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Pathways of Climate Variability, Agricultural Performance, and Conflict: A Machine Learning Approach to Complex Dependencies

Tulia Gattone[a], Donato Romano[a], Luca Tiberti[a,b]

[a]Department of Economics and Management, University of Florence, Italy
[b]Partnership for Economic Policy (PEP), Kenya

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DISEI, Università degli Studi di Firenze
Via delle Pandette 9, 50127 Firenze (Italia)
www.disei.unifi.it

Pathways of Climate Variability, Agricultural Performance, and Conflict: A Machine Learning Approach to Complex Dependencies*

Tulia Gattone[±], Donato Romano[+], Luca Tiberti[§]

Abstract

This study aims to empirically validate the framework proposed by Romano et al. (2025), which links climate variability to conflict through agricultural and market channels. We measure climate variability using the Standardized Precipitation-Evapotranspiration Index (SPEI) and connect it to crop yields, commercialization, household consumption, and conflict outcomes. Using socio-economic data from the World Bank LSMS-ISA project (waves 1–3, 2010–2016), we explore how changes in SPEI affect agricultural productivity, market participation, and household welfare. Our analysis proceeds in three stages. First, we test the hypothesized relationships using predictive machine learning models, mainly Artificial Neural Networks (ANNs), supported by Random Forest, Support Vector Machines, and Naive Bayes to confirm the agricultural channel's predictive power. Second, we use wave 4 of LSMS-ISA (2018–2019) as out-of-sample data using a stepwise ANN model to see if crop yield changes mediate SPEI's effect on conflict. Finally, we focus on causality by applying Causal Forests and Double ML for robustness, identifying varied effects and clarifying the relationships found earlier. Our findings suggest a climate–conflict link shaped by nonlinear effects, agricultural mediation, and differences across local economies.

Keywords: Climate change; Conflict; Machine learning; Artificial neural networks.

JEL codes: Q54; D74; C45; C53.

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[±] Department of Economics and Management, University of Florence, Florence, Italy. *tulia.gattone@unifi.it.*

[+] Department of Economics and Management, University of Florence, Florence, Italy. *donato.romano@unifi.it.*

[§] Department of Economics and Management, University of Florence, Florence, Italy, and Partnership for Economic Policy (PEP), Nairobi, Kenya. *luca.tiberti@unifi.it.*

1. Introduction

Climate shocks and violent conflicts are increasingly connected as global warming worsens. The Intergovernmental Panel on Climate Change (IPCC, 2022) notes that extreme events like droughts, floods, and heatwaves are happening more often and with greater intensity, affecting ecosystems, communities, and livelihoods. At the same time, violence, both state and non-state, is rising worldwide, especially in areas dependent on agriculture and natural resources (Rustad et al., 2024). For example, Sub-Saharan Africa has seen repeated violent clashes tied to competition over resources and disruptions in farming, making it a key region for studying the climate-conflict link (O'Loughlin et al., 2014).

Many studies have found a clear link between climate variability and conflict. Changes in rainfall and temperature raise the risk of violence, especially where people rely on climate-sensitive farming (see, *inter alia*, Hsiang et al., 2013; Koubi, 2019). Harsh weather like droughts and floods often lowers crop yields, increases food insecurity, and worsens economic hardships, which can lead to social unrest and violence (Caruso et al., 2016; Harari & La Ferrara, 2018). Meanwhile, competition for limited resources like water and farmland, made worse by climate scarcity, has been connected to rising tensions and violent conflicts (von Uexkull et al., 2016; McGuirk & Nunn, 2025).

Machine learning (ML), as shown by Letta et al. (2023), offers great potential for climate research by improving empirical analysis and testing theories. Traditional econometric models often assume linear relationships and fixed forms, limiting their ability to capture the complex, nonlinear links between climate variability and agricultural outcomes that affect conflict. ML methods excel at revealing these complexities through data-driven analysis, identifying varied effects and interactions among factors like pre-shock productivity, local adaptation, and climate exposure. This makes ML especially useful for understanding how weather changes impact agriculture and conflict. Techniques like artificial neural networks (ANNs) and deep neural networks (DNNs) have been key in climate research, modeling complex links between climate, agriculture, and conflict. Studies show they can detect nonlinear patterns, such as how climate anomalies raise conflict risks (Ge et al., 2022), monitor land-use changes in conflict areas (Mhanna et al., 2023), evaluate vulnerabilities from combined climate and conflict threats (D'Angeli & Vesco, 2024), and simulate policies to reduce climate-driven conflicts (Montanari et al., 2014).

Although we have made progress in understanding how climate variability relates to conflict, the exact pathways remain complex and not fully clear. Traditional econometric studies, as discussed by Burke et al. (2015), have provided important foundations but often assume linear relationships that may miss the complex, nonlinear links between climate, agriculture, and conflict. To overcome these limits, ML methods have recently become valuable for modeling complex interactions in large datasets (e.g., Athey & Imbens, 2016; Wager & Athey, 2018). For example, random forests are widely used in environmental studies to analyze land changes (see Gislason et al., 2006; Cui et al., 2022), while support vector machines (SVM) have been effective in classifying land cover and assessing agricultural productivity (see Huang et al., 2002; Noi & Kappas, 2018), both important for understanding conflict pathways. Artificial neural networks (ANNs) have also proven good at capturing nonlinear patterns in agriculture and predicting disruptions that may lead to conflict (e.g., Esquivel-Saenz et al., 2024).

This study adds to the literature by combining econometric and ML methods to explore how climate variability may affect conflict through agriculture. We focus on Nigeria, where climate shocks and conflict tend to be especially severe. Using the Standardized Precipitation Evapotranspiration Index (SPEI), we connect climate variability to crop yields, commercialization, household consumption, and conflict outcomes. Our analysis uses detailed microdata from the World Bank's Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA), which includes information on selling chains, helping us examine market participation as a possible way climate impacts the costs of conflict.

The empirical strategy unfolds in three stages. We begin by testing the structure of the hypothesized climate–agriculture–conflict relationships using predictive ML models. ANNs serve as the primary specification, and Random Forest, SVM, and Naive Bayes provide complementary checks on whether the agricultural and consumption channels consistently enhance predictive accuracy. The second stage moves from this initial "skeleton" analysis to a mediation exercise. Using LSMS-ISA wave 4 (2018-2019) as temporal out-of-sample data, we estimate a stepwise ANN model to examine whether variation in crop yields mediates the relationship between SPEI and conflict indicators. The final stage shifts from prediction to causality by applying Causal Forests and Double ML as a robustness check to identify heterogeneous effects and assess whether the pathways suggested by the predictive models remain meaningful when examined through a causal framework.

The paper is organized as follows. Section 2 reviews literature on the links between climate change, agriculture, and conflict. Section 3 explains the theoretical pathways connecting climate variability to conflict through agriculture. Section 4 provides descriptive statistics and data visuals to set the context. Section 5 details the empirical strategy. Section 6 presents the results and their implications. Section 7 offers robustness checks using ML methods. Finally, Section 8 concludes with policy implications and suggestions for future research.

2. Literature review

Climate variability significantly alters the availability of essential resources, such as water, fertile land, and grazing areas, which are critical for agricultural productivity (e.g., Koubi, 2019). In agrarian societies, the reliance on these resources makes communities especially vulnerable to climate-induced scarcity (Almer et al., 2017). Changes in precipitation patterns and temperature anomalies directly affect resource availability, leading to heightened competition for these assets (Fjelde & von Uexkull, 2012). This competition can escalate into localized tensions and, in extreme cases, violent conflicts, particularly in areas where institutional capacity to mediate disputes is limited (Buhaug et al., 2023; Koren & Schon, 2023). Resource depletion caused by climatic shocks often triggers displacement, as affected populations migrate in search of better living conditions (Reuveny, 2007). For instance, drought-driven migration in Syria has been linked to increased social tensions and unrest (Ash & Obradovich, 2020). However, the evidence is mixed; Petrova (2021) found that flood-induced migration in Bangladesh did not significantly increase protest activities in receiving districts, underscoring the context-dependent nature of this dynamic. These findings suggest that the relationship between migration, resource strain, and conflict is mediated by factors such as governance quality and social cohesion (e.g., Myers, 2002).

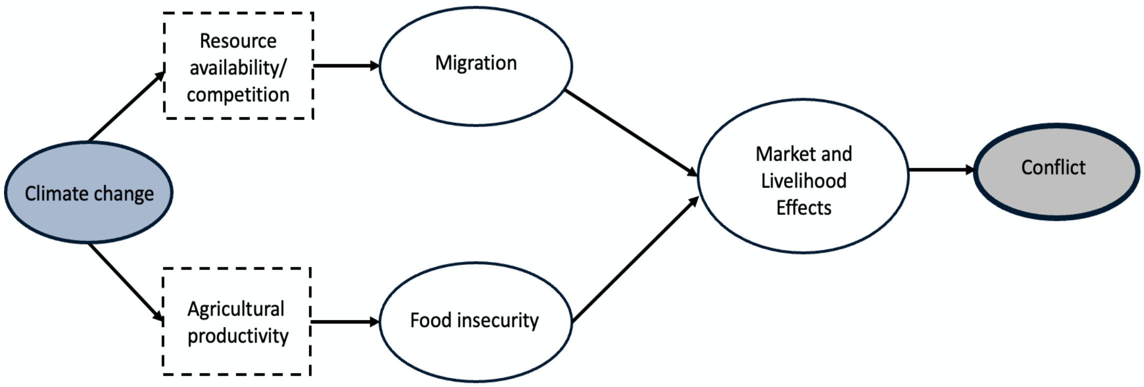
Agricultural systems are highly susceptible to climatic variability, with extreme weather events such as droughts and floods directly reducing crop yields and livestock productivity (e.g., Schlenker & Lobell, 2010; Caruso et al., 2016). These disruptions undermine food security and erode rural livelihoods, increasing the risk of conflict in regions where agriculture is the primary economic activity (Pacillo et al., 2022). For instance, Harari and La Ferrara (2018) demonstrated that lower rainfall during critical growing periods increased conflict risks in African countries between 1997 and 2011. The economic implications of declining agricultural productivity are profound. Reduced agricultural output often leads to higher food prices, placing additional financial strain on vulnerable households (Hendrix & Salehyan, 2012; Vesco & Buhaug, 2020). This dynamic has been observed in Indonesia, where decreases in rice yields during the growing season coincided with an uptick in violent incidents (Caruso et al., 2016). Declining agricultural income, coupled with rising costs for essential goods, creates economic hardships that can fuel grievances and social unrest (see, *inter alia*, Busby, 2018).

Socioeconomic inequalities and ethnic divisions often exacerbate the effects of climate-induced agricultural stress, rendering specific populations more vulnerable to conflict (Almer et al., 2017; Shemyakina, 2022). Unequal access to critical resources often exacerbates tensions, as disadvantaged groups bear a disproportionate share of the burden caused by agricultural disruptions. For example, the uneven distribution of irrigation infrastructure has been linked to disputes between farming communities (Salehyan & Hendrix, 2014). Institutional responses to climatic challenges play a central role in determining conflict outcomes. Regions with robust governance and well-implemented agricultural adaptation policies are better equipped to mitigate the risks of climate-induced instability (Buhaug & von Uexkull, 2021). Conversely, weak institutional capacity can exacerbate vulnerabilities, as governments struggle to address resource conflicts or stabilize agricultural systems (McGuirk & Nunn, 2025). This highlights the importance of governance in shaping the resilience of agricultural systems and communities to climate variability.

Feedback loops further complicate the relationship between climate, agriculture, and conflict. For instance, conflict can disrupt food production, exacerbating the very conditions that led to unrest (George et al., 2020). This bidirectional relationship is particularly evident in regions experiencing protracted conflicts, where repeated cycles of violence and agricultural decline reinforce one another (Wischnath & Buhaug, 2014). Understanding these feedback mechanisms is key for designing interventions that break the cycle of climate-induced instability.

3. The climate change-conflict dynamic via the agricultural sector

Our empirical investigation is based on the pathway framework developed by Romano et al. (2025). Their review brings together ten years of research on climate variability, agrifood systems, and conflict, organizing it into connected steps that show how climate anomalies move through agricultural, demographic, and market channels before leading to social unrest. Figure 1, which we include as the foundation for our study, provides a simplified view of these pathways.



