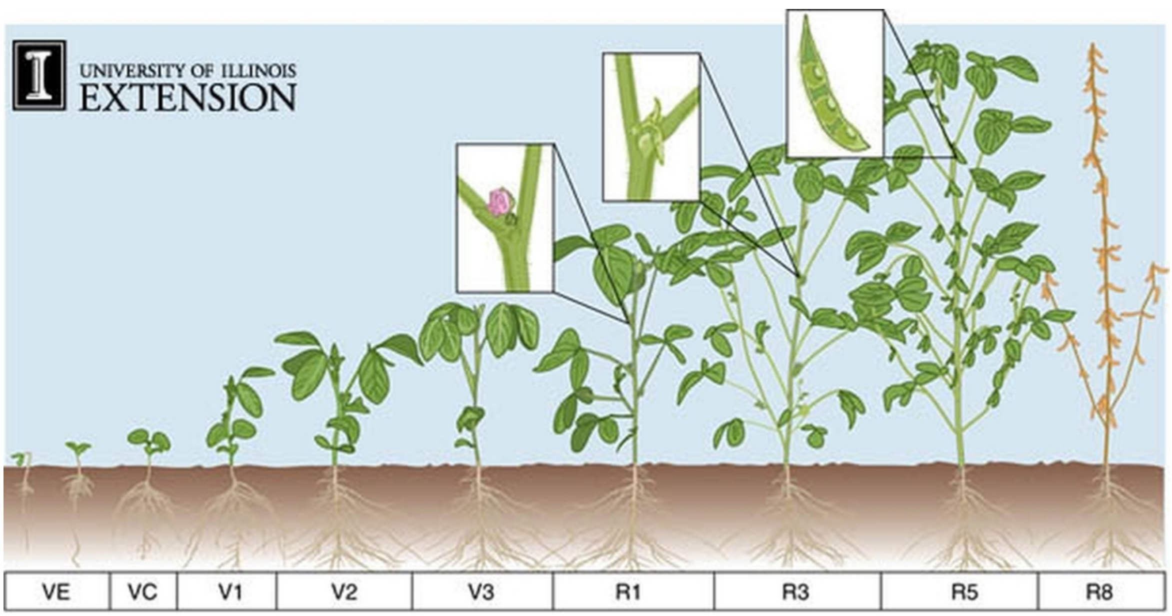

Figure 2.4 Soybean Growth Stage Development.
Source: (UNL, 2007)

The vegetative phase (V) covers development from emergence through flowering. After emergence, unifoliolate leaves on the first node unroll in addition to cotyledons and start the VC stage. The following vegetative stages are designed numerically from V1, V2, V3, through V(n), based on the number of nodes with trifoliolate fully developed leaves unrolled. The reproductive phase (R) stage from flowering through maturation is divided into 4 parts: These stages describe the development of flower (R1 and R2), pod (R3 and R4), seed (R5 and R6), and maturity (R7 and R8). Table 2.1 shows soybean vegetative and reproductive phase (Fehr and Caviness, 1891; Mcwilliams et al., 1999).

Table 2.1 Vegetative (R) and Reproductive (R) soybean growth stages

Vegetative Stages	**Description**	**Reproductive Stages**	**Description**
VE	Emergence	R1	beginning bloom, first flower
VC	cotyledon stage	R2	full bloom, flower in top 2 nodes
V1	first trifoliolate	R3	beginning pod, 3/16” pod in top 4 nodes
V2	second trifoliolate	R4	full pod, 3/4” pod in top 4 nodes
V3	third trifoliolate	R5	1/8” seed in top 4 nodes
V4	Fourth trifoliolate	R6	full size seed in top 4 nodes
V...	...	R7	beginning maturity, one mature pod
Vn	nth trifoliolate	R8	full maturity, 95% of pods on the plant are mature

Source: Adapted (Fehr and Caviness, 1891; Mcwilliams et al., 1999)

2.4. Soybean Crop Calendar

For Almeida (2005) the decision of the farmer in choosing the best period to start planting depends on a set of variables that define the average agricultural calendar of a region. Some of these variables basically involve prior planning that is not always predictable.

Soybean crop calendar was developed to help producers to prioritize and schedule work events in a timely way on the farm, as weather events and equipment breakdowns. However, if other practices within the farm in operation are prioritized, perhaps the farmer can better address the emergencies than will occur (Lee et al., 2007).

The initial conditions of the environment which can ensure the installation of crops, seed germination and plant growth, depend on the moisture available in the soil derived from rainfall. The best period to obtain the highest yield potential of a crop and, consequently, greater economic gain, among other factors, is when rainfall season starts. Therefore, November shows the thermal-photoperiodic conditions and early rainy season, which allow better utilization of genetic soybean

According to Embrapa Soja (2004) the preferred period to start the sowing date in the South region is November but, for some counties in Paraná state, it starts in early October and ends in early December. Warmer regions of the state with wet winter and high fertility soils are favorable for plant emergency to occur from early October. According to Almeida (2005) this trend of early sowing, and preference for early maturing cultivars, are due to the use of the same crop fields for a second crop of corn (winter cropping season). Figure 2.5 shows the Brazilian soybean crop calendar.

SOYBEAN (PLANTING - HARVEST)

REGION		9/23 to 12/21						12/21 to 3/20						3/20 to 6/21						6/21 to 9/23					
		Spring						Summer						Autumn						Winter					
		OCT		NOV		DEC		JAN		FEB		MAR		APR		MAY		JUN		JUL		AUG		SEPT	
CENTER-SOUTH	Planting		P	P	P																				
	Harvest											C	C	C	C										
NORTH-NORTHEAST	Planting			P	P	P	P	P																	
	Harvest													C	C	C	C	C							

P Concentration of Planting
C Concentration of Harvest

Figure 2.5. Brazilian soybean crop calendar.
Source: (Conab, 2013).

2.5. Remote sensing applied to agriculture

Remote sensing is becoming a useful tool for obtaining information about the Earth's resources, especially its vegetation cover (Hinzman et al., 1986). Accurate assessment of crop condition would be useful for more efficient and economic determination of the extent and severity of drought, diseases, insect infestations, and nutrient deficiencies (Hinzman et al., 1986; Labus et al., 2002).

To follow the agriculture dynamics remote sensing characteristics, like the global character, multispectral and repetitiveness, qualify it for this activity especially in large countries like Brazil (Sanches et al., 2005).

Remote sensing applications in Brazil had the first thematic mapping focusing on aerial imagery in the 40’s with punctual and quite specific studies. In the middle of the 80’s began the extensive mapping of Brazilian vegetation cover that included some agricultural crops of great importance to the country, like sugar cane and beans. Many of these initiatives have been altered and enhanced, are in full development and their results have been used for crop forecasting and the establishment of national policies to preserve the environment (Ponzoni and Shimabukuro, 2010).

2.5.1. Multi-temporal remote sensing images.

Remote sensing techniques with multi-temporal repetitive coverage have shown promise for use in estimating the agronomic parameters and monitoring the changes in these parameters during the crop growth cycle. An important goal of agricultural remote sensing research is to spectrally estimate crop variables related to crop conditions which can subsequently be entered into crop simulation and yield models (Huang et al., 2002).

The use of multi-temporal images of a crop field allows monitoring both the behavior of the crop throughout development as well as compare different behaviors over the years. A satellite image of a single date cannot provide sufficient spectral information to identify the entire crop grown in a particular station. But multi-temporal images can provide more information about planted area and directions about the growth and development of crops that can be key elements in the spectral discrimination of different crops (Sanches et al., 2005).

Still according to Sanches et al. (2005), the crop discrimination through satellite images is not a simple task and involves many factors. However, a multi-temporal analysis combined with cropping pattern, the experience of the interpreter and knowledge of the study area and crops, provides a good result in the identification of agricultural crops in satellite images.

According to Labus et al. (2002), most of these studies derived pre-harvest yield estimates with a single vegetation index observation or time-integrated vegetation indices over a specific time period for a few growing seasons. Examination of seasonal growth profiles over many growing seasons and identification of critical times in crop-growth cycles have been identified recently as potential research areas that could provide a basis for crop monitoring and prediction of final grain yield.

Some studies have proven that multi-temporal data of vegetation index from MODIS showed to be effective for agricultural monitoring and identifying crop areas, such as: Wardlow et al.(2006); Ren et al.(2008); Becker-Reshef et al. (2010); Mkhabela et al. (2011); Johann (2012); Moraes (2012).

2.5.2. Spectral behavior of vegetation

From the three components resulting from fractionation of incident solar radiation, interacting with the plant, this is reflection, absorption and transmission, the most important for yield plant is undoubtedly the absorption. However, for the majority of remote sensing, especially the orbital and suborbital systems, this measure of the radiation is impossible, except through inferences based on the behavior of quantities reflected and/or emitted by vegetation. In this aspect, the energy reflected by the vegetation has been the most used because it is in this range of the electromagnetic spectrum that has the largest amount of suborbital and orbital sensors capable of recording information of the Earth's surface (Moreira, 2007).

The interaction of solar radiation with the vegetation occurs mainly on leaves, plant organs highly specialized in absorbing electromagnetic radiation (EM), where the process of photosynthesis occurs (Salisbury and Ross, 1992; Nobel et al., 1993).The reflectance of the healthy vegetation varies depending on the wavelength regions with the most significant and distinct wavelength spectrum in the visible, near infrared and mid-infrared as shown in Figure 2.6.

The energy reflected by vegetation cover and captured by a satellite is influenced by the soil. The influence of soil in reflectance vegetation cover is related to the characteristics of the crop, like spacing, size, vigor and development phase (Guyot, 1989).

Agricultural crops with short development period present large changes in the amount of plant material in the canopy of the plantation during its phenological cycle, resulting difference in the possible interactions of electromagnetic radiation with the crop (absorption, transmission or emission and reflection), making it possible to monitor them, or register information of these crops through remote sensing (Formaggio, 1989).

Kollenkark et al. (1982) reported that the spectral reflectance of plant canopy can change depending on crop row spacing, plant population and sowing date and is influenced by the size, vigor and phenological stage.

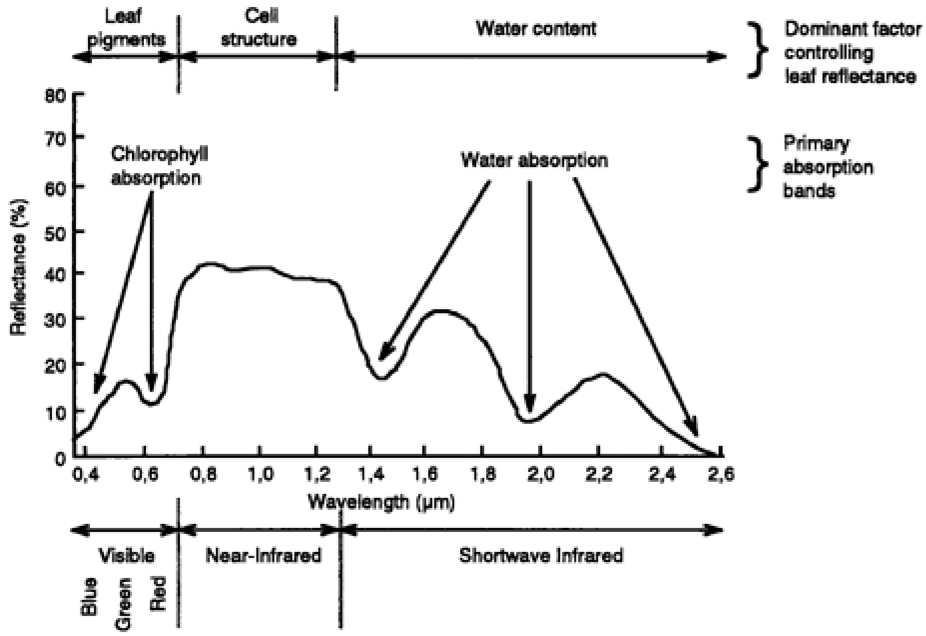

Figure 2.6 Typical spectral response characteristics of green vegetation.

Font: Adapted (Hoffer, 1978).

2.5.3. Vegetation Indices

According to Jensen (2006), vegetation indices (VI) are dimensionless radiometric measurements, which indicate the relative abundance and activity of green vegetation, including leaf area index (LAI), percentage of green cover, chlorophyll content, green biomass and absorbed photosynthetically active radiation (APAR).

The vegetation indices are mathematical combinations of the spectral response of different bands of the electromagnetic spectrum, and the major indices cited in the literature use the values of reflectance in two wavelength bands, red (V) and near infrared (NIR). The contrast of vegetation response at these wavelengths makes the vegetation highlighted in relation to other targets, facilitating their identification, and monitoring from remote sensing data (Asrar et al., 1984; Baret and Guyot, 1991). To differentiate the vegetation of other targets and different types of vegetation, numerous vegetation indices have been developed based on spectral measures (Huete, 1988).

Vegetation indices are widely used in crop growth monitoring and yield estimation based on remote sensing technology. Most of the VIs are condensed information which can reflect terrestrial vegetation cover and growth condition effectively and economically (Ren et al., 2008).

According to Tucker et al. (1980) VIs are correlated with photosynthetic activity in non-wilted plant foliage and are good predictors of plant canopy biomass, vigor or stress.

The EVI was developed to minimize the effects of the atmosphere and the background of the canopy that contaminate the Normalized Difference Vegetation Index (NDVI) (Jensen, 2006). Improving sensitivity into high biomass regions and enhancing vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences (Huete et al., 1999). This index is determined by equation 2.1.

$$EVI = G * \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + C_1 * \rho_{red} + C_2 * \rho_{blue+L}} \qquad (2.1)$$

Where G is gain or scaling factor (G=2.5); ρ nir/red/blue are atmospherically corrected or partially atmosphere corrected (Rayleigh and ozone absorption) surface reflectance; C1 and C2 are the coefficients of the aerosol resistance term; L is the canopy background adjustment for correcting nonlinear.

Wardlow et al. (2007) studied the various applications of MODIS VI (NDVI and EVI) for some crops in U.S. state of Kansas. Both produced similar seasonal variation and were highly correlated with all crops. However, they found some small but consistent differences between the two VIs. At the highest VI values, which correspond to the peak of growing season conditions of the crops, NDVI exhibited a range of values between 0.80 and 0.88 at the time of peak green biomass for all crops, while the EVI captured more variability in the vegetation changes of the crops at that time by maintaining a larger range of values of 0.60 to 0.82. The authors state that these results were consistent with the EVI project, which was intended to have improved sensitivity to vegetation changes over high biomass areas as compared to the NDVI, which tends to saturate (Huete et al., 2002).

2.5.4. The Moderate Resolution Imaging Spectroradiometer

The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor mounted aboard the Terra and Aqua satellites that is part of *Earth Observing System* (EOS) program formed by the U.S., Canada and Japan. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days. With sun-synchronous orbit at 705 km cross the equator line at 10:30 a.m. descending node (Terra) or 1:30 p.m. ascending node (Aqua). It provides high radiometric sensitivity (12 bit) in 36 spectral bands ranging in wavelength from 0.4 µm to 14.4 µm (NASA, 2013a). Table 2.2 shows the main characteristics of this sensor.

Table 2.2. Main characteristics of MODIS instrument.

Bandas Espectrais	Resolução Espectral (nm)	Resolução Espacial (m)	Bandas Espectrais	Resolução Espectral (nm)	Resolução Espacial (m)
1	620 - 670	250	19	915 - 965	1000
2	841 - 876		20	3660 - 3840	
3	459 - 479	500	21	3929 - 3989	
4	545 - 565		22	3929 - 3989	
5	1230 - 1250		23	4020 - 4080	
6	1628 - 1652		24	4433 - 4498	
7	2105 - 2155		25	4482 - 4549	
8	405 - 420	1000	26	1360 - 1390	
9	438 - 448		27	6535 - 6895	
10	483 - 493		28	7175 - 7475	
11	526 - 536		29	8400 - 8700	
12	546 - 556		30	9580 - 9880	
13	662 - 672		31	10780 - 11280	
14	673 - 683		32	11770 - 12270	
15	743 - 753		33	13185 - 13485	
16	862 - 877		34	13485 -13785	
17	890 - 920		35	13785 -14085	
18	931 - 941		36	14085 -14385	

Font: Adapted from (NASA, 2013b)

MODIS instrument provides a means for quantifying land surface characteristics such as land cover type and extent, snow cover extent, surface temperature, leaf area index, fire occurrence (NASA, 2013b). These data are made freely available by National Aeronautics and Space Administration (NASA) in Tiles of 10 degrees by 10 degrees at the Equator. The tile coordinate system starts at (0,0) (horizontal tile number, vertical tile number) in the upper left corner and proceeds right (horizontal) and downward (vertical). The tile in the bottom right corner is (35,17) (USGS, 2013). Figure 2.7 shows the arrangement of tiles across global coverage.

Global MOD13Q1 data are provided every 16 days at 250-meter spatial resolution as a gridded level-3 product in the Sinusoidal projection (NASA, 2013b). The MODIS VI products also provide consistent, spatial and temporal comparisons of global vegetation conditions which can be used to monitor the Earth’s terrestrial photosynthetic vegetation activity in support of phenologic, change detection, and biophysical interpretations (Solano et al., 2010).

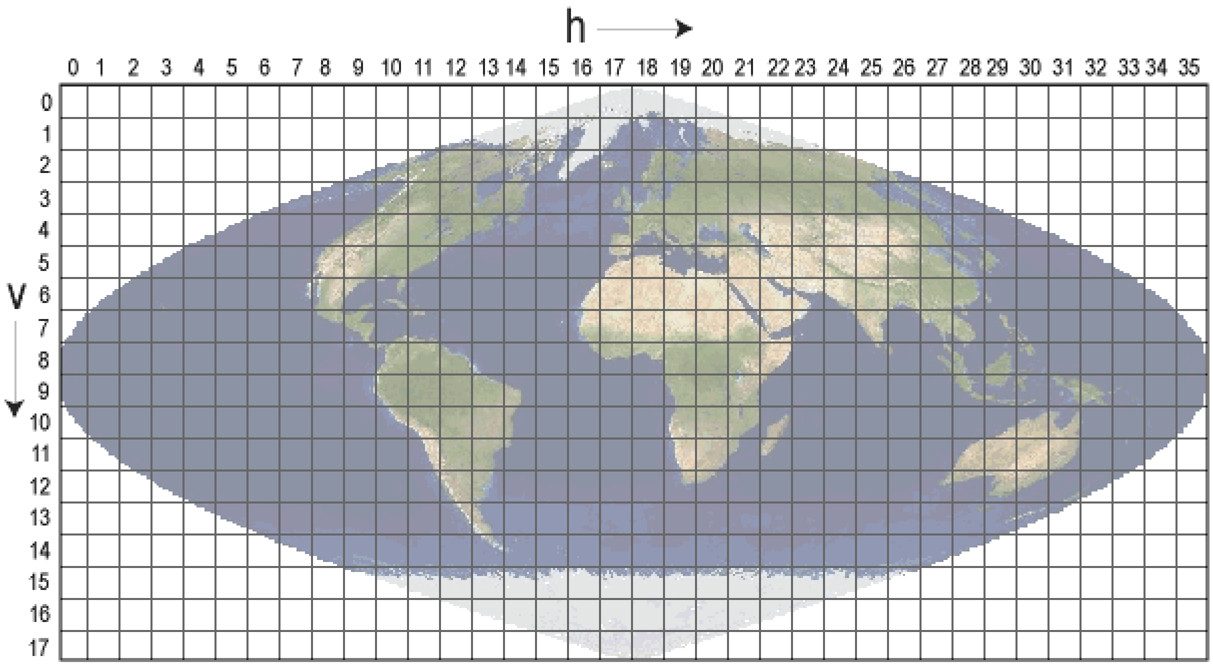

Figure 2.7. MODIS Sinusoidal Tiling System.
Font: (USGS, 2013)

2.6. The crop forecast system in Brazil

The Ministry of Agriculture, Livestock, and Food Supply (MAPA), through the Conab, systematically carries out assessments of agriculture crops to quantify and to follow up Brazilian production (Conab, 2013d). This crop assessment is extremely important for the formulation and implementation of agricultural policies.

According to Figueiredo (2005) these data have been used by operators of agribusinesses to support decision making. Estimates have direct influence on the behavior of internal and external prices of the products. Knowing exactly the extent of cultivated area and the expected yield is an asset to the public and the private sector.

Despite the importance of these data for the economy, once is closely linked to excess or shortage of products, in most cases the subjectivities determine a degree of uncertainty on the information generated (Motta et al., 2003).

According to Conab (2008), during the cropping season twelve surveys are conducted, six at field interspersed with six other in distance. In case of extreme weather conditions, field surveys are conducted in the affected areas. Since 1998, Conab decided to invest in the improvement of the evaluation of the crop assessment, using remote sensing technologies aiming to improve the treatment of the sample data and reach higher accuracy and reliability of the information produced.

In this regard, since 2004, through GeoSafras project Conab improved agricultural statistics of major crops in the country through the use of statistical models, remote sensing, GPS, GIS and agro-meteorological models, which has allowed monitoring at regional and national scales. In this project the estimated production is a result of two variables, the estimated cultivated area and the estimated yield (Conab, 2010).

To estimate cultivated area, Conab has been generating updated cropland mapping through satellite images. Based on the identification and delineation of each crop, then it is possible to calculate planted area by municipality and state. This method allows to find and to check, at field level, all cultivated areas in territorial levels, as well as studies on the expansion/contraction of areas and crop substitution. Estimates of cultivated area obtained from the cropland mapping complement the official crop data and serve as guidelines to the search parameters (Conab, 2013b).

To estimate crop yields, Conab performs monitoring (agro-climatic, agro-meteorological and spectral) of major crops, and uses prediction models on productivity loss in specific regions. Both provide indicative yield by the prediction of the impact of yield losses and assisting crop assessment (Conab, 2013c).

2.6.1. Yield estimates

Monitoring agricultural crops the during growing season is increasingly important for obtaining yield predictions before harvesting time (González-Sanpedro et al., 2008). This process aims to represent a simplified control that the environment has on the crop under field conditions, simulating its developments from sowing to harvesting (Johann, 2012).

According to Kastens et al. (2005) traditionally yield forecasting is made by compiling survey information provided through growing season or using an agro-meteorological model to simulate growth development of the crop. Johann (2012) states that simulation models assume the growth impact of agro-meteorological variables in the physical, chemical and physiological properties (photosynthesis, respiration and transpiration) of plants can be represented by simplified mathematical equations.

These simulations describe crop growth, development and yield formation processes driven by climate, management and soil conditions (Yuping et al., 2008). However, at regional scale these models of practical use are limited because of spatial differences in soil characteristics and crop growth determining factors such as nutrition levels, plant disease, herbicide and insecticide use, crop type, and crop variety, which would make informational and analytical costs excessive (Kastens et al., 2005; Launay and Guerif, 2005; Yuping et al., 2008).

On this basis, there is still a need to combine new methods to extract parameters from crop and growth conditions in order to improve the accuracy of models. Due to its advantage of providing timely information on crop conditions during the growing season in large areas, satellite remote sensing can be used in conjunction with crop models for predicting crop yields (Yuping et al., 2008; Becker-Reshef et al., 2010).

Spectral variables have been included on agro-meteorological models. This term expresses the differences in management practices, crop variety and stresses not accounted in the agro-meteorological model of Rudorff and Batista (1990). But this still uses punctual data of climate condition and soil proprieties that change for each crop/location. Moreover, in Brazil there is difficulty in obtaining timely meteorological information and the low density of stations in the country is responsible for leaving large agricultural areas without reliable, information especially in the case of rainfall data (Melo and Fontana, 2007).

2.6.2. Spectral model to estimate yield

Statistical regression-based methods are commonly used in conjunction with remote sensing data to estimate crop yield (Wall et al., 2008). These are based on empirical relationships between historical yields and reflectance based on vegetation indices. They are typically simple to implement and do not require numerous input data (Becker-Reshef et al., 2010).

Several studies have recognized that plant development, stress and yield capabilities are expressed in the spectral reflectance from crop canopies and could be quantified using spectral vegetation indices (Labus et al., 2002).

Maselli and Rembold (2001) built a regression model using thirteen years of AVHRR-NDVI and historical yield to estimate crop grain yield in North African countries. The model prediction capability was high with an RMSE ranging in 0.05 ton/ha to 0.18 ton/ha. For all countries/crops studied they found high determination coefficients between monthly NDVI and final yield during vegetative peak of the growing season.

Labus et al. (2002) examined seasonal growth profiles from AVHRR-NDVI for estimating wheat yield at regional and farm scales in Montana during 1989–1997 using a multiple linear regression. The authors found good relationship (R^2 adj. 0.753) between NDVI and yield was during vegetative peak and years with high biomass resulting in better yield forecast. They also state that NDVI profiles can provide good yield estimates at regional scale, especially during vegetative period of wheat.

Ren et al. (2008) related NDVI-MODIS data at county level in China with winter wheat production. Using a stepwise regression method, they found a relationship between the spatially accumulated NDVI and production. Their results showed the RMSE was 0.2142 t/ha. The authors claim that a good predicted yield of winter wheat could be reached about 40 days ahead of the harvest time. The author state that the spectral model had better performance than the agro-climate model tested in the same area (RMSE 0.233 ton/ha).

Becker-Reshef et al. (2010) developed a regression-based model using MODIS data to estimate winter wheat in Kansas, U.S. and the same model was applied in Ukraine. For Kansas the results closely matched with USDA/NASS report with 7% error while in Ukraine within 10% of the official reported. Besides the authors developed a model applicable for other regions, it generated estimates six weeks prior to harvest.

Mkhabela et al. (2011) evaluated the possibility of using MODIS data to forecast grain yield on the Canadian Prairies and also to identify the best time for making a reliable crop yield forecast by correlated and regression analyses. For all studied crops, the difference of predicted from the actual yield was within ±10% and the whole RMSE ranged from 0.15 ton/ha to 0.71 ton/ha. The authors also found the best time for making grain yield predictions can be made one to two months before harvest.

Johann (2012) created spectral and combined (spectral and agro-meteorological) models for summer soybean yield estimation with EVI-MODIS data in Brazil using statistical techniques of Stepwise and Best subsets methods. The best fits were obtained using a combined model with RMSE between 0.16 t/ha and 0.23 t/ha while the RMSE of spectral model were between 0.20 t/ha and 0.38 t/ha.

Bolton and Friedl, (2013) developed linear models to predict maize and soybean yield in the Central United States using spectral indices derived from MODIS data. To do this, they combined spectral indices with remotely sensed phenology metrics to account for geographic and inter annual variation in crop phenology. Correlations between vegetation indices and yield were highest 65–75 days after greenup for maize and 80 days after greenup for soybeans.

2.7. Cropland masking and its drawbacks

To run the crop yield forecast, some authors use the vegetation index averaged from cropland masks in their study area as input data. Several studies have improved the way to estimate and indentify cropland areas. Araújo et al. (2011) and Johann (2012) created cropland masks of summer crops in Paraná state using RGB composites. Arraes et al. (2013) developed a methodology which was able to generated masks of summer crops, based on second order polynomial equations, fitted to temporal NDVI profiles in Paraná State.

In the US areas another useful tool for identification of planted area is the CropScape - Crop Data Layer (CDL). The CDL is a rasterized land cover map using field level training data from extensive ground surveys, farmer reports provided to the U.S. Farm Service Agency (FSA), and using remotely sensed data from Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper (ETM+) and Advanced Wide Field Sensor (AWiFS) (Becker-Reshef et al., 2010).

These approaches can be very useful for identification and estimation of cropland area, this information is also often used as input data for modeling. Once cropland is mapped, the average vegetation index is applied to estimate yield.

Kastens et al., (2005) observed that the usual way of mapping cropland area sometimes is not as efficient. If the mapping is performed in heterogeneous or low production places there may be contamination of the pixel with other targets. Maselli and Rembold (2001) states that when these areas are used to generate estimates is possible only verify good results once perturbing effects of the environment, as natural vegetation and soil, are removed.

According to Maselli and Rembold (2001) decisive improvement in crop yield forecasting capability is linked to the selective consideration of VI values from cropped areas, because other vegetation types, having different seasonal developments, may introduce noise in the relationships VI/yield. Based on this, several efforts have been doing to find an alternative to choose reliable pixels to represent the crop to estimate yield.

Genovese et al. (2001) integrated NDVI data from NOAA-AVHRR with a land use map generated from CORINE Land Cover (Co-ordination of Information on the Environment), to reduce problems with non-pure pixels. They created CNDVI, which is based on the proportion of map targets. They tested a series of conditions on pixels keeping them as homogeneous as possible, the best pixels on these conditions were used to estimate crop yield in Spain.

Doraiswamya et al. (2007) used a percentage map to validate the classification of corn and soybeans in U. S. Illinois and Iowa states. This classification was performed through decision trees using MODIS-NDVI images and then compared with NASS classification made with Landsat ETM. Then they agregated the Landsat classification with MODIS and selected pixels with 90% or more of crop percentage. These pixels were used to test the discrimination of identification performed by the decision tree algorithm, thus verified that the classification has shown high accuracy.

Becker-Reshef et al. (2010) created a percentage map to select the purest winter wheat pixels in Kansas. Thoses pixels were used as input data in the regression linear model to estimate yield.

According to Kastens et al. (2005) all vegetation in a region integrates the seasonal cumulative growing conditions in some fashion and may be more indicative of a crop’s potential than the crop itself. For them this premise is most sound early in a crop growing season, when the VI response of the immature crop is not strong enough to be a useful indicator of final yield.

For this reason, Kastens et al. (2005) created the yield-correlation masking that is based on correlation at pixel level between final yield and NDVI-AVHRR during twelve years of study in Kansas, North Dakota, Illinois and Iowa, U.S. With this approach the authors created several masks with different sizes based on the quantity of crop that were within each pixel. Thus selected pixels most correlated with yield to generate estimates. Varying the amount of cropped area in each pixel the estimate error changed, however not all masks with 100% crop were the best. For some studied areas, masks with a smaller percentage of crops had better performance.

Maselli and Rembold (2001) verified that the USGS land-cover classification was not very effective for cropland identification, probably due to the definition of broad classes which contain mixed vegetation types. A specific method was therefore developed based on the assumption that cropped areas had NDVI values in the optimal yield forecasting period more correlated with final yield than did non-cropped areas. Correlation images were thus created and composed with mean NDVI images in order to estimate the distribution of agricultural and non-agricultural vegetation.

2.8. Temporal stability technique

When the planting period starts, the spectral signal of the crop is similar to the soil spectral signal. As the crop develops the vegetation cover increases by decreasing the soil influence. When the senescence period starts the vegetative vigor of the plant decreases, reducing the percentage of coverage, changing the spectral signal of the superficie again (Formaggio, 1989). This pattern can be useful to select pixels that have the same behavior during a period separating only planted areas.

Based on this, it is necessary to use a technique that separate targets or field with the same development pattern. Temporal Stability technique is widely applied in soil science to select fields with the same pattern (moisture) during a time.

Vachaud et al. (1985) introduced the concept of the temporal stability, which they described as the time invariant association between spatial location and classical statistic parametric values such as ranking observations from smallest to largest values, and identify the cumulative probability function as a normal distribution. They proposed this method in soil science for the purpose of reducing the number of field sampling sites while at the same time accurately characterizing the spatially averaged behavior of soil moisture (θ) of the study area over time.

Although surface soil moisture is highly variable, if measurements of soil moisture at the field or small watershed scale are repeatedly observed, certain locations can often be identified as being temporally stable and representative of the an area average (Vachaud et al., 1985). The same happens with crops with high spectral dynamic, according crop to growth progresses pixels occupied with crop also can be identified as temporally stable.

In regards to θ, temporal stability suggests that the pattern of spatial variability does not change with time when the individual θ measurements are ranked according to their magnitudes or when scaled against the mean value for the area under consideration (Van Pelt and Wierenga, 2001).

The principal tool employed for summarizing and assessing the statistics used in the temporal stability analysis is the mean relative difference plot. This plot compares a particular location to the average computed from all locations (Cosh et al., 2006). The technique is initialized by calculating the difference (Δij) between an individual sample and the daily spatial mean of (θij) at the same time from all locations as follow in equations (2.2) and (2.3):

$$\Delta ij = \theta_{ij} - \bar{\theta}_j \quad (2.2)$$

$$\bar{\theta}_{j} = \frac{1}{N} \sum_{i=1}^{N} \theta_{ij} \quad (2.3)$$

Where θij is the jth sample at the ith site of N sites within the study region. $\bar{\theta}_j$ is the computed spatial average among all sites for a given date and time j. The relative differences (δij) are then calculated from equation (2.4):

$$\delta_{ij} = \frac{\Delta_{ij}}{\bar{\theta}_j} \quad (2.4)$$

The relative difference from the temporal mean ($\bar{\delta} ij$) and its standard deviation ($\varsigma(\bar{\delta} ij)$) are determined for each location as:

$$\bar{\delta}_{ij} = \frac{1}{m} \sum_{j=1}^{m} \delta_{ij} \quad (2.5)$$

$$\varsigma(\bar{\delta}_i) = \left[\sum_{j=1}^{m} \frac{(\delta_{ij} - \bar{\delta}_i)^2}{m-1} \right]^{1/2} \quad (2.6)$$

Where m is the number of sampling days. Equations (2.4) and (2.5) are used to rank and plot the locations from lowest mean relative difference to highest. A site is considered temporally stable if the mean relative difference is near zero and there is a small standard deviation (Starks et al., 2006).

3. General Methodology

3.1. Study Area and period

The study was carried out in Paraná state, located between 22° and 27° South latitude, 48º and 54º West longitude with altitudes from 0 to 1300 meters. This area is characterized for presenting great diversity of climate, soils and topography that provide favorable environments for growing a large number of plant species. Various microclimates with distinct thermal and precipitation regimes can be observed throughout the state. The state is located in a region of climatic transition from a subtropical climate with milder winters north to a condition that approaches the south temperate climates, where winters are severe and the plant growth season is better defined (Iapar, 2013).

According to Conab (2013a) during 1990-2012 Paraná state ranked second in Brazil in soybean production (15.912,4 thousand tons in 2012), and relative to the southern region of Brazil, it is ranked first. I selected some counties from two different regions of the state, the western region that is known as the soybean belt and the east-central region (Figure 3.1).

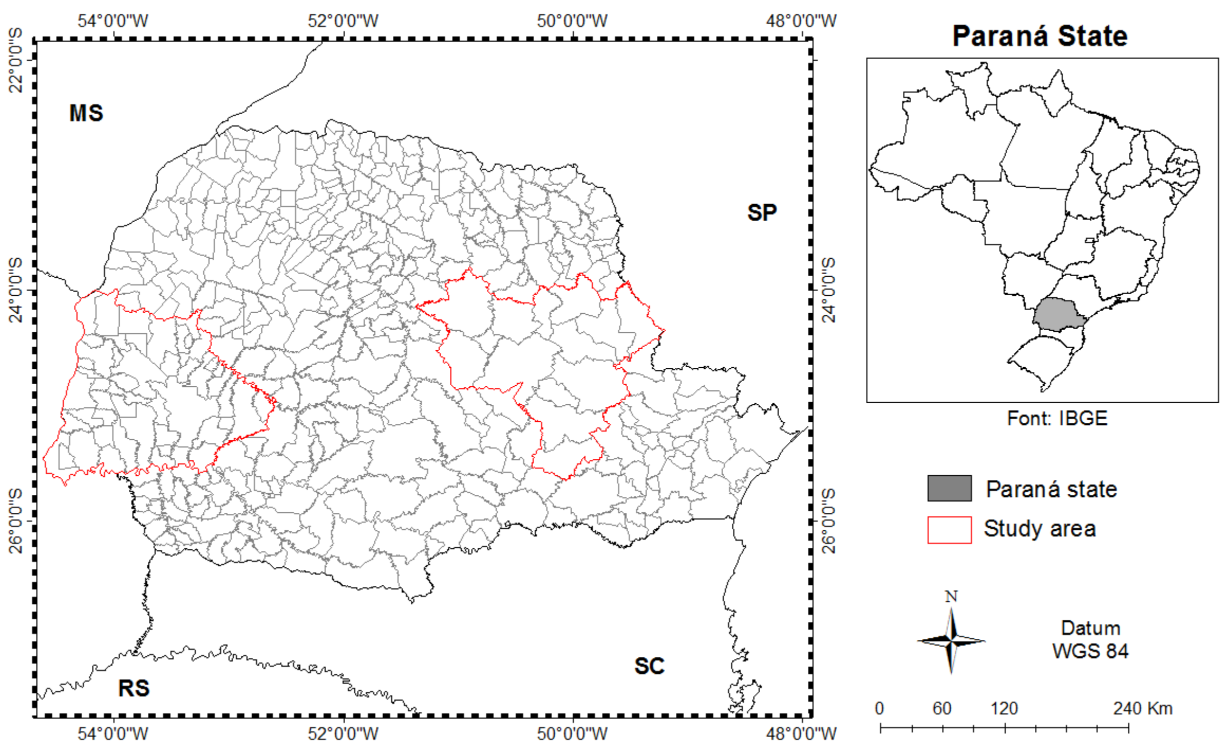

Figure 3.1. Study area location

I analyzed eleven years of the soybean cropping seasons during 2000/2001 to 2010/2011. Generally, the soybean growing season starts on October/November and ends on March/April. Since 2010, the Department of Agriculture and Supply of Paraná (SEAB) has been registering small percentage of planted area in September. Table 3.1 shows the soybean crop calendar to Paraná state since 2004/2005 crop season.

Table 3.1. Monthly percentage of sowing and harvesting for soybean crop season in Paraná State.*

Crop Year	***Condition***	***Sep***	***Oct***	***Nov***	***Dec***	***Jan***	***Feb***	***Mar***	***Apr***	***May***
2004/2005	Sowing	-	20%	93%	100%	-	-	-	-	-
	Harvesting	-	-	-	-	-	16%	60%	87%	100%
2005/2006	Sowing	-	37%	95%	100%	-	-	-	-	-
	Harvesting	-				1%	9%	64%	95%	100%
2006/2007	Sowing	-	23%	89%	100%	-	-	-	-	-
	Harvesting	-	-	-	-	-	13%	67%	96%	100%
2007/2008	Sowing	-	23%	86%	100%	-	-	-	-	-
	Harvesting	-	-	-	-	-	11%	56%	90%	100%
2008/2009	Sowing	-	24%	82%	98%	100%		-	-	-
	Harvesting	-	-	-	-	-	1%	51%	92%	100%
2009/2010	Sowing	-	25%	92%	100%					
	Harvesting	-	-	-	-	1%	17%	75%	98%	100%
2010/2011	Sowing	1%	47%	95%	100%	-	-	-	-	-
	Harvesting		-	-	-	-	5%	71%	98%	100%
2011/2012	Sowing	4%	51%	94%	99%	100%	-	-	-	-
	Harvesting		-	-	-	3%	22%	-	97%	100%
2012/2013	Sowing	3%	46%	97%	100%	-	-	-	-	-
	Harvesting		-	-	-	1%	39%	74%	98%	100%
2013/2014	Sowing	2%	47%	95%	-	-	-	-	-	-
current season	Harvesting		-	-	-	-	-	-	-	-

* Data from 2000/2001 until 2003/2004 was not provided. Source: SEAB/Deral (2013).

3.2. General Flowchart

Figure 3.2 shows the general flowchart of this thesis. The results are presented in paper form, therefore, the specifics methodologies are presented in each paper. In the first paper I generated the correlation maps between EVI images and historical yield. These maps were generated using two variables monthly and phenological stages.

In the second paper I tested the capability of correlation maps for estimating yield. I evaluated the yield estimates using these maps and then comparing the results with yield estimates from crop specific map.

In the last paper I applied the temporal stability technique on correlation maps to select stable pixels to yield estimate.

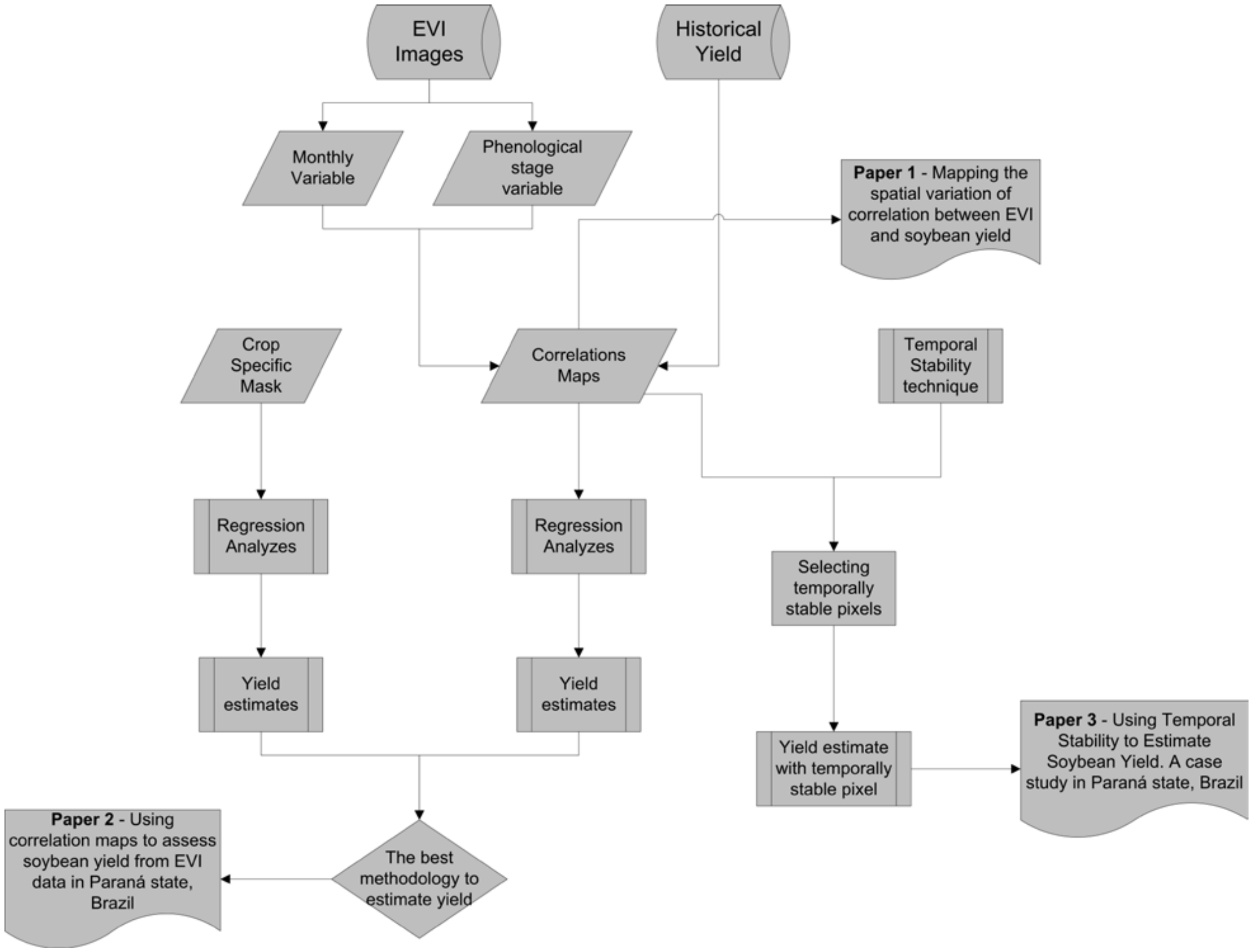

Figure 3.2. Flowchart of main steps of the thesis.

3.3. Data

The Satellite images from MODIS/Terra data were obtained from Brazilian State Base, a dataset held by Brazilian Agricultural Research Corporation, Agricultural Informatics (Embrapa Agropecuária Informática), which provide images derived from MOD13Q1 product (Esquerdo et al., 2011). This product is elaborated by LPDAAC/ EOS (Land Processes Distributed Active Archive Center/NASAs Earth Observing System), MOD13Q1 data are provided every 16 days at 250-meter spatial resolution as a gridded level-3 product in the Sinusoidal projection (NASA, 2013b).

To minimize cloud noise we created Maximum Value Composites (MVC) using an Interactive Data Language (IDL) routine. The MVC method selects the highest quality pixel from each composite time-frame (Holben, 1986).

From these MVCs we created two kind of variable: Monthly and phenological stages. The monthly variable corresponds to months of growing season (October to April). The accumulated variable corresponds to phenological periods of the crop, i.e. these images were accumulated according to each stage of the crop cycle, which are:

- Emergence to Maturity (EM);
- Emergence to Flowering (EF);
- Flowering to Grain filling (FG);
- Flowering to Maturity (FM).

Planted area, production and yield data were provided by SEAB at county level and the soybean crop calendar are available at state level.

3.4. Statistical Analysis

Statistical analyses were applied to the yield values of soybean and to EVI values per pixel for all county, all tests were applied in the R software and considering levels of significance of 5%. The normality of the regression residuals was obtained using the Shapiro-Wilk test (Shapiro and Wilk, 1965). To verify the absence of autocorrelation in the dataset we used the Durbin-Watson method. And the homoscedasticity test proposed by Breusch-Pagan was applied to test randomness of the data with zero mean and constant variance (Breusch and Pagan, 1979). After applying these tests were retained only those pixels that satisfied all the necessary conditions.

Simple linear regression models were generated for each phenological stage/month during the eleven years for each county, where the historical yield is the predicted variable and EVI data is the predictor variable.

To evaluate the model, we calculate Root Mean Squared Error (RMSE, equation 3.1) that gives an error magnitude with the impact of the outliers being amplified through the squaring operation. Mean Absolute Error (MAE, equation 3.2) quantifies the average magnitude of error and is reflective of model accuracy. The Index of Agreement (d, equation 3.3) developed by Willmott, (1981) measures distances of cloud dispersion of correlated data about the line 1:1.

Finally the Mann Withney test was applied in order to verify whether there is any significant difference between mean values of estimated data and mean values of observed data (Mann and Whitney, 1947).

$$RMSE = \sqrt{\left(\frac{1}{n} \times \sum_{i=1}^{n} (Yobs - Yest)^2\right)} \tag{3.1}$$

$$MAE = \frac{1}{n} \times \sum_{i=1}^{n} |Yobs - Yest| \tag{3.2}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (Yest - Yobs)^2}{\sum_{i=1}^{n} (|Yest - \overline{Yobs}|) + |Yobs - \overline{Yobs}|)^2} \tag{3.3}$$

4. Mapping the spatial variation of correlation between EVI and soybean yield

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Abstract: Timely and accurate yield estimate using remote sensing represent an important advance towards objective crop forecasting. Vegetation index values integrated over a period have been used to generate agronomic variables such as crop yield. The main goal of this study was to compare two methodologies to create a correlation map using MODIS/TERRA EVI and historical yield during the soybean crop cycle in Paraná state, Brazil, from 2000/2001 to 2010/2011. The first method consisted of using monthly Maximum Value Composites during the soybean crop season, and the second was made using growing season accumulated EVI, focusing on the crop phenological stage. It was possible to follow the variation of monthly correlation of the remote sensing variables and yield using the first method. December, January and February showed the strongest correlation, with 0.94, 0.97 and 0.97 respectively. The second method presented higher correlation than the first because it used accumulated EVI, with the period between Flowering to Maturity and Flowering to Grain Filling having the strongest correlation, with 0.97 and 0.96, while the period between Emergence to Flowering had correlation below 0.5. With these methodologies we found periods with potential for crop yield estimate.
Keywords: Crop stages, crop condition, EVI, correlation map.

4.1. Introduction

Timely and accurate yield estimation is an important goal in the search for objective crop forecasting in Brazil. This is essential in helping the government to plan storage and/or acquisition of food, serving as a support to food security, decision-making and management of natural resources. However, an operational crop yield estimating system is not currently available in the country.

The Brazilian Food Supply Agency (Conab) is responsible for monitoring and quantification of Brazilian agricultural production through surveys of agricultural crops. These surveys are extremely important for formulation and implantation of agricultural policy. These data have been used by agribusiness operators to support decision-making and influence the behavior of internal and external prices of products (Figueiredo, 2005).

One potential approach to developing an operational system is through the use of remote sensing techniques. Remote sensing and Geographic Information Systems (GIS) have been tested within the *Geosafras project*, carried out by Conab, with the goal of improving the crop monitoring and crop area/yield estimates for Brazil (Conab, 2010).

Among the available remote sensing data, the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, mounted aboard the Terra and Aqua satellites, provides land surface data such as vegetation indices like the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). The EVI was developed to optimize the spectral response of vegetation, improving the sensitivity in regions with higher biomass densities, propitiating to monitor the vegetation by the reduction of the effects of the canopy substratum (Huete et al., 1999). Besides, products from MODIS are reliable and are updated in near real time.

Vegetation index values integrated over a period have been used to generate agronomic parameters such as crop yield, because it includes the historic evolution of the biomass (Rasmussen, 1992; Maselli et al. 1993). According to Rudorff and Batista (1990), the integrated vegetation index represents well the intensity and the duration of the photosynthetic activity of the crop throughout the growing cycle.

Tucker et al. (1980) first identified a relationship between the NDVI and crop yield using experimental fields and ground-based spectral radiometer measurements. Final grain yields were found to be highly correlated with accumulated NDVI.

Rudorff and Batista (1990) integrated the vegetation index throughout the wheat growing season and correlated to final grain yield. Results indicated that reflected energy at certain stages of the crop development and at certain wavelength bands is highly related to the final grain yield.

Maselli et al. (1992) found strong correlations between integrated NDVI and final crop yield in the Sahel region of Niger using 3 years of AVHRR imagery. Junges & Fontana (2011) estimated wheat yield in Rio Grande do Sul state, Brazil, using NDVI integrated from June to October (1991-2006) and the results were satisfactory with estimation errors below 10%.

Based on that, it is important to detect growing season period where the crop is more correlated with yield aiming to find the exact moment to generate yield estimates. A correlation map is very useful to produce pixels that represent correct values to predict yield because it uses only pixels that represent the crop instead of pixels that represent average in surface or major non-crop surface within the field perimeter (Kastens et al., 2005; Hollinger, 2011). The main goals of this study was to map the variation of correlation between EVI-MODIS and soybean yield and find the most suitable period for yield forecasting.

4.2. Material and Methods

This study was carried out in the western (region 1) and eastern (region 2) regions of Paraná state, Brazil, Figure 4.1. These regions are responsible for a large amount of soybean production in the state. Comparing with others states, during the 1990-2012 period, Paraná state ranked second in Brazil in soybean production (15,912.4 thousand tons in 2012), and relative to the southern region of Brazil, it is ranked first (Conab, 2013a).

According to the Soybean Center of the Brazilian Agricultural Research Corporation (Embrapa Soja, 2007), in Paraná state the soybean crop season starts between October 15th and December 15th, but some counties in the midwest exhibit sowing prior to October 15th (Albrecht et al. 2008).

These regions were chosen because of differences between sowing dates. Araújo (2010) conducted a study on the onset of the soybean crop cycle in Paraná state using dekadal SPOT *Vegetation* imagery and ECMWF (Europe Centre Medium – Range Weather Forecasts) ten-day rainfall data between 2005/06 to 2007/08 cropping seasons. In this study the author found at least three onsets of the soybean crop cycle in the whole state, with results indicating that the western region has the beginning of soybean crop cycle varying between October 1st and November 1st and the eastern region in late November.

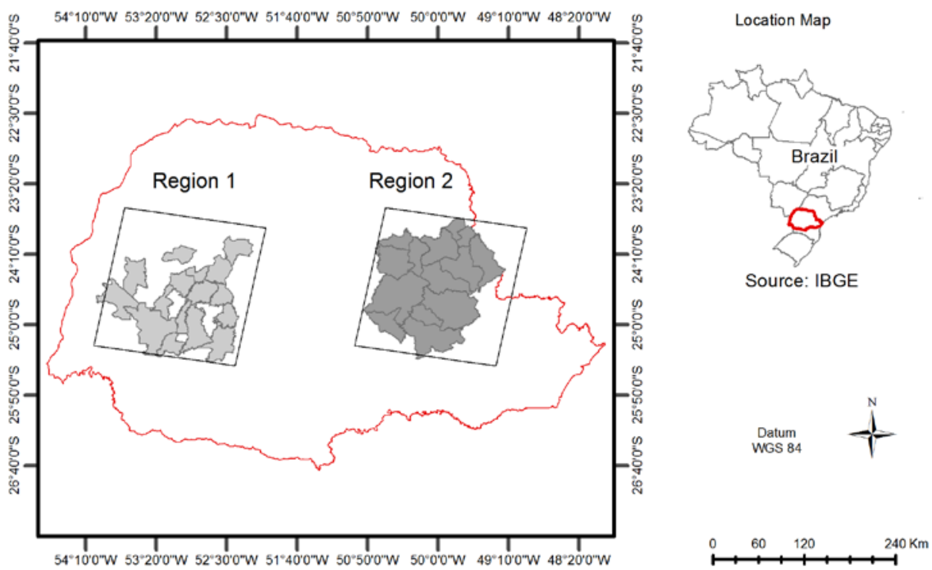

Figure 4.1 Study area illustrating the location of counties in regions 1 and 2.

Agricultural statistics for the soybean growing season were taken from the Department of Agriculture and Supply of Paraná (SEAB) database. These data are available at county level in all Paraná state. The data were used to create a time series of planting area, total production and yield over the 2000/2001 to 2010/2011 growing seasons.

This study is based on MODIS/Terra EVI Maximum Value Composite (MVC) because it was conducted during rainy season and consequently large amount of cloud cover. EVI images were acquired from the Agricultural Informatics Center of Embrapa. The MOD13Q1 data are provided every 16 days at 250-meter spatial resolution as a gridded level-3 product in the Sinusoidal projection (NASA, 2013).

4.2.1. Correlation Maps

There are many methodologies to establish relationship between vegetation indices and final yield. The main methods are either based on month vegetation indices values (Maselli and Rembold, 2001; Hollinger, 2011) or methods with accumulation of determined periods of crop stage (Tucker et al., 1980; Rasmussen 1992; Genovese et al., 2001; Kastens et al., 2005; Ren, et al., 2008; Junges & Fontana 2011). In this study both methods were used to test the ability to detect the variation of correlation.

