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Abstract

Climate change has had profound impacts on agricultural systems, altering crop productivity, changing precipitation patterns, spreading pests and diseases, reducing soil quality, displacing agricultural areas, and increasing the use of inputs such as fertilizers and pesticides, which in turn leads to an increase in atmospheric emissions. To address this issue, this research proposes the use of a multi-agent system-based model to analyze the vulnerability of sugarcane production, representing complex systems and adapting to changing conditions by integrating dynamic and uncertain variables. The main advantage of the model is that it enables the quantification and analysis of critical variables, including the use of fuel, fertilizers, and nitrogen oxide (N_2O) emissions. The results demonstrate how the increase in operating trend negatively impacts environmental performance, highlighting the fragility of the system. Meanwhile, the validation of the model through structural tests and extreme conditions confirmed its reliability in supporting decision-making processes. Likewise, the average vulnerability value of the system (0.54) indicates a moderately unstable condition, susceptible to climatic and economic changes. Complementarily, the IMPACT 2002+ methodology was applied to conduct a life cycle assessment (LCA) of sugarcane, encompassing its cultivation and industrial processing. It was found that the resources used in sugar mills have the most significant environmental impact in the categories of climate change, human health, ecosystem quality, and resource consumption. This impact is caused by CO_2 emissions, the use of toxic pesticides and heavy metals, and high dependence on fossil fuels such as coal, natural gas, and oil, mainly. These findings underscore the need to enhance environmental management in Mexico's sugar sector by adopting cleaner technologies, establishing reliable ecological databases, and implementing assessment tools such as multi-agent modeling and life cycle analysis.

Key words: climate change; life cycle assessment; agent-based modelling; sugarcane; agricultural vulnerability.

Introduction

Currently, changes in weather patterns have become increasingly uncertain, leading to increased vulnerability in the agricultural sector, causing disruptions in crop production worldwide, resulting in crop losses and jeopardizing food security (Tapia *et al*., 2017). In this regard, changes in climatic conditions have a significant impact on grain crops, as they are susceptible to phenomena such as droughts and heatwaves, the latter causing the most damage during the flowering and reproductive stages. This is because high temperatures interfere with fundamental physiological functions such as pollination and photosynthesis, reducing crop yield and causing harvest losses (Barnabás *et al*., 2008).

The study of vulnerable food systems has emerged as a means of strengthening and increasing food security, with the main aspects to be considered being access to and availability of resources through a spatio-temporal approach. Therefore, to achieve a better understanding of food systems about climate change at the micro and macro levels (Below *et al*., 2012; López Guevara, 2015), it is necessary to analyze trends and develop models to obtain possible future scenarios for crops and their relationship with the elements of the environment in which they grow.

Therefore, the development of techniques and technologies has been chosen, including protected agriculture, which involves carrying out activities under specific conditions. This consists of implementing structures that protect crops from potential risks by controlling parameters such as temperature, humidity, wind, and water. The implementation of techniques such as protected agriculture generates numerous advantages for farmers because it is a sustainable production system. In Mexico, over the last twenty years, protected agriculture has become increasingly important, mainly in the export of vegetables to countries such as Canada and the United States. By 2022, data from the Mexican agricultural census indicate that nearly 30,179 agricultural production units are operating under protected agricultural conditions (INEGI, 2023). Likewise, precision agriculture has been implemented for the management and administration of agricultural land through the detection of “spatial variability.” Precision agriculture relies on the use of image processing tools, including geographic information systems (GIS), global positioning systems (GPS), and satellite sensors, among others. The technique consists of implementing global positioning technologies and satellite imagery to analyze agricultural systems. The use and implementation of these techniques enable a homogeneous analysis of the system and the identification of the most vulnerable areas, allowing for the application of corrective actions and the optimization of the production system, thereby increasing its competitiveness by reducing costs (Del Borghi *et al*., 2022; Shafi *et al*., 2019). Precision agriculture is a tool for better managing resources, such as water, pesticides, and fertilizers, as well as optimizing the use of arable land and managing crop-related information. Viticulture is the sector in which optimal results have been achieved through the use of specific techniques.

However, advanced modeling tools have emerged that can incorporate simulation techniques such as system dynamics, discrete events, and agent-based modeling (ABM), which enable the study of complex systems by creating autonomous agents that interact with each other and their environment (Sterling and Taveter, 2018). Agent-based models enable the analysis of agricultural producers' reactions to climate change under conditions of uncertainty, allowing for the modification of farming policies and practices to mitigate the effects of climate change (Badillo-Márquez *et al*., 2021; Gonçalves *et al*., 2022). Under this approach, agent-based models employing programming techniques enable the simulation and representation of spatio-temporal interactions between agricultural indicators and their interactions with the environment (Berger and Troost, 2014; Rahman *et al*., 2022).

For their part, Salvini *et al*. (2016) implemented agent-based modeling to simulate carbon emissions over decades. The authors used a case study of a region in central Vietnam where acacia trees are grown, an area characterized by deforestation that hinders the development of agricultural activities. The modeling was based on information generated by the expertise of local politicians and farmers. As its primary contribution, the model enables the identification of the objectives, needs, and limitations of local farmers, providing various scenarios for environmental policies that lead to greater effectiveness in climate change mitigation and adaptation.

Mirzaei and Zibaei (2021) conducted studies to analyze the impact of climate change on water resources in the agricultural sector. The study aims to integrate tools, such as agent-based modeling, to examine the relationship between impacts and adaptation. The result was a multi-objective optimization model of economic, hydrological, and agronomic aspects capable of evaluating scenarios of the possible effects from climate change and the respective adaptation measures for irrigated agriculture to minimize problems related to water use, favoring the restoration of wetlands in the study area, in addition to achieving a 14% reduction in water use.

Reducing atmospheric emissions from agricultural activities is crucial to meeting current climate standards. The development and implementation of strategies and tools that encourage both small and large farmers to adopt these measures are essential to reducing agricultural vulnerability and achieving effective climate change mitigation. Recent research predicts that climate change will have socio-ecological repercussions resulting from both human activities and climatic factors that cause ecological imbalance and social unrest.

Therefore, it is essential to conduct an accurate assessment of agricultural vulnerability at the local or regional level that measures the degree of exposure to climate change and determines the capacity to adapt to it. However, when assessing agricultural vulnerability to climate change, it is essential to consider not only extreme weather events but also the environmental consequences expected in the medium and long term. In recent years, agricultural activities worldwide have increased their environmental impact due to the emissions they generate. In response to this problem, efforts to control polluting emissions into the atmosphere have intensified, aiming to reduce the impact on ecosystems, climate change, and human health by addressing chronic diseases primarily caused by poor air quality (McAuliffe *et al*., 2023).
Life cycle assessment (LCA) is a methodology used to examine the potential environmental impacts and resource consumption throughout all stages of a product's life cycle. This approach offers a comprehensive perspective, considering factors related to the natural environment, human health, and resource utilization. LCA involves collecting and analyzing data on inputs, outputs, and potential environmental effects associated with a product or process throughout its life cycle. A comprehensive analysis, known as "from cradle to grave," encompasses all phases, from product design and development, through raw material sourcing, production, and distribution, to maintenance, reuse, and final disposal (Jacquemin *et al*., 2012).

Nishihara Hun *et al*. (2017) evaluated the environmental impact of the sugarcane industry in Tucumán, Argentina, using the LCA methodology. The research covers different levels within the agricultural stage (farming, sugar production, and distillation). The scope of the analysis encompasses both the agricultural and industrial phases, spanning from sugarcane cultivation to the production of final products, including sugar and alcohol. The data for the inventory design were obtained mainly from local experts, sugarcane producers, and processing companies. The impact assessment was conducted using the CML 2001 model, which considers nine categories of environmental impact. The results reveal that the use of synthetic agrochemicals represents a significant contribution to the total impact.

Meanwhile, Selvaraj *et al*. (2021) conducted life cycle analysis studies in India, a region characterized by constant advances in agriculture to meet food demand and, in turn, by the overexploitation of agrochemicals, generating high emissions into the atmosphere and resulting in adverse effects on the environment, ecosystems, and human health. Among the crops studied, 21 crops stand out, divided into categories: cereals (rice, wheat, barley, maize and millet), fruits (apple, mango, banana and grapes), oilseeds (castor, rapeseeds, oilseed, and sunflower seeds), vegetables (potato, tomato, carrots, and beans), cash crops (coffee and cocoa) and others (coconut and sugarcane). The research involved developing impact indicators to identify the primary causes of emissions, generating recommendations, and exploring potential solutions. The indicators studied encompass 17 sustainable development goals, enabling the measurement of agricultural sustainability and the identification of areas for improvement or the development of new indicators. The research results reduce environmental impact without compromising the socioeconomic aspects associated with agricultural production of the crops studied.

Sugarcane is a key crop in Mexico, both economically and socially, due to its significant role in sugar production and its contribution to job creation, particularly in rural areas (CONADESUCA, 2020). Likewise, the sugar industry drives the development of various regions of the country and has a considerable influence on the national economy, with an annual production of 21,227,445 tons. The Agricultural Census for 2022 (INEGI, 2023) revealed that sugarcane was the most critical perennial crop in Mexico in terms of cultivated area, with 360,073 hectares. The census also identified Veracruz, Jalisco, and San Luis Potosí as the central sugarcane-producing states in Mexico.

In Mexico, sugarcane cultivation is often carried out using agricultural practices that usually overlook proper waste management. Land preparation and furrow layout are generally carried out following the slope, which promotes erosion and soil deterioration. Irrigation is applied in large volumes and an uneven manner. Likewise, fertilization is not based on an analysis of the soil's nutritional content or the specific needs of the crop to achieve optimal yield. In terms of pest, disease, and weed management, the intensive use of agrochemicals predominates (Canata *et al*., 2021; Landeros-Sánchez *et al*., 2016).

The objective of this research is to develop an analysis of agricultural vulnerability to climate change in sugarcane production through LCA and a multi-agent system, which allows for the evaluation of the impacts generated by the implementation of agrochemicals and the use of fossil fuels, primarily. Given this problem, the agent-based model enables the assessment of agricultural vulnerability and risk to climate change by identifying the physical and environmental variables that have the most significant impact on the sugarcane harvesting system. Therefore, the agent-based model allowed for a systemic study of the sugarcane production system to determine the causes of disasters and their functional relationship with the impacts of the system, thereby determining agricultural vulnerability and risk and establishing a vulnerability reference scale to perform a dynamic historical risk assessment to project the model's trends using the results of twelve sugarcane production cycles. The results enabled the identification of the most significant processes (climate change, ecosystem quality, human health, and resources), thereby determining the activities that contribute most importantly to the environment. This was achieved through the analysis of average impacts and/or endpoint categories *via* LCA. In stage 1, the agent-based model was used to determine the primary sources of ecological pollutant emissions, i.e., emissions from agricultural activities related to sugarcane production that release substances or energy into the environment (water, soil, air) that can alter its natural composition, affecting the balance of the ecosystem and the health of living beings. With the obtained results, the sugarcane cycle inventory (stage 2) has been to determine the inputs and outputs of the model, as well as midpoints and endpoints that will allow for an impact assessment through a LCA for the classification and characterization of variables to quantify the environmental impact of sugarcane production.

