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Article

Assessing the Vulnerability of Farming Households on the Caribbean Island of Hispaniola to Climate Change

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Abstract: This article assesses the individual vulnerability of 550 farming households, 430 in Haiti and 120 in the Dominican Republic, on the Caribbean island of Hispaniola to the impacts of climate change. This assessment is based on an integrated approach, using socio-economic and biophysical variables. The variables collected for each farm household were grouped into three categories: adaptive capacity, sensitivity, and exposure. Multiple correspondence analysis (MCA) was used to develop a vulnerability index for each farm household, enabling them to be classified according to their level of vulnerability to the impacts of climate change. A logistic regression model was then used to identify the main factors influencing their vulnerability. The results revealed that on the island of Hispaniola, 33.91%, 32.09%, and 34% of farming households were classified as very vulnerable, vulnerable, and less vulnerable. In Haiti, these proportions were 36.74%, 36.51%, and 26.75%, while in the Dominican Republic, they were 20%, 20%, and 60%. Agricultural households with highly accessible credit (OR = 0.16, $p < 0.001$) and university education (OR = 0.05, $p < 0.001$) were relatively less vulnerable to climate change impacts compared to their counterparts.

Keywords: climate change; vulnerability; farm household; island of Hispaniola



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1. Introduction

Climate has a considerable influence on agriculture, as this human activity is highly dependent on climatic variations [1,2]. The Intergovernmental Panel on Climate Change (IPCC), established in 1988 in response to widespread man-made greenhouse gas emissions, has warned that the agricultural sector will be particularly affected by climate change due to its intrinsic vulnerability [3]. The negative effects of climate change have different repercussions on agricultural production in many regions of the globe. These repercussions have significant socio-economic consequences on farm households in developing countries located in tropical latitudes [1,4,5].

On the island of Hispaniola, which includes Haiti and the Dominican Republic, as well as on the other islands in the Caribbean, the increased frequency and intensity of extreme weather phenomena such as drought, cyclones, and floods is already significantly affecting a vast number of territories and agricultural production basins [6–8]. This island was one of the territories most vulnerable to climate risks between 2000 and 2019 [9], and the agricultural sector is strongly impacted by these phenomena [8]. These changes have had a significant negative impact on farming practices, threatening the way of life and livelihoods of already vulnerable farming households [2,10]. The causes of this vulnerability are multidimensional [11,12]. Moreover, when individuals have limited access to the institutions and policies that govern their access to resources, they have few means of addressing the underlying causes of their vulnerability [13]. To date, the vulnerability of agricultural households on the Caribbean island of Hispaniola has not been assessed with multidimensional indicators. In this context, the present paper aims to fill this gap by

assessing the level of vulnerability to climate change within a sample of farming households from both parts of the island. We know that agricultural households are becoming more and more vulnerable to climate change. This vulnerability, according to the literature, can be explained by social, economic, and biophysical dimensions [2,10–13]. These three dimensions can explain the vulnerability of farming households on the Caribbean island of Hispaniola. In this context, it is assumed that the higher a farming household's level of dependency on natural and socio-economic resources is, the greater its vulnerability to climate change is. Given that, almost all farming households on the Caribbean island of Hispaniola depend directly on agricultural activities that are likely to change under the impact of climate change. We tested this hypothesis in our study region. In addition, we calculated a vulnerability index and related it to the potential factors determining this vulnerability, corresponding to the hypothesis we posed. This study has crucial importance in guiding policies and interventions aimed at strengthening the resilience of farm households to the challenges of climate change in this already highly fragile region of the world. The remainder of this article is organized as follows: Section 2 presents a review of the literature on vulnerability to climate change, measurement methods, and the main drivers of vulnerability. Section 3 presents the data and methodology of the research, including the construction of the vulnerability index of agricultural households. Section 4 presents the results, Section 5 presents the discussion, and Section 6 presents the conclusions and policy recommendations.

2. Literature Review

2.1. Conceptualizing Vulnerability to Climate Change

The term vulnerability is used differentially in different disciplines and contexts, ranging from medicine to poverty and development [14]. In studies on global environmental change, the concept of vulnerability is often derived from the social sciences [15–17]. In research on vulnerability, adaptation, and policy, Chambers [18] introduced the concept that vulnerability has two faces: an external face consisting of the risks, shocks, and stresses to which an individual or household is subjected, and an internal face which is powerlessness, meaning a lack of means to cope without damaging loss. Adger [19] also identified two components of vulnerability: the effects an event can have on humans (called adaptive capacity or social vulnerability) and the risk of such an event occurring (called exposure). In addition, Bohle [20] developed a conceptual framework for vulnerability called the double vulnerability structure, which includes exposure and adaptation. Here, the external perspective refers primarily to the structural dimensions of vulnerability and risk, while the internal dimension of vulnerability focuses on adaptation and the measures taken to overcome or at least mitigate the negative effects of economic and ecological changes [21]. The Second Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) [22] and Moser [23] shifted the focus of vulnerability from internal/adaptation to external/exposure and examined two similar but different factors: sensitivity and adaptive capacity (or resilience). In this report, the IPCC defines vulnerability as the extent to which climate change can damage or harm a system; vulnerability, therefore, depends not only on the sensitivity of the system but also on its ability to adapt to new climatic conditions [12,24]. According to Moser [23], any definition of vulnerability requires the identification of two components: sensitivity and resilience. Sensitivity refers to the responsiveness of a system to climatic influences and the extent to which this responsiveness could be affected by climate change. The IPCC's Third Assessment Report reconciles the two sides by adding a third component to vulnerability, defining it as "The degree to which a system is susceptible to or unable to cope with, adverse effects of climate change, including climate variability and extremes". Vulnerability is a function of the nature, magnitude, and rate of climate change to which a system is exposed, its sensitivity, and its adaptive capacity [25]. According to this definition, vulnerability comprises an external dimension represented by a system's exposure to climatic variations, as well as a more complex internal dimension including its sensitivity and adaptive capacity to stress factors [26]. The IPCC's Fourth Assessment Report, which

reports on recent progress in our understanding of climate change, contains a definition of vulnerability consistent with that of the Third Assessment Report [27]. In this framework, a highly vulnerable system would be highly sensitive to modest climate changes, where sensitivity includes the potential for significant adverse effects and for which adaptive capacity is severely limited. Other authors have also characterized vulnerability using these three dimensions. For example, Luers et al. [28] proposed a method for quantifying vulnerability based on its three components: exposure, sensitivity, and adaptive capacity. On the other hand, the 5th and 6th IPCC reports also redefine vulnerability. Vulnerability is seen as the propensity of a system or population to suffer the adverse effects of climate change, depending on exposure to climate risks and the sensitivity of the system. Vulnerability is seen as a key element in the risk equation: $\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability}$ [3]. This redefinition allows for vulnerability to be understood not in isolation, but as an integral part of the overall risk associated with climate change. In this context, vulnerability is a function of just two elements: sensitivity and adaptive capacity [3]. Turner et al. [29] recognized that vulnerability is not determined solely by exposure to hazards (disturbances and stress) but also depends on the sensitivity and resilience of the system subjected to such hazards. To date, the scientific community has so far conceptualized vulnerability differently depending on the disciplines, objectives to be achieved, and methodologies employed [4,14,30–36]. These differences limit the possibility of a standardized definition and methodological approach to assessing vulnerability. There is little consensus in the literature beyond the fact that there are multiple conceptualizations of vulnerability and that it is context-specific [4,37–39]. For example, in a comprehensive study, Nelson et al. [40] defined vulnerability as the susceptibility of a system to disturbance, determined by exposure to disturbance, sensitivity to disturbance, and adaptive capacity. In line with this definition, it is widely accepted that the vulnerability of human-environment systems to climate risks depends on their relative exposure to climate variability and change, their sensitivity to exposure, and their adaptive capacity. Similarly, several authors, in their research work, consider the vulnerability of any system in terms of these three components [13,36,41–45]. In this context, vulnerability is a function of just two elements: sensitivity and adaptive capacity. Thus, for the purposes of this study, vulnerability is seen as a function of three elements: exposure, sensitivity, and adaptive capacity, which are influenced by a range of biophysical and socio-economic factors. For this reason, we retain the classic definition of vulnerability (that of the 4th report) and retain exposure in order to contextualize and refine vulnerability. In the following section, we review the three main conceptual approaches. These are the socio-economic approach, the biophysical approach, and the integrated approach.

2.1.1. Socio-Economic Approach

The socioeconomic vulnerability assessment approach focuses primarily on the social, economic, and political aspects of society [13,31,44,46–48]. In this approach, vulnerability is essentially examined in terms of socioeconomic variables such as education, gender, wealth, health status, access to credit, access to information and technology, etc., which are responsible for variations in levels of vulnerability [49]. In this context, vulnerability is seen as an initial state or starting point (i.e., a variable describing the internal state of a system) that exists in a system before facing a hazardous event [34]. Thus, vulnerability is constructed by society in response to institutional and economic changes [34,50]. In general, the socioeconomic approach focuses on identifying the adaptive capacity of individuals or communities based on their internal characteristics. However, its main limitation lies in its focus solely on variations within society (i.e., differences between individuals or social groups). In reality, societies vary not only due to socio-political factors but also due to environmental factors. Thus, two social groups with similar socioeconomic characteristics but different environmental attributes may present different levels of vulnerability and vice versa [45]. Overall, this approach neglects—or considers as exogenous—the environment-related intensities, frequencies, and probabilities of environmental shocks such as drought

and floods. It also does not take into account the availability of natural resources to mitigate the negative impacts of these environmental shocks. For example, areas with easily accessible groundwater can better cope with drought by using this resource [34].

2.1.2. Biophysical Approach (Impact Assessment)

The biophysical approach is used to study the physical damage caused by climate change [27,42,51,52]. As cited by Gutu et al. [49], this method is sometimes known as impact assessment. For example, the monetary impact of climate change on agriculture can be measured by modeling the relationships between climate variables (temperature, rainfall, etc.) and farm income [34,53–55] or by modeling the relationships between crop yields and climate variables [34,56–58]. These impacts are most often estimated on the basis of climate forecasts or sensitivity indicators [51,59,60]. Kelly and Adger [50] described the biophysical approach as the final analysis answering research questions such as “How big is the climate change problem?” and “Do the costs of climate change exceed the costs of greenhouse gas mitigation?” Although the biophysical approach is highly instructive, it does have its limitations [33]. The main limitation is that it focuses primarily on physical damages such as yield, income, etc. [34]. For example, a 50% reduction in yield due to climate change does not have the same effect on poor households as on large ones. It does not take into account the adaptive capacity of individuals or social groups. Farming households are very often unable to cope with marginal changes in their yields or incomes, whereas better-off households can cushion their losses (smooth consumption, in technical terms) by relying on savings or the sale of some of their assets.