4.2.1.1. Correlation by Month

Because 16 days EVI composites were still affected by cloud noise, all the images were composed over monthly periods, generating seven images (October to April) for each cropping season during eleven years of study.

It is also necessary to emphasize that different crop specific masks were generated annually, one correlation map was generated to each month for the eleven years, therefore, eleven points were considered in the analysis relating to the years of the study, as carried out by Maselli & Rembold, (2001) and Kastens et al (2005). According to Kastens et al. (2005) this approach can eliminate the problem of crop rotation, which suggests that year-specific masks are needed rather than a single crop specific mask applied to all years.

Figure 4.2 shows the average EVI profile for soybean cropping season during the eleven years at region 1 (a) and region 2 (b). While in the region 1 the average profile starts in October, in region 2 it starts in November and ends in March and April, respectively. Vegetative peak for region 1 occurs between December and January as for region 2 it happens in January and February.

All correlations with the final historical yield were computed from each of the historical pixel-level EVI values. Figure 4.4a shows a flowchart outlining the main steps of this methodology.

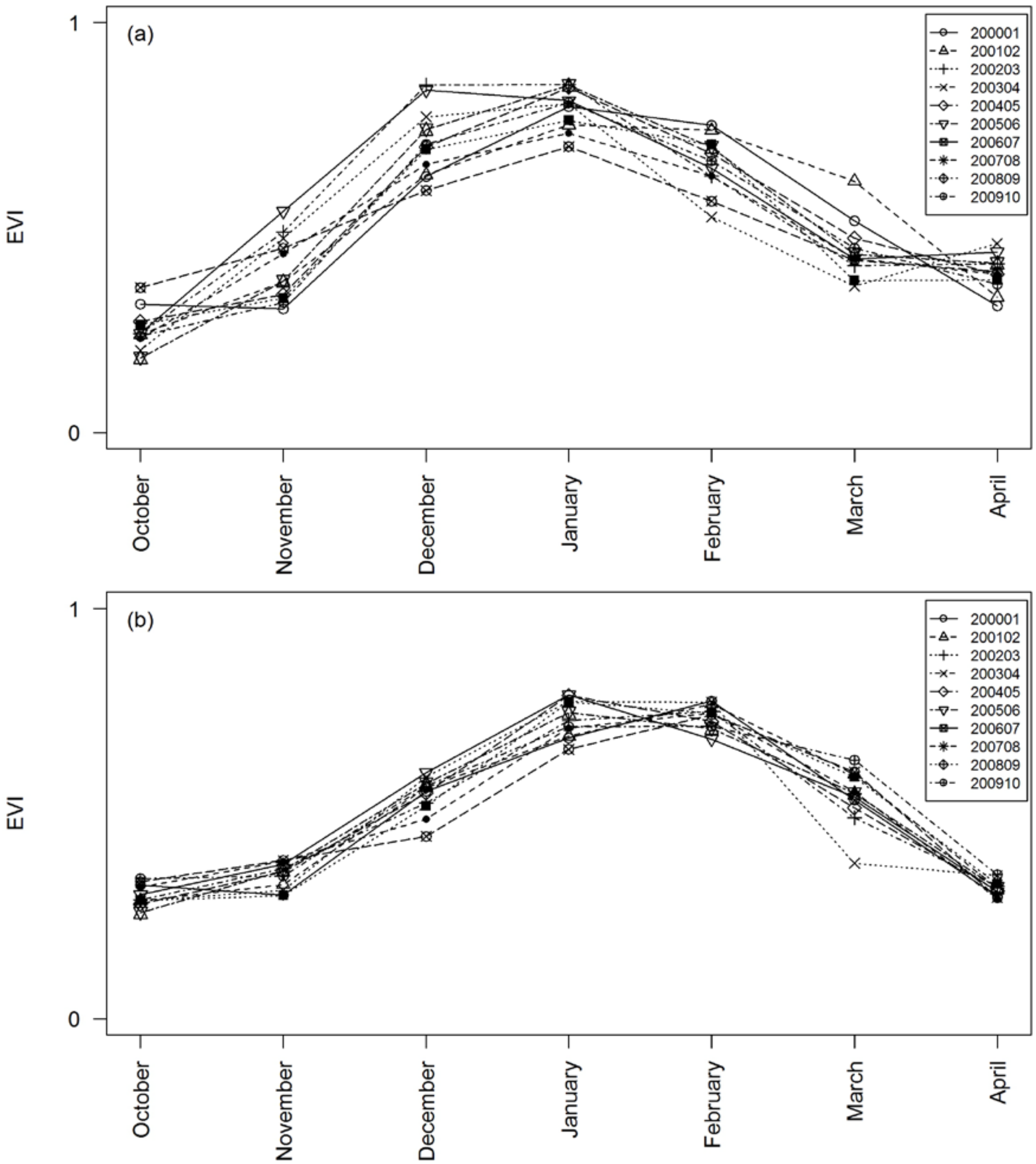

Figure 4.2 Average EVI profile for (a) region 1 and (b) 2.

4.2.1.2. Correlation Map by Cropping Season Stage

The second methodology was based in accumulated EVI based on the soybean phonological stages (Figure 4.3). According to Ren et al. (2008), crop yield is strongly affected by the growing conditions during each crop stage, thereby, based on crop development stage of soybean. The sum of MVCs values was calculated:

- Emergence to Maturity (EM);
- Emergence to Flowering (EF);

- Flowering to Maturity (FM);
- Flowering to Grain filling (FG).

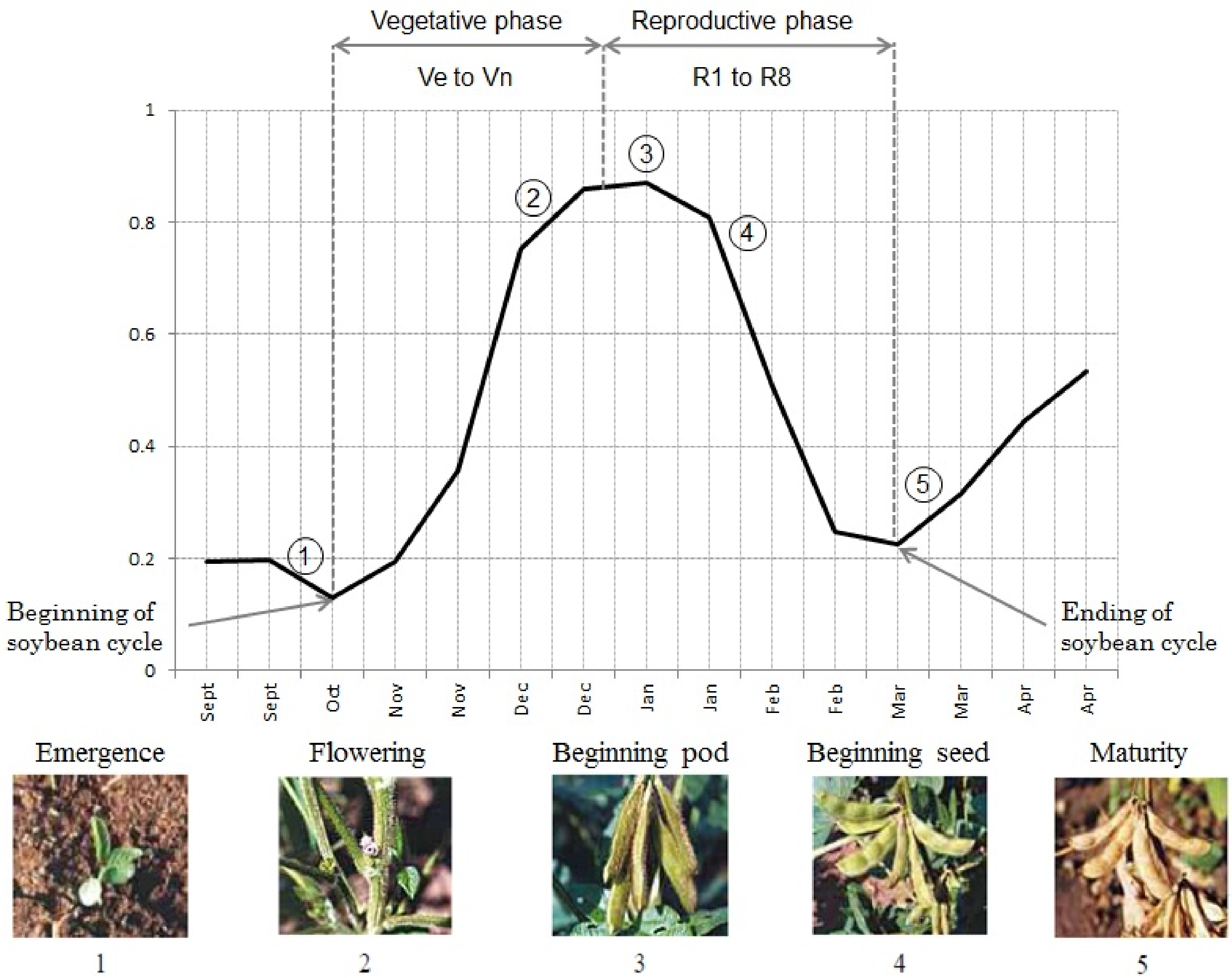

Figure 4.3 The soybean phenological stages used in this study.

After separating the MVCs according to crop stage cited above the correlation was computed in the same way as in the first methodology. Figure 4.4b shows a flowchart with the main steps.

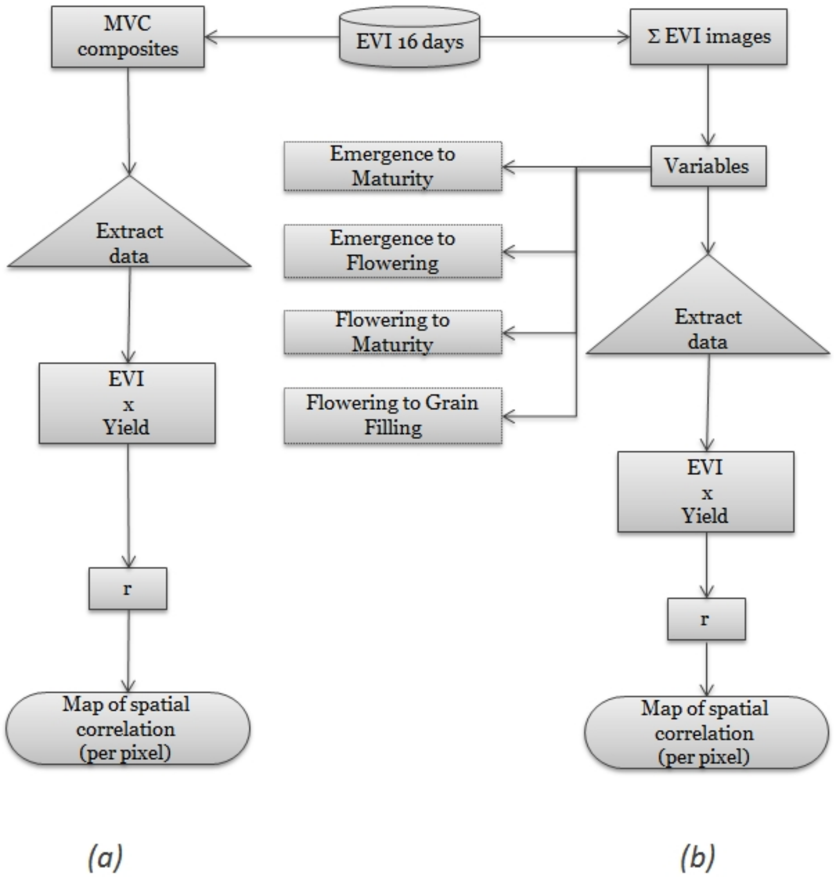

Figure 4.4 Flow chart illustrating the steps to compute the correlation maps (a) by month; (b) by crop phenological stage.

4.3. Results and Discussions

All steps were applied to all counties in the study area but Toledo, from region 1, and Ponta Grossa, from region 2, which were used to show the results.

4.3.1. Correlation Maps by Month

Figure 4.5 shows the histogram of each monthly correlation map for Toledo county. October (a) and November (b) had many pixels with negative correlation, this period correspond to emergence periods for soybean crop, and during this period the plant is still small in size, so the pixel has a spectral mixture of plant and soil. In December (c) and January (d) this scenario changed, and most of the pixels were concentrated between 0.40 - 0.60 of correlation, it happened because the cropping season reached maximum EVI values. From February (e) most of the correlation values were below to 0.50. March (f) and April (g), period that corresponds to senescence and harvest, the correlation ranged to 0 - 0.30 approximately. As the crop season progresses, the correlation coefficient tends to become stronger, thus the correlation coefficient shows a similar dynamic as the vegetation index.

For Ponta Grossa county, in region 2, the correlation was low in most of the growing season, December and January had pixels with high correlation and February had few pixels with correlation above 0.60. Figure 4.6 shows the histogram of each monthly correlation map for this county.

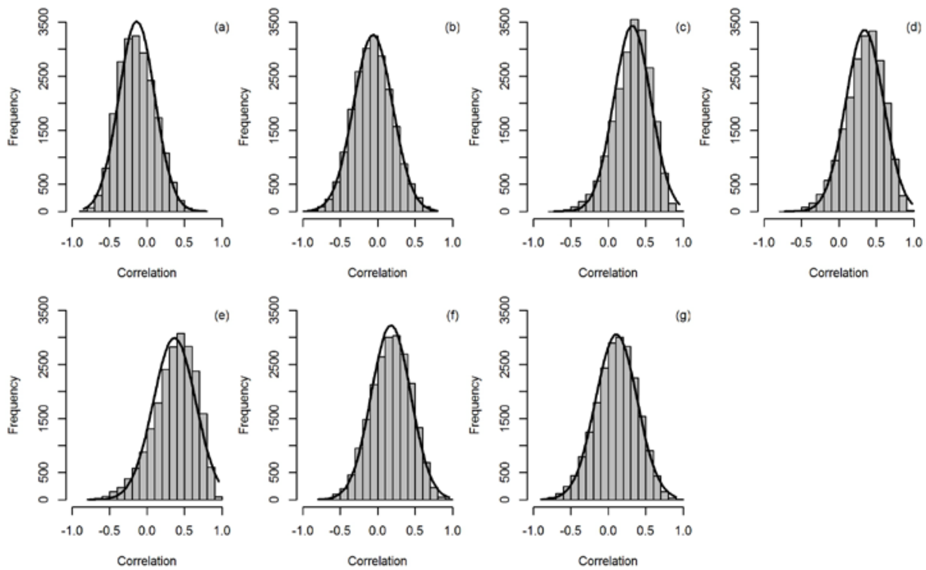

Figure 4.5 Histogram of monthly correlation maps for Toledo: (a) October; (b) November; (c) December; (d) January; (e) February; (f) March; (g) April.

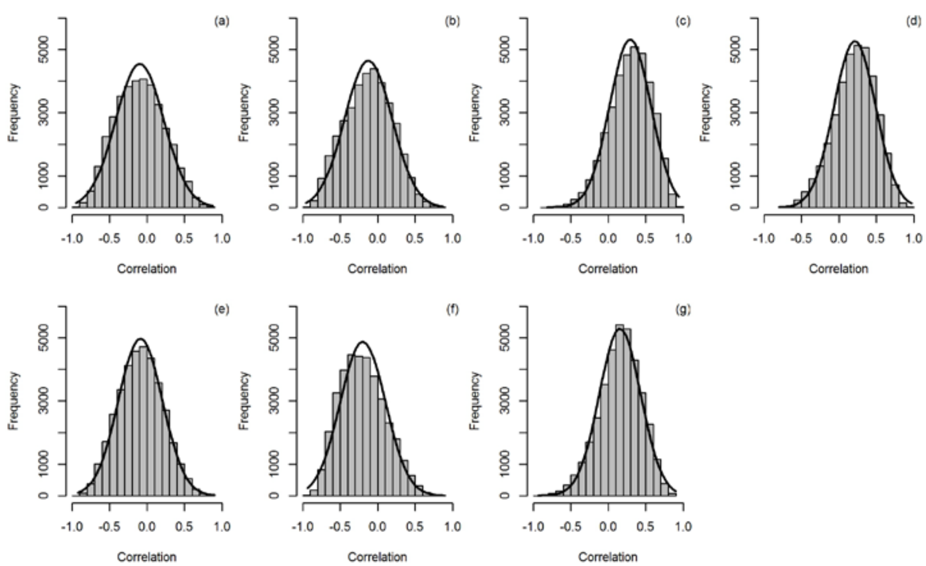

Figure 4.6 Histogram of monthly correlation maps for Ponta Grossa: (a) October; (b) November; (c) December; (d) January; (e) February; (f) March; (g) April.

This behavior could happen because Ponta Grossa has no intensification areas such as Toledo. The same behavior occurs for all counties at region 2. This low correlation can be explained by the spectral mixture of other targets in the pixel. Figure 4.7 shows the correlation maps for both counties.

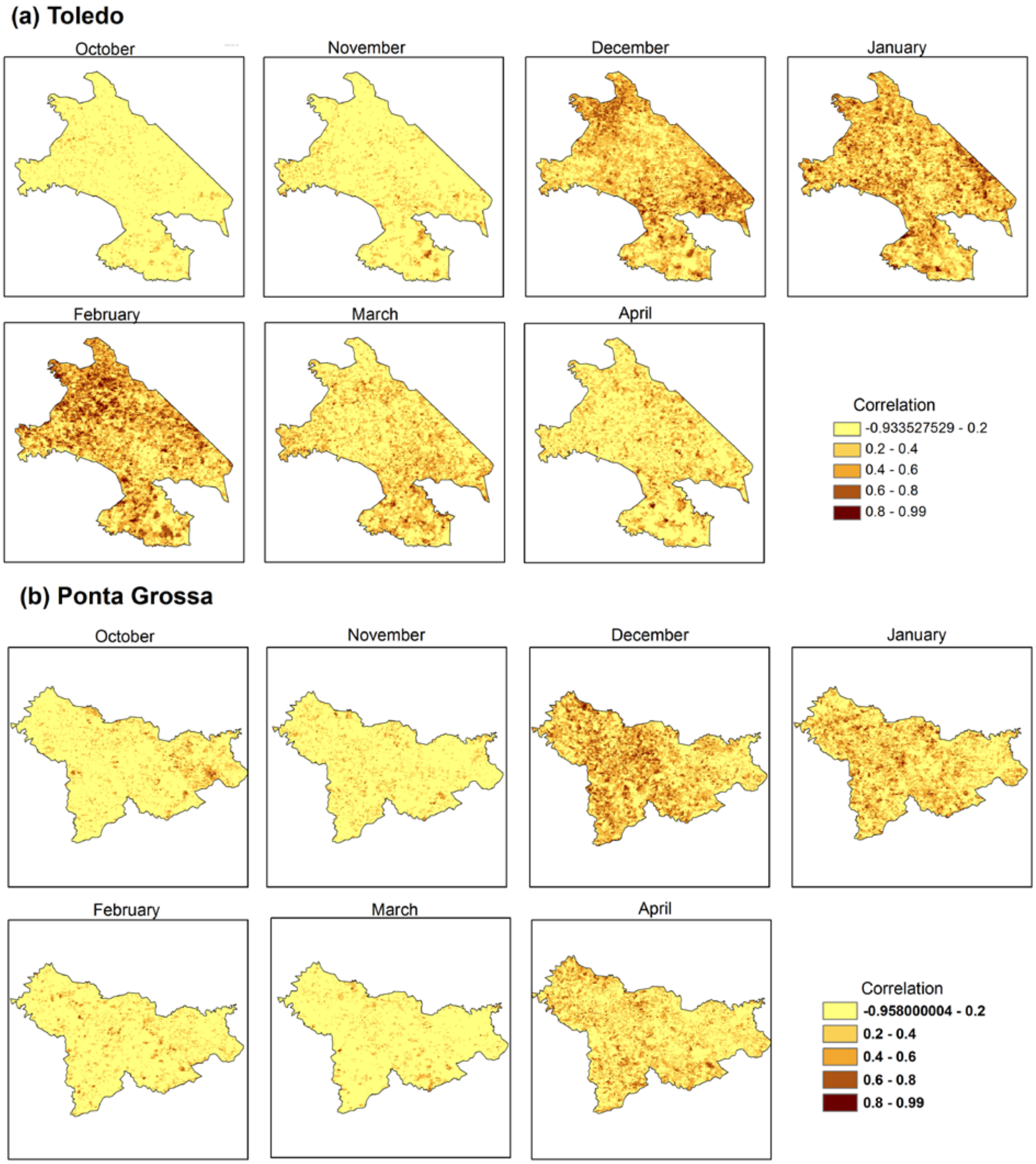

Figure 4.7 Monthly correlation maps: (a) Toledo; (b) Ponta Grossa.

4.3.2. Correlation Map by Crop Phenological Stage

The best results between EVI and historical yield were found using the accumulated time series of the EVI.

For Toledo most of the pixels in the EM stage (Figure 4.8a) consisted of a correlation lower than 0.60, since this variable comprised the entire growing season. The EF (Figure 4.8b) variable showed many areas with a correlation below 0 because this variable included some months prior to the growing season being fully developed. The FM (Figure 4.8c) period showed the highest correlations for most of the pixels, with values within 0.60 - 0.97, since this variable coincides with those months with the highest EVI values. Although the FG (Figure 4.8d) variable was composed of months with highest EVI values, this variable showed correlation lower than FM variable due to number of months used to compose it.

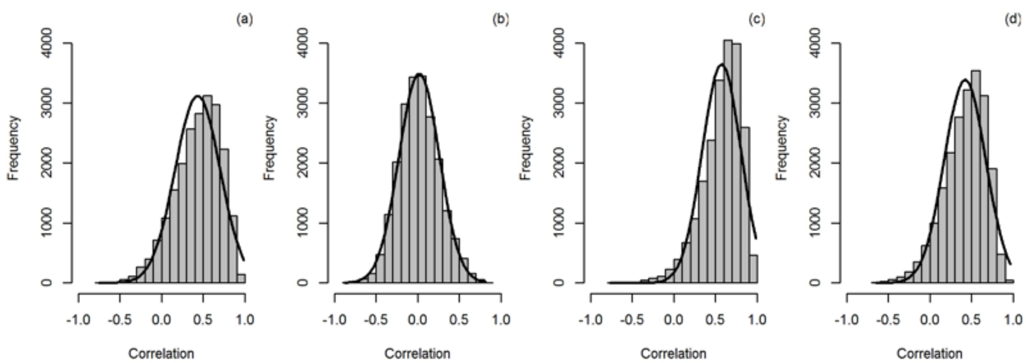

Figure 4.8 Histogram of correlation maps using phenological stages for Toledo: (a) Emergence to Maturity (EM); (b) Emergence to Flowering (EF); (c) Flowering to Maturity (FM); (d) Flowering to Grain filling (FG).

In Ponta Grossa (Figure 4.9) the behavior of the variation of the correlation follows the same pattern as in Toledo, but with much lower values. The only variable with high correlation was FM (Figure 4.9c) and, even when compared with Toledo, this correlation remains low. Figure 4.8 a, b and d show most of the pixels concentrated below 0.2 of correlation. Figure 4.10 shows the spatial variation of the correlation for each phenological stage.

In general, both methodologies had pixels that were well correlated with yield in the same period between December, January and February, which correspond with flowering to grain filling and maturity (for the last method), these periods corroborate with Hollinger (2011) that claims that to obtain better correlation values with yield the canopy should be closed enough to decrease the soil influence.

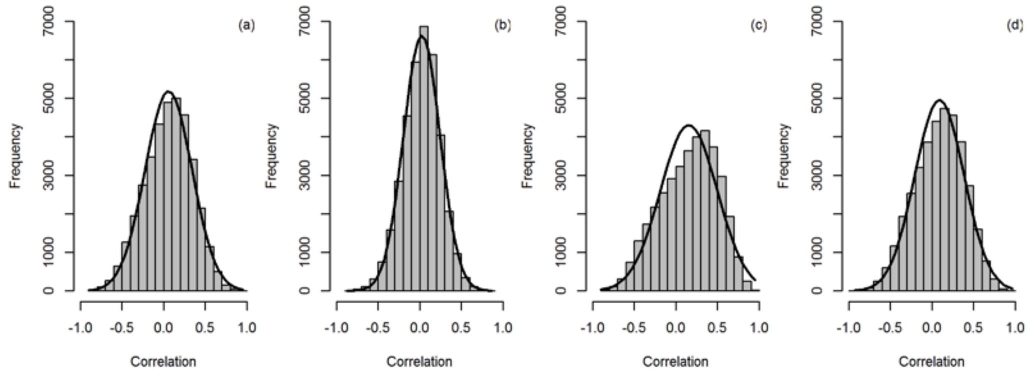

Figure 4.9 Histogram of correlation maps using phenological stages for Ponta Grossa: (a) Emergence to Maturity (EM); (b) Emergence to Flowering (EF); (c) Flowering to Maturity (FM); (d) Flowering to Grain filling (FG).

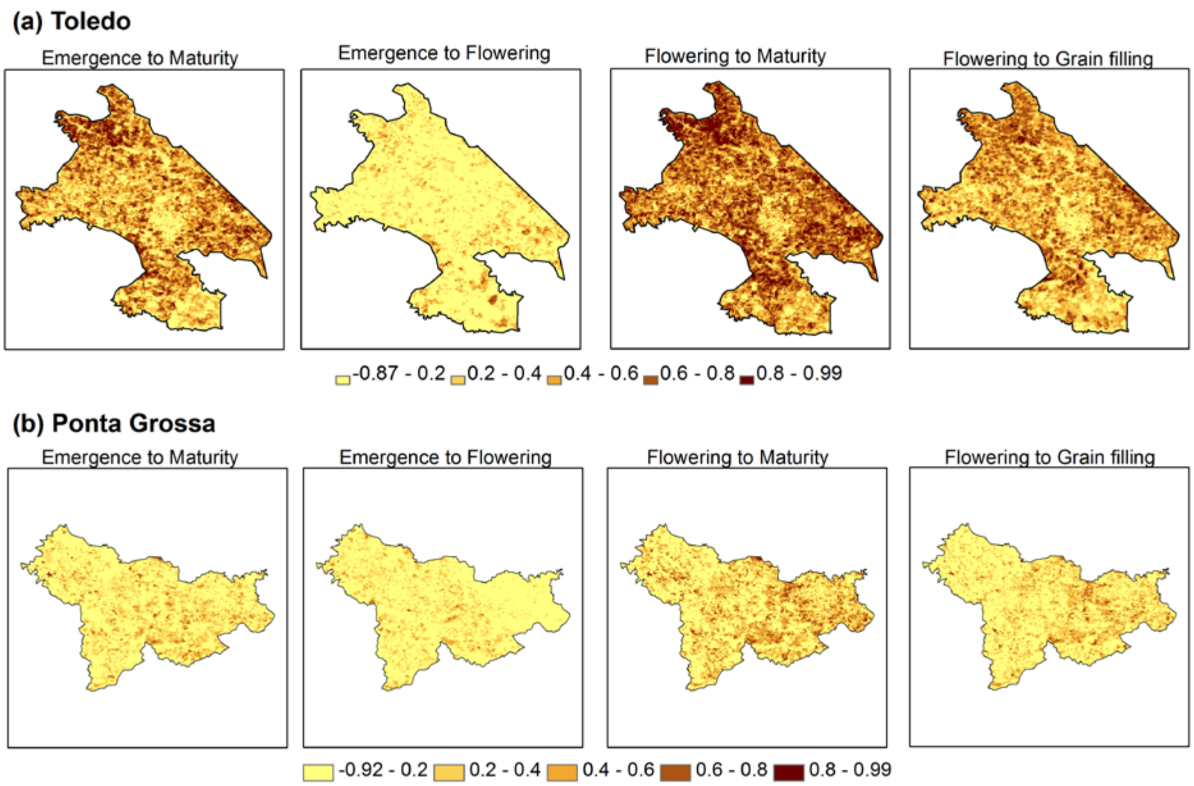

Figure 4.10 Correlation maps using phenological stage method: (a) Toledo; (b) Ponta Grossa.

These results also agree with other studies that have reported high correlation between vegetation index and yield during the same period. According to Mkhabela et al. (2011) this period are the most critical for crops and any water stress during this crop growth stage may result in reduction of grain yield.

The low correlation from the beginning of cycle to the flowering is directly related to low EVI values. According to Kastens et al. (2005), a correlation map is very well applied when the crop is still in early stage and has low vegetation response. Since this methodology is not constrained to include pixels dominated by cropland, they are not necessarily hindered by the weak and insensitive vegetation index responses exhibited by crops early in their respective growing seasons.

A correlation map cannot replace crop specific mask when quantifying planted area is needed, but it could be easily replaced when it needs to improve crop yield forecasts. According to Maselli & Rembold (2001) other vegetation types, having different seasonal developments, may introduce noise in the relationships Vegetation Indices/yield.

4.4. Conclusions

Finding cropping season periods which present best correlation with historical yield is an important step for estimating in advance. With these methodologies I detected possible periods or stages to estimate crop yield. These periods present different characteristics expressed by vegetation index and consequently have high or low correlation with final yield.

These results show that crop forecasting activity can be improved with the knowledge of the best potential periods for crop yield estimate. Both methodologies have flexibility to be applied to any region/crop where time series imagery and corresponding historical crop yield information are available.

In agreement with Rudorff & Batista (1990), Rasmussen (1992), Maselli & Rembold (2001) and Kastens et al. (2005), accumulated EVI has a strong relationship with historical yield and can be efficient for forecasting yield.

Future work would consist of evaluating both methodologies to build an yield estimation model and verify if periods with high correlation are the best to forecast yield.

Acknowledgement

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5. Using correlation maps to assess soybean yield from EVI data in Paraná state, Brazil

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Abstract Vegetation Indices are widely used to follow crop development and generally are used as input data in models to forecast yield. Several studies have shown that it is possible make accurate predictions a few weeks or even months before harvest. This study compares two methodologies to assess the yield forecast at county level in Paraná state during eleven years of study. The first method was based on correlation maps derived from relationship of EVI-MODIS data and yield, and the second was based on crop specific masks. A linear regression model was developed for both methodologies to forecasting soybean crop. The models were evaluated using R^2, RMSE, MAE, and the Willmott agreement index. The RMSE values ranged from 0.032 ton/ha to 0.17 ton/ha to correlation maps and for crop specific masks it ranged from 0.17 ton/ha to 0.29 ton/ha. The model was able to explain 73% to 98% of the variation in estimated yield to the first method, while the second was able to explain only -9% to 62%. Results showed that the correlation maps can be used to predict crop yield more effectively than crop specific masks.
Keywords: Soybean, vegetation indices, crop yield forecasting, EVI-MODIS.

5.1. Introduction

Monitoring agricultural crops during the growing season is increasingly important for obtaining yield predictions before harvest time (González-Sanpedro et al., 2008). This process aims to represent the role of the environmental factors on the crop under field conditions by simulating the development from sowing to harvest (Johann, 2012). These simulations describe crop growth, development and yield formation processes driven by climate, management and soil conditions (Yuping et al., 2008). However, at regional scale these models are of limited practical use because of spatial differences in soil characteristics and factors that determine crop growth such as nutrition levels, plant disease, herbicide and insecticide use, crop type, and crop variety, all of which would make informational and analytical costs excessive (Kastens et al., 2005; Launay & Guerif, 2005; Yuping et al., 2008). These types of models have been applied in Brazil to estimate yield previously (Junges & Fontana 2011; Johann 2012; Moraes 2012). In general, these models showed satisfactory results, but using experimental data at the regional level makes it difficult to transfer these results to other locations and or crops.

There is still a need to combine new methods to extract parameters from crop and growth conditions in order to improve the accuracy of such models. Due to its advantage of providing timely information on crop conditions during the growing season across large areas, satellite remote sensing can be used in conjunction with crop models for predicting crop yields (Yuping et al., 2008; Becker-Reshef et al., 2010). Vegetation indices (VIs) are widely used in crop growth monitoring and yield estimation based on remote sensing technology. Most of the vegetation indices are information-condensed which can reflect terrestrial vegetation cover and growth condition effectively and economically (Ren et al., 2008). The Enhanced Vegetation Index (EVI) has been tested in various studies (Gurung et al., 2009; Antunes et al., 2011; Sjöström et al., 2011; Gusso et al., 2012; Johann, 2012), because it has improving the sensitivity in regions with higher biomass densities, besides propitiating to monitor the vegetation by the reduction of the effects of the canopy substratum (Huete et al., 1999; Huete et al., 2002).

The use of spectral models has also been tested in several studies to estimate yield with generally good results. Labus et al. (2002) examined seasonal growth profiles developed from AVHRR-NDVI for estimating wheat yield at regional and farm scales in Montana for the years 1989–1997. Both regions and farms showed strong relationships between wheat yields and integrated NDVI over the entire growing season NDVI parameters. The use of AVHRR-NDVI growth profiles at the regional level provided the strongest yield estimates.

Ren et al. (2008) established relationship with winter wheat production and spatial accumulation of NDVI at the county level in China using a linear regression model to estimate winter wheat yield. The spectral model results were compared with an agro-climate model, the first showed that RMSE was 0,214 ton/ha and the second was 0,233 ton/ha. The authors claimed that a good predicted yield data of winter wheat could be obtained about 40 days ahead of harvest time.

Becker-Reshef et al. (2010) built a regression model to estimate winter wheat yield in Kansas (USA) using spectral data and applied the same model to Ukraine. The forecasts of production in Kansas closely matched the USDA/NASS reported numbers with a 7% error. The same regression model forecasted winter wheat production in Ukraine within 10% of the official reported production numbers. The authors state that besides generating forecast six weeks prior to harvest, this model benefits from the fact that it is simple, requires limited data, and can provide an indication of winter wheat production shortfalls and surplus prior to harvest in regions where minimal ground data is available.

Mkhabela et al. (2011) evaluated the use of NDVI-MODIS to forecast yield for four crops on the Canadian Prairies and also to identify the best time for making a reliable crop yield forecast. The RMSE values ranged from 8 to 25% for barley, 10 to 58% for canola, 10 to 38% for field peas and 6 to 34% for spring wheat. According to the authors for all the crops, the best time for making grain yield predictions was found to be on grain filling period in the sub-humid zone and semi-arid and arid zones. This implies that accurate crop grain yield forecasts using the developed regression models can be made one to two months prior to harvest.

Crop masks are required for some applications of yield forecasting and the values of the vegetation index are extracted within the crop mask, these values are then input into the yield model. However, decisive improvement in crop yield forecasting capability is linked to the selective consideration of NDVI values from cropped areas, because other vegetation types, having different seasonal developments, may introduce noise in the relationships between the VI and the associated crop yield (Maselli and Rembold, 2001a).

With the intention of eliminate crop specific masks, Kastens et al. (2005) created a yield-correlation masking between NDVI-AVHRR and yield during eleven years to forecast yield. According to the authors, all vegetation in a region integrates the season's cumulative growing conditions in some fashion and may be more indicative of a crop's potential rather than the crop itself. Thus, all pixels are considered for use in crop yield prediction.

Based on that, the main goal of this study was to evaluate and compare correlation maps between EVI and historical yield and crop specific masks from soybean crop season to investigate the potential of these methods in Paraná state during eleven years and to find the most suitable period for yield forecasting.

5.2. Materials and Methods

The study was conducted in four counties in Parana state, Cascavel and Toledo, located in the midwest, Castro and Ponta Grossa, located in the eastern region of the state (Figure 5.1). Compared with others states in Brazil, for the period of 1990-2012 Paraná state ranked second in Brazil in soybean production (15,850.6 million tons in 2013), and relative to the southern region of Brazil, it was ranked first (Conab, 2013e).

According to Köppen (1931) the climate of Paraná state is type CFA and CFB, Sub-tropical humid. It presents average yearly temperatures of 19°C, with the hottest month averaging above 22°C, and the coldest month below 18°C. The predominant soil types of this region are Latosoils, Clay soils, Neo-soils and Nitosoils (ITCG, 2008).

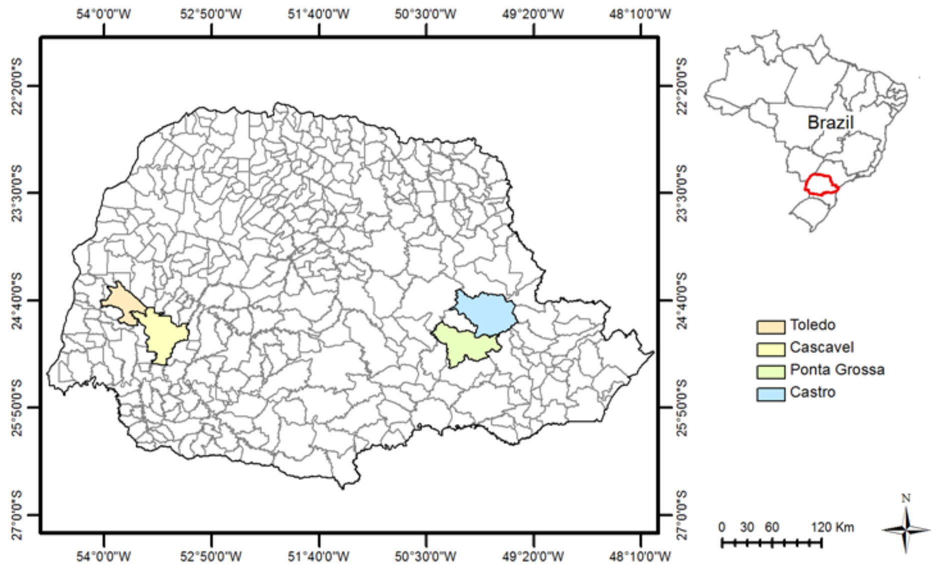

Figure 5.1 Paraná study area illustrating the location of counties in southern Brazil.

Agricultural statistics for the soybean growing season were collected from the Department of Agriculture and Supply of Paraná (SEAB) database, available at the county level for all of Paraná state. These data were used to create a time series of plant area and total production over the 2000/2001 to 2010/2011 growing seasons.

This study utilized the MODIS/Terra EVI 16-day Maximum Value Composite (MVC) because it was conducted during the rainy season and consequently a large number of clouds are often present and obscure the surface features. These images were downloaded from the Brazilian Agricultural Research Corporation, Agricultural Informatics (*Embrapa Informática Agropecuária*) for the period of 2000-2011.

To generate the correlation maps, the images were separated by crop season starting with sowing in October through harvest in April. Since the 16-day MVCs were still affected by clouds, all of these images were composed over the monthly period, thus obtaining seven images for each of the eleven study years.

Then correlation between EVI and historical yield at the pixel scale was calculated for each month generating a correlation value in each pixel. This resulted in maps for each month that represents the spatial variation of correlation between the vegetation index and yield in the eleven years. These correlation maps replaced the usual crop identification methods.

Masks were built based on different ranges of the correlation from these maps. Ten masks were generated corresponding to different ranges of the correlation; 0-10%, 11-20% until 100% of the correlation was incorporated.

For comparison purposes, we used a crop specific mask to estimate yield and compare with the methodology proposed here. For these crop specific masks, multi-temporal compositions were created in RGB color composed of every 16-day period (MODIS/EVI data), this process is described by Araújo et al. (2011). For each year of study this process was applied to generate a soybean crop mask. Figure 5.2 is highlighting the main methodological steps of this study.

The masks from both methodologies were applied on the time series using an Interactive Data Language (IDL) routine in order to keep only those pixels corresponding to the masks. These pixels were then organized to serve as input data to estimate the yield.

To access the yield a linear regression model was built (equation 5.1) for each mask using the R software package (R Development Core Team, 2012). The regression model used the average EVI time series from each mask to predict yield.

$$\mathrm{Y} = \mathrm{a} + \mathrm{b} \times \mathrm{EVI} \tag{5.1}$$

Where *Y* is the estimated yield of soybean; *EVI* is from monthly MVC composites; *a* is the intercept and *b* is the slope.

The statistical analysis was applied to the dataset considering a significance level of 5%. Shapiro-Wilk test verified the normality of residues of linear regression (Shapiro and Wilk, 1965). To ensure the absence of autocorrelation in the data, we utilized the Durbin-Watson method, and the homoscedasticity analysis proposed by Breusch-Pagan was used to assess the randomness of the data with zero mean and constant variance (Breusch and Pagan, 1979). The Mann Withney test (Mann and Whitney, 1947) was applied in order to verify whether there was any significant difference between mean values of the estimated data and mean values of the observed data.

All error values were calculated to compare observed yield and estimated yield. Root Mean Squared Error (RMSE, equation 5.2) gives an error magnitude with the impact of the outliers being amplified through the squaring operation. The Mean Absolute Error (MAE, equation 5.3) tells the average magnitude of error and is reflective of model accuracy. The adjusted determination coefficient (R^2 adj., equation 5.4) indicates how much of the Y range can be explained by variable X, indicating the accuracy of the model. Willmott agreement index (d, equation 5.5) developed by Willmott (1981) measures distances of cloud dispersion of correlated data about the 1:1 line.

$$RMSE = \sqrt{\left(\frac{1}{n} \times \sum_{i=1}^{n} (Yobs - Yest)^2\right)} \tag{5.2}$$

$$MAE = \frac{1}{n} \times \sum_{i=1}^{n} |Yobs - Yest| \tag{5.3}$$

$$R^2 adj = R^2 - \left[\frac{1}{n-2} \times (100 - R^2)\right] \tag{5.4}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (Yest - Yobs)^2}{\sum_{i=1}^{n} (|Yest - \overline{Yobs}|) + |Yobs - \overline{Yobs}|)^2} \tag{5.5}$$

where n is the number of data; R^2 is the coefficient of determination; *Yobs* is the observed yield, *Yest* is the estimated yield, and $\overline{Yobs}$ is the mean value of observed yield.

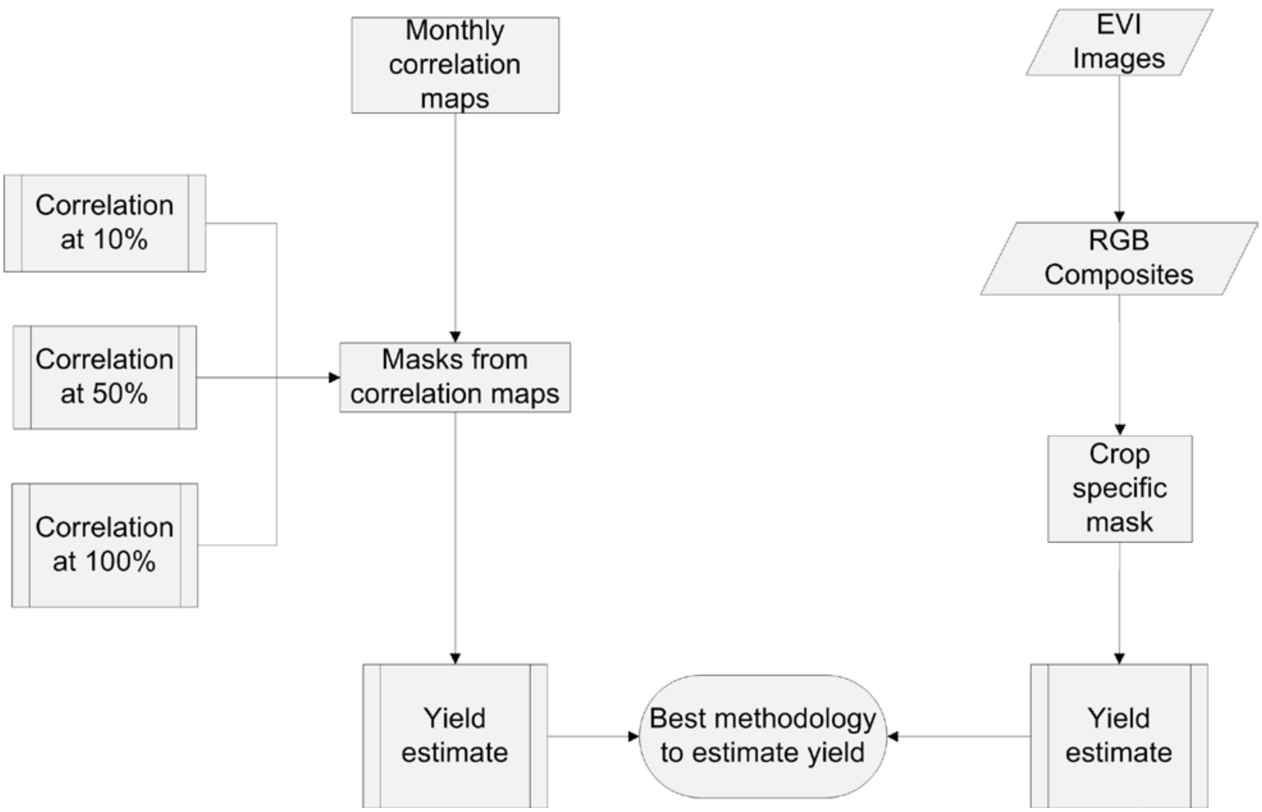

Figure 5.2 Main steps of study.

5.3. Results and Discussion

For Cascavel, the best estimates of yield were reached with correlation mask from 70% and the estimates values improved until 100% of correlation. In Toledo this occurs with correlation masks from 80%, in Castro and Ponta Grossa from 50%. Therefore, it is understood that there is no single, optimal value of the correlation mask for all of the counties, and it is necessary to test the values until reaching an optimum mask for each region, as suggested Kastens et al. (2005).

To compare the effectiveness of the proposed method, masks from the 91% to 100% of correlation were compared with crop specific masks as a function of the different stages of phenological development.

Generally for all counties the best prediction models were found when the correlation masks were used. R^2 adj was 73% to Cascavel, 87% to Toledo, 98% in Castro and 98% in Ponta Grossa. In contrast, the CSM the results were lower in all counties: Cascavel was 30%, Toledo 62%, Castro -9% and Ponta Grossa 36%. Table 5.1 show the RMSE, MAE and R^2 adjusted. Thus, the CM approach showed increased accuracy over the CSM approach. These results are in agreement with Johann (2012), that generated soybean estimated yield in Paraná state using a spectral model with CSM. The R^2 adj. ranged from 33% to 66%, i.e. the model used by the author were unable to achieve the increased precision when using the CSM.

The RMSE in Cascavel was 0.17 ton/ha for the CM and 0.26 ton/ha for CSM, in Toledo this values were 0.17 ton/ha (CM) and 0.29 ton/ha (CSM), Castro 0.045 ton/ha (CM) and 0.25 ton/ha (CSM) and Ponta Grossa was 0.032 ton/ha (CM) and 0.17 ton/ha (CSM). Therefore, the model error for the CM approach was lower than the CSM. These values are in agreement with Kastens et al. (2005) that used correlation maps to estimate soybean yield in Iowa and Illinois and obtained RMSE 0.15 ton/ha and 0.16 ton/ha respectively. In contrast, Ren et al. (2008) reached RMSE 0.21 ton/ha using the CSM approach, and Johann (2012) obtained values between 0.15 ton/ha to 0.22 ton/ha. The MAE reaffirm that the model used with CM is better than that used for CSM, the mean absolute error is always lower for the correlation map approach relative to the crop specific mapping.

A Willmott index of agreement (d) close to 1 signifies agreement between the estimated data and observed data. The d index for the CM approach was higher than 0.9 for all counties and for CSM was 0.73, 0.88, 0.15, 0.76 Cascavel, Toledo, Castro and Ponta Grossa respectively, i.e. lower than expected (Table 5.1).

Table 5.1 Statistical coefficients of models generated by county for both methodologies.

Cascavel				Toledo			
CM		CSM		CM		CSM	
p-value	0.001	**p-value**	0.037	**p-value**	0.000	**p-value**	0.002
RMSE	0.172	**RMSE**	0.269	**RMSE**	0.173	**RMSE**	0.294
MAE	0.103	**MAE**	0.213	**MAE**	0.119	**MAE**	0.243
d	0.925	**d**	0.736	**d**	0.967	**d**	0.887
R^2 Adj	0.730	**R^2 Adj**	0.330	**R^2 Adj**	0.870	**R^2 Adj**	0.620
Castro				Ponta Grossa			
CM		CSM		CM		CSM	
p-value	0.000	**p-value**	0.681	**p-value**	0.000	**p-value**	0.030
RMSE	0.045	**RMSE**	0.251	**RMSE**	0.032	**RMSE**	0.172
MAE	0.038	**MAE**	0.179	**MAE**	0.024	**MAE**	0.147
d	0.992	**d**	0.153	**d**	0.995	**d**	0.761
R^2 Adj	0.960	**R^2 Adj**	-0.09	**R^2 Adj**	0.980	**R^2 Adj**	0.360

*Significant at 5%

The overall model performance is shown in Figure 5.3, which demonstrates higher precision and accuracy were found for the model generated from the CM approach (left column in Figure 5.3) relative to the performance of the CSM approach (right column in Figure 3). Table 5.2 presents estimated values and observed values and their differences in percentage for all counties. In Cascavel the difference in percentage between observed and estimated yield from the CM is below 1.5% except in the last cropping season which was 17.26%. For the CSM, the difference ranged between -9.15% to 18.91% and again the largest variation in 2010/11. In Toledo this variation was -8.75% to 15.17% for the CM and 21.24% to 10.29% for the CSM. Castro showed the smallest difference for the CM among all counties with a range of errors between -1.61% to 2.92%. In the 2007/08 crop season, the CSM had the highest difference between observations and model estimates of 15.20%. Ponta Grossa also presented low values for CM was 2.35% to 1.14% and the CSM differences ranged between -10.25% to 6.87%.

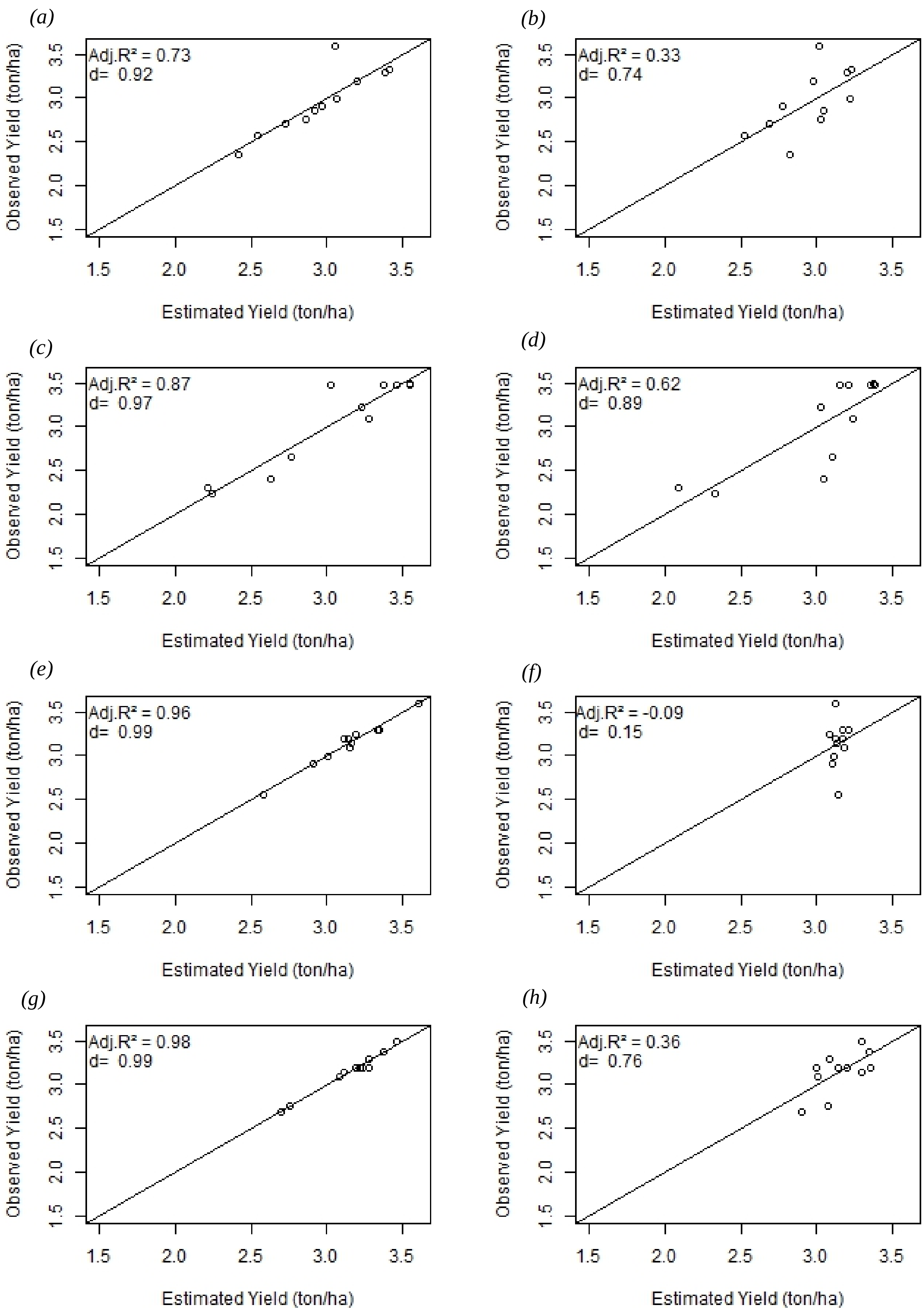

Figure 5.3 Relationship between estimated yield and observed yield (a) Cascavel CM; (b) Cascavel CSM; (c) Toledo CM; (d) Toledo CSM; (e) Castro CM; (f) Castro CSM; (g) Ponta Grossa CM; (h) Ponta Grossa CSM.

Table 5.2 Comparison of estimated (Est) to observed (Obs) soybean yield by counties for both methodologies.