Materials and Methods

The following section describes the main stages that comprise the methodology used in this research (Figure 1). In the first stage, an agent-based model was developed, incorporating socioeconomic and environmental variables modeled in system dynamics, to estimate the vulnerability of sugarcane production. In Stage 2, the inputs for the life cycle inventory of the LCA will be determined using the estimates of the variables obtained from the agent-based model.

Stage 1 is based on an agent-based model consisting of four main networks developed through system dynamics; each network encompasses information on land use, water resources, land value, and gas emissions, which were created in a doctoral research project by the authors (Badillo-Márquez *et al*., 2021). As part of the present research and to conduct the LCA, two networks involved in sugarcane production, transportation, and fertilizer use processes were identified. In stage 2, as mentioned above, the life cycle inventory for the life cycle impact assessment (LCIA) was developed using the information obtained in the intelligent agent model. The life cycle impact assessment comprises four subsystems: tillage, production, resource use, and harvesting.

Stage 1. Vulnerability assessment in the agricultural sector in sugarcane production: agent-based model

The agent-based model developed is fed by variables defined by time series and probability distributions under a systems dynamics approach that facilitates the representation and simulation of complex systems, such as agricultural systems, by allowing dynamic analysis of the system's behavior through the exchange of information between its variables, which contributes to understanding and optimizing the interactions between its components (Forrester and Senge, 1980). To gain a better understanding of the interrelationships within the agent model, a causal diagram was developed to represent the system's structure and simulate its behavior, identifying the decision variables that describe socioeconomic and environmental aspects. Figure 2 describes the causal diagram of the agent-based model (ABM). As shown, positive (+) or negative (-) relationships, indicating the type of influence that one variable exerts on another. Positive relationships imply that an increase or decrease in variable A generates a change in the same direction in variable B. In contrast, negative relationships indicate that any variation in variable A causes a contrary effect in variable B (Cedillo-Campos, 2008). The causal diagram shows a representation of dynamic variables, which are modeled through variables or parameters and time series described in Table 1. Therefore, the causal diagram shows a set of clusters representing the seven subsystems of the agent-based model.

Conceptualization

The agent-based model consists of seven networks or subsystems. In previous research by the authors (Badillo-Márquez *et al*., 2021), an agent-based model composed of four networks was developed. The Agricultural Land Yield Network estimates the availability of land for agricultural activities and the degree of vulnerability in the use of agricultural land due to soil overexploitation or degradation.

The Agriculture Value Network can estimate the added value of agricultural activities based on the flow of information related to productivity in the agricultural sector, problems in agricultural development, crop value, hours worked, and insurance for agricultural development. The Agricultural Water Resources Efficiency network estimates the vulnerability of water resources in the agricultural sector, as approximately 79% of agricultural activities carried out in Mexico do not utilize an irrigation system. The Environmental Contingency network considers greenhouse gas emissions and severe environmental phenomena that, due to their frequency and magnitude, pose a risk to agricultural harvests. For the development of this research, three networks were included, corresponding to tillage, transport, and the use of fertilizers and pesticides. The sugarcane tillage network refers to the set of agricultural operations carried out to prepare the soil and create optimal conditions for sugarcane cultivation, from planting to harvest. These tasks include clearing the land, leveling, subsoiling, plowing, harrowing, and furrowing, among others (CONADESUCA, 2020; PRONAC, 2009b). The sugarcane transport network consists of collecting the raw material available in the field with high efficiency, ensuring the timely and sufficient supply of cane to the factory, in the shortest time possible between harvest and milling, with minimal waste (leaves, trimmings, and soil). This network evaluates fossil fuel consumption, depending on the number of tons transported by the truck/tractor and the distance traveled. Finally, the fertilizers network considers the application of fertilizers based on the nutrient requirements of sugarcane. It is essential to recognize that excessive fertilization leads to significant environmental pollution in the agroecological system, as surface runoff from the system contaminates water sources, degrades soil quality due to acidification, and affects air quality (Li *et al*., 2016).

The variables that feed into the agent-based model to determine vulnerability are modeled using probability distributions that describe historical data from the period 20012024. Table 1 describes the main variables used.

Once the variables had been characterized, the main agents of the multi-agent model were defined, comprising four types of agents. The decision variables agent plays an active role, modeling the behavior of the networks to bring information to the decision center and determine. The vulnerability of sub-models agent (hydric, transport, fertilizers, agricultural land, agricultural value, and climatic) has a decision role. It is responsible for making decisions when modifying agrarian practices to minimize crop vulnerability. For its part, the Total system vulnerability agent plays a reactive role and models the information obtained by the agents to determine the system's vulnerability level, providing a stimulating response to unexpected events that occur within the system. Finally, the information network variables (population of agents) have a passive role, and their function is to store information through databases and distribute it to agents through networks.

Formulation and implementation

The mathematical formulation of the model involves making projections of the decision variables for each network or subsystem, which will be used to construct the life cycle inventory. This is achieved by evaluating behavior over time, adjusting the trend for each variable when $t>0$. For this phase, the time series used in the initial research, developed by Badillo *et al*. (2021), were recalculated, as there was an adjustment in the four-year variable projection. Table 2 displays the trend of the time series for $t>0$.
The simulation was performed using AnyLogic Persona Learning Edition 8.9.4 software (a free student version) in the System Dynamics library, with a period of 12 sugarcane harvest cycles when $t>0$.

Stage 2. LCA of sugarcane cultivation in the state of Veracruz, Mexico
This stage consists of four steps, which are described in Figure 1 (stage 2). In the first step, the purpose and scope of the study were determined by the preferences of the stakeholders, specifically the sugar mill managers. At this point, all criteria must be well established, including the objective, functional unit, system boundaries, and categories of impacts to be evaluated in the study.

Definition of the objective and scope of the study
The objective of this study is to assess the environmental damage associated with sugarcane production throughout its life cycle, identify areas with the most significant environmental impact, and explore ways to improve its performance. The boundaries of the system were established based on the selection of elements from the physical system to be modeled (inputs and outputs obtained in stage 1: agent-based model) and the scope of the study. Therefore, the input data for the life cycle inventory (LCI) are the result of averages generated during the study period 2001-2024 obtained from the outputs of the intelligent agent model, which allow future projections to be obtained.
The scope of the study is defined by the product system to be evaluated, which for this study is sugarcane production, including the subsystems: tillage, resources, production, and harvesting (defined in Stage 1) in the region of the state of Veracruz, Mexico, which has a wide variety of landscapes, from beaches and dunes to mountains and jungles. Its predominant climate is warm and subhumid, with average annual temperatures ranging from 0 to 28°C. Its soils are characterized by the presence of vertisols, feozems, luvisols, and acrisols, which can range from sandy loam to clayey textures, with varying levels of acidity and nutrient content.

Information gathering
The information gathering involves obtaining data for the construction of the Life Cycle Inventory (LCI), which includes information on the subsystems above. The information was obtained from open-access databases (CONADESUCA, 2020; INEGI, 2017, 2018, 2023), small and medium-sized producers, and information provided by the sugar mill belonging to the Porres® Group, where the study was conducted.

Life cycle inventory

Step 2 involves constructing the life cycle inventory (LCI), where the functional unit of the study is first defined. This definition quantifies the performance characteristics of inputs and outputs of the system by standardizing the data according to the functional unit. In this case, the functional unit was defined as one ton of sugarcane. Inputs and outputs serve as an indicator of uncertainty with statistical information (ISO, 2000; ISO, 2006b).

For the LCA, specialized software was used, which includes a database for the Life Cycle Inventory of the primary emissions associated with fertilizers, pesticides, herbicides, diesel use, resource use, and water efficiency, among others.

Emissions were calculated using the roundtable on sustainable biofuels (RSB) methodology, which is an internationally accepted standard that details how to calculate greenhouse gas (GHG) emissions and must be applied by all RSB-certified operators involved in the production, transformation, processing, marketing, transportation, or distribution of biomass and biofuels. The RSB methodology allows for the estimation of GHG emissions throughout the life cycle of biofuels, including those derived from land use (such as CO_2 and CH_4), agricultural activities (such as N_2O and NO_x), as well as from the processes of refining, production, transportation, storage of fuel, and its final combustion. It also considers NH_3 emissions resulting from the use of mineral fertilizers (Guittet *et al.*, 2018; Hennecke *et al.*, 2013).

The mathematical model, developed using the data obtained and the outputs of the agent-based model developed in Stage 1, is shown below.

Mathematical model

$$Load\ Sugar\ (Ton)\ f(x) = \{a, b, c\} = (10,14,24) \begin{cases} 0 \quad for\ t \leq 10; \\ \frac{(x-10)^2}{(14-10)(24-10)} \quad for\ 10 < x \leq 24; \\ \frac{1-(14-x)^2}{(14-10)(14-24)} \quad for\ 24 < x < 14; \\ 1\ \ para\ \ 14 \leq x\,; \end{cases} \qquad \textbf{(Eq. 1)}$$

$$Total\ Diesel\ (use) = 3.1\ Lt * \left(\frac{(Small\ Produces + Farmers) * 64 \frac{Ton}{Ha}}{9.73 \frac{Ton}{Ha}} \right) \qquad \textbf{(Eq. 2)}$$

$$\frac{Kg\ Diesel}{Ton\ Sugarcane} = \left[\left(36.2 \frac{MJ}{Lt} * Diesel\ Lt \right) * \left(\frac{1}{42.3} Kg\ Diesel * MJ \right) \right] \qquad \textbf{(Eq. 3)}$$

$$Total\ Distance\ (Km) = \frac{\left(Distance\ km * \frac{Total\ Kg\ Diesel}{Ton\ Sugarcane} \right)}{Total\ load} \qquad \textbf{(Eq. 4)}$$

$$\frac{Total\ Kg\ Diesel}{Ton\ Sugarcane} = \left[\frac{(Small\ Producers + Farmers) * 64 \frac{Ton}{Ha}}{9.73 \frac{Ton}{Ha}} \right] * \frac{Kg\ Diesel}{Ton\ Sugarcane} \qquad \textbf{(Eq. 5)}$$

$$Fertilizers \frac{Kg}{Ha} = Agricultural\ Lime + CH_4N_2O + KCl + (NH_4)_2SO_4 + (NH_4)_2HPO_4 \qquad \textbf{(Eq. 6)}$$

