Special/Standard Issue – Article/Review/Technical Note

Journal of Agricultural Engineering

https://www.agroengineering.org/

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Please cite this article as doi: 10.4081/jae.2024.1590

Submitted: 10/03/2024
Accepted: 30/05/2024

Intelligent system based on a satellite image detection algorithm and a fuzzy model for evaluating sugarcane crop quality by predicting uncertain climatic parameters

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Key words: intelligent system; sugarcane crop quality; effects on sugarcane phenology.

Contributions: AAAL, conceptualization; project administration; AEBM, AAAL, formal analysis, visualization; AEBM, IPE, software; validation; AEBM, methodology, writing-original draft; IPE, investigation; AEBM, AAAL, CGMS, RFA, supervision; AAAL, CGMS, RFA, writing-review and editing. All the authors approved the final version to be published.

Acknowledgments: the authors are grateful to CONAHCyT (the Mexican National Council of Humanities, Science, and Technology) for the support received during the Postdoctoral research stay.

Conflict of interest: the authors declare no potential conflict of interest.

Funding: none.

Abstract

The increase in uncertain weather affects agriculture, impacting crop yield and quality, mainly due to the interaction of climatic variables such as temperature, wind speed, and humidity. In addition, soil erosion and nutrient loss are regional problems aggravated by inadequate agricultural practices in developing sugarcane agriculture. The present research proposes an Intelligent System based on a detection algorithm and a fuzzy model to estimate the quality of the sugarcane crop and the probability of the presence of pests and diseases through the prediction of uncertain variables. Wind speed, cloudiness, humidity, and thermal amplitude were considered variables of interest because parameters out of control of these variables generate a state of thermal stress, triggering pests and diseases that reduce crop quality and sugar production. This research uses geospatial information to simplify the exchange of information through a detection algorithm using real-time satellite images and a fuzzy model to estimate crop quality and prevent climate change-related problems. The variables humidity and cloudiness determine sugarcane quality as they are related to crop phenology and the probability that the crop will develop pests and diseases. In contrast, the intelligent system showed a correlation of over 93% for predicting the variables of interest.

Introduction

Climate change has significantly impacted in recent years, affecting different areas. Being the agricultural sector, one of the main ones where adverse effects are observed, presenting changes in patterns of climatic variables, which in turn affect crops and harvests throughout the country, also causing the appearance of pests, from insects to diseases that can affect agricultural production.

As a result of climate change, there is a current record of numerous droughts, frosts, floods, storms, hurricanes, and strong southerly winds, which have caused an environmental imbalance that is negatively reflected in the agricultural sector, which in turn affects the supply and demand of the different foods in this sector, reflected in the different current prices, bringing with it significant impacts on crop yields (Semenov and Halford, 2009). Following this approach, (Popke et al., 2016) created subsystems to develop agricultural adaptation measures. The subsystems were based on the modeling of vulnerability indicators, which were assigned a weighting based on the positive or negative impact on the crop; subsequently, the risk factors of the system were categorized to prioritize the level of risk in order to provide a feasible solution to the problem in question. As a result, farmers adapted to the climatic conditions through new agricultural technologies. Previous studies have shown that sugarcane crop yield depends not only on the correct soil nutrition through the addition of NPK (nitrogen, phosphorus, and potassium) compounds but also on the correct distribution of residues related to exchangeable acidity, soil humidity (permanent wilting point, water saturation, field capacity, mainly) (Meza-Palacios et al., 2020). In addition to edaphic conditions, climatic variables play an essential role in the adequate growth of sugarcane. Previous research shows the study and analysis of the impact of precipitation and temperature variables to evaluate the influence on the growth of open field (sugarcane, *Saccharum officinarum*) and protected agriculture (strawberry, *Fragaria × ananassa*) crops. In both cases, an algorithm was developed to to search and detect areas could represent a risk to the crop in the event of temperature and precipitation levels that are unsuitable for crop development. The developed algorithm can detect temperatures above 38°C since, at these temperature levels, the crop´s photosynthesis, altering the sucrose concentration and affecting the regrowth and germination of sugarcane. Meanwhile, for the precipitation variable, zones with precipitation levels below 70 mm were detected, which cause water to concentrate in the sugarcane root and, to a lesser extent, in the plant, reduces the productive capacity of the sugarcane (Badillo-Márquez et al., 2021). In turn, with the results obtained by the algorithm for detecting risk zones for strawberry cultivation (Rodríguez-Aguirre et al., 2023), adaptation schemes were developed to mitigate the impact generated by climate change by optimizing the parameters related to harvesting (availability of resources) to increase crop yield and reduce costs related to the agricultural practices used.

Climate change generates agro-physiological impacts on sugarcane, mainly in the metabolic activity of molasses produced by soil changes in the areas where the plant is grown. (Ortiz Laurel et al., 2012; Sandhu et al., 2017). Changes in temperature and humidity patterns mainly affect the metabolic activity of sugarcane, affecting the absorption of herbicides in the plant, reducing their effectiveness, and increasing the presence of pests and diseases, in addition to increasing the rate of photosynthesis, generating more significant CO_2 generation (CONADESUCA, 2018). As mentioned above, in addition to the main climatic variables (temperature and precipitation), other variables affect not only the yield and production of sugarcane but also represent a threat to the phenology of the plant and consequently affect the quality of the crop. In this sense, the study of satellite images through remote sensing allows for estimating sugarcane crop yield and sucrose content through phenological monitoring of the crop (Ruiz-Jaramillo et al., 2019). For their part, Cravero and Sepúlveda (2021) propose the development of observation systems concerning climate based on satellite meteorological observation and high-resolution image models, thus generating a large amount of data through Big Data, providing information processing, also integrating information to other systems such as information in the cloud, thus expanding the capacity and impact of data analysis and information on climate factors, helping to understand the behavior and evolution of the environment to obtain a more dynamic analysis with information obtained in real-time to obtain data and subsequently analyze this information and the relationships with other variables that may arise. Climate change monitoring has changed how the environment and resources are managed, which has been an alarm in addition to the generation of Integrated Information Systems, which becomes valuable at the time of information analysis (Parodi et al., 2014). The present research aims to develop an Intelligent System based on an algorithm to detect the variables that threaten the phenology of the sugarcane crop through digital image processing (DIP) to detect areas that could potentially reduce the quality of the sugarcane crop, as well as a fuzzy model to increase the quality of the sugar crop in the southeastern region of Veracruz, Mexico. The research evaluated the variables extended cloudiness, humidity percentage, and thermal amplitude to determine the impact on the quality of the sugarcane crop and the probability of incidence of pests and diseases in the crop. The methodology used in the research is divided into five steps; in the first step, the study variables were selected for study. Subsequently, in the second step, satellite videos that monitor the variables were captured to form a database that feeds an algorithm or detection code (step three) to establish control parameters for the variables of interest (step four) and, finally, to develop a fuzzy logic model capable of determining the quality of the sugarcane crop (step five). With the development of the research, the estimation of crop quality provides tools for decision-making pre-harvest, during harvest, and post-harvest of sugarcane.