Note: Authors' elaboration from Romano et al. (2025).

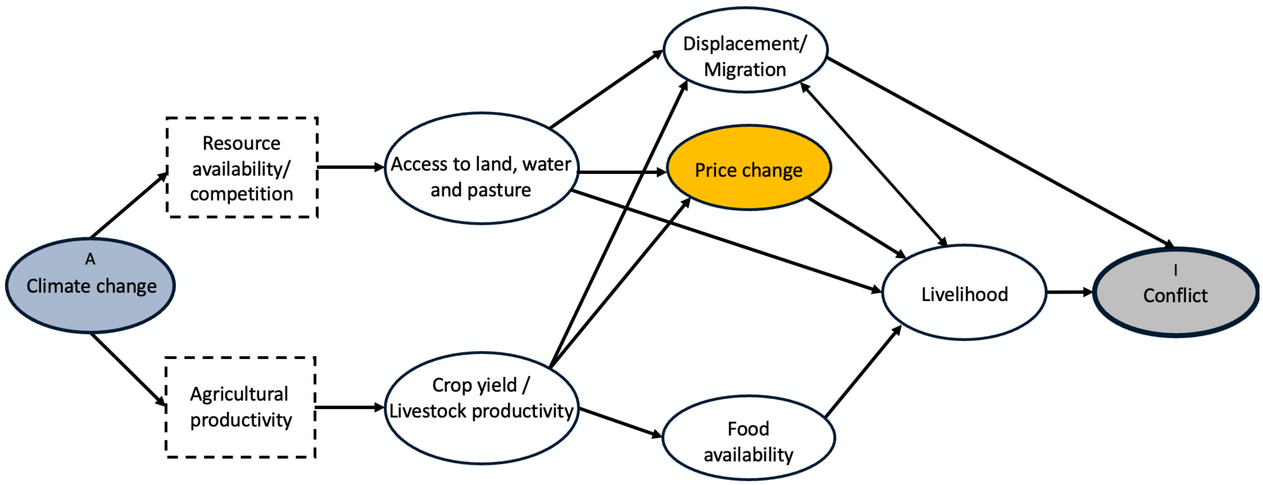
Figure 1. Stylized pathways representation.

The figure above shows climate change triggering two main processes: one related to resource availability and competition, and the other to agricultural productivity. These processes then affect migration and food insecurity, which together impact markets and livelihoods, leading to conflict. This structure is deliberately simplified to highlight key elements, such as resources and agricultural production; migration and food security; markets and livelihoods, while leaving out many contextual factors that might complicate understanding. Even in this simple form, Figure 1 provides a basic framework that supports much of the research on climate, agriculture, and conflict.

The discussion starts with climate variability, often measured by SPEI (see Vicente-Serrano et al., 2010), which summarizes water balance issues like droughts, extreme temperatures, and irregular rainfall. Romano et al. (2025) explain that climate variability triggers two main processes. One affects agricultural productivity by impacting crop yields and livestock health. The other increases competition over limited natural resources. Both are well documented. For example, erratic rainfall, long dry periods, and temperature extremes lower yields and harm livestock (Schlenker & Lobell, 2010; Harari & La Ferrara, 2018). Meanwhile, less water, shrinking pastures, and soil damage raise pressure on land and grazing areas, often causing tensions among groups relying on these resources (see Fjelde & von Uexkull, 2012; Buhaug et al., 2023; Carneiro et al., 2023). In Nigeria, drought-related land shortages have pushed pastoralists southward, leading to conflicts with farmers (e.g., Ikhuoso et al., 2020; Okunade & Kohon, 2023). So, the two starting points in Figure 1 are not just theoretical, they reflect real mechanisms seen in many studies and different environments.

From these initial disruptions, the framework moves to the effects on population and food security caused by climate shocks. Romano et al. (2025) highlight that both resource competition and drops in productivity can lead to increased migration. People may migrate as a way to cope or because they lose their livelihoods (Myers, 2002; Reuveny, 2007). Migration can also happen when conflicts over resources force people to leave. Food insecurity works similarly. When crop yields fall, or herders and farmers struggle to keep their livestock healthy, local food supplies come under pressure (Hendrix & Salehyan, 2012). Studies show that this pressure can cause households to sell livestock in distress, eat fewer calories, or switch to cheaper foods when incomes shrink (Busby, 2018; Vesco & Buhaug, 2020). Romano et al. (2025) link migration and food insecurity because both are middle steps where climate shocks turn into social stresses that affect host communities, job markets, and local governments.

While Figure 1 offers a helpful starting point, Romano et al. (2025) indicate that it overlooks an important mechanism: price dynamics. Their framework, shown in Figure 2, expands the model by adding a price node within the larger migration and food security section.



Source: Romano et al. (2025).

Figure 2. Climate-Conflict Pathways Representation.

Figure 2 puts price change at the center because climate shocks do more than just reduce supply. They also affect relative prices, increase volatility, and change how much households can buy. Market prices can jump sharply due to lower production, transport problems, or shifts in demand caused by migration. By showing price change as a separate factor, Figure 2 makes clear that households experience climate shocks not only through less food availability but also through higher costs for basic foods.

This separation is important when looking at how impacts are spread within rural economies, which are rarely neutral. Households have very different market positions. Net food buyers suffer direct losses from price spikes, while some net sellers might benefit temporarily. McGuirk and Burke (2020) show that price shocks affect conflict dynamics differently depending on whether they come from production or consumption. While climate-conflict studies often focus on scarcity causing grievances, price instability can make these pressures worse, even if availability stays the same. The 2007–2008 global food price crisis showed how sudden spikes can destabilize markets and threaten livelihoods, leading to research that highlights food markets' role, not just production shocks, in vulnerability (Headey & Fan, 2008). Romano et al. (2025) add to this by including price change directly in the agrifood-conflict pathway, which Figure 1 misses but Figure 2 includes.

As the pathway moves from resource availability, production, migration, and prices toward livelihoods, market structure becomes more important. Montalbano et al. (2018) and Gattone (2024) show that market exposure varies among smallholder farmers. Households are part of complex value chains with different levels of integration and access to buyers, intermediaries, and processors. Montalbano et al. (2018) also link market position to welfare outcomes, introducing a "positioning dummy" to show how direct sales to primary markets or private buyers can bring higher profits and reflect better management. This is important for Romano et al. (2025)'s framework because it means the market and livelihood parts in Figures 1 and 2 must consider not just income changes but also differences in how households face market risks. When climate shocks lower yields or disrupt land and water access, households relying on weak market channels see bigger income drops and faster food insecurity. This lowers the cost of joining conflicts, matching findings in conflict studies (see Blattman & Miguel, 2010). On the other hand, households better connected to downstream markets may face fewer problems even with production shocks. So, market structure doesn't just pass shocks along; it shapes how they turn into grievances.

The migration and food security nodes also interact with price change in ways that extend beyond the obvious. Migration can place pressure on food markets and raise local prices in receiving regions. Food insecurity can emerge even in surplus regions if transportation systems, storage facilities, or market intermediaries fail to absorb climatic shocks efficiently. This dynamic is emphasized in Figure 2, which shows price change linking back to both food availability and livelihood conditions. When livelihoods deteriorate, grievances intensify, especially in settings with limited economic diversification. Market downturns, job losses, and sudden increases in staple food prices reduce the opportunity cost of joining violent groups or participating in local disputes, particularly when state institutions lack the capacity to provide support or mediate tensions.

The final node in the structure, conflict, emerges as the culmination of these interlinked mechanisms. Conflict is not conceptualized as the product of any single node but rather as the result of cumulative pressures traveling through climate variability, resource and production constraints, migration and displacement, food insecurity, market disruptions, and price fluctuations. Romano et al. (2025) emphasize that these pressures can reinforce one another. For instance, migration may amplify local resource competition in host regions, while price spikes may worsen food insecurity among displaced populations. Conflict itself creates feedback loops, as demonstrated by Dabalen and Paul (2014), George et al. (2020), and Ecker et al. (2023) who show that violence undermines food production, reduces dietary diversity, and worsens nutrition outcomes. These feedback loops often result in self-perpetuating cycles of vulnerability.

The structure shown in Figures 1 and 2 suggests that the climate–agriculture–conflict link works through layers, and this idea shapes how we build our ANN models. The first layer shows the immediate effects of climate variability, like disruptions in agricultural productivity and increased competition for natural resources. These shocks lead to migration pressures and food insecurity, which most studies have focused on. But as Romano et al. (2025) point out, this first layer only tells part of the story. A second, more complex layer appears when these farming disruptions interact with markets, livelihoods, and price changes. This layer doesn't just add on to the first; it changes how climate shocks spread by affecting household buying power, exposure to food price swings, and unequal market opportunities. Since these factors influence how farming stress turns into social instability, our ANN framework must reflect this two-layer structure: the first hidden layer models the agricultural and resource channels from Figure 1, while the second hidden layer includes market and livelihood factors from Figure 2, like price shocks and value-chain positions. By designing the ANN to match this layered pathway, we can test if the data fit the theory. Confirming this layered structure is a key first step. It lets us check if the data creates a pattern that matches the theory and if climate shocks move through the nodes as expected.

Once the predictive skeleton is confirmed, our empirical strategy shifts to the second task: assigning substantive meaning to these nodes. Here, causal ML tools such as Causal Forests and Double ML allow us to move beyond prediction and examine which pathways carry the climate signal, how heterogeneous these effects may be across households, and whether the intermediary nodes inferred by the ANN correspond to empirically identifiable mechanisms. In this way, the combination of ANN-based skeleton validation and causal ML node identification provides a coherent and theoretically grounded approach for investigating how climate variability may translate into conflict.

4. Data and descriptive statistics

Our analysis uses socio-economic microdata from the LSMS-ISA surveys for Nigeria. We focus mainly on the first three waves (2010–2016) because only they provide the detailed data needed to measure market participation, crop commercialization, and household consumption. These micro-level data show how farming households fit into value chains and how much of their agricultural output reaches the market. This is important for the conceptual framework by Romano et al. (2025) and the commercialization approach by Montalbano et al. (2018) and Gattone (2024). So, the predictive part of the analysis uses only Waves 1–3, since only these years fully track farmers' commercial activities.

All variables are grouped into a 0.5-degree grid, a common method in climate–agriculture studies (Hijmans et al., 2005). This grid approach helps combine different data sources while keeping spatial comparisons accurate. Conflict data come from the Armed Conflict Location and Event Data (ACLED) Project, which records conflict events with exact locations (Raleigh et al., 2010). These events are placed into grid cells and matched with climate conditions during the crop-growing season before the conflict year. This order follows the conceptual framework:

climate stress affects agricultural results, which then influence vulnerabilities related to market access, income, or food security before conflicts occur.

A key part of the climate data is the choice of drought index. We use the standard SPEI in the predictive analysis to support the conceptual framework, while "*SPEI Crop*" values appear in the Appendix to show more detailed, crop-season-specific drought patterns. SPEI Crop, an agricultural drought monitor by Vicente-Serrano et al. (2023), differs from the classic SPEI in two main ways. First, it uses weekly ERA5 reanalysis data and includes crop spatial masks, which lets us directly link climate anomalies to crop growth stages. Second, its finer time scale provides more observations during important agricultural periods, helping us identify when and how severe droughts are.

The socio-economic variables in the analysis cover both agricultural performance and household welfare (see Table 1 below).

Table 1. Main Variables Used.

Variable Name	Definition	Unit of Measurement	Dataset
SPEI	Standardized Precipitation-Evapotranspiration Index, a measure of drought stress	Index (standardized)	SPEI Dataset
avg_YinVCs	Average total crop quantity sold in the market selling/value chain	Kilograms (kg)	LSMS-ISA
avg_total_cons_ann_adj	Average per capita consumption over the last 7 days, averaged over two visits	Local currency unit, per capita (inflation-adjusted)	LSMS-ISA
avg_hhlabor	Average number of household members in the working age (per grid cell)	Number of individuals	LSMS-ISA
avg_nchild	Average number of children per household	Number of children	LSMS-ISA
count_hhid	Average number of households per grid cell	Number of households	LSMS-ISA
conflict_yes_no	Conflict event occurrence dummy	Binary (1 if conflict event exists, 0 otherwise)	ACLED Conflict Event Data

Avg_YinVCs shows the average amount of crops sold along the market value chain in each grid cell, reflecting farmers' commercial focus. This variable comes from the value chain framework by Gattone (2024), which sees market positioning as a series of intermediaries linking producers to buyers. *Avg_total_cons_ann_adj* acts as a proxy for household well-being by measuring per capita consumption adjusted for inflation. Demographic variables like *avg_hhlabor* and *avg_nchild* provide data on household labor supply and dependency ratios, both influencing vulnerability to climate and economic shocks. *Count_hhid,* the number of LSMS households per grid, shows the density of farming communities.