CH_4N_2O= Urea
KCl= Potassium chloride
$(NH_4)_2SO_4$= Ammonium sulfate
$(NH_4)_2HPO_4$= Diammonium phosphate

$$DAP\ (18\%N - 46\%P_2O_5 - 0\%K_2O) = Chemical\ component * \frac{Average\ DAP\ kg}{Ton\ sugarcane} \quad \textbf{(Eq. 7)}$$

$$Total\ Fertilizers \frac{Kg}{Ha} = Fertilizers \frac{Kg}{Ha} * \left[\left(Small\ Producers + Farmers \frac{Ton}{Ha}\right) * 64 \frac{Ton}{Ha}\right] \quad \textbf{(Eq. 8)}$$

$$N_2O\ fertilizers\ emissions = \left[\begin{array}{c}\left(\frac{44}{28} * EF1 + Ntot + NCr\right) + \left(EF4 * \frac{14}{17} * Fertilizer\ NH_3\right) + \\ \left(EF5 * \frac{14}{62} * Fertilizers\ NO_3\right)\end{array}\right]$$

EF1=0.01
EF4=0.01
EF5=0.0075
Ntot=Total Nitrogen input
NCr=Nitrogen contained in crop residues **(Eq. 9)**

$$Pesticide\ \frac{Kg}{Ha} = \frac{Total\ area\ with\ pesticide\ Ha}{Planted\ area\ Ha} * 64\ Ton/Ha \quad \textbf{(Eq. 10)}$$

$$N_2O\ emissions\ by\ agriculture\ f(x;\mu,\sigma) = \frac{1}{x(1728)\sqrt{2\pi}} e^{-(\ln\ (x) - 32667)^2/2(1728)^2} \quad \textbf{(Eq. 11)}$$

$$Total\ (N_2O) = N_2O\ emissions\ by\ fertilizers + N_2O\ emissions\ by\ agriculture \quad \textbf{(Eq. 12)}$$

$$Tillage\ area = Planted\ area * Mechanized\ area\ (\%) \rightarrow For\ crop\ type\ and\ study\ area \quad \textbf{(Eq. 13)}$$

$$Tillage\ area\ (case\ study\ in\ Veracruz) = 22108\ Ha * 17.5\% = 3869\ Ha \quad \textbf{(Eq. 14)}$$

$$Agricultural\ burning\ \frac{Ton}{Ha} = Production\ for\ crop_i \left(\frac{Ton}{Ha}\right) * \frac{Dry\ matter\ Kg}{Crop\ Kg} * \\ \%\ Wastes\ susceptible\ to\ burning * 1e^{-9} Ton/Mg$$

Hydric resources available (HyRes): Total water volume available from various supply sources (well, river, spring, water dam, open-air water well, water bank and other sources) (Badillo-Márquez *et al*., 2021)

$$\frac{dHyRes}{dt} = HyRes_{t=1} + \left(\frac{1}{9722\sqrt{2\pi}} e^{-(x - 4.64E^5)^2/2(9722)^2}\right) 0.76. \quad \textbf{(Eq. 15)}$$

Water Resource Efficiency (WREff) indicates the efficiency of underground and surface water supply in the agricultural sector for the geographical area of the study case (Badillo-Márquez *et al.*, 2021)

$$\frac{dWREff}{dt} = WREff_{t=1} + \frac{\frac{dHyRes}{dt}}{\left[\left(\frac{1}{0.0272\sqrt{2\pi}}e^{-(x-0.7637)^2/2(0.0272)^2}\right)(UndS+SupS)\right]} \quad \textbf{(Eq. 16)}$$

Using the data obtained from the mathematical model, the variables that will serve as inputs to the LCI were defined. One of the characteristics of a correct LCI is the balance between the inputs and outputs of each of the categories (*Mi*) to be evaluated (equation 17) by the allocation factor (Ai).

$$M_i = \left(\sum inputs_i - \sum outouts_i\right) * A_i \quad \textbf{(Eq. 17)}$$

Table 3 shows the inputs and outputs to the Life Cycle Inventory, where three main categories of impact assessment can be observed: soil preparation for planting, sugarcane production, and resources employed in the mill. The soil preparation for planting category encompasses emissions generated by tilling the land for planting in the study area, sugarcane harvesting, areas affected by chemical and/or physical degradation, as well as natural disasters. It also includes diesel used in machinery for soil preparation and fertilizer use.

The sugarcane production category encompasses the efficiency of water used in crop production, mainly in irrigation systems. It also includes the use of diesel in machinery, as well as the application of pesticides and herbicides to combat the presence and spread of pests and/or diseases, and the burning of sugarcane.

Finally, the category of resources employed in the mill includes the three main resources: water, energy, and diesel for transporting cane from the field to the mill.

Impact assessment

In step 3, the LCIA was carried out in accordance with ISO 14044:2006, which establishes the requirements and provides guidelines for conducting LCAs. This includes defining the objective and scope of the study, analyzing the LCI, assessing the impacts (LCAI), and interpreting the results. In addition, it covers aspects related to reporting, critical review of the study, limitations of the analysis, the interrelationship between its different phases, and the conditions for applying value criteria and optional elements (ISO, 2006b).

The impact categories determine the midpoints for global warming and toxicity (divided into 11 subcategories, Table 7), as well as the endpoints for human health and ecosystem quality. The LCIA enables each main flow identified in the LCI to be associated with its corresponding environmental impacts, initially through intermediate-level indicators (midpoints) and subsequently by connecting them to the categories of damage or results (endpoints). For this assessment, the IMPACT 2002+ method was employed, a hybrid model that integrates various impact categories and considers multiple environmental harms (Jolliet *et al.*, 2003). This methodological approach allows for the analysis of environmental impacts throughout a product's life cycle, integrating both intermediate and final impact categories, providing a comprehensive perspective that encompasses factors such as climate change, human health, resources, and ecosystem integrity.

Limitations of the study

The limitations of the system depend on the physical system selected for modeling, the objective, and the scope of the study. The stages, processes, and flows of the model that must be considered for the boundaries are the inputs and outputs of the agent model, primarily in the transport stage, including fertilizers and resources used in sugarcane agriculture. Because the production of sugarcane under the LCA study includes different stages in which the environmental impact can be assessed, the initial boundaries of this system include the following inclusion criteria: currently, this study contemplates including agriculture, the transport of cane to the mill, the standard sugar production process, and the cogeneration of electricity from bagasse. The stages that are expected to be omitted are ethanol production, distribution of sugar as the final product, and marketing. It should be recognized that an LCA study is an iterative technique and that, as data and information are gathered, various aspects of the scope, initial boundaries, and other aspects may require modification to meet the original objective of the study.

Stage 4 of interpreting results is described in the following section.

Results

Agent-based modeling

One of the primary advantages of implementing agent-based modeling is the ability to integrate both environmental and social models through information networks or sub-models composed of individual entities capable of performing tasks autonomously, thereby aiding the decision-making process. The results shown below are from an agent-based model developed in system dynamics using AnyLogic Personal Learning Edition 8.9.4 software (a free student version) to assess the vulnerability of sugarcane production in a 12-cycle simulation. The agent model has an element of uncertainty, as it considers historical and empirical data, as well as emerging events related to phenomena caused by climate change, which easily increases the model's level of complexity.

Therefore, a sensitivity analysis was performed on the agent model to understand the behavior of the variables in the face of variations that may affect the model's results, thereby allowing: i) the identification of critical variables that have the greatest impact on the model's results and performance, ii) risk management by understanding these variations through the identification of potential opportunities by evaluating scenarios that reduce uncertainty, and iii) improving the accuracy of the model by identifying errors or inconsistencies, thereby ensuring that the model reflects the current reality of the system, providing more reliable results and validating the model.

Sensitivity analysis

To validate the model, dimensional consistency and extreme condition tests were applied, following Forrester and Senge (1980). Dimensional consistency allows us to analyze whether the equations and time series used in the model reflect the reality of the system, standardizing the output values in the functional units used, such as kilograms per hectare (kg/ha), tons (tons), kilograms of diesel, gigatons of carbon dioxide equivalent ($GtCO_2eq$), etc. Meanwhile, to measure the system's vulnerability, a scale of 0 to 1 was used, both for the vulnerability of each subsystem and the total vulnerability value, with 1 representing the highest vulnerability value.

For its part, the extreme conditions test enables the identification of errors in the model architecture through an analysis of different scenarios in the face of potential variations related to uncertainty. To create scenarios, five scenarios were proposed that reflect an increase and/or decrease in the current trend for the year 2024. The trend projections were eliminating the trend (-100%), halving the trend (-50%), continuing the current trend without modification (0%), and increasing the trend (+50% and +100%).

The sensitivity analysis considered the critical variables: i) kilograms of diesel per ton of sugarcane, ii) kilograms of fertilizer used per hectare, iii) total diesel use per liter per hectare, and iv) total nitrous oxide (N_2O) emissions.

Figure 3 shows the results of the sensitivity analysis for the critical variables.

As can be seen in Figure 3 a,c, with the downward trend in scenario 1 (-100%), diesel fuel consumption is very low, as demand for fuel for both land preparation machinery and transportation were significantly reduced due to the lack of a trend. In contrast, for scenarios 2 and 3 (-50% and current trend), the model's performance is as expected, following the demand trend. Scenarios 4 (+50%) and 5 (+100%) show an exponential increase due to excessive fuel use, which will directly impact emissions into the atmosphere.

Figure 3b shows that fertilizer use (kg/ha) in scenario 1 maintains low levels, while scenarios 2-5 exhibit a trend toward equilibrium starting in cycle 3. This is because growth in sugarcane production generally leads to an increase in fertilizer use, although this connection is not necessarily direct or proportional. Fertilization must be adapted to specific soil conditions and crop needs. Increasing its use does not guarantee better yields; on the contrary, excessive fertilizer can have a negative impact on both plants and the environment.

In Figure 3d, as agricultural activities decrease with the trend (scenario 1), atmospheric emissions of nitrous oxide (N_2O) decrease, while scenario 2 shows an almost balanced state due to a downward trend, as can be seen as the trend increases from scenario three onwards, emissions rise, reaching their highest peak in scenario 5 in cycle 10. The increase in nitrous oxide emissions as the trend continues is primarily due to the use of nitrogen fertilizers and the burning of agricultural residues.

