New Agroclimatic Digital Images Classification System

and Risk Zone Mapping

LUCIANO PUGSLEY[1]
PAULO ESTEVÃO CRUVINEL[2]
PAULO HENRIQUE CARAMORI[3]
[1]Department of Computation – Federal University of São Carlos, P.O.Box 676, 13565-905 São Carlos, SP, Brazil
pugsley@dc.ufscar.br
[2]EMBRAPA –Agricultural Instrumentation, P.B.Box 741, 13560-970 São Carlos, SP, Brazil
cruvinel@cnpdia.embrapa.br
[3]IAPAR –Agronomic Institute of Parana, P.B.Box 48, 86001-970 Londrina, Pr, Brazil
caramori@pr.gov.br

Abstract. This paper presents a methodology to support farm decision-making by characterizing regional potential and climatic risks involved during agricultural crop cycles. It introduces agricultural zoning based on a system that classifies digital images of agroclimatic indices. The methodology uses as a first step analyses and processing of climatic data from weather stations through GIS tools. These results are interpolated to generate images of several limiting parameters of agricultural crops. In the second step, these images are segmented using techniques, such as regional growing segmentation by pixel aggregation and regional split/merging segmentation. By using the resulting description of characteristics, the system allows linking the region to recorded geodesic data, generating geo-referenced maps for data storage, information overlay, derivative maps generation, and vector analyses of risk factors necessary in each image. Through arithmetic operations of digital images and risk analyses with parameter vector, the system generates a matrix of results corresponding to a single image of pseudoregions. These regions are merged into larger similar regions, following theoretical decision methods such as that for optimal statistical classification. As the result, the system makes it possible to generate maps containing homogeneous zones with optimized planting dates.

1 Introduction

The term agricultural zoning refers to a group of techniques used to identify regions in which climatic, edaphic and social-economic conditions are suited to a specific agricultural crop (Ometto [1]). To this end, several criteria are established based on factors such as vegetal species, water and temperature needs, disease susceptibility, soil acidity tolerance, etc.

The first Brazilian attempt to identify the best planting periods with tools such as geostatistics or SIG was developed by Assad et al. [2], in which the results of water balance simulation were spatialized for upland rice. Starting with analysis of the pluviometric regime, they represented spatially the parameters of rice water balance, simulating for Brazilian producing regions. They succeeded in mapping favorable, intermediate, unfavorable, and extremely unfavorable areas, according to planting dates, variety, and soil types.

Because of this pioneer work in rice zoning developed for central plateau regions, the Brazilian Ministry of Agriculture decided to finance a national agricultural zoning program, using state-of-the-art methodology, aiming at identifying planting periods of lowest climatic risk for each crop homogeneous zones. The project aimed at providing such information and subsequently conditioning federal financial aid to implementing it in selecting crops and determining planting dates.

The most widely known application and probably pioneering of the digital revolution in agriculture is the modification of the procedure for collecting agrometeorological parameters, that went from a primitive manual process, with discrete sampling susceptible to various types of mistakes, to a totally automated measurement system that offers continuous data recording of extreme reliability. Since then, systems depending on automatic sensor monitoring in the field have contributed not only to productivity increase, but also to improving agricultural product quality and are serving the environmenting in turn, this led to a tendency to integrate different data sources in order to better manage agricultural production. Such management, due to the metrically localized conditions, was conventionally called precision agricrop (Coghlan [3]; Plucknett & Winkelmann [4]).

This paper presents map modeling of various environments, based on image processing techniques, aimed at supporting decision-making in agricultural processes. Researches developed at the Department of Computation – Federal University of São Carlos and at Embrapa - Agricultural Instrumentation, which has developed instruments, sensors, and methodologies contributing to conservationist and precision agricrop progress in Brazil, (Cruvinel [4], [5], [6], [7], [8], [9], [10], [11], [12] e [13]; Cruvinel and Crestana [14] and Crestana et al.[15]) in partnership with IAPAR, Agronomic Institute of Parana, have contributed to this development, so as to benefit the national agricrop through maximum use of the new technological tendency towards precision agricrop with intensive use of digital images processing.