2.1.3. Integrated Approach

The integrated assessment approach combines socioeconomic (adaptive capacity) and biophysical (exposure and sensitivity) approaches to determine vulnerability [12,14,21,26,33,34,36,61,62]. The vulnerability mapping approach [34] is another related example, in which socioeconomic and biophysical factors are combined to indicate the level of vulnerability through mapping. Füssel [33] and Füssel and Klein [26] argued that the IPCC’s [25] definition, which conceptualizes climate vulnerability in terms of adaptive capacity, sensitivity, and exposure, fits the integrated approach to vulnerability analysis. According to Füssel and Klein [26], the risk-hazard framework (biophysical approach) corresponds best to sensitivity. Adaptive capacity (broader social development) is largely consistent with the socioeconomic approach [33]. Moreover, Nelson et al. [40] demonstrated that the use of biophysical modeling alone, without integrating socio-economic determinants (adaptive capacity), leads to totally erroneous results, thus sending the wrong message to political decision-makers. Although the integrated assessment approach corrects the weaknesses of other approaches, it also has certain limitations. The main limitation is that there is no standard method for combining biophysical and socioeconomic indicators [34,45,49]. This approach uses different datasets, ranging from socioeconomic datasets (e.g., race and age structure of households) to biophysical factors (e.g., earthquake frequency); these datasets certainly have different, and as yet unknown, weights. Cutter, Mitchell, and Scott [51] explained that because this analysis provides no common measure for determining the relative importance of social and biophysical vulnerability, nor for determining the relative importance of each individual variable, great caution is called for. The other weakness of this approach is that it does not account for the dynamism of vulnerability. For example, adaptation is characterized by a continuous change of strategies to take advantage of opportunities [63–65]; thus, this dynamism is lacking in the integrated assessment approach. Despite its weaknesses, this approach has much to offer in terms of policy decisions [12]. Thus, we adopted this approach to assess the vulnerability of farming households on the island of Hispaniola.

2.2. Methods for Measuring Vulnerability to Climate Change

On the basis of the approaches discussed above, there are numerous methods for measuring vulnerability to climate change. Interdisciplinary research on vulnerability generally advocates two main approaches. These are econometric approaches and indicator-based multi-criteria approaches [4,34,36,44,49]. Thus, these two measurement methods are discussed below.

2.2.1. Econometric Method

The econometric method has its roots in the literature on poverty and development [36]. It is based on the reconstitution of an econometric model for a given system (household, region, country, etc.) and makes it possible to assess the expected or observed effects of a climate change-related issue [45]. This method uses household-level socio-economic survey data to analyze the level of vulnerability of different social groups [34,36]. It is divided into three main categories: vulnerability as expected poverty (VEP) [66], vulnerability as expected low utility (VEU) [67], and vulnerability as uninsured expression to risk (VER) [68]. Thus, we present in Table 1 some examples of econometric methods for assessing vulnerability.

Table 1. Some examples of econometric methods for vulnerability assessment.

Methods	Description	References
Vulnerability as Expected Poverty (VEP)	<ul style="list-style-type: none"> - A person’s vulnerability is conceived as the probability that this person will soon become poor if he or she is not currently poor, or that this person will continue to be poor if he or she is currently poor. - Consumption (income) is used as a proxy for well-being. - This method is based on estimating the probability that a given shock, or set of shocks, will move household consumption below a given minimum level (e.g., consumption poverty line) or force the consumption level to remain below the minimum requirement if it is already below that level. 	[66]
Vulnerability as a low expected utility	<ul style="list-style-type: none"> - Vulnerability is defined as the difference between the utility derived from a certain level of certainty. - Equivalent consumption above which the household would not be considered vulnerable and the expected utility of consumption. - The disadvantage of this method is that it is difficult to take account of individual preferences. 	[67]
Vulnerability as uninsured exposure to risk	<ul style="list-style-type: none"> - It is based on an ex-post evaluation of the loss of well-being caused by a shock. - The impact of shocks is assessed using panel data to quantify the variation in induced consumption. - The value of the loss incurred due to shocks is equivalent to the amount paid as insurance to keep a household as well off as it was before the shock. - This method requires several databases 	[68]

Source: Deressa et al. [34]; Zaatra [45].

2.2.2. Indicator Method

The indicator method is based on the selection of certain potential indicators to indicate levels of vulnerability [4]. This indicator-based method is suitable for vulnerability assessments since vulnerability is a theoretical phenomenon that cannot be measured directly like observable phenomena [4]. Indicators are used to operationalize theoretical concepts through latent variables that serve as operational representations of a system’s characteristics, qualities, or properties [4,69–71]. This method enables vulnerability to be quantified by systematically combining the various indicators selected [4,34,46,48,62,72,73]. We speak of a multi-criteria approach insofar as the different dimensions of vulnerability can be synthesized through the indicators and variables that are mobilized [45]. Typically, a quantitative vulnerability assessment based on multi-criteria indicators involves several steps: defining the objective, context, and conceptual framework of the study; indicator

selection; data collection and management; indicator aggregation; and presentation of results [4,66]. When conceptualizing vulnerability, exposure, sensitivity, and adaptive capacity are made explicit. Researchers use indicators to represent these key aspects that define the vulnerability of a given system [4]. These three aspects are often combined in a multi-criteria composite index because of their ability to capture multiple dimensions of vulnerability [4,31,66,67,74–77]. However, despite the feasibility of using indicators to assess vulnerability, this approach is subject to numerous pitfalls and has attracted much criticism [64,67,77,78]. For example, Birkmann [75] highlights the shortcomings of up-scaling and down-scaling indicators due to the challenges of contextualizing indicators and approaches in different contexts and scales. Other challenges and uncertainties are related to the selection of indicators [78,79], uncertainty about the robustness of the validity of indicators and conceptual frameworks [64,71], the accuracy and accessibility of data [71], the aggregation and weighting of indicators [64,80], and the lack of transparency in methodology and assumptions [4,64]. Despite the challenges posed by indicator-based methods, they provide valuable tools to enable the assessment of the causes of vulnerability and ways to reduce it [4,13,31,34,45,70,76,80]. Thus, we adopted the indicator method to develop and calculate a vulnerability index to assess the vulnerability of farming households on the Caribbean island of Hispaniola to climate change and its main drivers.

2.3. Factors Influencing Vulnerability

Vulnerability is essentially context-dependent, and the factors that make a system vulnerable to a hazard depend on the nature of the system and the type of hazard in question [30]. The factors that make farming households in the Caribbean region vulnerable to drought, for example [8], will not be identical to those that make areas of a wealthy industrialized country like Norway vulnerable to floods, windstorms, and other extreme weather events. Isolation and income diversity could be important determinants of drought vulnerability for farming households in the Caribbean region, while the drivers of storm and flood vulnerability in Norway could be the quality of physical infrastructure and the effectiveness of land-use planning [30]. Several studies provide interesting classifications of vulnerability factors [27,45,66,81]. By way of example, we can cite the following classifications. The United Nations [81] distinguished four groups of factors that influence vulnerability: physical factors, which describe the exposure of vulnerable elements in a region; economic factors, which describe the economic resources of individuals, population groups, and communities; social factors, which describe the non-economic factors that determine the well-being of individuals, population groups, and communities, such as levels of education, security, access to basic human rights, and good governance; and environmental factors, which describe the state of the environment in a region. Nevertheless, certain factors are likely to influence vulnerability to a wide variety of hazards in different geographical and socio-political contexts. These include development factors such as poverty, health status, economic inequality, and elements of governance, to name but a few [31,33,44,46–48]. These factors can be called generic determinants of vulnerability, as opposed to specific determinants relevant to a particular context and a particular type of risk, such as the price of a particular food crop [30]. Although there are some variations in the relative importance of the different generic factors, they can be seen as the foundation on which specific measures to reduce vulnerability and facilitate adaptation are built. The concept of generic, as opposed to hazard- and context-specific, vulnerability determinants is useful if we wish to undertake comparative vulnerability assessments at the national level. Generic vulnerability assessments can tell us how well equipped a country is to cope with and adapt to climate change. However, the aim of the study presented here was not to assess “generic” vulnerability but rather to identify the key factors influencing a specific level of vulnerability based on individual farm household data.

3. Materials and Methods

3.1. Study Areas

Located in the north of the Caribbean region, Hispaniola (17.6°–20.0° N and 68.3°–74.5° W) is an island divided into two sovereign and independent states: the Dominican Republic to the east, and the Republic of Haiti to the west (Figure 1). The island is part of the Greater Antilles group of the Caribbean archipelago, with a surface area of 76,480 km², making it the second-largest and most populous island in the Caribbean, with over 21 million inhabitants [8]. The Dominican Republic occupies two-thirds of the eastern part of the island, covering an area of 48,310.97 km² (excluding maritime territory), while Haiti, itself more mountainous, covers an area of 27,750 km² [82]. As in many Caribbean islands, the annual rainfall cycle has two peaks (April–May and August–October) and a minimum (November–March). Between June and July, there is a period of relatively lower rainfall, with a mid-summer drought observed in the Caribbean [8].

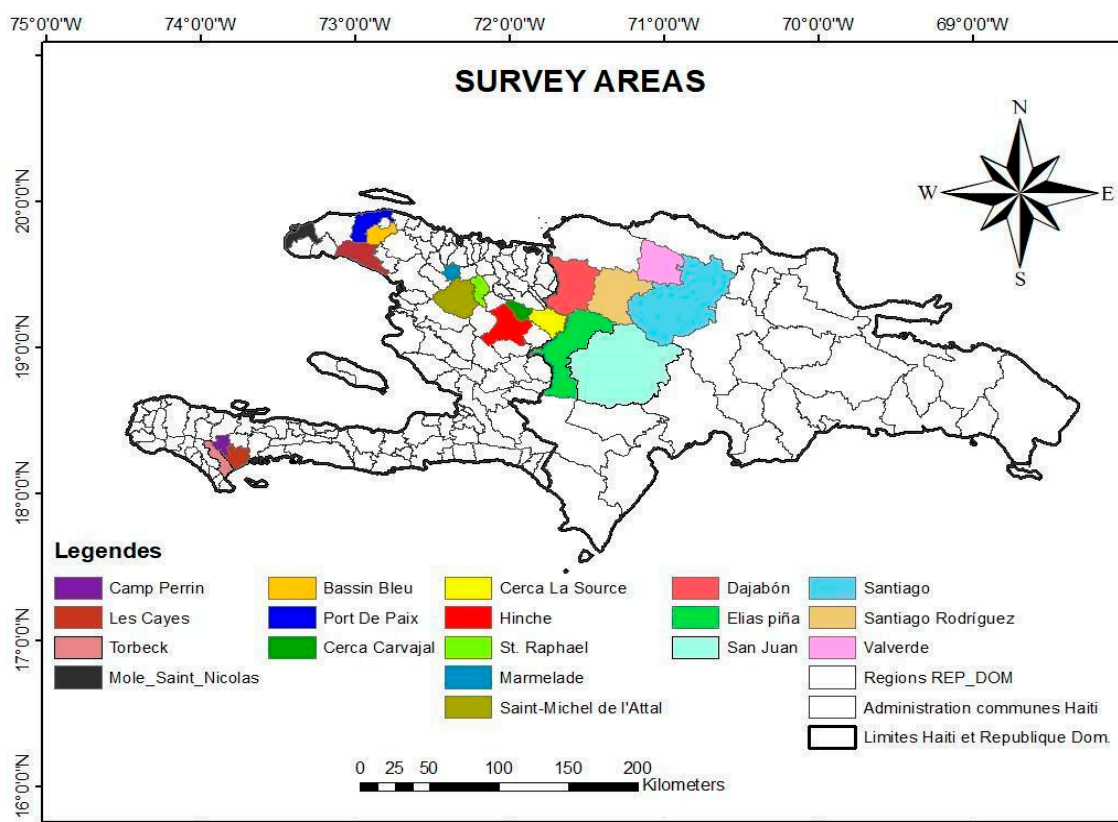


Figure 1. Field survey area. Data source: CNIGS, [83].

