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Retraction: Bayesian networks applied to climate conditions inside a naturally ventilated greenhouse (*IOP Conf. Series: Materials Science and Engineering* **872** 012028)

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Bayesian networks applied to climate conditions inside a naturally ventilated greenhouse

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Abstract. The prediction of gradients in a naturally ventilated greenhouse is difficult to achieve, due to the inherently stochastic nature of the airflow. Bayesian networks are numerical uncertainty techniques that can be used to study this problem. A set of experimental data was obtained: air temperature, air humidity, wind speed, and CO_2 concentration at one and three meters above the ground in the growing space. The data set was discretized and used to develop a Bayesian Network model that describes the relationships between the studied variables. The model shows the differences that allow to identify the degree of dependence of the variables, as well as to quantify their inference.

1. Introduction

Extremely high temperatures are common in greenhouses during the summer, causing problems for farmers who do not have cooling equipment to prevent overheating [1]. Inside greenhouses, the proper distribution of climatic parameters, such as airflow, air temperature, air humidity and CO2 concentration, are the main factors influencing the uniformity of crop growth. At present, numerous studies have been carried out on natural ventilation, focusing on understanding the relationships between the variables that define climate within the greenhouse, as shown below.

A greenhouse with zenithal windows facing the wind direction or windward works better than those facing the opposite or leeward direction, while in greenhouses with side windows the opposite is true, indicating that the wind direction affects the ventilation level[3][4].

Researchers in [5]determined that the airflow above the crop is greater than indoors and below it. The wind inside the greenhouse causes warm and humid air to escape through the zenithal windows, but it is not yet known how increased ventilation influences better uniformity in climatic conditions, due to the lack of information on air movement and its relation to cooling efficiency and environmental uniformity [6].

The effect of solar radiation and temperature are often related by establishing models that take into account the heating of the wall and the specific heat of the material the greenhouse is made of. The transfer of radiation within the crop itself remains the main concern, as it determines the two main physiological functions of crops: transpiration and photosynthesis. This problem has not yet been solved and is likely to receive much attention in the coming years [7].

[8]analyzed the data obtained from a Computational Fluid Dynamics (CFD) model, showing that the higher external temperature is a fundamental parameter that defines the general behavior of the temperatures inside the greenhouse, while the wind direction defines the temperatures in specific regions of the greenhouse. According to [9], they determined that the average air temperature inside the greenhouse can vary between 28.2-32.9º C, when an external temperature is 26º C, with variations of 13º C with respect to the outside [10] [11][12].

On the other hand, [13] they obtained that the thermal radiation without the participation of the air alters the distribution of the temperature of the air in the superior zone, and this one in turn affects the temperature of the air for conduction and convection. The thermal conditions of the walls of a greenhouse define the high air temperatures, but do not affect their distribution. Radiation plays an important role in heat distribution and relative humidity influences heat transfer.

Some studies, such as [14][15][16], simulated moisture distributions inside the greenhouse, obtaining good approximations with different methods, including CFD models. The study of humidity is important for the interaction between the crop and its environment. Only a few studies have succeeded in obtaining gradient models in greenhouses. Currently, there are no models to predict CO2 gradients as it directly influences crop assimilation[17].

Predicting gradients in a greenhouse is difficult, due to the inherently stochastic nature of airflow and the number of factors that influence the definition of climatic conditions, so it is necessary to apply new techniques that take into account many variables at once. The aim of this study is to address the problem by using the Bayesian Network approach to describe the relationships between variables in a poorly ventilated greenhouse. Bayesian Networks (BN) are numerical uncertainty techniques that make use of Bayesian inference as a heuristic method [18] [19][20].