Cascavel							**Toledo**						
		CM		CSM					CM		CSM	
Year	Obs ton/ha	Est ton/ha	diff (%)	Est ton/ha	diff (%)	Year	Obs ton/ha	Est ton/ha	diff (%)	Est ton/ha	diff (%)
2000/01	3.20	3.20	0.00	2.98	7.34	200001	3.47	3.37	2.82	3.21	8.00
2001/02	2.90	2.97	-2.24	2.77	4.54	200102	3.23	3.23	0.13	3.02	6.89
2002/03	3.30	3.39	-2.54	3.20	3.13	200203	3.47	3.46	0.42	3.35	3.43
2003/04	2.75	2.86	-3.85	3.03	-9.15	200304	2.40	2.63	-8.75	3.05	-21.24
2004/05	2.36	2.41	-2.44	2.83	-16.65	200405	2.65	2.76	-4.02	3.10	-14.63
2005/06	2.70	2.72	-0.82	2.68	0.63	200506	2.23	2.25	-0.82	2.33	-4.37
2006/07	2.85	2.91	-2.19	3.05	-6.46	200607	3.10	3.28	-5.47	3.23	-4.17
2007/08	2.99	3.07	-2.61	3.22	-7.31	200708	3.48	3.55	-1.89	3.39	2.77
2008/09	2.58	2.54	1.57	2.53	2.05	200809	2.30	2.22	3.73	2.09	10.13
2009/10	3.32	3.41	-2.49	3.23	2.83	200910	3.50	3.55	-1.39	3.37	3.79
2010/11	3.59	3.06	17.26	3.02	18.91	201011	3.48	3.02	15.17	3.16	10.29
Castro						**Ponta Grossa**					
		CM		CSM				CM		CSM	
Year	Obs ton/ha	Est ton/ha	diff (%)	Est ton/ha	diff (%)	Year	Obs ton/ha	Est ton/ha	diff (%)	Est ton/ha	diff (%)
2000/01	3.20	3.14	2.01	3.17	1.00	200001	3.20	3.19	0.42	2.99	6.87
2001/02	3.15	3.16	-0.29	3.13	0.69	200102	3.10	3.09	0.39	3.01	3.13
2002/03	3.30	3.34	-1.09	3.21	2.78	200203	3.38	3.37	0.29	3.35	0.99
2003/04	3.10	3.15	-1.61	3.18	-2.43	200304	3.30	3.28	0.64	3.09	6.90
2004/05	2.55	2.58	-1.25	3.14	-18.75	200405	3.15	3.11	1.15	3.29	-4.29
2005/06	3.00	3.01	-0.38	3.11	-3.59	200506	2.76	2.76	0.03	3.08	-10.25
2006/07	3.30	3.34	-1.28	3.17	4.05	200607	3.20	3.28	-2.35	3.35	-4.49
2007/08	3.60	3.61	-0.36	3.12	15.20	200708	3.20	3.24	-1.19	3.20	-0.02
2008/09	2.90	2.91	-0.47	3.11	-6.65	200809	2.70	2.70	0.06	2.90	-6.91
2009/10	3.25	3.19	1.75	3.09	5.35	200910	3.20	3.21	-0.50	3.14	1.90
2010/11	3.20	3.11	2.92	3.13	2.36	201011	3.50	3.46	1.10	3.29	6.17

The identification of pixels well correlated with historical yield instead of a map of agricultural areas is a significant step in the context of an operational yield forecasting. This is clearly shown here since the non-significant results of the CSM approach are mainly due to the fact that EVI is representative of all crops in the area (pixel), and thus is highly influenced by dominant crops, becoming less related to the non-dominant crops that often can be the crop of interest. However, for the CM approach, it does not happen because the focus is on highly correlated areas (pixels) with yield (Maselli & Rembold, 2001; Kastens et al., 2005; Mkhabela et al., 2011).

5.4. Conclusion

This study has shown that remotely sensed based yield regression model was developed and applied at the county level in two different regions in Paraná state. The correlation maps demonstrated increased performance of the yield model in all counties relative to a more traditional crop specific approach. While the model-based on crop specific mask showed poor results, the correlation maps gave results more closely matched with the official yield reports.

The study also demonstrated the limitations of crop specific masks when used to estimate yield especially when this task is conducted with low spatial resolution images. The correlation maps proved to be more efficient at predicting yield since it is based on the relationship of EVI and crop yield, eliminating those factors that could influence the results in negative way.

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6. Using Temporal Stability to Estimate Soybean Yield: A case study in Paraná state, Brazil

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Abstract Crop identification for yield estimation using remote sensing data can be a difficult task due to the timing of data collection and crop development because the vegetation may be immature or located in places that have a low density of planted area. When using images of medium to low spatial resolution this task becomes more difficult due to mixing of heterogeneous areas within the pixel. The primary goal of this study was to assess whether selected pixels can be used to estimate yield of soybean crop in Paraná state, Brazil. We used correlation maps between the Enhanced Vegetation Index (EVI) and yield using the temporal stability method. We estimated yield values using two approaches the first for each month of the growing season and the second for each phenological stage of the growing season, in order to verify for which periods the yield estimates were closest to officially reported data. Among all periods of the crop season (planting date, flowering, vegetative peak and senescence) planting date was the period that showed the lowest precision while the vegetative peak was the period with best agreement. The RMSE was 0.187 ton/ha for February and 0.193 ton/ha for the Flowering to Maturity period and agreement between official yield and estimated yield was 96% and 95.8% respectively. The temporal stability method proved to be an efficient tool to replace the need for masking remotely sensed data for calculating yield.

Keywords: Forecast yield; Agricultural Monitoring; EVI; Temporal Stability.

6.1. **Introduction**

Soy is an important grain to Brazil's economy and one of the most important grains in the world, being one of the primary oilseeds used for animal consumption of soybean meal, and for human consumption of the oil (Goldsmith, 2008). With this demand of grains, it is essential that the country has a system of crop forecasting and monitoring agricultural production that is capable of forecasting yield with good accuracy.

Timely and accurate crop yield forecasting at the regional scale are essential for an operational program as well as enhancing food security and decision making from a policy perspective. Satellite remote sensing techniques have been used for this purpose because of their ability to view large land surfaces synoptically with high temporal frequency (Prince, 1990). Data from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor mounted aboard the Terra and Aqua satellites are commonly used because it has a high temporal resolution and moderate spatial resolution, enabling monitoring at regional scale. These data are updated in near real time and distributed without cost.

MODIS provides land surface data such as vegetation indices like the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). Vegetation indices indicate environmental conditions of a region like biomass, leaf area index, soil coverage and radiation interception (Jensen, 2006). The EVI was developed to optimize the spectral response of vegetation, with improved sensitivity into high biomass regions and enhancing vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences (Huete et al., 1999).

Statistical regression-based methods are commonly used in conjunction with remotely sensed data to estimate crop yield (Wall et al., 2008). These are based on empirical relationships between historical yields and reflectance based vegetation indices. They are typically simple to implement and do not require numerous inputs (Becker-Reshef et al. 2010). Ren et al. (2008) related MODIS/NDVI data at county level in China with winter wheat production, then using a stepwise regression method they found a relationship between the spatially accumulated NDVI and production. Their results showed the RMSE was 0.2142 t/ha. The authors claim that a good predicted yield of winter wheat could be reached about 40 days ahead of the harvest time.

Mkhabela et al. (2011) using correlated and regression analyses to forecast grain yield found the best time for making grain yield predictions can be made one to two months before harvest. Johann (2012) created spectral and combined (spectral and agro-meteorological) models for summer soybean yield estimation with MODIS data in Brazil using statistical techniques of Stepwise and Best subsets methods. The best fits were obtained using combined model with RMSE between 0.16 t/ha and 0.23 t/ha while the RMSE of spectral model were between 0.20 t/ha and 0.38 t/ha.

To run the crop yield forecast, some authors use the vegetation index averaged from crop specific subsets (masks) as input data, but sometimes this average value does not match the reality of a crop in the field (Kastens et al. 2005). Still according to Kastens et al. (2005) all vegetation in a region integrates the seasonal cumulative growing conditions in some fashion and may be more indicative of a crop's potential than the crop itself. The authors built a yield correlation mask between historical yield and NDVI images for Iowa, Illinois, Kansas and North Dakota and used a cross validation exercise to select the best pixels for crop forecasting.

Genovese et al. (2001) tested a series of conditions on pixels keeping them as homogeneous as possible; for example, a region was kept where the crop area represented 10% or more of the arable land area. Thus, decreasing the measurement error and selecting the best pixels on these conditions to estimate crop yield in Spain. The results were generally satisfying except for Madrid that the percentage prediction error was above 30%.

Becker-Reshef et al. (2010) used a winter wheat percentage map to select the best pixels and run a linear model to forecast yield in Kansas and Ukraine. The forecasted yield in Kansas closely matched the USDA/NASS reported numbers with a 7% error. The same regression model forecast winter wheat production in Ukraine within 10% of the official reported production numbers six weeks prior to harvest.

Rojas (2007), Araújo et al. (2011) and Johann et al. (2012) used satellite images to build a crop specific mask. The crop specific masks were used to quantify planted area and still serve as input data in yield estimate models. The inconvenience with this technique is the necessary processing time, it needs a fairly long time series of data and small fields may not be mapped due to the spatial resolution. The crop specific mask also has other problems such as the crop rotation practices, which may prevent the use of a single crop mask for multiple years to run the yield estimate and low spectral response of a crop early in its development are minimally informative (Kastens et al., 2005).

One approach to avoid this long process is to select pixels that can be representative based on the temporal stability technique. The temporal stability was created by Vachaud et al. (1985), and was applied in soil science to determine representative locations within a field for soil moisture monitoring. The basis of this technique is that some sites in the field always displayed behavior that was approximately equal to the spatially averaged mean, while other portions of the study area generally represent extreme values with respect to the spatial distribution. When all sites were ranked by relative moisture values, certain sites showed persistence towards the spatial mean and the temporal fluctuations of those sites were the same as that of the field average.

This technique may be useful to select pixels that have the same development pattern during the crop season and these pixels could have the best profile to estimate the total yield, since they are more representative and thus would eliminate the need for the usual crop masking process.

The use of vegetation indices to estimate yield has focused on average values of vegetation indices based on crop masks and generated estimates at the end of the season. Here, we examine the yield estimates based on the temporal dynamics of the crop season at monthly and phenological timescales. The objective of this study was to assess the applicability of the temporal stability method to estimating county level yield in agricultural crops.

6.2. **Material**

6.2.1. **Study area**

This study was conducted in Toledo County located in the midwest of Paraná, Brazil (Figure 6.1). Paraná state is responsible for high soybean production in Brazil, and from 1990-2012 this state was ranked second in Brazil in soybean production (15.424 million tons in 2011) (Conab, 2012). In addition, the midwest of Paraná is responsible for more than 29% of production in the state (SEAB, 2012).

According to Albrecht et al. (2008) the preferential period to soybean sowing date in Paraná state is November, however, this sowing date may vary between October 15th to December 15th. The Department of Agriculture and Supply of Paraná (SEAB) is an agency responsible for monitoring conditions of crop areas in Paraná state, and release percentage of planted/harvest crop area. Table 6.1 shows information from 2004/2005 to 2010/2011 crop season.

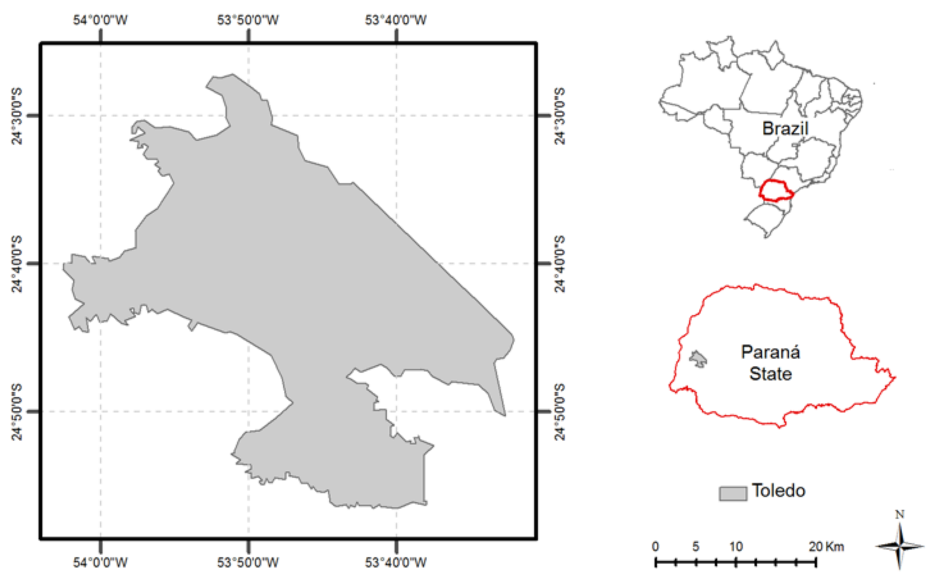

Figure 6.1 Study area illustrating the location of Toledo County in southern Brazil.

Table 6.1 Monthly percentage of sowing and harvesting soybean crop season in Paraná State*.

Crop Year	*Condition*	*Oct*	*Nov*	*Dec*	*Jan*	*Feb*	*Mar*	*Apr*	*May*
2004/2005	Sowing	20%	73%	6%	-	-	-	-	-
	Harvesting	-	-	-	-	16%	50%	27%	7%
2005/2006	Sowing	37%	58%	5%	-	-	-	-	-
	Harvesting				1%	8%	55%	31%	5%
2006/2007	Sowing	23%	66%	11%	-	-	-	-	-
	Harvesting	-	-	-	-	13%	54%	29%	4%
2007/2008	Sowing	23%	63%	14%	-	-	-	-	-
	Harvesting	-	-	-	-	11%	45%	34%	10%
2008/2009	Sowing	24%	58%	16%	2%	-	-	-	-
	Harvesting	-	-	-	-	1%	50%	41%	8%
2009/2010	Sowing	50%	47%	3%					
	Harvesting	-	-	-	1%	16%	58%	21%	4%
2010/2011	Sowing	47%	51%	2%	-	-	-	-	-
	Harvesting	-	-	-	-	5%	80%	13%	2%

* Data from 2000/2001 until 2003/2004 was not provided. Font: SEAB/Deral (2013).

6.2.2. Data

We worked with eleven years of EVI data from MODIS/Terra (2000 – 2011) provided every 16 days at 250-meter spatial resolution acquired from the MODIS products database created by the Brazilian Agricultural Research Corporation, Agricultural Informatics (*Embrapa Agropecuária Informática*) *http://www.modis.cnptia.embrapa.br/geonetwork/srv/pt/main.home*. To minimize possible noise in the data due to clouds, we calculated Maximum Value Composite (MVC) using an Interactive Data Language (IDL) routine. The MVC method selects the highest quality pixel from each composite time-frame (Holben, 1986).

Annual crop statistics data from 2000/2001 to 2010/2011 for soybean growing were obtained from SEAB. This agency is responsible for collecting agricultural statistics at the state level and transferring this information for the Brazilian Institute of Geography and Statistics (IBGE) and for Brazilian Food Supply Agency (Conab) which are responsible for national agricultural statistics.

6.3. **Methods**

6.3.1. Application of the temporal stability technique for yield estimation

Vachaud et al. (1985) introduced the concept of temporal stability, which they described as the time invariant association between spatial location and classical statistic parametric values, such as ranking observations from smallest to largest values, and identify the cumulative probability function as a normal distribution. They proposed this method in soil science for the purpose of reducing the number of field sampling sites while at the same time accurately characterizing the spatially averaged behavior of soil moisture (θ) of the study area over time.

In regards to θ, temporal stability suggests that the pattern of spatial variability does not change with time when the individual θ measurements are ranked according to their magnitudes or when scaled against the mean value for the area under consideration (Van Pelt and Wierenga, 2001).

The principal tool employed for summarizing and assessing the statistics used in the temporal stability analysis is the mean relative difference plot. This plot compares a particular location to the average computed from all locations (Cosh et al., 2006). The technique is initialized by calculating the difference (Δ_{ij}) between an individual sample and the daily spatial mean of (θ_{ij}) at the same time from all locations as follow in equations (6.1) and (6.2):

$$\Delta ij = \theta_{ij} - \bar{\theta}_j \tag{6.1}$$

$$\bar{\theta}_j = \frac{1}{N} \sum_{i=1}^{N} \theta_{ij} \tag{6.2}$$

where θij is the *j*th sample at the *i*th site of *N* sites within the study region. $\bar{\theta}_j$ is the computed spatial average among all sites for a given date and time *j*. The relative differences (δ_{ij}) are then calculated from equation (6.3):

$$\delta_{ij} = \frac{\Delta_{ij}}{\bar{\theta}_j} \tag{6.3}$$

The relative difference from the temporal mean ($\bar{\delta}_{ij}$) and its standard deviation ($\varsigma(\bar{\delta}_{ij})$) are determined for each location as:

$$\bar{\delta}_{ij} = \frac{1}{m} \sum_{j=1}^{m} \delta_{ij} \tag{6.4}$$

$$\varsigma(\bar{\delta}_i) = \left[\sum_{j=1}^{m} \frac{(\delta_{ij} - \bar{\delta}_i)^2}{m-1}\right]^{1/2} \tag{6.5}$$

where *m* is the number of sampling days. Equations (6.4) and (6.5) are used to rank and plot the locations from lowest mean relative difference to highest. A site is considered temporally stable if the mean relative difference is near zero and there is a small standard deviation (Starks et al., 2006).

We used correlation maps to the study area at the pixel level through the correlation between soybean historical yield and EVI. These correlation maps were built using two approaches: the first was based on months of the growing season (October to April) and the second based on the phenological stage of the soybean crop defined as the following: Emergence to Maturity (EM), Emergence to Flowering (EF), Flowering to Grain filling (FG), Flowering to Maturity (FM).

From the variation of the correlation over the eleven years of growing season data, we can assess the applicability that each period could have on improving the accuracy of end of season yield forecasts. If there is a practice of crop rotation at some location, then there will be a change in the spectral response, therefore this profile would have at least one point deviating from the trend line and decreasing the correlation and consequently this pixel will be excluded from the analysis.

The correlation maps will replace the usual crop mask such as those employed by Rojas (2007), Araújo et al. (2011) and Johann (2012). If successful, we intend to reduce the process for mapping cultivated areas as shown by these authors.

In order to accomplish this objective, we needed to select the most representative pixels within the correlation maps, i.e. pixels that show mean stable correlation during the growing season. To do this applied the technique described above with some adaptions for our data and considering as follow:

θ_{ij}: the correlation value at pixel *i* and month *j*;

N: number of pixels in the correlation map in the month;

m: number of months.

For our purposes, each correlation map for Toledo County has 21181 pixels, so each pixel was considered a site and each month was considered a time measurement.

We applied the technique for all data and calculated the mean relative difference for all pixels. As suggested by Martinez-Fernandez and Ceballos (2003) and Starks et al. (2006), we filtered these pixels using mean relative difference values between -5% to 5% and standard deviation between -2% to 2% to find the pixels that are more stable in the correlation maps. Next, we ranked these values from lowest to highest mean relative difference to quantify the temporal stability at each pixel.

Finally, we used the stable pixels to select the vegetation index values to create a regression model to assess the ability of using temporally stable pixels to improve yield forecasts.

6.3.2. Linear regression model to test best pixels from temporal stability

We created a monthly linear regression model based on pixels selected by temporal stability technique using the R software package (R Development Core Team, 2012). The regression model used the *EVI* time series to predict yield in two different ways. For those pixels selected in monthly correlation maps, we applied MVC *EVI* by month. For the pixels chosen by the phenological stage, we used accumulated *EVI* according to the stages of the crop season.

$$\mathrm{Y} = \mathrm{a} + \mathrm{b} \times \text{Monthly EVI} \tag{6.6}$$

$$\mathrm{Y} = \mathrm{a} + \mathrm{b} \times \sum \text{EVI} \tag{6.7}$$

where *Y* is the estimated yield of soybean; monthly *EVI* is from monthly MVC composites; $\sum$ EVI is the spatially accumulated EVI of soybean crop stages; *a* is the intercept and *b* is the slope.

The statistical analysis was applied to the dataset using the R program considering a significance level of 5%. Shapiro-Wilk test verified the normality of residues of linear regression (Shapiro and Wilk, 1965). To ensure the absence of autocorrelation in the data, we utilized the Durbin-Watson method, and the homoscedasticity analysis proposed by Breusch-Pagan was used to assess the randomness of the data with zero mean and constant variance (Breusch and Pagan, 1979). The Mann Withney test (Mann and Whitney, 1947) was applied in order to verify whether there was any significant difference between mean values of the estimated data and mean values of the observed data.

To evaluate the statistical model, we calculated the Root Mean Squared Error (RMSE, equation 6.8) that gives an error magnitude with the impact of the outliers being amplified through the squaring operation. Mean Absolute Error (MAE, equation 6.9) quantifies the average magnitude of error and is reflective of model accuracy. The Index of Agreement (d, equation 6.10) developed by Willmott (1981) measures distances of cloud dispersion of correlated data about the 1:1 line. Figure 6.2 illustrate the main steps of this study.

$$RMSE = \sqrt{\left(\frac{1}{n} \times \sum_{i=1}^{n} (Yobs - Yest)^2\right)} \tag{6.8}$$

$$MAE = \frac{1}{n} \times \sum_{i=1}^{n} |Yobs - Yest| \tag{6.9}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (Yest - Yobs)^2}{\sum_{i=1}^{n} (|Yest - \overline{Yobs}|) + |Yobs - \overline{Yobs}|)^2} \tag{6.10}$$

where *n* is the number of data; *Yobs* is the observed yield, *Yest* is the yield estimated by the model, and $\overline{Yobs}$ is the mean value of observed yield.

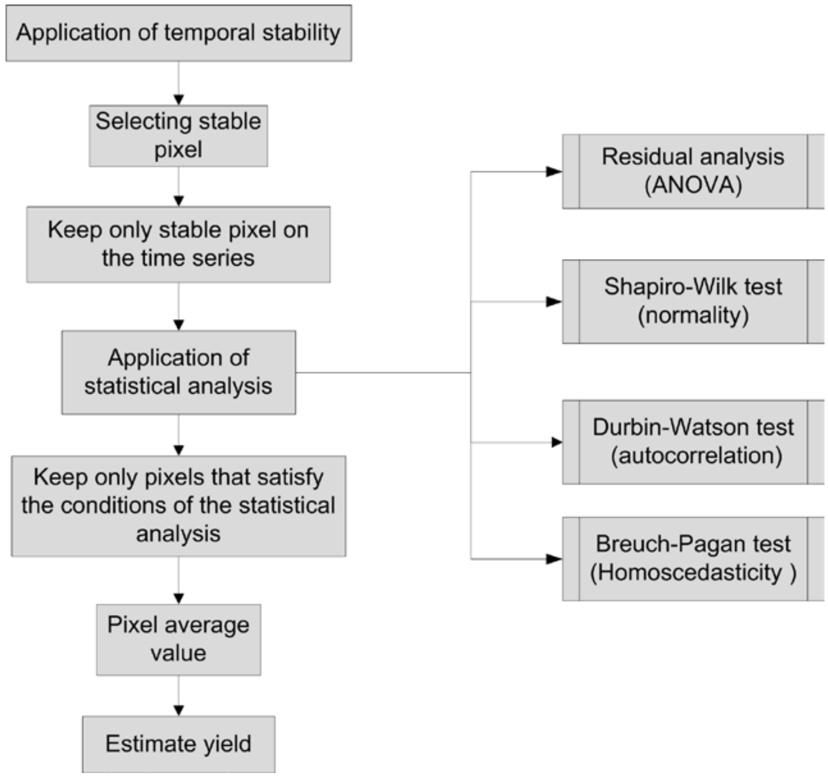

Figure 6.2 Flowchart of the main steps of this study.

6.4. **Results**

6.4.1. Temporal Stability

Pixels that presented mean relative differences near zero and small standard deviations were selected. From the available 21,181 pixels in the county, 1,805 pixels were selected from the monthly methodology (Figure 6.3a), and 2,049 pixels by the phenological methodology (Figure 6.3a) because they presented mean behavior in each of the correlation maps. Mean relative difference plot is shown in Figure 6.4b and 6.4b, where the pixels are ranked from the smallest to largest correlation.

Near zero mean relative difference indicates that the value at that time is close to the spatial mean at that time, indicating that these pixels are considered the most representative of the spatial average in the county while pixels with large absolute values of mean relative difference are less representative of the spatial average. The errors bars show the standard deviation of the mean relative difference that is an indicator of the pixel's ability to capture the highest stability.

The temporal stability is explained by the EVI value that is most closely related to the average EVI value throughout the growing season. Thus, these pixels had the same average development and were therefore selected. We utilized these pixels as input to the linear model to calculate the estimated yield. We verified that all pixels were stable inside the mean relative difference range, all pixels showed the existence of a significant time-stability according to Starks et al. (2006) parameters, thus we could select pixels more representative in the data set.

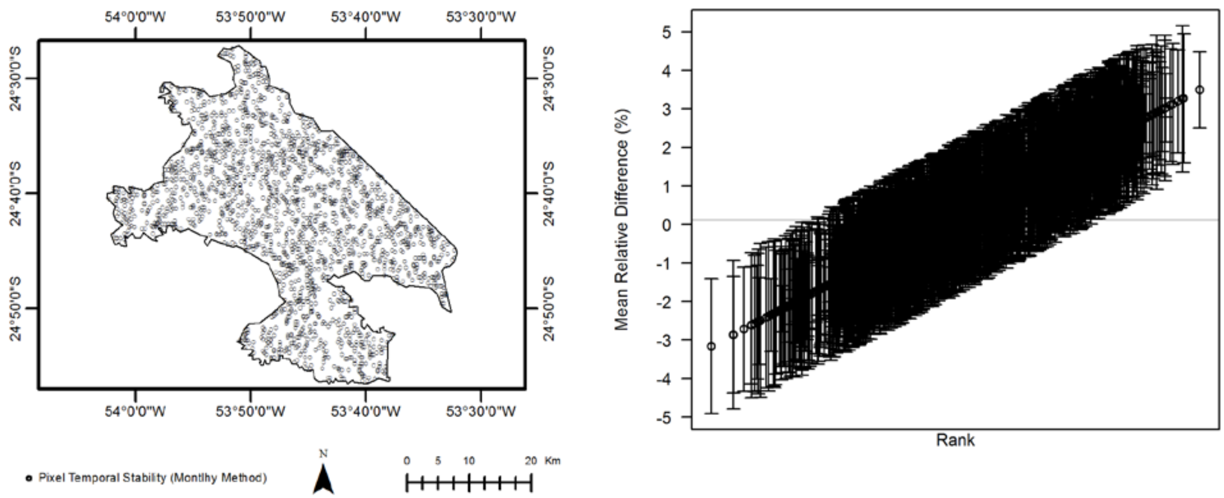

Figure 6.3 (a) Temporally stable pixels selected using the monthly method; (b) Mean relative difference plot for the 1805 monthly selected pixels

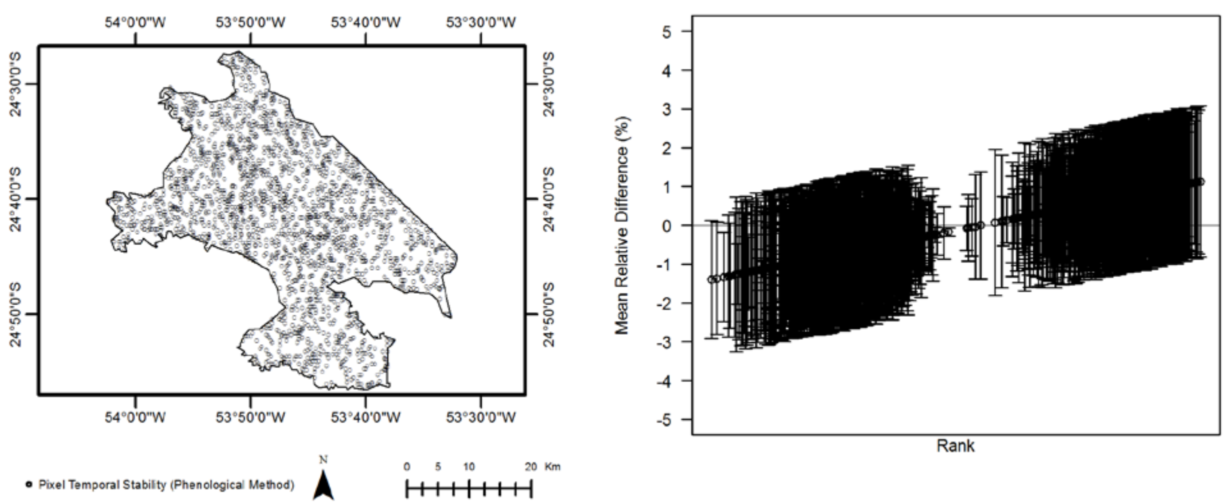

Figure 6.4 (a) Temporally stable pixels selected using the phenological method; (b) Mean relative difference plot for the 2049 phenologically selected pixels

6.4.2. Regression model

In this approach we ran the linear regression model for each month using the first methodology (Table 6.2) and for each phenological variable for the second methodology (Table 6.3) aiming to find the period which is best for estimating accurate yields.

For the first method, the models that did not show good estimates of yield were associated with the planting period (October and November). This occurred due to the relatively high soil signal and low crop signal in the vegetation index. Yield variation for this period was 57% and 56.8% for October and November respectively. Verifying the accuracy for these models, we found higher error values when compared with the other months: the RMSE was 0.312 ton/ha and 0.313 ton/ha. The same occurred for the MAE which ranged in 0.26 ton/ha to 0.268 ton/ha, the index of agreements was 0.866 for October and 0.865 for November and the variability of point in the line was higher (Figure 6.5a and b).

The December model had RMSE of 0.287 ton/ha and MAE of 0.236 ton/ha showing smaller values; indicating lower accuracy in estimates when compared with January and February. The variability of points along the 1:1 line was also reduced (Figure 6.5c), the concordance between observed data and estimated data was 0.893 and the yield variation was explained in 63.7%.

We verified that February was the month most closely correlated with yield; explaining 84.6% of the yield variation. Moreover, it was the month that showed less variability around the regression line (Figure 6.5e). We confirmed also a high degree of precision through the index of agreement of 0.961. The RMSE was 0.187 ton/ha and MAE 0.166 ton/ha indicating that this model had the highest accuracy.

The models generated for January and March showed similar results to February, but slightly smaller. The yield estimated for theses months had a variation of 75.5% for January and 77.5% for March, RMSE was 0.236 ton/ha and 0.226 ton/ha, MAE 0.188 ton/ha and 0.172 ton/ha and index of agreement of 0.934 and 0.94 for January and March respectively (Figure 6.5d and f).

April corresponds to the harvest period and had low accuracy with an RMSE of 0.391 ton/h and the MAE was 0.34 ton/ha. Yield for this model varied approximately 32.5%. However, there was low variability of points in the regression line when compared with October and November (Figure 6.5g) and index of agreement of for 0.736. The decrease of the accuracy of this month is explained by the decrease in EVI in this period.

For the phenological method, the EM model had a yield variation of 79%, with an RMSE of 0.216 ton/ha and MAE 0.161 ton/ha and corroboration with this high accuracy the index of agreement was 0.947 (Figure 6.6a).

The model for EF that corresponded to October, November and December had worse results than the first methodology. The accuracy of the model was high when compared with the others periods; with the RMSE of 0.49 ton/ha and MAE 0.46 ton/ha; consequently the index of agreement was 0.108 and yield variability was explained in -9.9% (Figure 6.6b).

For FG period that correspond to December, January and February the accuracy was lower than EM variable with RMSE of 0.273 ton/ha and MAE 0.223 ton/ha the yield variation was 67% and index of agreement 0.906 (Figure 6.6c).

The FM stage that was composed of December, January, February and March had the best results for the phenological methodology. The yield variation was explained in 83.6%, and the index of agreement was 0.958 i.e, the estimated yield is close to observed yield. Moreover, the RMSE of 0.193 ton/ha and MAE of 0.166 ton/ha confirmed the high degree of accuracy for this variable (Figure 6.6d).

Table 6.2 Monthly methodology: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha), p-values obtained by the F test.

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.47	2.95	17.7	3.21	8.0	2.97	17.0	3.36	3.4	3.61	-3.9	3.33	4.3	3.33	4.3
200102	3.23	3.25	-0.5	3.06	5.4	3.31	-2.5	3.10	4.2	3.45	-6.3	3.25	-0.6	3.25	-0.6
200203	3.47	3.14	10.5	3.78	-8.3	3.22	7.8	3.35	3.6	3.24	7.1	3.26	6.6	3.26	6.6
200304	2.40	2.84	-15.4	2.42	-1.0	2.94	-18.3	2.98	-19.5	2.43	-1.4	2.38	0.7	2.38	0.7
200405	2.65	2.87	-7.6	2.86	-7.4	2.83	-6.2	2.90	-8.7	2.88	-8.1	2.22	19.2	2.22	19.2
200506	2.23	2.77	-19.5	2.63	-15.1	2.47	-9.6	2.26	-1.3	2.45	-8.9	2.61	-14.6	2.61	-14.6
200607	3.10	3.12	-0.7	2.56	21.2	3.29	-5.8	3.27	-5.1	3.00	3.4	3.20	-3.0	3.20	-3.0
200708	3.48	3.68	-5.5	3.30	5.5	3.11	11.7	3.37	3.2	3.55	-2.0	3.33	4.4	3.33	4.4
200809	2.30	2.08	10.7	2.83	-18.7	2.13	8.0	2.05	12.2	2.18	5.3	2.66	-13.5	2.66	-13.5
200910	3.50	3.26	7.3	3.44	1.7	3.58	-2.1	3.43	2.1	3.38	3.6	3.59	-2.6	3.59	-2.6
201011	3.48	3.36	3.6	3.21	8.4	3.47	0.3	3.24	7.3	3.14	10.9	3.48	0.1	3.48	0.1
p-value		0.0043*		0.0044*		0.0019*		0.0003*		0.00004*		0.0002*		0.0392*	
RMSE		0.312		0.313		0.287		0.236		0.187		0.226		0.391	
MAE		0.260		0.268		0.236		0.188		0.166		0.172		0.340	
Adj. R^2		0.570		0.568		0.637		0.755		0.846		0.775		0.325	
d		0.866		0.865		0.893		0.934		0.961		0.940		0.736	

*Significant at 5%.

Table 6.3 Phenological methodology: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha), p-values obtained by the F test.

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FG	Diff (%)	FM	Diff (%)
200001	3.47	3.41	1.7	3.04	14.1	3.54	-2.0	3.27	6.2
200102	3.23	3.24	-0.4	3.04	6.1	2.88	12.2	3.29	-1.9
200203	3.47	3.40	2.1	3.03	14.4	3.30	5.0	3.40	2.1
200304	2.40	2.60	-7.7	3.04	-21.1	3.00	-19.9	2.63	-8.7
200405	2.65	2.53	4.8	3.03	-12.6	2.97	-10.7	2.47	7.3
200506	2.23	2.71	-17.8	3.05	-26.9	2.46	-9.3	2.58	-13.6
200607	3.10	2.71	14.3	2.89	7.4	3.11	-0.4	3.37	-7.9
200708	3.48	3.28	6.2	2.99	16.2	3.45	0.9	3.41	1.9
200809	2.30	2.25	2.0	3.01	-23.6	2.05	12.1	2.10	9.7
200910	3.50	3.66	-4.3	3.10	12.9	3.29	6.3	3.50	-0.1
201011	3.48	3.52	-1.0	3.08	13.0	3.26	6.9	3.29	5.8
p-value		0.0001*		0.7588		0.0012*		0.00005*	
RMSE		0.216		0.499		0.273		0.193	
MAE		0.161		0.464		0.223		0.166	
Adj. R^2		0.794		-0.099		0.670		0.836	
d		0.947		0.108		0.906		0.958	

*Significant at 5%.

The EF variable showed relatively poor performance since it utilized the initial period of the crop growth that has high influence of soil signal. Even with using December data, it was not possible to obtain good estimates.

The good results for EM can be explained since it is the accumulated value over the growing season period. The same could have occurred with the FG stage although it had good results, they were lower than the EM stage. This is because the temporal period composing this data was relatively short when compared to the first.

For the monthly methodology, the best period to estimate yield was January, February and March, and for the phenological methodology the most suitable period was the FM stage. Therefore, both methods had approximately the same period as the most suitable for estimating yield since the best months in the first were also used in the second.

Though we have the same period to estimate yield in both methodologies, those generated from the monthly estimate were slightly better when compared to the phenological method. Considering only the best period for both (e.g. February and FM), the monthly method showed better performance than the phenological approach. This occurred because of the way that FM variable was composed since it used information about crop maturation generating reduced values.

We compared estimated yield with observed yield for both methodologies, the relative error varied from -19.5 to 21.2% for the monthly approach while the results from the phenological method ranged from -26.9 to 16.2. Through this difference, we also found that yield is increasing since January and February, and the FM stage had the smallest values of the relative error in most of the years while the beginning and the end of the growing season this difference had some significant fluctuations.

For the FM period the RMSE ranged to 0.18 ton/ha to 0.28 ton/ha and the yield variation was between 63.7% to 84.6% while Johann (2012) using soybean crop masks in the same region to estimate yield observed an RMSE of 0.29 ton/ha and yield variation of 27.9%. This indicates that temporally stable pixels could have the best performance for yield estimates.

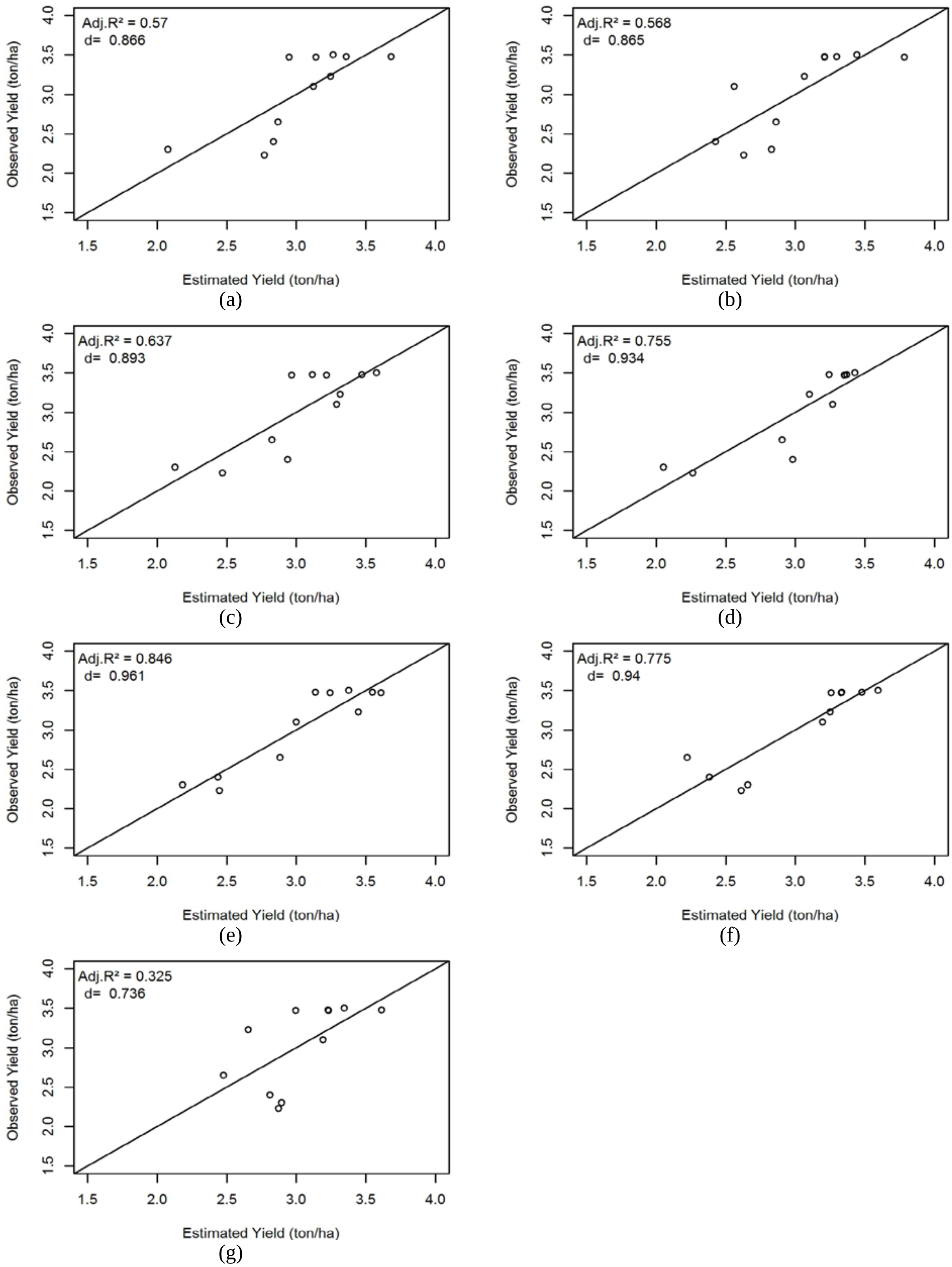

Figure 6.5 Relationship between observed and estimated yield for the monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

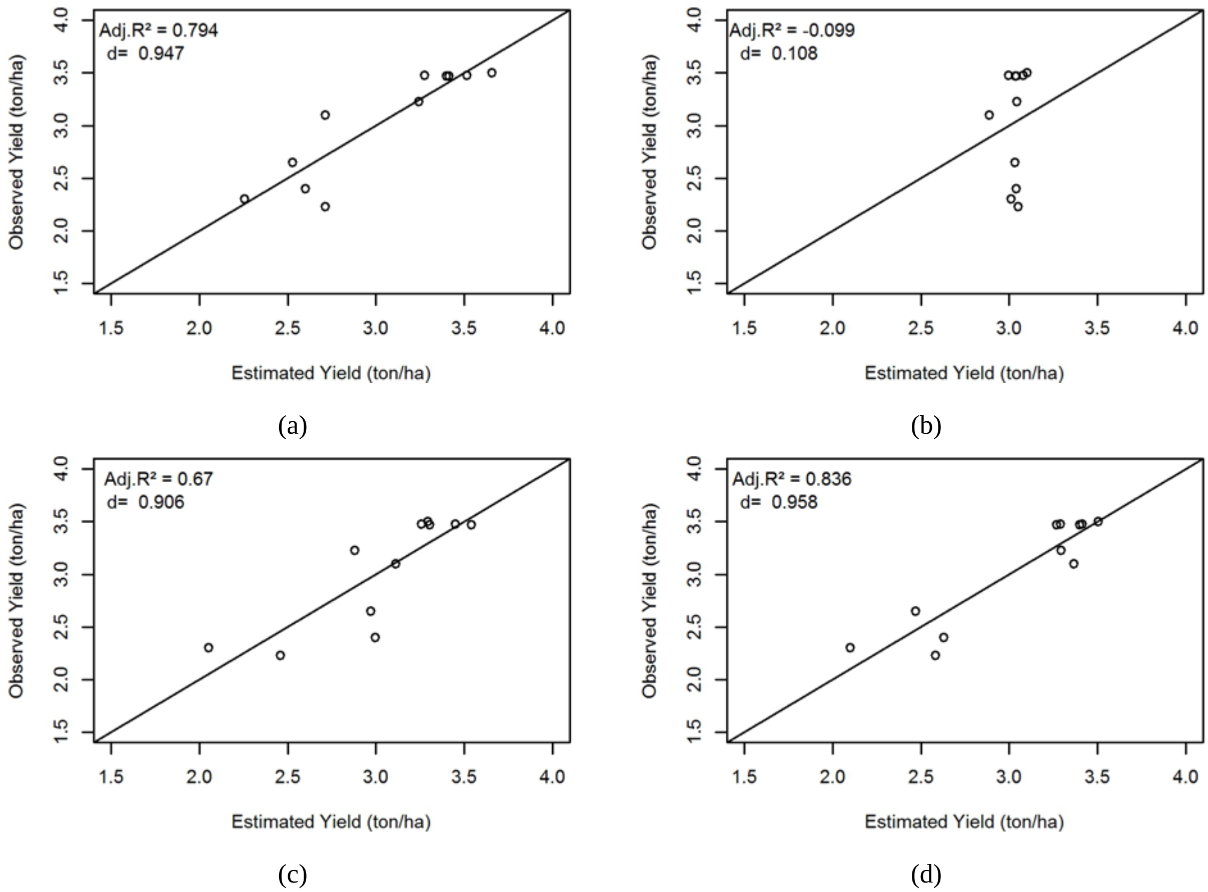

Figure 6.6 Relationship between observed and estimated yield for the various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Analyzing some of the best performing pixels selected by temporal stability showed that they were distributed throughout the county during the growing season. Figure 6.7a shows the ten most temporally stable pixels for the monthly methodology and Figure 6.7b for the phenological methodology. In the monthly method, one pixel is placed in the urban area and another placed in a riparian area while all the other pixels selected by temporal stability were soybeans (yellow target on the Landsat image). For the phenological methodology three pixels that belonged to Emergence to Flowering stage were placed in the city.

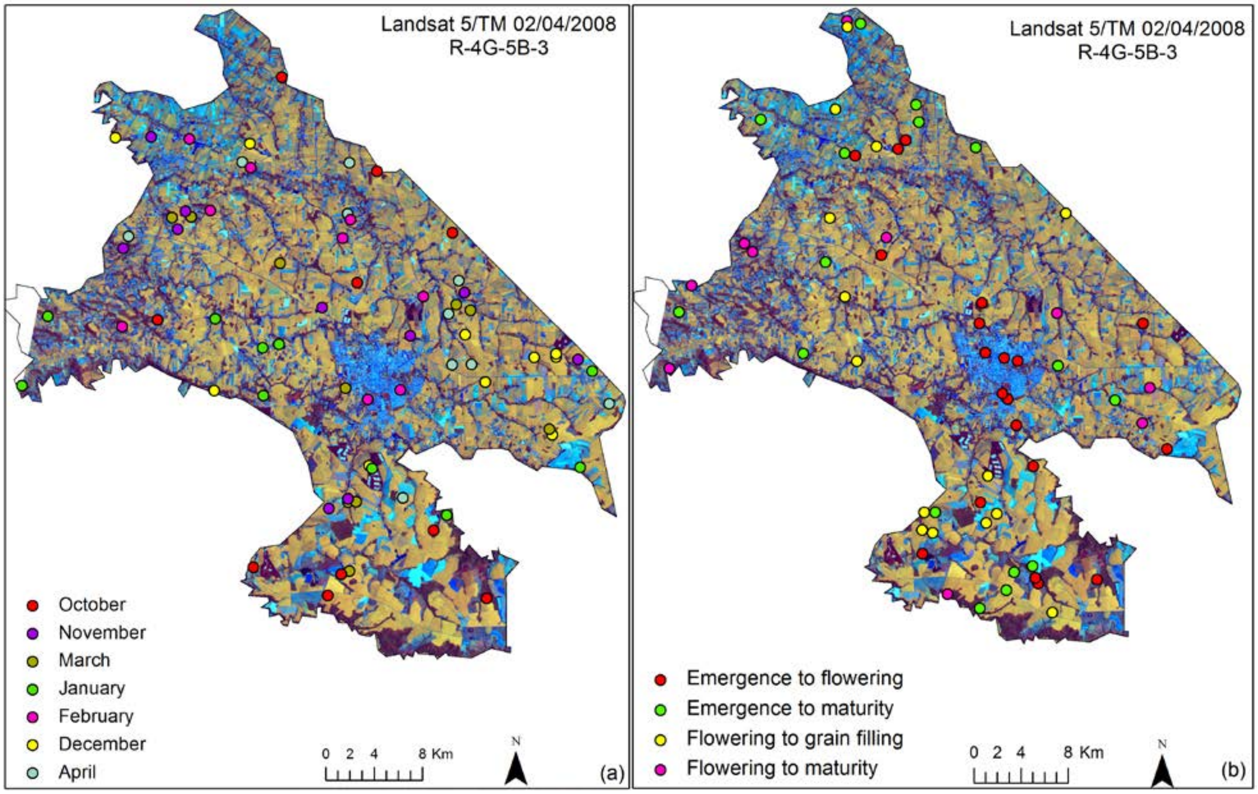

Figure 6.7 The 10 most temporally stable pixels (a) for each month; the 20 most temporally stable pixels (b) for each phenological stage.

6.5. **Discussion**

Understanding the evolution of monthly yield over a growing season is fundamental due to the importance in estimating price, maintaining stock and the management of agricultural policies. Therefore, forecasting with a high degree of reliability would help agribusiness in operational sectors, commercialization and give the government reliable data to help reduce negative economic impacts.

Selecting pixels with the same temporal development pattern can be a good predictor of yield and could help to improve yield forecasting. In general, the most stable pixels were soybean as shown in Figure 6.6, but some other targets were included because, at some times in the analysis, they had similar behavior to those soybeans pixels.

Therefore, by applying a regression analysis at either the monthly scale or at the phenological stage, we verified some changes, for example, the EF stage used information from the initial period of the growing season and consequently weak spectral responses were detected, but due to low values of others targets with the same behavior they are selected. This explains the relatively poor performance in estimating yield for these months/stage. The regression analysis using others months/stages with high EVI signal resulted in those pixels with low responses being eliminated and the remaining pixels were higher values.

Another important fact is the reduction of cost in the forecasting process because of utilization of low cost imagery; moreover these images are distributed in near real time making the system agile to perform the forecast. Thus, we have a low cost forecasting system, with rapid updates, monitoring each month/phenological stage. Our results are in agreement with those of Ren et al. (2008) and Mkhabela et al. (2011) who could make a soybean yield prediction at least one month before harvest.

The EVI images provided conditions of environmental data (Jensen, 2006) and because of this we did not use ancillary data such as soil properties and meteorological data. This would limit the method when applied to other areas with limited data availability (Rudorff and Batista, 1990; Kastens et al. 2005).

6.6. **Conclusions**

A new method of selecting pixels was analyzed to perform accurate yield estimation. The temporal stability method was effective in selecting pixels. This method helped to eliminate pixels that were not considerate representative, retaining only those that could represent a good profile in the yield estimation.

The forecasting methodology was based on generating estimated yield at the county level where we obtain yield estimate information based on temporally stable pixels during the growing season. Moreover, we could follow the evolution of yield by month/stages and found the best period to generate a reliable yield before the harvest, this task is very important to support governmental agencies in regulating market prices. The difference in this work was selecting pixels with the same monthly behavior and not based on soybean coverage as made in crop specific methodology.

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7. General Conclusions

Establish the correlation between EVI and yield helped to identify pixel to use them as a good indicator to estimate yield.

- The correlation maps allowed verify the most suitable period to estimate yield. In both methodologies the best correlation was found during vegetative peak, thus concluding that both can be used for this purpose.
- The application of correlation maps to estimate the yield was higher when compared with crop specific masks. As the correlation increase the performance of estimate yield increased, i.e., as the higher the correlation between EVI and yield the better will be the estimate. Thus, I conclude that the crop specific masks used in this study can be good for estimating planted area, but it was not efficient to generate estimates.

The temporal stability technique was well applied in the correlation maps, selecting temporally stable pixels during the growing season period. Among all the pixels of the maps the methodology selected only those that were within pattern average of each map, thereby it is possible to use for this purpose.

Generation of estimates by month and by phenological stage allowed follow the crop development over the cycle, moreover, I found that the first paper is in agreement with the results of the third paper, stating that the most suitable period to estimate yield is during the vegetative peak.

- At first the estimate yield was taken per pixel, i.e. for each stable pixel, a linear regression was generated. This approach showed very promising results, but the fact of not having yield data at the pixel level limited of knowing if that estimate was correct, once the yield values could be overestimate or underestimate the. Because of this, I run a linear regression analysis with all stable pixels for each county, the results were slightly lower, but were very close to the official data.
- Although the two approaches used to estimate yield showed very similar results, monthly estimate was slightly higher than the estimate by phenological stage, in which I used accumulated data.

The methodology used in this study was efficient for generating estimates; the major differences was producing this data monthly and monitor the crop throughout the cycle.

However, there is still need for improvements such as the inclusion of weather variables which we believe will achieve more promising results.

As future work, I suggest using surface temperature data from MODIS sensor for inclusion of meteorological variable, thus the methodology would still use only spectral data, but it would make the methodology more reliable. I also verified the need to remove cities of the study area, since there were few pixels of this target in the selection.

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9. Appendix

1. Correlation Maps

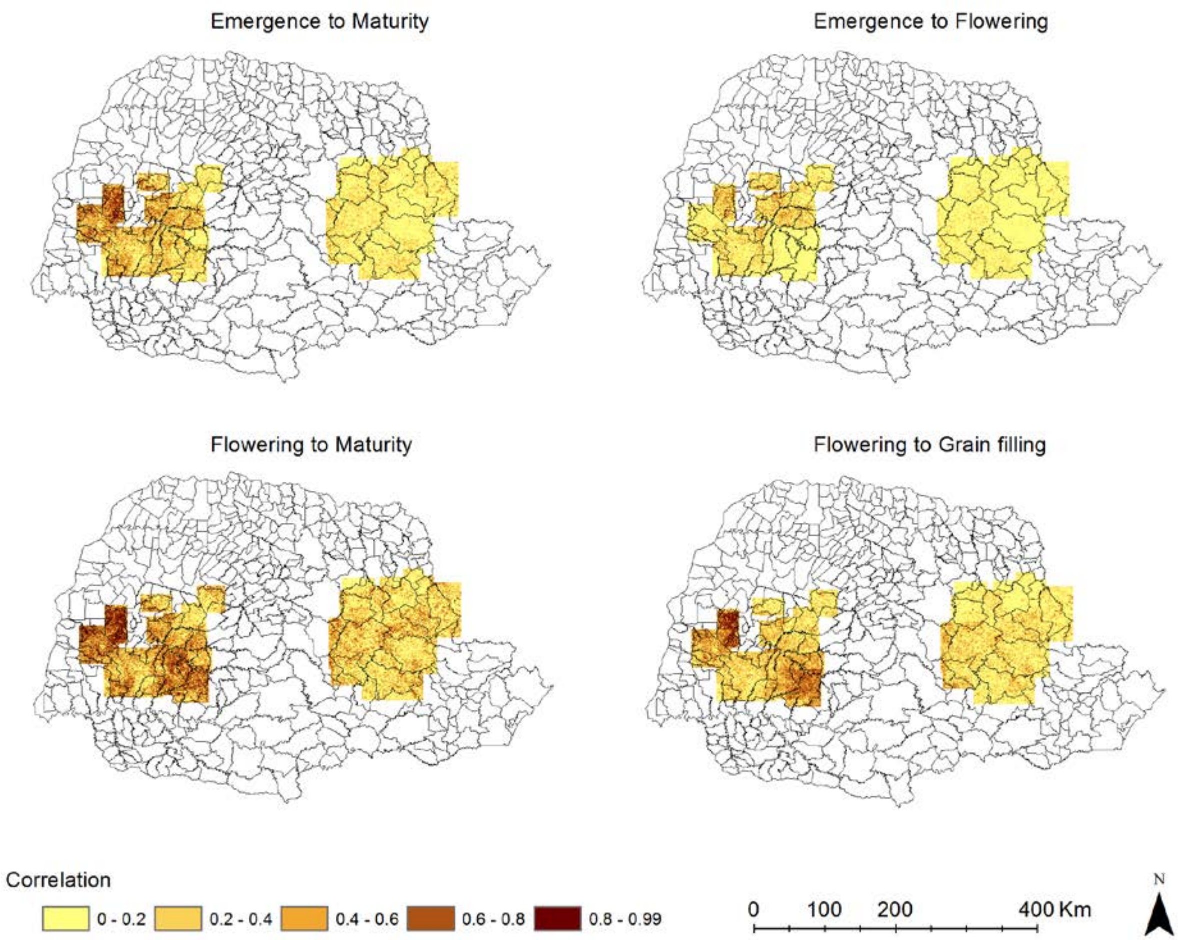


Figure 9.1 Correlation maps using phenological stage method.