The choice of Hispaniola Island in the Caribbean region is justified by the fact that the two countries that share this same island territory, Haiti and the Dominican Republic, are increasingly being affected by extreme weather events [8,82] and suffer the consequences differently in terms of their agriculture [6]. This makes it the Caribbean island most vulnerable to the impacts of climate change [84]. In addition, agro-ecological sectors that constitute genuine agricultural basins undergoing change, such as the Cibao in the Dominican Republic (Santiago, Valverde, Santiago Rodriguez, etc.), are among the most fertile and productive regions on the island. On the Haitian side, areas such as the Cayes plain, Artibonite, and the arid north-west have not yet been studied in-depth. Given the size of the island of Hispaniola, it was deemed useful to limit our field of study to 18 communes/provinces (Table 2). These 18 areas reflect the 16 agro-ecological areas, ranging from dry or irrigated plains to humid mountains, of the two parts of the island of Hispaniola.

Table 2. Study area on the island of Hispaniola.

Department	Municipalities	Population	Surface Area (Km ²)	Geographical Coordinates	Altitude (m)	Survey	
						Frequency	%
Centre (Haiti)	Hinche	120,867	588.4	19°09' N, 72°01' O	237	60	10.9
	Cerca-la-source	56,532	345	19°10' N, 71°47' O	371	60	10.9
	Cerca-Carvajal	23,254	156.9	19°16' N, 71°57' O	459	30	5.45
Nord'Ouest (Haiti)	Port-de-paix	185,707	351.75	19°57' N, 72°50' O	36	30	5.45
	Bassin bleu	57,697	214.83	19°47' N, 72°48' O	198	30	5.45
	Môle saint Nicolas	3075	227.07	19°48' N, 73°23' O	36	40	7.27
Artibonite en Haïti	Saint Michel de l'Attalaye	136,876	613.74	19°17' N, 72°04' O	420	30	5.45
	Marmalade	34,609	108.94	19°31' N, 72°21' O	759	30	5.45
Nord (Haiti)	Saint Raphaël	53,755	183	19°17' N, 72°04' O	373	30	5.45
Sud (Haiti)	Aux cayes	151,696	191.11	18°11' N, 73°45' O	70	30	5.45
	Camp perrin	40,962	151.42	18°19' N, 73°51' O	424	30	5.45
	Tobeck	78,603	201.86	18°10' N, 73°49' O	40	30	5.45
Elias piñas (RD)	Hondo valle	10,647	128.53	18°43' N, 71°42' O	890	20	3.63
Santiago (RD)	Santiago de los caballeros	283,651	236.51	18°77' N, 70°44' O	199	20	3.63
Dajabón (RD)	Dajabón	25,983	253.4	19°33' N, 71°42' O	35	20	3.63
Valverde (RD)	Santa cruz de Mao	49,475	409.66	19°34' N, 75°05' O	85	20	3.63
Santiago Rodriguez (RD)	Monción	11,753	101.61	19°26' N, 71°10' O	372	20	3.63
San Juan	Las matas de Farfán	70,586	636.64	18°52' N, 71°31' O	415	20	3.63

Sources: Paul et al. [85]; Duvil [82].

These 18 areas offer a privileged setting for this study, as the main impacts of climate variability on the agricultural sector are manifested in these regions.

3.2. Data Collection

Surveys were carried out between June and October 2023 in 18 communes and provinces among 550 heads of households (made up of men and women). In each commune, 30 heads of agricultural households in Haiti (except in the communes of Hinche and Cerca-la-Source, where we surveyed 40 heads of household) and 20 heads of agricultural households per province in the Dominican Republic were selected, following an aerial sampling from a list of people meeting the criteria defined below. This number

is based on studies by Ouédraogo et al. [86] in Burkina Faso (30 farms per department), Kabore et al. [87] in north-central Burkina Faso, and Arun and Yeo [88] in Nepal (the same number per district). The selection of heads of farming households on the island of Hispaniola was carried out with the assistance of agricultural officers and local stakeholders. Two selection criteria were used: a minimum age of 35 and a minimum experience of 15 years. This selection was necessary to ensure that the households interviewed had sufficient experience to understand climate change and its impact on agricultural production. The selected households answered an individual questionnaire comprising 80 closed and open-ended questions during face-to-face interviews in the local language (Spanish in the Dominican Republic and Creole in Haiti) between the 15 interviewers (10 graduating students in agronomic sciences, 3 agricultural technicians, and 2 agricultural engineers) and the 550 respondents. Data was collected using the ODK Collect v. 2023.2.3 application and recorded on the Kobotoolbox server, following an identical protocol. Each interview lasted between 50 and 60 min. The survey focused on household characterization, level of education, household size, ancestral knowledge of weather and climate forecasting, access to social networks, access to credit, off-farm income, farm size, number of livestock, marketing circuit, as well as climatic and telluric hazards and level of perception (of rainfall and temperatures). In addition, relevant secondary data on the agroecological characteristics of each commune/province were obtained from the Ministry of Agriculture, Natural Resources and the Environment (MARNDR) (https://agriculture.gouv.ht/statistiques_agricoles/, accessed on 2 October 2023) and the Haitian Innovation Center for Biotechnology and Sustainable Agriculture (CHIBAS) (<https://uniq.edu.ht/chibas/presentation/>, accessed on 15 July 2023). Table 2 describes the 23 variables selected for the development of a vulnerability index.

3.3. Development of an Individual Vulnerability Index for Agricultural Households

This study aimed to assess the individual vulnerability of farming households on the Caribbean island of Hispaniola to the impacts of climate change using the integrated approach through a vulnerability index. As indicated in the literature review, the use of indices is faced with numerous ambiguities, including those related to the choice of the right indicators, the directions of relationships with vulnerability, the weights assigned, and the optimal scale [4,44,64,70,71,77,78,80,89,90]. To minimize these ambiguities, we chose a scale of analysis that reflects the reality of farming households on the island of Hispaniola. As Deressa et al. [34] and Gutu et al. [49] pointed out, vulnerability analysis can be conducted at different scales, ranging from the local or household [46,91], national [62], and regional [80,92] to the global [4,30,71]. The choice of analysis scale is dictated by research objectives, methodologies used, and data availability [4,13,66]. For this study, the scale of analysis was set at the farm household level. Indeed, most previous studies using aggregated data at regional, national, and district levels have neglected variations at the individual level. However, this approach is crucial for assessing the vulnerability of farm households living in small island states such as the Caribbean island of Hispaniola, which comprises around 16 agro-ecological zones. In our study, the direction of the relationship in the vulnerability indicators (i.e., their sign) was determined by following the procedure used by Deressa et al. [34] and Neset et al. [4], who assigned a negative value to exposure and sensitivity and a positive value to adaptive capacity and then calculated the vulnerability indicator accordingly. Thus, we chose indicators that reflect the socio-economic and biophysical characteristics of farming households on the Caribbean island of Hispaniola.

3.3.1. Choice of Variables for the Vulnerability Assessment of Farming Households

Vulnerability to climate change is a complex and multidimensional topic influenced by many interconnected factors [12,44]. Although many variables representing this vulnerability are not directly measurable, the creation of an index can be useful for comparing similar systems and for helping policymakers understand the underlying processes and de-

terminants of vulnerability. The construction of such an index involves several steps. First, it is necessary to select the relevant variables and indicators. Next, weights are assigned to these indicators, and finally, they are aggregated to form an overall index. Indicators and indices provide a simplified representation of a complex reality, but the methodology used to select them is crucial, as inappropriate indicators could compromise the validity of the index. The choice of indicators is limited by the abstract nature of vulnerability itself [12]. Two main approaches are used to select these indicators: the data-driven approach and the theory-driven approach [81]. Ideally, theories provide a framework for understanding the nature and causes of vulnerability, but they are also limited by data availability. Thus, the best approach is to combine the two, checking the representativeness of theoretically based indicators with data from reliable sources [44] and taking into account local knowledge from group discussions [12]. In this study, a balanced combination of theoretical and data-driven approaches was used for variable choice and indicator selection, adopting the definition of the concept of vulnerability as a function of exposure, sensitivity, and adaptive capacity [13,25,27,36,42,44,54,93–95]. Figure 2 shows the various components of this integrated vulnerability.

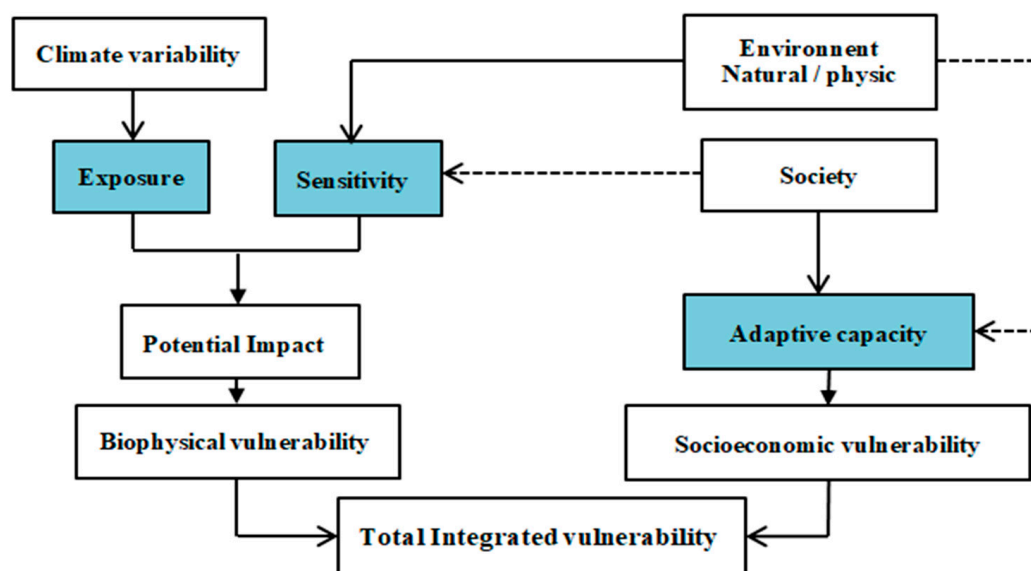


Figure 2. Integrated vulnerability component. Source: Fritzsche et al. [92]; adapted by the authors.