2. Materials and methods

Sampling and air flow measurements were applied using omnidirectional anemometry. A set of experimental data was obtained over a period of 36 hours from 20-21 September 2019, using sensors placed in the central part of the greenhouse. The data set consists of the variables: Air temperature, Air humidity, Wind speed and CO_2 concentration. The measurements were obtained at two heights: one meter inside the crop and three meters above the ground on the crop. Temperature and humidity measurements were made at four-minute intervals using an LM335-type sensor. The CO_2 concentration was determined by means of a carbon dioxide sensor type FYA600CO$_2$H. The air speed and direction were determined by omnidirectional anemometers, whose operating range is from 0 ms-1 to 20 ms-1 with an accuracy of 0.03 m s-1. The data were discretized by means of the ELVIRA system [21], as shown below for using it in the development of the Bayesian Network model that describes the relationships between all the variables [22][23].

The greenhouse is located at the following coordinates: longitude 102° 22' W; latitude 24° 37' N; and altitude 2004 m. The surface of the greenhouse is 785.8 m². The greenhouse is 5.60 m high and 4.4 m high to the gutter, with a north-south orientation. It has four zenithal windows, one in each building, (0.85 m wide and 30 m long) and four wall windows. The windows on the north and south walls are 2.6 m wide and 20 m long, and the windows on the east and west walls are 2.7 m wide and 30 m long. All the windows are roll-up. The zenith and side windows constitute 10% and 25% of the total coverage, respectively, as shown in Figure 1. The Lycopersicumpimpinellifolim species was used as a crop, with a density of 2.7 plants/m².
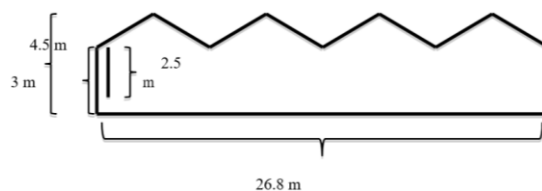

Figure 1. Greenhouse geometry.

The behavior of the studied variables was similar both in the corridors and inside the crop, however, at one meter high, the temperature was higher during the day and lower at night, while humidity was lower, as shown in Figure 2.

The analysis of BN was carried out using ELVIRA software version 0.162 in three stages suggested by[19].

1. Preprocessing: It was carried out using the "average" and consists in the discretization of the massive data by means of the algorithm, using two intervals with the same frequency.
2. Processing: According to [20], the best Bayesian network structure is obtained using the K_2 algorithm.
3. Post-processing: A dependency analysis was performed.

Subsequently, the data set was analyzed at 3-hour intervals, to develop a discrete time BN. In order to validate the model, a data set different to the one used in the learning stage was applied. The first measurements were made from September 22-25 and corresponded to the "observed data", the second data set was measured from September 20-21 and corresponded to the "expected data". The objective of this test was to check the BN to obtain a better solution, comparing probability distributions.

A) Average Temperature (°C).
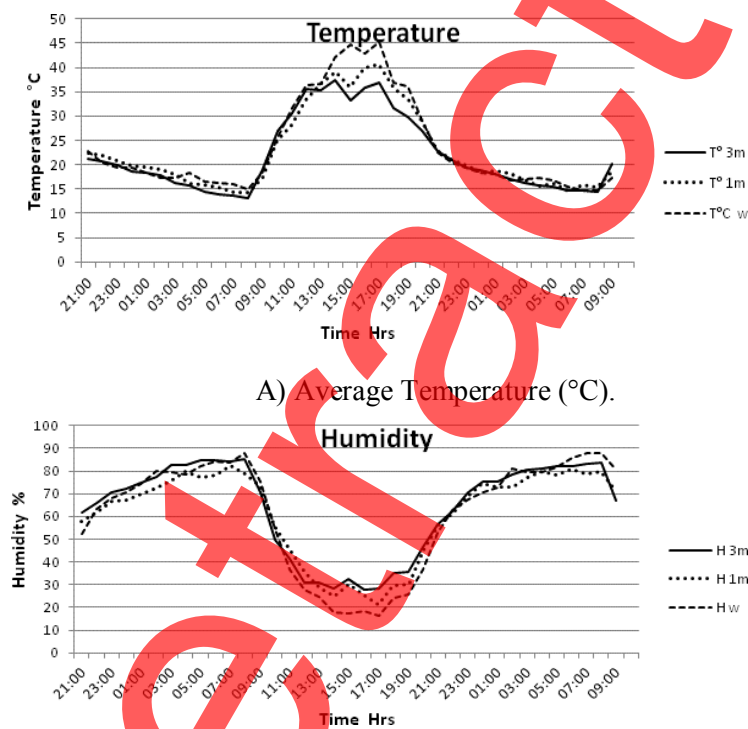
B) Relative humidity (%) at a height of three meters (3m), one meter (1m) and in the corridors without cultivation (w).