Figures 3 and 4 summarize the spatial and statistical patterns of the main variables. The maps in Figure 3 show clear differences in drought conditions, household distribution, and conflict presence over the survey years. Appendix Figure A.1 confirms that these patterns stay the same when using SPEI Crop instead of the standard SPEI, showing that the spatial differences in climate anomalies are real and not due to the drought indicator chosen.

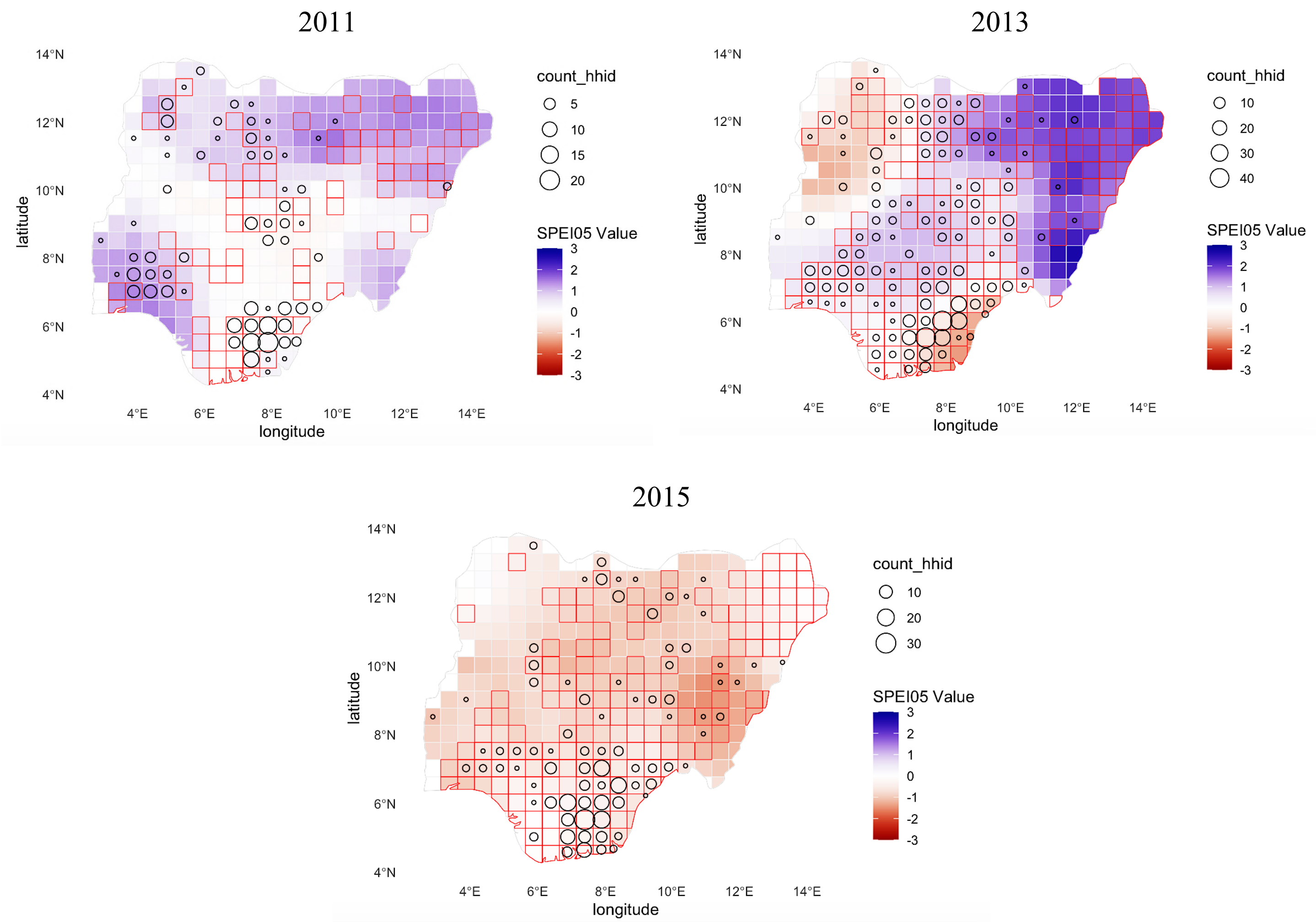


Figure 3. Household Count, Standard SPEI Values, and Conflict Presence.

The 2011 wave shows a mix of wet and dry anomalies, with conflicts mainly in southern and central Nigeria. By 2013, drought conditions worsened, creating clear differences in SPEI values that match conflict-prone areas. In 2015, SPEI showed widespread drought without heavy wet periods, and conflicts gathered in the southern regions where most surveyed households live. Using SPEI Crop (see Figure A.1) instead of the standard SPEI makes the drought and wetness signals clearer, especially in the central and northeastern regions.

Figure 4 shows the distribution of important agricultural and socio-economic variables.

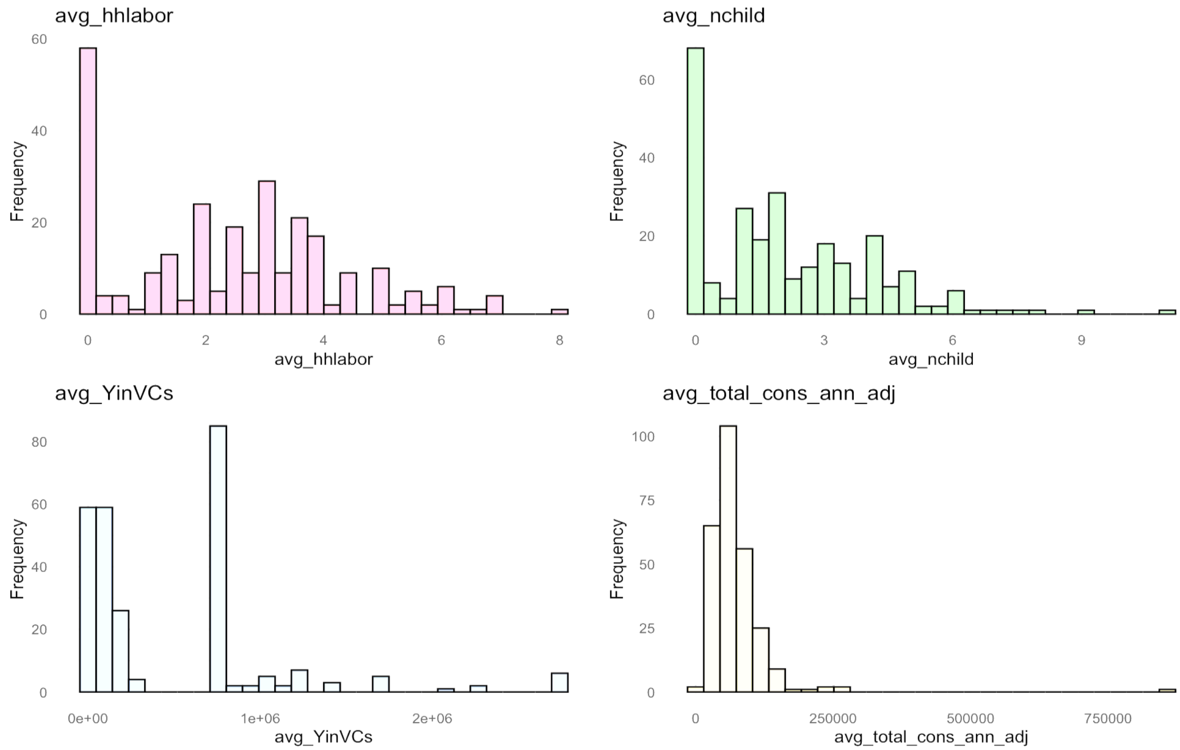


Figure 4. Summary Statistics for the Considered Variables.

The histogram for *avg_YinVCs* shows that most farming households engage in relatively modest commercial activity, consistent with a subsistence-oriented agrarian structure. *Avg_total_cons_ann_adj* displays a heavily skewed distribution with many low-consumption households, underscoring widespread economic vulnerability. *Avg_hhlabor* and *avg_nchild* reveal pronounced demographic heterogeneity. These patterns reinforce the idea that climate shocks interact with pre-existing economic and labor constraints, potentially amplifying livelihood stress in ways consistent with the pathway structure of Figures 1 and 2.

Finally, Figure A.2 in the Appendix disaggregates these variables by conflict status. Conflict-affected grid cells show higher crop commercialization and more variability in consumption, a pattern consistent with the idea that households more exposed to markets may also be more exposed to volatility when climate shocks unfold. This observation aligns with the conceptual pathway that foregrounds market mechanisms, price shocks, and livelihood disruptions at the second layer of Figure 2's structure.

Together, these data provide a coherent micro–macro foundation for testing the skeleton of the Romano et al. (2025) framework using ANN-based predictive models. The inclusion of *avg_crop_yield_mon_adj_ln* in the subsequent stages of our analysis allows us to assess whether agricultural productivity, proxied by crop yield, functions as a meaningful mediator consistent with the second block of the conceptual pathway. The violin plots in Figure A.3 in Appendix show marked differences in the distribution of crop yields across survey years, reinforcing the idea that agriculture is a variable channel through which climate variability may operate.

5. Empirical framework

To examine whether climatic variability affects conflict through agricultural and market-mediated pathways, the empirical analysis begins with a baseline model reflecting the conceptual structure of Figures 1 and 2. The dependent variable is a binary conflict indicator aggregated at the 0.5° grid level, and the specification includes grid and time fixed effects to absorb unobserved heterogeneity.[1] The baseline equation is designed only as a structural anchor; its role is to approximate the blocks of the conceptual skeleton proposed by Romano et al. (2025) rather than to serve as the primary identification strategy:

$$Conflict_{it} = \alpha + \beta_1 avg\_YinVCs_{it} + \beta_2 avg\_total\_cons\_ann\_adj_{it} + \beta_3 SPEI_{it} + \delta' X_{it} + \gamma_i + \tau_t + \epsilon_{it}$$

Here, *avg_YinVCs* captures grid-level commercialization intensity; $avg\_total\_cons\_ann\_adj$ reflects inflation-adjusted household consumption; and SPEI measures climatic stress. The vector X_{it} includes household-level demographic controls such as average household labor supply, number of children, and household size per grid cell. Grid fixed effects (γ_i) absorb time-invariant spatial heterogeneity, while year fixed effects (τ_t) control for aggregate temporal shocks.

Yet the baseline model is only a preliminary step. Given the nonlinear and hierarchical structure of the climate–agriculture–conflict pathway, conventional econometric models are unable to capture the layered dynamics implied by Figures 1 and 2. In particular, mediation effects embedded in the conceptual framework, especially those involving productivity, prices, and household livelihoods, cannot be detected convincingly under standard OLS logic. For this reason, the empirical strategy proceeds in three clearly separated stages.

The first stage uses an ANN implemented with the *neuralnet* package to test whether the observed data follow the two-layer skeleton implied by Figures 1 and 2. This stage draws exclusively on LSMS-ISA Waves 1–3, since only these waves contain information on crop commercialization and selling positions. By comparing the ANN-predicted conflict outcomes with observed patterns, we assess whether climatic shocks propagate through the agricultural and consumption channels in a manner consistent with the conceptual model. The use of ANN at this stage is grounded in the fact that neural networks can learn complex, nonlinear functional relationships without imposing parametric form restrictions; Goodfellow et al. (2016) emphasize that neural networks are particularly effective at learning hierarchical representations.