Materials and Methods

This section describes the methodology developed for this research, which is integrated into five steps (Figure 1). In the first step, the variables of interest were selected to estimate the quality of the sugarcane crop harvested in the study area. Subsequently, once the study variables were selected, real-time videos were taken from satellite images to create a database that would feed a detection algorithm. In step three, based on the database, the information from each captured video was transformed into a *Python* code that complied with the characteristics of interest (detection threshold, RGB scale, etc.) for subsequent testing and validation. With the results obtained in the code validation, control parameters were established for the input variables to the fuzzy logic model (step four), with which it is possible to estimate the quality of the sugarcane crop, as well as the incidence of pests and diseases present (step five) in order to improve agricultural practices to obtain better yields of the product with better quality. The following describes the steps that make up the general methodology.

Selection of variables of interest

Mexico is among the leading sugarcane producers worldwide, with an annual production growing significantly in volume. By 2023, 809,882 tons of sugarcane will be harvested, with the state of Veracruz being one of the leading producers with a 36.7% share (297,709 tons) (SIAP and SADER, 2024). Sugarcane is one of the leading products grown in Mexico; in recent years, there has been increased interest in efficiently combating diseases that damage crops (pests and diseases), increasing crop quality and thus avoiding economic losses (InfoAgro, 2022b). Within sugarcane varieties, it is estimated that it would take an average of 15 years to obtain a seed capable of coping with climatic stress, drought, pests, and diseases (InfoAgro, 2022a); however, the process of selecting resistant varieties is a long-term process and currently in Mexico it is difficult for primary farmers to have access to this type of practices. Sugarcane crop yield is determined by four main factors: edaphic, agronomic, human, and climatic (CONADESUCA, 2018).

Previous research suggests that the interaction between the variables wilting point, electrical conductivity, pH, amount of organic matter, and exchangeable acidity allows estimating non-nutritional disorders to determine the fertility and efficiency of the harvested soil (PRONAC, 2009; Badillo-Márquez et al., 2021). Agronomic factors can be modified to a certain extent and refer to agricultural management practices for the crop, such as irrigation systems, nutrition through fertilizers (Hasan et al., 2021), and plant health. Proper management of these promotes crop adaptation to uncontrollable conditions or uncertain parameters such as climatic factors. Human factors are directly related to agronomic factors since these are based on the decisions and expertise of the farmer that directly affect the crop and are primarily based on external conditions such as agricultural prices, crop profitability, sustainability of the agricultural sector, availability of agricultural land, availability, government support to the field, infrastructure, and efficiency of water resources (INEGI, 2023), mainly.

Finally, climatic factors directly influence crop yield and the decisions made for its management.

For the development of the research, the variables humidity, cloudiness, and thermal amplitude were considered. An optimum humidity level for the sugarcane crop avoids root damage affecting plant growth due to excess humidity. In contrast, a low humidity level generates water stress in the plant, slowing vegetative development in stalks and increasing sucrose concentration. For this research, values of between 50%-70% relative humidity were considered optimal for obtaining adequate vegetative growth that stimulates the growth of stems due to formation, elongation, and tillering; with this range of relative humidity, it is considered that under these conditions, the plant uses 60-100m^3 of water to produce a ton of sugarcane (PRONAC et al., 2009).

The variable cloudiness is directly related to wind speed and solar radiation since wind speeds higher than 15 km are considered detrimental to the plant, causing damage to the stem and leaves, so the more significant the presence and density of cloud masses, the more the plant's growth is compromised. The presence of clouds interferes with the capture of solar radiation, generating an interceptor layer that impedes photosynthetic capacity and reduces the concentration of sugars, mainly in the plant's upper leaves, which are responsible for capturing about 65% of the necessary solar radiation.

Thermal amplitude is one of the most influential factors for plant growth. Low levels of thermal amplitude impede plant germination, delaying plant growth and increasing sucrose concentration, while high levels of thermal amplitude alter the concentration of sucrose, whose molecule is broken down into glucose and fructose, resulting in a decrease in the accumulation of sugars (SAGARPA, 2012; CONADESUCA, 2020).

Therefore, this research proposes an Intelligent System based on a detection algorithm by monitoring the variable's relative humidity, cloudiness, and thermal amplitude to develop a fuzzy logic model based on expertise that allows modifying the agronomic and human factors to plan the planting of the crop considering critical phases that impair the maturation and yield of sugarcane.

Satellite image capture

A satellite image represents the information captured by a sensor mounted on an artificial satellite. These sensors collect the information reflected by the Earth's surface, which is then sent back to the Earth and suitably processed, providing valuable information on the area's characteristics. The image capture process was carried out using databases of governmental agencies through the acquisition of satellite videos in real-time from the *GOES Este* satellite for the Southeast zone (SMN and CONAGUA, 2023b). The *GOES Este* satellite belongs to the geographic information services of the National Meteorological System. It provides geographic information on soil vegetation, cloud tops, wind speed, thermal amplitude, precipitation, and temperatures. The *GOES Este* satellite allows monitoring of the state of the variables, such as wind speed on a scale of -5 to >100 km/h, thermal sensitivity from -15 to >80°C, humidity percentage, and cloud tops.