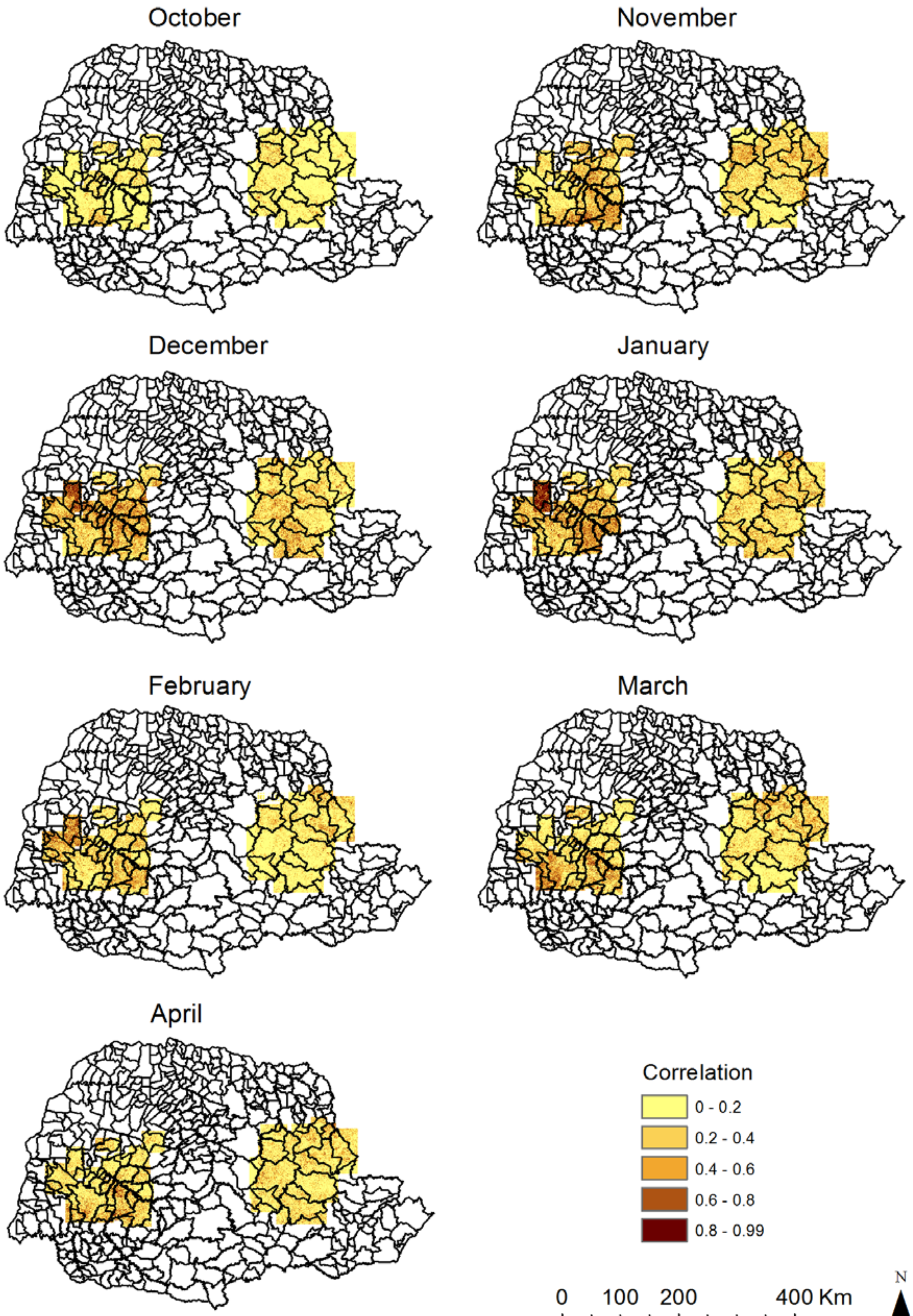


Figure 9.2 Correlation maps using monthly method.

2. Estimate Yield with correlation maps and crop specific mask

Table 9.1 Statistical coefficients of models generated for Cascavel using correlation maps.

10%	RMSE	MAE	D	R^2 Adj	20%	RMSE	MAE	D	R^2 Adj
October	0.32	0.29	0.44	0.03	October	0.35	0.29	0.07	-0.11
November	0.35	0.28	0.11	-0.10	November	0.33	0.29	0.45	0.02
December	0.35	0.29	0.08	-0.11	December	0.34	0.28	0.31	-0.04
January	0.34	0.29	0.18	-0.08	January	0.34	0.29	0.31	-0.04
February	0.29	0.26	0.69	0.23	February	0.35	0.29	0.05	-0.11
March	0.27	0.24	0.74	0.33	March	0.32	0.27	0.52	0.09
April	0.34	0.28	0.18	-0.09	April	0.27	0.24	0.76	0.34
30%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**40%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.34	0.29	0.21	-0.08	October	0.33	0.27	0.36	-0.02
November	0.31	0.27	0.58	0.13	November	0.29	0.25	0.67	0.23
December	0.32	0.26	0.46	0.05	December	0.30	0.23	0.61	0.17
January	0.32	0.27	0.49	0.06	January	0.30	0.24	0.63	0.19
February	0.34	0.27	0.26	-0.07	February	0.33	0.26	0.39	-0.02
March	0.34	0.29	0.34	-0.04	March	0.35	0.29	0.03	-0.11
April	0.21	0.18	0.88	0.59	April	0.17	0.14	0.93	0.74
50%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**60%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.32	0.25	0.48	0.05	October	0.30	0.23	0.61	0.16
November	0.26	0.23	0.77	0.36	November	0.25	0.20	0.81	0.45
December	0.27	0.21	0.73	0.31	December	0.25	0.19	0.81	0.45
January	0.28	0.21	0.70	0.27	January	0.26	0.18	0.77	0.38
February	0.32	0.23	0.56	0.09	February	0.30	0.22	0.63	0.15
March	0.34	0.29	0.27	-0.07	March	0.32	0.26	0.51	0.06
April	0.16	0.13	0.93	0.75	April	0.18	0.13	0.92	0.72
70%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**80%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.28	0.19	0.72	0.30	October	0.26	0.17	0.77	0.36
November	0.22	0.17	0.86	0.55	November	0.22	0.17	0.86	0.57
December	0.21	0.17	0.88	0.59	December	0.19	0.13	0.90	0.66
January	0.24	0.16	0.82	0.46	January	0.22	0.14	0.86	0.55
February	0.29	0.20	0.69	0.22	February	0.28	0.19	0.74	0.29
March	0.29	0.22	0.67	0.22	March	0.27	0.19	0.75	0.33
April	0.18	0.13	0.92	0.71	April	0.17	0.12	0.92	0.73
90%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**100%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.22	0.15	0.86	0.55	October	0.33	0.29	0.38	-0.02
November	0.22	0.15	0.86	0.55	November	0.20	0.13	0.90	0.65
December	0.17	0.10	0.93	0.75	December	0.18	0.11	0.92	0.71
January	0.21	0.12	0.88	0.59	January	0.17	0.10	0.92	0.73
February	0.27	0.17	0.76	0.33	February	0.25	0.15	0.80	0.41
March	0.26	0.18	0.78	0.38	March	0.29	0.21	0.70	0.25
April	0.18	0.11	0.92	0.70	April	0.13	0.09	0.96	0.84

Table 9.2 Statistical coefficients of models generated for Toledo using correlation maps.

10%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**20%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.47	0.40	0.47	0.02	October	0.50	0.45	0.23	-0.09
November	0.50	0.46	0.18	-0.09	November	0.48	0.43	0.38	-0.02
December	0.50	0.46	0.03	-0.11	December	0.48	0.43	0.39	-0.03
January	0.48	0.45	0.37	-0.03	January	0.41	0.35	0.72	0.27
February	0.47	0.40	0.48	0.02	February	0.49	0.44	0.31	-0.06
March	0.49	0.46	0.27	-0.08	March	0.49	0.42	0.29	-0.06
April	0.50	0.46	0.11	0.01	April	0.47	0.41	0.43	0.02
30%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**40%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.48	0.43	0.38	-0.03	October	0.46	0.39	0.53	0.07
November	0.46	0.40	0.52	0.08	November	0.42	0.36	0.66	0.21
December	0.46	0.39	0.54	0.07	December	0.43	0.35	0.66	0.19
January	0.37	0.32	0.79	0.40	January	0.34	0.29	0.84	0.50
February	0.47	0.41	0.50	0.04	February	0.44	0.38	0.61	0.13
March	0.46	0.38	0.48	0.05	March	0.43	0.36	0.64	0.20
April	0.44	0.38	0.58	0.14	April	0.40	0.34	0.72	0.30
50%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**60%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.43	0.36	0.64	0.17	October	0.38	0.30	0.77	0.35
November	0.39	0.33	0.75	0.34	November	0.33	0.27	0.84	0.51
December	0.39	0.31	0.74	0.32	December	0.35	0.29	0.81	0.45
January	0.32	0.27	0.86	0.55	January	0.29	0.24	0.89	0.63
February	0.41	0.34	0.71	0.26	February	0.37	0.29	0.80	0.40
March	0.38	0.31	0.76	0.37	March	0.32	0.27	0.85	0.54
April	0.34	0.28	0.83	0.48	April	0.29	0.23	0.89	0.64
70%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**80%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.36	0.28	0.81	0.41	October	0.29	0.21	0.89	0.62
November	0.30	0.25	0.88	0.60	November	0.26	0.22	0.91	0.69
December	0.30	0.26	0.88	0.59	December	0.25	0.22	0.93	0.73
January	0.26	0.21	0.92	0.71	January	0.22	0.16	0.95	0.80
February	0.33	0.25	0.84	0.51	February	0.30	0.22	0.88	0.60
March	0.28	0.22	0.90	0.64	March	0.25	0.17	0.92	0.71
April	0.23	0.17	0.94	0.78	April	0.17	0.14	0.97	0.87
90%	**RMSE**	**MAE**	**D**	**R^2 Adj**	**100%**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.49	0.44	0.29	-0.07	October	0.48	0.44	0.37	-0.03
November	0.50	0.46	0.14	-0.10	November	0.50	0.46	0.14	-0.10
December	0.18	0.15	0.96	0.86	December	0.13	0.11	0.98	0.92
January	0.14	0.11	0.98	0.91	January	0.17	0.12	0.97	0.87
February	0.28	0.19	0.91	0.66	February	0.26	0.16	0.92	0.71
March	0.26	0.16	0.92	0.69	March	0.33	0.24	0.85	0.51
April	0.14	0.10	0.98	0.92	April	0.27	0.22	0.91	0.67

Table 9.3 Statistical coefficients of models generated for Castro using correlation maps.

10%	RMSE	MAE	D	R² Adj	20%	RMSE	MAE	D	R² Adj
October	0.17	0.13	0.82	0.47	October	0.24	0.17	0.36	-0.01
November	0.24	0.16	0.40	0.01	November	0.23	0.19	0.57	0.11
December	0.22	0.17	0.66	0.19	December	0.23	0.14	0.48	0.08
January	0.23	0.18	0.53	0.08	January	0.23	0.17	0.44	0.04
February	0.23	0.16	0.48	0.05	February	0.24	0.19	0.42	0.00
March	0.22	0.17	0.54	0.13	March	0.24	0.19	0.33	0.19
April	0.21	0.17	0.66	0.21	April	0.23	0.16	0.53	0.12
30%	**RMSE**	**MAE**	**D**	**R² Adj**	**40%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.22	0.17	0.56	0.13	October	0.20	0.16	0.70	0.29
November	0.18	0.16	0.81	0.45	November	0.15	0.13	0.88	0.61
December	0.20	0.14	0.73	0.33	December	0.24	0.17	0.29	-0.04
January	0.21	0.16	0.68	0.26	January	0.18	0.15	0.81	0.44
February	0.22	0.18	0.63	0.19	February	0.18	0.17	0.80	0.14
March	0.22	0.18	0.57	0.14	March	0.20	0.15	0.74	0.32
April	0.19	0.14	0.78	0.40	April	0.14	0.12	0.90	0.66
50%	**RMSE**	**MAE**	**D**	**R² Adj**	**60%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.17	0.13	0.84	0.52	October	0.14	0.11	0.90	0.66
November	0.13	0.12	0.92	0.71	November	0.10	0.09	0.95	0.81
December	0.13	0.11	0.92	0.70	December	0.10	0.09	0.95	0.82
January	0.15	0.13	0.89	0.62	January	0.12	0.10	0.93	0.74
February	0.15	0.14	0.88	0.59	February	0.12	0.11	0.93	0.75
March	0.18	0.13	0.81	0.45	March	0.16	0.11	0.87	0.56
April	0.12	0.10	0.93	0.75	April	0.12	0.10	0.94	0.76
70%	**RMSE**	**MAE**	**D**	**R² Adj**	**80%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.12	0.10	0.93	0.75	October	0.22	0.15	0.61	0.18
November	0.09	0.08	0.97	0.86	November	0.07	0.06	0.98	0.91
December	0.09	0.08	0.96	0.86	December	0.07	0.06	0.98	0.92
January	0.10	0.08	0.95	0.82	January	0.09	0.07	0.97	0.87
February	0.11	0.09	0.95	0.80	February	0.08	0.07	0.97	0.88
March	0.14	0.09	0.91	0.68	March	0.12	0.08	0.93	0.74
April	0.11	0.09	0.94	0.79	April	0.08	0.06	0.98	0.90
90%	**RMSE**	**MAE**	**D**	**R² Adj**	**100%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.14	0.11	0.89	0.64	October	0.22	0.14	0.58	0.15
November	0.06	0.05	0.99	0.94	November	0.07	0.05	0.98	0.91
December	0.07	0.05	0.98	0.91	December	0.05	0.04	0.99	0.96
January	0.06	0.05	0.98	0.93	January	0.05	0.04	0.99	0.96
February	0.13	0.09	0.93	0.72	February	0.18	0.14	0.81	0.45
March	0.11	0.07	0.95	0.79	March	0.12	0.07	0.94	0.76
April	0.06	0.05	0.99	0.99	April	0.14	0.12	0.89	0.64

Table 9.4 Statistical coefficients of models generated for Ponta Grossa using correlation maps.

10%	**RMSE**	**MAE**	**D**	**R² Adj**	**20%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.17	0.15	0.76	0.36	October	0.21	0.17	0.45	0.05
November	0.16	0.15	0.81	0.44	November	0.20	0.16	0.52	0.09
December	0.21	0.16	0.44	0.02	December	0.20	0.15	0.64	0.17
January	0.21	0.17	0.44	0.03	January	0.20	0.17	0.55	0.13
February	0.16	0.14	0.81	0.45	February	0.20	0.18	0.58	0.15
March	0.15	0.11	0.84	0.49	March	0.21	0.14	0.54	0.07
April	0.18	0.15	0.73	0.31	April	0.20	0.16	0.62	0.17

30%	**RMSE**	**MAE**	**D**	**R² Adj**	**40%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.19	0.15	0.62	0.19	October	0.18	0.13	0.73	0.32
November	0.17	0.14	0.75	0.35	November	0.13	0.11	0.89	0.62
December	0.16	0.12	0.83	0.48	**December**	**0.12**	**0.09**	**0.92**	**0.71**
January	0.17	0.15	0.77	0.39	January	0.14	0.13	0.87	0.59
February	0.16	0.15	0.80	0.42	February	0.13	0.12	0.90	0.64
March	0.18	0.12	0.75	0.33	March	0.13	0.10	0.89	0.62
April	0.17	0.14	0.78	0.41	April	0.11	0.09	0.93	0.75

50%	**RMSE**	**MAE**	**D**	**R² Adj**	**60%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.17	0.13	0.78	0.40	October	0.15	0.11	0.84	0.52
November	0.10	0.08	0.95	0.79	November	0.07	0.05	0.97	0.89
December	0.09	0.07	0.96	0.83	December	0.06	0.05	0.98	0.91
January	0.12	0.11	0.92	0.70	January	0.09	0.08	0.95	0.82
February	0.10	0.08	0.95	0.80	February	0.08	0.08	0.96	0.85
March	0.11	0.08	0.93	0.74	March	0.09	0.07	0.95	0.82
April	0.07	0.06	0.97	0.88	April	0.08	0.07	0.97	0.97

70%	**RMSE**	**MAE**	**D**	**R² Adj**	**80%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.13	0.10	0.88	0.61	October	0.11	0.09	0.93	0.74
November	0.05	0.04	0.99	0.94	November	0.05	0.04	0.99	0.94
December	0.05	0.04	0.99	0.95	December	0.04	0.03	0.99	0.97
January	0.07	0.06	0.97	0.90	January	0.05	0.04	0.99	0.95
February	0.05	0.05	0.99	0.94	February	0.04	0.03	0.99	0.96
March	0.08	0.07	0.96	0.85	March	0.08	0.07	0.97	0.86
April	0.08	0.07	0.97	0.87	April	0.06	0.05	0.98	0.92

90%	**RMSE**	**MAE**	**D**	**R² Adj**	**100%**	**RMSE**	**MAE**	**D**	**R² Adj**
October	0.07	0.06	0.97	0.89	October	0.22	0.16	0.16	-0.07
November	0.06	0.05	0.98	0.93	November	0.21	0.13	0.46	0.01
December	0.03	0.02	1.00	0.98	December	0.03	0.02	1.00	0.99
January	0.04	0.03	0.99	0.97	January	0.03	0.02	0.99	0.98
February	0.06	0.05	0.98	0.92	February	0.21	0.17	0.47	0.03
March	0.08	0.07	0.97	0.86	March	0.21	0.16	0.50	0.07
April	0.04	0.03	0.99	0.97	April	0.22	0.17	0.26	-0.05

Table 9.5 Statistical coefficients of models generated for all counties using crop specific mask.

Cascavel	RMSE	MAE	D	R^2 Adj	Toledo	RMSE	MAE	D	R^2 Adj
October	0.33	0.29	0.37	-0.02	October	0.48	0.42	0.40	-0.02
November	0.34	0.30	0.26	-0.08	November	0.50	0.46	0.05	-0.11
December	0.32	0.27	0.52	0.08	December	0.43	0.36	0.65	0.18
January	0.27	0.21	0.74	0.33	January	0.29	0.24	0.89	0.62
February	0.34	0.30	0.30	-0.06	February	0.45	0.39	0.61	0.12
March	0.35	0.29	0.04	-0.11	March	0.48	0.41	0.36	-0.03
April	0.33	0.29	0.36	-0.02	April	0.47	0.42	0.42	0.01
Castro	**RMSE**	**MAE**	**D**	**R^2 Adj**	**Ponta Grossa**	**RMSE**	**MAE**	**D**	**R^2 Adj**
October	0.25	0.18	0.02	-0.11	October	0.20	0.17	0.56	0.11
November	0.25	0.19	0.11	-0.10	November	0.19	0.18	0.63	0.19
December	0.24	0.17	0.44	0.01	December	0.13	0.11	0.90	0.66
January	0.25	0.18	0.15	-0.09	January	0.17	0.15	0.76	0.36
February	0.25	0.18	0.01	-0.11	February	0.23	0.16	0.03	-0.11
March	0.22	0.18	0.59	0.13	March	0.19	0.14	0.65	0.20
April	0.25	0.18	0.16	-0.09	April	0.16	0.13	0.82	0.46

3. Estimate Yield using correlation maps and temporal stability.
    - Eastern region

Table 9.6 Monthly methodology for Arapoti county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha)

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.1	2.9	6.8	3.0	4.8	3.1	0.3	3.1	-0.8	3.1	-1.6	3.1	0.1	3.0	3.7
200102	3.4	3.2	4.3	3.1	7.8	3.2	7.0	3.1	8.2	3.1	9.1	3.1	8.5	3.2	5.3
200203	3.0	3.4	-12.8	3.1	-4.4	3.1	-2.4	3.1	-2.5	2.9	4.0	3.3	-10.3	3.2	-5.2
200304	3.2	3.2	-1.3	3.1	3.4	3.0	5.8	3.1	3.1	2.8	15.5	3.0	6.1	2.9	8.4
200405	2.0	2.2	-7.9	2.1	-4.7	3.1	-35.1	3.1	-35.0	2.9	-30.3	2.1	-4.9	2.2	-9.2
200506	2.8	2.8	-0.2	2.9	-2.6	3.1	-10.8	3.1	-10.6	2.8	-1.0	3.1	-10.2	2.8	-0.2
200607	3.3	3.2	3.4	3.4	-4.3	3.1	6.4	3.1	5.8	3.1	3.6	3.1	5.9	3.2	2.8
200708	3.4	3.4	0.7	3.3	4.3	3.2	7.1	3.1	11.2	3.2	6.5	3.3	3.8	3.3	2.4
200809	3.3	3.4	-2.1	3.5	-6.0	3.2	3.9	3.1	5.5	3.3	0.3	3.2	1.6	3.2	3.4
200910	3.2	3.1	3.3	3.3	-1.9	3.0	6.8	3.1	4.3	3.3	-2.6	3.1	1.7	3.5	-8.2
201011	3.4	3.2	5.1	3.3	3.2	3.1	11.1	3.1	10.9	3.5	-3.3	3.5	-2.5	3.5	-4.1
RMSE		0.176		0.143		0.385		0.388		0.317		0.190		0.164	
MAE		0.134		0.133		0.271		0.274		0.209		0.156		0.146	
Adj. R^2		0.773		0.849		-0.087		-0.107		0.260		0.736		0.802	
d		0.941		0.962		0.157		0.079		0.679		0.930		0.949	

Table 9.7 Phenological methodology for Arapoti county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.10	3.10	0.08	3.09	0.48	3.32	-6.70	3.07	1.14
200102	3.38	3.09	9.52	3.09	9.49	3.30	2.48	2.97	13.88
200203	3.00	3.11	-3.63	3.09	-2.80	2.66	12.88	3.20	-6.33
200304	3.19	3.09	3.34	3.09	3.26	3.20	-0.46	3.06	4.38
200405	2.00	3.08	-34.98	3.09	-35.36	2.58	-22.53	3.00	-33.44
200506	2.78	3.10	-10.33	3.09	-9.97	2.99	-6.87	3.09	-10.07
200607	3.26	3.02	8.05	3.13	4.00	3.21	1.44	3.05	7.04
200708	3.40	3.08	10.27	3.10	9.62	3.07	10.74	3.08	10.45
200809	3.30	3.09	6.72	3.09	6.80	3.54	-6.83	3.04	8.67
200910	3.20	3.14	2.04	3.07	4.24	2.92	9.41	3.22	-0.76
201011	3.40	3.12	8.91	3.08	10.24	3.21	5.95	3.24	5.05
RMSE		0.388		0.389		0.276		0.379	
MAE		0.274		0.271		0.230		0.281	
Adj. R^2		-0.105		-0.109		0.442		-0.057	
d		0.070		0.028		0.803		0.280	

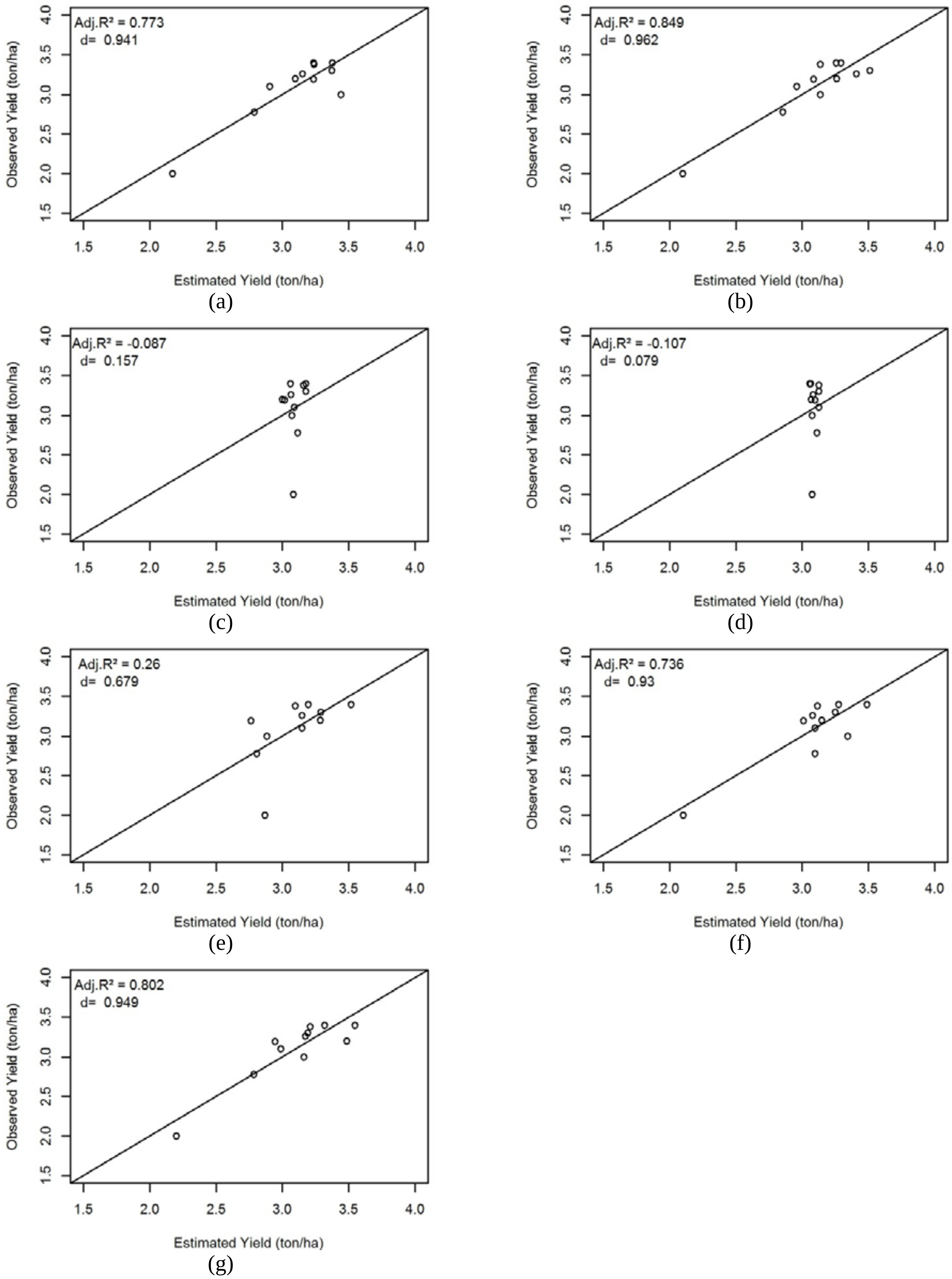


Figure 9.3 Relationship between observed and estimated yield for Arapoti county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

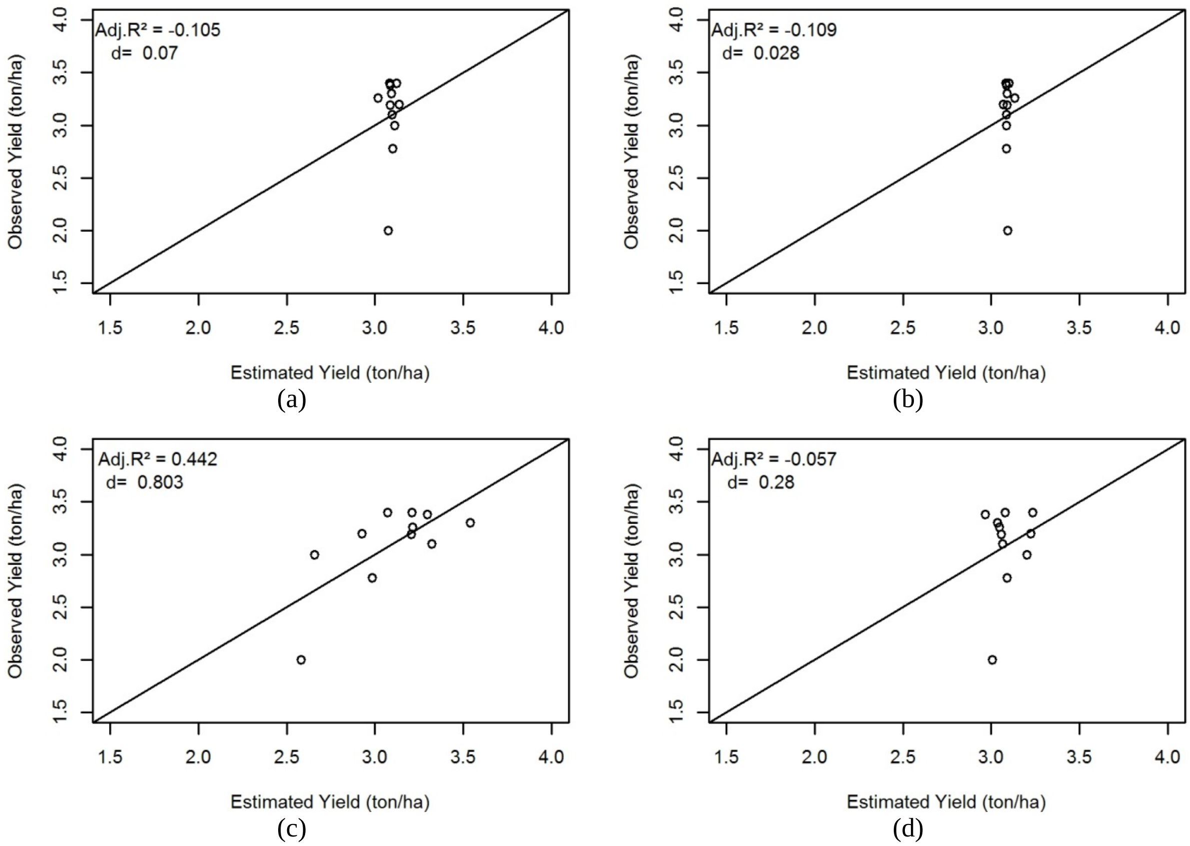


Figure 9.4 Relationship between observed and estimated yield for Arapoti county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.8 Monthly methodology for Carambei county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha)

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.2	3.0	6.1	3.1	4.3	3.2	-0.7	3.1	2.9	3.1	3.2	2.9	8.8	3.2	-1.5
200102	3.1	3.2	-3.8	3.1	1.0	3.0	4.6	3.0	2.4	3.1	0.1	3.0	3.1	3.1	-1.2
200203	3.5	3.2	7.3	3.1	11.5	3.4	2.8	3.4	1.1	3.2	6.7	3.1	12.2	3.2	8.0
200304	3.1	3.0	3.5	3.1	2.5	3.3	-4.1	3.0	4.0	3.2	-1.0	3.0	6.0	3.3	-3.2
200405	2.6	2.5	2.3	3.1	-15.0	2.6	-1.5	2.7	-5.3	2.9	-9.9	3.2	-18.0	2.8	-6.5
200506	2.8	3.1	-8.2	3.1	-8.5	2.7	4.2	2.7	4.8	2.8	1.3	3.1	-9.2	2.5	11.1
200607	3.4	3.4	-0.4	3.1	7.1	3.3	2.7	3.4	-0.9	3.5	-3.3	3.1	7.4	3.2	5.0
200708	3.2	3.4	-6.7	3.1	1.9	3.1	1.6	3.3	-5.4	3.3	-3.7	3.0	4.8	3.2	-1.9
200809	2.3	2.4	-4.6	3.1	-27.3	2.4	-5.5	2.6	-12.5	2.3	-1.0	3.0	-25.1	2.7	-16.4
200910	3.3	3.4	-4.0	3.1	5.3	3.3	-2.9	2.9	11.1	3.4	-5.6	3.2	1.7	3.0	8.8
201011	3.6	3.3	8.2	3.1	17.2	3.7	-1.7	3.7	-2.7	3.2	12.8	3.3	8.3	3.7	-2.5
RMSE		0.176		0.370		0.094		0.169		0.184		0.354		0.211	
MAE		0.156		0.285		0.087		0.140		0.138		0.293		0.174	
Adj. R^2		0.750		0.108		0.928		0.767		0.725		-0.015		0.641	
d		0.933		0.076		0.983		0.939		0.924		0.380		0.895	

Table 9.9 Phenological methodology for Carambei county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.200	3.101	3.2	3.046	5.1	3.157	1.4	3.230	-0.9
200102	3.100	3.072	0.9	3.101	0.0	2.800	10.7	3.089	0.4
200203	3.450	3.082	11.9	3.068	12.5	3.327	3.7	3.504	-1.6
200304	3.150	3.091	1.9	3.082	2.2	3.232	-2.5	3.243	-2.9
200405	2.600	3.084	-15.7	3.068	-15.3	2.908	-10.6	2.813	-7.6
200506	2.810	3.098	-9.3	3.090	-9.1	2.907	-3.3	2.791	0.7
200607	3.350	3.035	10.4	3.178	5.4	3.250	3.1	3.179	5.4
200708	3.150	3.085	2.1	3.066	2.8	3.083	2.2	3.069	2.6
200809	2.260	3.080	-26.6	3.085	-26.8	2.343	-3.5	2.285	-1.1
200910	3.250	3.074	5.7	3.054	6.4	3.172	2.5	3.052	6.5
201011	3.600	3.119	15.4	3.082	16.8	3.740	-3.8	3.666	-1.8
RMSE		0.370		0.369		0.155		0.112	
MAE		0.289		0.286		0.129		0.087	
Adj. R^2		-0.108		-0.102		0.805		0.898	
d		0.060		0.081		0.950		0.976	

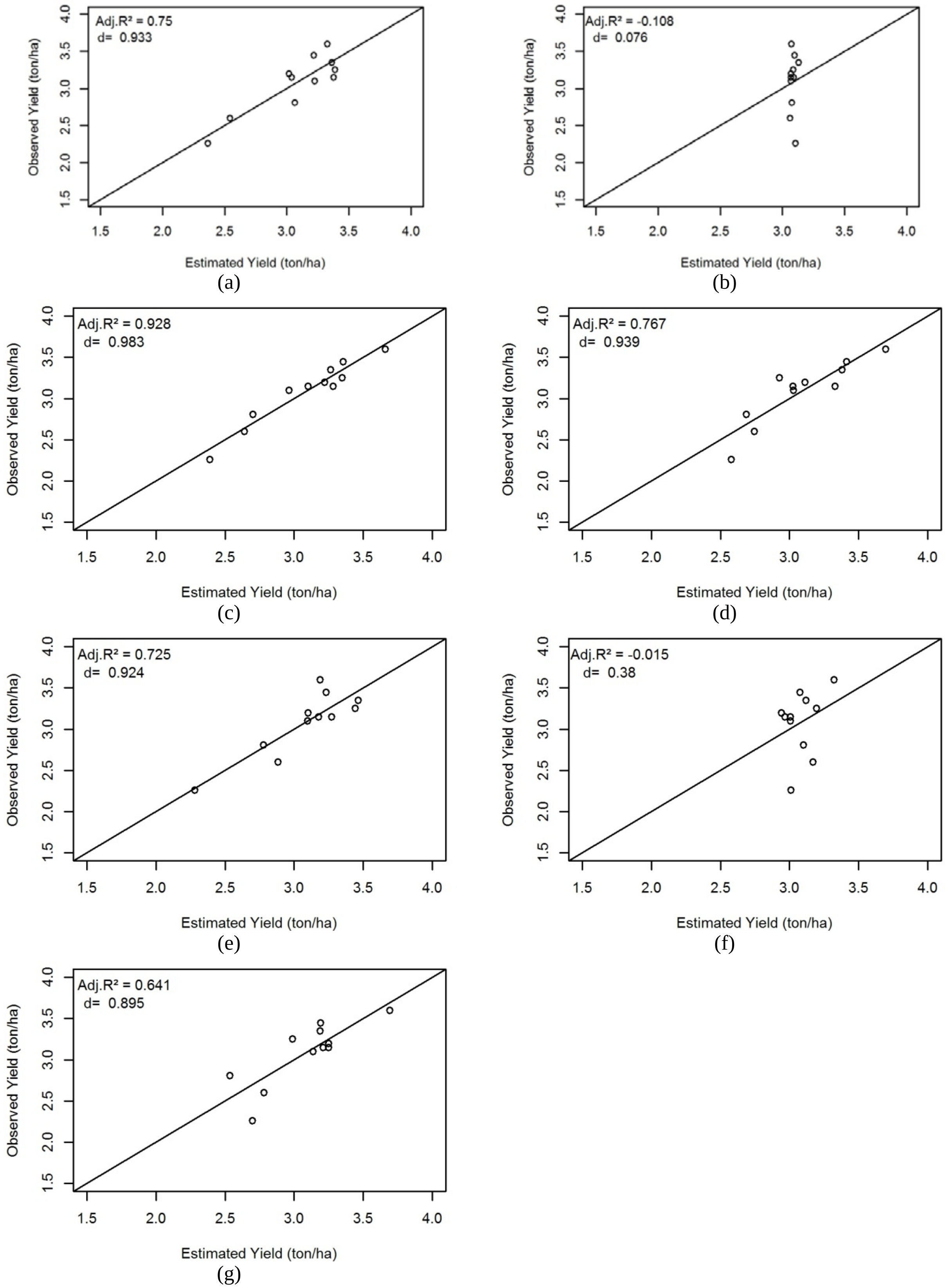


Figure 9.5 Relationship between observed and estimated yield for Carambei county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

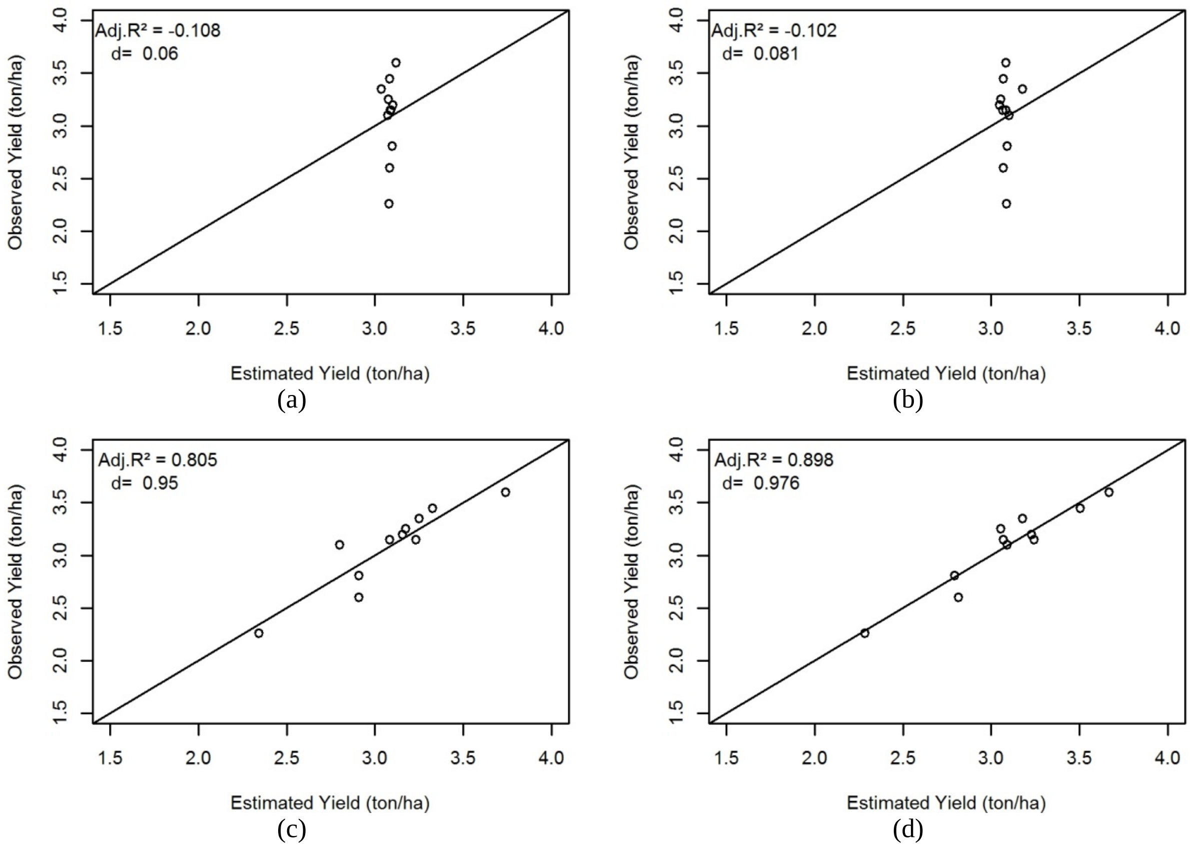


Figure 9.6 Relationship between observed and estimated yield for Carambei county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.10 Monthly methodology for Castro county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha)

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.2	3.0	6.3	3.3	-2.5	3.1	2.4	3.0	5.0	3.0	6.3	3.1	1.7	3.2	-0.3
200102	3.2	3.2	-2.1	3.3	-4.5	3.2	-2.3	3.1	0.1	3.1	0.2	3.1	0.6	3.1	0.4
200203	3.4	3.3	3.4	3.2	5.3	3.4	1.5	3.3	4.5	3.3	3.4	3.2	5.7	3.4	1.3
200304	3.1	3.1	-1.4	3.2	-2.3	3.2	-2.9	3.2	-2.5	3.2	-4.2	2.9	6.1	3.2	-2.7
200405	3.2	3.1	0.1	3.4	-6.5	3.3	-4.8	3.1	1.3	3.4	-7.2	3.3	-3.9	3.3	-5.1
200506	3.0	3.0	-0.4	3.1	-2.2	2.9	2.0	3.0	-0.3	3.0	1.1	3.1	-2.2	2.9	3.7
200607	3.3	3.4	-2.3	3.2	4.5	3.3	0.0	3.3	-0.3	3.3	1.1	3.3	0.6	3.1	7.4
200708	3.1	3.3	-4.6	3.1	-0.2	3.0	3.6	3.2	-2.2	3.2	-1.5	3.2	-1.2	3.1	2.5
200809	2.6	2.6	-2.1	2.7	-4.8	2.6	-2.4	3.2	-18.5	2.7	-4.8	2.7	-5.5	2.8	-8.7
200910	3.2	3.3	-1.8	3.0	7.1	3.2	-0.1	3.1	3.9	3.2	2.2	3.3	-1.1	3.2	1.7
201011	3.5	3.4	4.3	3.3	5.5	3.4	2.5	3.2	8.5	3.4	2.8	3.5	-1.5	3.5	-0.6
RMSE		0.100		0.146		0.083		0.212		0.121		0.103		0.125	
MAE		0.082		0.130		0.070		0.136		0.100		0.083		0.096	
Adj. R^2		0.786		0.544		0.853		0.037		0.683		0.770		0.667	
d		0.945		0.857		0.964		0.420		0.912		0.939		0.907	

Table 9.11 Phenological methodology for Castro county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.20	3.15	1.52	3.10	3.13	3.23	-0.97	3.19	0.30
200102	3.15	3.09	1.87	3.18	-0.90	2.86	10.12	3.25	-3.12
200203	3.40	3.21	6.00	3.21	6.01	3.25	4.62	3.19	6.48
200304	3.10	3.04	1.91	3.09	0.46	3.25	-4.64	3.26	-5.04
200405	3.15	3.19	-1.38	3.16	-0.26	3.11	1.23	3.12	1.00
200506	3.00	2.97	1.15	3.05	-1.66	3.22	-6.75	3.16	-5.06
200607	3.30	3.51	-6.08	3.56	-7.18	3.35	-1.40	3.21	2.91
200708	3.13	3.16	-0.95	3.20	-2.05	3.15	-0.71	3.14	-0.22
200809	2.58	2.77	-7.02	2.76	-6.55	2.88	-10.47	3.05	-15.33
200910	3.25	3.19	2.00	3.12	4.16	3.17	2.53	3.10	4.91
201011	3.50	3.47	0.83	3.34	4.64	3.29	6.45	3.09	13.15
RMSE		0.112		0.133		0.172		0.218	
MAE		0.088		0.107		0.140		0.164	
Adj. R^2		0.730		0.623		0.368		-0.020	
d		0.926		0.888		0.763		0.386	

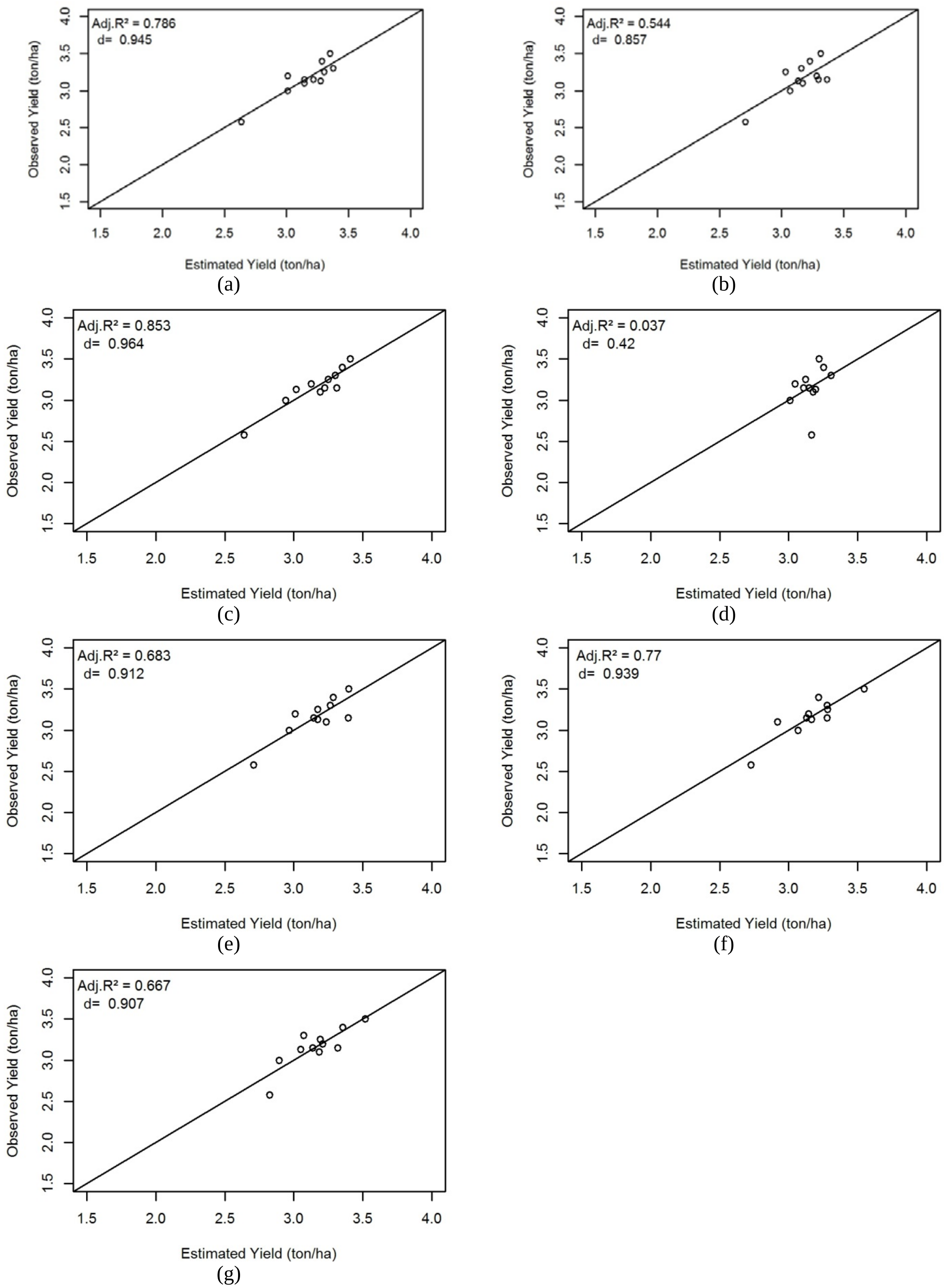
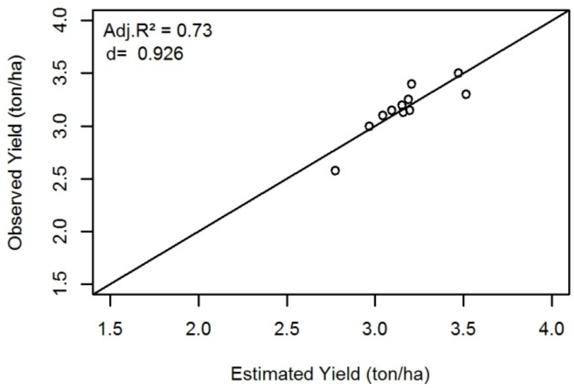
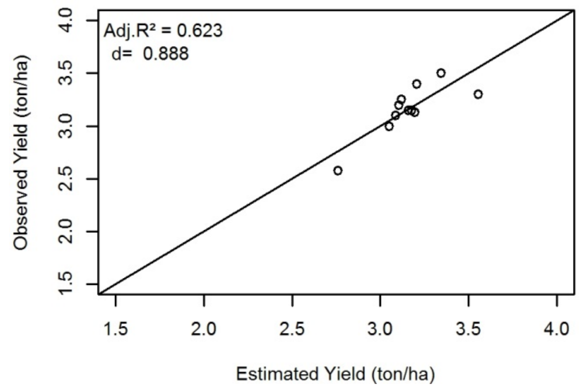


Figure 9.7 Relationship between observed and estimated yield for Castro county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.