After testing and validating the skeleton, the second stage turns to the question of whether mediation effects exist. Here, an ANN implemented in *keras* is used to model the layered structure explicitly: the first portion of the network maps climatic variation to agricultural productivity, while the second portion maps agricultural disruptions and consumption losses to conflict incidence. This architecture incorporates the variable *avg_crop_yield_mon_adj_ln*, a monetary-value crop yield measure adjusted for inflation through the consumer price index. This variable captures agricultural productivity more comprehensively than commercialization alone and becomes essential when evaluating whether climate variability generates changes in yields that subsequently affect consumption and conflict. Standard linear models are ill-suited for detecting mediation when relationships are nonlinear or interact across layers; the Keras ANN allows us to assess whether the empirical data support the existence of such channels.

The third stage focuses on causality. We use Causal Forests as developed in Athey et al. (2019). These methods give unbiased estimates of varying treatment effects when unconfoundedness holds and help show how climate shocks, agricultural disruptions, and market exposure impact different ecological zones and livelihood types. We then check the causal forests results with Double ML, following Chernozhukov et al. (2018). This method uses orthogonal estimating equations to reduce bias in complex machine learning models. In our study, Double ML makes sure the causal forests findings reflect real causal relationships rather than patterns specific to the model.

Traditional econometric models like logit, Generalized Additive Models (GAM), and Structural Equation Models (SEM) are included in the appendix. They offer useful descriptive benchmarks but are not the best for testing a hierarchical conceptual pathway. Similarly, random forest, SVM, and Naive Bayes models appear in the robustness checks. Their role is more limited: they confirm that the predictive relationships found by the neural networks are not just due to one modeling choice. Random forest, described by Breiman (2001), captures nonlinear interactions and reduces overfitting by averaging. SVM models find separating hyperplanes in high-dimensional spaces, as explained by Cortes and Vapnik (1995). Naive Bayes provides a probabilistic baseline

[1] SPEI is included as a continuous treatment variable. For estimation purposes, all continuous covariates, including SPEI, are standardized to mean zero and unit variance using the training sample.

assuming independence, as Murphy (2012) describes. These models help make sure the predictive power of the first-stage ANN does not rely on a single modeling approach.

All models use standardized variables to make results comparable across algorithms. This step is essential for neural networks and useful for most machine learning methods. Table 2 lists all the models used and has been updated to include the Keras ANN for mediation analysis, along with the causal forests and Double ML methods in the robustness checks for causal identification.

Table 2. Econometric and ML models used for testing.

Model	Pros	Cons	Function in the Analysis
Classic Econometrics			
Logit Model *(Appendix)*	- Simple and interpretable results - Handles linear relationships well	- Cannot capture nonlinearities - Sensitive to multicollinearity	Baseline comparison with classical econometrics
GAM Model *(Appendix)*	- Flexible to model nonlinear relationships - Interpretable smooth functions	- Computationally intensive for large datasets - Requires careful selection of smoothing parameters	Descriptive benchmark for conflict incidence
SEM Model *(Appendix)*	- Explicitly models indirect paths consistent with conceptual layers	- Requires parametric identification; limited flexibility	- Classical mediation benchmark for Figures 1 and 2
Main ML Econometrics			
ANN1 Model	- Captures complex patterns - Models complex relationships between variables	- Requires substantial data - Low interpretability	- Nonlinear relationship between SPEI and Agriculture
ANN2 Model	- Handles nonlinearities and interactions - Effective for hierarchical relationships	- Difficult to interpret individual contributions	- Nonlinear relationship between Agriculture and Conflict Incidence
Unified ANN Model	- Integrates relationships across multiple stages (SPEI → Agriculture → Conflict)	- Even more data-intensive - High complexity	- End-to-end nonlinear relationship between SPEI, Agriculture, and Conflict Incidence
Causal Forests	- Estimates heterogeneous causal effects	- Requires complex computation	- Identifies causal nodes and heterogeneous climate impacts
ML Robustness Checks			
Random Forest	- Robust to overfitting - Handles nonlinear relationships and interactions well	- Limited interpretability of individual predictions - Computationally expensive	- Confirms predictive patterns across models
Naive Bayes	- Fast and efficient - Works well with categorical and binary data	- Assumes feature independence - Can perform poorly with complex interactions	- Confirms whether predictive patterns persist even under restrictive assumptions
SVM	- Effective in high-dimensional spaces - Handles nonlinearities with kernel functions	- Sensitive to the choice of kernel and parameters - Computationally expensive	- Confirms nonlinear predictive boundaries
Double ML	- Reduces bias in causal estimation	- Sensitive to nuisance estimates	- Robustness check for causal forests

6. Results and Discussions

The classical econometric results are reported in Appendix Tables A.1. and A.2. These models retain all household-level controls, grid and time fixed effects, and the number of households per grid, and they offer a transparent starting point. Yet their limitations are evident: each specification struggles to accommodate nonlinearities, layered transmissions, and feedback loops that are essential to the climate–agriculture–conflict nexus.

6.1. Predictive Analysis

The unified ANN is constructed explicitly to reproduce the layered theory represented in Figures 1 and 2. Figure 5 presents the empirical ANN architecture corresponding to Figure 1, the two-layer skeleton.

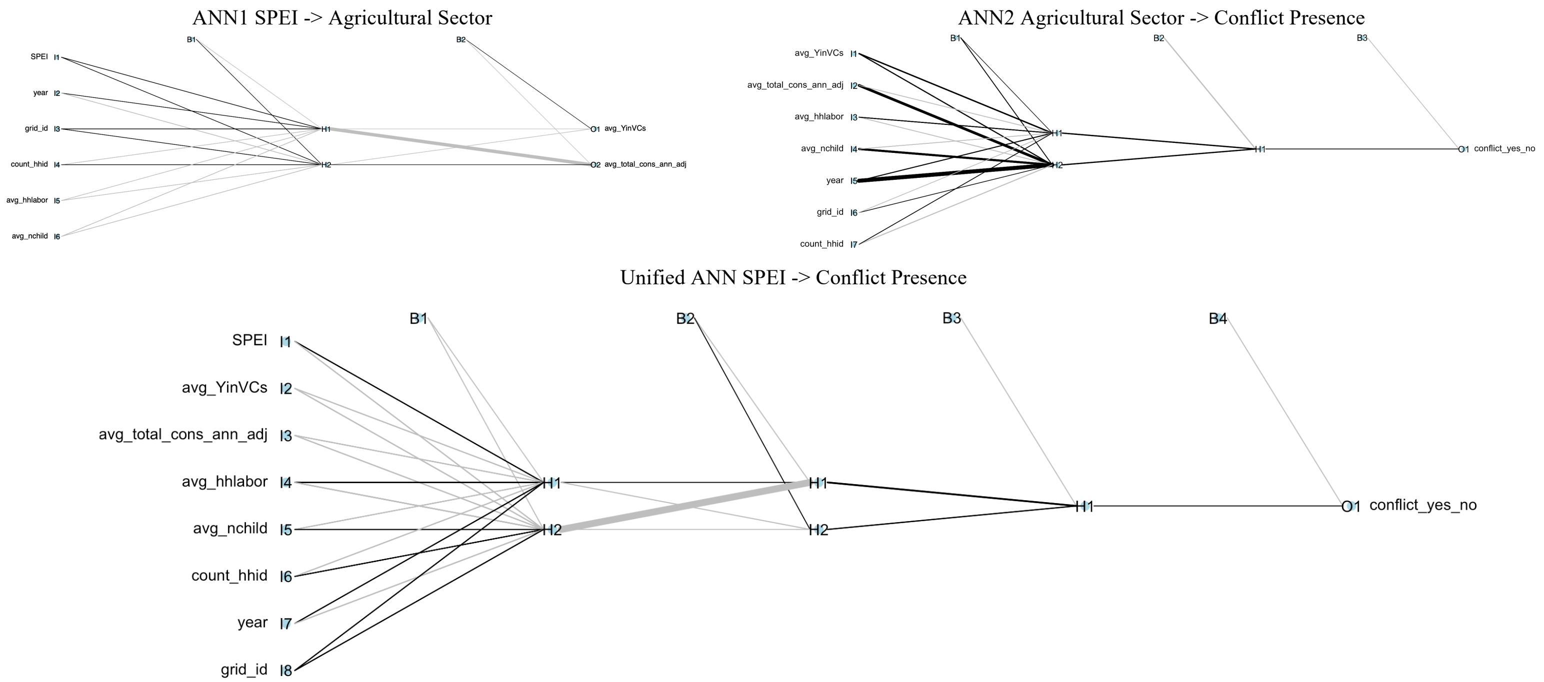


Figure 5. ANN SPEI -> Agricultural Sector

In Figure 5, the hidden nodes H1 and H2 act as the first layer of aggregation, absorbing climate variability through SPEI together with demographic and spatial controls. What stands out is the consistent strength of the connections emanating from SPEI. The thickness of the edges illustrates how the model learns that these inputs anchor the first-stage transformations. This pattern appears consistent with the conceptual intuition that climate anomalies affect agriculture and livelihoods before influencing other socio-economic channels. The fact that this node emerges as dominant, despite being entered on equal footing with all other predictors, suggests that the ANN internally reconstructs the theoretical ordering: climate first, agricultural and livelihood conditions second.

The second representation (Figure 6), aligned with the extended structure in Figure 2, highlights deeper structural differentiation. Here, the network forms three sequential hidden layers rather than a single intermediary bridge.

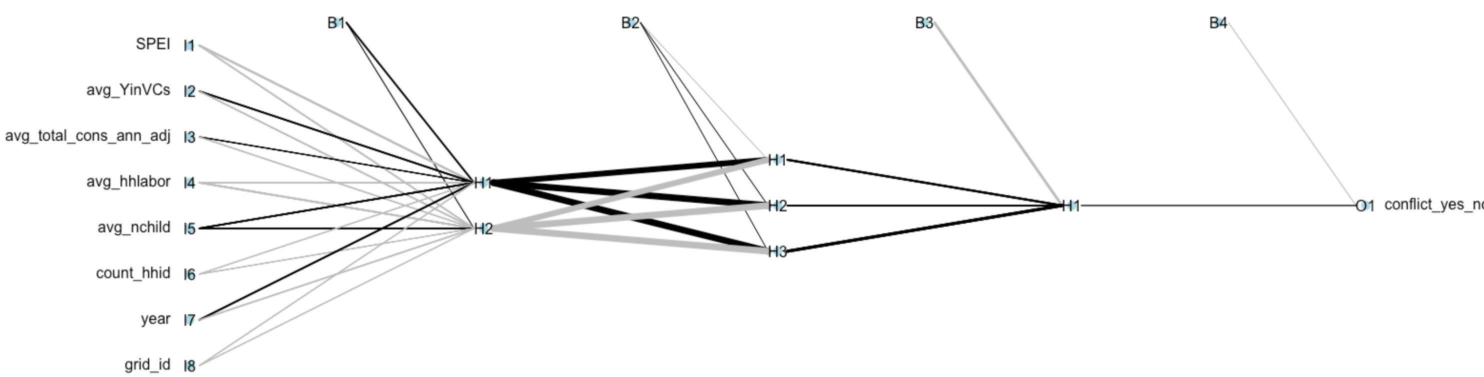


Figure 6. ANN SPEI -> Agricultural Sector (with Price node)

The emergence of a third hidden node (H3) is particularly revealing. Its activation patterns show that the ANN distinguishes agricultural quantity (*avg_YinVCs*) from welfare dynamics (*avg_total_cons_ann_adj*), suggesting a division that maps closely onto the price/market layer introduced in Figure 2. In other words, once the ANN is forced to solve the predictive task, it learns that commercialization and consumption belong to distinct mechanisms, and that each transmits climate shocks differently. This distinction is not imposed; it arises organically from the training process, lending empirical weight to the two-layer conceptual framework.

Across both ANN structures, the relative thickness of the edges connecting H1–H2–H3 to the output layer shows that the network attributes most of the predictive burden to the nodes that summarize agricultural and welfare conditions. The final hidden layer before the conflict node (O1) consistently receives its strongest signals from the nodes that combine SPEI with market-mediated mechanisms. This suggests that the ANN "recognizes" that conflict incidence is less about climate anomalies per se and more about how those anomalies translate into disruptions in farming output, market transactions, and consumption smoothing.

The predictive accuracy patterns in Figure 7 reinforce this interpretation.