The study area belongs to the southeastern region of Veracruz, Mexico; it belongs to the coastal plain (18 36035.8" N 95 31034.7" W). The predominant climate in the area is warm-humid (about 41%), with an average annual temperature of 28°C and an average rainfall of 1,500 mm. The humid and sub-humid climates mainly favor the development of crops such as citrus, mango, coffee, rice, pineapple, vanilla, banana, corn, and sugar cane (INEGI, 2021).

The capture videos were taken for three months, corresponding from September to November, since sugar cane is in the final growth stage before being harvested during the harvest season in Veracruz. The average number of videos captured was four per day, resulting in a database of 360 videos with an average duration of 15 seconds, the videos were taken in the same location since sugarcane cultivation is carried out in the study area. The videos were sectioned into frames for their study. The videos were captured randomly at different times during the day to have a greater diversity of information regarding climatic variability and to avoid biases. The channel for video capture was RGB since it presents excellent image sharpness and resolution (Wang, 2014). Subsequently, each video was fragmented into ten frames for analysis and development of the code, where each area of interest was assigned a color for identification in image processing.

Development of the detection code

The RGB color scale allows us to determine the range in which the pixels of the area of interest oscillate—the grayscale ranges from [0, 255] values ranging from black to white. Meanwhile, color pixels are represented through color spaces such as the RGB channel. For the detection of the encoding of the pixels around interest of the RGB channel, the videos were fragmented into frames to facilitate the study of each image. Then, each image was passed to negative to reduce noise and detect the color thresholds of the target function through detection labels. This allowed a better interpretation of the image and increased the definition, favoring the interpretation of the colors contained in the image. Table 1 shows the RGB scale coding for each label.

The labels determine under which threshold the pixels in the risk zone oscillate in the variables of interest. In Table 1, the labels *"redBajo1," "redAlto1," "redBajo2,"* and *"redAlto2"* oscillate in a predominant range towards red, indicating wind gusts above 20 km/h, temperatures above 40°C and a meager humidity percentage (<7%), which represents a high risk in the quality of the sugarcane crop due to reduced cane growth. The labels "yellowBajo2" and "yellowAlto2" look for zones within the orange-yellow range where thermal amplitude values indicate temperatures from 32°C, wind gusts from 12 km/h, and a humidity percentage from 17%, which represent a potential risk in sugarcane quality (SMN and CONAGUA, 2023b).

Subsequently, preloaded image libraries were used to load the detection code (Figure 2) to facilitate the search of the range in which the scale of the labels oscillates (Table 1).

For the development of the code, followed by the libraries, the labels were introduced with their respective scales to recreate the color thresholds; then, the videos were entered. The resulting coded algorithm is shown in Figure 2, which integrates the 360 videos in mp4 format. The function of the code is to define the beginning and end of each video and extract the information through the fragmentation of each video, obtaining an estimated 3,600 images.

For the processing of satellite images, the code has the function of internally fragmenting the images that make up each video and weighting each fragmented part; this weighting goes from a value of 0 to 255 (RGB scale), where each number represents a specific color characteristic. As shown in Figure 3, during fragmentation, the images obtained go through an initial stage where each image is shown as it was captured, i.e., with its original attributes, then they go through a negative capture stage where the image is binarized to grayscale to determine the scale in which the pixels that make up the image oscillate. The grayscale oscillates between values of [0, 255] ranging from black to white, while the color pixels are represented through color spaces within the RGB channel. Once the image is binarized, it passes through a filter to reduce the noise contained by nature in the image; the filter's purpose is to allow the extraction of information through increased image quality. The filter used is the average filter method, a grouping method where the average of a vector [i, j] is calculated; this process seeks to group a dominant color pattern within a matrix, creating a two-dimensional filter. This same process is repeated throughout the image to standardize the color layers in a given region, obtaining the averages of the pixels; and with that, the noise is standardized to the nearest integer value of the mean.

Subsequently, the image goes through the stage of background elimination and color separation through a *mask*. The mask aims to separate the colors in the study area cataloged as risk, extracting only the required information. If the colors are different from the *mask*, the pixel becomes black. Otherwise, they retain their color. As a result, *"clean images"* are obtained, facilitating the extraction of information through the detection of labels (Table 1) when there is a risk to the crop. The image enhancement steps are shown in Figure 3.

Image detection systems focus on the search and navigation within an image database, in addition to the recognition of certain features such as color, texture, and spatial location at a local or global level depending on whether information of the image as a whole or specific region is desired (Canada et al., 2021; Gopikrishnan et al., 2022), even with image processing, there is the possibility of the appearance of noise in the image, so it is necessary to implement an algorithm capable of reducing it to the maximum (Rodriguez-Aguirre et al., 2023). Figure 4 shows the image obtained after processing.

Obtaining control parameters for the variables of interest

Image processing allows the selection of areas of interest that could potentially put the sugarcane crop at risk through the creation of algorithms. With the development of the detection algorithm, it is possible to monitor the control variables to estimate the quality of the sugarcane crop; this allows for establishing control parameters for each variable and, thus, making modifications in the agronomic factors to maximize the yield and quality of the crop. Table 2 shows the values of the control parameters for the variables thermal amplitude, wind speed, and humidity based on the colors obtained for the variable cloudiness. The values shown in Table 2 were established according to the density map observed in the digital image processing concerning the values of the colorimetric scale defined by governmental agencies in Mexico: National Meteorological Service (SMN) and the National Water Commission (CONAGUA) (SMN and CONAGUA, 2023a).