Thus, the indicators for each vulnerability sub-sector, i.e., exposure, sensitivity, and adaptive capacity, are presented in Table 2 and discussed as follows:

Adaptive Capacity (AC)

Adaptive capacity is defined as the ability of a system to modify or change its characteristics or behavior in order to better cope with existing or anticipated external factors [4,92]. In most works on vulnerability, adaptive capacity is generally considered as a set of factors determining a system's ability to design and implement adaptive measures [14,27,36,44,45]. Key characteristics determining the adaptive capacity of a community or region include economic wealth, technology, information, skills, infrastructure, institutions, and equity [24,93–98]. For this study, the choice of adaptive capacity variables was made based on previous studies and expert opinions (Table 3). Ultimately, 15 variables (6 social and 9 economic) were used for this study.

Table 3. Statistical description of model variable adaptive capacity (social and economic) by vulnerability category and distribution of farm households according to the criteria chosen for the classification of vulnerability to climate change.

Variable for Studying the Vulnerability of Agricultural Households	Notes	ID de la Classe	Agricultural Household Number	Level_Vulnerability of Agricultural Households	% of Agricultural Households
Variable adaptive capacity					
Variable Social					
Farming experience					
15 to 30	1	EXP1	179	Highly vulnerable	33.55
31–50	2	EXP2	318	Vulnerable	57.82
51 and more	3	EXP3	53	Less vulnerable	9.64
Household size					
7 and more	1	MEN1	315	Highly vulnerable	57.27
4 to 6	2	MEN2	73	Vulnerable	29.45
1 to 3	3	MEN3	162	Less Vulnerable	13.27
Member of professional agricultural organizations					
1	1	OPA1	167	Highly Vulnerable	30.36
2	2	OPA2	224	vulnerable	40.72
3 and more	3	OPA3	159	Less vulnerable	28.70
Access to social media for information on climate trends and agriculture					
No access	1	SFN1	138	Highly vulnerable	25.09
Agricultural technology	2	SFN2	226	Vulnerable	41.09
Above Bac +4	3	SFN3	186	Less vulnerable	33.82
Sources of information on climate and weather trends					
Sign and change in the environment	1	SIC1	233	Highly vulnerable	42.36
Mutual aid between farmers	2	SIC2	213	Vulnerable	38.73
Scientific documents (books, articles, etc.)	3	SIC3	104	Less vulnerable	18.91
Level of agricultural training					
No training	1	NFA1	91	Highly vulnerable	73.04
Agricultural technology	2	NFA2	401	Vulnerable	16.58
Higher than Bac +4	3	NFA3	57	Less vulnerable	10.38
Variable economic					
Off-farm income					
No access	1	REA1	237	Highly vulnerable	43.09
Sometimes	2	REA2	173	Vulnerable	31.45
Very often	3	REA3	140	Less vulnerable	25.45
Land status					
FVI > 50%	1	SFO1	220	Highly vulnerable	40
FVI < 50%	2	SFO2	118	Vulnerable	21.45
The earth belongs to me	3	SFO3	212	Less vulnerable	38.55

Table 3. Cont.

Variable for Studying the Vulnerability of Agricultural Households	Notes	ID de la Classe	Agricultural Household Number	Level Vulnerability of Agricultural Households	% of Agricultural Households
Crop insurance					
No crop insurance	1	ARE1	444	Highly vulnerable	80.73
Single-risk insurance	2	ARE2	43	Vulnerable	7.82
Multi-risk insurance	3	ARE3	63	Less vulnerable	11.45
Livestock owner					
No livestock	1	PRB1	169	Highly vulnerable	21.45
Less than 3 livestock units	2	PRB2	118	Vulnerable	30.73
Own more than 3 livestock units	3	PRB3	263	Less vulnerable	47.82
Irrigation					
No Irrigation, dry surface		IRR1	274	Highly vulnerable	49.82
Yes, surface irrigated		IRR2	134	Vulnerable	24.36
Yes, irrigated area		IRR3	142	Less vulnerable	25.82
Phytosanitary treatments					
No treatment	1	TPH1	189	Highly vulnerable	34.36
Systemic	2	TPH2	285	Vulnerable	51.82
Reasoned and preventive	3	TPH3	76	Less vulnerable	13.82
Type of fertilization					
No fertilization	1	FER1	189	Highly vulnerable	34.36
Chemical	2	FER2	250	Vulnerable	45.45
Organic	3	FER3	111	Less vulnerable	11.18
Farming tools					
Less than 3 farm implements	1	OUT1	221	Highly vulnerable	40.18
3 to 5 farming tools	2	OUT2	144	Vulnerable	26.18
More than 5 farm implements	3	OUT3	185	Less vulnerable	33.64
Marketing channel					
Local market	1	CC1	148	Highly vulnerable	26.91
Communal market	2	CC2	347	Vulnerable	63.09
National and international markets	3	CC3	55	Less vulnerable	10

Source: Computed from HH survey 2023.

Exposure

Exposure is defined as the presence of people, livelihoods, species or ecosystems, environmental resources or services, infrastructure elements or economic, and social or cultural assets in a place or context susceptible to damage [98]. Of all the elements that contribute to vulnerability, exposure is the only one that is directly linked to climatic parameters [45]. In much of the literature on vulnerability [44,62,99], exposure is conceptualized in terms of climate variability (e.g., temperature increase, precipitation variability, and change) or any event likely to occur and damage a given system. It is generally accepted that increasing temperature and decreasing rainfall are both detrimental to agriculture on the already hot and water-poor Caribbean island of Hispaniola [6,8,83]. Since data on future climate probabilities are not available in Haiti (only climate data from East-CRU University in the UK, but the 50 km × 50 km resolution is too large), we were forced to make a very

simple assumption. Thus, we hypothesized that households who perceive their farms as being subject to high temperature variability and rainfall variability and change are more exposed. Two variables were, therefore, selected for this study: rainfall variability (VAP) and temperature variability (VAT) as perceived by farm households (Table 4).

Table 4. Statistical description of exposure variables (biophysical) by vulnerability category and distribution of farming households according to the criteria chosen for the classification of vulnerability to climate change.

Variable for Studying the Vulnerability of Agricultural Households	Notes	ID de la Classe	Agricultural Household Number	Level_Vulnerability of Agricultural Households	% of Agricultural Households
Variable exposure (Biophysics)					
Temperature variability					
High variability	1	VAT1	86	Highly vulnerable	13.64
Low variability	2	VAT2	427	Vulnerable	77.64
Very low variability	3	VAT3	37	Lessly vulnerable	6.73
Rainfall variability					
High variability	1	VAP1	91	Highly vulnerable	16.55
Low variability	2	VAP2	424	Vulnerable	77.09
Very low variability	3	VAP3	35	Less vulnerable	6.36

Source: Computed from HH survey 2023.

Sensitivity

In the context of this study, sensitivity refers to the responsiveness of a system to climatic hazards. It also refers to human activities that influence the physical composition of a system, such as cultivation methods [34,45,93,99]. This notion is often represented in the form of a “dose-response” model: the more sensitive a system, the higher the rate or magnitude of a negative response to a given hazard [93]. Sensitivity can vary considerably from one system, sector, or population to another [46]. In their case study of Ethiopian agriculture, Deressa et al. [34] estimated that areas where climatic extremes (droughts and floods) are more frequent will be more sensitive due to yield loss and, hence, loss of livelihoods. O’Brien et al. [62] developed a climate sensitivity index based on climatic variables (drought, rainfall). Similarly, Maiti et al. [44] used rainfed area, number of marginal farms, agricultural productivity, etc., as sensitivity indicators. Zaatra [45] studied soil type, crop diversification, and varieties as sensitivity indicators. Overall, the authors consider sensitivity to be an intrinsic condition of a system that makes it particularly vulnerable. It translates into a propensity to be affected, favorably or unfavorably, by the manifestation of hazards. However, it was not possible to find this type of data reliably on the island of Hispaniola, more precisely in Haiti. In this context, we were forced to make a simple assumption for each sensitivity variable studied. In this context, we first asked farm households to recall how often, in the past, their livelihoods had been significantly affected by climate (drought, floods, cyclones). Thus, this study argues that farm households who feel that their farms are subject to higher frequencies of climate extremes (e.g., drought and floods, cyclones, etc.) are more vulnerable due to loss of agricultural yields and, thus, livelihoods [13,34,44,62,100]. Similarly, we assume that farming households located in areas prone to telluric hazards are more sensitive. This is justified by the fact that some communes in Haiti and the Dominican Republic have been hard hit by earthquakes, landslides, and rockslides in recent decades. In this context, we assume that in areas where earthquakes, landslides, or rockslides are more significant, farming households are more sensitive, as they can strongly affect household income, housing, health, etc. This will require expenditure that could be very high in the future. This will require expenditure

that could be very costly and put the household in a difficult situation for the purchase of seeds, chemical fertilizers, labor, or pesticides, etc., which are important elements in finding yields. Finally, we used other variables such as crop diversification. We assumed that the more diversified the household farm, the less sensitive it is, due to the system’s ability to minimize the various risks associated with climate change. A total of six variables were taken into account to calculate the degree of sensitivity of the farming households studied. These were land-based hazards (AT), drought (SEC), flooding (INN), cyclone frequency (ALC), plot topography (PEN), altitude (ALT), and crop diversification (DIV) (Table 5).

Table 5. Statistical description of sensitivity variables (environmental) by vulnerability category and distribution of farming households according to the criteria chosen for the classification of vulnerability to climate change.