Figure 4 illustrates the results of projecting the system's impact variables. Figure 4a as shown the results of the projection of the variables "raw sugarcane milled" (ton/ha) versus "harvested area" (ha). As can be seen in the graph, the relationship between the two variables is proportional from cycle two onwards because, as more sugarcane is planted, the harvest is expected to be proportional. However, these quantities cannot be equal because there are

always losses during the harvest stage, whether due to environmental issues such as weather conditions, problems during the cutting stage, plant diseases, incorrect agricultural practices, or losses during transport. The graph shows that the lowest expected amount of sugarcane is in cycle 4, with 1,096,800 tons/ha, while cycle 12 has the highest peak, at 1,393,419 tons/ha. In Figure 4b, the projection of N2O emissions from fertilizers versus N2O emissions from agriculture (i.e., all activities for pre- and post-harvest soil preparation, such as mechanical and manual tillage, use of machinery, etc., that cause physical and/or chemical degradation) for cycles 1 and 2 shows that emissions from fertilizer use are 22% lower than those from agriculture. From cycle three onwards, nitrous oxide emissions from both fertilizer use and agriculture begin to behave proportionally, with higher emissions in cycle 5 for fertilizer use at 10,022 (Gt CO2eq) and for agricultural emissions in cycle 12 at 35,629 (Gt CO2eq).
Table 4 presents the results of the critical variables and impact variables, along with their respective units of measurement, based on a simulation of 12 cycles for the model, assuming the current trend (year 2024).

Determination of system vulnerability

To determine vulnerability, a vulnerability factor was assigned to each network or subsystem based on its objectives, expertise, and historical data from open information systems (CONADESUCA, 2020; CONAGUA, 2018, 2020; Inifap, 2018; PRONAC, 2009a; SIAP and SADER, 2024; SMN and CONAGUA, 2023) and data provided by the sugar mill. Table 5 at the top shows the vulnerability scale for the expected values of the networks: agricultural land yield, agricultural water resources efficiency, agricultural value, and greenhouse gas (GHG) emissions and risk situation. The bottom section shows the scale of vulnerability for the expected values of the networks: fertilizers, transport, and tillage.
According to the vulnerability scale presented in Table 5, the vulnerability factors for each network in the agent model were determined. Table 6 presents the results for each simulation cycle, yielding a final average vulnerability value of 0.54, indicating a medium vulnerability.

LCA

This section presents the results of LCI and LCIA analysis. The results are described by functional unit for the eleven midpoint impact categories and the four end-point categories (climate change, ecosystem quality, resources, and human health) following the IMPACT 2002+ methodology.

Analysis of environmental emissions

The climate change category contributed 1,238 kg CO_2 eq, with 78% coming from the resources used in the mill, followed by sugarcane production and tillage with 12% and 10%, respectively. For the ecosystem quality category in general, there were higher emissions from the resources used in the mill, with aquatic ecotoxicity accounting for 296,365. 6 kg TEC water, followed by terrestrial acidification and eutrophication with 81.76 kg SO_2 eq, terrestrial ecotoxicity with 86,004, and finally land occupation with 4,615 m2org.arable.

In the human health category, regarding human toxicity, the contribution was greater due to the use of resources in the mill, accounting for 42% of the total (1,254.5 kg). Ionizing radiation emissions were mainly emitted by sugarcane production, accounting for 37% (1,895.5 BqC-14eq). Ozone depletion had almost the same level of emissions from sugarcane production and the resources used in the mill, with 35.1% (0.0000463 kg CFC-11 eq) and 36% (0.00004752 kg CFC-11 Eq), respectively. Respiratory (inorganic) effects were primarily emitted by the resources used in the mill, accounting for a 48% share (1.4256 kg $PM_{2.5}$ Eq).

Finally, for the resources category, the resources used in the mill had a greater share, for mineral extraction with 81% (13.122 MJ primary) and non-renewable energy with 76.6% (5,149.05 MJ surplus).

Table 7 presents the total relative contributions, in percentage, of the four endpoint categories and their respective midpoints. As shown in the table, the total emissions per functional unit are the sum of the emissions generated by each subsystem (sugarcane production, soil preparation for plowing (tillage), and resources employed in the mill).

Likewise, in general, the mill generates the highest percentage of emissions, followed by soil preparation and sugarcane production.

Figure 5a shows the relative contribution of each impact to the Climate change endpoint for each subsystem. As shown in the figure, sugarcane production emissions primarily consist of carbon dioxide (96%, from three sources) and methane (2%). Soil preparation is influenced mainly by carbon dioxide (97%), methane (2%), and the remainder (1%). Meanwhile, the resources used in the mill are affected mainly by carbon dioxide (95%) and methane (3%).

Figure 5b shows the relative contribution of each impact to the final point of ecosystem quality. Emissions from sugarcane production are affected by the presence of aluminum (49%) and chromium (5%). Zinc, mercury, and lambda-cyhalothrin from pesticides also contribute. Emissions from soil preparation are primarily due to the presence of zinc (82%). Emissions generated by the resources used in the sugar mill are mainly due to aluminum (48%), zinc (18%), and mercury (7%).

For the human health category, Figure 6a shows that particulate matter mainly affects emissions from sugarcane production, soil preparation, and the resources used in the mill. Antimony contributes to emissions generated by sugarcane production and the resources used in the mill. Meanwhile, nitrous oxide is mainly present in emissions generated by soil preparation.

Figure 6b shows the relative contribution of each impact to the final point for each subsystem's resources. The figure shows that sugarcane production is mainly affected by the presence of coal (48%), natural gas (23%), crude oil (17%), and uranium (6%). Soil preparation is mainly affected by crude oil (77%), coal (9%), natural gas (11%), and uranium (2%). The emissions generated by the resources used in the mill are mainly contributed by coal (52%), crude oil (23%), natural gas (17%), and uranium (4%).

Discussion

The effects of climate change have had serious repercussions for the environment, primarily affecting agricultural systems. These impacts are largely based on variations in climatic variables, such as temperature and precipitation levels.

In this sense, the agricultural supply chain has been aggravated in recent years by growing food demand and increasing population density. In addition, the expansion of arable land, pastures, plantations, and urban areas around the world, as well as increased consumption of energy, water, and fertilizers, have caused changes in land cover due to uncontrolled agricultural development and the use of biofuels, which cause numerous environmental and socioeconomic impacts, such as greenhouse gas emissions, water availability and pollution, deforestation, loss of biodiversity, and loss of access to land. This has impacted not only food systems but also the quality of ecosystems, climate change, resource availability, and even human health. This poses monumental challenges for agriculture, as the accelerated development of some crops affects the reproductive phase and consequently reduces crop yields due to heat stress.

A multi-agent system offers a way to represent and analyze complex systems, especially those involving multiple actors or agents. Applying this type of system to the estimation of agricultural vulnerability allows for greater adaptability, facilitating its adjustment and response to changes in the environment or new demands, without compromising its operation or performance.

In addition, it provides the flexibility needed to integrate new functionalities, support workloads greater than those initially anticipated, or adjust to different users and contexts. Under this approach, the present research allows for the modeling of decision variables that involve dynamism and uncertainty to determine agricultural vulnerability.

One of the main advantages of the model proposed in this research is its ability to perform a sensitivity analysis, which allows us to identify critical variables that have a greater impact on the behavior of the system. Specifically, variables related to diesel use, fertilizer application, and N_2O emissions showed high sensitivity to variations in operating trends. The five scenarios proposed (from -100% to +100% with respect to the current trend for 2024) reveal how variations in resource demand directly and exponentially affect environmental performance. In the maximum reduction scenario (-100%), diesel and fertilizer use is minimal, showing low emission levels. However, in the increase scenarios (+50% and +100%), the excessive use of these inputs produces accelerated growth in emissions, especially nitrogen oxides, one of the main greenhouse gases with strong global warming potential.

The non-linearity observed in the model's responses to different trend levels demonstrates the fragility of the system in the face of increases in production.

The structural validation of the model, by considering dimensional consistency and extreme conditions, ensures that the equations, functional units, and logic of the model adequately represent the reality of the system. In addition, the implementation of different extreme scenarios made it possible to verify the robustness of the model under limit conditions, ensuring its usefulness for decision-making processes based on reliable simulations.

The results in Figures 3 and 4 provide clear evidence of the causal relationships between the use of inputs and environmental impacts. As can be seen, the more sugarcane is planted, the greater the proportional increase in sugarcane harvested, although this growth is limited by factors such as management losses, climate, and disease, which is common in agricultural simulation studies. On the other hand, nitrous oxide emissions show that fertilizers are the main source until cycle 5, and subsequently the rest of agricultural activities contribute with greater intensity.

The determination of the vulnerability of the system by assigning weights to different networks (such as yield, water, agricultural value, and emissions) yielded an average value of 0.54, indicating medium vulnerability. This value reflects an unstable equilibrium, in which small disturbances in climatic, economic, or logistical conditions could trigger significant effects on the sustainability of the system. This methodological approach is particularly valuable for agricultural planning in regions vulnerable to extreme weather events.

However, one of the main limitations of the study is uncertainty, given that this plays a crucial role in making climate projections and vulnerability estimates. Modeling uncertain parameters enables the estimation of their behavior and the impact on the system under study. However, the lack of information systems and/or government reporting makes it difficult to validate the projections generated. Therefore, for this stage, three characteristics within multi-agent systems were evaluated:

i) Dynamism, since the study of complex systems addresses problems at the micro-level, due to the cause-and-effect relationship defined in the causal diagram, and at the macro-level, where the relationships between the elementary subsystems are studied.
ii) Flexibility, since the multi-agent system can make changes within the system to achieve the objective, in addition to the ability to develop work plans that lead to adaptation actions.
iii) Adaptability. As a generic model, the multi-agent system provides the basis for assessing the vulnerability of crops with characteristics similar to those of the crop under study (sugar cane) through variations in the dynamic variables of the model that relate to the characteristics of the crop and the study area. Environmental problems require particular and careful analysis using efficient tools that provide detailed explanations of the environmental impacts generated by a system. In Mexico, the sugar industry lacks environmental databases that enable the evaluation of life cycle impacts.

The results obtained from the LCI and LCIA analysis, which applied the IMPACT 2002+ methodology, clearly identify the main environmental hotspots in the sugarcane production system, spanning from cultivation to industrial processing. According to the results, the resources used in the sugar mill generate the most significant number of impacts in the four end-point categories evaluated: climate change, ecosystem quality, human health, and resources.

In the climate change category, the mill is responsible for 78% of total emissions (1,238 kg CO_2eq), mainly due to the use of fossil fuels and electricity during the transformation process.

Although emissions from cane production (12%) and soil preparation (10%) are lower, they are still significant, particularly due to the use of agricultural machinery and nitrogen fertilizers, which are the main emitters of nitrogen oxides (NO_x) and methane (CH_4).
In terms of ecosystem quality, significant emissions associated with the use of heavy metals and pesticides were identified, especially in the industrial processing stage. The high aquatic ecotoxicity load (296,365.6 kg TEC water) indicates possible liquid discharges with metal or chemical residues without adequate treatment. Likewise, the use of lambda-cyhalothrin and other insecticides highlights an urgent need to transition to less toxic and more efficient agrochemicals.
In the human health category, the results indicate that the most significant impact is associated with the inhalation of particulate matter (PM2.5) and exposure to toxic substances, including antimony and mercury. These emissions affect not only farmers and agricultural and industrial producers, but also nearby communities. Therefore, the sugar sector must strengthen occupational protection measures and monitor air pollutants more rigorously, especially during bagasse burning and the use of heavy machinery.
The resource category reflects a high dependence on non-renewable energy, with the mill's use of resources accounting for more than 76% of total consumption. The use of sources such as coal, natural gas, and crude oil significantly increases the environmental burden of the final product, negatively impacting the sustainable viability of the system.