2 Digital Images Segmentation Techniques

Digital images processing techniques were presented in several papers by Mascarenhas [16], [17], [18], [19], dealing with segmentation and classification techniques based on statistics processing of Bayesian inference, due to its basic platform for map modeling of environmental variables intended for use in decision-making in agricultural processes. Since segmentation information for image analysis can be extracted in these techniques some steps are common, such as subdividing the image into its component parts depending on the problem to be solved, and to interrupt this subdivision when the interested object is isolated (Gonzalez [20]).

Algorithms of monochromatic image segmentation usually are based on one or two gray-scale value properties: discontinuity and similarity. In the first category, the image is divided into gray levels based on abrupt changes. The second category is based on thresholding segmentation, growing regions represented by pixel aggregation, and split and merging of regions.

Thresholding is one of the most important techniques in image segmentation. The most simple kind of thresholding is the partition of image histogram using only one threshold (T). Thus, segmentation is carried out by tracing the image pixel-pixel and labeling each pixel as either an object or background, depending on whether the gray level of that pixel is higher or lower than the T level.

Segmentation oriented by region aims at partitioning an image into its regions. Let R be the whole image representation. The segmentation is viewed as a process partitioning R into N sub-regions, R1, R2,..., RN, such that: (a) all pixels must be in a given region; (b) regional pixels must be connected; (c) the regions must be disjoined; (d) the regions must be related to the properties that must be satisfied by the pixels in a given segmented region; (e) regions Ri and Rj are different since they have different properties. The growing-region segmentation by pixel aggregation is a procedure that groups pixels or sub-regions into larger regions. Summing up: beginning with a set of pixels called seeds, growing regions are digitally imaged by appending to each seed point those neighboring pixels that have similar properties, such as gray level, texture, and color.

Regional split and merging is an alternative technique for aggregated growing-region segmentation. This technique subdivides an image initially into a set of arbitrary, disjoined regions and then merges and/or splits the regions in order to satisfy the basic segmentation conditions mentioned previously. To satisfy these conditions, an algorithm split and merge follows these steps: subdivision of any R in four disjoined R_i quadrant, where $P(R_i) = False$; joining all of adjacent Rj and R_k regions for which $P(R_j \cup R_k) = True$; and for which no merging or split is possible. This particular splitting technique is conveniently represented as a quadtree, i. e., a tree in which each knot has four descendents.

3 Materials and Methods

The decision system method for agroclimatic digital images classification and risk-zone mapping was developed utilizing an optimum statistic classifier.

Probability is important in standard recognition due to general the lack of precision charactering what standard classes are generally produced. It is possible to approximate an optimum classification, having the lowest probability of committing classification errors. The probability of an x pattern belonging to a ωi class is represented by $p(w_i / x)$. L_{ij} represents the loss occurring x is said to belong to ω_j when in fact it belongs to ω_i (Duda [21]). Since x pattern can belong to any of the M classes considered, the average loss by which x is assigned for the ω_j class is known as conditional average loss or

$$r_j(\mathbf{x}) = \sum_{k=1}^{M} L_{kj} p(w_k / \mathbf{x})$$

conditional average risk:

If $r_1(x), r_2(x),..., r_M(x)$ is calculated for each x pattern and attributes the pattern to the class with lowest loss, the total average loss with due respect to all the decisions will be minimum. The classifier that minimizes total average loss is called Bayes Classifier. Thus, the Bayes Classifier attributes an unknown pattern x to the ω_i class if:

$$r_i(\mathbf{x}) < r_j(\mathbf{x}),\ para\ j=1,2,\ldots,M;\ j \neq i$$

The procedures described below will be developed within the analysis methodology and correspond to the most important procedures in Picture-1.