Variable for Studying the Vulnerability of Agricultural Households	Notes	ID de la Classe	Agricultural Household Number	Level Vulnerability of Agricultural Households	% of Agricultural Households
Variable environnementale (Biophysique)					
Ground slope					
Less than 10% slope	1	PEN1	162	Highly vulnerable	26.91
Slopes from 10 to 25%	2	PEN2	255	Vulnerable	63.09
Slope greater than 25%	3	PEN3	133	Less vulnerable	10
Production diversity					
Monoculture	1	DIV1	210	Highly vulnerable	38.19
Two main crops	2	DIV2	110	Vulnerable	20
Several main crops	3	DIV3	230	Less vulnerable	41.81
Climatic hazards (cyclones)					
>4 hazards	1	ALC1	168	Highly vulnerable	30.55
2 to 3 hazards	2	ALC2	168	Vulnerable	30.55
<2 hazards	3	ALC3	214	Less vulnerable	38.91
Telluric hazards					
>4 hazards	1	AT1	378	Highly vulnerable	68.73
2 to 3 hazards	2	AT2	83	Vulnerable	15.09
<2 hazards	3	AT3	89	Less vulnerable	16.18
Altitude					
Low	1	ALT1	200	Highly vulnerable	36.36
Mean	2	ALT2	284	Vulnerable	51.64
High	3	ALT3	66	Less vulnerable	12
Drought					
High sensitivity	1	SEC1	344	Highly vulnerable	62.55
Mean sensitivity	2	SEC2	200	Vulnerable	36.36
Low sensitivity	3	SEC3	6	Less vulnerable	1.09
Flood					
High sensitivity	1	INN1	71	Highly vulnerable	12.91
Mean sensitivity	2	INN2	184	vulnerable	33.45
Low sensitivity	3	INN3	295	Less vulnerable	53.64

Source: Computed from HH survey 2023.

In this study, we selected 23 variables to calculate the vulnerability index of each farm household on the island of Hispaniola.

3.4. Calculating the Vulnerability Index for Each Farm Household

Having selected the appropriate variables, it is now necessary to normalize them in order to bring the indicator values within a comparable range [12,21,40,44,80,101]. Indeed, in this study, the determining variables for each vulnerability component were calculated from the survey results by standardizing the quantitative variables using the min-max method and the qualitative variables by defining the three classes and intervals according to a standardized field from 0 to 1. The direction of variation for each variable increases from negative to positive ratings. In addition, for each of the 23 variables, each farm household was asked to rate on a scale of 0 to 10, based on their experience and knowledge, their opinion of the importance of each variable on their vulnerability and their operation. These responses on the 0 to 10 scale were then discretized into three categories: Very vulnerable, Vulnerable, Less vulnerable (see example in Table 6 for the experience variable).

Table 6. Assessment grid for experience-related adaptability.

Class	Scale	Intervals	Description	Ca. Normalized	Label	Vulnerability Categorization
15–30	0–3	0–0.33	Low adaptive capacity	0.165	EXP1	Highly vulnerable
31–50	4–7	0.33–0.66	Mean adaptive capacity	0.495	EXP2	Vulnerable
51 and more	7–10	0.66–1	Highly adaptive capacity	0.83	EXP3	Less vulnerable

Source: Computed from HH survey 2023.

Next, we assigned weights to these indicators. Indeed, some studies follow equal weighting [78,99], but this can be too arbitrary and lead to an overweighting of some less important indicators while underweighting the more important ones [12]. Weighting can also be based on expert judgment [78,79], but this approach is often criticized for being too subjective and is often limited by the availability of specialists in the field or by the lack of consensus [12,21]. Weight assignment by principal component analysis (PCA) is, therefore, preferred and frequently used in research over the previous two methods [12,21,34,40,44,102–106], but this procedure could not be applied in this study since the majority of variables were qualitative. As a result, the data transformed into categories were used to perform a Multiple Correspondence Analysis (MCA) to determine the weight of the 23 variables. The first two axes of the MCA were used as weights for the variables. These first two axes were used because they captured the highest percentage of the total variance in the data. Thus, weights were averaged across the 3 levels of each variable on the two axes. The MCA was run separately for the selected social and economic (Adaptive Capacity) and environmental (Sensitivity and Exposure) indicators in R software (4.3.2) to assign weights. The weights of the first component of the MCA are used as weights for the indicators. The weights assigned to each indicator range from −1 to +1, with the indicator sign indicating the direction of the relationship with other indicators used to construct the respective index. The magnitude of the weights describes the contribution of each indicator to the value of the index. A stepwise MCA was performed for the indicators. The first stage of the MCA was carried out separately for each farm household’s indicators in order to observe the relative importance of indicators within each category. From the weights obtained in the first step of the MCA, individual index values for each household were calculated. To calculate the final score for each farm household, we transformed (normalized) the categorical data into scores (0.185, 0.495, 0.83, respectively). These initial scores are equal to the average of the ranges of each of the 23 variables for the three categories (see example in Table 3). This method of using interval-averaged scores followed the principles that were applied in the calculation of the vulnerability index by Zaatra [45]. Thus, the final database was obtained by multiplying the standardized variables (initial score) of

the level of each variable by its average weight on the first two dimensions of the MCA to construct the indices (social, economic, and environmental separately). Thus, to calculate the individual vulnerability index for farm households, we used the sum of the final scores of the social variables added to the sum of the final scores of the economic variables to form the adaptive capacity component. Similarly, the sum of the final scores of the exposure variables was summed to the sum of the final scores of the sensitivity variables to form the biophysical component of farm households.

$$V = AC - B \text{ where, } B = (S + E); \text{ then}$$

$$V = AC - (S + E) \quad (1)$$

V is the vulnerability index;

AC is the adaptive capacity index (social and economic variable);

B is the biophysical index (E is exposure and S is sensitivity).

Next, to categorize the level of vulnerability of each farm household, we used the percentile-based classification method. Values below or equal to the 33rd percentile were categorized as very vulnerable, and those above the 33rd percentile and below or equal to the 66th percentile were categorized as vulnerable, and finally, those above the 66th percentile were categorized as less vulnerable. The overall vulnerability index made it easier to compare individual farm households between the two countries. A higher value of the vulnerability index indicates lower vulnerability.

3.5. Determinants of Vulnerability

Choices of Potential Determinants

In this study, we selected four potential factors to determine the vulnerability of farming households on the Caribbean island of Hispaniola. Four factors were chosen based on existing literature and their relevance in the context of vulnerability to climate change [12,13,19,21,34,45,50,54,61,72,76,81,91,92]. These include country, access to credit, level of education, and farm size. Country of origin (Haiti or Dominican Republic) was considered the main factor in this study to examine the impact of different national contexts. Furthermore, it is assumed that the vulnerability of farming households on the Caribbean island of Hispaniola can be explained by social, economic, and biophysical dimensions. In this context, we captured these dimensions using three variables: access to credit, farm size, and level of education. These variables, chosen as factors, were excluded from the calculation of the vulnerability index. The choice of these three variables was made taking into account their distribution and following the basic hypothesis of our study: the more a farm household depends on natural and socio-economic resources, the higher its vulnerability to climate change, as most farm households are directly dependent on agricultural activities, which are likely to be affected by climate change. We tested this hypothesis in our study region. Indeed, each of these factors was broken down into three modalities (or categories) defined on the basis of the literature [45,93] and expert opinion. In addition, we decided to weigh only access to credit and country in our analyses due to the uneven distribution of their observations. This weighting aims to better understand the complex dynamics between countries, credit access, and their joint impact on vulnerability. It also enables more balanced and representative analyses of the different sub-populations studied.

3.6. Statistical Modeling

In this study, we opted for an ordinal logistic regression model. The ordinal logit model is used when the outcome variable is categorized on an ordinal scale, as in the present case where our dependent variable, which is the level of vulnerability of farm households, is classified as follows: (1) very vulnerable, i.e., farm households for which the difference between adaptive capacity and sensitivity/exposure is less than or equal to the 33rd percentile; (2) vulnerable, i.e., farm households for which the difference between

adaptive capacity and sensitivity/exposure is greater than the 33rd percentile and less than or equal to the 66th percentile; and (3) less vulnerable, i.e., farm households for which the difference between adaptive capacity and sensitivity/exposure is greater than the 66th percentile. This is a powerful model for modeling the probability of belonging to a category as a function of several explanatory variables. It is particularly useful for showing movement between these vulnerability classes, explaining who moves in and out of vulnerability. It takes into account the order of the categories and offers an intuitive interpretation of the effects of the variables through odds ratios.

4. Results

4.1. Description of the Vulnerability of Farming Households on the Island of Hispaniola

Preliminary analyses indicate that farming households on the Caribbean island of Hispaniola have different social, economic, and biophysical characteristics. In the next section, we describe the social, economic, and environmental vulnerability of farming households on the island of Hispaniola.

4.1.1. Social Vulnerability

The social vulnerability of farming households on the island of Hispaniola to climate change is linked to their low social profile. According to the results presented in Table 7, over 73.04% of agricultural households surveyed had not received any agricultural training. This lack of training reduces their ability to understand the constraints induced by climate change and to adopt new, improved technologies. Regarding household size, over 70.54% of respondents reported having four or more dependent family members. This high figure may indicate an increased level of vulnerability during certain periods of climate change-induced shocks (Table 7). Household participation in local institutions such as Tipa and mutual solidarity is an important measure of the level of household social capital. The more involved a household is in agricultural networks, the more likely it is to obtain support and access information. However, the survey reveals that some 57.27% of farming households are not members of agricultural organizations. This highlights a potential lack of support and access to information for these households, increasing their vulnerability to climate change.

Table 7. Variables of social vulnerability and their contributions to vulnerability level.

Variables of Social Vulnerability and Their Effect on Vulnerability Level		
Social Vulnerability Variables	Percentage (%)	Contribution to Vulnerability Level
Age: person over 45	61.08	+
Sex: Head women household	29.69	–
Household size: Households of more than 4 people	70.54	+
Level to agricultural formation: No access to farmer extension	73.04	+
Level and access to agricultural extension information: No access to farmer extension	10.38	–
Access to indigenous early warning information: Having no access	18.90	–
Farming experience: Lack of farming experience of <15 years	32.54	–
Agricultural network: no member of institutions or associations	57.27	+
Social network: Who has access at least to the internet, radio, or television	32.78	–
Variables of economic vulnerability and their effect on vulnerability level		
Economic Vulnerability Variables	Percentage (%)	Contribution to vulnerability level
Non-farm or sometime income, diversity of income sources: Have no non-farm income or sometime	74.54	+

Table 7. Cont.

Variables of Social Vulnerability and Their Effect on Vulnerability Level		
Social Vulnerability Variables	Percentage (%)	Contribution to Vulnerability Level
Ownership of livestock: Own less than 3 units of tropical livestock	47.82	–
Land status: FVI < 50%	40	–
Land under irrigation: No access to irrigation at all	74.18	+
Land cultivated with commercial fertilizer: Having no access to fertilizer at all	34.36	–
Insecticide and pesticide supply: Having no access to use insecticide and pesticide supply	34.36	–
Access to credit: Having no access to credit	79.28	+
Farm tools: Own more than 5 farm tools	33.64	–
Crop assurance: Having access to crop assurance	88.55	+
Commercialization circuit: At least part of the product is sold on the local market	26.91	–
Environmental vulnerability indicators and their effect on vulnerability level		
Environmental vulnerability variables (measures of sensitivity and exposure)	Percentage	Contribution to vulnerability level
Rainfall: People facing exposure to a moderate and high rainfall variability	93.64	+
High temperature: People facing exposure to a moderate and high temperature variability	91.28	+
Land topography: Slope > 25%	26.91	–
Crop diversity: Less than 50% of the 2 main crops grown in the area	63.09	+
Fertility level: Low fertility (cannot produce without using much fertilizer)	25.09	–
Frequency of hazards teluric: People facing less than 2 natural hazards per year	16.18	–
Frequency of cyclones: People facing less than 2 natural hazards per year	69.46	+
Frequency of drought: People facing a high and moderate sensibility per year	98.91	+
Frequency of flood: People facing a high and moderate sensibility per year	66.36	+
Altitude: People with plots at high altitude	36.36	–

Source: Computed from HH survey of 2023.