Mitigation strategies

Based on the results obtained regarding the vulnerability of sugarcane cultivation, a work plan is proposed that considers adaptation actions when vulnerability levels in cultivation increase, resulting in reduced crop yield at harvest and decreased production value, and consequently increased emissions into the atmosphere. For their part, the main components of the sugarcane production system include climatic factors, soil, and management. Climatic and soil-related factors are considered uncertain parameters because, although factors such as soil use and fertility are influenced by both climatic conditions and anthropogenic actions, in this case, the information networks or subsystems developed in system dynamics consider soil degradation as a factor related to climatic conditions. Therefore, the work plan is based on possible changes and improvements in the management of agricultural practices.
Based on studies reported by the National Sugarcane Agroindustry Program (CONADESUCA, 2020; PRONAC, 2009a), surveys conducted with sugarcane producers, 46.9% of the observations indicated that their primary concern or aspect for sugarcane production is focused on the use and application of fertilizers and soil nitrification, as this is one of the most frequent problems in crop development.
The aspects to consider are the frequency of fertilizer application in sugarcane, which should be done within 12-16 months of the plant's age, as the plant reaches its maximum concentration of sucrose and purity in its juice at that time. In addition to the maturity of the cane, regrowth of the cane over several cycles should be considered to reduce production

costs; however, adequate soil nutrition is necessary, as a decrease in crop yield can be observed over these cycles.
Likewise, an assessment is made to determine whether the soil on the farmland has been depleted by drought. If so, it is recommended to opt for a type of irrigation system, such as gravity, drip, or sprinkler; otherwise, the temporary irrigation system commonly used for sugarcane cultivation in the study region can be continued. The scheme considers foliar fertilization, i.e., application at the level of the plant's foliage, to reduce problems related to soil nutrition. Therefore, the frequency distribution of N-P-K nutrients per kg ha^{-1} is considered in two different loads: ≤50 and 50-100, as they have a proportional distribution in percentage of each compound (N, P_2O_5, K_2O). The application of fertilizers throughout each cycle helps reduce losses due to leaching and prevent salinization, which inhibits root growth. It is important to note that nitrogen is often applied in two or three rounds during the cycle due to its high mobility in the soil. Yield is also linked to soil conditioning and fertilization. This includes practices such as applying organic matter (compost, manure, crop residues), controlling pH with agricultural lime or gypsum depending on the type of limitation, and balanced fertilization with N, P, K, and essential micronutrients, in combination with crop rotation and the use of legumes to improve biological nitrogen fixation. These measures are complemented by the application of foliar fertilizers and biostimulants, which promote plant metabolism under adverse conditions.
Figure 7 proposes a working plan for managing sugarcane cultivation under adaptation conditions when vulnerability levels increase. The first plan considers fertilizer application in cycles 1 to 5 because the need for replanting is lower during this period. As shown in the figure, the proportions (%) of N-P-K nutrient addition are displayed for a load of 50 to 100 Kg ha^{-1}. Only two fertilizer applications are considered, as the distance between cycles is short (<5).

Conclusions

Climate change has had a profound impact on agricultural systems, exacerbated by alterations in key climate variables such as temperature and precipitation. These effects, combined with population growth, increased food demand, and the uncontrolled expansion of agricultural activities, have led to significant imbalances in ecosystems, affecting not only food production but also environmental quality, resource availability, and human health.
Given this scenario, this research demonstrates the use of a multi-agent model as a tool for understanding and simulating the complexity of agricultural systems under conditions of uncertainty. The ability of agents to operate autonomously, communicate, and adapt to changing scenarios allows for a more accurate assessment of agricultural vulnerability, considering critical variables such as the use of diesel, fertilizers, and nitrogen oxide emissions. The sensitivity analysis applied to the model confirmed that increases in the operational trend exponentially raise environmental impacts, highlighting the fragility of the system in scenarios of production intensification.

The structural validation of the model, through dimensional consistency and extreme condition tests, ensures its robustness as a decision-making support tool. The determination of a medium vulnerability level (0.54) indicates instability, where minor disturbances in climatic and/or economic conditions could have significant effects on the system's sustainability.

For its part, the analysis of LCI and LCIA, conducted under the IMPACT 2002+ methodology, enables the identification of the main environmental critical points in the sugarcane production system in Mexico. It was found that sugar mills are responsible for most of the impacts in the evaluated categories (climate, ecosystem, human health, and resources), primarily due to the intensive use of non-renewable energy, pesticides, heavy metals, and the generation of hazardous atmospheric emissions.

Given this situation, there is an urgent need to reduce dependence on fossil fuels, adopt clean technologies, optimize the use of fertilizers and pesticides, and strengthen environmental and health protection policies in the sector. The Mexican sugar industry, which currently lacks robust environmental databases, must incorporate life cycle analysis and dynamic modeling tools as key elements in transitioning to a more sustainable, resilient, and climate-adapted agricultural system.

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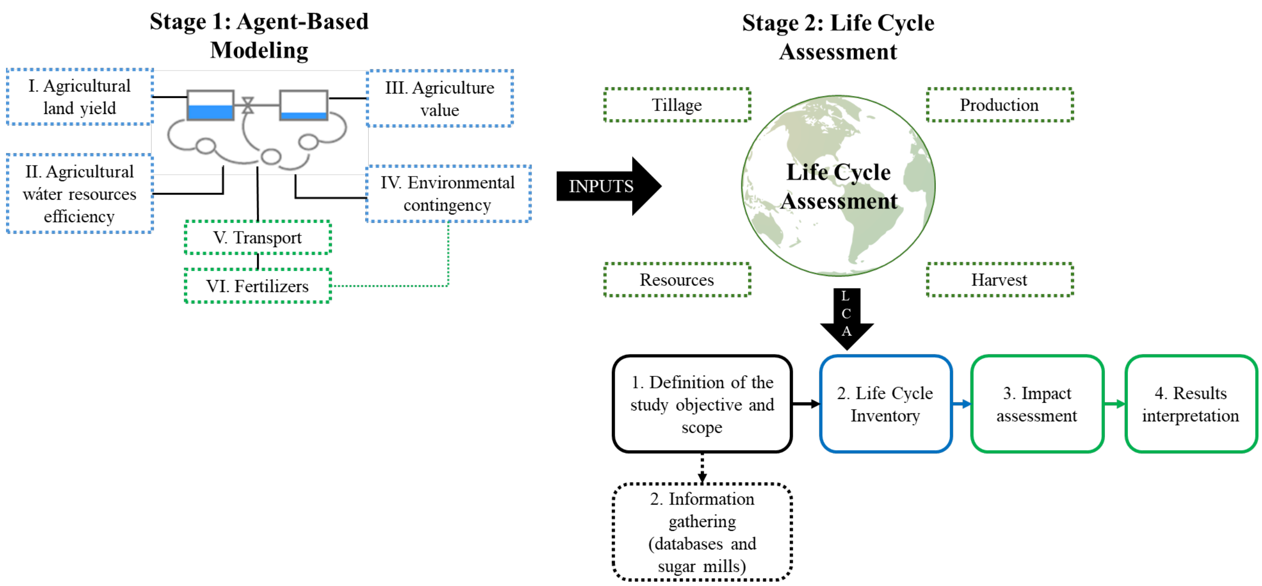


Figure 1. General methodology proposed to quantify the environmental impact of sugarcane production.

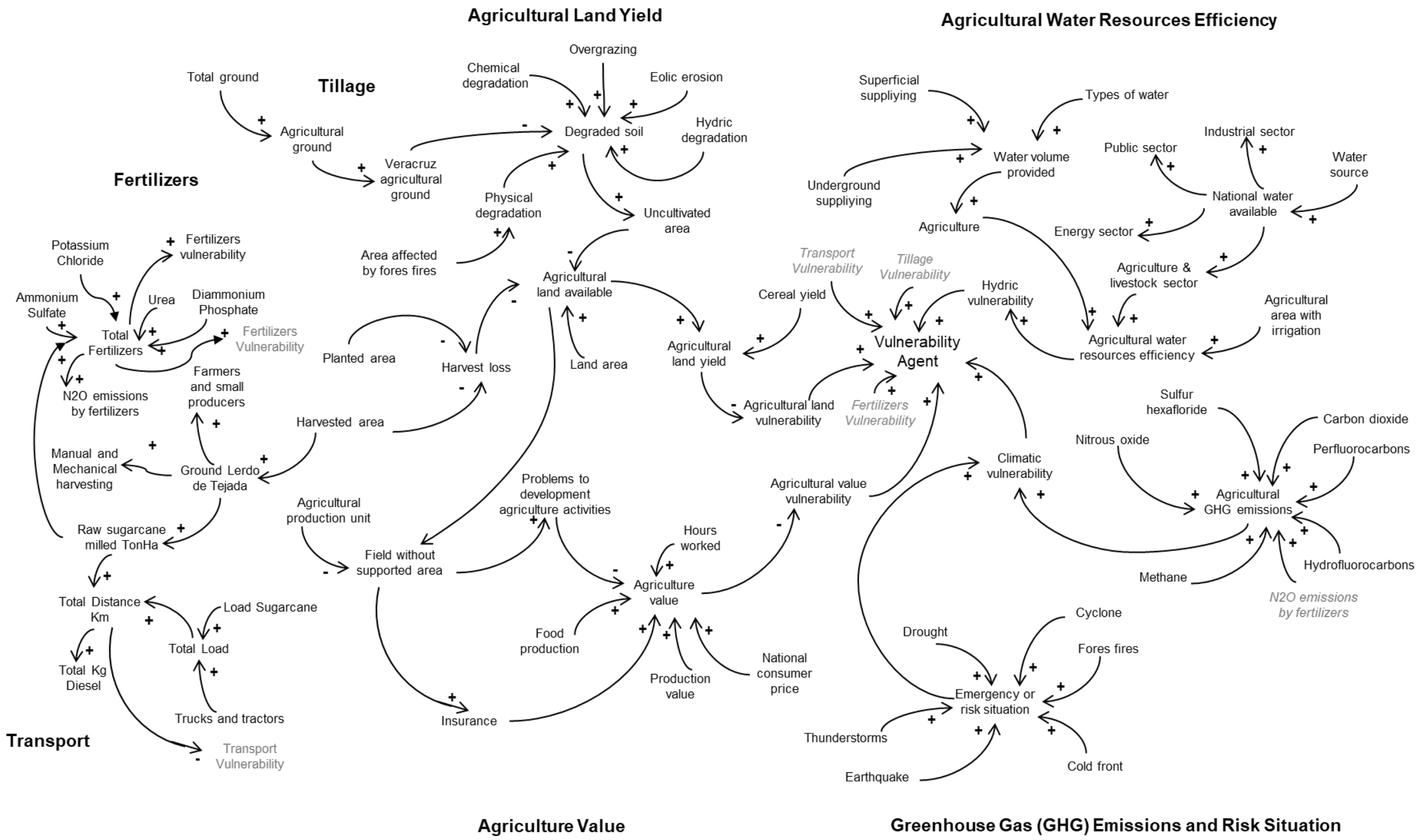


Figure 2. Causal diagram of the agent-based model.