1. ***Crop Cycle Acceptance***. Reception of planting, blooming, and crop cycle dates. This value is counted from sowing, followed by plant emergence, blooming, and finally harvest. By connecting the crop cycle from different planting periods with climatic risks, it is possible to identify planting periods with less risk and, thus, higher productive potential (Caramori et al.[22] and Wrege et al.[23]).

2. ***Water Balance Calculation by ten-day-periods and crop cycle***. This method is used to obtain agrometeorological data. Analyzing water balance sequentially during many years, water deficiency frequency suffers crop suffers by the can be identifies and risk estimated for the analyzed planting period (Wrege et al.[23]). This risk is verified during crop establishment and blooming periods.

3. ***Risk Factor Frequency Calculation***. Identifying probability of risk factor by ten-day-periods as mentioned above.

4. ***Water Deficiency and Rain Excess Interpolation***. This process maps water deficiency during crop establishment and blooming, and rain excess during harvesting, utilizing Kriging's interpolation method. The process uses ten-day-period values for seasonal water deficiency and generates a geodesic database with latitudinal, longitudinal, and the risk factor values.

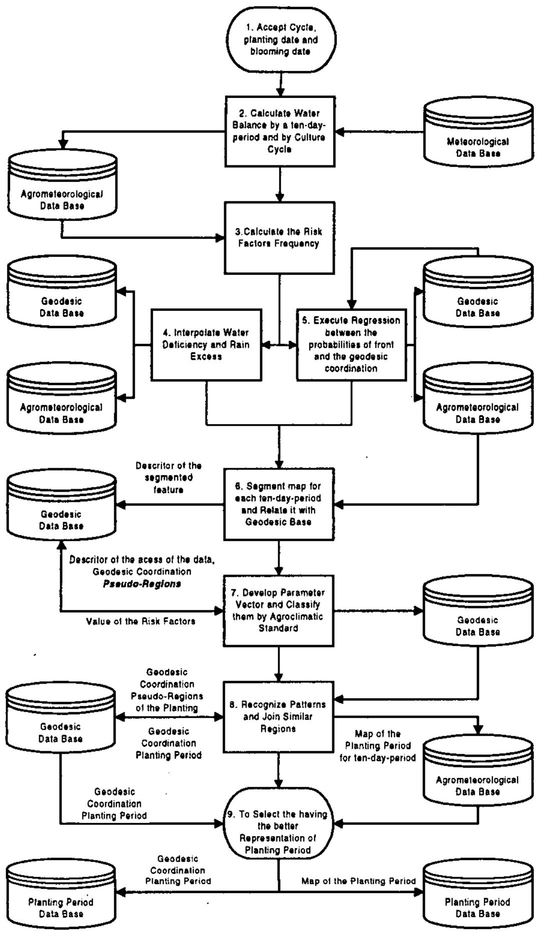
5. ***Regression between frost probabilities and geodesic coordinates***. This step allows frost-probability mapping accompanying regional topology owing to its effects on minimum temperature data. The regression equation utilized is: *FrostRisk =a + b altitude + c latitude*; a, b, and c are regression equation constants.

6. ***Map Segmentation for each ten-day-period and its Relation to the Geodesic Base***. Each previously map is segmented, utilizing the appropriate digital image segmentation technique. This segmentation aims at relating the geodesic data to each map, allowing data storage, information linkage, and derivative map acquisition. Another function of this procedure is the creating of a weight vector of the risk factors for each image. For instance, 10% water deficiency risk for establishment, 20% for water deficiency in blooming, and 15% for rain excess during harvest.

7. ***Development of Parameter Vectors and their Classification by Agroclimatic Standards***. According to the geo-referenced maps, the system creates a vector whose elements correspond to each environmental map. The first element corresponds to a value from of the frost risk map and the second element to a value for excess rain in the harvest map, the third to water deficiency during establishment, and the fourth, to water deficiency during blooming. It should also provide a result matrix by arithmetic operations in digital images and risk analyses with the parameter vector based on agroclimatic standards established for each environmental factor. Based on the result matrix, a geo-referenced image may be constructed corresponding to a pseudo-region planting map, for each ten-day-period.