In summary, the level of vulnerability of farming households on the Caribbean island of Hispaniola in terms of social capital is high.

4.1.2. Economic Vulnerability

Economic vulnerability focuses primarily on the economic status of individual farm households. The economic status of farming households on the Caribbean island of Hispaniola varies in terms of wealth, access to credit, technology, and so on. Most of these households are considered economically vulnerable to the effects of climate change. For example, a large majority of respondents (79.28%) have no access to credit, over 74.54% have limited off-farm sources of income, over 88.55% have no single-risk or multi-risk agricultural insurance, over 73.64% have small farms, and over 74.18% have no area of

irrigated or irrigable land. These data indicate a high level of economic vulnerability among farm households (Table 7).

4.1.3. Environmental (Biophysical) Vulnerability

Small-scale farming households have faced many environmental challenges in recent years, particularly on the Caribbean island of Hispaniola, where most households are directly dependent on agricultural activities, making them vulnerable to climate change. Thus, variables measuring environmental vulnerability are major determinants of the vulnerability of agricultural households. The results presented in Table 7 highlight several environmental factors that contribute significantly to this vulnerability. For example, high rainfall variation was observed by over 77.09% of households, while over 77.63% noted temperature fluctuations and 62.54% were affected by drought. In addition, frequent soil degradation due to erosion, low levels of soil fertility, and the need to diversify crops are also important factors contributing to this environmental vulnerability.

4.2. Vulnerability of Farming Households to Climate Change

To analyze the vulnerability of each household, the variables presented in Tables 3–5 were used. Table A1 presents the results of the multiple correspondence analysis (MCA) and the factor scores for each level of vulnerability (see Table A1 in Appendix A). Indeed, the vulnerability index of each farm household is calculated using the formula in Equation (1), where percentiles are used as a method to classify each household according to their level of vulnerability: very vulnerable, vulnerable, and less vulnerable. According to the results of the vulnerability index, the majority of farming households in Haiti (73.25%) fall into the vulnerable and very vulnerable categories (Table 8). In contrast, only 40% of farm households in the Dominican Republic fall into these two categories. We, therefore, classify farm households according to the range of their vulnerability index.

Table 8. Classification of the farmers by the range of their vulnerability index.

Country	Vulnerability Index	Vulnerability Level	Number Farmers of the Vulnerability Level	Percentage of HHs (%)
Haiti	<33e percentile	Highly vulnerable	158	36,74
	>33e <66e percentiles	Vulnerable	157	36,51
	>66e percentile	Less vulnerable	115	26,75
Total			430	100
Dominican Republic	<33e percentile	Highly vulnerable	24	20
	>33e <66e percentiles	Vulnerable	24	20
	>66e percentile	Less vulnerable	72	60
Total			120	100

Source: Computed survey of 2023.

Similarly, the results also indicate that 26.75% of farm households in Haiti belong to the least vulnerable category, while this figure rises to 60% in the Dominican Republic. This suggests a significant disparity in the vulnerability levels of agricultural households between Haiti and the Dominican Republic. Figure 3 shows the level of vulnerability for farm households by country.

This difference highlights the ability of farming households in the Dominican Republic to better cope with environmental challenges, probably owing to factors such as access to resources, more sustainable farming practices, or more effective adaptation measures. These results provide important insights for targeting interventions to strengthen the resilience of farming communities to climate change in each country.

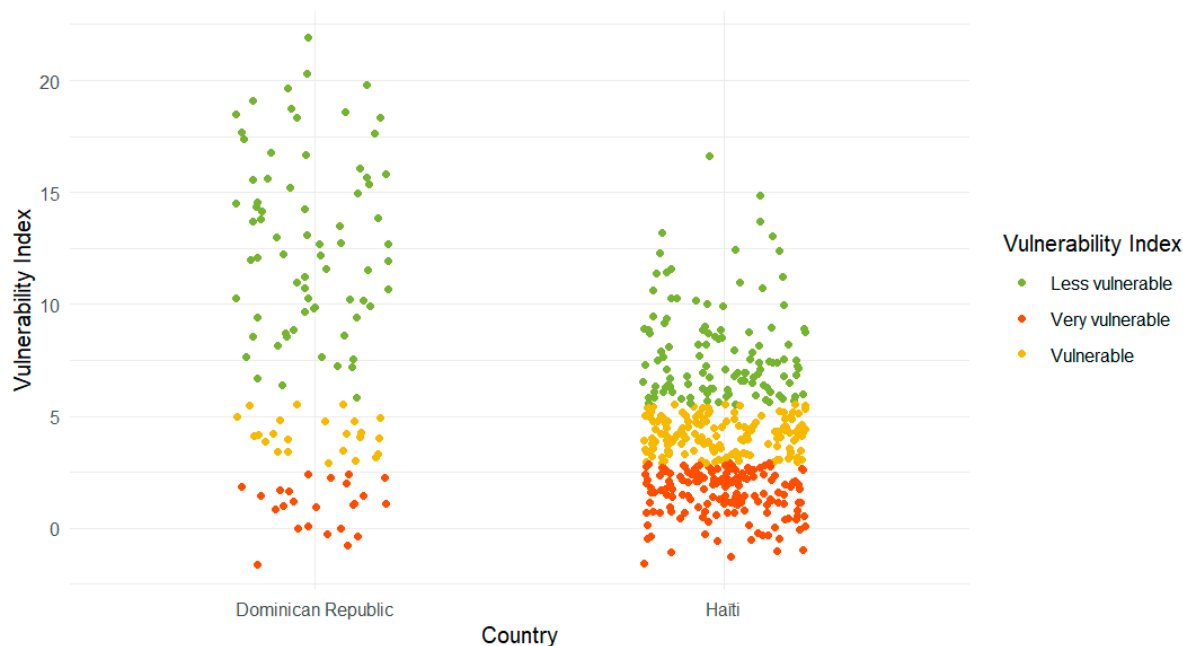


Figure 3. Vulnerability index for each farmer by country. Source: Computed from HH survey 2023.

4.3. Factors That Significantly Influence Farm Households' Vulnerability to Climate Change

In this section, the central question is to determine which factors have a significant influence on the vulnerability of farming households to climate change.

4.3.1. Level of Vulnerability of the Country (Haiti vs. Dominican Republic)

For the purposes of this study, the country is considered to be the main factor. Haiti and the Dominican Republic, two countries sharing the island of Hispaniola, face similar environmental challenges but differ in their vulnerability to climate change. For example, the result of the logistic regression model shows that farm households in Haiti are 9.49 times more likely to be classified as more vulnerable than farm households in the Dominican Republic (DR), indicating a significantly increased risk of higher levels of vulnerability in Haiti ($p < 0.001$). This vulnerability of Haitian farming households to climate change can be explained by poverty (low adaptive capacity) and mountain farming (high sensitivity). The results of the regression model clearly show that farming households living in the same geographical area and facing the same climatic risks can have different levels of capacity and vulnerability. This analysis also highlights the disparities in vulnerability between Haitian and Dominican farming households, underlining the importance of specific policies and strategies to strengthen the resilience of farming communities to climate change. Despite this disparity, the situation of Haiti and the Dominican Republic in the face of climate change remains a worrying reality, requiring concerted action at local, regional, and international levels. Both countries must continue to strengthen their adaptive capacity in order to minimize the impacts of climate change on their respective populations, particularly farming households.

4.3.2. Level of Education

In this study, the level of education, measured by the number of school years completed by the farm household, is considered an important factor influencing vulnerability to climate change. Education is recognized as playing a central role in the farming community, as it represents a store of knowledge and know-how. Analysis of the logistic regression model for level of education produced several significant results (Table 9). For example, the odds ratio (OR = 0.44) suggests that the probability of being "Very vulnerable" vs. "Less vulnerable" decreases. Thus, farm households classified as "Less Vulnerable" are around 56% less likely to move to a higher level of vulnerability compared to those classified

as “Very Vulnerable”, this result being statistically significant ($p < 0.05$). Similarly, the probability (OR = 1.99) of moving from “Very Vulnerable” to “Vulnerable” increases. Thus, farm households classified as “Vulnerable” are around 99% more likely to move to a higher level of vulnerability compared to those classified as “Very Vulnerable”, and this result is also statistically significant ($p < 0.05$).

Table 9. Results of the logistic regression model.

Variables	Variable Level	Odds_Ratio	Lower_CI	Upper_CI	p_Value
Level of vulnerability	Less vulnerable Very vulnerable	0.44	0.23	0.81	$p < 0.05$
Level of vulnerability	Very vulnerable Vulnerable	1.99	1.08	3.66	$p < 0.05$
Country	Haiti	9.49	4.30	20.93	$p < 0.001$
Level of education	Secondary	0.37	0.16	0.86	$p < 0.05$
Level of education	University	0.05	0.01	0.17	$p < 0.001$
Farm size	Operator Medium	11.35	4.16	30.93	$p < 0.001$
Farm size	Small operator	8.38	3.31	21.18	$p < 0.001$
Access to credit	Very accessible	0.15	0.05	0.45	$p < 0.001$
Country: Level of education	Haiti: University	10.96	3.04	39.44	$p < 0.001$
Country: Farm size	Haiti: Operator Medium	0.13	0.04	0.40	$p < 0.001$
Country: Farm size	Haiti: Small operator	0.16	0.05	0.47	$p < 0.001$

Source: Computed from HH survey of 2023. Odds Ratio: A measure of the association between an exposure and an outcome, indicating the odds of the outcome occurring with the exposure compared to without; Lower CI: Lower bound of the 95% Confidence Interval, indicating the lower limit within which the true odds ratio is expected to fall with 95% confidence; Upper CI: Upper bound of the 95% Confidence Interval, indicating the upper limit within which the true odds ratio is expected to fall with 95% confidence; p -value: A measure of the statistical significance of the results, indicating the probability that the observed association occurred by chance.

Furthermore, the odds ratio (OR = 0.37) shows that a secondary level of education in Haiti significantly reduces the level of vulnerability ($p < 0.05$). Farm households with secondary education in Haiti are 63% less likely to move to a higher level of vulnerability than those in the Dominican Republic. Furthermore, the odds ratio (OR = 0.05) shows an even greater reduction in the level of vulnerability for those with university education, with very strong statistical significance ($p < 0.001$) (Figure 4). In this context, farm households with university education in Haiti are around 95% less likely to move to a higher level of vulnerability compared to those in the Dominican Republic. We, therefore, present the distribution of the vulnerability index by level of education and by country.