Development of the fuzzy logic model to estimate the quality of the sugarcane crop and the incidence of pests and diseases

After validation of the detection algorithm (see section 3) and having the values of the control parameters of the variables, the fuzzy logic (FL) model was built to estimate the quality of the sugarcane crop, as well as the probability of incidence of the presence of pests and diseases in the crop. The fuzzy logic model was designed in MatLab® by implementing the *Mandami* inference engine, which is integrated by membership functions for the four input variables and two output variables. The basic principle of FL is based on implementing linguistic variables to process imprecise natural language composed of numbers and human expressions (Sivanandam et al., 2007). In this sense, the linguistic variable can describe the state of an object or phenomenon through fuzzy sets and membership functions. A membership function defines the value of the associated linguistic variable by indicating to what degree it belongs to the fuzzy set (Zadeh, 2008; Grosan and Abraham, 2011). The *Crop Quality* model is integrated by four input variables, cloudiness, wind speed, humidity percentage, and thermal amplitude, which, through their interaction, not only estimate crop quality but also the probability of incidence of pests and diseases. This is because the input variables define the crop yield and the decrease and synthesis of sucrose in the crop. For the architecture of the fuzzy sets, triangular, trapezoidal, S-type, and Z-type membership functions were used. In the FL process, inference rules established through experience are used to characterize the system behavior (Shokouhyar et al., 2019); in this case, the experience is defined by farmers and sugarcane producers. The inference rules base their logic on the IF-THEM conditional represented by a Fuzzy Associative Memory (FAM). A FAM is a matrix representing the consequence of the combination of each inference rule (Nedjah et al., 2014). Table 3 shows the number of inference rules, type of fuzzy set, and parameters used (linguistic labels and intervals) in the architecture of the input and output variables of the *Crop Quality* model.

Results

Prediction of variables through satellite images

Based on the data from satellite video images, a detection code was obtained to determine the control parameters of the variables of interest to feed the fuzzy models and thus estimate crop quality and the incidence of pests and diseases that could potentially jeopardize the harvest. For the development of the detection code, a total of 3600 images obtained from 360 videos with an average duration of 15 seconds were obtained at random times to have a more robust database. The detection code performs a pre-processing to each video frame to subtract those main features of interest to perform the image processing and the detection process. In the validation stage, a database corresponding to a capture period of 12 days was taken, taking a video approximately every 4.5 hours. The database used for validation does not include videos used for the development of the detection code.

Figure 5 shows the confidence level between the satellite data and the data obtained through the prediction of the detection code.

To corroborate the effectiveness of the prediction of the detection code developed in *Phyton*, 60 videos were used, which were not used in the development of the code to avoid bias on the part of the software. The detection code obtained a correlation of 0.941228 between the satellite values and the prediction obtained (Figure 5), which indicates that the detection code is valid. With the results obtained at this stage, the parameters of the variables of interest for constructing the *Crop Quality* fuzzy model can be estimated.

Prediction of crop quality and incidence of pests and diseases through a fuzzy model

The construction of the fuzzy model was carried out in the Matlab® software from the variable parameters obtained in the image processing through the detection code described in Table 3. As mentioned above, the architecture of the linguistic labels for each variable is defined by triangular, trapezoidal, S-Type, and Z-Type functions. After constructing the variables, 432 inference rules were determined from all possible combinations between input variables (4) and output variables (2). For the validation of the model, historical climatic data on wind speed and thermal amplitude were taken as a reference and correlated with the results obtained in the prediction of the variables. Figure 6 shows the results obtained in this stage.

For validation, a sample of 60 open-access data in Mexico was taken from the National Meteorological Service (SMN) and the National Water Commission (CONAGUA). As can be seen in Figure 9, the prediction of the *wind speeds* variable obtained a correlation coefficient of 0.9252. In contrast, the *thermal amplitude* variable obtained a correlation coefficient of 0.9124, which indicates that the prediction model is suitable for emulating the behavior of the variables in the fuzzy logic model.

With the development of the model, response surfaces were determined, which explore the relationships between several explanatory variables (inputs) and one or more response variables (outputs), where a sequence of experiments designed to obtain an optimal response (inference rules) through an operating medium (inference model) are used (Ljung et al., 2014). Figure 7 presents the response surfaces obtained in the fuzzy model.

Figure 7 shows the interaction between the input variables that maximize the quality of the sugarcane crop (a and b). As can be seen in both cases, the *humidity* variable plays a significant role as the variable with the greatest impact since it is the variable that maximizes the quality of the sugarcane crop, given that, in order to achieve a higher sucrose concentration and better product purity, *humidity* levels range between 38-50%. As seen in a and b, the interaction of the *humidity* variable reaches maximum levels at 40% and above. On the other hand, the *cloudiness* variable (item a) is considered the second variable with the most significant impact because if the sky is clear (blue linguistic label), it helps in the absorption of humidity in the sugarcane root and not in the leaves of the plant, increasing sugarcane growth. As cloudiness increases, sugarcane growth is reduced. As shown in Figure 7, the *wind speeds* impact variable (item b) in interaction with the *humidity* variable, increasing crop quality because the wind can pull leaves off the plant, breaking inflorescences and disarticulating the plant. The sugarcane inflorescence is a panicle or spike that reaches a length ranging from 30 to 60 centimeters long. Mechanical wind damage causes a reduction in the quality of the crop, favoring the development of fungi, pests, and diseases.

Likewise, in the evaluation of pest incidence in the sugarcane crop (Figure 7, items c and d), the fuzzy model showed that the variable with the most significant impact and that favors the presence of pests is the *thermal amplitude*, in combination with the variables *wind speed* and *humidity,* because, as mentioned above, mechanical injuries break the plant, weakening its stem and root, favoring diseases at the primary and secondary levels. In addition, at high temperatures (> 42°C), nutrient absorption is reduced by the presence of soil dehydration. It is essential to mention that although the sugarcane crop needs a high level of solar radiation to thrive, active hydration and adequate soil aeration are essential. Otherwise, solar radiation damages the crop, generating humidity retention only in the plant leaves and not in the root, causing pest proliferation. Next, Eqs. (1)-(3) model the membership functions of the fuzzy model of the output variable *Crop Quality*. Eqs. (4)-(5) represent the membership functions of the linguistic labels of the output variable *Probability Pests*.