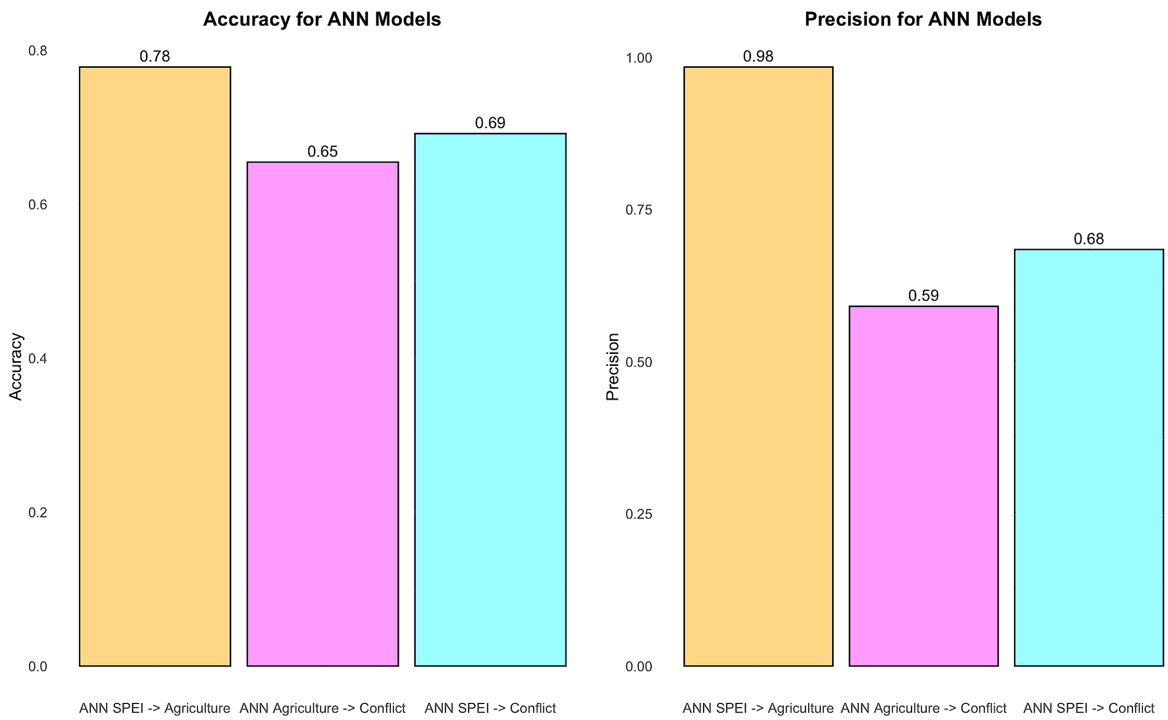


Figure 7. Performance Metrics ANN Models.

The ANN that implements the first layer of the skeleton (SPEI → Agriculture) achieves the highest accuracy and precision. This is consistent with the idea that the climate shock mechanism is the most statistically stable component of the system. Climatic anomalies have a comparatively direct effect on agricultural outcomes, and the ANN identifies this relationship with little ambiguity.

Once agricultural performance is linked to conflict (Agriculture → Conflict), accuracy decreases. This drop may reflect the noisier nature of conflict processes, which rarely depend on a single mechanism. Yet the ANN still extracts a clear predictive structure, with performance above classical methods and with precision far higher than expected for such a sparsely distributed outcome.

The unified ANN (SPEI → Agriculture → Conflict) strikes a balance. Its accuracy remains high enough to suggest that the conceptual skeleton contains real statistical content, while its precision indicates that the model extracts meaningful mappings across layers. The fact that the unified ANN performs better than classical econometric baselines is not trivial. It offers indirect confirmation that the ANN is indeed capturing the two-layer structure suggested by Figures 1 and 2. The pattern across models suggests that the skeleton is not simply a narrative device; it carries predictive value. Each layer contributes information that the ANN identifies and organizes in ways consistent with the theory. In that sense, the structure appears to be empirically learnable, or at least not arbitrary. The hidden nodes act like empirical confirmations of the theoretical nodes: climate effects, agricultural adjustments, and market-mediated livelihood dynamics. The fact that the ANN reconstructs this hierarchy without being explicitly instructed to do so is difficult to dismiss as coincidence.

As an alternative specification, the main model was re-estimated using SPEI Crop. The results, presented in Figures A.4 and A.5 in the Appendix, broadly confirm the two-layer structure, though with some variation in magnitude and direction. In the ANN1 model, *SPEI_crop* displays a strong influence on agricultural outcomes, reinforcing the role of seasonal drought in limiting agricultural productivity. In ANN2, *avg_YinVCs* remains a dominant contributor to conflict risk, while *avg_total_cons_ann_adj* has a more negligible effect. In the unified ANN model, *SPEI_crop* continues to be influential, suggesting that even when mediated through agricultural and livelihood channels, crop-period climate shocks are associated with increased conflict risk. Performance metrics in Figure A.5 confirm the reliability of this specification: the unified ANN achieves an accuracy of 0.73 and a precision of 0.65.

Once this skeleton is established, the analysis turns to the stepwise ANN in Keras. Unlike the unified model, the stepwise design examines each block separately and sequentially. The first step models the effect of SPEI on crop yield; the second step uses the predicted yield values to estimate consumption; the third step passes predicted consumption into the conflict module. The Keras architecture follows the order of the conceptual pathway but does not collapse all relationships into a single structure. This approach allows us to examine the existence of mediation effects in a nonlinear setting. Ordinary least squares cannot detect such mediation reliably, as it imposes linearity and cannot disentangle the way nonlinear shocks propagate across intermediate layers. The stepwise ANN in Keras, by contrast, tracks whether predictions at each stage maintain explanatory power when passed downstream. The use of LSMS-ISA Wave 4 as a temporal hold-out set allows an external examination of the climate→yield→consumption→conflict chain.

6.2. Mediation Analysis

The mediation analysis relies on the fourth wave of the LSMS ISA (2018-2019), which is used as a temporal hold-out sample following Cerqua et al. (2024). This wave does not contain the detailed commercialization variables that are central in the first three waves, so the model substitutes them with a more general measure of agricultural output: crop yield. This substitution allows us to examine agricultural productivity directly, which is essential once the goal shifts from validating the skeleton to testing whether the agricultural channel mediates the effect of climate on conflict outcomes. The analysis proceeds in three connected steps. In the first step, ANN1 estimates how variation in SPEI influences crop yield. In the second step, ANN2 uses the predicted values of crop yield to model household consumption. In the third and final step, ANN3 passes the predicted consumption values forward to estimate the likelihood of conflict occurrence. Rather than three independent networks, this architecture treats each step as feeding into the next, which preserves the causal ordering implied by the conceptual framework.

Figure 8 presents the loss and Mean Squared Error (MSE) curves for each stage.

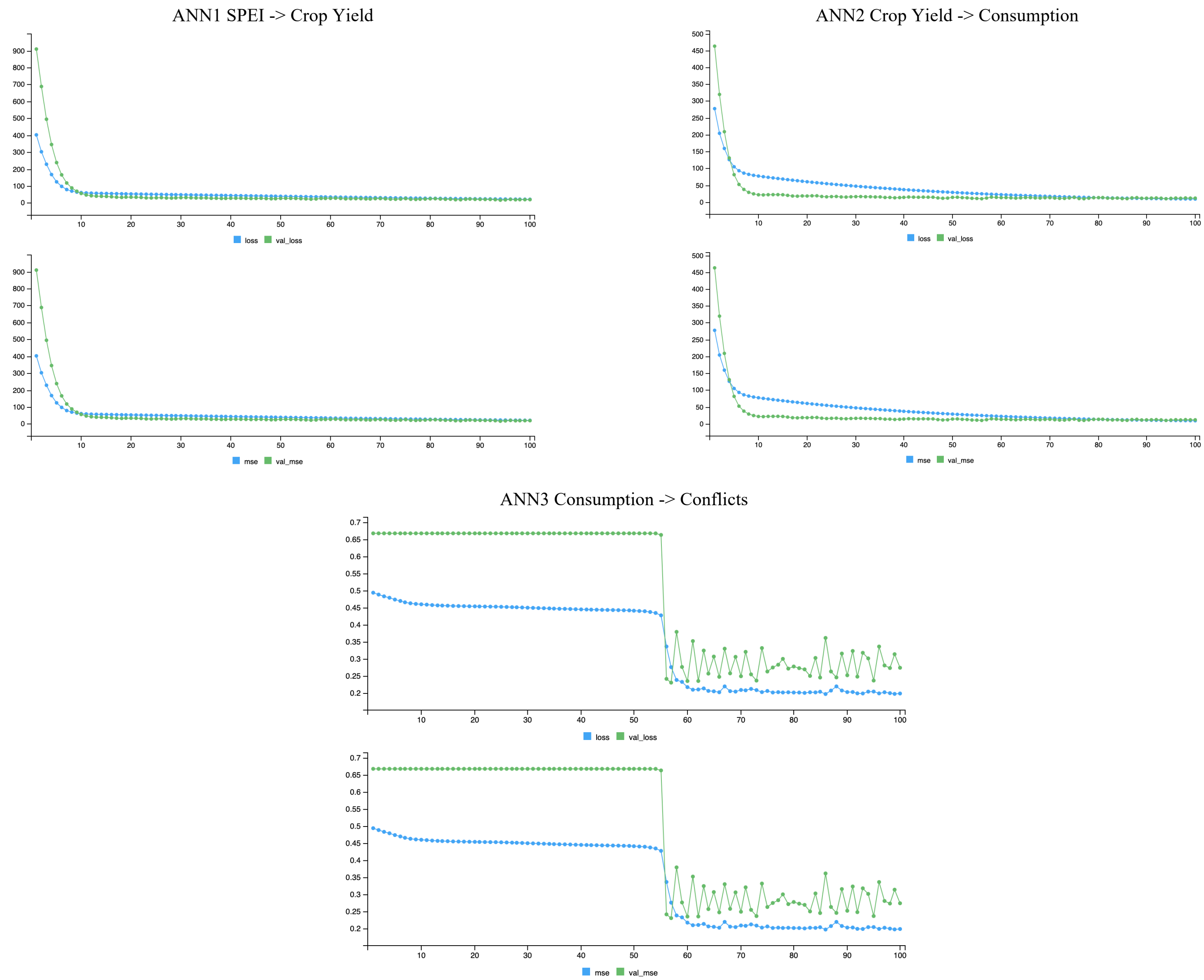


Figure 8. ANN Stepwise Keras

ANN1 and ANN2 show quick drops in both loss and mean squared error (MSE), then settle into stable convergence. This means they consistently learn the links from SPEI to crop yield and from crop yield to consumption. ANN3 shows more variation in validation metrics, especially after epoch 60, but the overall downward trends in loss and MSE suggest there is an underlying pattern rather than just random noise. The higher instability in ANN3 is expected because conflict is affected by a mix of climate, agricultural, and socio-economic factors that household survey data only partly capture.

A direct comparison with the unified ANN Keras model, shown in Figure A.6 in the Appendix, helps clarify why the stepwise design performs better. When all variables are introduced at once, the unified model shows learning but its validation loss and MSE oscillate sharply. This instability suggests that directly estimating the combined climate, agricultural, and consumption effects on conflict in a single architecture may obscure the sequential nature of the transmission mechanism. The model tends to overfit the training sample and struggles to generalize. This pattern fits with the idea that the climate-agriculture-conflict nexus may require the network to respect the causal ordering to recover a stable signal. The stepwise ANN avoids this problem by giving the model only the relevant part of the process at each step. This design fits better with the theory, where climate variability first affects yields, then household welfare, and finally conflict outcomes. This likely explains why all three networks converge more smoothly and have lower validation errors. It also highlights the mediation process: SPEI affects crop yield, crop yield influences consumption, and consumption impacts conflict. The predictive learning seen at all three stages supports the idea of this mediation channel.

The SEM models in Figure A.7 offer a useful benchmark. They represent a classical approach to mediation, estimating linear paths from SPEI to crop yield, crop yield to consumption, and consumption to conflict. Across the three specifications, the coefficient linking SPEI to crop yield is negative but not statistically significant, and the link from crop yield to consumption is small and mostly insignificant. The consumption to conflict path is marginally significant only in one of the three models. This mixed pattern shows how sensitive linear models are to specification choices and how strongly their results rely on strict functional form assumptions.