The interaction between Haiti and the level of university education shows a significant increase in vulnerability (OR = 10.97). This result suggests a strong decrease in the level of vulnerability for those with university education in Haiti, compared to the Dominican Republic. This result is statistically highly significant ($p < 0.001$). Thus, agricultural households with university education in Haiti have a 997% chance of moving to a higher level of vulnerability compared to those in the Dominican Republic. It is clear that farm households with a higher level of education on the Caribbean island of Hispaniola have a higher adaptive capacity and are less vulnerable to climate change. In this context, it is clear that policies aimed at improving education, while taking into account national specificities, could play a crucial role in reducing the vulnerability to climate change of farming households on the island of Hispaniola. By investing in education and designing appropriate educational programs, governments could strengthen the ability of farm households to cope with environmental challenges, thereby contributing to the resilience of farming communities in both countries.

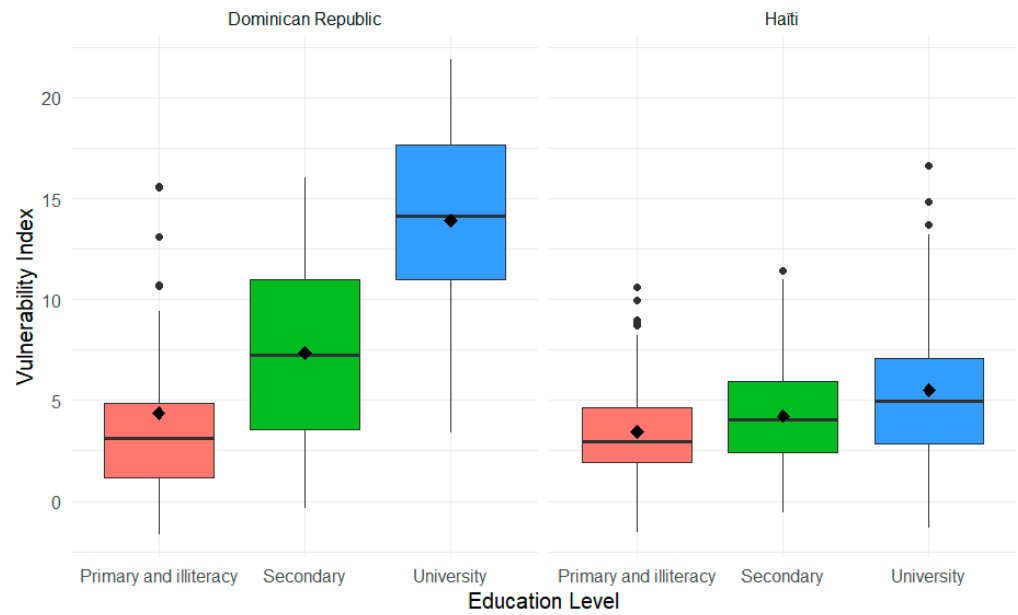


Figure 4. Distribution of vulnerability index by level education and country. Source: Computed from HH survey 2023.

4.3.3. Farm Size (TEX)

Farm size is a crucial element in increasing the crop productivity of farm households on Hispaniola Island. In this study, the analysis of the logistic regression model for farm size shows that the probability of vulnerability in Haiti has increased (OR = 9.49), which is highly significant ($p < 0.001$), suggesting that being in Haiti is associated with an increased level of vulnerability compared to the Dominican Republic.

Medium-sized farms significantly increase vulnerability (OR = 11.35, $p < 0.001$) (Figure 5). Similarly, small farms also increase vulnerability (OR = 8.38, $p < 0.001$). The interaction between being a farming household in Haiti and having a medium-sized farm significantly reduces vulnerability (OR = 0.134, $p < 0.001$). Similarly, the interaction between being an agricultural household in Haiti and having a small farm also significantly reduces vulnerability (OR = 0.165, $p < 0.001$). Thus, we present the distribution of the vulnerability index as a function of farm size.

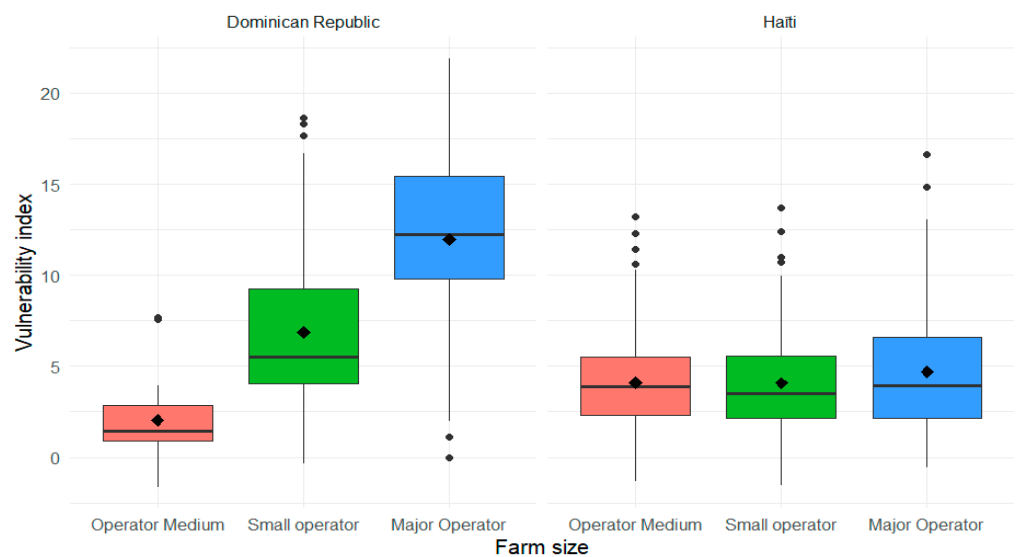


Figure 5. Distribution of the vulnerability index as a function of size. Source: Computed from HH survey of 2023.

In summary, the analyses show that farming households with access to large farms have a greater capacity to adapt to climate change and are less vulnerable.

4.3.4. Access to Credit (ACR)

Access to credit has proven to be a related factor encouraging the adoption of new farming methods and securing climate change adaptation investments. Once a farming household can obtain credit from more formal sources, it can access essential inputs such as fertilizers and improved seeds, as well as plowing services. In the study area, access to agricultural credit is one of the major challenges for small farming households seeking to overcome their vulnerability to the impact of climate change, especially in times of crisis. The results of the logistic regression model (OR = 0.15) show that when credit is very accessible, the level of vulnerability decreases. This result is highly significant ($p < 0.001$).

This indicates that improving access to credit is an important factor in reducing vulnerability. Since the results of the study show that when credit is highly accessible, the level of vulnerability decreases, it appears that farm households without access to credit are highly vulnerable to the risks induced by climate change. Thus, we present the distribution of vulnerability index by level to credit by country (Figure 6).

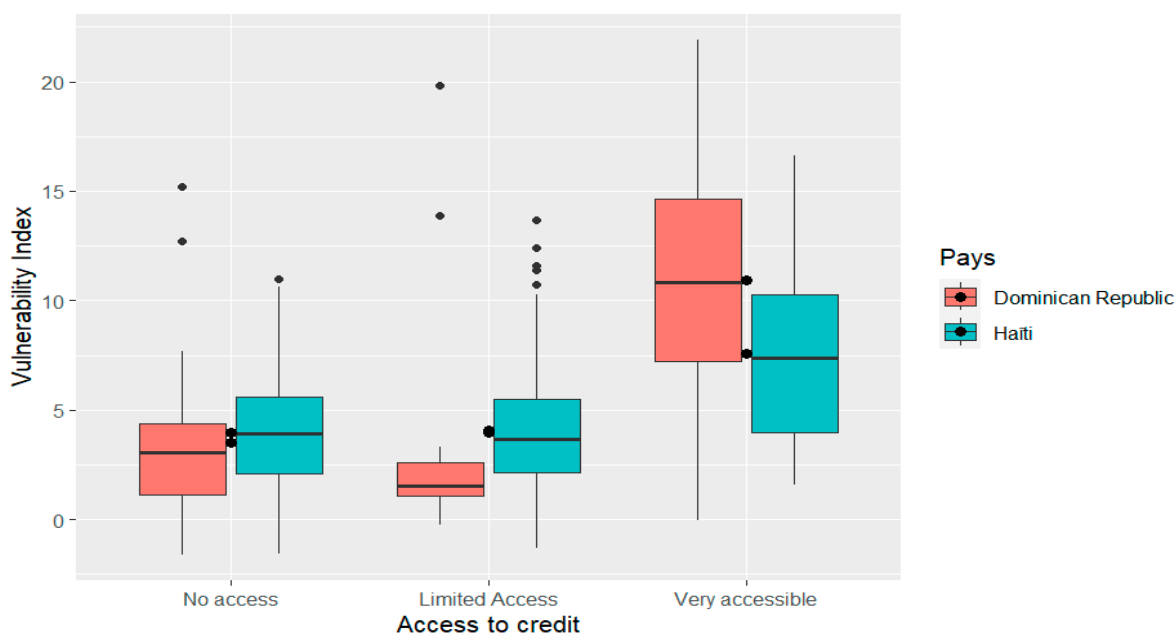


Figure 6. Distribution of vulnerability index by level to credit by country. Source: Computed from HH survey of 2023.

These results underline the crucial importance of access to agricultural credit in reducing the vulnerability of small farm households to climate change on the island of Hispaniola, and they highlight the significant disparities between Haiti and the Dominican Republic in terms of the impact of access to credit on vulnerability. Consequently, policies aimed at improving access to agricultural credit, particularly in times of crisis, could play a key role in promoting the resilience of farming communities on the island of Hispaniola.

5. Discussion

Agriculture is one of the most vulnerable sectors to climate change, and it has been the subject of multiple studies in recent years [4,107]. In an attempt to describe and compare agricultural vulnerability in different regions of the world, and at the household level, various quantitative assessments of vulnerability to climate change have been conducted, generating composite indices based on sets of indicators [4,13,34,46,48,62,73,74,108]. These indicators generally cover several dimensions of the vulnerability concept, capturing a

system's exposure, sensitivity, and adaptive capacity [93]. These three aspects are often combined in a composite index [76]. Consequently, composite indices are suitable for vulnerability assessments due to their ability to capture multiple dimensions of vulnerability [76]. In the context of this study, we developed a vulnerability index using indicators to assess the individual vulnerability of farming households on the Caribbean island of Hispaniola.

Although the use of indicators is feasible for vulnerability assessments in the agricultural sector, the approach has considerable pitfalls, and it has been widely criticized for arguably being insensitive to contextual differences and spatial and temporal distributions of impacts, particularly in terms of scaling, applicability, weighting, utility, and policy implications, sometimes producing oversimplified assessments [4,64,67,68,74,78,109–111]. This body of research has also encountered a number of limitations, particularly with regard to the quantification of variables and the integration of vulnerability [12,13,44,77,83].