$$Crop\ Quality\ (Good) = Tr(r; 3.5, 5, 6) \begin{cases} 0; 3.5 \leq r \\ 1 - \left(\frac{5-r}{5-3.5}\right); 3.5 \leq r \leq 5 \\ 1 - \left(\frac{r-5}{6-5}\right); 5 \leq r \leq 6 \\ 0; 6 > r \end{cases} \tag{1}$$

$$Crop\ Quality\ (Fair) = Tr(r; 1.5, 3, 4) \begin{cases} 0; 1.5 \leq r \\ 1 - \left(\frac{3-r}{3-1.5}\right); 1.5 \leq r \leq 3 \\ 1 - \left(\frac{r-3}{4-3}\right); 3 \leq r \leq 4 \\ 0; 4 > r \end{cases} \tag{2}$$

$$Crop\ Quality\ (Poor) = Tr(r; 0, 1, 2)\begin{cases} 0; 0 \leq r \\ 1 - \left(\frac{1-r}{1-0}\right); 0 \leq r \leq 1 \\ 1 - \left(\frac{r-1}{2-1}\right); 1 \leq r \leq 2 \\ 0; 2 > r \end{cases} \tag{3}$$

$$Probability\ Pests\ (Yes) = \mu_S = \mu_S(r; 1,2,2)\begin{cases} 0; r \leq 1 \\ 2\left(\frac{r-1}{2-1}\right)^2; 1 \leq r \leq \frac{1+2}{2} \\ 1 - 2\left(\frac{r-1}{2-1}\right)^2; \frac{1+2}{2} \leq r \leq 2 \\ 1; r \geq 2 \end{cases} \tag{4}$$

$$Probability\ Pests\ (No) = \mu_z(r) = 1 - \mu_S(r) \tag{5}$$

Where *Tr*; *µs* and *µz* represent the type of function adopted by the fuzzy set for the linguistic labels of the variables, i.e. triangular, S-type and Z-type, respectively; and r is the value taken by the input variable to the model. In the output variable *probability pests*, the Z-type function is the inverse of the S-type function since the variable can only take two values, in this case, whether pests are present or not. Finally, a final validation was performed using the fuzzy model's historical data of poor, fair and good crop quality as input values.

The historical data for validating the fuzzy model were extracted from open-access government sources in Mexico (SIAP and SADER, 2024).

With the validation of the model, a correlation coefficient of 0.9351 was obtained, which indicates that the model is suitable for estimating the post-harvest quality of sugarcane (Figure 8).

Discussion

The growing increase in meteorological events entails a high degree of uncertainty for developing agricultural activities, mainly impacting crop yields and quality. Wind and temperature significantly impact crop maturation; the degree of impact depends on the type of crop, growth stage, and soil characteristics of the location. One of the region's main impacts is soil erosion due to dehydration caused by the evaporation of soil humidity due to the lack of non-implementation of irrigation systems in the absence of rainfall. In addition, the inadequate use of agricultural practices results in reduced soil quality due to nutrient loss. At the plant level, non-optimal values of the *wind speed* variable can physically damage the sugarcane crop, especially at an early stage when the plant has not yet reached the necessary maturity, causing stem breakage, loss of leaves, and deformation of the sugarcane.

The *cloudiness* variable is intrinsically related to the *wind speeds* variable since, in the fuzzy model, the value of the *cloudiness* variable corresponds to a value associated with the *wind speeds* variable expressed in km/h. Similarly, the thermal sensation affects the crop from the germination stage and initial development of crop growth, the *thermal amplitude* variable models this parameter. Low temperatures can delay germination, while high temperatures can cause damage from germination to the appearance of the first leaves.

The interaction of high wind chill and wind speed can cause thermal stress in the sugarcane crop, increasing evaporation and water loss, causing drought damage and physical damage to the plant due to mechanical action, resulting in a low-quality crop. To counteract this problem, the *humidity* variable plays a vital role in reducing heat stress since the sugarcane crop is more resistant to short periods of drought when the soil retains adequate humidity, allowing the plant to continue growing even in periods of moderate drought thanks to the regulation of soil temperature, improving root development of the plant, favoring the absorption of nutrients, resulting in an optimal accumulation of sucrose in the stems and tissues of the plant, optimizing sugar production.

In summary, wind and temperature are important environmental factors influencing crop success. Growers must monitor and manage these factors to optimize the growth and yield of their crops, either by implementing soil conservation practices and proper irrigation systems or selecting crop varieties resistant to specific wind and temperature conditions. Thus, the adequate presence of humidity is crucial for sugarcane cultivation, as it can have both positive and negative effects, depending on factors such as water management, soil characteristics, and agricultural practices. Therefore, growers must maintain an optimal balance in humidity levels to maximize sugarcane growth and yield.

Previous research has used geospatial information to simplify the storage and exchange of geographic data to create databases (Rodríguez-Aguirre et al., 2023). However, with the development of the detection algorithm through satellite images extracted in real-time and the fuzzy model, it is possible to establish the control parameters for the variables of interest, *wind speeds*, *cloudiness, thermal amplitude,* and *humidity*, and thus be able to estimate the resulting quality of the sugarcane crop harvest and the probability of incidence of pests and diseases, This tool will serve as support for decision making, which will allow farmers to make modifications in the agricultural practices used to develop adaptation measures that lead to the mitigation of the impact of climate change through the optimization of planting, harvesting, and post-harvesting parameters to counteract agro-physiological impacts that influence edaphic changes in the planting zone.

Conclusions

Climate change represents a significant threat to sugarcane cultivation due to its impact on rainfall patterns, temperatures, the frequency of extreme weather events, and the distribution of pests and diseases. In addition, crop quality depends on uncertain variables such as wind speed, thermal amplitude, and humidity, influencing the sugarcane life cycle, i.e., from planting to harvest. With the development of the Intelligent system based on an algorithm of detection through image processing, it is possible to estimate the behavior of uncertain variables to determine the impact on the crop of interest in the study area. The optimization of the detection algorithm allows presentation and search functionalities through the fragmentation of video frames to obtain a repository of images of the variables of interest (*cloudiness, wind speeds, humidity, and thermal amplitude). With them,* it is possible to detect areas of climatic stress for the sugarcane crop. The detection algorithm is based on identifying and recognizing specific characteristics, such as color in the study area, making it possible to detect the risk to crop quality. The main advantage of the implementation of the detection algorithm lies in the identification of harvest risk at the maturity stage of the plant, allowing to obtain a higher harvest quality through the development and implementation of strategies to face these challenges and ensure the resilience and sustainability of sugarcane production in the future.