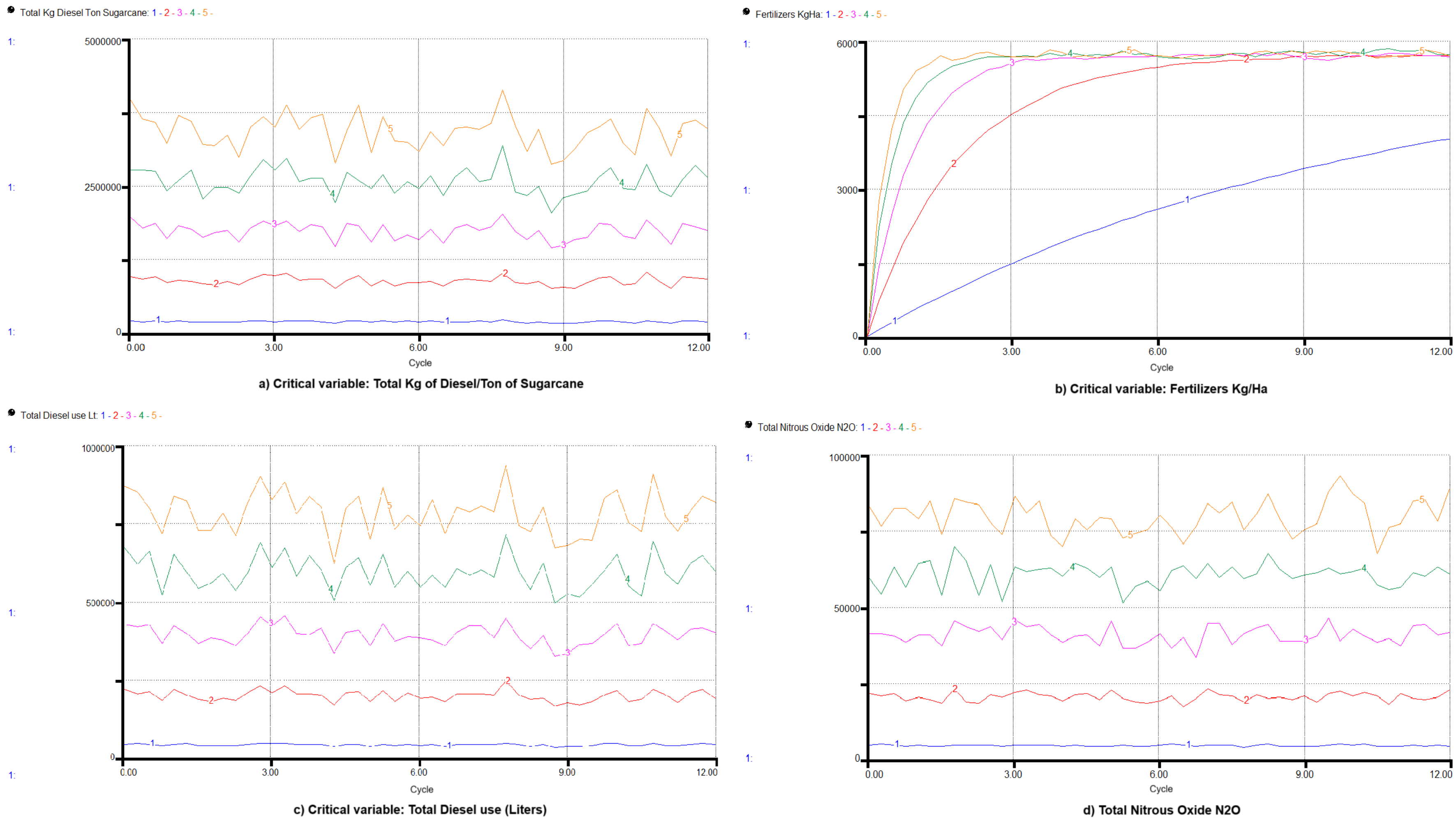


Figure 3. Sensitivity analysis for critical variables of the agent-based model.

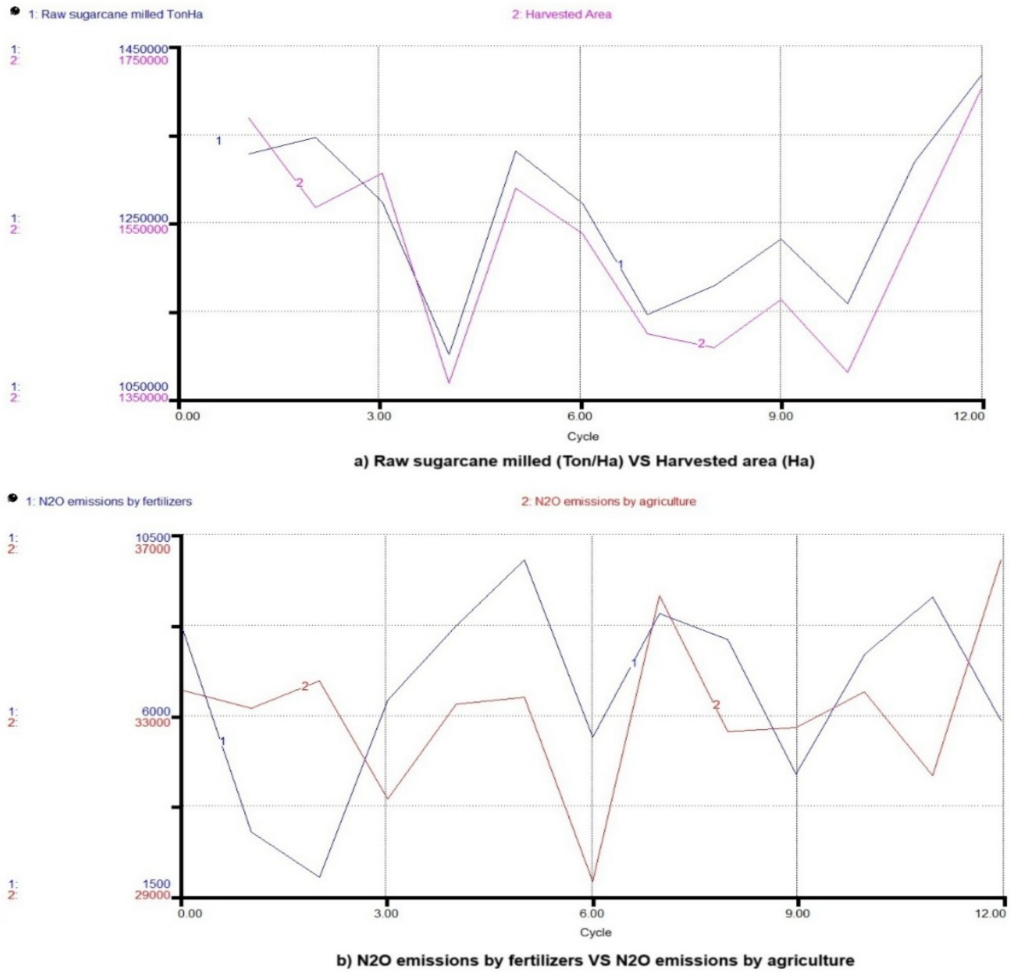
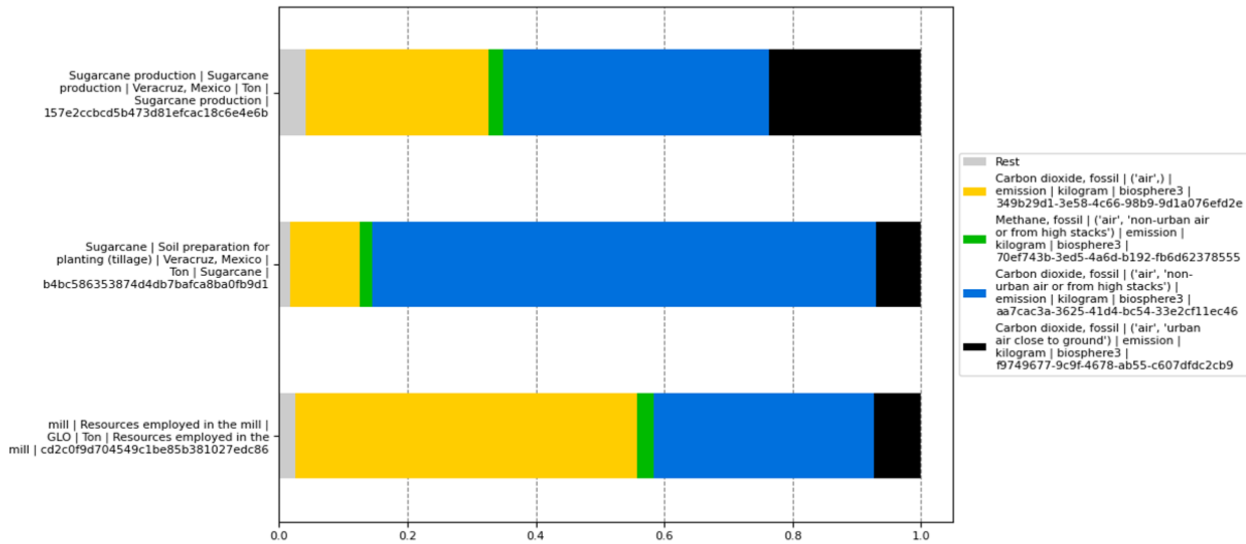
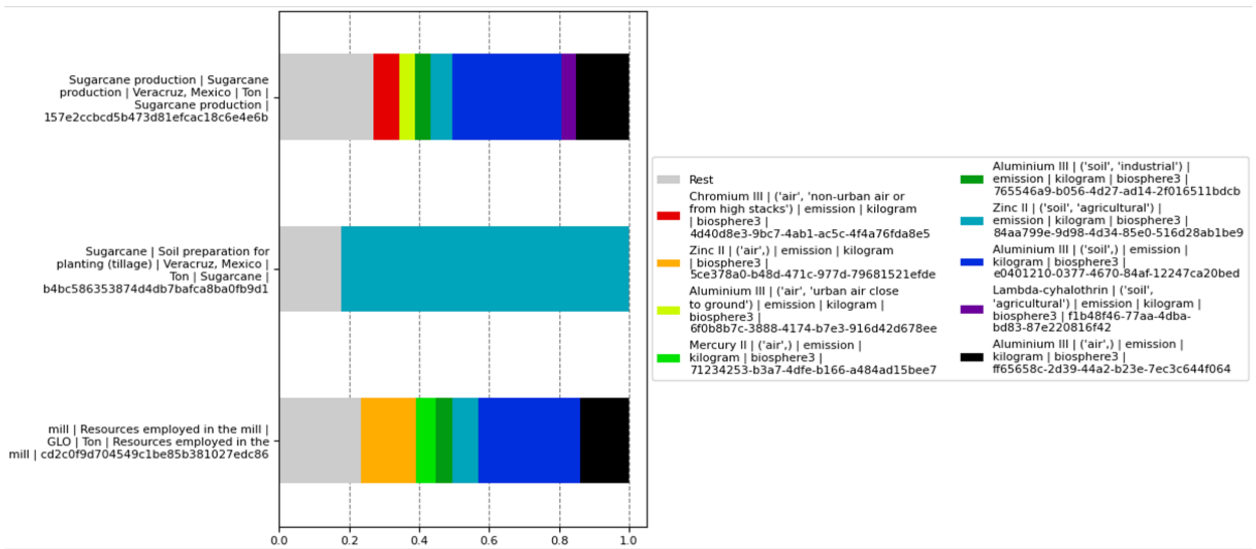


Figure 4. Projection of impact variables from the agent-based model.