However, unlike conventional assessment approaches, which are mainly based on objective data, this work focuses on endogenizing the declarations of farming households in 18 different agro-ecological zones on the Caribbean island of Hispaniola to assess their vulnerability. These statements, which correspond to a personal and subjective assessment of the role of different variables on their vulnerability, contributed to a better understanding of the factors shaping vulnerability. In this study, variables were calculated from the survey results by standardizing quantitative variables using the min-max method and qualitative variables by defining classes according to a standardized field of 0 to 1 on a scale of 0 to 10. This method followed the principles applied in Zaatra's [45] vulnerability study.

During the self-assessment exercise, farm households assigned low scores to variables they considered irrelevant and also to those whose influence as a component of their vulnerability (uncertainty) they were unaware of. Their statements may also be linked to the difficulties they had experienced, their current decisions and practices, and the skills and resources that can be implemented at the farm level, as indicated by various scientific research studies [21,45,112,113]. In this context, the fact of having considered the perceived exposure of farm households and not being objective necessarily affects the results, and they should, therefore, not be over-interpreted. However, in line with the literature [4,33,36,45,70,78], our vulnerability assessment was highly sensitive to variable selection and representation. Indeed, variable selection and validation were based on bibliography, field visits, and consultation with resource actors and experts. For each vulnerability component, a specific calculation method was used. Unlike other authors who use principal component analysis (PCA) [12,21,34,40,44,103–106], equal weighting [82,103], or expert judgment [78,80,114] to assign weights to the different variables for calculating the agricultural household vulnerability index to climate change, we used multiple correspondence analysis (MCA) to assign different weights to the three categories of all vulnerability variables, taking into account the diversity of impact of the variables used. To do this, we used farm household declarations to weigh the different variables.

Another generally observed limitation of vulnerability assessments [4,36,44,70] is that they fail to address the interactions between the different components of vulnerability (adaptive capacity, sensitivity, exposure). Their approach makes it possible to reassess the indicators usually used to assess sensitivity, exposure, and adaptive capacity in terms of their practicality and applicability, as well as their link with climate change. It also helps to identify missing indicators. For example, for exposure to climate change, rainfall variation is reported as the most important climate issue, generating the highest vulnerability in this study. Several studies have suggested that farm households attach greater importance to recent climatic events in shaping their perceptions of risk [21,113]. With regard to sensitivity, the variables drought, flooding, and crop diversification are declared to be the most important sensitivity factors. For adaptive capacity, the factors declared as most important are for social variables: level of agricultural training, household size, and agricultural network; and for economic capital: crop insurance, access to credit, existence of off-farm income, and access to irrigated land. With the exception of accessibility

to endogenous information on climate, cyclones, and telluric hazards, which are more qualitative factors, and the land tenure status of farms, the majority of the variables in our approach are already widely addressed in the literature as determinants of agricultural vulnerability [4,13,14,34,45,94,108,115].

Although these determinants of farm household vulnerability have already been widely addressed in several regions of the world, it was important to determine which factors have a significant influence on the vulnerability of farm households in these two countries, Haiti and the Dominican Republic, which share the same island territory [8,85] and are affected differently in their agriculture [6]. Thus, the result of the regression model shows that certain factors, such as level of education, influence the vulnerability of farming households on the island of Hispaniola. This result is in line with previous studies conducted by Deressa et al. [34], Arunrat et al. [115], Zaatra [45], and Nor Diana et al. [97], which showed that farming households with a higher level of education have a greater capacity to adapt to climate change compared to those with a lower level of education due to their greater exposure to new knowledge and technologies. These households are also more likely to acquire skills and knowledge about current adaptation practices than their less-educated counterparts and are, therefore, less vulnerable, as highlighted by Abdul-Razak and Kruse [116]. Similarly, farm size is a factor influencing the vulnerability of farming households on the Caribbean island of Hispaniola. This finding corroborates previous work conducted by Nhemachena and Hassan [117], Gutu et al. [49], Nabikolo et al. [118], Defiesta and Raperia [119], Alauddin and Sarker [120], Abdul-Razak and Kruse [116], and Arunrat et al. [115], who highlight that farm households with large farms generally have a greater capacity to adapt to climate change. This is made possible by higher capital gains, larger farm areas, and the ability to practice new farming methods on their land, which reduces the vulnerability of farm households [45]. In summary, it is clear that farm households with access to large farms have a greater capacity to adapt to climate change and are less vulnerable. Indeed, access to credit is also a factor influencing the vulnerability of farming households on the Caribbean island of Hispaniola. This finding is in line with previous findings by Shewmake [121], Hassan and Nhemachena [117], Defiesta and Raperia [119], Frank and Penrose Buckley [100], and Abdul-Razak and Kruse [116], who also highlighted that households with poor access to agricultural credit are more vulnerable to climate change than their counterparts with better access to credit. Thus, farm households with access to credit are economically more capable of adapting to climate change.

6. Conclusions

This study assessed the vulnerability of farming households on the Caribbean island of Hispaniola to climate change by developing an integrated index that takes into account the social, economic, and environmental factors of each household. Vulnerability assessment approaches were adopted, combining biophysical and socio-economic indicators. Socio-economic indicators include wealth, level of education, and access to technology, while biophysical indicators include irrigation potential, frequency of extreme climatic and land events, changes in temperature and precipitation, topography, and altitude. These indicators were grouped into three categories to reflect the adaptive capacity, sensitivity, and exposure of farm households. Multiple Correspondence Analysis (MCA) was used to develop a vulnerability index for each farm household, ranking them according to their level of vulnerability to the impacts of climate change. Vulnerability was calculated by combining sensitivity and exposure, and then subtracting adaptive capacity. Next, to categorize the level of vulnerability of each farm household, we used the percentile-based classification method. Values below or equal to the 33rd percentile were categorized as very vulnerable, those above the 33rd percentile and below or equal to the 66th percentile were categorized as vulnerable, and finally, those above the 66th percentile were categorized as less vulnerable. The results reveal that Haitian farming households are relatively more individually vulnerable to climate change than Dominican farmers. This heightened vulnerability of Haitian farming households is attributed to their low level of education, limited

access to agricultural credit, and limited farm ownership. In general, the vulnerability of Haitian farming households to climate change is strongly associated with poverty (low adaptive capacity) and mountain farming (high sensitivity). This analysis highlights the disparities in vulnerability between Haitian and Dominican farm households, underlining the importance of specific policies and strategies to strengthen the resilience of farming communities to climate change. Indeed, farming households living in the same geographical area and faced with the same climate risks may present different levels of capacity and vulnerability. Categorizing the level of vulnerability can, thus, help policy-makers identify farming households that are not currently vulnerable but are at a high risk of becoming so in the future. This identification will make it possible to strengthen the adaptive capacities of farm households, while focusing on policies aimed at creating off-farm livelihood opportunities, which will not only improve household cash incomes, but also reduce their dependence on natural resources. Greater financial assets mean more choice in productive investment. However, this needs to be supported by community education, the provision of relevant training, and vocational education to develop the human capacity to utilize existing opportunities and assets. As agriculture remains the mainstay of the community, the development of basic infrastructure such as irrigation facilities is essential. Finally, the construction of all-weather roads linking rural areas to the nearest commercial centers will help to create markets for their agricultural produce and also improve their access to inputs, information, and non-agricultural employment opportunities.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Factor score for the mean in the multiple correspondence analysis of the first and second dimensions of each vulnerability level.

Variable	Acronym	Level Vulnerability	Facteur Comportement
Social vulnerability variables			
Farming experience	EXP	Less vulnerable	0.056
		Vulnerable	0.171
		Highly Vulnerable	0.458

Table A1. Cont.

Variable	Acronym	Level Vulnerability	Facteur Comportement
Member of professional agricultural organizations	OPA	Less vulnerable	2.593
		vulnerable	1.071
		Highly Vulnerable	0.345
Sources of information on climate and weather trends	SIC	Less vulnerable	3.557
		vulnerable	1.189
		Highly Vulnerable	0.526
Level of agricultural training	NFA	Less vulnérable	5.610
		vulnerable	0.793
		Highly vulnerable	0.002
Access to social media for information on climate trends and agriculture	NFS	Less vulnerable	
		vulnerable	1.929
		Highly vulnerable	2.326
Household size	MEN	Less vulnerable	0.040
		vulnerable	0.266
		Highly Vulnerable	0.012
Economic vulnerability variables			
Phytosanitary treatments	THP	Less vulnerable	2.511
		vulnerable	1.363
		Highly Vulnerable	2.056
Extra-agricultural income	REA	Less vulnerable	3.583
		vulnerable	1.149
		Highly vulnerable	0.515
Land status	SFO	Less vulnerable	1.171
		vulnerable	0.478
		Highly vulnerable	0.690
Crop insurance	ARE	Less vulnerable	5.894
		Vulnerable	1.393
		Highly vulnerable	2.559
Livestock owner	PRB	Less Vulnérable	1.689
		Vulnérable	0.625
		High vulnérable	0.980
Land irrigated	IRR	Less vulnerable	3.813
		Highly vulnerable	1.190
		Vulnerable	1.709
Type of fertilization	FER	Less vulnerable	2.398
		vulnerable	1.184
		Highly vulnerable	2.984
Agricultural tools	OUT	Less vulnerable	2.178
		vulnerable	0.563
		Highly vulnerable	0.966

Table A1. Cont.

Variable	Acronym	Level Vulnerability	Facteur Comportement
Economic vulnerability variables			
Agricultural marketing circuit	CC	Less vulnerable	2.469
		vulnerable	1.220
		Highly vulnerable	0.706
Biophysical vulnerability variables			
Altitude	ALT	Less vulnerable	1.529
		vulnerable	0.345
		Highly vulnerable	0.006
Land slope	PEN	Less vulnerable	0.050
		vulnerable	0.458
		Highly vulnerable	0.744
Crop diversification	DIV	Less vulnerable	0.953
		vulnerable	0.018
		Highly vulnerable	1.594
Climatic hazards	ALC	Less vulnerable	1.082
		vulnerable	1.185
		Highly vulnerable	0.013
Telluric hazards	AT	Less vulnerable	0.161
		vulnerable	0.274
		Highly vulnerable	0.041
Rainfall variability	VAP	Less vulnerable	0.831
		vulnerable	1.541
		Highly vulnerable	4.461
Temperature variability	VAT	Less vulnerable	0.676
		vulnerable	1.598
		Highly vulnerable	5.123
Drought	SEC	Less vulnerable	2.383
		vulnerable	1.253
		Highly vulnerable	0.479
Flood	INN	Less Vulnerable	0.616
		Vulnerable	2.247
		Highly Vulnerable	0.689

Source: Computed from HH survey of 2023.

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