The effectiveness of the detection algorithm represents a solid basis for estimating parameters that could affect sucrose concentration and compromise crop quality, from the germination stage, root development, and growth to maturation. The image processing algorithm had an accuracy of 0.941228, which indicates that it is suitable and reliable for making predictions. The fuzzy model accurately predicted values in the variables of interest, wind speeds, and thermal amplitude in its test phase of 0.9124 and 0.9252, respectively. In contrast, in the prediction phase of the output variables (Crop et al.), it obtained an effectiveness of 0.9351. Finally, it can be concluded that the progress of the detection algorithm developed in this research allows the creation of an information repository that shows how the uncertain parameters behave in the study area. The results obtained by the fuzzy model will be helpful in the development of agricultural adaptation strategies for subsequent harvest seasons.

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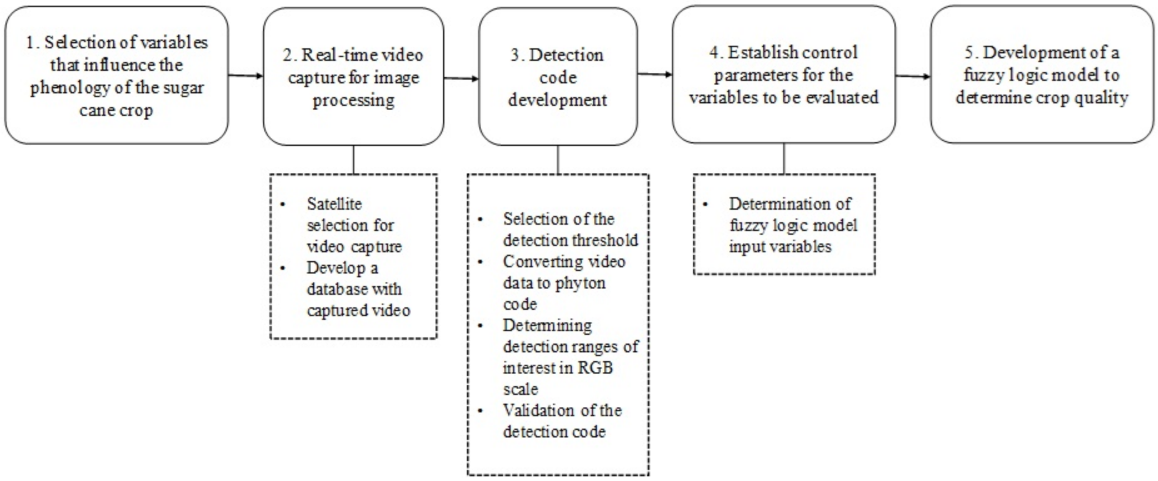

Figure 1. The general methodology proposed for estimating sugarcane crop quality through a satellite detection and fuzzy logic algorithm.

```python
import matplotlib.pyplot as plt
import matplotlib.animation
from IPython.display import YouTubeVideo,clear_output, Image, display, HTML
import cv2
import numpy as np
```

```python
cap = cv2.VideoCapture("Tope de nubes 29-11-23   7-00p.m.mp4")
redBajo1 = np.array([0, 100, 20], np.uint8)
redAlto1 = np.array([8, 255, 255], np.uint8)
redBajo2=np.array([175, 100, 20], np.uint8)
redAlto2=np.array([179, 255, 255], np.uint8)
amarilloBajo2 = np.array([0, 100, 45],np.uint8)
amarilloAlto2 = np.array([225, 250, 255],np.uint8)

while True:
  ret,frame = cap.read()
  if ret==True:
    frameHSV = cv2.cvtColor(frame, cv2.COLOR_BGR2HSV)
    maskRed1 = cv2.inRange(frameHSV, redBajo1, redAlto1)
    maskRed2 = cv2.inRange(frameHSV, redBajo2, redAlto2)
    maskamar= cv2.inRange(frameHSV,amarilloBajo2,amarilloAlto2)
    maskRed = cv2.add(maskRed1, maskRed2)
    maskRedvis = cv2.bitwise_and(frame, frame, mask= maskRed)
    maskRedvis2 = cv2.bitwise_and(frame, frame, mask= maskamar)
    cv2.imshow('frame', frame)
    cv2.imshow('maskamar', maskamar)
    cv2.imshow('maskRed', maskRed)
    cv2.imshow('maskRedvis', maskRedvis)
    cv2.imshow('maskRedvis2', maskRedvis2)
    if cv2.waitKey(1) & 0xFF == ord('s'):
      break
cap.release()
cv2.destroyAllWindows()
```

Figure 2. ***Python*** **libraries used for the development of the detection algorithm for the extraction of information from satellite video images.**

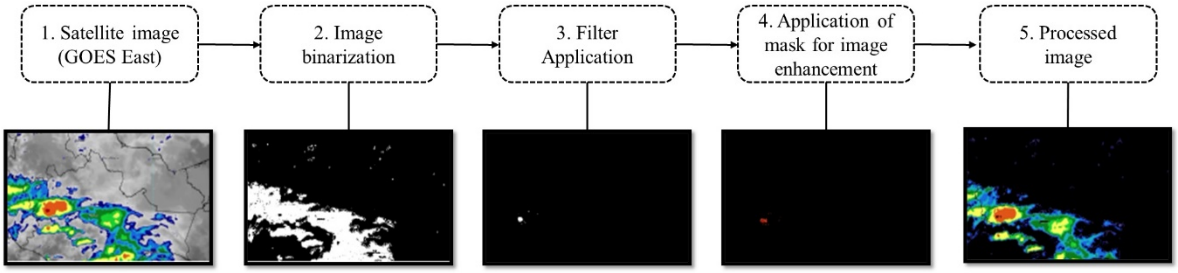

Figure 3. Processing steps for image enhancement through *Phyton* to extract information from satellite video.