8. ***Pattern Recognition and Merging of similar regions***. This process identifies all points and regions that can be joined into similar regions, following theoretical decision methods to decide if a point or region belongs to a given planting period. This procedure is necessary so that the map on resulting from these processes does not contain as many planting zones as the quantity of image pixels.

9. ***Map Selection Representing Planting Period***. This process corresponds to classification of a vector with the total weight of each generated image of the planting periods, with the objective of selecting the image best representing the planting period. For example, in the case of ten different planting periods existing for a crop, the vector of weights possesses ten elements representing the ten generated images. The element representing the lowest risk is then regarded as the best representation for the planting periods. For the formation of each weight of the image, the system should compose weights for the risk factors. For example, 10% risk for water deficiency in establishment, 20% for water deficiency in blooming, and 15% for rain excess at harvesting, generating a total risk of 45%.

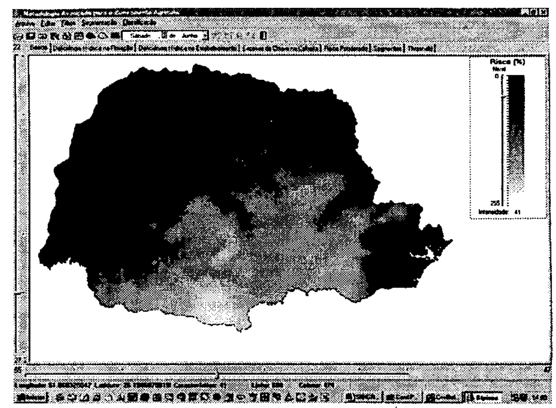


Picture 1 System structure for agroclimatic digital images classification and risk zone mapping.

4 A Case Study – Parana State

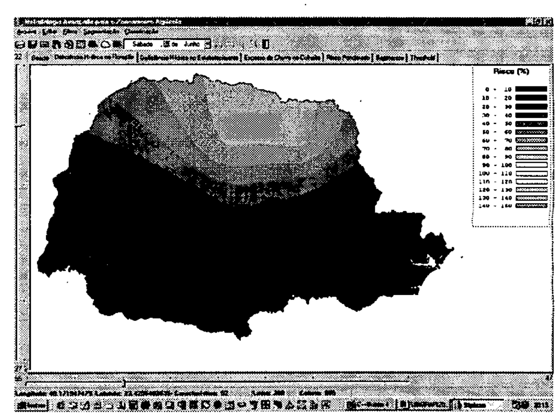
This case study demonstrates the application of the new agroclimatic image classification system and risk zone mapping for the wheat cropin, as well as meteorological data for Parana State. In the first stage, a series of climatic data was analyzed and processed. This analysis resulted in risk factor identification, e.g., water deficiency and rain excess, which interpolated provided an agroclimatic digital image. Pictures 2 and 4 show these images.

The gray shades of the map in Picture 2 represent the scale in frost risk percentage in Parana. Tones close to black correspond to the lowest risks and tones closest to white to highest risks. This frost risk map presents values that start at 0% in the North and rise 45% in the South.



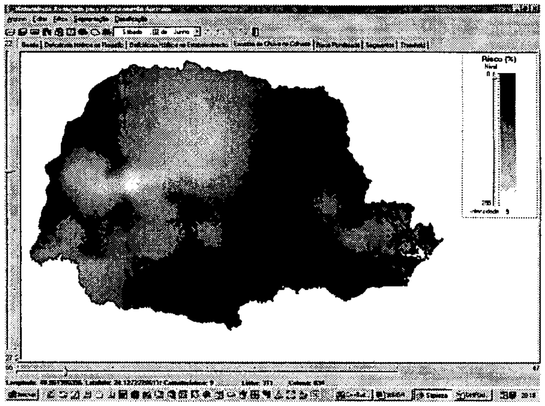
Picture 2 Map of frost risk in the first ten-day-period of June in Parana

In Picture 3 the water deficiency risk map for wheat blooming is shown. Its gray scale represents values ranging from 0% to 10% in intensities approaching black. Values nearing 100% approach white.