(a)



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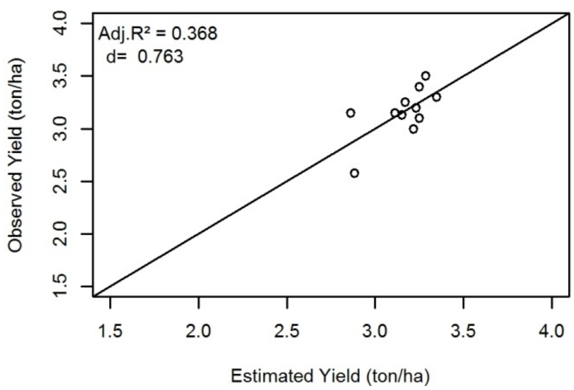

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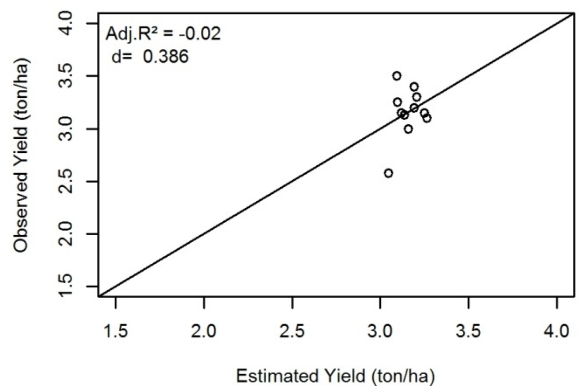


(d)

Figure 9.8 Relationship between observed and estimated yield for Castro county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.12 Monthly methodology for Curiuva county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha)

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	2.5	2.9	-12.3	2.7	-8.2	2.7	-6.7	2.4	2.5	2.3	7.7	2.8	-9.1	2.7	-8.9
200102	2.7	2.8	-2.6	2.9	-7.8	2.5	9.3	2.8	-3.7	3.0	-11.2	2.8	-2.7	2.8	-2.7
200203	2.4	2.7	-10.6	2.2	11.4	2.7	-12.6	2.7	-12.1	2.4	-2.0	2.8	-13.7	2.8	-13.2
200304	3.3	2.7	20.6	3.1	7.4	3.2	3.1	2.8	17.7	3.2	1.4	2.8	17.2	2.7	19.8
200405	2.9	2.8	2.1	2.9	-3.0	2.8	3.6	2.9	-1.0	2.9	-2.1	2.9	-1.4	2.7	4.4
200506	2.5	2.8	-10.4	2.6	-5.7	2.5	-2.6	2.7	-7.7	2.6	-3.7	2.8	-10.8	2.8	-11.1
200607	3.0	2.8	6.9	2.8	7.1	3.0	0.0	3.1	-4.6	3.0	0.4	2.8	7.6	2.8	7.6
200708	2.5	2.8	-10.7	2.8	-13.5	2.5	0.2	2.8	-10.9	2.6	-6.3	2.7	-10.3	2.8	-12.0
200809	2.5	2.8	-10.8	2.6	-3.6	2.4	4.2	2.3	5.9	2.5	-1.2	2.7	-9.4	2.8	-11.2
200910	3.0	2.8	5.3	2.8	4.6	3.1	-5.3	3.0	0.5	2.7	8.6	2.8	7.7	2.8	5.7
201011	3.4	2.8	22.1	3.0	11.7	3.2	6.8	3.0	13.2	3.1	8.3	2.7	24.6	2.8	21.2
RMSE		0.334		0.231		0.169		0.253		0.171		0.334		0.336	
MAE		0.289		0.211		0.137		0.203		0.135		0.288		0.298	
Adj. R^2		-0.093		0.480		0.722		0.376		0.716		-0.094		-0.104	
d		0.182		0.827		0.923		0.758		0.923		0.152		0.119	

Table 9.13 Phenological methodology for Curiuva county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	2.5	2.5	-1.1	2.5	1.1	2.7	-6.8	2.8	-12.1
200102	2.7	2.6	2.3	2.8	-4.0	2.6	2.2	2.9	-5.6
200203	2.4	2.4	1.0	2.7	-10.0	2.8	-12.9	2.6	-6.3
200304	3.3	3.0	10.7	3.0	10.4	2.9	12.9	2.9	14.1
200405	2.9	2.8	1.7	3.0	-4.8	3.0	-5.1	2.8	3.1
200506	2.5	2.6	-6.1	2.5	-2.6	2.7	-9.1	2.7	-9.7
200607	3.0	3.2	-6.5	3.2	-5.9	2.8	8.2	2.8	7.6
200708	2.5	2.7	-10.0	2.6	-5.7	2.2	9.5	2.8	-12.3
200809	2.5	2.7	-8.7	2.8	-10.9	2.8	-11.5	2.8	-12.2
200910	3.0	2.6	13.7	2.6	14.9	3.0	-1.3	2.6	16.6
201011	3.4	3.3	2.7	2.9	16.9	3.0	14.0	2.9	16.3
RMSE		0.202		0.261		0.264		0.317	
MAE		0.164		0.222		0.236		0.293	
Adj. R^2		0.601		0.333		0.318		0.018	
d		0.881		0.743		0.719		0.465	

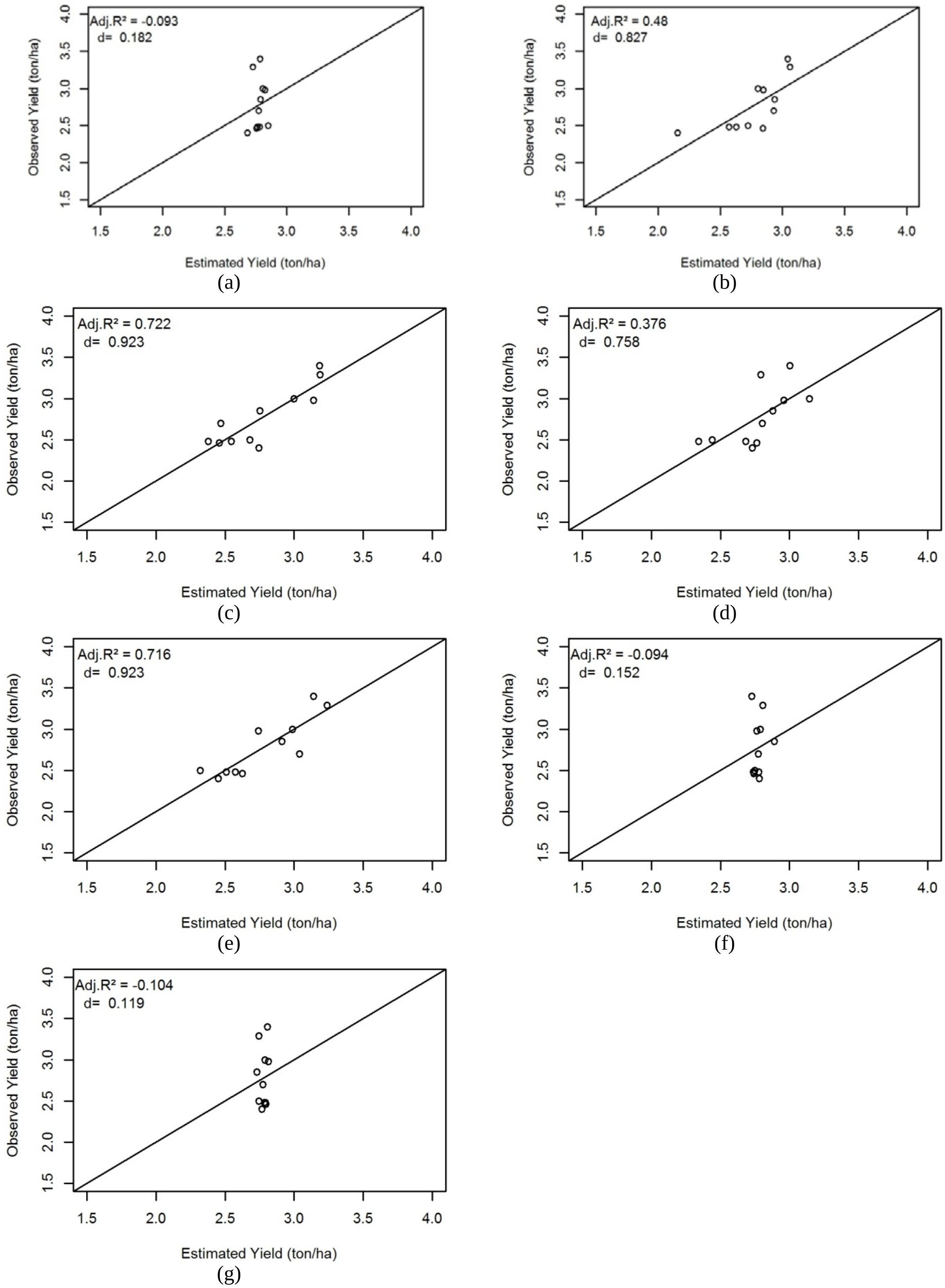


Figure 9.9 Relationship between observed and estimated yield for Curiuva county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

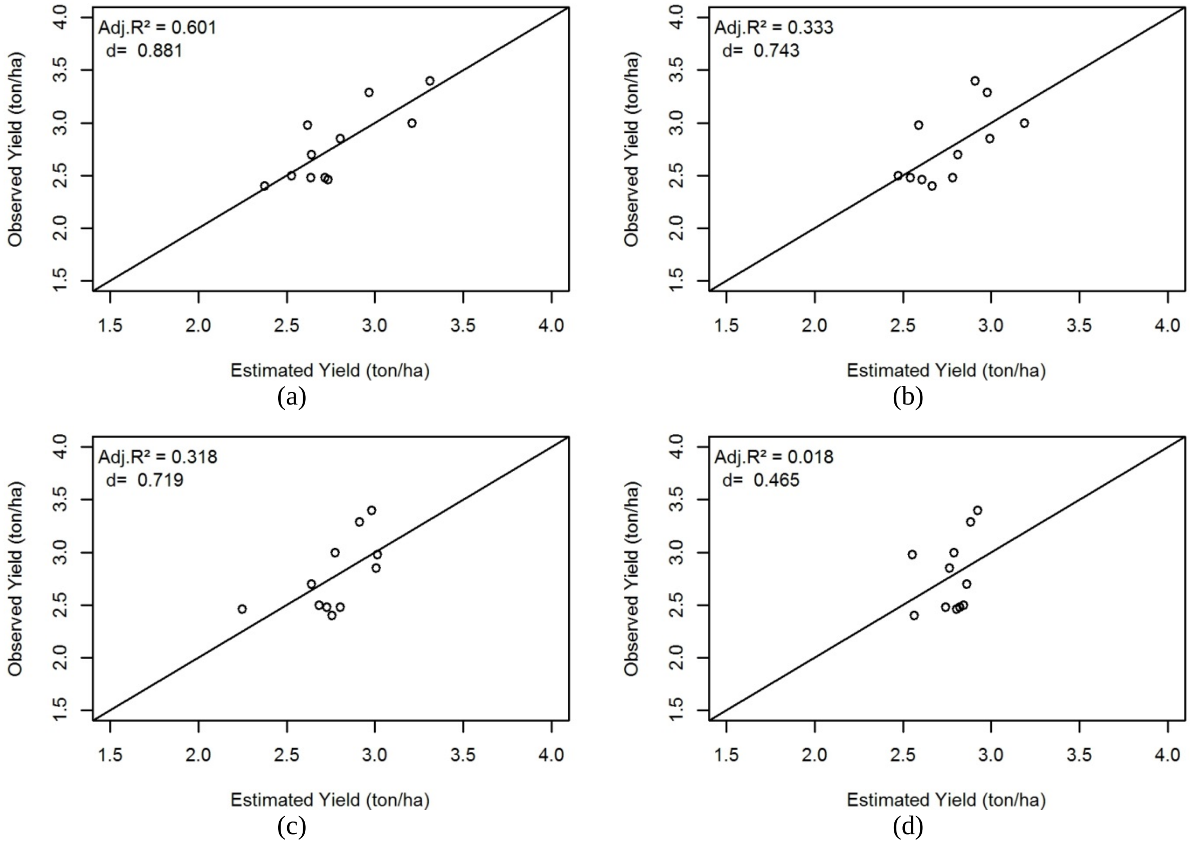


Figure 9.10 Relationship between observed and estimated yield for Curiuva county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.14 Monthly methodology for Ipiranga county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.0	3.1	-3.5	3.1	-2.9	2.9	3.0	3.0	1.1	3.0	0.6	2.9	2.7	3.1	-4.6
200102	2.7	3.2	-14.3	3.0	-9.8	3.0	-10.2	2.8	-4.2	2.8	-4.3	2.8	-3.0	3.1	-14.2
200203	3.2	3.2	2.3	3.2	1.1	3.2	-0.1	3.3	-2.9	3.2	2.1	3.3	-0.6	3.1	3.0
200304	3.0	3.1	-4.6	3.0	-0.3	3.0	-0.6	2.9	1.7	3.0	0.3	3.0	-0.5	3.1	-4.4
200405	3.1	3.1	-1.5	3.0	4.1	3.1	-1.5	3.2	-3.7	3.2	-3.7	3.2	-2.0	3.1	-1.5
200506	3.1	3.1	-1.1	3.3	-4.9	3.3	-5.0	3.2	-1.7	3.0	2.3	3.0	3.0	3.1	-1.3
200607	3.3	3.2	4.7	3.4	-1.8	3.3	1.0	3.3	-1.4	3.3	-1.3	3.3	1.3	3.1	4.8
200708	3.1	3.2	-2.1	3.0	3.9	3.2	-2.4	3.1	-0.9	3.0	3.6	3.2	-3.4	3.1	-1.4
200809	3.3	3.1	5.9	3.3	0.1	3.0	9.6	3.1	7.5	3.3	0.9	3.4	-2.6	3.1	4.8
200910	3.3	3.1	3.4	3.2	1.0	3.2	0.3	3.2	0.1	3.3	-1.3	3.3	-1.2	3.1	3.5
201011	3.5	3.2	10.9	3.2	9.6	3.3	5.9	3.4	4.3	3.5	0.7	3.3	6.3	3.1	11.3
RMSE		0.199		0.150		0.153		0.105		0.071		0.092		0.200	
MAE		0.155		0.111		0.112		0.084		0.059		0.076		0.157	
Adj. R^2		-0.103		0.376		0.344		0.694		0.859		0.765		-0.111	
d		0.103		0.762		0.762		0.917		0.965		0.938		0.021	

Table 9.15 Phenological methodology for Ipiranga county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.0	3.1	-3.7	3.1	-3.7	3.2	-4.9	3.0	1.2
200102	2.7	3.1	-12.9	3.0	-10.4	3.0	-9.1	2.9	-5.4
200203	3.2	3.1	2.6	3.1	3.6	3.2	0.6	3.1	4.8
200304	3.0	3.1	-3.9	3.1	-2.7	3.1	-2.1	3.0	1.0
200405	3.1	3.1	-0.9	3.2	-1.8	3.1	-0.7	3.1	1.2
200506	3.1	3.2	-3.3	3.2	-3.4	3.3	-5.4	3.2	-3.5
200607	3.3	3.1	8.0	3.0	10.9	3.2	2.4	3.3	-0.6
200708	3.1	3.2	-2.1	3.2	-2.2	3.1	0.3	3.3	-5.5
200809	3.3	3.2	3.1	3.2	1.6	3.2	2.3	3.3	1.5
200910	3.3	3.2	1.4	3.3	-1.2	3.2	1.9	3.3	-2.5
201011	3.5	3.1	11.5	3.2	9.1	3.0	14.7	3.2	7.7
RMSE		0.194		0.178		0.179		0.124	
MAE		0.152		0.143		0.126		0.100	
Adj. R^2		-0.054		0.120		0.106		0.572	
d		0.293		0.589		0.590		0.871	

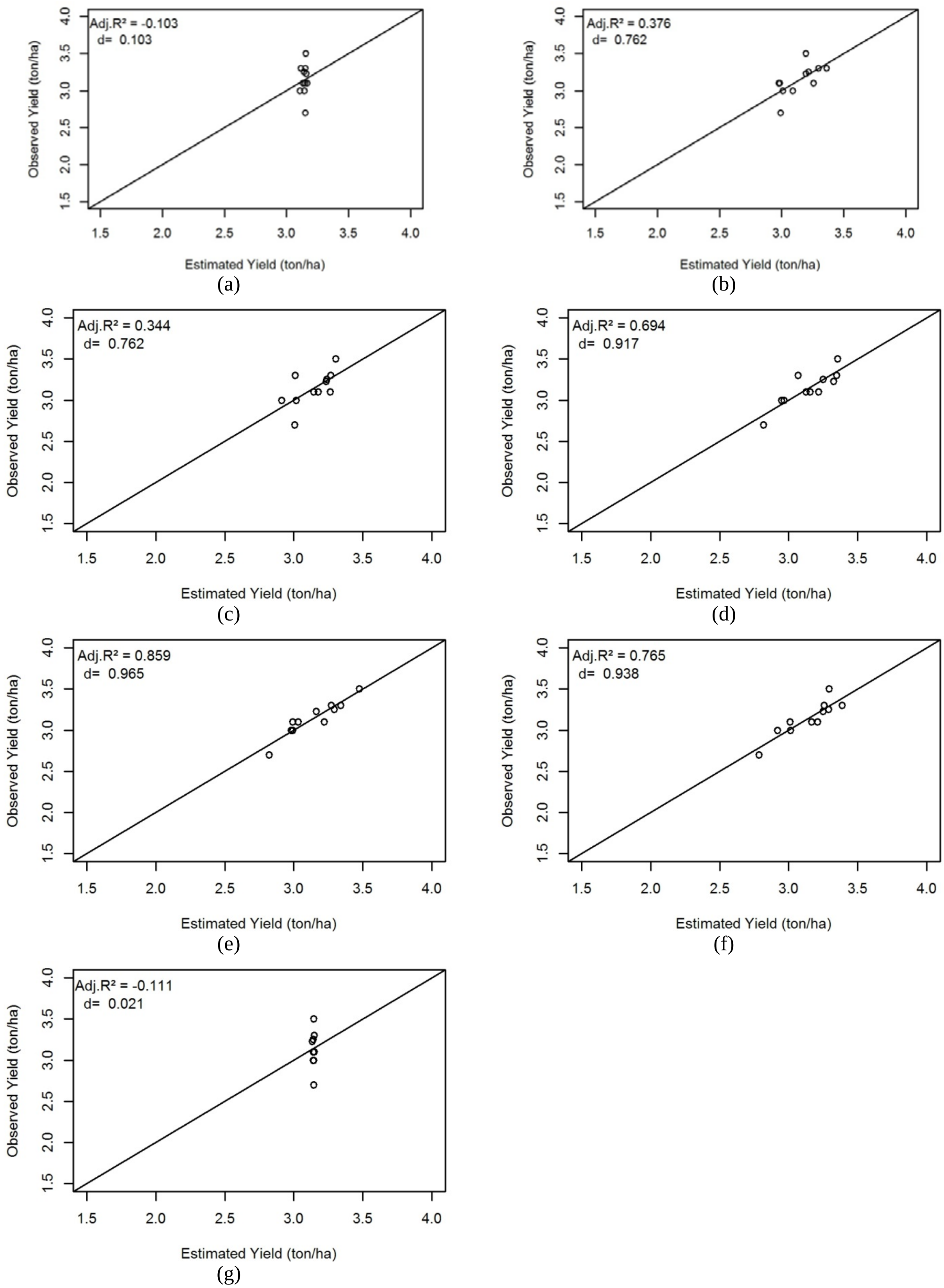


Figure 9.11 Relationship between observed and estimated yield for Ipiranga county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

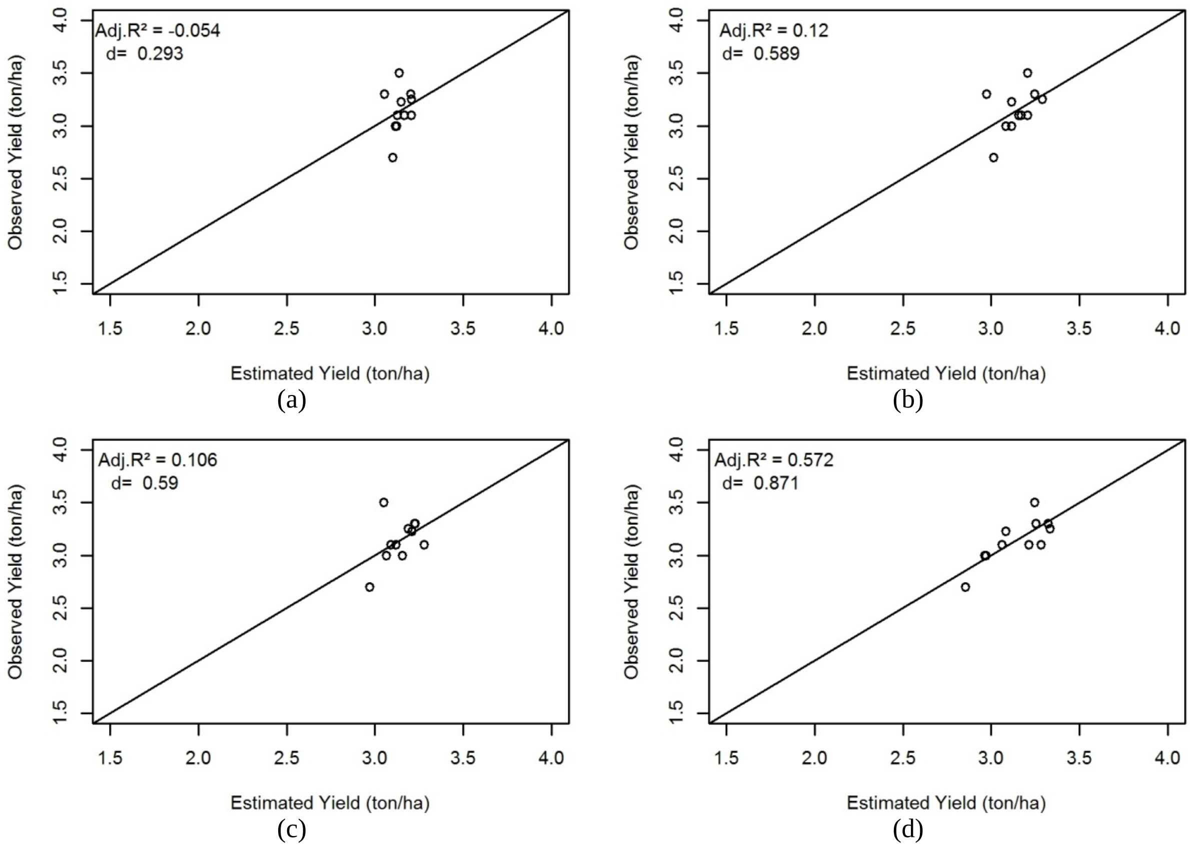


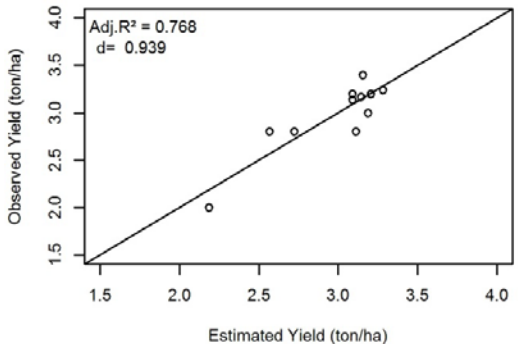
Figure 9.12 Relationship between observed and estimated yield for Ipiranga county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.16.Monthly methodology for Jaguariaiva county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

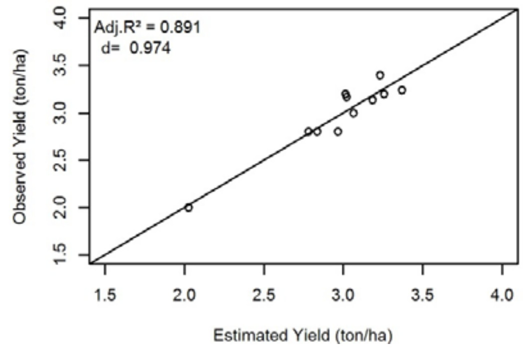
Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	2.8	2.6	9.1	3.0	-5.7	2.6	9.4	2.6	6.7	3.0	-7.1	3.1	-10.6	3.1	-9.2
200102	3.2	3.2	-0.2	3.0	6.2	3.0	6.5	3.0	6.9	2.7	16.8	3.3	-2.4	3.1	3.9
200203	3.0	3.2	-5.9	3.1	-2.1	3.2	-6.5	2.9	4.6	3.1	-2.9	2.7	9.9	3.1	-1.7
200304	3.1	3.1	1.6	3.2	-1.4	3.2	-2.0	2.9	7.8	3.0	4.6	2.9	7.0	3.1	1.7
200405	2.0	2.2	-8.5	2.0	-1.2	2.3	-13.8	2.5	-20.3	2.3	-12.6	2.8	-28.9	2.0	-1.7
200506	2.8	2.7	2.9	2.8	-1.2	2.7	2.9	2.7	2.3	2.8	-0.3	2.9	-2.5	3.1	-9.0
200607	3.2	3.3	-1.2	3.4	-3.8	3.3	-3.2	3.4	-4.5	3.2	0.6	3.2	2.5	3.0	6.7
200708	3.2	3.1	0.8	3.0	5.0	3.0	5.9	3.3	-2.9	3.0	6.8	3.0	6.2	3.1	3.7
200809	2.8	3.1	-10.1	2.8	0.7	2.8	0.2	2.7	1.8	3.3	-14.2	2.8	-1.1	3.1	-10.3
200910	3.2	3.1	3.5	3.3	-1.8	3.2	-0.7	3.3	-3.5	3.1	2.6	3.1	3.8	3.1	4.3
201011	3.4	3.2	7.6	3.2	5.1	3.4	0.8	3.4	0.5	3.2	5.1	2.9	16.0	3.0	11.5
RMSE		0.166		0.114		0.164		0.203		0.245		0.327		0.209	
MAE		0.134		0.095		0.132		0.159		0.193		0.241		0.177	
Adj. R^2		0.768		0.891		0.775		0.654		0.499		0.106		0.636	
d		0.939		0.974		0.940		0.899		0.848		0.540		0.897	

Table 9.17 Phenological methodology for Jaguariaiva county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

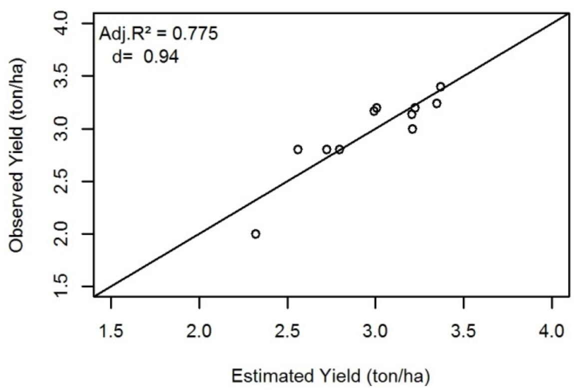
Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	2.8	2.9	-3.7	2.8	-0.9	2.9	-2.2	2.8	-0.2
200102	3.2	3.0	7.4	3.1	2.4	2.6	21.1	3.1	4.4
200203	3.0	2.9	1.9	2.9	3.7	3.0	-0.9	3.1	-4.3
200304	3.1	2.9	6.7	3.1	2.3	3.1	2.7	3.1	1.3
200405	2.0	2.2	-11.0	2.6	-23.6	2.5	-19.0	2.1	-6.1
200506	2.8	2.9	-2.7	2.9	-3.1	2.7	2.2	2.7	4.4
200607	3.2	2.9	10.2	3.6	-9.3	3.3	-0.6	3.2	1.1
200708	3.2	3.2	-0.9	2.9	7.6	3.1	3.9	3.0	4.2
200809	2.8	2.9	-4.2	2.9	-4.7	2.9	-3.4	2.8	0.3
200910	3.2	3.1	2.8	2.8	13.9	3.2	-1.5	3.4	-6.3
201011	3.4	3.7	-7.5	3.1	11.1	3.5	-2.7	3.4	0.6
RMSE		0.180		0.280		0.230		0.110	
MAE		0.156		0.220		0.149		0.088	
Adj. R^2		0.729		0.342		0.558		0.899	
d		0.926		0.748		0.868		0.976	



(a)



(b)



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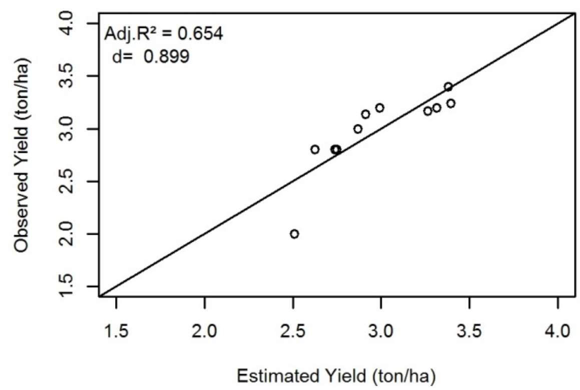

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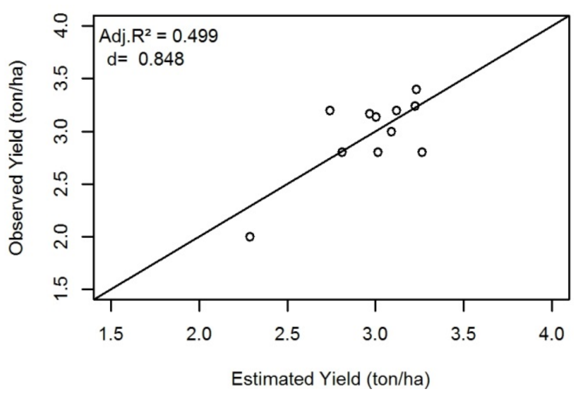

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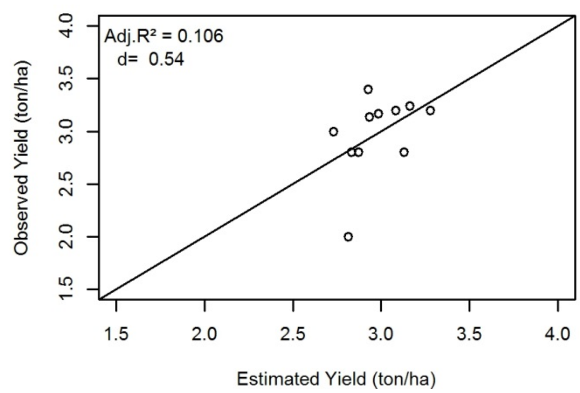

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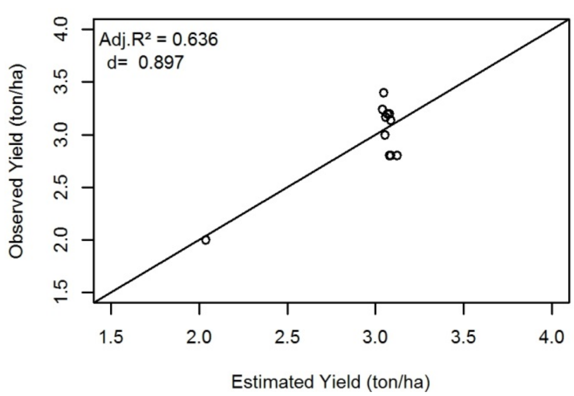


(g)

Figure 9.13 Relationship between observed and estimated yield for Jaguariaiva county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

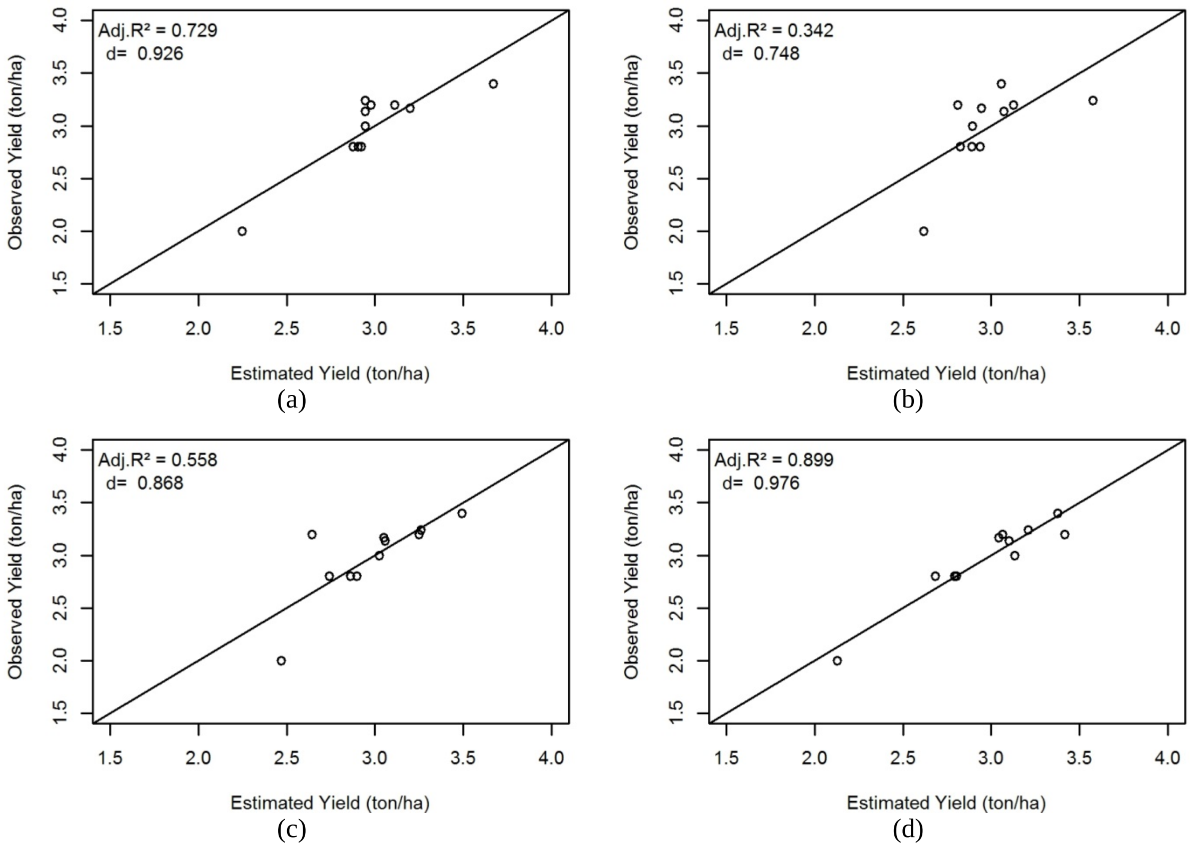


Figure 9.14 Relationship between observed and estimated yield for Jaguariaiva county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.18 Monthly methodology for Pirai do Sul county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.0	2.9	4.5	3.0	0.3	3.0	1.3	2.9	4.7	3.1	-2.3	3.1	-1.8	2.9	3.3
200102	3.1	3.1	-0.4	3.0	2.3	3.1	-0.4	3.0	2.4	3.0	4.7	3.1	1.5	3.1	1.0
200203	3.0	3.0	-1.6	3.1	-2.2	3.0	-1.5	3.0	-1.6	2.9	2.9	3.1	-1.8	3.0	1.0
200304	3.1	3.1	-1.1	3.0	4.2	3.1	-0.2	3.1	-1.0	3.0	3.1	3.1	1.3	3.1	-0.7
200405	2.6	2.6	-0.3	2.7	-3.8	2.7	-3.9	2.7	-4.7	2.7	-2.4	3.1	-14.8	2.8	-7.7
200506	3.0	3.0	0.5	3.0	-0.5	2.9	2.3	2.9	3.5	3.1	-3.4	3.1	-1.8	2.9	3.0
200607	3.3	3.3	-0.5	3.3	-1.1	3.4	-2.2	3.4	-1.9	3.1	4.8	3.1	8.1	3.3	0.2
200708	3.1	3.2	-3.3	2.9	5.4	3.0	4.6	3.1	-0.1	3.1	0.7	3.1	1.4	3.0	4.2
200809	2.8	2.8	-1.0	2.8	-2.0	2.8	0.4	2.8	-1.0	2.9	-4.6	3.1	-8.6	2.8	-1.4
200910	3.1	3.2	-2.4	3.3	-5.3	3.2	-3.6	3.2	-3.2	3.2	-3.6	3.1	1.6	3.2	-2.5
201011	3.5	3.3	5.4	3.4	2.5	3.4	3.0	3.4	2.7	3.5	-0.2	3.1	14.7	3.5	-0.7
RMSE		0.080		0.097		0.079		0.084		0.100		0.224		0.915	
MAE		0.059		0.082		0.065		0.073		0.089		0.159		0.068	
Adj. R^2		0.858		0.792		0.863		0.843		0.780		-0.111		0.820	
d		0.965		0.947		0.966		0.961		0.943		0.014		0.954	

Table 9.19 Phenological methodology for Pirai do Sul county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.0	3.0	1.7	3.0	1.7	3.0	1.7	3.0	1.7
200102	3.1	3.1	-0.4	3.0	-0.4	2.8	-0.4	3.0	-0.4
200203	3.0	2.9	2.1	3.0	2.1	3.1	2.1	3.2	2.1
200304	3.1	2.9	-7.7	3.0	-7.7	3.1	-7.7	3.1	-7.7
200405	2.6	2.9	4.8	2.9	4.8	2.8	4.8	2.6	4.8
200506	3.0	2.9	-17.8	3.0	-17.8	3.0	-17.8	3.0	-17.8
200607	3.3	3.5	14.3	3.5	14.3	3.3	14.3	3.3	14.3
200708	3.1	3.2	6.2	3.1	6.2	3.0	6.2	3.0	6.2
200809	2.8	2.9	2.0	2.9	2.0	2.9	2.0	2.9	2.0
200910	3.1	3.1	-4.3	3.0	-4.3	3.2	-4.3	3.2	-4.3
201011	3.5	3.3	-1.0	3.2	-1.0	3.4	-1.0	3.4	-1.0
RMSE		0.138		0.160		0.124		0.096	
MAE		0.108		0.122		0.092		0.082	
Adj. R^2		0.577		0.437		0.660		0.794	
d		0.869		0.801		0.905		0.948	

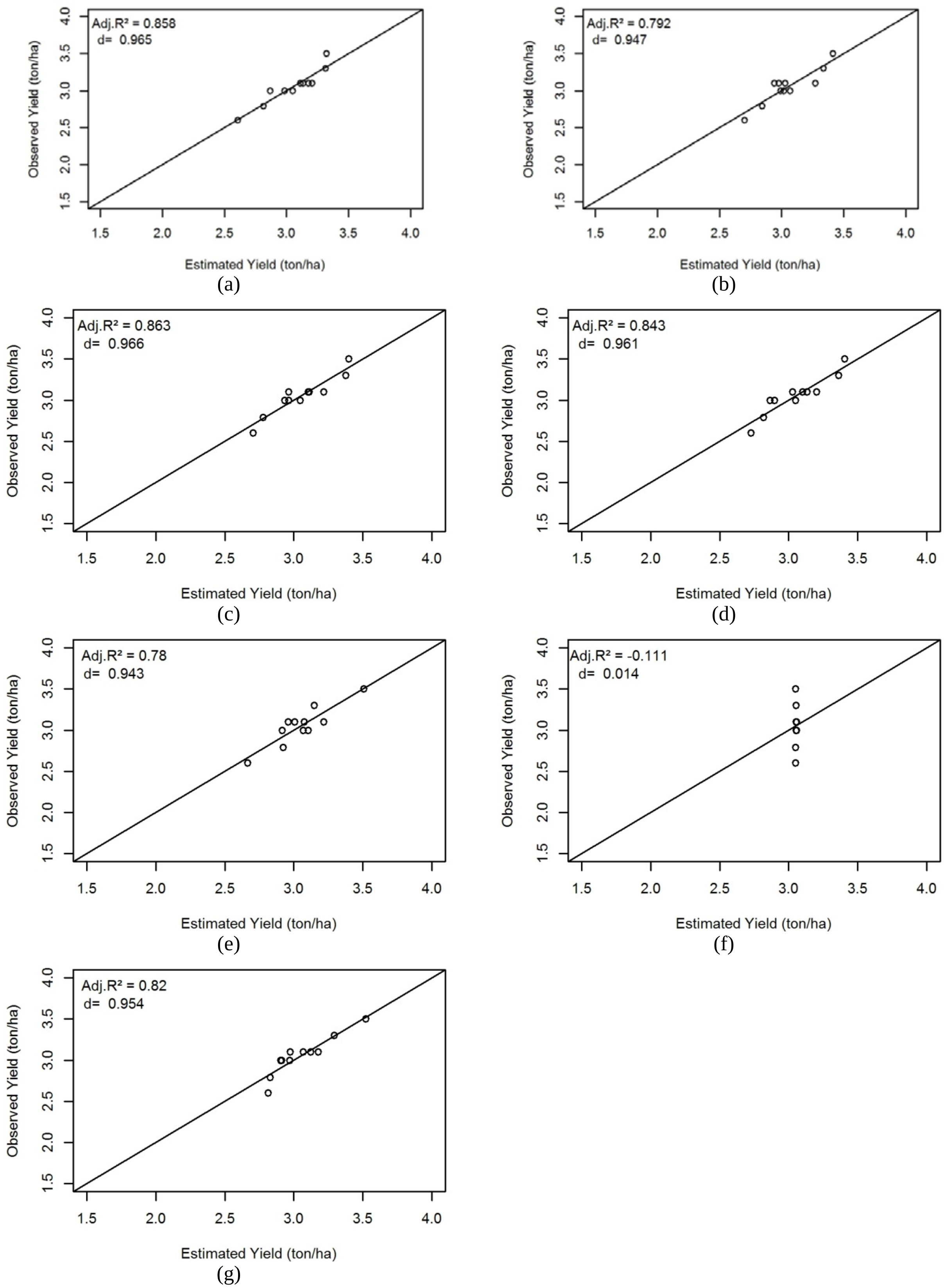


Figure 9.15 Relationship between observed and estimated yield for Pirai do Sul county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

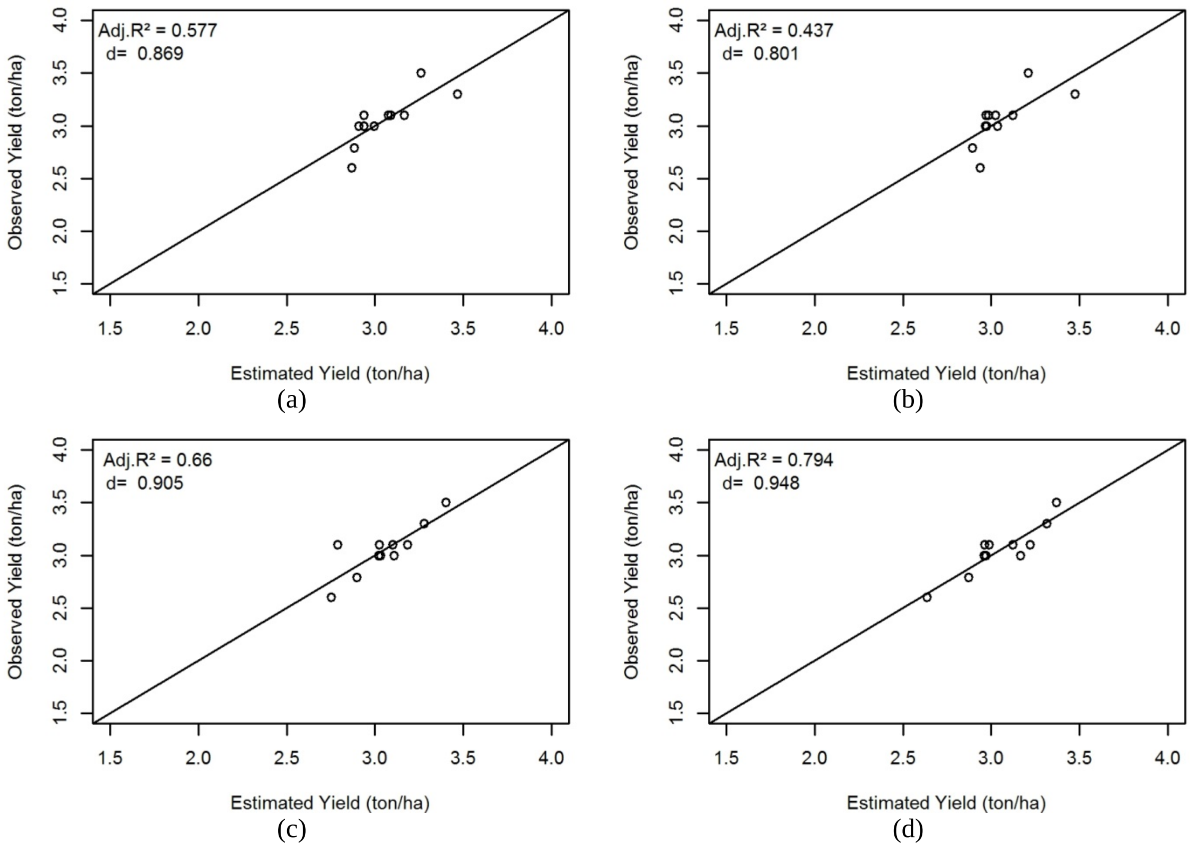


Figure 9.16 Relationship between observed and estimated yield for Pirai do Sul county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.20 Monthly methodology for Ponta Grossa county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.2	3.0	8.0	3.3	-3.2	3.2	0.7	3.1	2.8	3.2	0.3	3.2	-1.1	3.2	1.6
200102	3.1	3.2	-2.9	3.2	-1.9	3.2	-2.0	3.1	0.9	3.0	1.8	3.1	0.1	3.2	-1.8
200203	3.4	3.3	3.8	3.3	3.7	3.3	2.4	3.4	-1.1	3.3	2.3	3.3	1.6	3.1	7.3
200304	3.3	3.3	0.5	3.2	2.4	3.3	-0.8	3.2	2.3	3.3	0.1	3.2	3.5	3.2	4.5
200405	3.2	3.2	-2.6	3.3	-4.5	3.0	3.5	3.2	-1.4	3.3	-3.5	3.2	-0.5	3.2	-0.2
200506	2.8	2.9	-3.6	2.9	-3.9	2.8	-0.9	2.7	0.6	2.9	-5.0	2.8	-0.1	3.2	-12.5
200607	3.2	3.3	-3.4	3.2	0.6	3.3	-1.6	3.3	-2.5	3.2	-0.5	3.2	-0.6	3.2	1.3
200708	3.2	3.2	-0.8	3.2	-1.3	3.2	0.5	3.3	-1.6	3.2	-1.3	3.2	1.1	3.2	1.4
200809	2.7	2.7	-1.3	2.6	2.7	2.7	-0.5	2.7	-1.6	2.6	3.2	2.7	-1.0	3.1	-14.2
200910	3.2	3.3	-3.1	3.2	1.3	3.2	-1.1	3.2	-0.4	3.2	0.5	3.3	-1.9	3.1	1.6
201011	3.5	3.3	5.4	3.4	4.1	3.5	-0.2	3.4	1.9	3.4	2.2	3.5	-1.1	3.1	11.1
RMSE		0.119		0.094		0.051		0.055		0.073		0.047		0.227	
MAE		0.101		0.085		0.041		0.049		0.058		0.037		0.165	
Adj. R^2		0.696		0.810		0.944		0.935		0.885		0.951		-0.111	
d		0.916		0.951		0.987		0.985		0.972		0.989		0.026	

Table 9.21 Phenological methodology for Ponta Grossa county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.2	3.3	-3.4	3.2	0.3	3.2	-0.7	3.2	-1.4
200102	3.1	3.2	-4.4	3.2	-2.4	2.9	7.4	3.1	-1.5
200203	3.4	3.3	3.3	3.2	4.9	3.4	-0.4	3.4	0.6
200304	3.3	3.3	-1.2	3.2	3.2	3.3	1.0	3.3	-0.9
200405	3.2	3.1	0.9	3.1	0.4	3.2	-0.8	3.2	0.0
200506	2.8	3.0	-9.3	3.1	-12.1	2.9	-4.4	2.8	-0.5
200607	3.2	2.9	10.0	3.0	8.2	3.2	-1.3	3.3	-1.6
200708	3.2	3.1	1.9	3.2	0.8	3.2	0.2	3.2	0.2
200809	2.7	2.9	-6.7	3.1	-13.3	2.7	-1.4	2.7	1.4
200910	3.2	3.2	-0.2	3.2	0.3	3.2	-1.2	3.2	0.8
201011	3.5	3.2	8.8	3.2	9.7	3.4	1.5	3.4	2.8
RMSE		0.174		0.216		0.080		0.043	
MAE		0.141		0.158		0.055		0.035	
Adj. R^2		0.342		-0.009		0.860		0.960	
d		0.747		0.327		0.965		0.991	

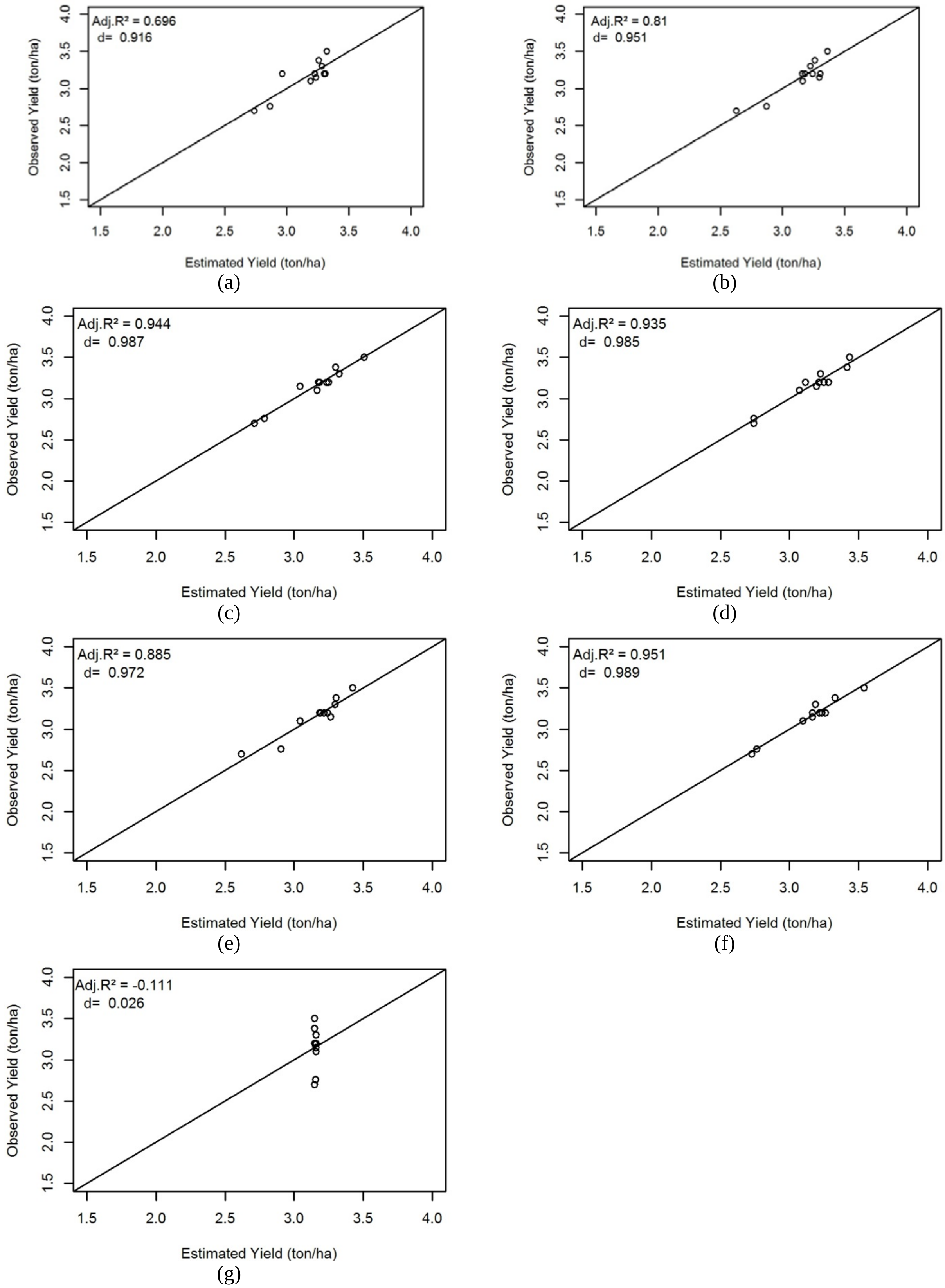


Figure 9.17 Relationship between observed and estimated yield for Ponta Grossa county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

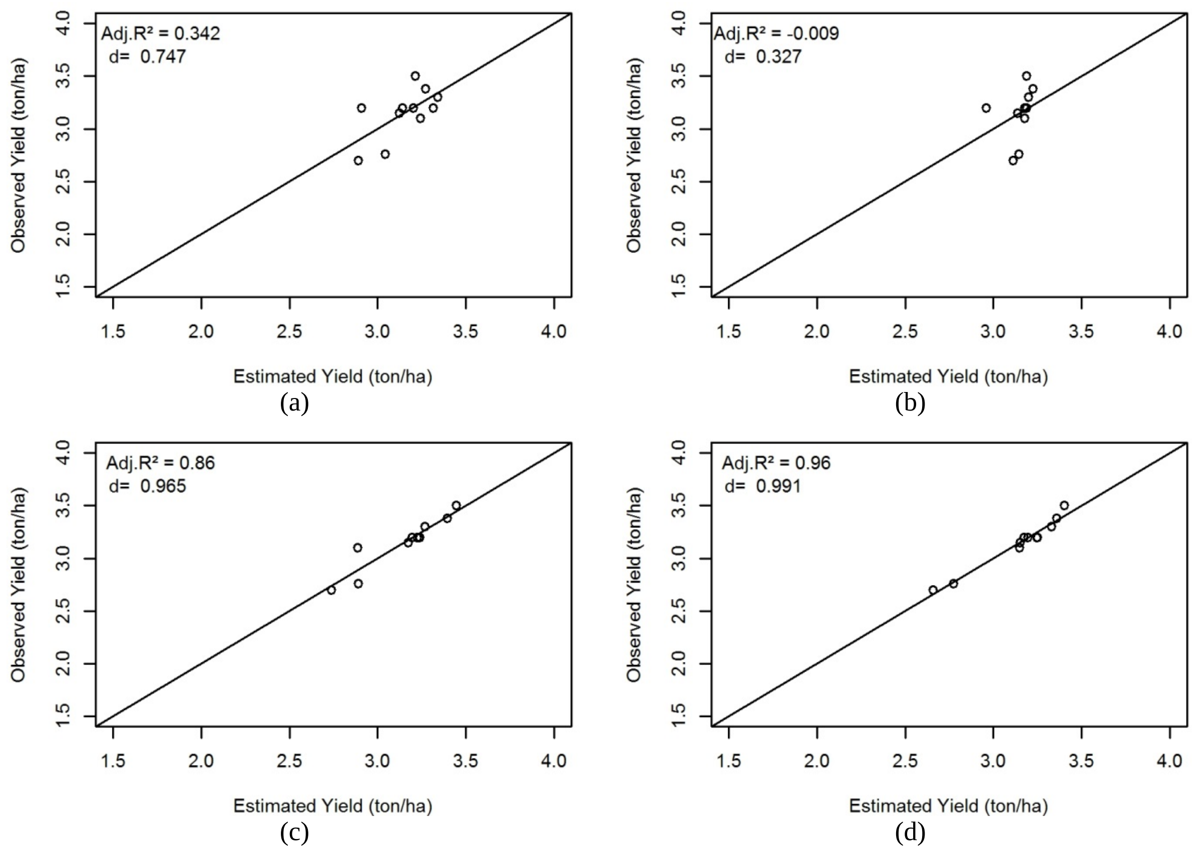


Figure 9.18 Relationship between observed and estimated yield for Ponta Grossa county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.22 Monthly methodology for São José da Boa Vista county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	2.5	2.7	-6.1	3.1	-18.4	2.6	-2.3	2.5	0.7	2.8	-11.6	2.9	-12.5	3.0	-17.6
200102	3.0	2.8	8.8	3.1	-1.7	2.7	11.6	2.8	8.5	2.8	8.7	3.2	-6.0	3.0	-1.0
200203	3.2	3.4	-4.7	3.0	5.2	3.2	-0.2	3.0	8.1	3.0	7.7	3.2	1.5	3.0	5.3
200304	3.0	3.1	-3.1	3.0	-1.4	2.9	3.3	2.9	2.2	2.7	10.3	2.8	6.1	3.0	-0.9
200405	2.2	2.3	-4.5	3.1	-27.3	2.4	-8.6	2.7	-16.4	2.7	-17.6	2.8	-20.6	3.1	-27.4
200506	3.0	2.9	2.5	3.0	-0.8	2.9	2.4	2.9	3.8	2.8	6.2	3.1	-2.4	3.0	-1.3
200607	3.0	2.9	4.5	3.0	-0.2	3.1	-3.8	3.2	-6.0	3.2	-7.7	2.8	8.1	3.0	-1.3
200708	3.3	3.5	-5.3	3.0	8.3	3.3	-1.3	3.2	1.6	3.3	0.5	3.3	-0.7	3.0	9.0
200809	3.2	3.1	1.4	3.0	4.9	3.2	-0.8	3.2	-1.8	3.1	1.4	2.9	9.9	3.1	2.2
200910	3.4	3.3	1.5	3.1	10.7	3.5	-2.2	3.4	-0.3	3.3	2.1	3.5	-3.4	3.0	12.3
201011	3.7	3.5	4.6	3.1	20.6	3.6	1.6	3.7	-0.7	3.7	0.1	3.1	19.8	3.1	20.7
RMSE		0.141		0.386		0.130		0.182		0.238		0.309		0.386	
MAE		0.128		0.276		0.098		0.131		0.192		0.244		0.274	
Adj. R^2		0.853		-0.107		0.874		0.754		0.579		0.288		-0.109	
d		0.963		0.070		0.969		0.934		0.870		0.701		0.060	