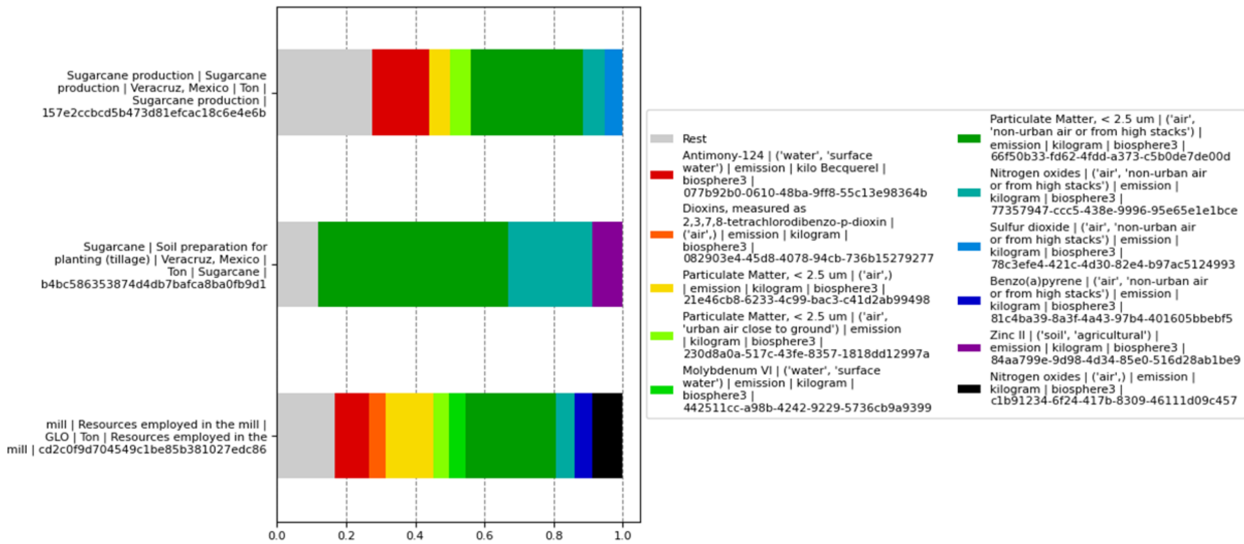


a) Climate Change

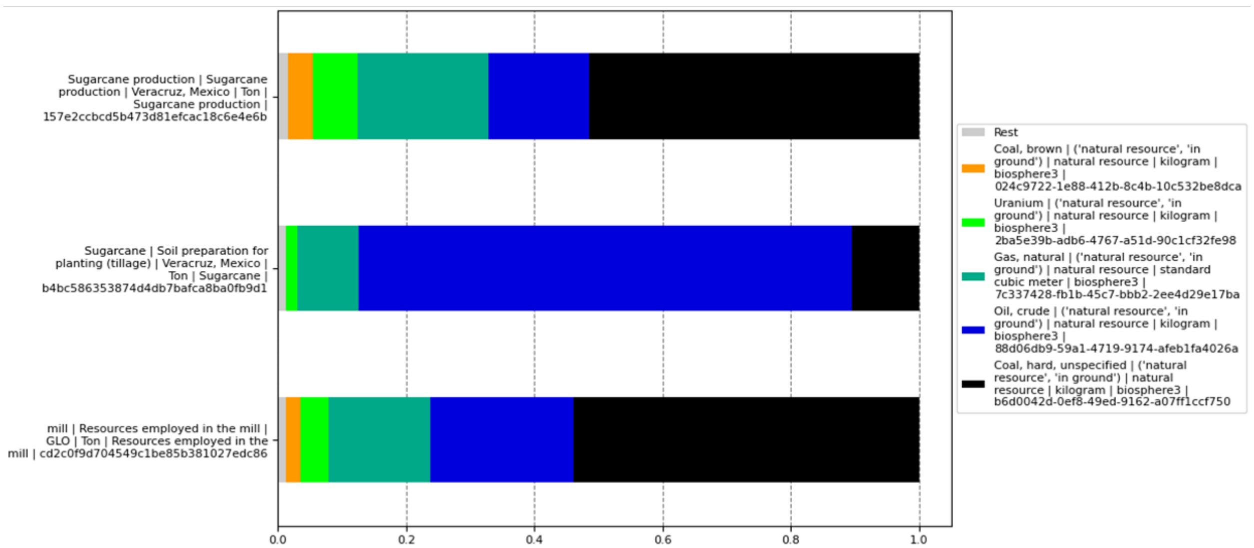


b) Ecosystem Quality

Figure 5. Contributions related to the Climate Change and Ecosystems Quality categories.



a) Human Healt



b) Resources

Figure 6. Contributions related to the Human Health and Resources categories.

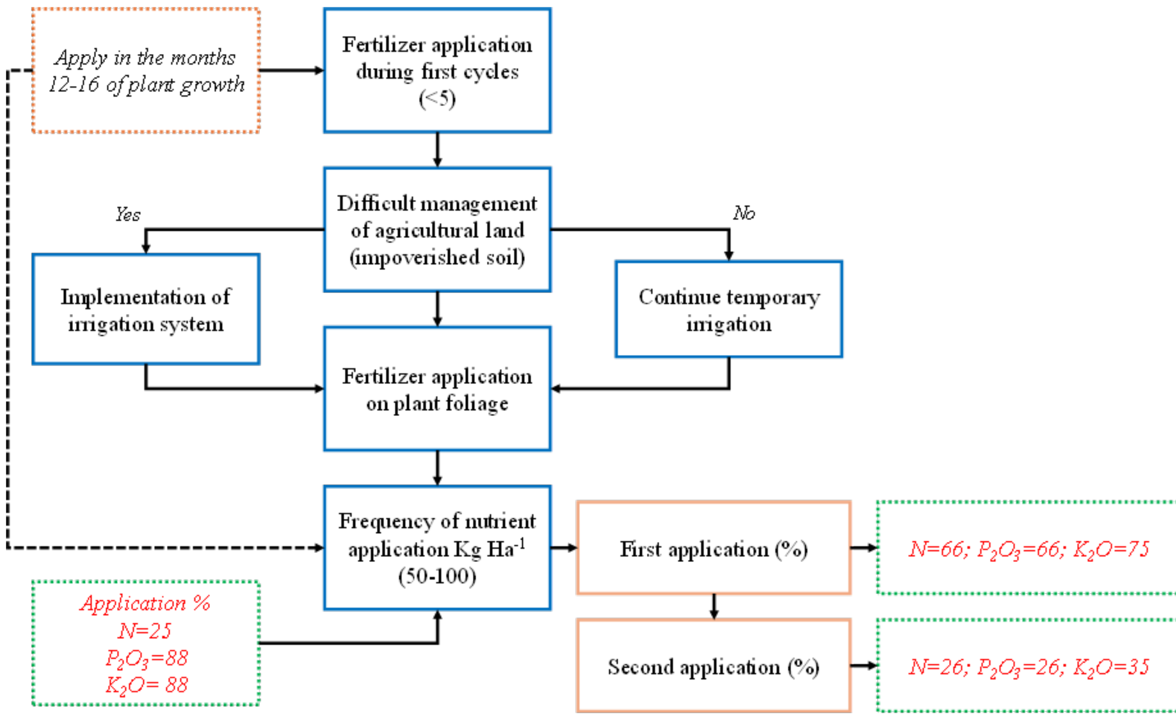


Figure 7. Adaptation scheme for sugar cane cultivation.

Table 1. Variables of vulnerability indicators agent model.

Variable	Definition	Units
Agricultural ground	Extension of agricultural land	Ha
Total ground	Extension of land in Mexican territory	Ha
Area affected by forest fires	Extent of land affected by forest fires	Ha
Physical degradation	Soil degradation caused by physical aspects: compaction (Fc), loss of function and productivity (Fu), waterlogging (Fa), decreased water availability (Fd)	Ha
Chemical degradation	Chemical-originated soil degradation: reduction of fertility and organic matter content (Qd), pollution (Qp), salinization and/or alkalization (Qs), eutrophication (Qe)	Ha
Overgrazing	Agricultural area affected by intensive grazing for an extended period	Ha
Eolic erosion	Surface wear due to wind	Ha
Hydric erosion	Segregation and sedimentation of water particles in the soil due to rain or surface runoff	Ha
Uncultivated area	Area unsuitable for agricultural activities due to severe or extreme degradation	Ha
Planted / harvested area	Agricultural area planted and harvested	Ha
Agricultural land yield	Agricultural area yield per hectare	Kg/Ha
Agricultural production unit	Agricultural statistical unit for measuring agricultural production in a given area	m^2
Field support area	Agricultural area with some support for carrying out farming activities	Ha
Insurance	Agricultural area with insurance for agricultural activities. It can have various origins	Ha
NCPI	National consumer price index, an indicator to estimate the evolution of prices of properties and services in Mexico	-
GDP	Gross domestic product, base 2013	MUS$
Agriculture value	Agricultural value added is about GDP	MUS$
Water source	Origin of water according to its type of source: water well, storage, river, dam, spring, open water well, etc.	Hm^3
Water supplying	Underground and superficial water supply	Hm^3
National water availability	Volume of available water, which is distributed to various sectors	Hm^3
Types of water	Volume of water according to its classification: white water, treated wastewater, brackish water, raw sewage, etc.	Hm^3
Water efficiency	Efficiency of water resources for the development of agricultural activities	Kg/m^3
Emergency risk situation	Natural events are classified as a state of emergency or disaster that poses a risk to agricultural activities. Includes: forest fires, storms, cold fronts, frost, cyclones, earthquakes, droughts	Events

Agriculture GHG emissions	Greenhouse gas emissions (GHG) produced by the development of agricultural activities	Gt CO_2eq
CO_2, CH_4, N_2O, HFC, PFC, SF_6 emissions	Carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride emissions	Gt CO_2eq

Table 2. Analysis of the trend of the variables of the agent-based model.