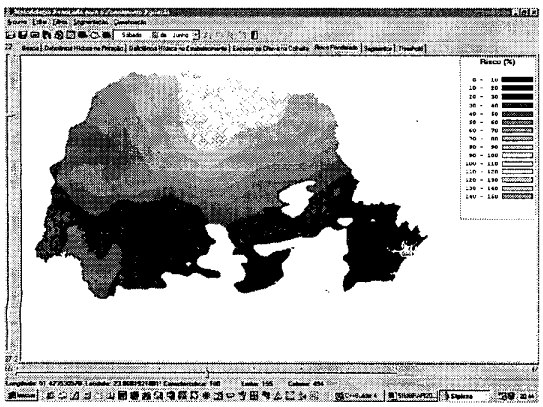


Picture 3 Map of water deficiency risk wheat blooming, in the first ten-day-period of June in the Parana State.

Picture 4 presents a gray scale to demonstrate regions with excess rain occurrence during harvest. The sum of water deficiency risks in blooming, crop establishment, and excess rain at harvest, generated the map in Picture 5 that corresponds to the total risk in the first ten-day-period of June. From this map is subtracted frost values superior to 30%, since they are too high for wheat to cultivation.

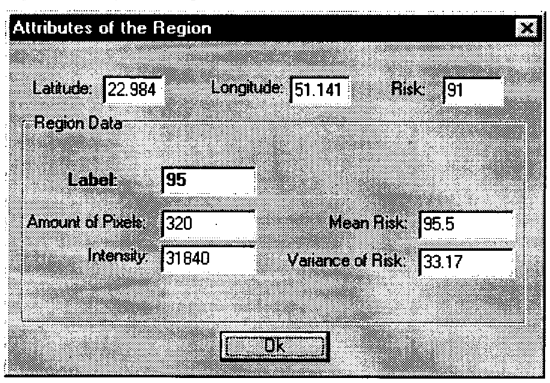


Picture 4 Map of excess rain risk during wheat harvest in the first ten-day-period of June in Parana.



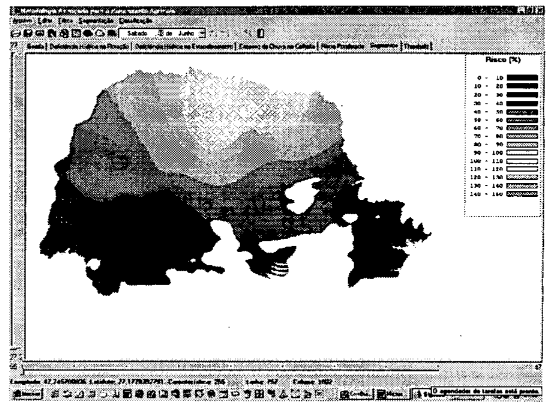
Picture 5 Map of the total wheat crop risk in the first ten-day-period of June in Parana.

For each ten-year-period the system develops a map similar to Picture 7 and then a process for classifying the regions in the map takes place to determine if the pixels in that region really belong to it.



Picture 6 Attributes of a segmented region.

According to the risk map in Picture 5, the agroclimatic digital images classification system processes segmentation to obtain values, such as average, intensity, and pixel quantity of each segmented region. Picture 7 demonstrates the map resulting from segmentation of pixel aggregation. Picture 6 shows a small screen with the data from one of the regions in the map.