Table 9.23 Phenological methodology for São José da Boa Vista county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	2.5	3.1	-18.1	3.1	-18.2	3.0	-17.4	2.8	-12.1
200102	3.0	2.9	2.0	3.0	-1.6	2.8	7.4	2.7	11.4
200203	3.2	3.1	2.4	3.0	4.9	3.1	3.4	3.0	6.3
200304	3.0	2.9	2.3	3.0	-1.3	3.0	0.8	2.9	4.7
200405	2.2	3.0	-25.8	3.0	-27.0	3.1	-27.5	2.9	-24.1
200506	3.0	3.1	-4.7	3.1	-1.9	3.1	-1.7	3.2	-5.0
200607	3.0	2.7	10.9	3.0	0.6	3.1	-3.3	3.0	-0.5
200708	3.3	3.1	5.8	3.0	8.6	3.1	6.0	3.2	3.3
200809	3.2	3.1	2.9	3.0	3.4	3.0	3.7	2.8	11.7
200910	3.4	3.3	3.8	3.1	10.5	3.1	8.7	3.5	-2.5
201011	3.7	3.1	18.7	3.0	21.8	3.1	19.9	3.5	6.9
RMSE		0.359		0.386		0.376		0.298	
MAE		0.268		0.277		0.277		0.238	
Adj. R^2		0.039		-0.108		-0.052		0.340	
d		0.396		0.042		0.215		0.742	

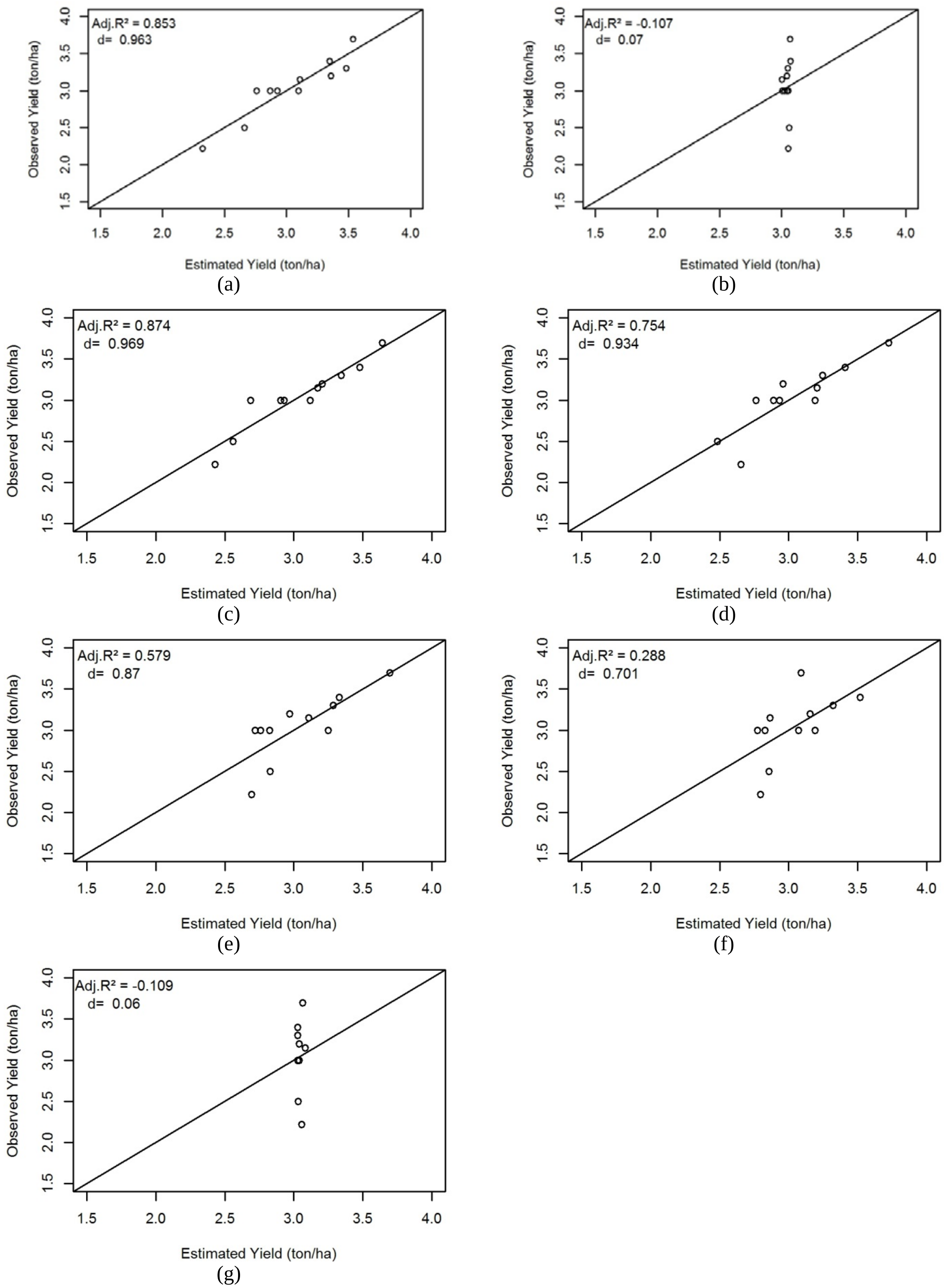


Figure 9.19 Relationship between observed and estimated yield for São José da Boa Vista county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

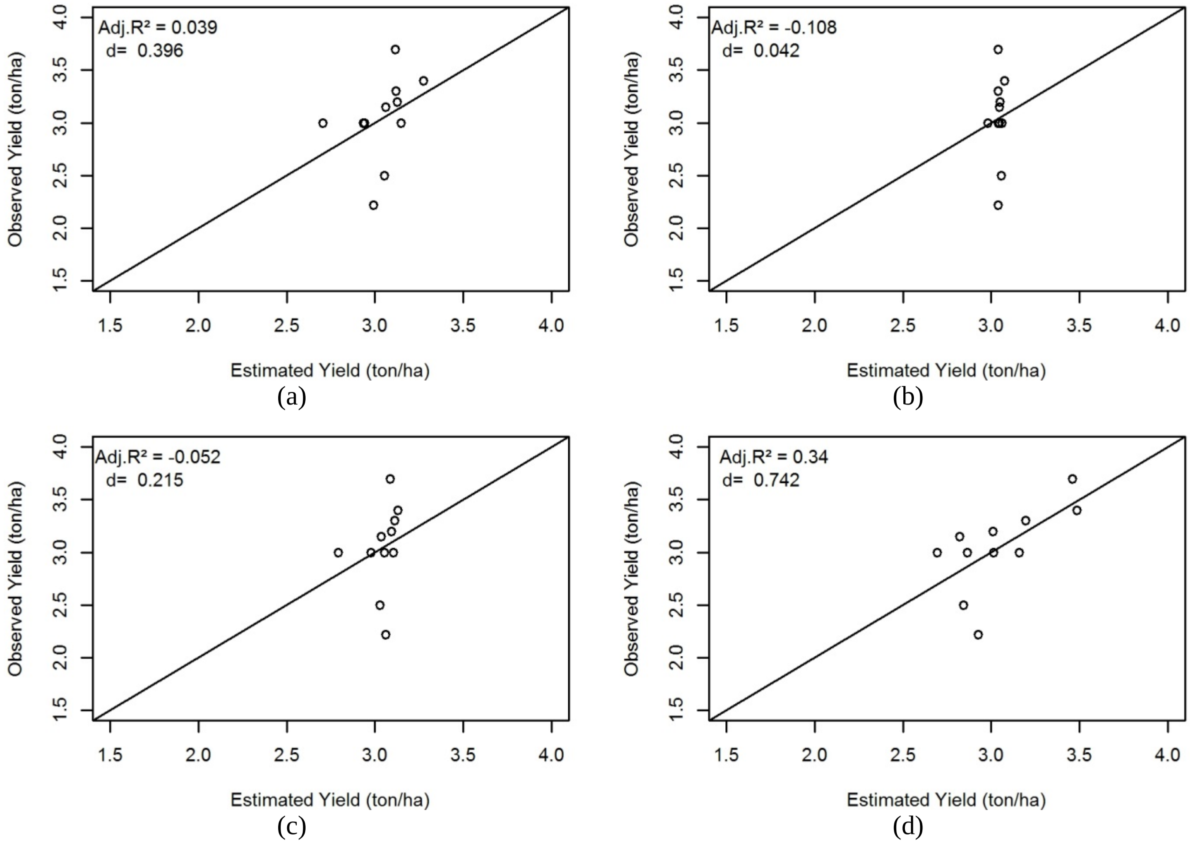


Figure 9.20 Relationship between observed and estimated yield for São José da Boa Vista county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.24 Monthly methodology for Senges county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	2.7	2.5	8.6	2.8	-4.8	2.6	2.7	2.6	3.5	2.6	3.2	2.6	1.8	2.7	0.8
200102	3.0	3.0	1.4	2.8	8.7	2.9	2.2	2.8	6.4	2.9	2.9	2.9	5.0	2.8	6.0
200203	3.0	3.2	-6.8	3.0	1.6	2.9	3.4	3.0	0.1	2.8	6.5	3.0	1.3	2.7	9.5
200304	3.0	3.0	1.0	2.7	9.6	3.0	-0.1	2.8	6.5	2.7	12.1	2.8	5.7	2.9	4.5
200405	1.9	2.1	-10.5	2.1	-10.5	2.3	-18.0	2.6	-28.1	2.3	-16.6	2.2	-14.5	2.4	-20.7
200506	2.7	2.6	4.4	2.7	-1.5	2.5	6.8	2.5	6.1	2.6	2.8	2.6	2.1	2.6	4.4
200607	3.2	3.2	-1.8	3.2	-2.3	3.3	-5.3	3.2	-1.1	3.1	1.5	2.8	11.4	2.9	7.6
200708	3.2	3.3	-3.9	3.1	2.0	2.8	12.3	3.2	1.1	3.2	1.5	3.1	2.4	3.2	1.6
200809	2.8	2.9	-4.8	2.9	-2.8	2.9	-1.8	2.7	2.5	3.2	-12.3	3.2	-12.7	3.0	-7.9
200910	3.1	3.1	1.5	3.5	-10.3	3.4	-8.8	3.4	-8.9	3.2	-3.8	3.2	-2.2	3.5	-10.2
201011	3.5	3.2	10.4	3.2	9.4	3.3	5.9	3.1	12.0	3.4	1.5	3.5	-1.2	3.4	3.6
RMSE		0.167		0.198		0.215		0.284		0.208		0.200		0.238	
MAE		0.140		0.166		0.173		0.197		0.163		0.153		0.198	
Adj. R²		0.796		0.713		0.664		0.412		0.684		0.709		0.589	
d		0.947		0.922		0.904		0.784		0.914		0.922		0.876	

Table 9.25 Phenological methodology for Senges Vista county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	2.7	2.7	-1.2	2.9	-7.9	2.7	-2.3	2.6	3.4
200102	3.0	2.8	8.3	2.9	3.0	2.5	22.0	2.7	9.4
200203	3.0	2.9	3.6	2.9	3.1	3.0	-0.2	2.9	2.9
200304	3.0	3.0	-0.4	2.9	3.3	2.9	2.2	2.9	4.2
200405	1.9	2.5	-23.4	2.9	-34.8	2.6	-27.0	2.2	-14.1
200506	2.7	2.6	4.1	2.9	-6.8	2.8	-4.0	2.7	0.8
200607	3.2	2.7	16.6	3.0	4.9	2.9	7.8	3.0	4.1
200708	3.2	3.1	2.5	2.9	9.6	2.9	8.6	3.1	3.6
200809	2.8	3.1	-10.0	2.9	-3.3	3.0	-6.1	3.0	-6.9
200910	3.1	3.4	-8.4	2.9	8.2	3.3	-4.9	3.4	-10.0
201011	3.5	3.2	8.0	2.9	20.8	3.4	4.1	3.4	1.6
RMSE		0.280		0.389		0.302		0.187	
MAE		0.222		0.279		0.223		0.157	
Adj. R²		0.429		-0.104		0.337		0.745	
d		0.807		0.066		0.743		0.932	

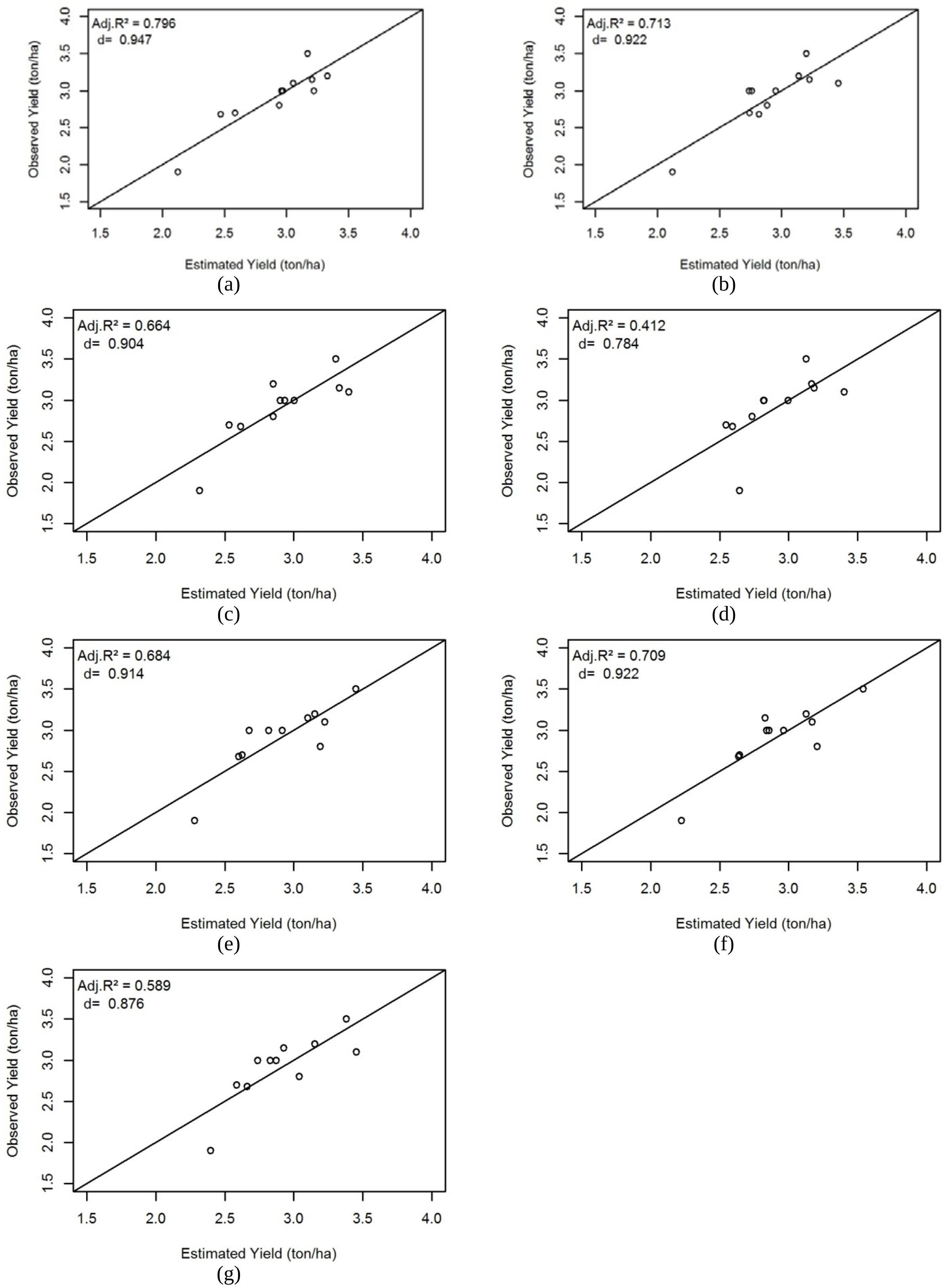


Figure 9.21 Relationship between observed and estimated yield for Senges county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

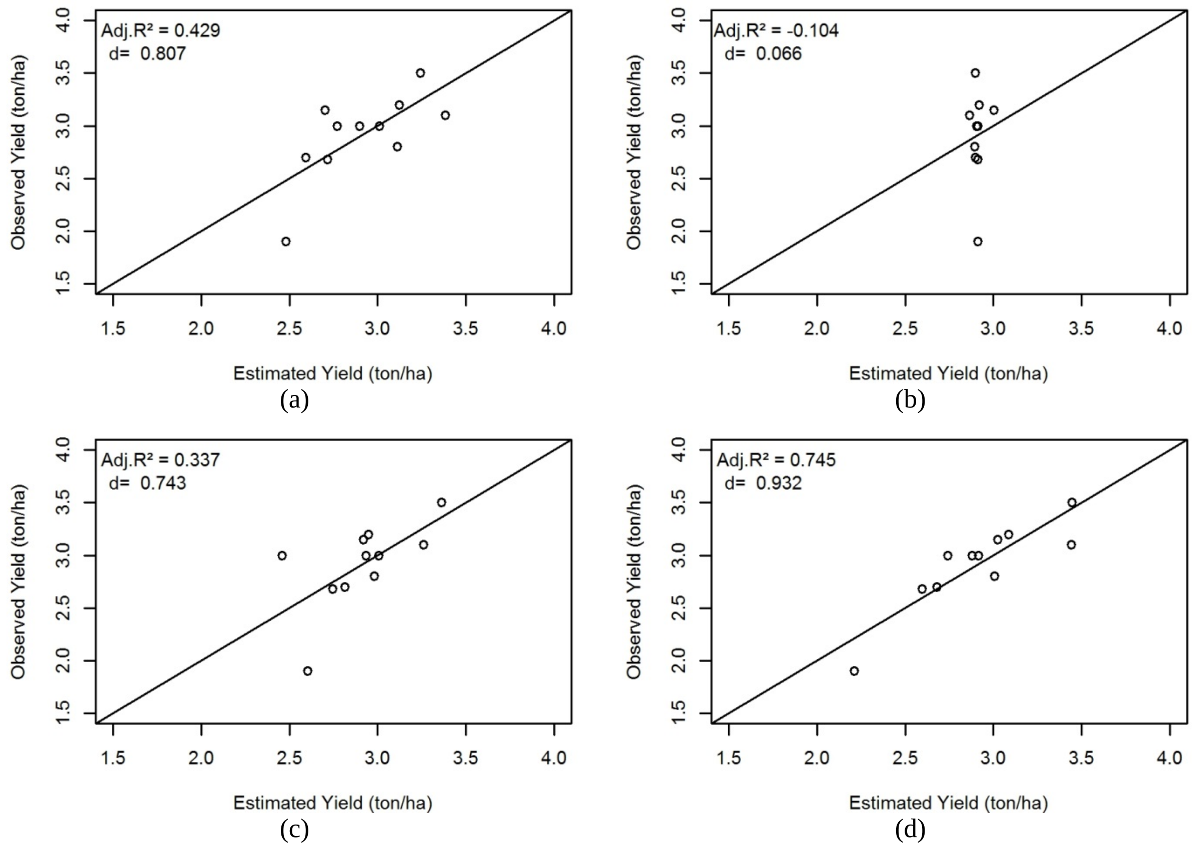


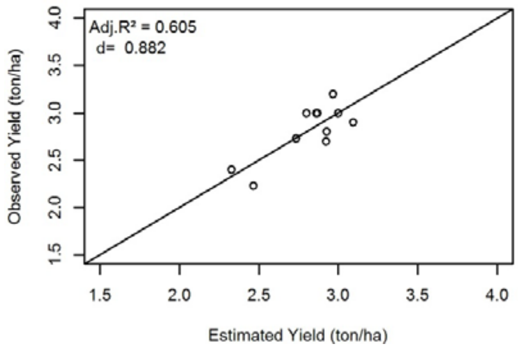
Figure 9.22 Relationship between observed and estimated yield for Senges county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.26 Monthly methodology for Telêmaco Borba county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

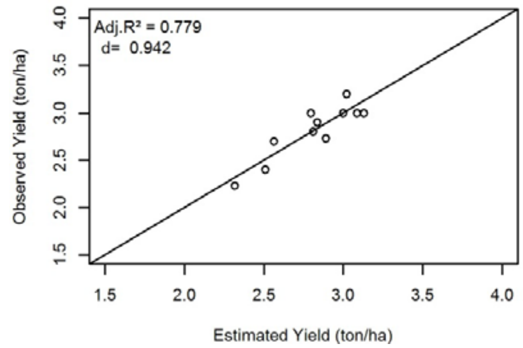
Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	2.9	3.1	-6.3	2.8	2.2	3.0	-2.3	2.8	5.4	3.0	-2.0	2.9	0.5	2.9	0.9
200102	3.0	2.9	4.8	2.8	7.2	2.7	9.9	2.6	16.1	2.8	8.0	2.7	10.1	2.9	4.6
200203	3.0	2.9	4.6	3.1	-2.8	3.0	1.5	3.0	-0.4	2.9	1.7	3.0	1.1	2.9	3.8
200304	2.8	2.9	-4.3	2.8	-0.3	2.9	-4.0	2.8	1.8	2.6	8.9	2.8	-0.5	2.9	-3.7
200405	2.2	2.5	-9.5	2.3	-3.7	2.4	-6.7	2.7	-17.5	2.4	-7.5	2.4	-7.1	2.4	-6.3
200506	2.4	2.3	3.2	2.5	-4.4	2.4	-1.2	2.6	-6.7	2.5	-3.8	2.4	1.8	2.3	4.0
200607	3.0	2.8	7.2	3.0	0.0	3.0	-1.0	3.0	1.2	2.9	5.1	2.8	6.4	2.8	7.6
200708	2.7	2.9	-7.6	2.6	5.4	2.7	1.4	2.9	-6.9	2.7	-1.1	2.9	-7.7	2.9	-6.4
200809	2.7	2.7	-0.1	2.9	-5.5	2.7	-0.2	2.8	-0.8	2.9	-7.4	2.8	-4.0	2.9	-6.3
200910	3.0	3.0	0.0	3.1	-4.1	3.2	-5.5	3.0	-1.0	3.1	-1.9	3.0	-1.2	3.1	-2.7
201011	3.2	3.0	7.9	3.0	5.9	3.0	7.9	2.9	8.9	3.2	-0.2	3.2	0.3	3.1	4.5
RMSE		0.164		0.122		0.137		0.226		0.143		0.137		0.139	
MAE		0.142		0.106		0.106		0.165		0.118		0.102		0.129	
Adj. R^2		0.605		0.779		0.721		0.248		0.698		0.723		0.717	
d		0.882		0.942		0.925		0.699		0.917		0.927		0.924	

Table 9.27 Phenological methodology for Telêmaco Borba county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

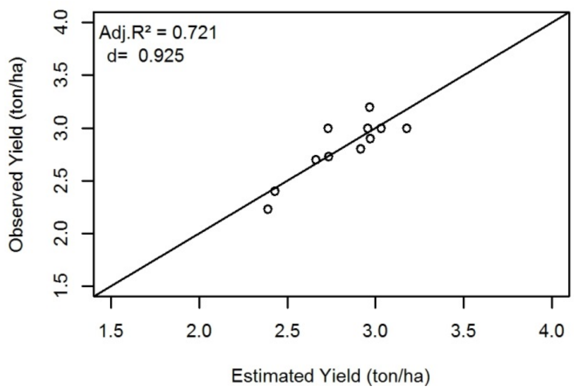
Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	2.9	2.9	0.3	2.9	1.7	2.9	0.7	2.9	0.4
200102	3.0	2.8	7.6	2.8	6.1	2.6	16.4	2.7	11.8
200203	3.0	2.9	3.1	2.9	4.3	2.9	2.7	3.0	0.3
200304	2.8	2.8	1.1	2.8	-1.5	2.8	-0.9	2.8	1.7
200405	2.2	2.5	-9.8	2.5	-10.6	2.6	-13.2	2.4	-8.8
200506	2.4	2.5	-3.3	2.5	-3.6	2.5	-3.7	2.4	0.4
200607	3.0	2.6	13.5	2.7	12.8	2.8	5.4	2.8	5.7
200708	2.7	2.9	-5.7	3.0	-9.8	2.8	-3.5	2.8	-4.3
200809	2.7	3.0	-8.0	3.0	-8.2	2.9	-7.3	2.9	-5.0
200910	3.0	3.1	-4.3	3.0	-1.3	3.1	-3.8	3.2	-5.0
201011	3.2	3.0	5.4	2.9	9.9	3.0	7.1	3.1	2.7
RMSE		0.185		0.207		0.202		0.149	
MAE		0.157		0.177		0.162		0.116	
Adj. R^2		0.496		0.365		0.397		0.674	
d		0.844		0.779		0.795		0.910	



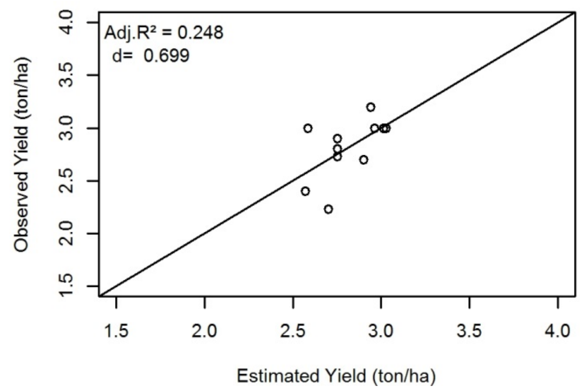
(a)



(b)



(c)



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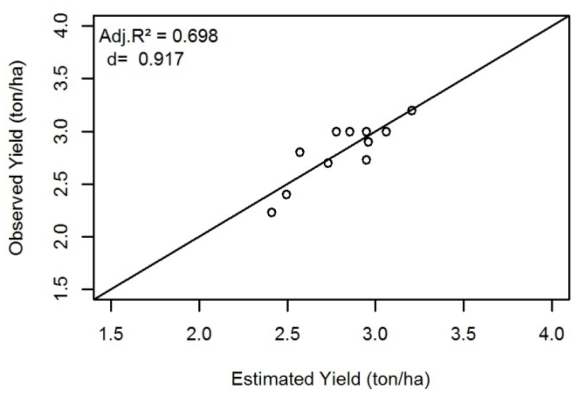

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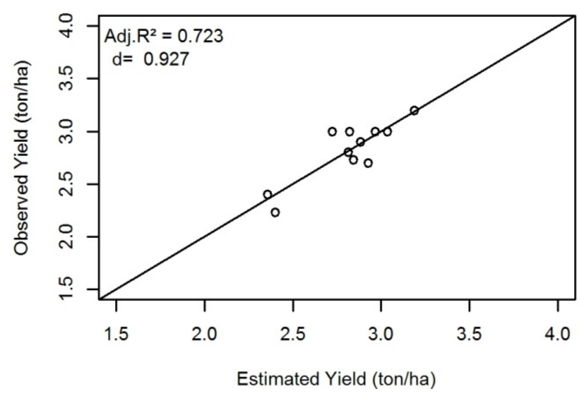

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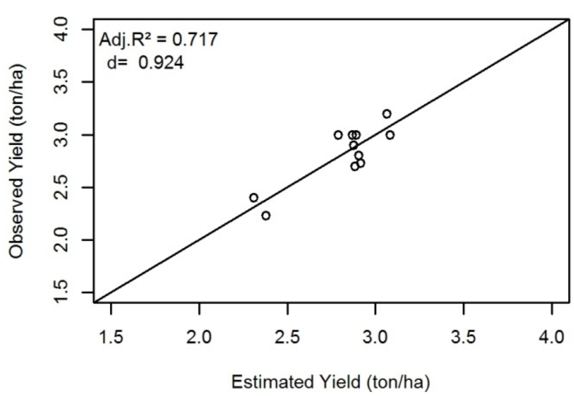
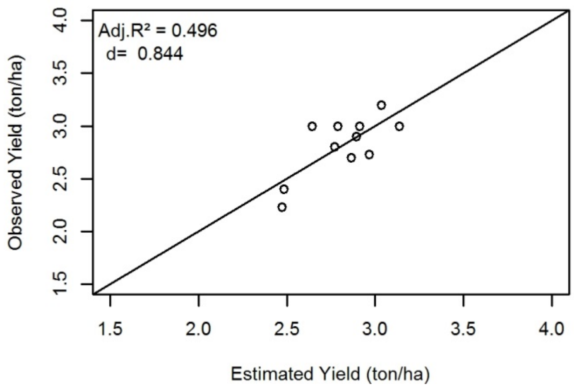
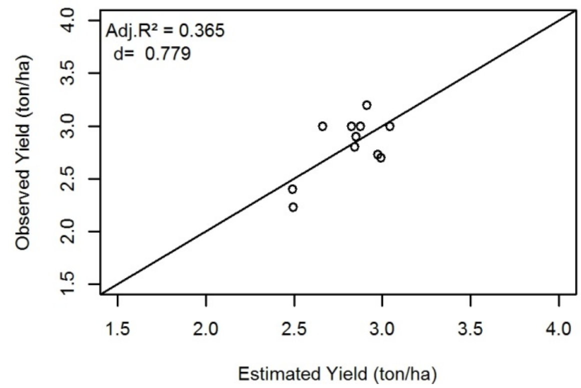


(g)

Figure 9.23 Relationship between observed and estimated yield for Telêmaco Borba county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.



(a)



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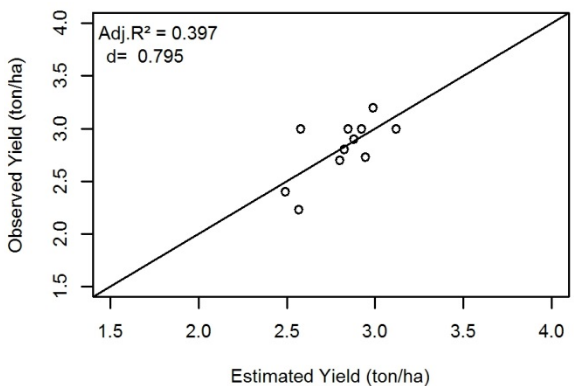
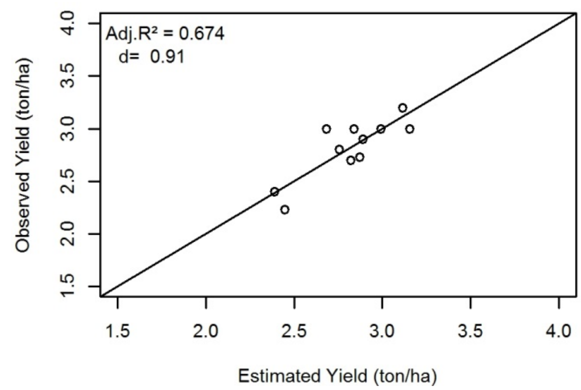


(c)



(d)

Figure 9.24 Relationship between observed and estimated yield for Telêmaco Borba county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.28 Monthly methodology for Tibagi county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.2	3.0	6.3	3.1	0.3	3.2	-0.4	3.0	6.5	3.1	1.4	3.2	-2.9	3.3	-3.2
200102	3.1	3.0	3.1	3.0	4.0	3.0	2.9	2.9	7.1	3.0	5.1	3.0	4.2	3.0	2.9
200203	3.4	3.0	10.7	3.4	-1.1	3.2	3.5	3.4	-1.2	3.5	-2.6	3.3	0.4	3.5	-2.9
200304	3.1	3.0	2.9	2.9	5.6	3.1	-0.8	3.0	3.0	3.2	-2.7	3.1	0.6	3.0	2.6
200405	2.3	3.0	-25.4	2.4	-5.7	2.4	-7.7	2.5	-8.6	2.5	-9.1	2.3	-0.8	2.4	-7.7
200506	2.5	3.0	-17.6	2.7	-6.4	2.6	-2.9	2.6	-4.2	2.5	1.0	2.6	-4.4	2.6	-4.2
200607	3.2	3.0	7.5	3.4	-4.0	3.4	-5.8	3.4	-3.3	3.1	3.1	3.1	5.7	3.2	2.7
200708	3.1	3.0	0.4	2.8	9.3	2.9	5.5	3.2	-3.8	3.0	0.6	3.0	0.8	2.8	8.9
200809	2.8	3.0	-8.3	2.8	-2.1	2.6	6.1	2.6	4.7	2.7	2.9	2.9	-4.1	2.7	3.1
200910	3.1	3.0	4.6	3.4	-6.7	3.2	-3.0	3.2	-0.5	3.1	1.9	3.1	3.1	3.3	-3.4
201011	3.5	3.0	15.5	3.3	6.1	3.4	1.9	3.5	-0.4	3.6	-2.1	3.6	-3.3	3.5	0.6
RMSE		0.355		0.157		0.122		0.130		0.103		0.099		0.125	
MAE		0.282		0.138		0.107		0.111		0.086		0.083		0.111	
Adj. R^2		-0.108		0.785		0.869		0.851		0.907		0.914		0.864	
d		0.052		0.944		0.968		0.963		0.978		0.980		0.966	

Table 9.29 Phenological methodology for Tibagi county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.2	3.1	3.2	3.0	4.4	3.2	-0.4	3.2	-1.9
200102	3.1	3.0	2.3	3.0	2.8	2.7	14.9	3.0	2.7
200203	3.4	3.1	9.4	3.0	11.3	3.4	-1.2	3.4	-1.9
200304	3.1	3.0	2.8	3.0	2.8	3.0	3.6	2.9	5.9
200405	2.3	3.0	-24.8	3.0	-25.3	2.5	-10.0	2.3	-2.6
200506	2.5	3.0	-17.3	3.0	-17.4	2.5	-0.8	2.5	1.4
200607	3.2	2.9	12.7	3.0	8.4	3.3	-0.8	3.3	-0.9
200708	3.1	3.0	2.1	3.0	1.4	3.1	-2.5	3.1	-0.9
200809	2.8	3.0	-8.7	3.0	-8.6	2.8	-2.7	2.8	-2.9
200910	3.1	3.1	3.1	3.0	4.2	3.2	-2.0	3.2	-2.4
201011	3.5	3.0	15.3	3.0	16.0	3.4	1.4	3.4	3.3
RMSE		0.352		0.355		0.152		0.083	
MAE		0.278		0.281		0.102		0.073	
Adj. R^2		-0.090		-0.111		0.795		0.939	
d		0.148		0.015		0.948		0.986	

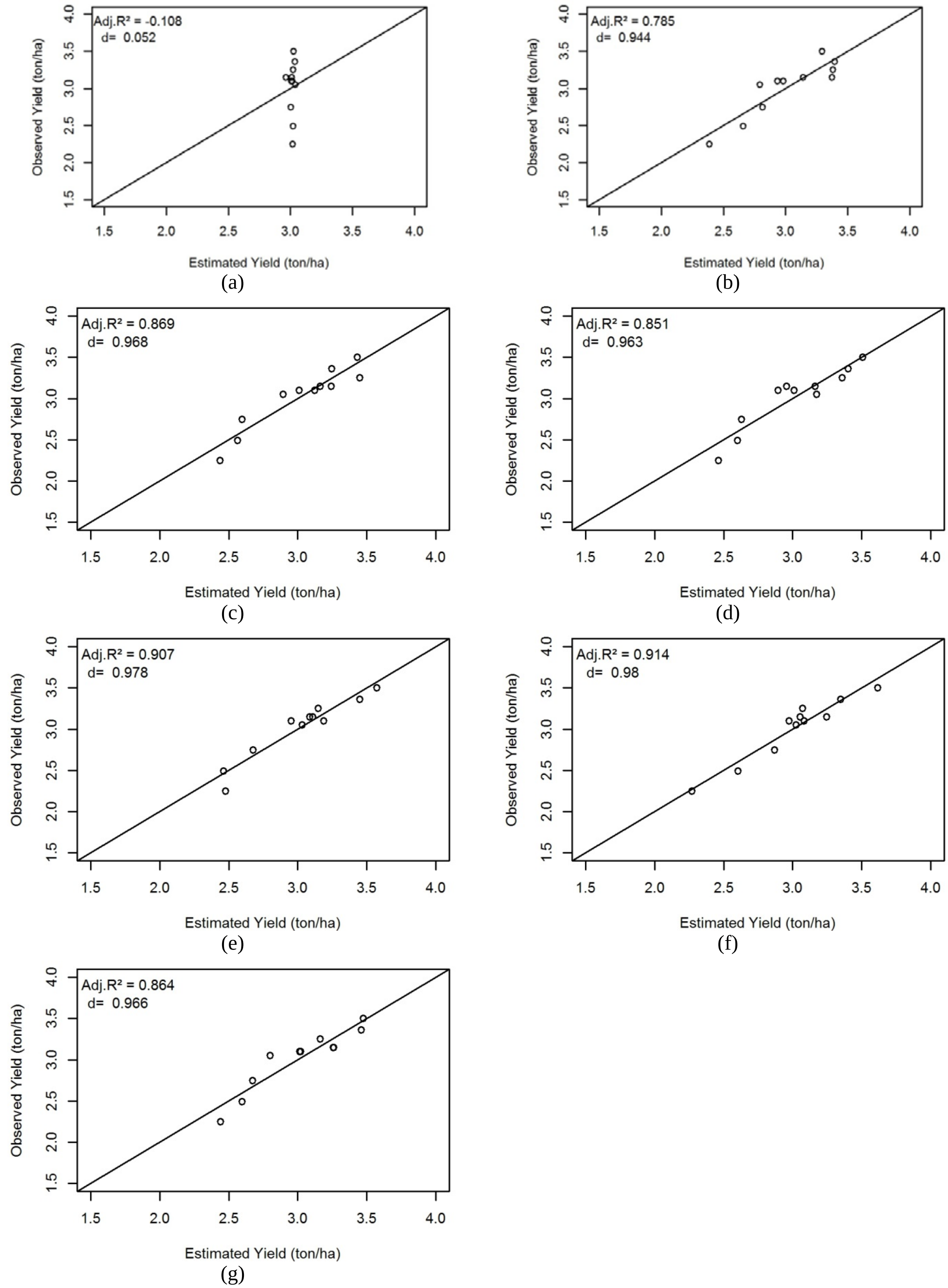


Figure 9.25 Relationship between observed and estimated yield for Tibagi county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

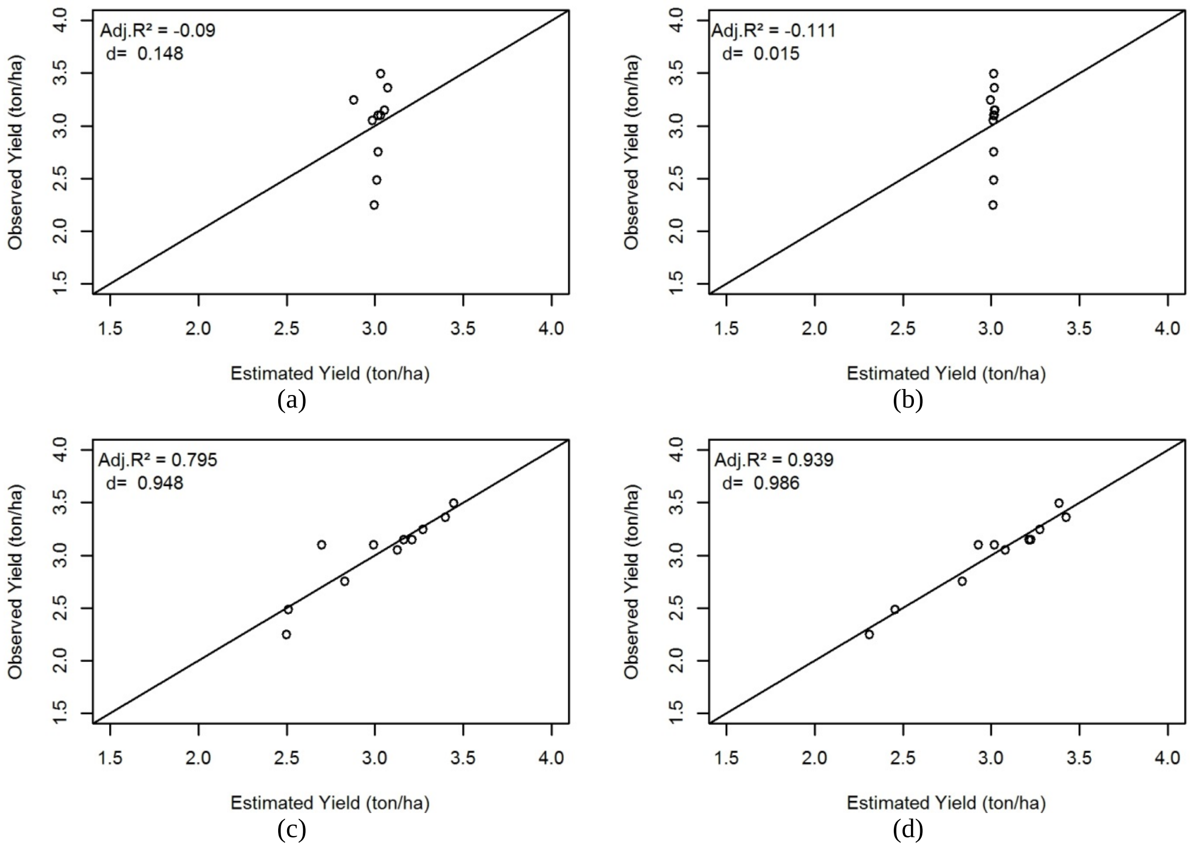


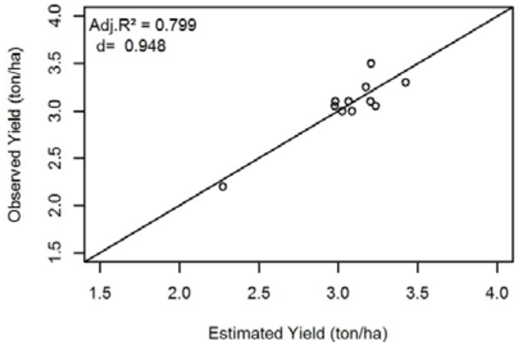
Figure 9.26 Relationship between observed and estimated yield for Tibagi county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.30 Monthly methodology for Ventania county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

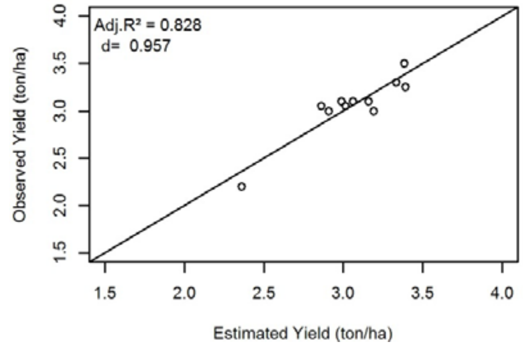
Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.1	3.0	4.0	3.1	1.3	3.2	-1.6	2.9	8.4	3.3	-5.7	3.2	-3.1	3.0	3.0
200102	3.1	3.0	2.4	3.0	1.2	3.1	-1.0	3.0	3.2	2.9	5.6	2.9	3.9	3.0	0.6
200203	3.3	3.4	-3.6	3.3	-1.0	3.2	2.6	3.3	1.4	3.1	5.5	3.4	-2.5	3.3	1.3
200304	3.0	3.1	-2.7	2.9	3.2	3.1	-3.5	3.1	-2.8	2.8	5.9	2.8	5.4	2.8	5.9
200405	2.2	2.3	-3.3	2.4	-6.7	2.4	-9.2	2.9	-24.3	2.7	-17.7	2.3	-6.0	2.5	-10.6
200506	3.1	3.2	-3.3	3.0	3.8	2.9	5.5	2.9	6.9	3.3	-5.9	3.1	-1.2	2.9	5.3
200607	3.3	3.2	2.4	3.4	-4.2	3.2	0.6	3.2	0.5	3.0	9.1	3.0	7.3	3.2	1.8
200708	3.1	3.2	-5.8	2.9	6.6	2.9	5.4	3.2	-4.0	2.9	5.9	3.2	-4.3	3.1	-2.9
200809	3.0	3.0	-0.8	3.2	-6.0	2.9	4.0	2.8	6.7	3.1	-3.5	3.1	-1.9	2.9	1.7
200910	3.1	3.1	1.2	3.2	-1.9	3.4	-9.9	3.2	-3.2	3.1	-1.1	3.1	1.0	3.4	-10.1
201011	3.5	3.2	9.1	3.4	3.4	3.3	6.7	3.3	7.1	3.4	1.4	3.5	0.9	3.4	3.3
RMSE		0.131		0.121		0.166		0.258		0.213		0.116		0.159	
MAE		0.109		0.106		0.138		0.186		0.181		0.101		0.127	
Adj. R^2		0.799		0.828		0.676		0.216		0.466		0.842		0.702	
d		0.948		0.957		0.908		0.638		0.817		0.961		0.917	

Table 9.31 Phenological methodology for Ventania county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.10	3.10	-0.16	3.06	1.43	3.20	-3.16	3.19	-2.83
200102	3.05	3.01	1.34	3.06	-0.22	2.64	15.49	2.96	2.95
200203	3.30	3.38	-2.35	3.06	7.95	3.36	-1.73	3.46	-4.63
200304	3.00	3.18	-5.74	3.06	-1.89	3.06	-1.84	2.97	0.99
200405	2.20	2.60	-15.44	3.06	-28.11	2.71	-18.72	2.41	-8.70
200506	3.10	3.03	2.35	3.06	1.37	3.06	1.35	2.99	3.65
200607	3.25	2.91	11.63	3.07	5.71	3.19	1.84	3.08	5.65
200708	3.05	3.19	-4.42	3.06	-0.39	2.94	3.73	3.04	0.40
200809	3.00	3.15	-4.82	3.06	-1.88	2.96	1.21	2.86	4.78
200910	3.10	2.77	11.94	3.05	1.55	3.19	-2.87	3.32	-6.68
201011	3.50	3.32	5.46	3.06	14.48	3.34	4.76	3.37	3.96
RMSE		0.215		0.307		0.212		0.140	
MAE		0.175		0.181		0.148		0.124	
Adj. R^2		0.457		-0.111		0.473		0.771	
d		0.822		0.012		0.816		0.939	



(a)



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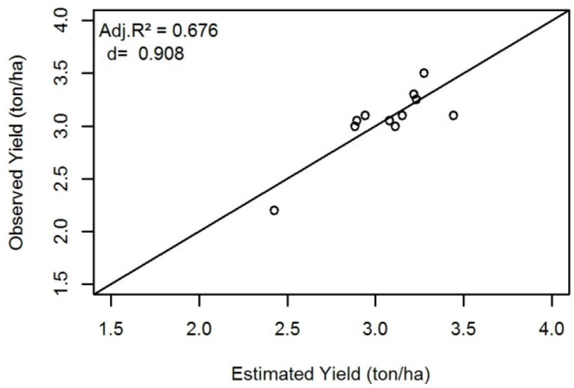

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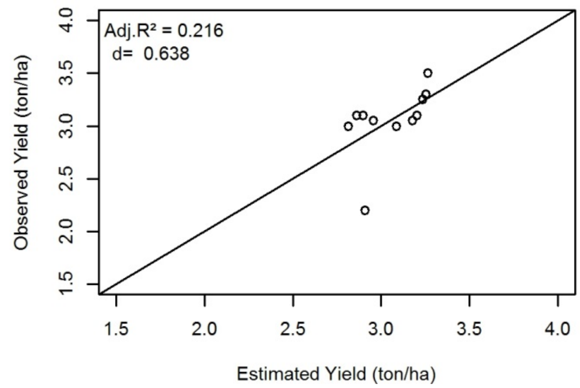

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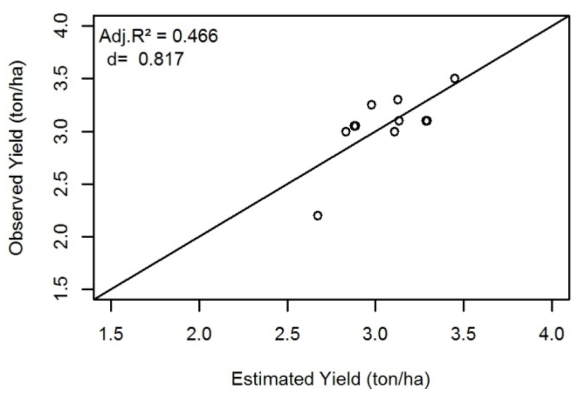
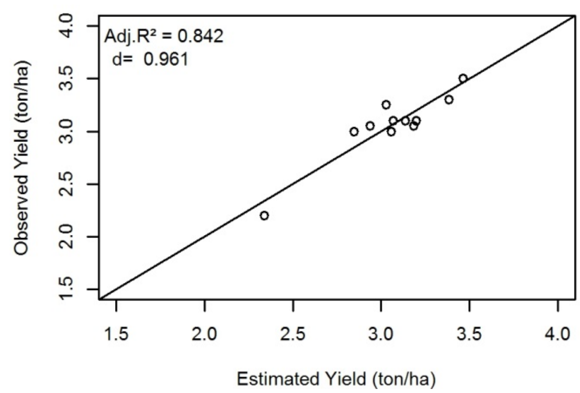


(e)



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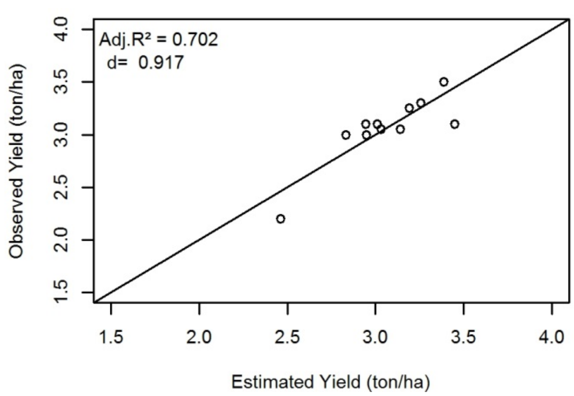


(g)

Figure 9.27 Relationship between observed and estimated yield for Ventania county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

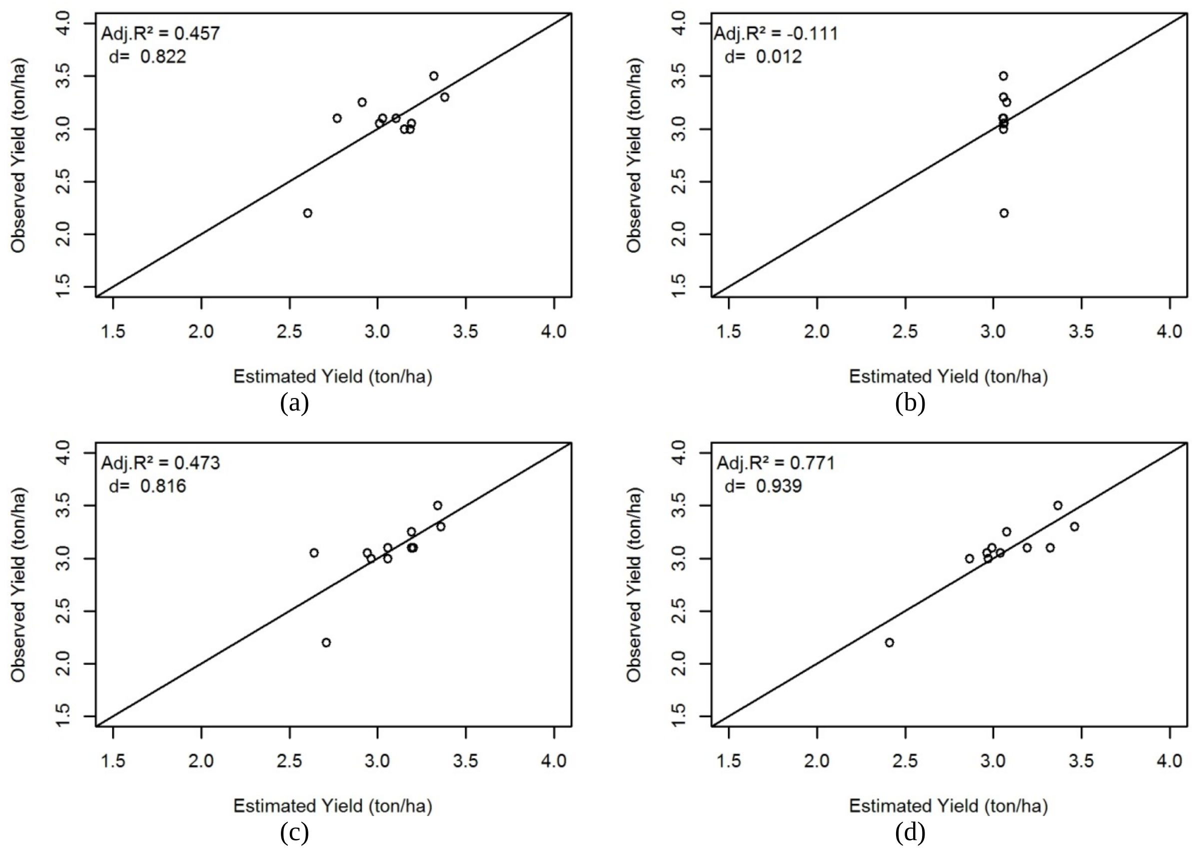


Figure 9.28 Relationship between observed and estimated yield for Ventania county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.32 Monthly methodology for Wenceslau Braz county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	2.4	2.3	2.4	2.7	-9.8	2.7	-11.7	2.6	-7.7	2.6	-6.1	3.2	-24.2	3.1	-23.7
200102	3.0	3.0	1.6	3.0	-1.5	2.7	10.1	2.8	8.5	3.0	-0.1	3.2	-5.1	3.0	-1.4
200203	3.5	3.3	6.7	3.1	13.7	3.2	10.5	3.2	9.4	3.2	11.1	3.2	10.7	3.4	2.9
200304	3.0	3.1	-4.1	2.9	4.2	3.0	-0.4	2.9	4.8	2.9	3.3	3.2	-4.8	3.1	-3.4
200405	2.6	2.8	-5.5	3.0	-11.8	2.8	-5.5	3.0	-11.6	2.6	0.0	3.1	-16.8	3.2	-18.7
200506	3.2	3.2	0.8	3.2	0.7	3.3	-0.9	3.3	-0.6	3.3	-1.4	3.2	1.8	3.0	6.2
200607	3.3	3.2	4.2	3.2	3.8	3.4	-1.5	3.3	2.5	3.3	0.5	3.1	6.9	3.1	6.8
200708	3.5	3.6	-4.1	3.7	-5.7	3.5	-1.3	3.6	-2.8	3.5	0.0	3.2	9.2	3.2	10.0
200809	3.2	3.3	-3.5	2.9	6.9	3.0	4.2	3.1	0.5	3.2	-2.6	3.2	-0.8	2.9	7.9
200910	3.3	3.4	-1.9	3.4	-2.7	3.5	-5.8	3.5	-4.6	3.5	-5.2	3.1	5.3	3.1	5.0
201011	3.7	3.6	3.3	3.6	1.5	3.6	1.9	3.7	1.1	3.7	0.0	3.1	17.5	3.4	8.3
RMSE		0.124		0.213		0.186		0.183		0.134		0.368		0.341	
MAE		0.111		0.174		0.146		0.148		0.085		0.296		0.271	
Adj. R^2		0.875		0.631		0.719		0.727		0.853		-0.109		0.049	
d		0.969		0.892		0.922		0.925		0.963		0.056		0.450	