Yet, the ANN Keras architecture does not impose linearity and captures the nonlinearities and thresholds that the SEM is unable to detect. The differences in performance between the direct unified model and the stepwise design also point toward a layered mechanism. The fact that ANN1 and ANN2 converge cleanly while ANN3 shows more noise is consistent with the idea that the later stages of the mediation chain involve more complex processes.

6.3. Causal Analysis

The final stage of the analysis turns from prediction to causality. After validating the two-layer structure with the ANN models, we use Causal Forests as reinterpreted by Letta et al. (2023, 2024) to identify the heterogeneous treatment effects of SPEI on conflict and, in doing so, to assign substantive meaning to the nodes revealed in the predictive skeleton. This step matters because the earlier ANN analysis could tell us which pathways were active, but not why or for whom they mattered. Causal forests allow us to probe the distribution of treatment effects across local economic and agricultural conditions, which provides a way to label the hidden nodes that the predictive framework had already hinted at.

Figure 9 presents the distribution of the estimated individual treatment effects of SPEI on conflict.

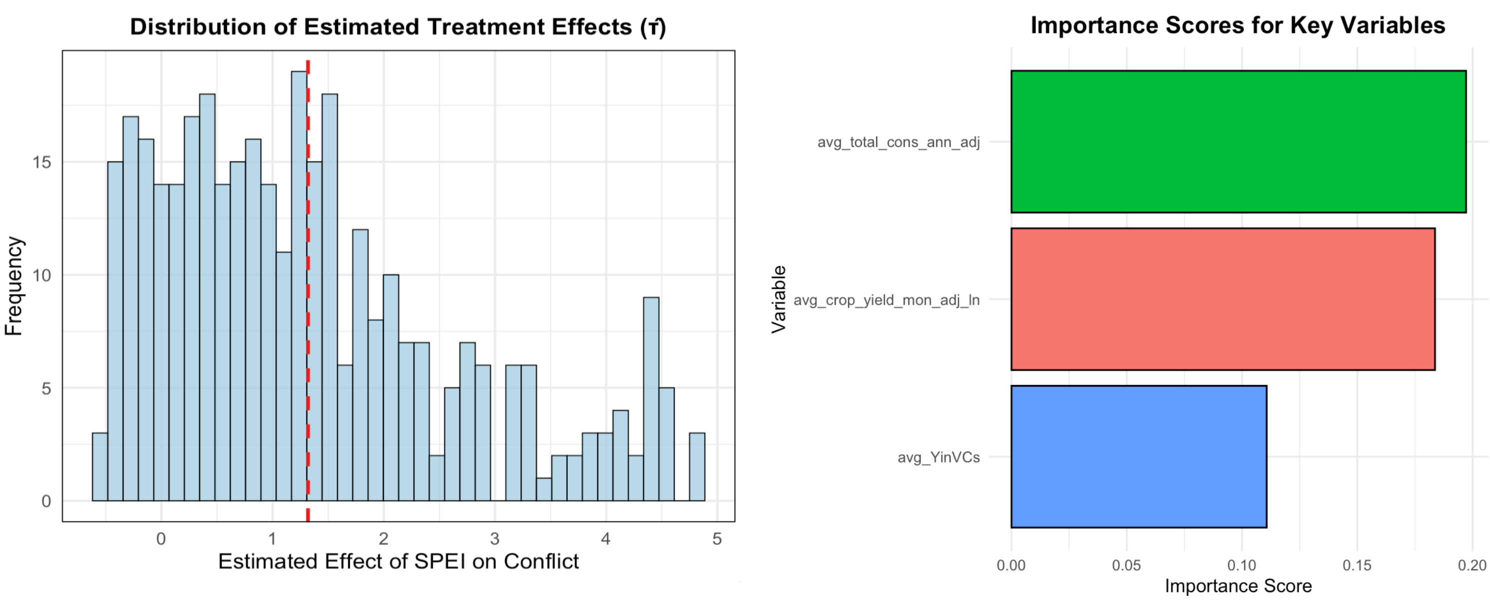


Figure 9. Causal Forests Results

The estimates vary widely across observations, which appears consistent with the idea that climate shocks do not affect all areas or households in the same way. Most treatment effects fall between zero and two, with a mode just above one. The red vertical line marks the average treatment effect, highlighting that while the mean effect is positive, a nontrivial share of observations lie well above or below that value. This dispersion provides preliminary evidence that the climate-conflict relationship is heterogeneous and that such heterogeneity is structured by agricultural and consumption conditions rather than by uniform responses. In other words, the forest suggests that there are latent subgroups whose economic and agrarian characteristics amplify or dampen the effect of climatic stress, which aligns with the structure suggested by the ANN predictive models.

The variable importance scores in causal forests, shown in the second panel of Figure 9, help clarify which economic variables drive this heterogeneity. Household consumption and crop yield adjusted in monetary terms emerge as the two most important predictors of treatment heterogeneity, followed by crop commercialization. This ordering gives us a first indication of how the nodes in the ANN skeleton should be interpreted. What the predictive model treated as abstract hidden units now become concrete mechanisms: agricultural productivity, market participation, and household welfare jointly structure the way climatic variability translates into conflict.

Figure 10 provides further insight into how these three mediators shape the treatment effect. The first panel displays the estimated treatment effect of SPEI across levels of crop yield.

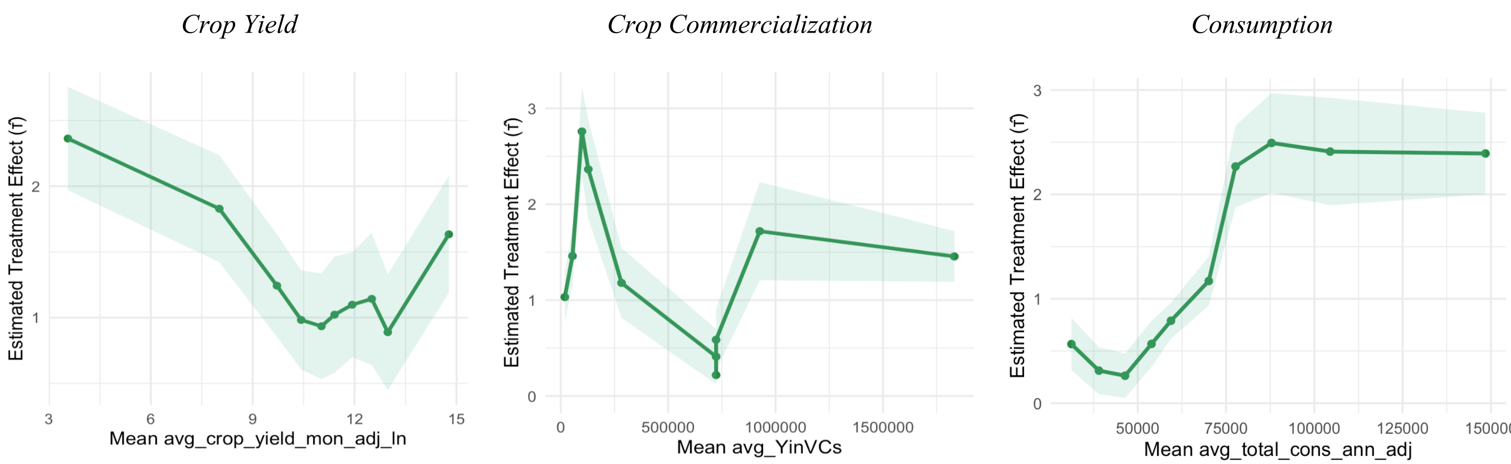


Figure 10. Conditional Average Treatment Effect (CATE)

The negative slope suggests that when yields are low, climatic anomalies translate into relatively large increases in conflict risk, while higher yields dampen this effect. This pattern may indicate that households with lower productivity have fewer buffers against climatic shocks, making them more sensitive to disruptions. As yields rise, the treatment effect of climate declines and eventually stabilizes. This result assigns a clear meaning to one of the ANN nodes: the agricultural productivity node represents a buffering mechanism that weakens the climate-conflict relationship as productivity improves.

The second panel of Figure 10 examines how the treatment effect varies with crop commercialization. Here the treatment effect is largest at very low levels of commercialization, declines sharply as commercialization increases, and then rises again at higher levels. This non-monotonic pattern suggests that market participation generates both protective and vulnerability mechanisms. Households with almost no engagement in markets may be particularly exposed to climatic variability because they rely heavily on their own production and lack access to external buffers. As commercialization increases, households gain access to markets that help smooth risks, which appears to reduce the treatment effect. Yet at high commercialization levels, exposure to price volatility or supply chain shocks may create new vulnerabilities, making the climate-conflict link stronger again. This nonlinear shape reflects the hypothesized second layer of Figure 2, where market structures mediate how climate shocks propagate.

The last panel of Figure 10 turns to household consumption. Here the estimated treatment effect first declines at lower consumption levels, then rises steeply around the middle of the distribution, and eventually stabilizes at the upper end. This pattern may indicate that extremely poor households have little to lose and thus do not react as strongly to climate shocks in conflict terms, while households with moderate and rising consumption face higher exposure to market fluctuations, price shocks, or resource pressures. At very high consumption levels, the effect appears to reach a saturation point where additional wealth no longer intensifies the response to climate stress.

Even so, these heterogeneous treatment effect patterns give us the language needed to interpret the nodes in the predictive framework. The agricultural productivity node corresponds to the buffering role of higher yields. The commercialization node reflects a nonlinear vulnerability mechanism driven by market exposure. The household consumption node embodies livelihood fragility and saturation dynamics. The results from causal forests thus complete the empirical narrative: what the ANN skeleton identified as abstract functional intermediaries now reveal themselves as concrete economic channels through which climatic variability shapes conflict risk.

Table 3 brings together the main results from the three stages of the empirical strategy. The first stage focuses on prediction and examines whether the ANN structure reflects the conceptual skeleton linking climate variability to agricultural performance and eventually conflict. The second stage turns to mediation, using the stepwise ANN in Keras to assess whether the SPEI effect on conflict operates through agricultural productivity and household welfare. The final stage uses Causal Forests to attach substantive meaning to the hidden nodes identified in the predictive exercise. Across these stages, the evidence points to a layered climate–agriculture–conflict relationship in which agricultural productivity, commercialization, and household consumption serve as key transmission mechanisms.

Table 3. Summary of results.

Stage of Analysis	Model / Relationship	Main Findings	Interpretation and Contribution
Prediction: Validating the Skeleton	ANN1 (SPEI → Agriculture)	SPEI consistently shows a strong contribution to agricultural outcomes, including commercialization and consumption.	Confirms that climate variability directly affects agricultural productivity. ANN captures nonlinearities and thresholds not visible in Logit or GAM.
	ANN2 (Agriculture → Conflict)	Higher commercialization and higher consumption predict a greater likelihood of conflict, with nonlinear patterns.	Suggests that market exposure and livelihood conditions shape vulnerability to climate shocks. Reveals interactions missed in classical regressions.
	Unified ANN (SPEI → Agriculture → Conflict)	SPEI is associated with conflict once agricultural and consumption channels are included.	Indicates a mediated pathway. The sign reversal of SPEI supports the two-layer structure suggested by Romano et al. (2025).
Mediation: Testing the Agricultural Channel	Stepwise ANN Keras (SPEI → Crop Yield → Consumption → Conflict)	ANN1 and ANN2 converge smoothly. Crop yield predicts consumption, and consumption predicts conflict. ANN3 shows more noise but still learns a structured relationship.	Provides empirical support that the effect of climate on conflict operates through agricultural productivity and household welfare. The sequential architecture aligns with the conceptual mediation chain.
Causality: Naming the Nodes	Causal Forests (Heterogeneous Treatment Effects)	Treatment effects vary widely. Average effect slightly above one, but distribution reveals strong heterogeneity.	Confirms that climate does not affect all households equally. Highlights the need to interpret hidden ANN nodes as distinct economic channels.
	Variable Importance (Yield, Commercialization, Consumption)	Consumption and crop yield are the strongest mediators, followed by commercialization.	Provides substantive meaning to the ANN nodes. The most influential channels are agricultural productivity and welfare.
	Conditional Treatment Effects (Partial Dependence)	1. Treatment effect declines as yield rises. 2. Effect strongest at low commercialization, dips, then rises again at high commercialization. 3. Treatment effect grows with consumption until plateauing at high levels.	Identifies three distinct mechanisms: buffering by higher yields, nonlinear vulnerability across commercialization levels, and livelihood saturation in consumption. Gives economic identities to the predictive skeleton.