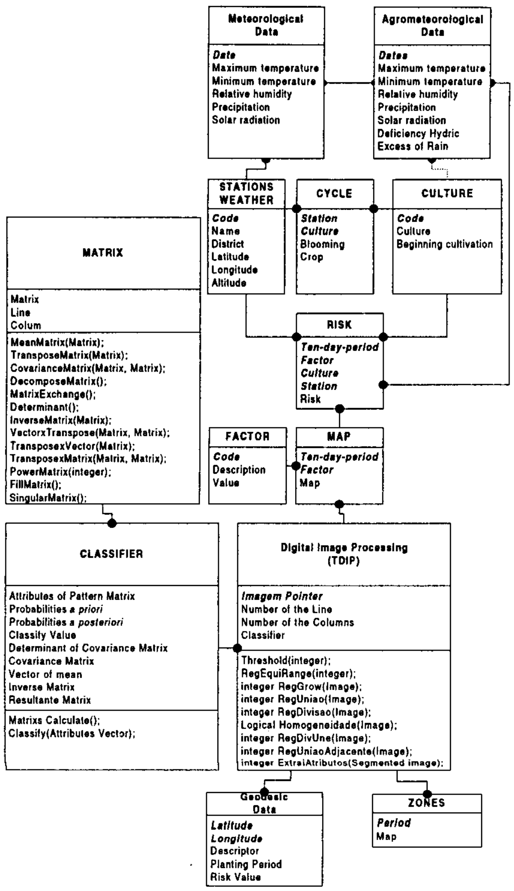


Picture 7 Segmented map by the region growing method by pixel aggregation.

5 Results and Discussion

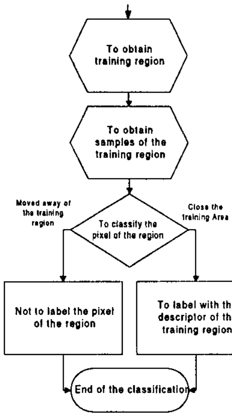
The system allows visualizing risk maps, for frost occurrence, water deficiency during blooming and crop establishment, and excess rain at harvest. Based on risk percentages, the system calculates the risk and develops map of total risk. As described in the diagram presented in Picture 1, the system carries out map segmentation with the aim of analyzing regions and planting period, although regional intersection can occur. In this case, the next step is classification by theoretical decisions, as in the case of Bayesian classification. This classifier determines to which region a given pixel belongs. From then on, the system defines for each created region the best planting period for a given crop within the ten-year-period analyzed. This step verifies each regionalized map by a ten-year-periods and produces a final agricultural zoning map relating the lowest risks with respective ten-year-period.

The diagram in Picture 8 describes the main classes of objects for agroclimatic digital images classification and risk zone mapping. The Digital Image Processing class has developed routines based on a technique, including arithmetic image processing, including pixel addition and subtraction; and image segmentation and classification routines. The segmentation routine for region growing by pixels aggregation – RegGrow, as well as the segmentation routine by split and merging of adjacent regions – RegDivUne, were developed based on algorithms presented by Pitas [24].



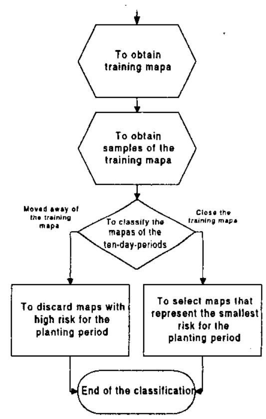
Picture 8 Class Diagram of the new system for agroclimatic digital image classification and zone risk mapping.

The diagram in Picture 9 demonstrates the routine of the Classifier in Picture 8 that implements the Bayesian Classifier. Before executing the routine, some information should be fed to the Classifier class, so as to obtain training region data: vector mean, covariance matrix of training region; reading of unknown region x attribute vectors (region to be qualified). The Classifier then classifies the pixel in question and, if it is close to the training region, the pixel ins labeled as belonging to a certain class. The classification type used in the decision algorithm was Bayesian quadratic.