Table 9.33 Phenological methodology for Wenceslau Braz county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	2.4	3.0	-18.8	3.1	-23.2	2.9	-17.5	2.7	-12.6
200102	3.0	3.0	-0.3	3.1	-4.6	2.7	11.5	2.7	10.0
200203	3.5	3.3	7.6	3.1	12.1	3.0	16.5	3.3	7.3
200304	3.0	2.9	3.9	3.2	-5.3	3.0	-1.0	2.8	5.6
200405	2.6	2.9	-11.0	3.2	-17.5	3.0	-12.7	2.9	-11.0
200506	3.2	3.3	-0.7	3.1	3.8	3.2	-0.1	3.1	4.1
200607	3.3	2.8	19.9	3.3	1.2	3.2	4.4	3.3	1.2
200708	3.5	3.5	-0.2	3.2	9.0	3.5	0.6	3.6	-4.5
200809	3.2	3.3	-3.3	3.1	0.1	3.3	-3.8	3.1	0.6
200910	3.3	3.4	-3.5	3.1	7.1	3.3	0.9	3.5	-4.5
201011	3.7	3.5	6.5	3.2	17.1	3.7	1.3	3.6	3.6
RMSE		0.282		0.365		0.267		0.206	
MAE		0.208		0.289		0.190		0.180	
Adj. R^2		0.351		-0.086		0.417		0.652	
d		0.760		0.153		0.796		0.898	

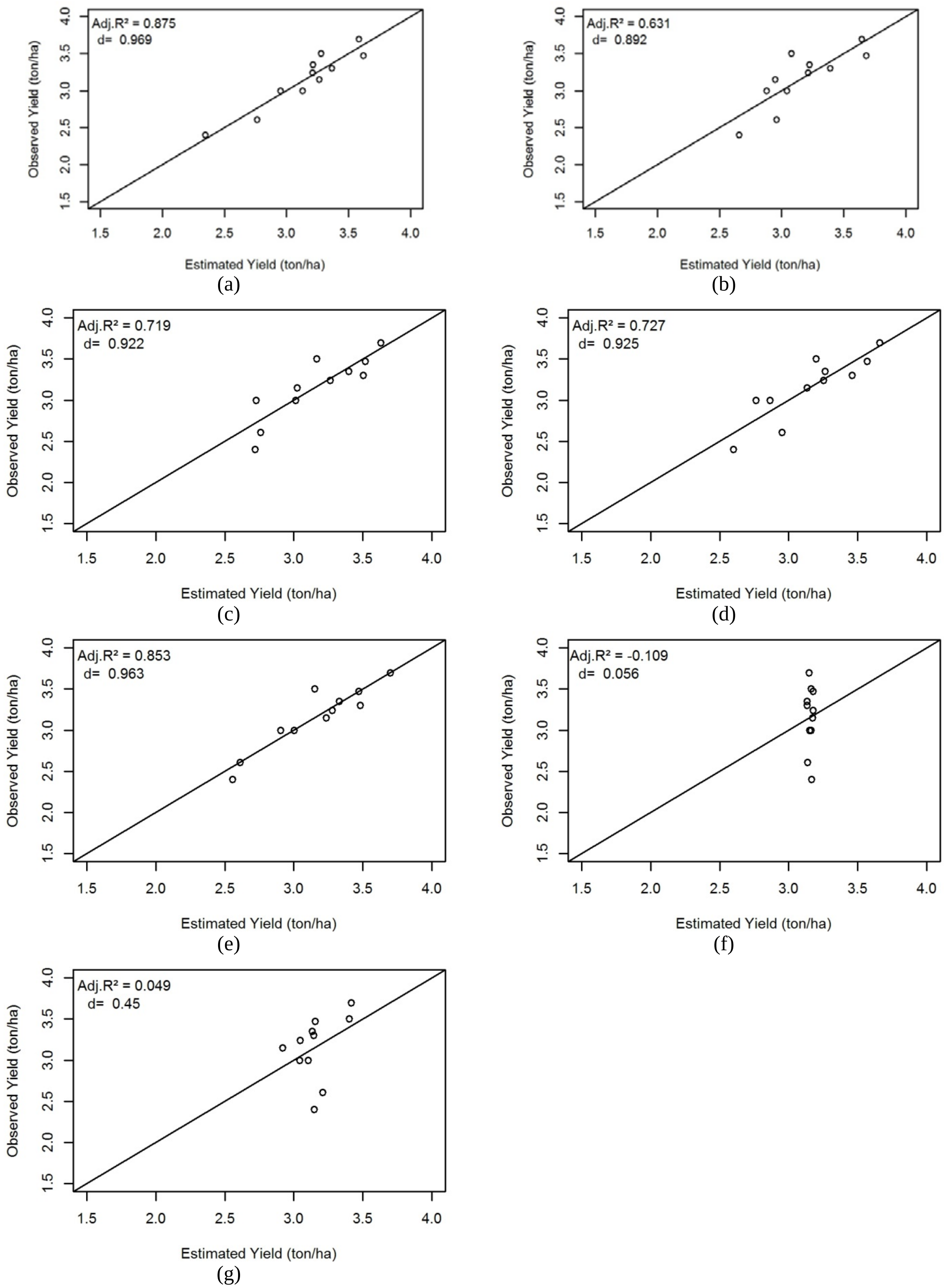


Figure 9.29 Relationship between observed and estimated yield for Wenceslau Braz county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

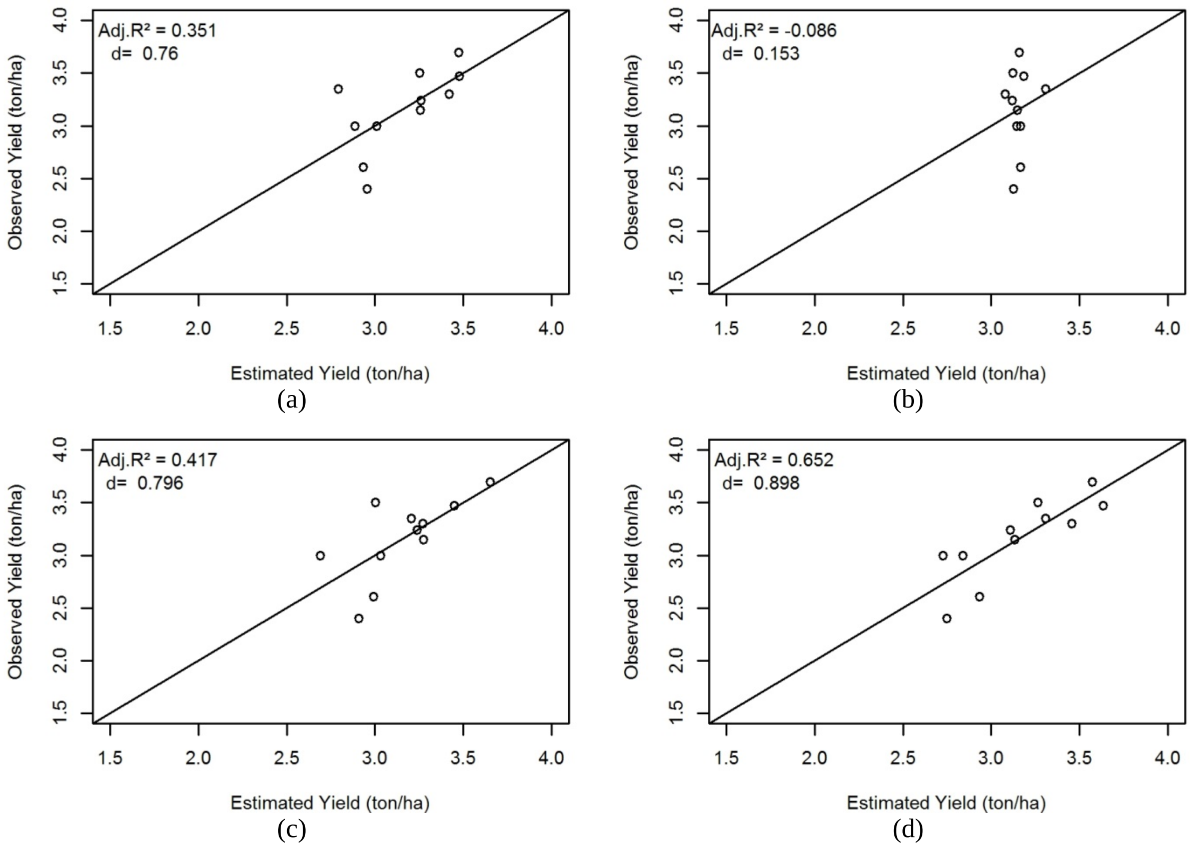


Figure 9.30 Relationship between observed and estimated yield for Wenceslau Braz county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

- Midwest region

Table 9.34 Monthly methodology for Campo Mourão county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.0	3.0	-0.6	2.9	2.0	3.1	-4.0	2.9	3.3	2.6	15.0	3.1	-3.4	3.0	-0.6
200102	3.0	2.9	3.8	3.0	0.0	2.9	4.2	3.2	-7.0	2.9	1.5	2.9	1.5	2.6	13.7
200203	3.1	3.0	5.2	2.9	8.2	2.7	14.6	3.0	3.2	3.0	4.9	2.8	12.6	2.9	8.2
200304	2.7	2.9	-4.9	2.8	-2.1	2.9	-6.6	2.9	-5.4	2.9	-5.5	2.7	0.6	2.7	0.8
200405	2.3	2.8	-19.1	2.9	-22.0	2.7	-16.2	2.6	-12.5	2.8	-18.5	2.5	-9.7	2.8	-17.9
200506	2.7	2.7	-1.6	2.9	-6.8	2.7	-1.2	2.7	0.7	2.7	-2.6	3.1	-13.3	2.7	-0.3
200607	3.1	2.8	10.2	2.9	7.5	3.2	-4.5	3.2	-3.7	3.2	-4.5	3.2	-2.4	3.0	1.6
200708	3.0	2.9	3.2	2.8	5.1	2.9	1.9	2.8	7.4	3.0	-0.6	2.8	5.2	3.2	-5.8
200809	2.4	3.0	-18.8	2.8	-15.3	2.5	-2.5	2.5	-5.4	2.6	-8.2	2.7	-10.8	2.6	-6.9
200910	3.0	2.7	8.6	2.8	6.8	2.8	7.3	3.0	0.2	2.8	6.2	2.9	4.1	2.9	4.6
201011	3.4	3.0	14.1	2.9	16.5	3.2	6.8	2.9	18.9	3.0	12.3	2.9	15.4	3.3	2.5
RMSE		0.299		0.307		0.221		0.227		0.254		0.251		0.219	
MAE		0.236		0.242		0.181		0.176		0.205		0.205		0.161	
Adj. R^2		-0.010		-0.070		0.440		0.410		0.260		0.280		0.450	
d		0.398		0.224		0.814		0.788		0.693		0.722		0.814	

Table 9.35 Phenological methodology for Campo Mourão county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.0	3.1	-2.9	2.9	1.7	3.1	-2.4	3.0	-0.2
200102	3.0	2.9	4.6	2.9	3.1	2.7	10.5	2.9	3.9
200203	3.1	3.1	0.0	2.9	8.4	3.1	-0.1	3.2	-0.8
200304	2.7	2.9	-5.5	2.9	-6.3	2.9	-6.3	2.9	-5.2
200405	2.3	2.5	-7.5	2.9	-20.3	2.6	-12.2	2.5	-7.3
200506	2.7	2.7	-1.7	2.9	-7.4	2.6	3.0	2.6	3.0
200607	3.1	2.7	12.7	2.7	13.3	3.1	0.5	3.2	-2.8
200708	3.0	2.9	2.1	2.9	4.6	3.0	0.8	2.9	2.4
200809	2.4	2.4	-0.7	2.8	-15.0	2.3	3.0	2.3	2.5
200910	3.0	3.0	-0.2	2.9	2.1	3.0	1.0	2.9	3.6
201011	3.4	3.4	-1.3	2.9	16.0	3.3	2.2	3.4	0.8
RMSE		0.140		0.308		0.147		0.096	
MAE		0.099		0.255		0.105		0.082	
Adj. R^2		0.778		-0.076		0.753		0.895	
d		0.943		0.225		0.935		0.975	

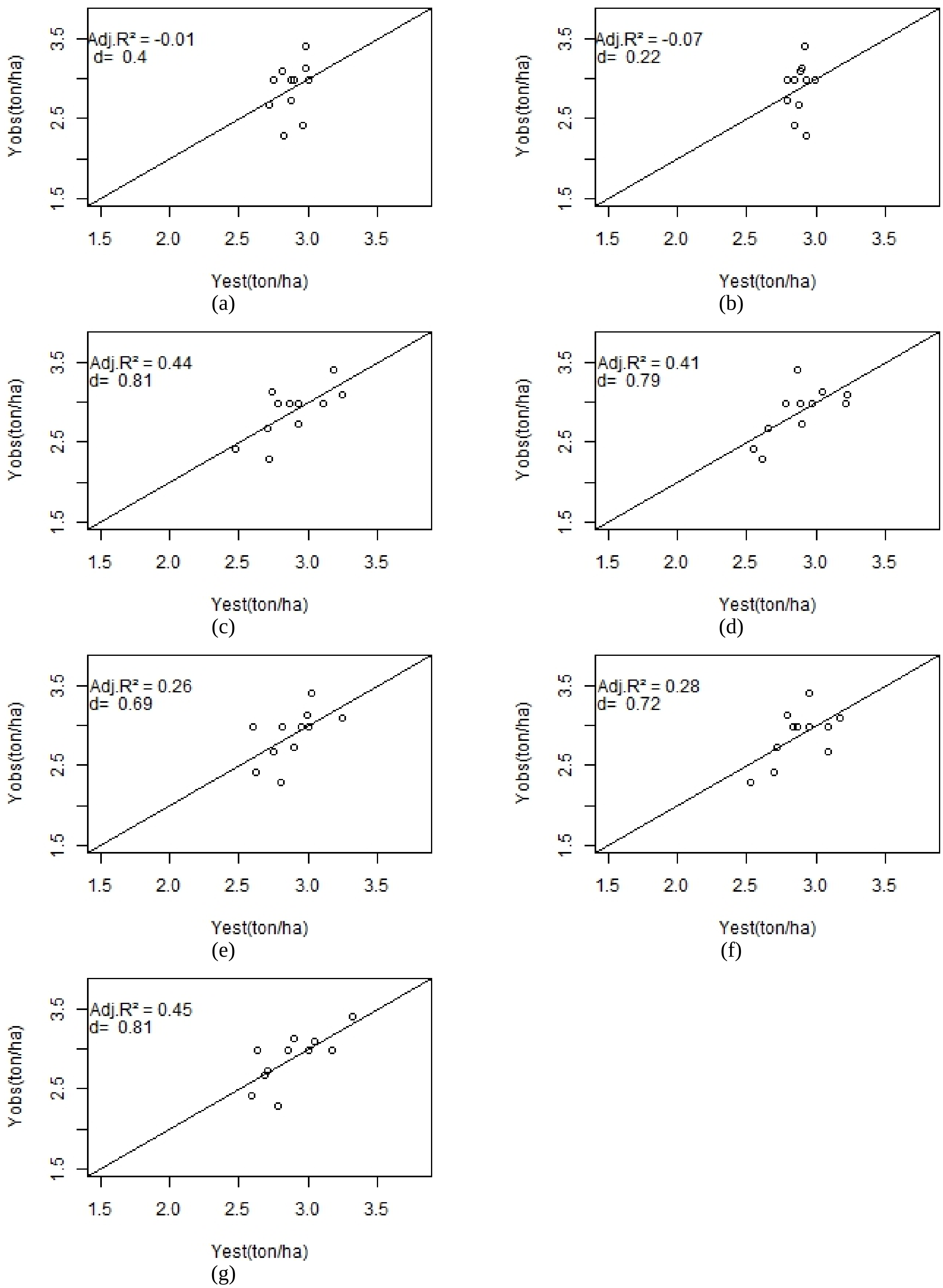


Figure 9.31 Relationship between observed and estimated yield for Campo Mourão county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

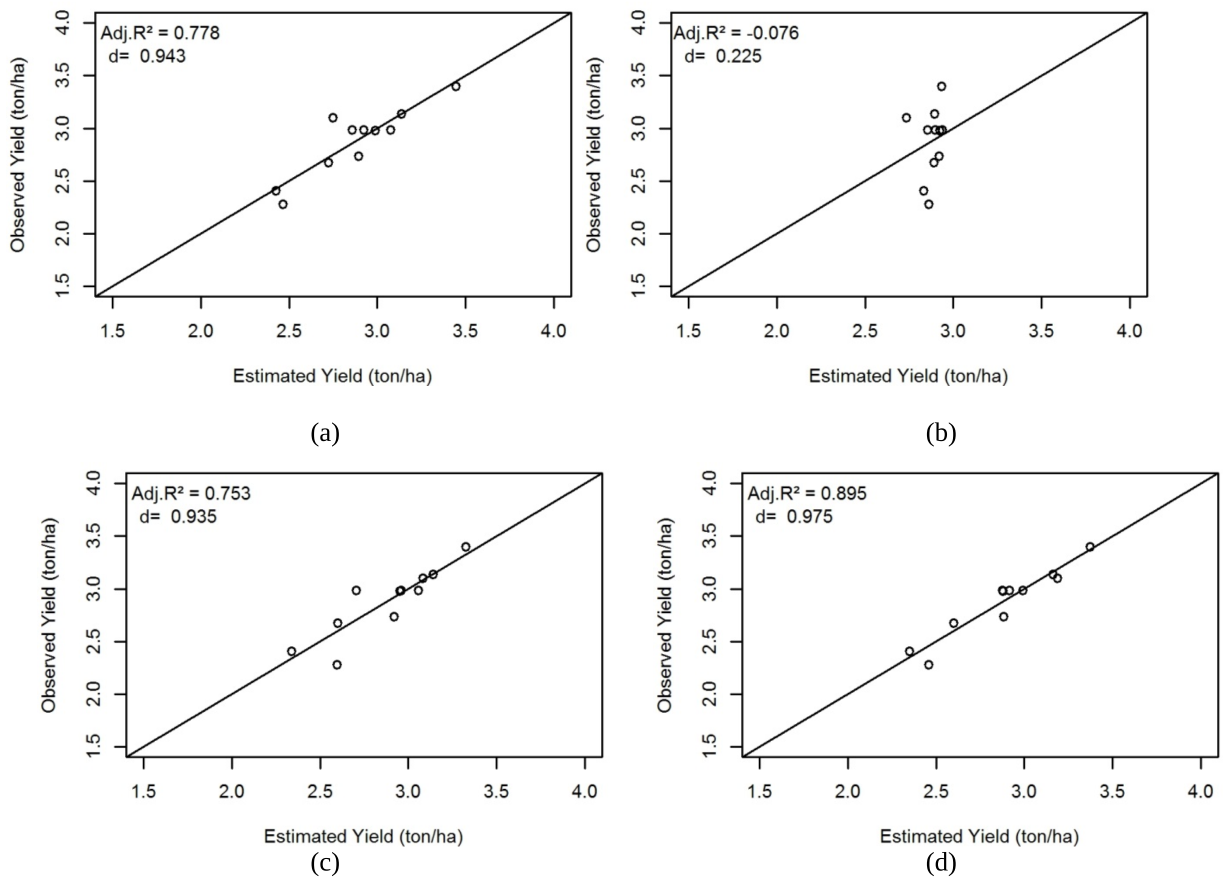


Figure 9.32 Relationship between observed and estimated yield for Campo Mourão county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.36 Monthly methodology for Cascavel county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.2	2.8	14.8	3.2	0.9	3.1	4.7	3.1	3.4	3.4	-5.2	3.4	-6.7	3.1	2.4
200102	2.9	2.7	6.6	2.9	-1.4	3.0	-1.8	2.7	7.1	2.8	3.0	2.8	3.6	2.9	-1.2
200203	3.3	3.1	6.2	3.5	-5.6	3.1	6.3	3.3	-1.3	3.2	3.4	3.2	1.8	3.5	-4.8
200304	2.8	2.7	0.7	2.8	-0.5	2.9	-6.7	3.0	-7.3	2.7	1.5	2.7	2.3	2.8	-2.5
200405	2.4	2.6	-10.0	2.4	-1.3	2.6	-10.7	2.3	2.8	2.6	-9.5	2.3	0.9	2.2	5.5
200506	2.7	3.1	-14.2	2.7	-0.8	2.6	5.2	2.8	-5.0	2.9	-8.4	2.9	-5.3	2.8	-3.8
200607	2.9	3.0	-4.1	3.0	-3.5	2.9	-1.3	2.8	1.7	2.7	7.1	3.0	-4.6	3.0	-5.4
200708	3.0	3.2	-5.7	2.9	3.5	2.8	6.8	3.0	0.5	3.0	-0.3	2.9	3.0	3.0	1.0
200809	2.6	2.8	-7.6	2.7	-3.1	2.6	-2.2	2.7	-5.0	2.7	-3.6	2.8	-6.3	2.7	-5.7
200910	3.3	3.0	9.2	3.4	-1.9	3.6	-7.2	3.3	0.4	3.0	11.4	3.1	7.1	3.3	2.0
201011	3.6	3.5	4.0	3.2	13.2	3.4	6.6	3.5	2.8	3.6	0.2	3.4	4.0	3.2	12.4
RMSE		0.251		0.151		0.179		0.118		0.173		0.141		0.159	
MAE		0.222		0.100		0.161		0.098		0.139		0.126		0.126	
Adj. R^2		0.420		0.790		0.700		0.870		0.720		0.820		0.770	
d		0.807		0.945		0.917		0.969		0.924		0.953		0.938	

Table 9.37 Phenological methodology for Cascavel county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.2	3.3	-3.2	3.2	0.2	3.3	-3.5	3.2	0.5
200102	2.9	3.0	-4.3	2.8	3.4	2.7	7.4	3.0	-4.1
200203	3.3	3.2	4.7	3.3	-0.9	3.3	1.0	3.1	5.2
200304	2.8	2.8	-1.7	2.8	-0.4	3.0	-7.9	2.9	-4.8
200405	2.4	2.4	-1.6	2.6	-10.2	2.6	-10.5	2.4	-1.6
200506	2.7	2.8	-3.0	2.8	-3.2	2.6	4.0	2.7	1.7
200607	2.9	2.6	10.6	2.6	10.7	2.8	0.2	3.0	-5.6
200708	3.0	3.2	-7.6	3.0	-0.1	3.1	-4.6	3.3	-9.4
200809	2.6	2.7	-4.1	2.7	-3.8	2.6	-0.6	2.5	1.6
200910	3.3	3.3	2.0	3.5	-5.3	3.4	-1.0	3.3	1.6
201011	3.6	3.3	8.4	3.3	9.5	3.1	15.5	3.1	14.9
RMSE		0.162		0.167		0.202		0.193	
MAE		0.138		0.125		0.150		0.142	
Adj. R^2		0.758		0.743		0.624		0.657	
d		0.935		0.930		0.887		0.901	

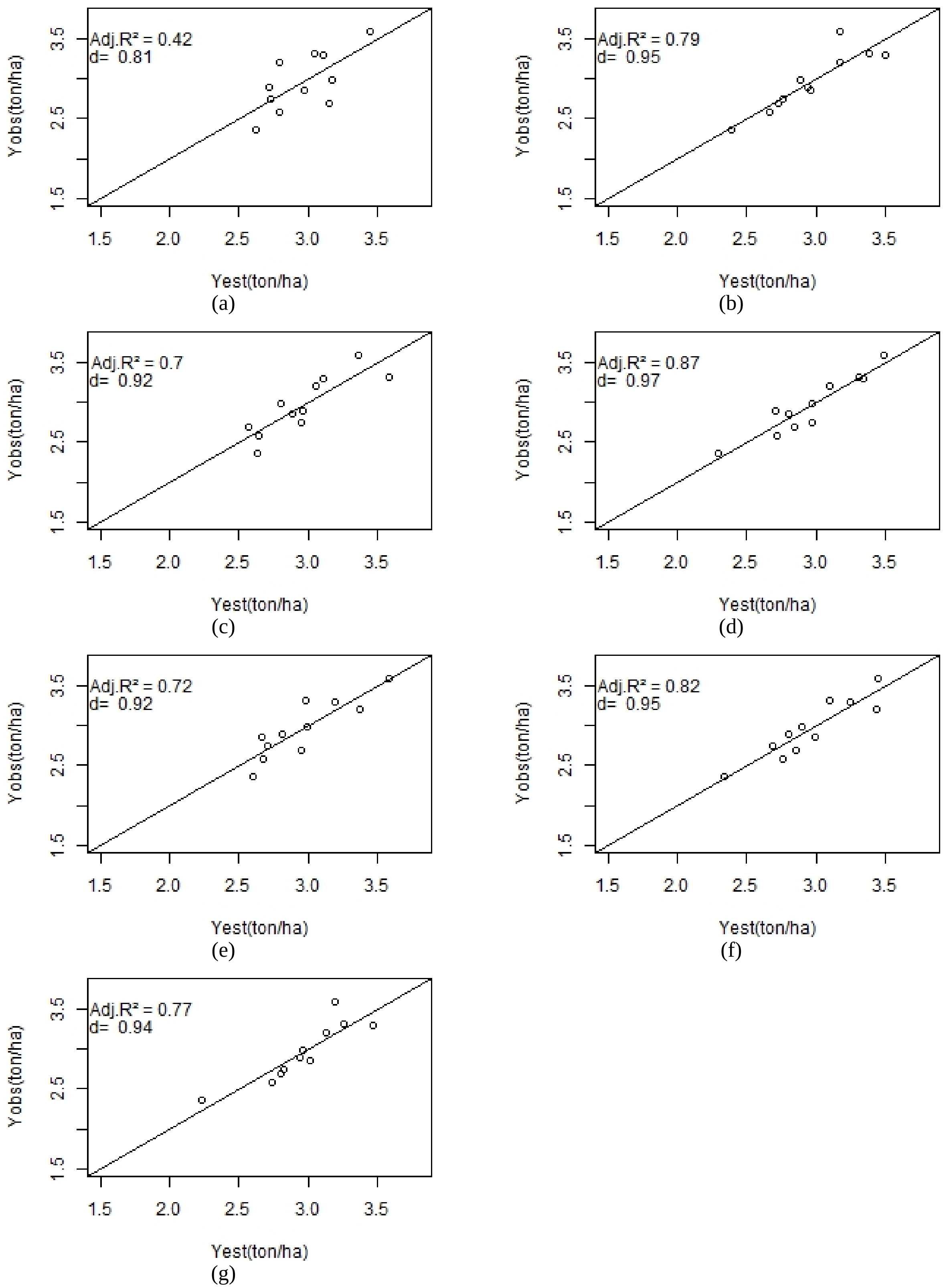


Figure 9.33 Relationship between observed and estimated yield for Cascavel county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

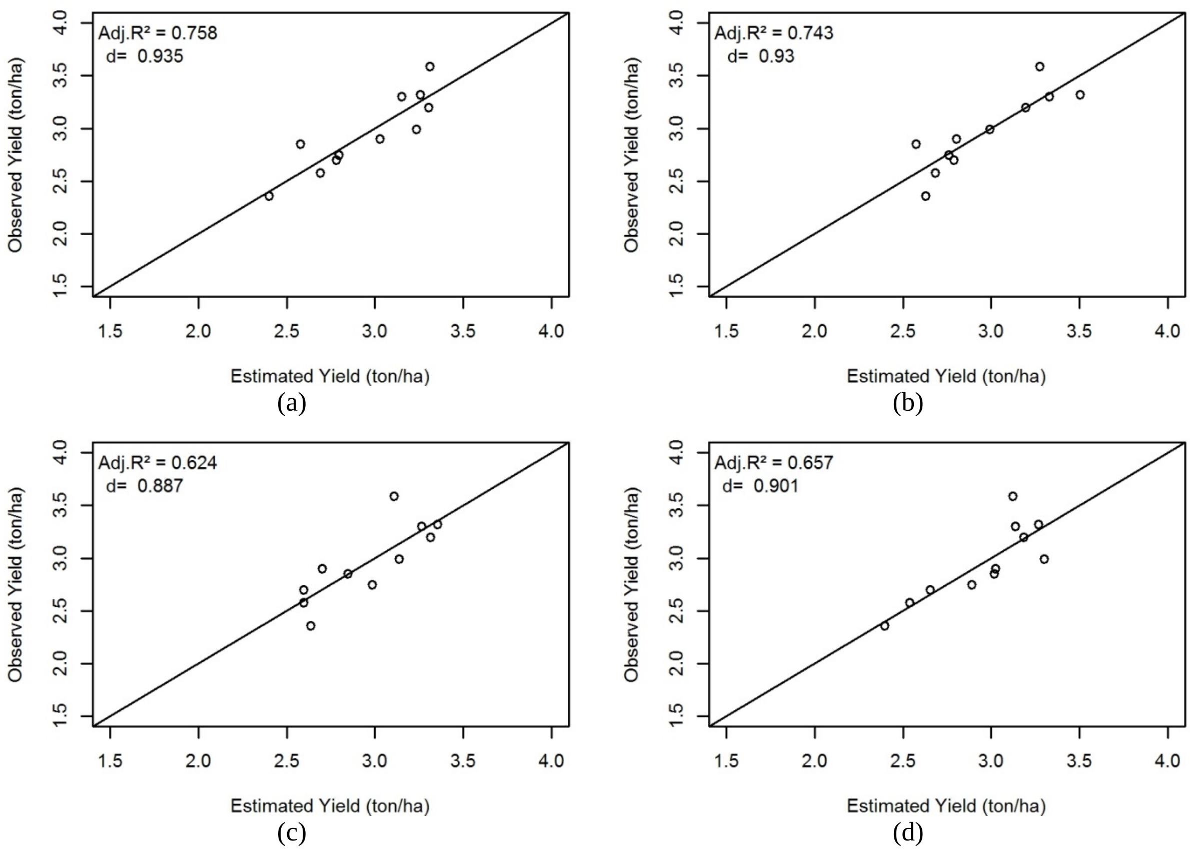


Figure 9.34 Relationship between observed and estimated yield for Cascavel county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.38 Monthly methodology for Catanduvas county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.3	3.3	0.1	3.3	0.6	3.1	5.0	3.1	6.1	3.0	9.9	3.1	6.5	3.3	-0.1
200102	2.8	2.9	-4.1	3.1	-9.4	2.9	-4.7	2.8	1.3	3.1	-10.2	3.0	-8.1	2.9	-3.2
200203	3.2	2.9	10.2	3.4	-4.4	3.1	2.6	3.3	-2.7	3.2	2.3	3.0	6.4	3.3	-3.2
200304	2.8	3.0	-9.3	2.7	2.7	2.7	1.2	2.7	0.7	2.7	1.3	3.1	-10.0	2.7	3.5
200405	2.9	2.8	1.4	3.0	-6.5	3.0	-4.9	3.1	-7.4	3.0	-4.8	3.1	-6.7	3.0	-5.1
200506	3.1	3.2	-5.1	3.3	-7.7	3.1	-1.6	3.2	-3.3	3.3	-6.5	3.1	-2.2	3.3	-6.4
200607	3.5	3.4	2.4	3.3	5.0	3.6	-3.6	3.6	-3.5	3.2	7.7	3.6	-1.8	3.4	3.5
200708	3.6	3.7	-2.3	3.2	12.8	3.5	1.5	3.6	0.3	3.6	0.1	3.3	8.8	3.4	4.8
200809	3.1	3.3	-6.9	3.0	1.6	3.3	-5.5	3.0	1.5	3.1	-2.1	3.1	-1.1	3.5	-11.1
200910	3.4	3.2	7.2	3.3	4.6	3.6	-3.4	3.3	2.5	3.4	1.5	3.1	9.8	3.2	8.5
201011	3.8	3.5	6.3	3.7	0.7	3.3	13.4	3.6	4.6	3.7	0.9	3.8	-1.8	3.5	8.8
RMSE		0.186		0.200		0.176		0.121		0.174		0.182		0.144	
MAE		0.159		0.162		0.139		0.100		0.135		0.143		0.110	
Adj. R^2		0.620		0.560		0.660		0.840		0.670		0.640		0.770	
d		0.888		0.865		0.903		0.960		0.907		0.894		0.940	

Table 9.39 Phenological methodology for Catanduvas county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.3	3.2	3.5	3.2	2.7	2.9	12.0	3.2	1.8
200102	2.8	3.1	-8.3	3.0	-5.5	2.7	2.9	3.1	-9.7
200203	3.2	3.1	5.3	3.0	7.5	3.2	-0.1	3.2	-0.6
200304	2.8	2.8	-2.5	2.9	-4.9	3.1	-9.6	3.3	-15.7
200405	2.9	3.1	-9.3	3.0	-5.0	3.1	-7.3	3.1	-7.1
200506	3.1	3.1	0.1	3.2	-3.5	3.4	-9.2	3.3	-5.9
200607	3.5	3.6	-2.1	3.8	-7.2	3.3	4.4	3.4	3.4
200708	3.6	3.4	6.8	3.4	5.2	3.5	3.1	3.3	10.5
200809	3.1	3.4	-9.7	3.3	-6.9	3.3	-6.5	3.2	-3.0
200910	3.4	3.1	12.3	3.3	4.9	3.3	4.7	3.2	5.5
201011	3.8	3.6	3.9	3.3	12.4	3.6	5.8	3.1	20.7
RMSE		0.218		0.212		0.216		0.306	
MAE		0.186		0.194		0.191		0.243	
Adj. R^2		0.477		0.506		0.489		-0.028	
d		0.833		0.836		0.837		0.405	

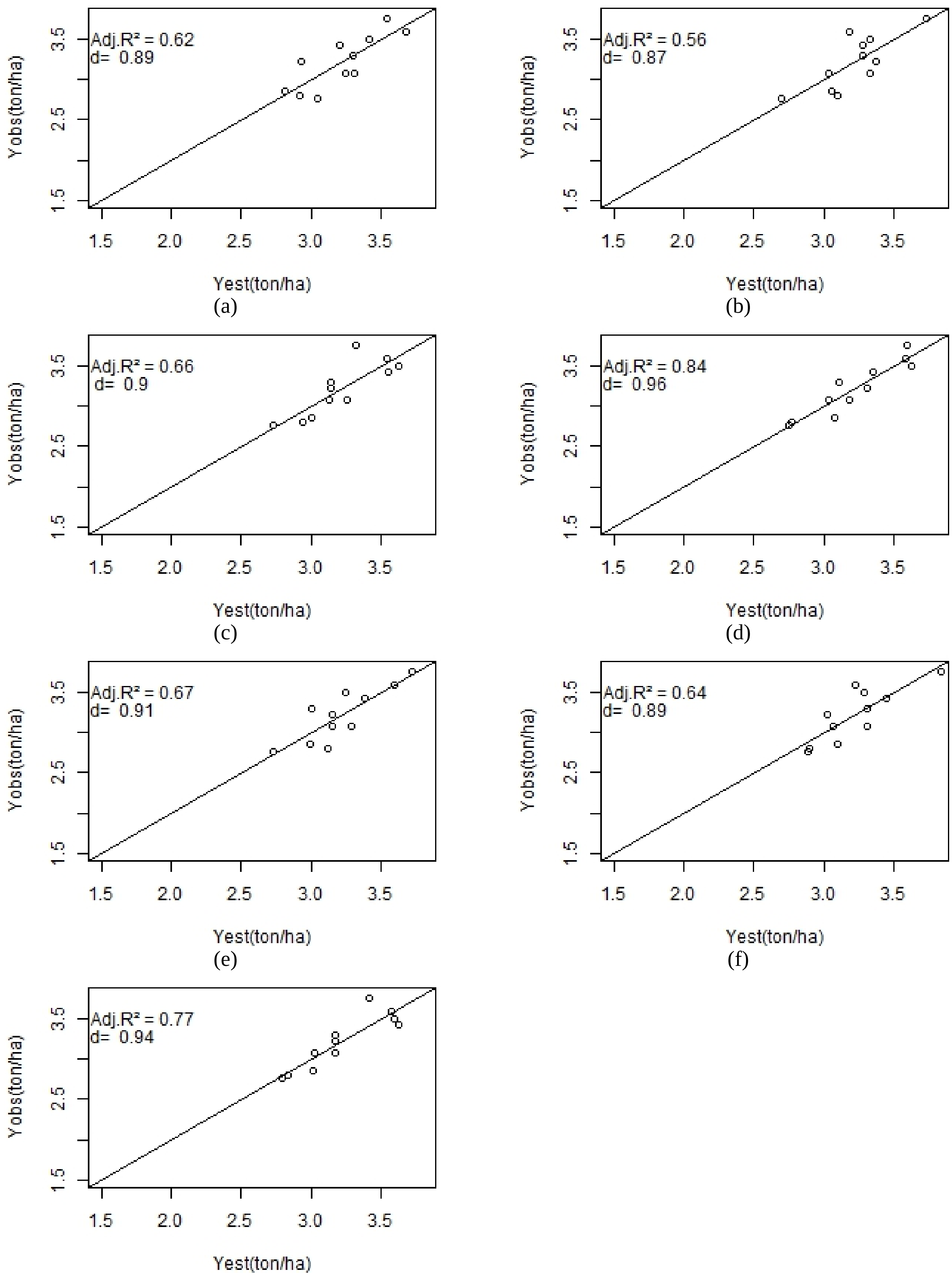


Figure 9.35 Relationship between observed and estimated yield for Catanduvas county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

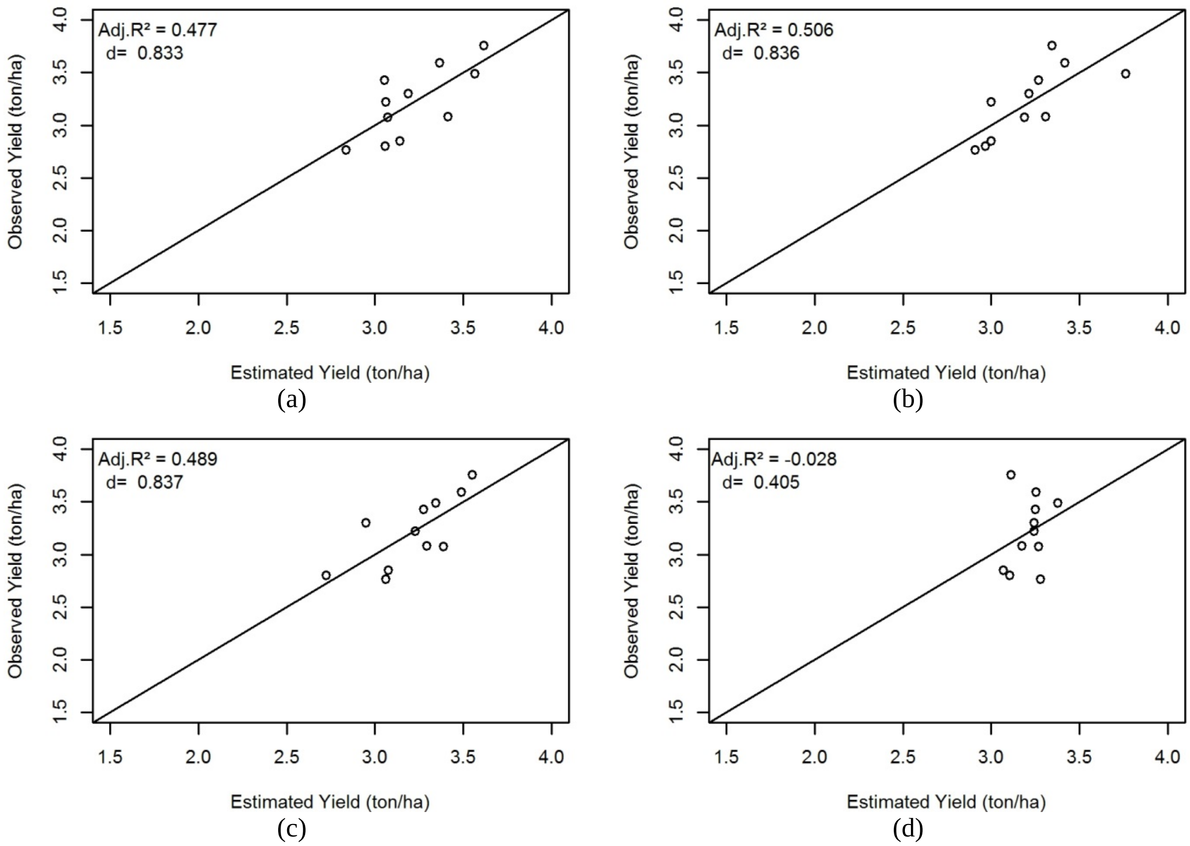


Figure 9.36 Relationship between observed and estimated yield for Catanduvas county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.40 Monthly methodology for Goioerê county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.5	3.0	17.3	3.3	4.7	3.2	7.6	3.3	4.8	3.5	-0.3	3.1	11.5	3.2	10.7
200102	3.2	3.3	-3.7	3.3	-2.6	3.5	-8.4	3.1	3.3	3.2	-0.4	3.2	-0.2	2.7	21.1
200203	3.0	2.8	7.1	2.9	4.0	3.2	-4.0	3.1	-3.2	2.7	13.3	3.2	-5.1	3.1	-2.4
200304	2.5	2.8	-9.1	2.7	-5.5	2.2	13.2	2.6	-3.6	2.5	2.7	2.3	9.4	2.5	-0.5
200405	1.9	2.5	-23.9	2.0	-3.3	2.2	-12.1	2.1	-9.1	2.5	-24.0	2.2	-10.9	2.4	-19.0
200506	3.0	2.8	3.9	3.1	-5.8	3.2	-8.5	3.2	-8.7	2.6	13.8	2.8	5.0	3.1	-4.8
200607	3.2	3.0	5.3	3.6	-12.3	3.1	1.7	3.3	-2.2	3.1	2.2	3.3	-2.7	3.2	1.2
200708	3.1	2.8	9.1	2.8	10.3	2.9	7.5	2.8	8.8	3.0	2.1	3.3	-4.6	3.1	1.0
200809	2.5	2.5	0.4	2.7	-8.6	2.7	-7.1	2.3	7.9	2.7	-7.9	2.6	-4.6	2.5	-1.6
200910	3.7	3.9	-3.6	3.3	11.8	3.5	7.0	3.5	7.4	3.6	4.0	3.8	-1.8	3.8	-2.4
201011	3.4	3.5	-3.7	3.2	6.6	3.3	2.9	3.6	-5.8	3.6	-5.8	3.3	3.3	3.5	-4.0
RMSE		0.286		0.241		0.224		0.186		0.261		0.176		0.251	
MAE		0.228		0.211		0.210		0.173		0.192		0.150		0.176	
Adj. R^2		0.620		0.730		0.770		0.840		0.690		0.860		0.710	
d		0.888		0.927		0.939		0.960		0.911		0.965		0.921	

Table 9.41 Phenological methodology for Goioerê county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.5	3.3	4.8	3.5	0.5	3.0	15.7	3.2	8.4
200102	3.2	3.1	2.3	3.1	2.5	2.6	21.6	3.1	4.2
200203	3.0	3.1	-1.8	3.0	2.3	3.0	-0.3	3.1	-1.7
200304	2.5	2.5	-1.1	2.7	-8.3	2.8	-8.8	2.5	1.9
200405	1.9	2.3	-17.2	2.4	-19.5	2.6	-26.4	2.4	-18.0
200506	3.0	2.9	1.0	2.9	1.4	2.7	8.5	2.9	3.3
200607	3.2	2.8	15.6	2.6	22.1	3.1	4.5	3.3	-1.8
200708	3.1	3.2	-1.7	3.0	4.9	3.5	-10.9	3.3	-5.0
200809	2.5	2.4	3.8	2.5	-1.6	2.7	-6.9	2.2	11.2
200910	3.7	3.7	1.3	3.6	3.1	3.5	5.5	3.6	2.7
201011	3.4	3.7	-7.9	3.7	-8.1	3.5	-2.8	3.6	-5.3
RMSE		0.209		0.260		0.356		0.196	
MAE		0.151		0.189		0.293		0.162	
Adj. R^2		0.798		0.689		0.417		0.823	
d		0.949		0.915		0.794		0.955	

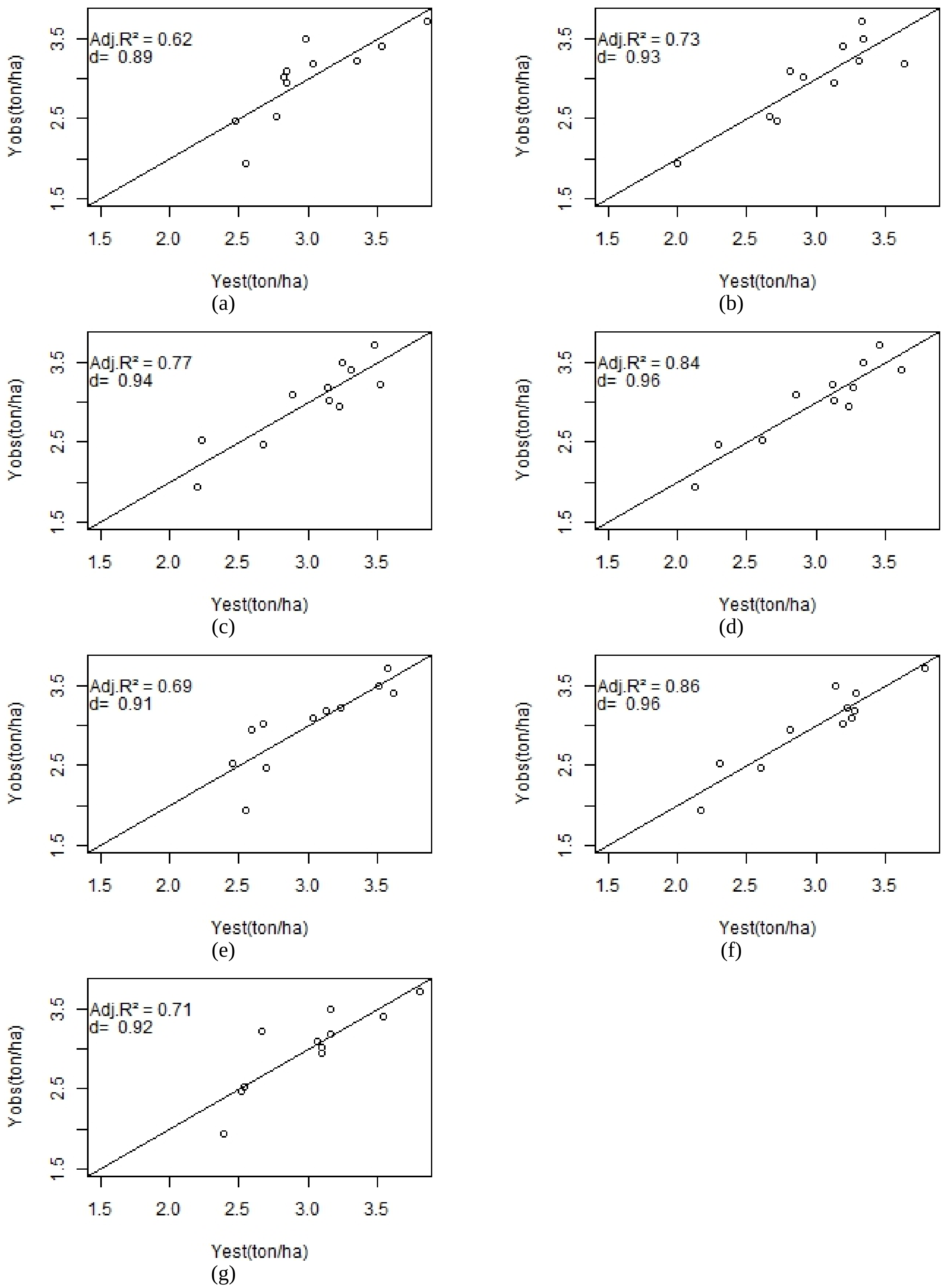


Figure 9.37 Relationship between observed and estimated yield for Goioerê county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

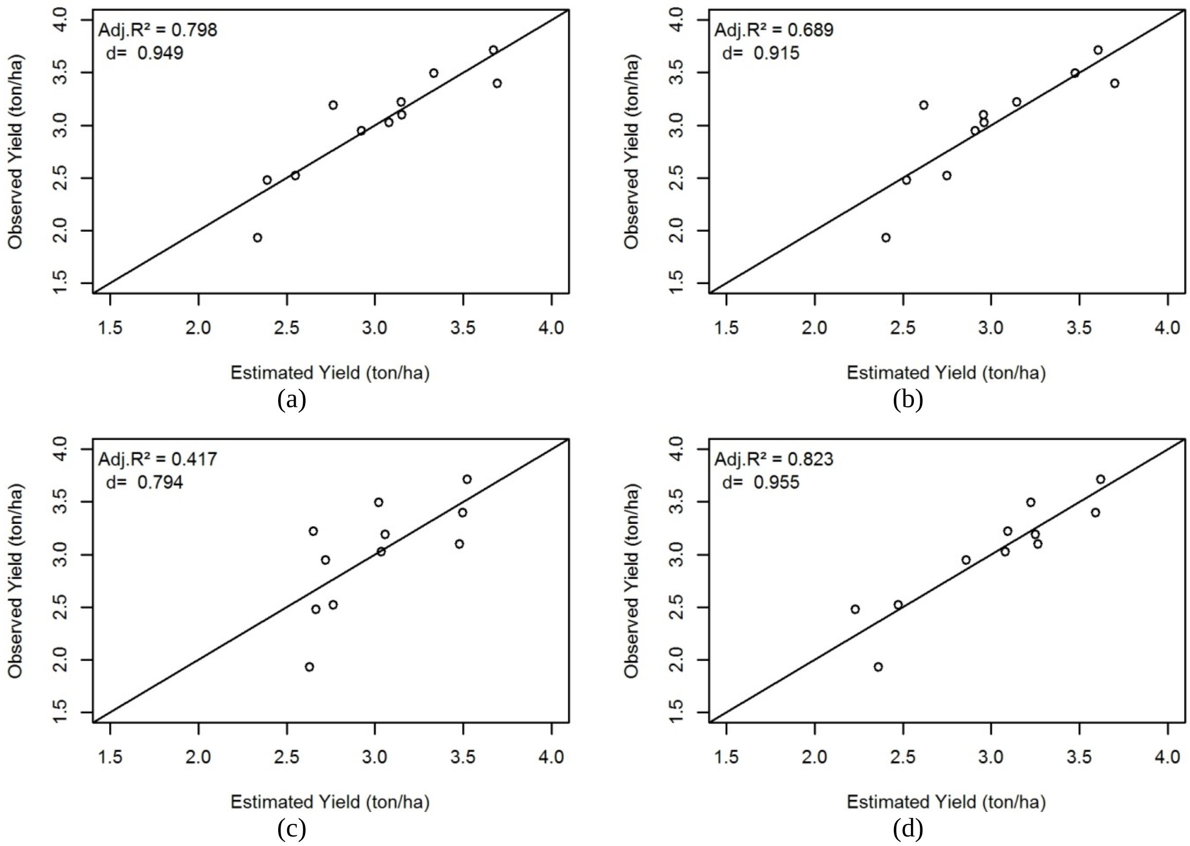


Figure 9.38 Relationship between observed and estimated yield for Goioerê county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.42 Monthly methodology for Guaraniaçu county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	2.9	2.7	3.9	2.8	0.6	3.1	-7.6	2.8	0.3	2.8	2.9	2.8	0.5	3.0	-5.7
200102	3.0	2.9	0.5	2.9	0.3	3.1	-4.1	2.9	3.1	3.0	-2.5	2.8	4.6	3.1	-4.2
200203	3.1	3.1	0.4	3.1	0.6	3.0	4.8	2.9	6.8	3.0	2.5	3.1	-0.4	3.1	-0.3
200304	2.8	2.8	-2.0	2.7	2.5	2.8	-2.9	2.7	1.0	3.0	-7.7	2.9	-5.7	2.9	-4.5
200405	2.9	2.8	3.8	2.8	4.2	3.1	-5.8	3.0	-3.1	3.0	-2.5	2.7	5.9	2.8	5.1
200506	2.9	3.2	-9.0	3.0	-4.4	2.8	4.1	3.0	-2.7	2.7	8.6	2.9	0.1	2.7	4.7
200607	3.2	3.1	4.5	3.3	-2.7	3.1	3.4	3.3	-2.1	3.1	3.7	3.2	-0.9	3.1	1.6
200708	3.1	3.1	-2.6	2.9	4.9	3.0	2.4	3.0	0.6	3.1	-0.3	3.2	-4.2	3.0	2.0
200809	2.3	2.5	-5.6	2.6	-10.6	2.4	-4.2	2.5	-5.1	2.5	-7.7	2.5	-5.6	2.4	-2.9
200910	3.0	3.0	2.2	3.2	-4.2	3.0	0.3	3.2	-4.9	2.9	3.4	3.0	-0.3	3.0	0.2
201011	3.3	3.1	3.7	3.0	8.6	3.0	9.4	3.1	6.0	3.3	-0.2	3.1	5.8	3.1	3.8
RMSE		0.124		0.143		0.149		0.114		0.131		0.113		0.106	
MAE		0.102		0.115		0.131		0.095		0.108		0.089		0.092	
Adj. R^2		0.700		0.610		0.570		0.750		0.670		0.750		0.780	
d		0.919		0.882		0.869		0.934		0.906		0.934		0.944	

Table 9.43 Phenological methodology for Guaraniaçu county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	2.9	2.9	-2.3	2.8	1.2	3.0	-4.1	3.0	-4.2
200102	3.0	3.0	-1.3	2.8	4.0	2.7	9.8	2.9	1.5
200203	3.1	3.2	-3.2	2.9	8.6	3.1	-1.1	3.2	-2.0
200304	2.8	2.8	-0.6	2.9	-5.9	2.9	-4.9	2.9	-4.0
200405	2.9	2.9	0.4	3.0	-4.6	2.9	1.6	2.7	6.9
200506	2.9	3.0	-4.4	2.9	0.7	2.9	-0.3	2.9	-1.2
200607	3.2	2.9	8.8	3.3	-2.3	3.2	-0.3	3.2	-0.8
200708	3.1	2.9	4.6	3.0	0.6	3.1	-1.1	3.0	1.1
200809	2.3	2.4	-3.4	2.8	-15.6	2.5	-7.7	2.5	-5.8
200910	3.0	3.2	-4.5	2.8	7.8	3.1	-1.9	3.1	-2.3
201011	3.3	3.1	5.7	3.1	5.4	3.0	9.8	2.9	10.7
RMSE		0.127		0.189		0.146		0.134	
MAE		0.105		0.149		0.110		0.105	
Adj. R^2		0.690		0.316		0.587		0.654	
d		0.913		0.737		0.873		0.899	

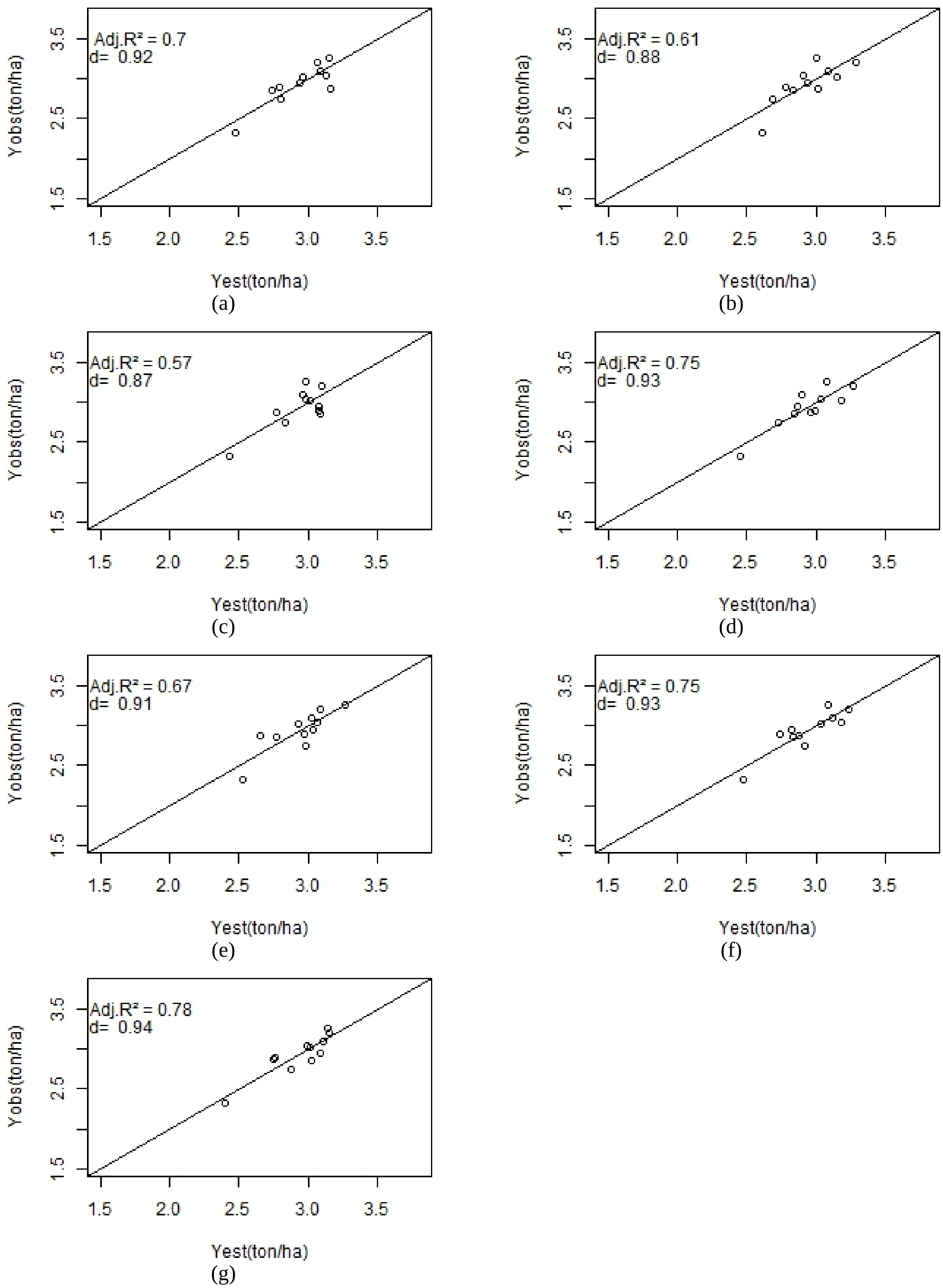
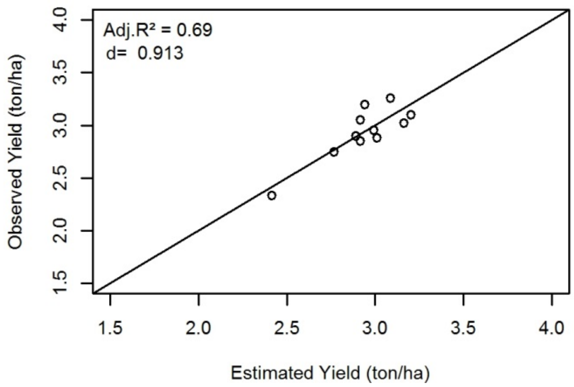
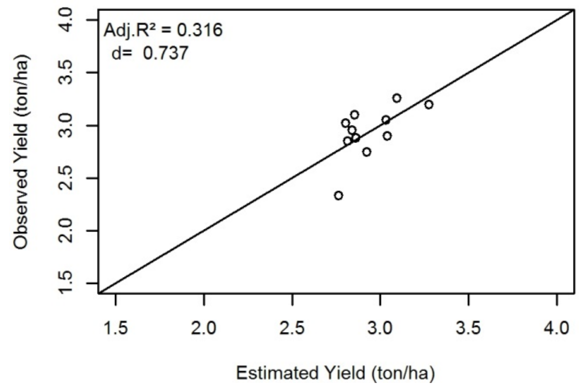


Figure 9.39 Relationship between observed and estimated yield for Guaraniaçu county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.