Figure 2. Climatic conditions in the central part of the greenhouse.

3. Results and discussion

A BN model was obtained with 87.5% accuracy, calculated in the post-learning stage using the ELVIRA software, which shows the relationships between the studied variables. Table 1 describes the "Expected Data" as the most likely states of the variables. The validation of the BN model is shown in Table 2.

Figure 3 shows the relationships between variables considering both day and night, so it is important to establish this model in a partial way, since the relationships between variables are not the same in the day and night, making it necessary a more detailed analysis in smaller time intervals. This

model shows that when the air speed is less than 0.4 m/s it does not affect other variables. The concentration of CO_2 at 1 m and 3 m are directly related. CO_2 concentration at 3 m and Relative Humidity at 1 m are inversely proportional to the temperature at 3 m.

Table 1. Conditional probability distribution between CO_2 over air temperature at 3 m, air temperature at 3 m over relative humidity at 1 m, and CO_2 at 3 m over CO_2 at 1 m.

CO_2 3m \ T°3m	14º C	25º C	38º C	T° 3m \ H 1m	27%	54%	82%	CO_2 3m\CO_2 1m	240 ppm	330 ppm	*402 ppm*
300 ppm	0.070	0.147	0.81	14º C	0.08	0.08	0.824	300 ppm	0.866	0.067	*0.0625*
375 ppm	0.067	0.734	0.188	25º C	0.07	0.8	0.125	375 ppm	0.067	0.866	*0.0625*
450 ppm	*0.867*	*0.140*	*0.070*	*38º C*	*0.88*	*0.14*	*0.065*	*450 ppm*	*0.067*	*0.067*	*0.875*

Table 2. Validation of the BN model

Relationship	Observed data	Expected data
CO_2 3m\T° 3m	r = -0.9998	r = -0.9998
T° 3m\H 1m	r = -0.9083	r = -0.9058
CO_2 3m\CO_2 1m	r = 0.9994	r = 0.98518
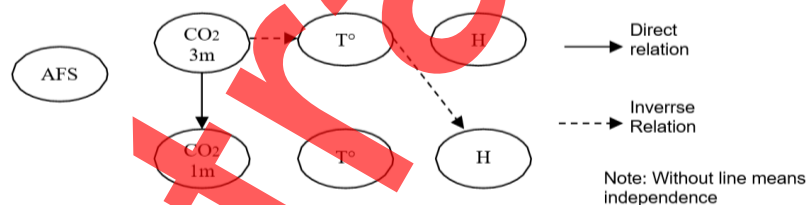
Figure 3. BN model for a 36-hour data set in the central part of the greenhouse: Airflow velocity at 3m (AFS 3m), CO_2 concentration at 1m (CO2 1m), CO_2 concentration at 3m (CO2 3m), Temperature at 3m (TºC 3m), Temperature at 1m (TºC 1m), Relative humidity at 3m (H 3m), and Relative humidity at 1m (H 1m).

This analysis showed that the airflow velocity does not affect the other variables when the air speed is low, as it does not promote heat exchange. This is consistent with previous studies from [2][4][10]. While CO_2 concentrations at 1 m and 3 m are directly proportional, CO_2 at 3 m is inversely proportional to air temperature at 3 m, and so is humidity at 1 m.