7. Robustness checks

The robustness checks conducted in this study serve to validate the findings of the ANN models and their alignment with classical econometric approaches, ensuring that the results are both statistically sound and theoretically consistent. The goal is not to outperform the ANN but to verify whether the same variables retain predictive relevance when the functional form changes. In that sense, these checks speak directly to the stability of the predictive layer of the conceptual framework.

Figure 11 depicts a decision tree constructed using the main agricultural variables, namely SPEI, *avg_YinVCs*, and *avg_total_cons_ann_adj*.

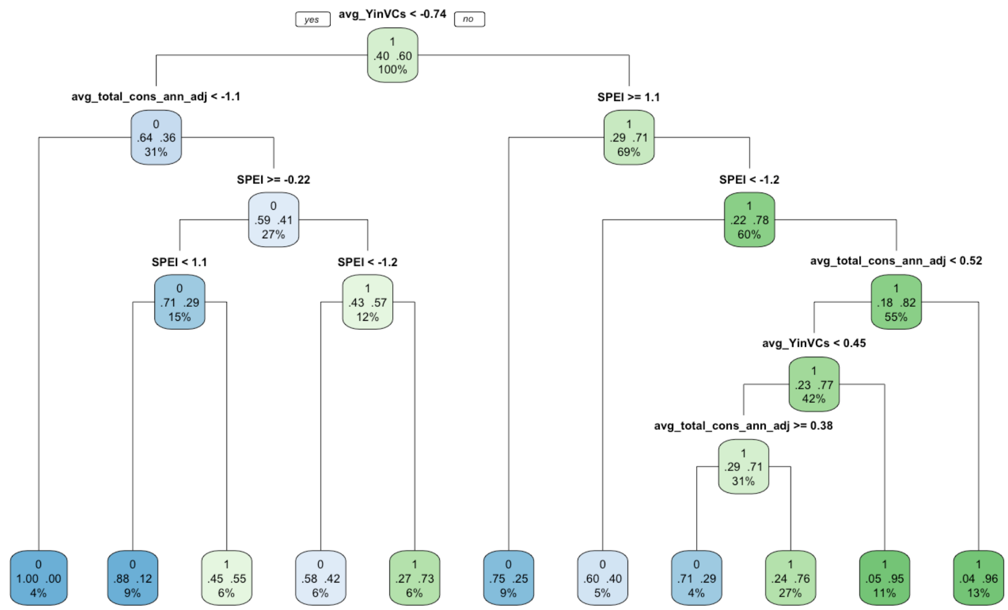


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Figure 11. Decision Tree with Main Agricultural Variables

The tree offers a transparent view of the inferred decision structure. The root node splits on *avg_YinVCs*, suggesting that commercialization intensity is the most informative initial discriminator for conflict risk. Subsequent splits involve SPEI and household consumption. Several thresholds display an interpretable pattern: for instance, SPEI values below roughly minus 1.2 combined with low consumption sharply increase predicted conflict presence. The tree's sequential logic mirrors the layered dynamics observed in the ANN skeleton, where climate variability feeds into agricultural and livelihood pressures before manifesting in conflict outcomes. Its clarity reinforces the plausibility of the pathways identified in the main predictive analysis.

Figure 12 presents the importance scores of the variables *SPEI*, *avg_YinVCs*, and *avg_total_cons_ann_adj* across three ML models: Random Forest, Naive Bayes, and SVM.

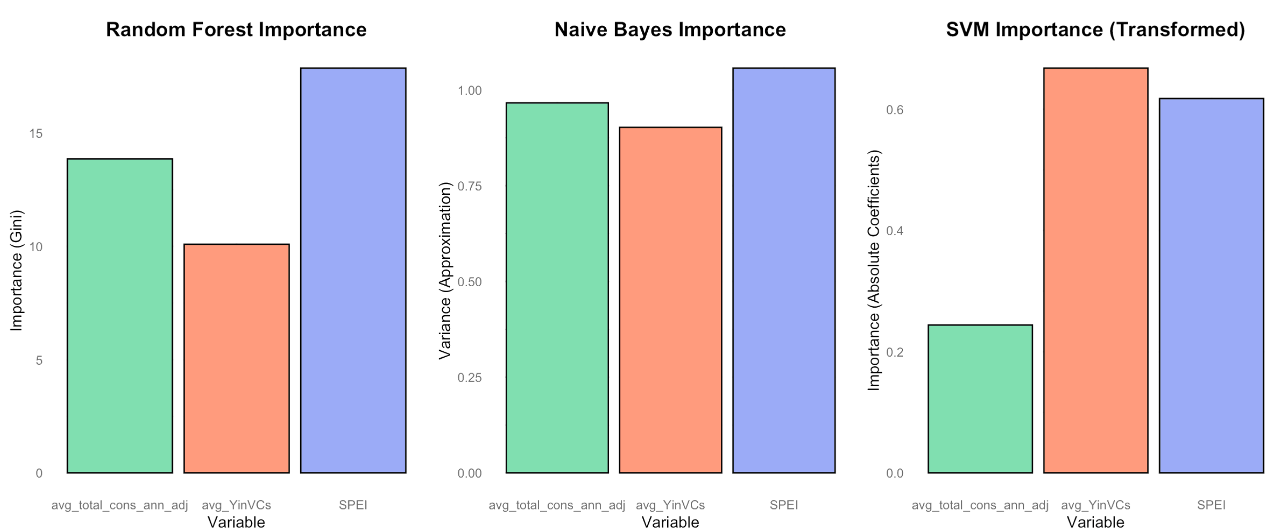

Figure 12. Importance Scores per Model

Across the three models, the ordering varies slightly, yet all consistently attribute meaningful predictive weight to SPEI, *avg_YinVCs*, and *avg_total_cons_ann_adj*. Random Forest places SPEI first, highlighting climatic variability as the most influential feature in nonlinear tree-based models. Naive Bayes produces a more even distribution of importance scores, though consumption retains a slight edge. SVM prioritizes *avg_YinVCs*, indicating that commercialization intensity provides the strongest separating surface under the radial-kernel classification. The modest differences across these three methods are informative: they suggest that while the ANN captures more complex structures, the core variables remain robust drivers regardless of algorithm.

Figure 13 compares the accuracy and precision metrics across these benchmark models.

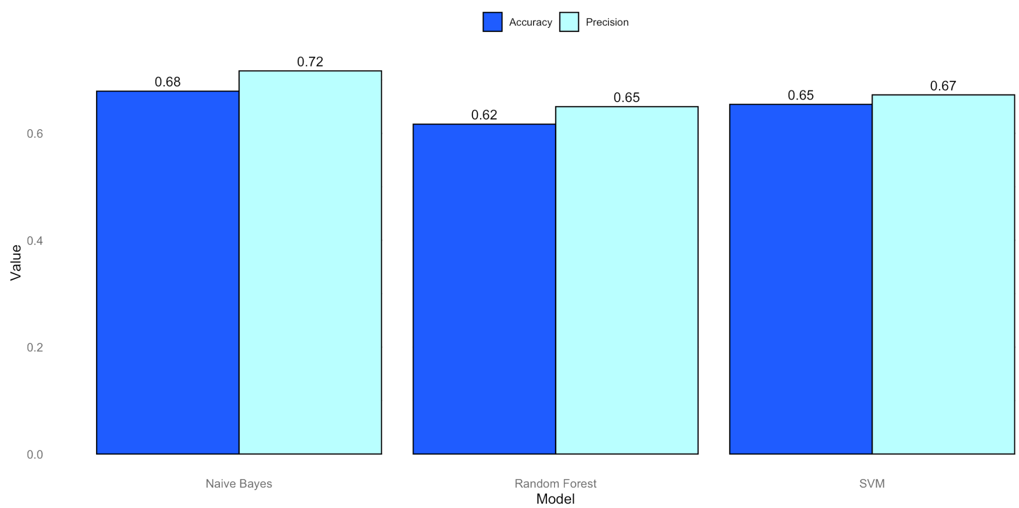

Figure 13. Accuracy and Precision Metrics for Each Model

Naive Bayes achieves the highest precision (0.72) and maintains competitive accuracy (0.68), making it the most effective in correctly identifying conflict cases. SVM balances accuracy (0.65) and precision (0.67), while Random Forest performs slightly lower on accuracy (0.62) but with similar precision (0.65). These levels are close to the ANN results, though consistently below them. This pattern aligns with the ANN's strength in capturing nonlinear interactions and hierarchical relationships, yet the fact that the alternative models reach similar accuracy ranges strengthens the claim that the relationships uncovered in the ANN are not spurious.

For transparency, the robustness checks were implemented as follows. Random Forest used 100 trees and three predictors at each split (via *randomForest*). A Decision Tree was estimated using rpart to provide an interpretable structure. The SVM employed a radial kernel with 10-fold cross-validation to refine hyperparameters. Naive Bayes was estimated using *e1071* with default hyperparameters. Confusion matrices were used to calculate accuracy and precision for each model. These technical choices ensure a fair comparison with the ANN models and avoid overfitting.

These robustness exercises confirm that the predictive structure identified by the ANN is stable across fundamentally different classification approaches. The decision tree's conditional thresholds reflect the same two-stage progression from climate variability to agricultural disruption and conflict. The variable importance analyses echo the ANN's internal hierarchy, in which SPEI, commercialization, and consumption emerge as the main discriminators. Accuracy and precision levels across models remain within tight bounds, suggesting that the ANN's predictive signal is not sensitive to the choice of algorithm.

The final stage of the robustness tests turns from prediction to mediation and causality. The purpose of the Double ML analysis is therefore to test whether the nodes uncovered in the ANN skeleton, and later reinforced by the stepwise Keras mediation architecture, reflect causal transmission channels rather than predictive artefacts. In this sense, causal forests and the multi-mediator Double ML exercise allow us to assign substantive names to the ANN hidden nodes: the data-driven layers that the neural network appears to construct correspond, in the causal framework, to climate-induced yield shocks, market participation constraints, and consumption instability.

This Double ML component proceeds by estimating, in a sequential manner, each of the structural equations implied by the hypothesized transmission chain. Random Forest learners (implemented via *mlr3*'s *regr.ranger*) flexibly partial out confounding variation, while orthogonalization ensures that the estimated coefficients on each mediator reflect local causal effects rather than spurious associations. This procedure follows the partially linear regression logic discussed by Chernozhukov et al. (2018) but extends it to multiple ordered mediators following Zenati et al. (2025). In doing so, it mirrors the conceptual architecture of Figures 5 and 6 (predictive skeleton with and without prices) while allowing each sub-path to be estimated in a manner robust to high-dimensional confounding and nonlinearities.

The analysis is conducted twice. The first specification excludes crop yield and therefore captures only the market-based segment of the mediating chain. The second introduces the full ordered structure: SPEI affects crop yield; crop yield influences commercialization; commercialization shapes household consumption; and consumption alters the probability of conflict. The comparison between these two specifications is informative, because the absence of yield suppresses part of the causal sequence that the predictive ANN had already suggested is central. This comparison is therefore a natural robustness test for the node naming that we wish to validate.

Figure 14 presents the decomposition of direct and indirect effects estimated through the Double ML mediation framework.