(a)



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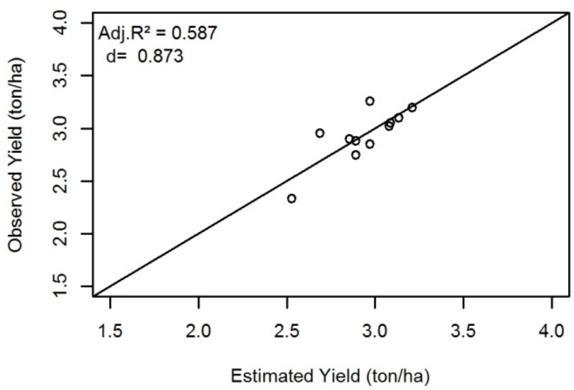

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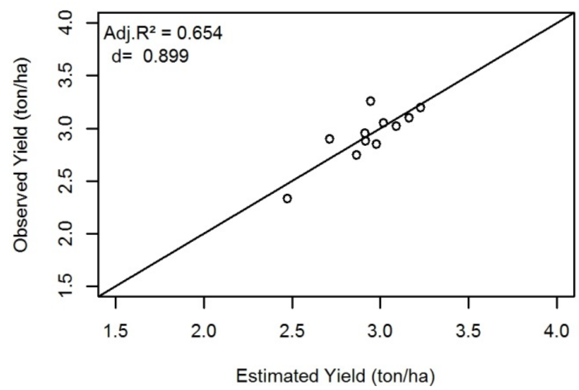


(d)

Figure 9.40 Relationship between observed and estimated yield for Guaraniaçu county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.44 Monthly methodology for Juranda county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.2	2.9	10.2	3.1	2.3	3.4	-7.1	3.2	0.9	3.2	1.6	3.4	-6.5	2.7	19.4
200102	3.2	3.1	3.5	2.8	16.7	3.0	7.4	3.1	4.4	2.9	10.5	3.1	6.0	3.1	3.4
200203	3.1	3.4	-9.9	3.2	-4.7	3.2	-3.8	3.3	-6.5	2.8	9.2	3.4	-8.3	3.2	-2.6
200304	2.7	2.8	-4.3	2.5	8.9	2.7	-0.5	2.9	-5.7	3.2	-14.9	2.8	-3.0	2.9	-6.4
200405	2.6	2.7	-2.1	2.7	-3.4	2.8	-6.8	2.9	-10.1	2.5	4.0	2.6	0.3	2.9	-9.6
200506	2.6	2.5	6.0	2.8	-5.9	2.9	-10.5	2.7	-1.1	2.5	3.4	2.8	-5.2	2.5	4.9
200607	2.6	2.7	-2.0	2.8	-4.6	2.7	-2.7	2.9	-8.7	3.1	-14.5	2.5	3.2	3.0	-11.2
200708	3.3	3.5	-4.5	3.1	6.8	3.0	10.4	3.1	7.6	3.3	1.9	3.4	-1.0	3.4	-3.1
200809	2.3	2.5	-9.3	2.8	-16.0	2.3	1.7	2.1	11.1	2.7	-14.7	2.6	-11.4	2.4	-4.9
200910	3.7	3.4	10.5	3.7	1.2	3.3	14.9	3.5	6.7	3.5	5.6	3.5	8.1	3.5	5.4
201011	3.4	3.3	1.7	3.4	-1.2	3.5	-3.2	3.3	2.6	3.1	8.2	2.9	17.5	3.2	4.8
RMSE		0.207		0.231		0.235		0.194		0.283		0.237		0.236	
MAE		0.176		0.185		0.193		0.173		0.241		0.193		0.200	
Adj. R^2		0.730		0.660		0.650		0.760		0.490		0.640		0.640	
d		0.926		0.904		0.896		0.936		0.841		0.896		0.899	

Table 9.45 Phenological methodology for Juranda county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.2	3.4	-5.2	2.9	9.2	3.1	2.2	3.1	3.9
200102	3.2	3.1	5.9	3.1	4.9	3.0	7.4	3.0	7.4
200203	3.1	2.7	14.3	2.8	11.6	3.0	3.4	2.7	14.7
200304	2.7	3.1	-12.6	3.4	-19.4	3.2	-13.6	3.2	-13.9
200405	2.6	2.9	-11.8	2.7	-2.4	2.9	-11.0	2.9	-11.2
200506	2.6	2.8	-6.2	2.9	-10.1	2.9	-10.8	2.6	0.9
200607	2.6	2.5	6.5	2.7	-1.2	3.1	-15.7	2.7	-1.2
200708	3.3	3.2	5.9	3.3	0.3	2.8	19.2	3.4	-1.6
200809	2.3	2.5	-6.2	2.6	-10.6	2.7	-13.9	2.5	-6.5
200910	3.7	3.6	5.1	3.3	14.4	3.0	23.0	3.7	2.0
201011	3.4	3.3	4.5	3.3	2.9	3.1	9.7	3.2	5.5
RMSE		0.244		0.306		0.394		0.231	
MAE		0.226		0.240		0.352		0.184	
Adj. R^2		0.620		0.404		0.013		0.660	
d		0.890		0.800		0.465		0.905	

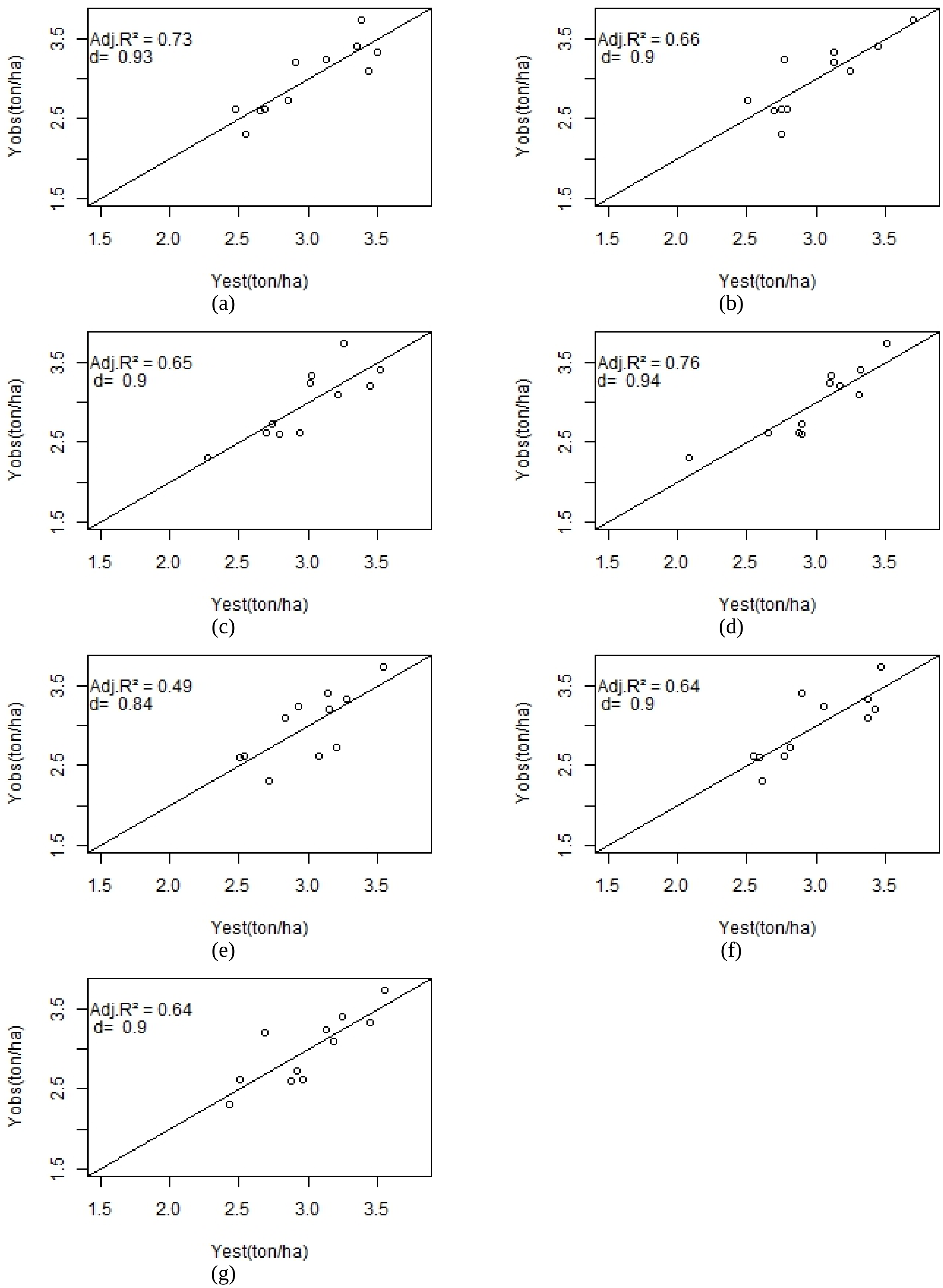


Figure 9.41 Relationship between observed and estimated yield for Juranda county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

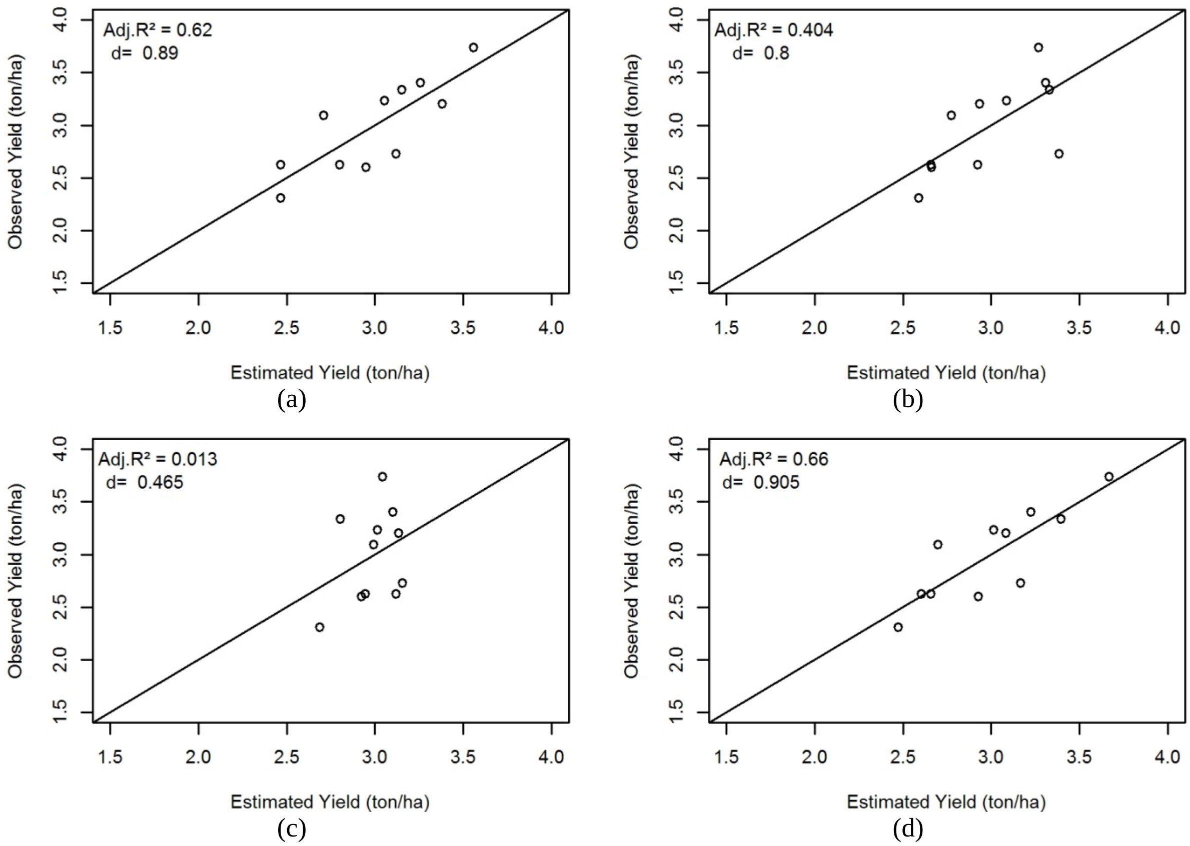


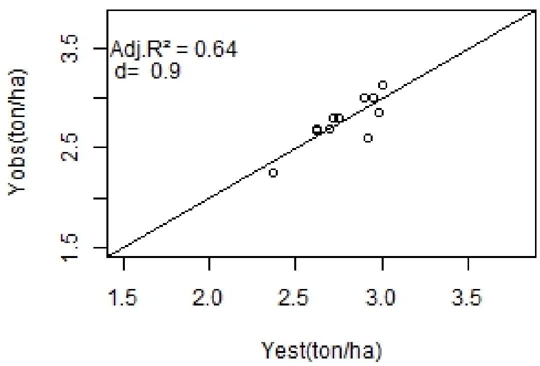
Figure 9.42 Relationship between observed and estimated yield for Juranda county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.46 Monthly methodology for Laranjal county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	2.8	2.7	3.0	2.8	1.4	2.9	-3.3	2.9	-3.3	2.9	-3.3	2.8	-1.1	2.8	-0.7
200102	2.7	2.7	0.2	2.5	6.8	2.7	1.8	2.8	-4.2	2.6	2.7	2.9	-7.5	2.9	-6.0
200203	2.9	3.0	-4.4	2.7	6.0	2.9	-3.4	3.0	-5.3	3.0	-4.8	2.9	-2.7	2.7	4.3
200304	2.7	2.6	2.3	2.8	-5.4	2.8	-5.6	2.7	-0.8	2.6	4.0	2.8	-3.4	2.6	2.5
200405	2.3	2.4	-4.8	2.6	-12.4	2.3	-2.1	2.3	-2.0	2.5	-10.4	2.5	-10.4	2.5	-10.3
200506	2.6	2.9	-10.9	2.6	-1.3	2.6	-1.5	2.6	0.5	2.8	-7.9	2.7	-4.4	2.6	-0.6
200607	2.8	2.8	1.8	2.7	1.8	2.8	-1.4	2.8	-0.8	2.6	6.8	2.7	3.8	2.6	5.9
200708	3.1	3.0	4.4	3.1	2.4	2.9	9.9	2.9	7.5	3.0	6.2	2.9	7.3	3.1	2.0
200809	2.7	2.6	2.8	2.7	1.0	2.7	0.3	2.6	3.4	2.7	-0.6	2.7	-0.2	2.6	2.8
200910	3.0	2.9	3.7	3.1	-3.3	3.0	-1.3	3.0	0.6	2.8	6.9	2.6	15.1	2.9	3.9
201011	3.0	2.9	1.8	2.9	3.1	2.8	6.7	2.9	4.3	3.0	0.3	2.9	3.5	3.1	-3.7
RMSE		0.129		0.138		0.124		0.106		0.156		0.183		0.126	
MAE		0.103		0.111		0.095		0.084		0.135		0.148		0.106	
Adj. R^2		0.640		0.590		0.670		0.760		0.480		0.280		0.660	
d		0.900		0.875		0.905		0.936		0.824		0.730		0.904	

Table 9.47 Phenological methodology for Laranjal county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	2.8	2.8	-1.7	2.7	3.7	2.8	-1.5	2.9	-2.1
200102	2.7	2.7	-1.3	2.7	-1.1	2.5	9.9	2.6	1.9
200203	2.9	2.9	-2.2	2.7	4.7	2.9	-2.8	2.9	-1.8
200304	2.7	2.7	0.2	2.6	1.8	2.8	-3.3	2.7	0.8
200405	2.3	2.5	-11.1	2.6	-12.3	2.5	-9.1	2.3	-4.0
200506	2.6	2.8	-8.7	2.6	1.1	2.7	-4.3	2.7	-5.3
200607	2.8	2.6	9.4	3.0	-8.1	2.9	-4.4	3.0	-5.9
200708	3.1	2.8	12.3	3.0	3.5	2.9	8.7	2.8	10.8
200809	2.7	2.8	-1.8	2.9	-5.7	2.7	1.1	2.6	2.2
200910	3.0	3.0	-0.8	2.8	8.1	3.0	0.4	3.0	-1.5
201011	3.0	2.8	5.7	2.9	4.1	2.8	5.4	2.9	4.6
RMSE		0.179		0.163		0.149		0.130	
MAE		0.137		0.137		0.125		0.103	
Adj. R^2		0.309		0.426		0.519		0.635	
d		0.725		0.796		0.840		0.891	



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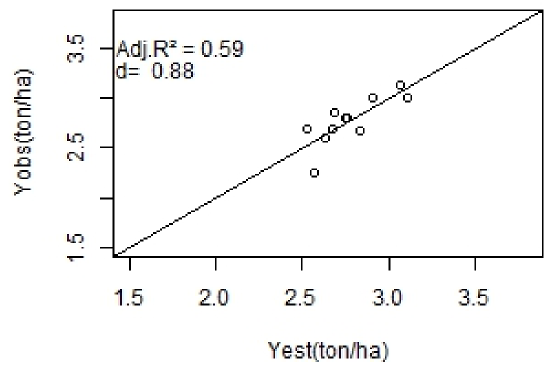

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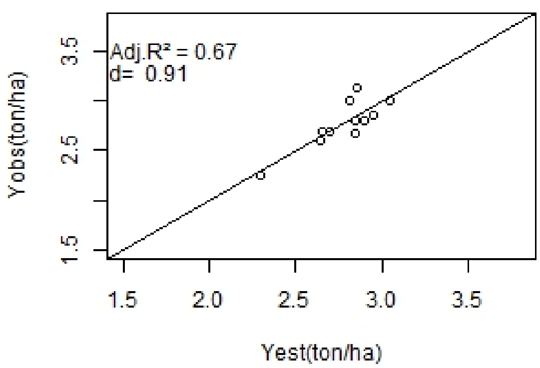

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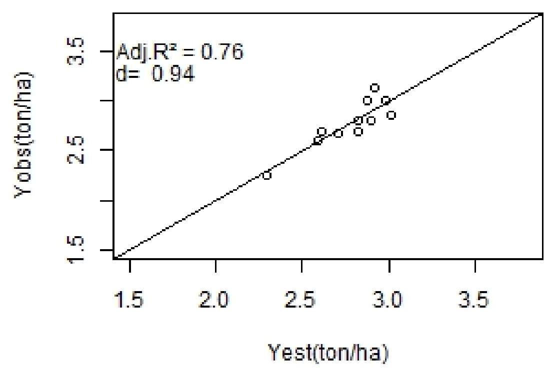

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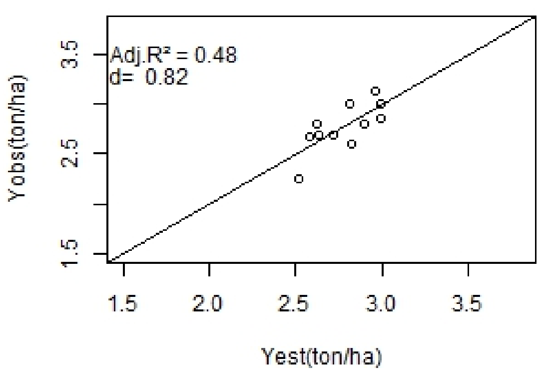

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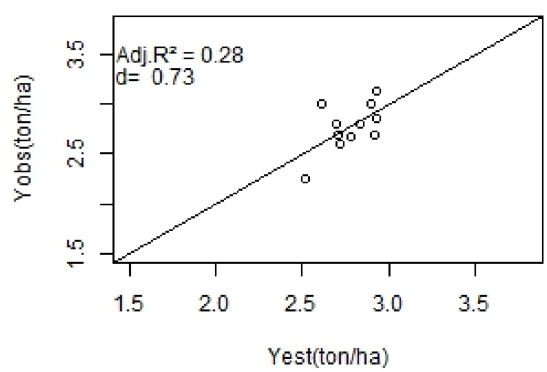

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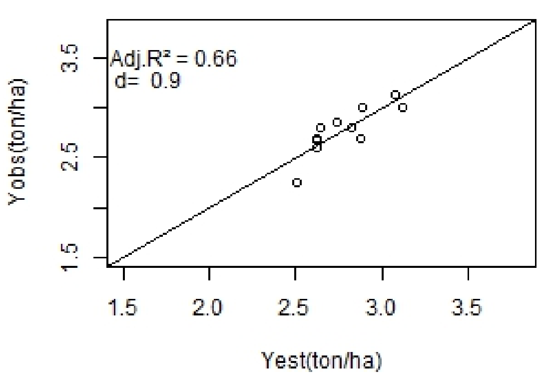


(g)

Figure 9.43 Relationship between observed and estimated yield for Laranjal county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

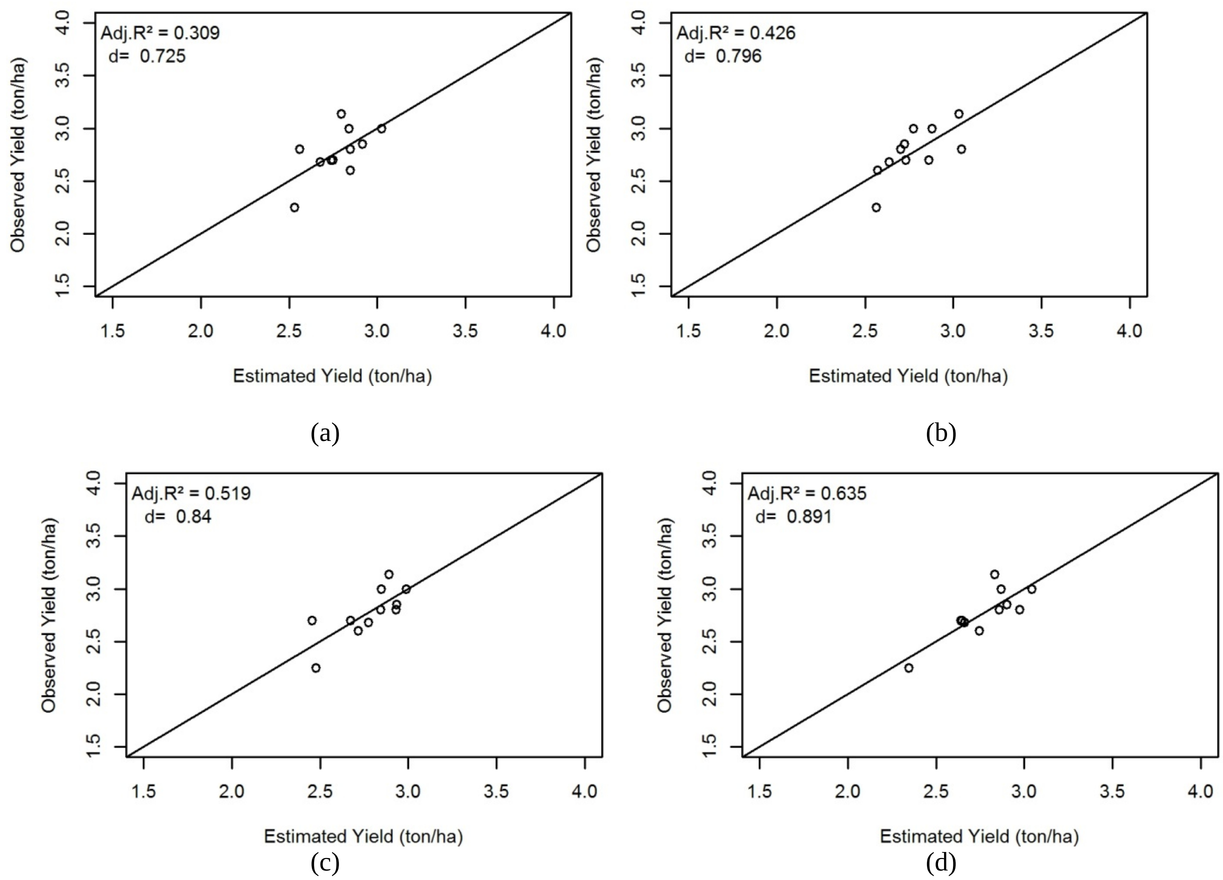


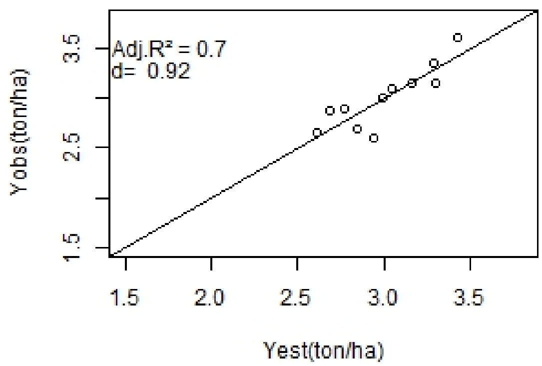
Figure 9.44 Relationship between observed and estimated yield for Laranjal county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.48 Monthly methodology for Mamborê county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

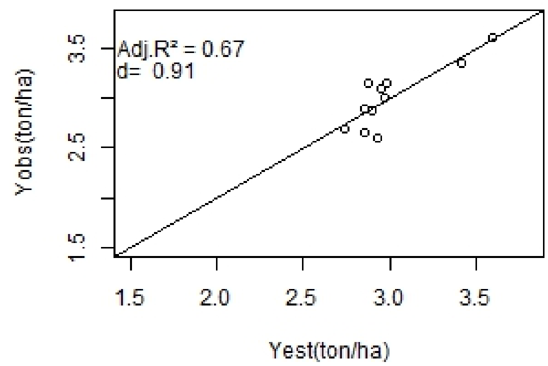
Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.0	3.0	0.3	3.0	1.0	3.1	-3.0	3.2	-6.4	2.9	2.4	2.9	2.7	2.9	4.2
200102	2.9	2.7	7.0	2.9	-0.8	2.8	3.5	2.8	3.3	3.0	-4.9	2.9	-1.1	2.8	0.9
200203	3.1	3.0	1.9	2.9	5.1	3.2	-2.3	3.0	3.0	3.1	-1.4	2.9	8.3	3.2	-2.5
200304	2.9	2.8	4.2	2.8	1.3	2.8	2.4	2.8	2.5	2.9	1.0	2.9	0.2	2.9	0.6
200405	2.7	2.6	1.6	2.8	-7.0	2.8	-5.7	2.7	-3.5	2.8	-4.1	2.9	-7.2	2.7	-3.6
200506	2.6	2.9	-11.7	2.9	-11.5	2.8	-5.8	2.8	-6.2	2.7	-3.8	2.8	-6.7	2.7	-3.7
200607	3.1	3.2	-0.5	3.0	5.6	3.2	-2.6	3.3	-4.3	3.0	4.5	2.9	6.8	3.1	0.4
200708	3.1	3.3	-4.4	2.9	9.4	3.1	1.1	3.3	-3.4	3.0	5.4	3.4	-7.6	3.5	-8.8
200809	2.7	2.8	-5.6	2.7	-1.7	2.6	4.3	2.6	3.7	2.7	-1.7	2.7	-1.1	2.7	0.0
200910	3.4	3.3	2.1	3.4	-1.7	3.1	7.1	3.3	2.9	3.2	5.5	3.3	2.5	3.2	6.1
201011	3.6	3.4	5.4	3.6	0.3	3.6	0.9	3.3	8.6	3.7	-3.1	3.5	3.0	3.4	6.3
RMSE		0.153		0.161		0.117		0.146		0.114		0.155		0.141	
MAE		0.121		0.121		0.103		0.132		0.104		0.129		0.106	
Adj. R^2		0.700		0.670		0.830		0.730		0.840		0.690		0.750	
d		0.916		0.908		0.956		0.925		0.959		0.915		0.932	

Table 9.49 Phenological methodology for Mamborê county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.0	3.1	-2.6	3.1	-3.0	3.1	-2.9	3.0	-1.2
200102	2.9	3.0	-5.4	2.9	-2.2	2.7	7.5	3.0	-3.4
200203	3.1	3.1	-0.4	3.1	1.2	3.2	-2.8	3.2	-2.6
200304	2.9	3.1	-5.4	2.9	-1.9	2.9	-0.8	3.0	-4.3
200405	2.7	2.8	-6.8	2.8	-5.0	2.9	-8.0	2.7	-2.4
200506	2.6	2.7	-4.2	2.7	-4.5	2.6	-0.8	2.6	-1.1
200607	3.1	2.8	10.5	2.7	14.5	3.2	-1.0	3.2	-2.7
200708	3.1	3.1	1.7	3.1	0.6	3.2	-0.9	3.1	3.2
200809	2.7	2.5	6.4	2.7	-0.9	2.6	2.8	2.5	7.5
200910	3.4	3.4	-0.8	3.4	-2.1	3.3	2.7	3.3	2.1
201011	3.6	3.4	7.1	3.5	3.4	3.5	4.4	3.4	5.1
RMSE		0.162		0.145		0.116		0.108	
MAE		0.137		0.104		0.093		0.097	
Adj. R^2		0.668		0.733		0.828		0.851	
d		0.908		0.930		0.956		0.963	



(a)



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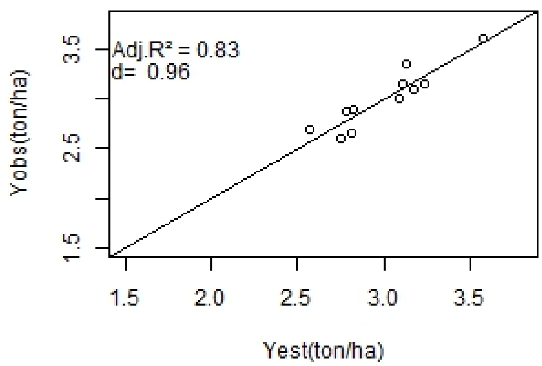

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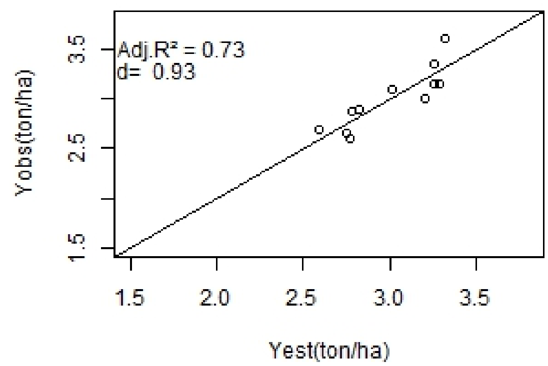

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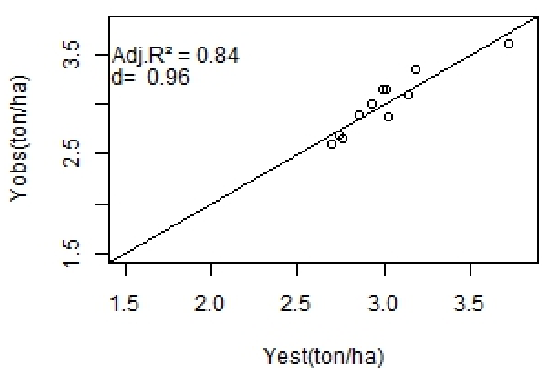

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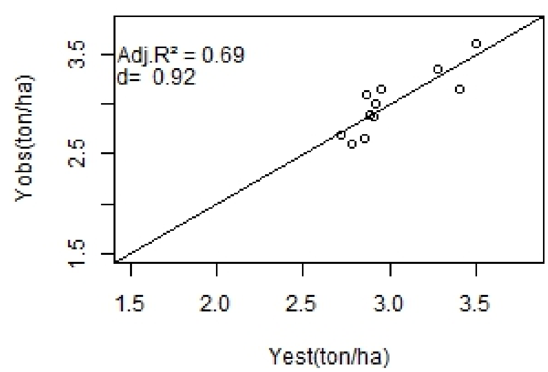

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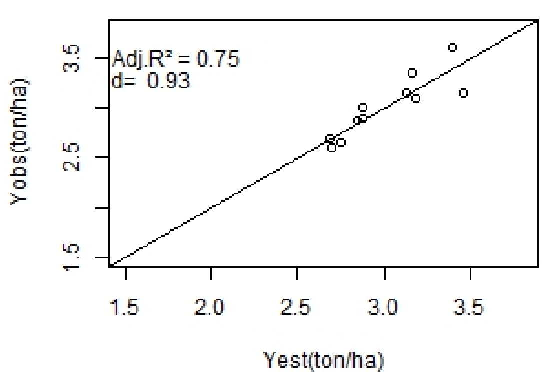


(g)

Figure 9.45 Relationship between observed and estimated yield for Mamborê county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.

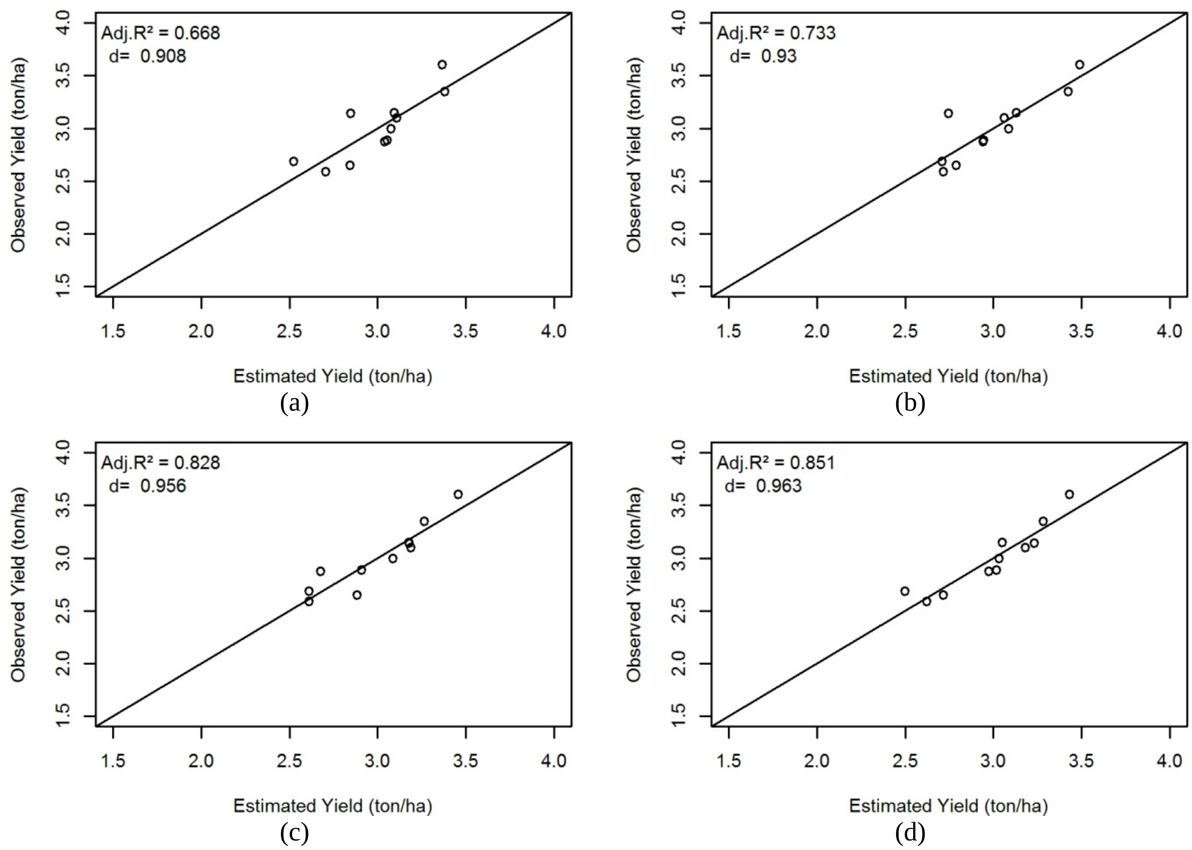


Figure 9.46 Relationship between observed and estimated yield for Mamborê county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).

Table 9.50 Monthly methodology for Nova Cantu county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (Est_Month) (ton/ha).

Crop Season	Obs Y	Est Oct	Diff (%)	Est Nov	Diff (%)	Est Dec	Diff (%)	Est Jan	Diff (%)	Est Feb	Diff (%)	Est Mar	Diff (%)	Est Apr	Diff (%)
200001	3.1	3.0	3.2	3.2	-2.7	2.9	5.8	2.7	13.7	3.1	1.0	3.1	-1.2	2.8	12.5
200102	3.1	3.1	-0.5	3.1	0.8	3.0	1.9	2.9	5.1	2.8	11.5	3.1	0.1	3.2	-4.1
200203	3.1	3.1	-1.1	3.2	-2.4	3.2	-2.5	2.9	7.0	3.2	-2.4	3.2	-2.3	3.1	0.2
200304	2.7	2.9	-5.7	2.7	0.0	2.6	2.9	2.7	1.9	2.8	-2.6	2.6	4.5	2.6	3.1
200405	2.6	2.7	-5.3	2.7	-4.0	2.7	-2.8	2.8	-8.0	2.7	-2.1	2.5	3.8	2.8	-7.5
200506	2.4	2.3	6.0	2.7	-11.9	2.7	-10.1	2.9	-17.9	2.5	-2.2	2.6	-7.4	2.5	-3.4
200607	2.4	2.7	-10.2	2.4	-0.8	2.6	-8.1	2.7	-9.9	2.7	-12.0	2.6	-7.4	2.6	-6.4
200708	3.0	3.1	-2.6	3.0	1.7	2.9	2.6	3.0	1.2	2.9	3.3	2.8	6.9	3.1	-4.0
200809	3.0	2.9	5.1	2.9	5.8	2.8	9.8	3.1	-3.4	2.9	2.7	3.0	0.9	3.0	2.2
200910	3.1	3.0	2.7	3.1	-0.4	3.3	-6.3	2.9	6.2	2.9	6.6	3.0	3.7	3.0	2.5
201011	3.2	2.9	8.5	2.8	13.8	3.0	6.5	3.1	4.0	3.3	-4.1	3.2	-1.5	3.1	4.8
RMSE		0.151		0.169		0.173		0.196		0.164		0.120		0.157	
MAE		0.130		0.114		0.154		0.143		0.131		0.099		0.131	
Adj. R^2		0.690		0.610		0.590		0.480		0.630		0.810		0.670	
d		0.912		0.888		0.877		0.827		0.894		0.950		0.907	

Table 9.51 Phenological methodology for Nova Cantu county: Observed Yield (Obs Y) (ton/ha), Estimated Yield (EM, EF, FG, FM) (ton/ha).

Crop Season	Obs Y	EM	Diff (%)	EF	Diff (%)	FF	Diff (%)	FM	Diff (%)
200001	3.1	2.9	7.2	2.9	6.7	3.0	2.2	2.9	5.8
200102	3.1	2.9	6.8	2.9	6.7	2.9	7.4	2.9	5.8
200203	3.1	2.9	8.7	2.9	7.1	3.0	4.6	2.9	7.2
200304	2.7	2.9	-5.6	2.9	-5.6	2.9	-4.7	2.8	-4.4
200405	2.6	2.8	-7.8	2.9	-10.2	2.9	-11.1	2.8	-8.3
200506	2.4	2.9	-16.5	2.9	-16.6	2.7	-11.4	2.8	-14.8
200607	2.4	2.8	-15.4	2.9	-17.1	3.0	-18.5	2.9	-18.4
200708	3.0	3.1	-2.3	2.9	5.4	2.9	4.1	3.0	-0.1
200809	3.0	2.9	4.2	2.9	4.8	2.7	10.7	2.8	7.2
200910	3.1	2.9	6.9	2.9	8.3	2.9	6.4	2.9	7.2
201011	3.2	2.8	13.7	2.9	10.5	2.9	10.1	2.8	12.7
RMSE		0.277		0.286		0.271		0.279	
MAE		0.248		0.260		0.239		0.241	
Adj. R^2		-0.040		-0.109		0.002		-0.058	
d		0.298		0.059		0.432		0.311	

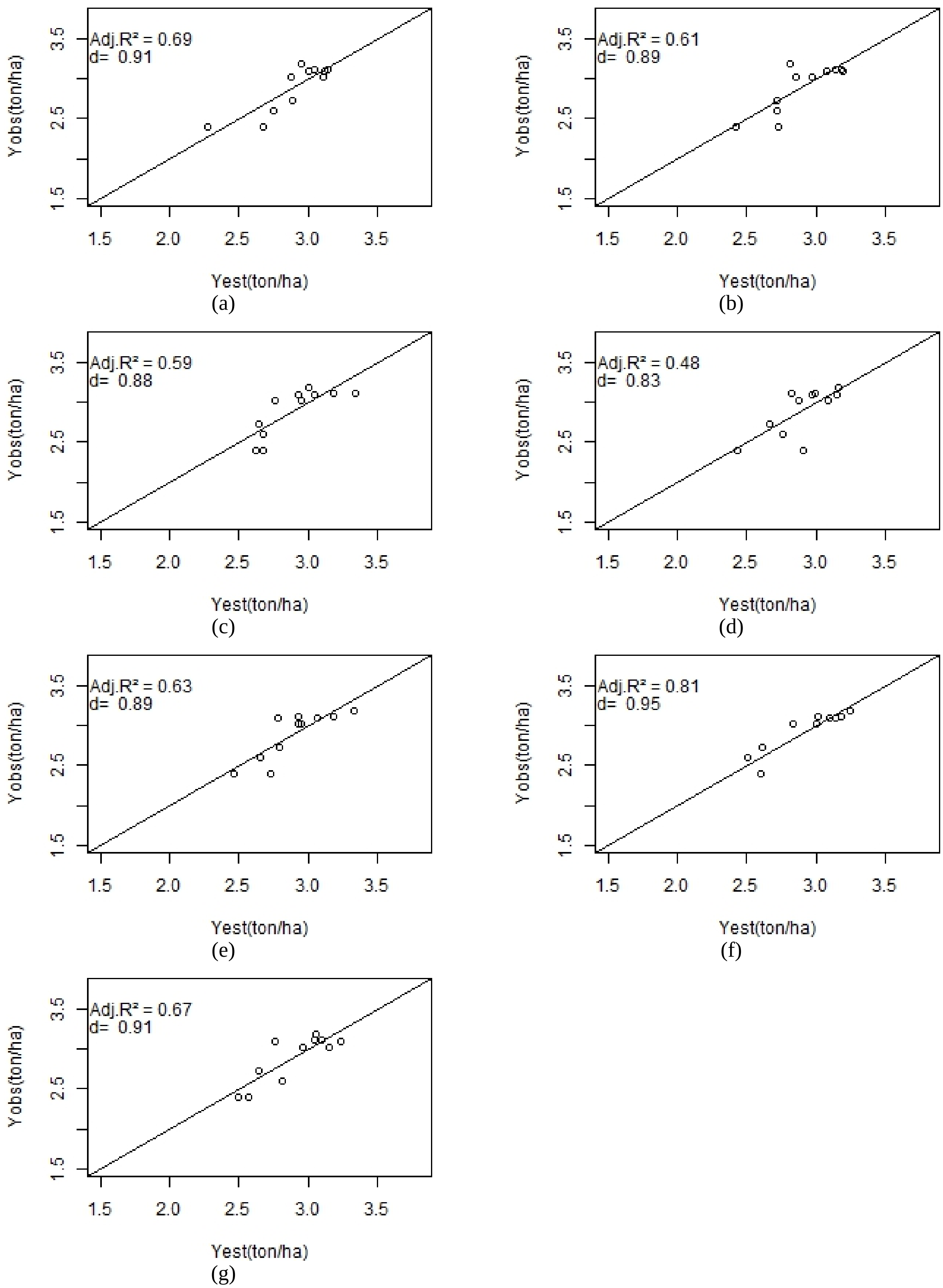
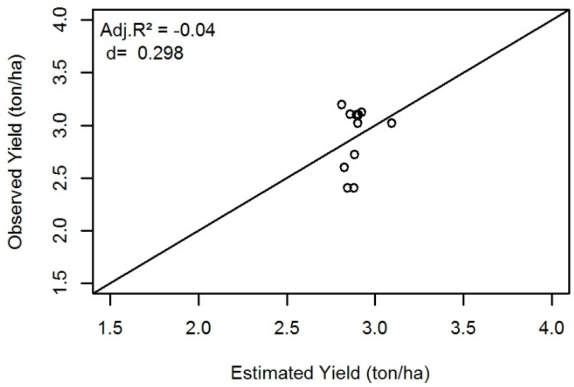


Figure 9.47 Relationship between observed and estimated yield for Nova Cantu county using monthly approach (a) October, (b) November, (c) December, (d) January, (e) February, (f) March, (g) April.



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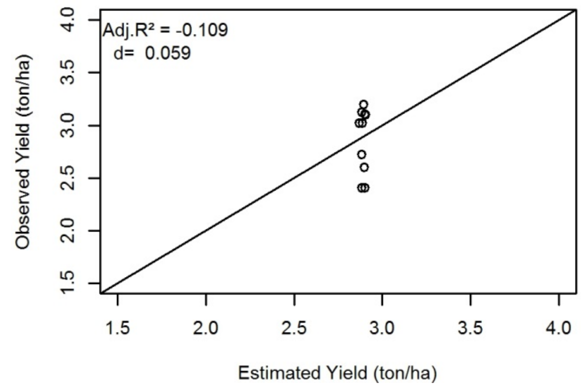

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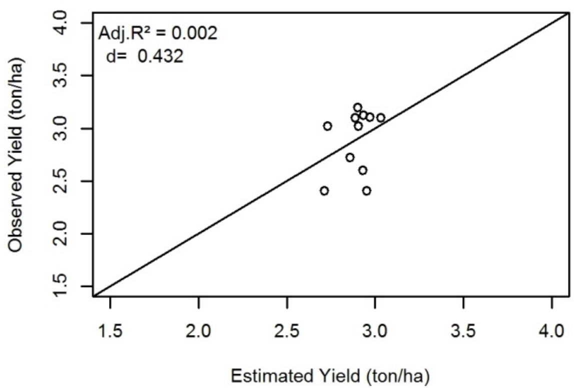

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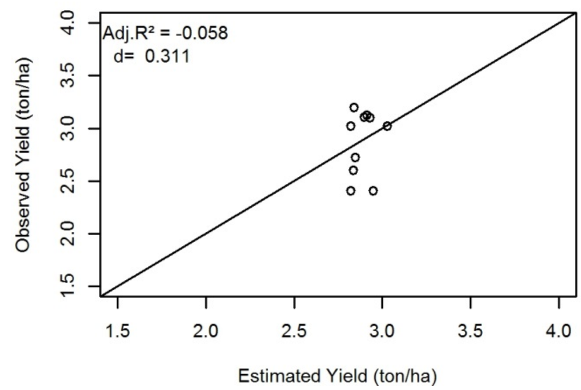

(d)

Figure 9.48 Relationship between observed and estimated yield for Nova Cantu county using various phenological stages (a) Emergence to Maturity - EM, (b) Emergence to Flowering - EF, (c) Flowering to Grain Filling - FG, (d) Flowering to Maturity (FM).