CO_2 concentrations at 1 and 3 m are closely related, both at night and during the day, CO_2 at 1 m functions as a source of CO_2 that increases its value at 3 m rising rapidly above the crop by density difference. During the day, the crop consumes CO_2 initially at 1 meter, and the increase in temperature makes the CO_2 less dense and passes to the upper layers. This does not happen with temperature and humidity, as they behave differently during the day and at night over 1 and 3 m, with a higher temperature during the day and lower humidity in 1 m than at 3 m. In the evening, these relationships are reversed (19:00 - 07:00). The inverse relationship of CO_2 and humidity with the temperature at 3 m shows that this variable is the most important, since its variation causes changes in other variables both during the day and at night. Humidity at 1 m is the most sensitive variable.

07:00-10:00. The air temperature at 3 m increases, influencing the cultivation area, the air humidity at 3 m and the CO_2 concentration at 1 m, which decreases when the air temperature increases and heats the lower layers to 1 m (T º C_BD).

10:00-13:00. The concentration of CO_2 at 1 m (CO_2_B) decreases due to increased air temperature and photosynthetic activity. The humidity of the air at 3 m shows a direct relationship with the humidity at 1 m, which decreases with increasing temperature. The CO_2 concentration at 3 m decreases its value, but not under the influence of the temperature inside the greenhouse, possibly due to ventilation.

13:00-16:00. The maximum temperature and minimum humidity values for air and CO_2 were reached inside the greenhouse in this period. The CO_2 concentration at 1 m (CO_2_B) shows direct influence with the air temperature of 3 m (TºC_AD) which is indicative of the suspension in the photosynthesis by overheating.

16:00-19:00. Lower air temperature and plant photosynthesis is again expressed in the inverse relationship between CO_2 at 1 meter (CO_2_B) and air temperature of 3 m (TºC_AD). Inversely to the period between 7:00 and 10:00, when the air temperature at 3 m (10 ft) decreases, the air temperature at 1 m (T C_BD º) also decreases its values from this point until the following day's dawn. The humidity of the air begins to increase.

19:00-22:00. The sun sets and plants stop photosynthesis, which is expressed by the inverse relationship between the air temperature at 3 m (TºC_AD), and the CO_2 at 1m (CO_2_B), which is increased by plant respiration, increases the CO_2 concentration to 3 m (CO2-A). The air temperature at 1 m (TºC_B) is higher than at 3 m (TºC_A), and therefore decreases, presenting an inverse relation with the air humidity at 3 m (H_AD), which increases.

22:00-01:00. The trend is similar to the previous period, however, the CO_2 concentration in 1 m shows the inverse relationship with the air temperature in 3 m due to breathing.

01:00-04:00. CO2 at 1 m shows the inverse relationship to air temperature in 3 m due to breathing.

04:00-07:00. At this point, higher levels of CO_2 concentration, air humidity and lower air temperature have been achieved. At the end of this period, there is a greatest difference in air humidity at 3 m and 1 m. The lowest temperature is recorded at 3 m, showing an inverse relationship with the highest humidity level at 1 m, suggesting that humidity rises due to the effect of the crop's respiration.

4. Conclusion

Using a BN model, it is possible to observe and quantify the relationships between the variables Temperature, Relative Humidity, Airflow Velocity and CO_2 concentration. BN model shows that the Air Flow Rate does not affect the other variables when the air speed is low. Discrete-time BN models show the relationships between variables that suggest the physiological processes of the crop and the interaction with its environment. The state of a physiological process in the crop is represented by a conditional probability value in a given time interval and this changes throughout the day. Using a BN model, it is possible to conceptualize the growing space as a subsystem different from the corridors and the area above the crop, which interact with its environment inside the greenhouse. Conditional probability distributions are a quantitative measure of the relationships between variables and show the most likely state of these variables. BN models have the ability to show the relationships between variables involving physiological processes of crops inside a greenhouse.

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