Picture 9 Decision based on Bayesian quadratic algorithm of each pixel region.

The classifier in the case of Picture 10 classifies the unknown map and if it is close to the training map, it selects the map representing the smallest risk for the planting period. The classification type used in the decision algorithm linear Bayesian.



Picture 10 Decision based on Bayesian linear algorithm of each map of the planting period.

6 Conclusion

This paper presented a new system for agroclimatic digital image classification and risk zone mapping. The results indicate the potentialities of this method for managing and programming information for different meteorological database systems, and for calculating risk factor frequencies aggregated to a specific environment, based on the use of map segmentation and classification techniques by means of digital image processing.

References

[1] J.C. Ometto. Bioclimatologia Vegetal. Ed. Ceres, São Paulo, 1981. 413 p.

[2] E. D. Assad; E.E. Sano; H.S. Bezerra; S.C. Silva & E.J.V. Lobato. Uso de modelos numéricos de terreno na espacialização de épocas de plantio. In: , Assad, E.D. & Sano, E.E., eds. Sistema de Informações Geográficas - Aplicações na Agricultura, p. 311-327, 1998.

[3] A. Coghlen. Hi-tech farming to save the environment? New Scientist n.23, p.25, Sept., 1995.

[4] P.E. Cruvinel. Minitomógrafo de raios-X e raios gama computadorizado para aplicações multidisciplinares. Campinas: UNICAMP-FEE, 1987. Tese Doutorado.

[5] P.E. Cruvinel; R. Cesareo; S. Crestana; S. Mascarenhas. X-ray and gamma ray computerized minitomograph scanner for soil science. IEEE Transactions on Instrumentation and Measurement, New York, v.39, n.5, p.745-750, Oct. 1990.

[6] P.E. Cruvinel; P.S.P. Herrmann; Torre-Neto. A. Estação instrumental para coleta e medida automática de parâmetros climatológicos. In: ENCONTRO NACIONAL DE FÍSICA DA MATÉRIA CONDENSADA, 16, Caxambu-MG, maio 1993. Resumos estendidos do Grupo de Instrumentação... São Paulo: Sociedade Brasileira de Física, 1993. p.72-76.

[7] P.E. Cruvinel; S.R. Vieira; E.R. Minatel; S. Crestana. Automatização de método para análise do volume de gotas de chuva natural ou artificial e sua distribuição com técnicas do processamento de imagens digitais. São Carlos: EMBRAPA-CNPDIA, 1996a. 5p. (EMBRAPA-CNPDIA. Comunicado Técnico, 4).

[8] P.E. Cruvinel; S. Crestana. Opportunities and use of digital signal processors in tomography scanners dedicated to agricrop. In: WORKSHOP BRASILEIRO DE ARQUITETURAS ALTERNATIVAS USANDO DSPs, São Carlos - SP, ago. 1996. Anais... São Carlos:UFSCar, 1996b. p.93-97.

[9] P.E. Cruvinel, S. Crestana. Técnica de indução de raios X por partículas na identificação e medida da concentração de elementos e elementos-traço em solos e plantas. São Carlos: EMBRAPA-CNPDIA, 1996c. 5p. (EMBRAPA-CNPDIA. Pesquisa em Andamento, 4).

[10] P.E. Cruvinel; S. Crestana. The use of a TMS320C40 in an X and γ rays computerized minitomography scanner (MCT) dedicate to agricrop. In: TEXAS INSTRUMENTS SIXTH ANNUAL TMS320 EDUCATORS CONFERENCE, Texas-U.S.A, 1996d.

[11] P.E. Cruvinel; S. Crestana; M.J.A. Armelin; P.E. Artaxo. Studying zinc in an agricultural field using particle induced X-ray emission (PIXE) and instrumental neutron activation analysis (INAA). Soil and Plant, 1996e. Ref. P168. P. 302.