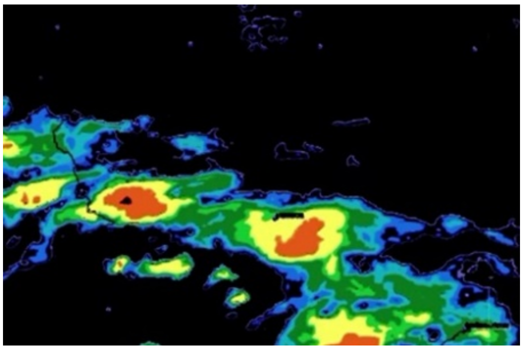

Figure 4. The image was processed through the detection algorithm coded in *Phyton*.

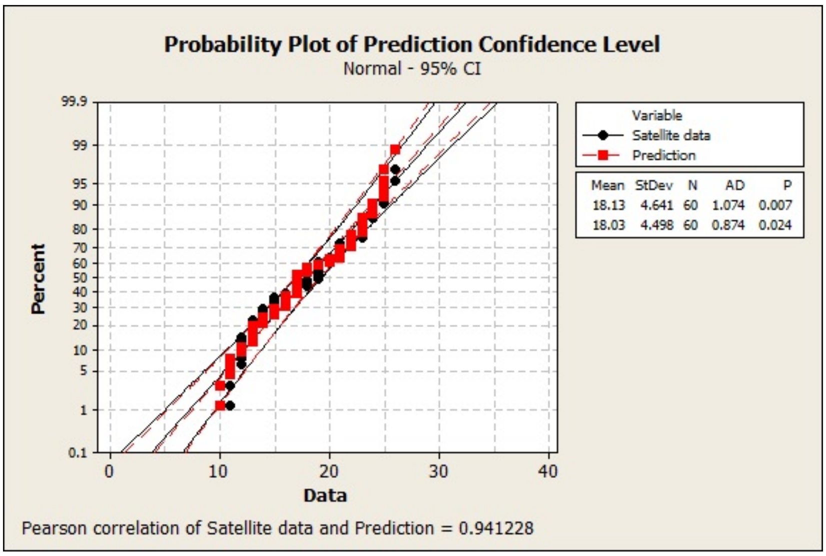

Figure 5. The confidence level of the detection code developed in *Phyton* for predicting parameters on variables of interest.

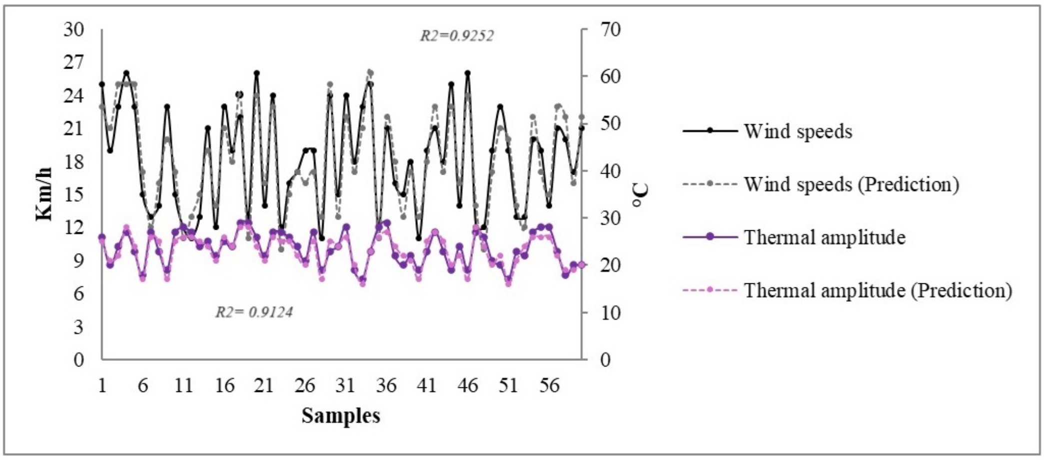

Figure 6. Correlation and validation of the data obtained in the variable prediction stage vs. historical climate data for wind speeds and thermal amplitude variables.

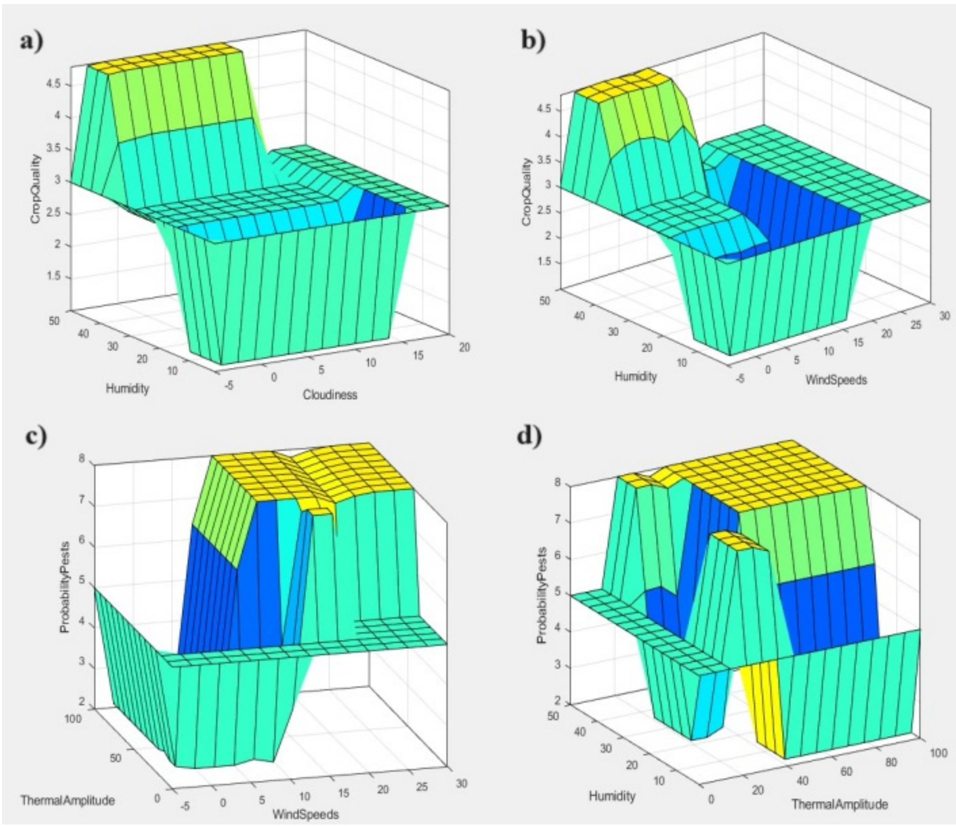

Figure 7. Response surfaces obtained from the *Crop Quality* model.