Time series	Kind of trend	Mathematical model
Veracruz harvested area	No trend	7.11%
Harvested area	Upward	$f(t) = \frac{1}{1763811\sqrt{2\pi}} e^{-(\ln(t) - 21185388)^2 / 2(1763811)^2}$
Ground Lerdo de Tejada (Ha)	Upward	$Harvested\ area * 13\%$
Mechanical harvesting	Downward	$Ground\ Lerdo\ de\ Tejada * 17.5\%$
Manual harvesting	Upward	$Ground\ Lerdo\ de\ Tejada * 82.5\%$
Preharvest burn	Upward	$Ground\ Lerdo\ de\ Tejada * 89\%$
Farmers	Upward	$Ground\ Lerdo\ de\ Tejada * f(t; a, b, c) \begin{cases} 0 \quad for\ t \leq 70\% \\ \frac{(t - 70\%)^2}{(75\% - 70\%)(83\% - 70\%)} \quad for\ 70\% < t \leq 83\% \\ \frac{1 - (75\% - t)^2}{(75\% - 70\%)(83\% - 70\%)} \quad for\ 83\% < t < 75\% \\ 1 \quad for\ 75\% \leq t \end{cases}$
Small producers	Upward	$Ground\ Lerdo\ de\ Tejada * f(t; a, b, c) \begin{cases} 0 \quad for\ t \leq 20\% \\ \frac{(t - 20\%)^2}{(23\% - 20\%)(25\% - 20\%)} \quad for\ 20\% < t \leq 25\% \\ \frac{1 - (23\% - t)^2}{(23\% - 20\%)(25\% - 23\%)} \quad for\ 25\% < t < 23\% \\ 1 \quad for\ 25\% \leq t \end{cases}$
Sugar (ton/Ha)	No trend	64
Raw sugarcane milled (Ton/Ha)	Upward	$(Smaill\ Producers + Farmers) * Sugar$
Standar sugar (Ton) (9.73 Ton/Ha CONADESUCA)	Upward	$\frac{Raw\ sugarcane\ milled}{9.73}$
Cane bagasse (Ton)	Upward	$Standar\ sugar * 2.6123$
Diesel (Lt) produces per ton sugar	No trend	3.1
Diesel (Lt)	No trend	1.63
Trucks and tractors	No trend	639

Total load (ton)	Upward	$Load\ sugar * Trucks\ and\ tractors$
Distance (km) (average)	No trend	30
Agricultural lime (kg/ha)	Downward	$5000 \le t \le 5500$
Urea CH_4N_2O (kg/ha)	Upward	$138 \le t \le 155;\quad N = 46\%$
Potassium chloride (KCl)	Upward	$120 \le t \le 150;\quad K = 60\%$
Ammonium sulfate $(NH_4)_2SO_4$ (kg/ha)	Upward	$120 \le t \le 150;\quad N = 21\%\ \ S = 24\%$
Diammonium phosphate $(NH_4)_2HPO_4$ (Kg/Ha)	Upward	$60 \le t \le 75;\quad N = 18\%\ \ P = 46\%$
Fertilizers NH_3	Upward	$f(t;\mu,\sigma) = \frac{1}{t(214631)\sqrt{2\pi}} e^{-(\ln(t)-952489)^2/2(214631)^2}$
Fertilizers NO_3	Upward	$f(t;\mu,\sigma) = \frac{1}{t(1099221)\sqrt{2\pi}} e^{-(\ln(t)-3672704)^2/2(1099221)^2}$
Underground supplying (UndS)	Upward	$f(t;\mu,\sigma) = \frac{1}{t(23.6)\sqrt{2\pi}} e^{-(\ln(t)-504.8)^2 / 2(23.6)^2}$
Superficial supplying (SupS)	Upward	$f(t;\mu,\sigma) = \frac{1}{t(162.4)\sqrt{2\pi}} e^{-(\ln(t)-2383)^2 / 2(162.4)^2}$

Table 3. Inputs and outputs of the Life Cycle Inventory of sugarcane production.

Variables	Average	Units
Soil preparation for planting (tillage)		
Ground harvested sugarcane (case study)	17049.35	ha
Harvested sugarcane	63.223	ton/ha
Uncultivated area (physical and chemical degradation)	886.5	ha
Diesel	1.56	kg/ton
Lime	7.243	kg/ton
Urea	2.32	kg/ton
Potassium chloride (KCl)	2.172	kg/ton
Diammonium phosphate $(NH_4)2HPO_4$	1.034	kg/ton
Ammonium sulfate $(NH_4)\ SO_4$	1.69	kg/ton
Sugarcane production		
Agricultural water resources efficiency	1.623	mm/ton
Diesel (machines)	2.83	kg/ton
Pesticide lambda cyhalothrin ($C_{23}H_{19}ClF_3NO_3$)	0.071875	kg/ton
Pesticide aluminum phosphide (AlP)	0.0010787	kg/ton
Herbicide ametrine ($C_9H_{17}N_5S$)	0.26956	kg/ton
Sugarcane burning	$4.7232e^{-7}$	ton/ha
Resources employed in the mill		
Water	32.3	m^3/ton
Energy (kWh)	0.71	kWh/ton
Diesel (transport)	1.395	kg/ton

Table 4. Values of interest variables for each simulated cycle.

Variable unit cycle	Raw sugarcane milled (ton/ha)	N_2O emissions by agriculture (GtC_2Oeq)	N_2O emissions by fertilizer (GtC_2Oeq)	Harvested area (Ha)	Fertilizers (kg/ha)	Total diesel per sugarcane (kg/ton)	Total nitrous oxide N_2O (GtC_2Oeq)	Total diesel use (Lt/ha)
	1,383,600	33,271	3,685	1,667,700	5,322	1,834,087	84,356	418,902
2	1,330,012	33,816	1,682	1,566,736	5,818	1,764,493	86,254	403,007
3	1,377,439	31,333	6,843	1,605,633	5,749	1,841,024	78,148	420,487
4	1,096,800	33,232	8,252	1,366,394	5,610	1,561,658	76,263	356,680
5	1,291,342	33,506	10,022	1,587,855	5,623	1,845,366	81,389	421,478
6	1,250,308	32,661	5,795	1,536,851	5,688	1,795,019	84,342	409,979
7	1,220,461	35,995	8,361	1,421,888	5,690	1,657,743	66,748	378,625
8	1,122,365	32,765	7,852	1,407,527	5,709	1,604,758	88,996	366,524
9	1,204,044	32,617	4,875	1,461,435	5,685	1,693,402	84,690	386,770
10	1,135,365	33,707	7,125	1,378,415	5,843	1,546,195	82,604	353,148
11	1,278,682	32,895	9,289	1,540,893	5,623	1,789,256	83,940	408,663
12	1,393,419	35,629	5,970	1,699,684	5,819	1,882,142	77,697	429,878

Table 5. Vulnerability scale.

Vulnerability		Land yield	Agriculture value	Water resources efficiency	GHG emissions	Emergency or risk situation	Fertilizers	Transport	Tillage
Scale	Label	Value (kg/ha)	Value (% GDP)	Value (kg/m^3)	Value (Gt CO2 eq)	Value (events)	Value (kg/ha)	Value (kg/ton)	Value (ha)
0-0.37	Low	>4,464	>5.2	> 2.2	<60,000	<4,100	<2876	<1,370,000	<1,139,000
0.38-0.68	Medium	3,262-4,464	3.4-5.2	12.2	60,000-190,000	4,100-15,950	2876-6932	1,370,000-1972,000	1,139,000-1,731,000
0.69-1	High	<3,262	<3.4	<1	>190,000	15,950	>6932	>1,972,000	>1,731,000

Table 6. Vulnerability results for each subsystem.

Cycle	I	II	III	IV	V	VI	VII	VIII	Final value
1	0.39	0.78	0.5	0.71	0.42	0.62	0.55	0.54	0.56
2	0.56	0.84	0.49	0.57	0.5	0.49	0.48	0.38	0.54
3	0.54	0.7	0.42	0.56	0.54	0.47	0.52	0.53	0.54
4	0.55	0.85	0.5	0.62	0.45	0.52	0.51	0.48	0.56
5	0.55	0.87	0.47	0.62	0.49	0.63	0.51	0.5	0.58
6	0.47	0.73	0.5	0.51	0.53	0.59	0.43	0.45	0.53
7	0.41	0.64	0.48	0.56	0.52	0.55	0.53	0.31	0.50
8	0.56	0.76	0.45	0.7	0.54	0.57	0.55	0.52	0.58
9	0.54	0.63	0.42	0.53	0.4	0.54	0.42	0.43	0.49
10	0.42	0.69	0.43	0.54	0.43	0.63	0.58	0.53	0.53
11	0.38	0.66	0.47	0.62	0.4	0.5	0.58	0.55	0.52
12	0.54	0.63	0.48	0.67	0.42	0.64	0.44	0.44	0.53

Subsystems: I) Land yield, II) Agriculture value, III) Water resources efficiency, IV) GHG emissions, V) Emergency or risk situation, VI) Fertilizers, VII) Transport, and VIII) Tillage.

Table 7. Percentage results of the total relative contributions of midpoints and endpoints.

Endpoints	**Midpoints**	**Sugarcane production (%)**	**Soil preparation for planting (tillage) (%)**	**Resources employed in the mill (%)**	**Total emissions per functional unit**
Climate change	Climate change	12	10	78	1,238 Kg CO_2 eq
Ecosystem quality	Aquatic ecotoxicity	12.3	5.7	82	361,421.45 Kg TEG water
	Land occupation	27.4	7.6	65	7.1 m2org.arable
	Terrestrial acidification and nutrification	11.8	15.2	73	112 Kg SO_2 eq
	Terrestrial ecotoxicity	10.2	23.4	66.4	129,523.7 Kg TEG soil
Human health	Human toxicity	25.9	32.1	42	2.987 Kg
	Ionising radiation	37	35	28	5123 Bq C-14 eq
	Ozone layer depletion	35.1	28.9	36	1.32 E^{-4} Kg CFC-11 eq
	Respiratory effects (inorganics)	25	27	48	2.97 Kg $PM_{2.5}$ eq
Resources	Mineral extraction	6.11	12.89	81	16.2 MJ primary
	Non-renewable energy	8.4	15	76.6	6,722 MJ surplus