[12] P.E. Cruvinel; S. Crestana; P.E. Artaxo; J.V. Martins; M.J.A. Armelin. Studying the spatial variability of Cr in agricultural field using both particle induced X-ray emission (PIXE) and instrumental neutron activation analysis (INAA) technique. Nuclear Instruments and Methods in Physics Research B, Amsterdam, v.109/110, p.247-251, 1996f.

[13] P.E. Cruvinel; E.R. Minatel; M.L. Mucheroni; S.R. Vieira; S. Crestana. Na automatic method based on image processing for measurements of drop size distribution from agricultural sprinklers. In: SIMPÓSIO BRASILEIRO DE COMPUTAÇÃO GRÁFICA E PROCESSAMENTO DE IMAGENS, 9., Caxambu-MG, out. 1996. Anais do SIBGRAP 96I. Caxambu: SBC/UFMG, 1996g. p.39-46.

[14] P.E. Cruvinel; S. Crestana; L.A.C. Jorge. Métodos e aplicações do processamento de imagens digitais. In: CRESTANA, S.; CRUVINEL, P.E.; MASCARENHAS, S.; BISCEGLI, C.I.; MARTIN-NETO, L.; COLNAGO, L.A., ed. Instrumentação agropecuária: contribuições no limiar do novo século. Brasília: EMBRAPA-SPI, 1996. Cap.3, p.91-151.

[15] S. Crestana; P.E. Cruvinel. Tomografia: do hospital a lavoura. Ciência Hoje, Rio de Janeiro, v.21, n.121, p.20-24, junho.1996.

[16] N.D.A. Mascarenhas. Breve Introdução ao Reconhecimento Estatístico de Padrões. Apresentado no Simpósio "Inteligência Artificial" da 39ª Reunião Anual da SBPC, Brasília, DF, julho, 1987 (INPE-4206-PRE/1087) (artigo convidado).

[17] N.D.A. Mascarenhas. Processamento Digital de Imagens: Um Resumo das Principais Técnicas. Apresentado no Seminário de Informática em Saúde, Porto Alegre, RS, outubro, 1987a (INPE-4404-PRE/1220) (artigo convidado).

[18] N.D.A. Mascarenhas. Introdução ao Processamento Digital de Imagens, Anais da Jornada EPUSP-IEEE em Computação Visual, São Paulo, SP, Brasil, dezembro de 1990, pp. 385-420 (Minicurso convidado) (Relatório INPE-5212-MD/46).

[19] N.D.A. Mascarenhas;C.A.N. Santos; P.E. Cruvinel. Transmission Tomography under Poisson Noise Using the Anscombe Transformation and Wiener Filtering of the Projections. Nuclear Instruments and Methods in Physics Research, Section A, vol. 423, 1999, pp. 265-271.

[20] R. C. Gonzalez & R. E. Woods. Digital Image Processing, Addison-Wesley Publishing Company, Massachusetts, 1992.

[21] R. O. Duda & P.E. Hart. Pattern Classification and Scene Analysis. John Wiley & Sons, New York, 1973.

[22] P.H. Caramori, S.L. Gonçalves, M.S. Wrege, A.C. Gerage, J. Gomes. Zoneamento Agroclimático da Cultura do Milho no Estado do Paraná. IAPAR, Londrina, 1999. 24p. ilust. (IAPAR, Informe da Pesquisa, 129).

[23] M.S. Wrege, S.L. Gonçalves, P.H. Caramori, M.E.C. Vasconcellos, D. Oliveira, M. Abucarub Neto, E. Borrozino, J.H. Cavigliono. Risco de deficiência hídrica na cultura do milho no Estado do Paraná. Pesquisa Agropecuária Brasileira, 1999, v.34, n.7., p.1119-1124.

[24] I. Pitas. Digital image processing algorithms. Pretice Hall international series in acoustics, speech, and signal processing. 1993.