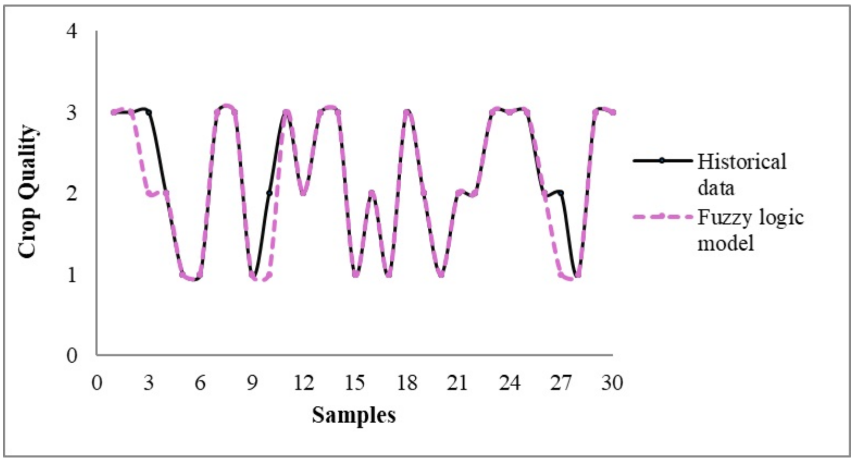

Figure 8. Validation of the fuzzy logic model to determine the quality of the sugarcane crop through the comparison of historical data.

Table 1. RGB scale for each label of the detection code in *Phyton*.

Label	RGB Scale
redBajo1	[0, 100, 20]
redAlto1	[8, 255, 255]
redBajo2	[175, 100, 20]
redAlto2	[179, 255, 255]
amarilloBajo2	[0, 100, 45]
amarilloAlto2	[225, 250, 255]

Table 2. Parámetros de control para las variables de interés (inputs).

Observed color of the cloudiness variable	Thermal amplitude (°C)	Wind Speeds (Km/h)	Humidity (%)
Blue	<13	<6	50-28
Cyan	13.1-16	6.1-9	27-23
Sage	16.1- 27	9.1-12	22-18
Green	27.1-32	12.1-16	17-10
Yellow	32.1-45	16.1-23	9-6
Orange-Red	> 45.1	>23.1	<6

Table 3. Crop Quality model: fuzzy sets and operation intervals.

<table>
<tr><th colspan="4">Input</th><th rowspan="3">Knowledge base</th><th colspan="4">Output</th></tr>
<tr><th rowspan="2">Variable</th><th colspan="3">Diffuse sets</th><th rowspan="2">Variable</th><th colspan="3">Diffuse sets</th></tr>
<tr><th>Label</th><th>Membership function</th><th>Interval</th><th>Label</th><th>Membership function</th><th>Interval</th></tr>
<tr><td rowspan="4">Cloudiness</td><td>Blue</td><td>Trapezoidal</td><td>[0, 4, 6, 9]</td><td rowspan="14">432 Inference rules</td><td rowspan="9">Crop Quality</td><td rowspan="3">Good</td><td rowspan="3">Triangular</td><td rowspan="3">[3.5, 5, 6]</td></tr>
<tr><td>Green</td><td>Trapezoidal</td><td>[7, 8, 11, 13]</td></tr>
<tr><td>Yellow</td><td>Triangular</td><td>[12, 14, 16]</td></tr>
<tr><td>Red</td><td>Trapezoidal</td><td>[14, 16, 18, 20]</td><td rowspan="3">Fair</td><td rowspan="3">Triangular</td><td rowspan="3">[1.5, 3, 4]</td></tr>
<tr><td rowspan="4">Wind Speeds</td><td>Weak</td><td>Triangular</td><td>[-5, 3, 8]</td></tr>
<tr><td>Half</td><td>Triangular</td><td>[6.5, 10, 15]</td></tr>
<tr><td>Strong</td><td>Triangular</td><td>[12, 16, 19]</td><td rowspan="3">Poor</td><td rowspan="3">Triangular</td><td rowspan="3">[0, 1, 2]</td></tr>
<tr><td>Risk</td><td>Triangular</td><td>[18, 30, 30]</td></tr>
<tr><td rowspan="3">Humidity</td><td>Low</td><td>Trapezoidal</td><td>[1, 6, 10, 20]</td></tr>
<tr><td>Medium</td><td>Trapezoidal</td><td>[15, 26, 34, 43]</td><td rowspan="5">Probability pest</td><td rowspan="3">Yes</td><td rowspan="3">S-type</td><td rowspan="3">[1, 2, 2]</td></tr>
<tr><td>Optimal</td><td>Trapezoidal</td><td>[38, 40, 50, 50]</td></tr>
<tr><td rowspan="3">Thermal amplitude</td><td>Slight</td><td>Trapezoidal</td><td>[0, 5, 15, 20]</td></tr>
<tr><td>Adequate</td><td>Triangular</td><td>[18, 25, 38]</td><td rowspan="2">No</td><td rowspan="2">Z-type</td><td rowspan="2">[0, 0, 1]</td></tr>
<tr><td>High</td><td>Trapezoidal</td><td>[36, 50, 100, 100]</td></tr>
</table>