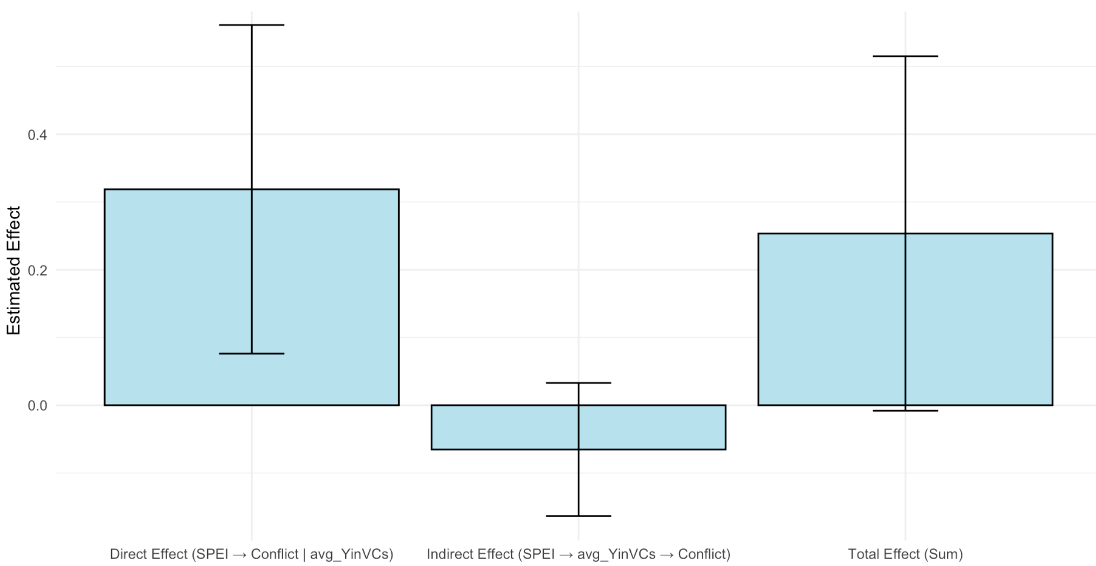

Figure 14. Double ML Mediation Framework

The first set of plots (Figure 14) displays the decomposition obtained when the mediation chain excludes crop yield. The direct effect of SPEI on conflict is positive and relatively large, and the indirect effect operating through commercialization is small and marginally negative. This pattern suggests that in the absence of a yield mechanism, markets provide a modest buffering role. Commercialization appears to absorb part of the climate shock rather than magnify it. This result aligns with the broader empirical literature in which stronger market integration can partially shield households from the most immediate consequences of climatic stress. The total effect remains positive, but the absence of agriculture as an explicit mediator reduces the interpretability of the chain. In practical terms, the ANN's predictive skeleton had already indicated that the agricultural node is essential; the Double ML decomposition confirms that omitting this node leads to a partial and somewhat distorted view of the causal process.

Figure 15 reports the full set of estimated path coefficients obtained from the multi-mediator Double ML model considering crop yield.

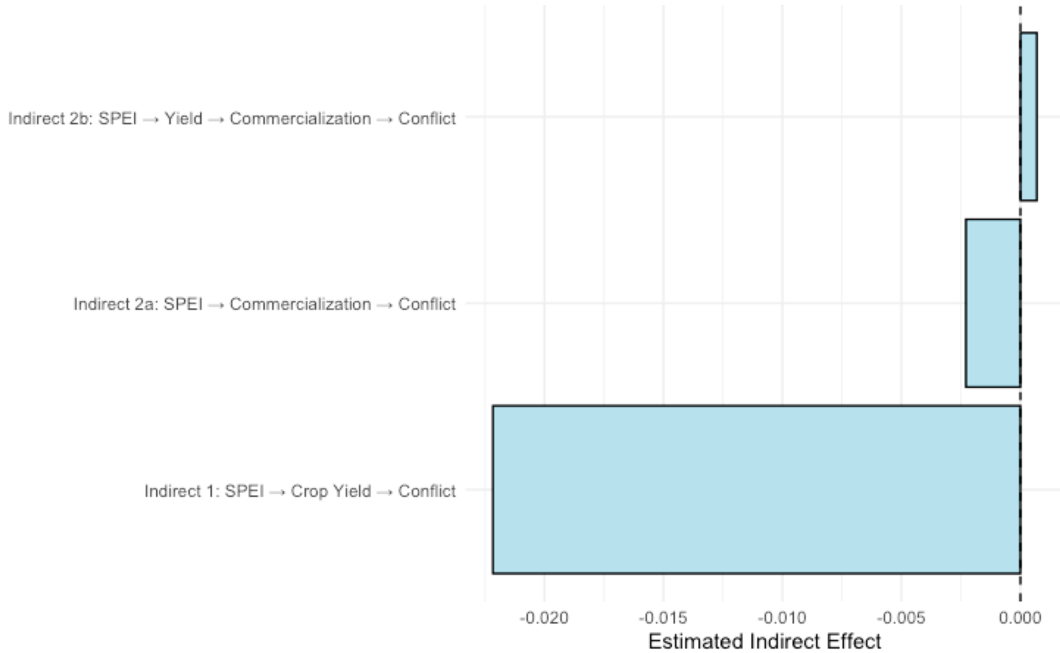

Figure 15. Double ML Mediation Framework with crop yield

Figure 15 reports the full Double ML decomposition when two mediators, crop yield (M1) and commercialization (M2), are included. The figure reveals three distinct indirect channels. The first pathway, running from SPEI through crop yield and then directly to conflict (Indirect 1), is negative and relatively large in magnitude. The second pathway, in which SPEI affects conflict through commercialization alone (Indirect 2a), is also negative but smaller. These two negative components jointly indicate that climate variability tends, on average, to reduce conflict through its depressing effects on agricultural production and market engagement, likely reflecting temporary contractions in economic activity, mobility, and market participation. A third pathway (Indirect 2b) works in the opposite direction: the sequential chain SPEI → crop yield → commercialization → conflict produces a small positive effect. This reflects the fact that changes in yield feed into commercialization patterns in ways that can, in certain contexts, heighten vulnerability or competition, generating a conflict-enhancing channel.

The comparison between Figures 13 and 14 therefore provides causal validation of the multi-layer structure inferred from the ANN. Without crop yield, the indirect effect is minimal; with it, the multi-mediator chain becomes active. This shift indicates that the ANN's hidden layers are not arbitrary but reflect statistically identifiable mediating processes. In short, the causal forests and the Double ML architecture allow us to give explicit economic names to the ANN nodes: yield, commercialization, and consumption.

The results provide credible evidence that the layered predictive architecture uncovered in the ANN is not merely a statistical pattern but corresponds to causal processes operating within rural economies. Crop yield emerges as the first critical node: climate anomalies affect conflict risks far more strongly when they depress agricultural production. Commercialization acts as the second node: low market participation magnifies the effect of yield shocks on consumption volatility. Consumption serves as the final node: reductions in consumption dramatically elevate conflict risk, consistent with livelihood-based theories of social instability.

The Double ML analysis broadly supports the interpretation of the ANN nodes. The hidden node capturing yield shocks represents the agricultural production channel. The second hidden node corresponds to commercialization constraints and market linkages. The third aligns with household consumption and welfare levels. The layered structure implied by the ANN thus acquires a clear economic and causal interpretation.

8. Conclusions

The interplay between climate variability, agricultural performance, and conflict has emerged as a critical area of study due to its significant implications for socio-economic stability and sustainable development (see Hendrix & Salehyan, 2012; Burke et al., 2015). Climate variability, often manifested through altered precipitation patterns, temperature extremes, and prolonged droughts, significantly disrupts agricultural systems, particularly in regions reliant on rain-fed farming (Lobell et al., 2008; Schlenker & Lobell, 2010). These disruptions are frequently associated with reduced yields and volatile markets, leading to cascading effects on livelihoods, including resource competition, migration pressures, and deteriorating food security (Fjelde, 2015). Such agricultural vulnerabilities have been identified as predictors of conflict, particularly in fragile settings where institutional capacities are weak (e.g., Raleigh & Urdal, 2007; Hsiang et al., 2013). This dynamic relationship emphasizes the need for analytical frameworks that capture the complexities of these interconnected pathways, enabling policymakers to develop targeted interventions to mitigate risks and foster resilience.

ML techniques have proven invaluable in climate change research, particularly in modeling the complex relationships between climate variability, agricultural dynamics, and conflict. Studies have demonstrated the application of ML frameworks, such as ANNs, DNNs, and other advanced algorithms, to identify and analyze nonlinear relationships and spatiotemporal patterns. For example, Ge et al. (2022) employ time-series ML methods to model armed conflict risks, revealing how climate anomalies, including temperature and precipitation extremes, elevate conflict probabilities globally. Similarly, Obukhov and Brovelli (2023) stress how ML-based predictive models, integrated with geospatial conditioning factors, can pinpoint conflict-prone areas and uncover significant socioeconomic and governance predictors. In the agricultural domain, Mhanna et al. (2023) demonstrate the utility of ML in tracking land-use changes caused by conflict and climate interactions, emphasizing its role in sustainable land and water resource management. Ladi et al. (2022) provide a broader perspective on the role of ML in climate adaptation and mitigation, showing its capability to address complexities in climate-impacted systems, particularly in urban settings. D'Angeli and Vesco (2024) further argue that ML frameworks are critical for assessing the compounded vulnerabilities arising from climate-induced disasters and armed conflicts. Still, Montanari et al. (2014) utilize ANNs to model coastal land-use conflicts, underscoring their ability to simulate policy scenarios and inform sustainable conflict mitigation strategies. Lastly, Okewu et al. (2019) propose a DNN-based system for analyzing climate-induced farmer-herder clashes in Nigeria, demonstrating its utility in formulating socially inclusive policies and proactive conflict prevention measures.

This study conceptualizes the pathways linking climate variability to conflict through agriculture by treating climatic shocks not as isolated meteorological fluctuations but as disturbances that reverberate through production systems, market linkages, and household livelihoods. Drought and rainfall anomalies, captured here through standard SPEI and SPEI Crop, appear to weaken agricultural performance in ways that alter commercialization opportunities and destabilize consumption. These disruptions then spill over into broader economic and social systems, heightening the likelihood of conflict under conditions where vulnerability and exposure intersect. We do not claim that agriculture is the only pathway linking climate and conflict, but in this setting it appears to be a central one. By structuring the analysis around this cascading logic, the study moves from theoretical expectations to empirical validation, creating a coherent bridge between conceptual models and observed data.

ANNs provide an especially suitable platform for examining these relationships because they can approximate nonlinearities, thresholds, and interaction effects that standard econometric approaches struggle to detect. When the hidden layers are arranged to mimic the hypothesized sequence of climate impacts, first agricultural production, then market participation, then household consumption, and finally conflict, the ANN architecture begins to reveal internal structures that resemble the conceptual skeleton. In other words, the network learns a layered representation that maps directly onto the mechanisms anticipated by Romano et al. (2025).

The step-wise ANN constructed in Keras provides even stronger confirmation of the layered system. By splitting the analysis into sequential components, i.e., SPEI to crop yield, crop yield to consumption, and consumption to conflict, the Keras model stabilizes both the learning curves and the validation metrics in a way that the unified ANN could not fully achieve. The Keras model therefore supports the presence of a genuine mediation effect: climate shocks propagate through agricultural performance before influencing consumption and subsequently conflict.

The causal analysis based on Causal Forests strengthens this interpretation. The distribution of estimated treatment effects suggests meaningful heterogeneity in how climate anomalies translate into conflict risk, which is precisely what one would expect if the effect travels through multiple economic layers. Importantly, the CATE patterns reveal that the marginal effect of SPEI declines as crop yields increase: poor agricultural performance amplifies the conflict-inducing impact of climate stress. The treatment effect also varies with commercialization intensity. Low market participation is associated with higher conflict sensitivity to climate shocks, while better-integrated households show partial insulation. Consumption displays a saturation pattern: households with very low and very high consumption show different sensitivities to climate shocks, reflecting distinct vulnerability profiles. These non-linear CATE shapes closely resemble the structure learned by the ANN's activation functions, providing causal justification for the network's internal representation.

The robustness analysis using Double ML delivers the final and most decisive evidence. When the model excludes crop yield, the indirect effect of climate on conflict through commercialization remains small and slightly negative. This finding implies that markets absorb some of the climatic stress in the absence of a production shock. However, once crop yield is introduced as the first mediator, the chain becomes active: climate shocks depress yields; lower yields reduce commercialization; reduced commercialization weakens consumption; and weakened consumption increases conflict risk. The total indirect effect becomes strictly positive and non-trivial, and the decomposition closely maps to the ANN's hierarchical structure.

These findings carry clear policy implications. Interventions aimed at enhancing agricultural resilience, such as improved irrigation infrastructure, climate-smart farming practices, and better market integration, are key in buffering rural households against climate-related shocks. Equally important is the need to address the socio-economic fallout of agricultural disruptions, including food insecurity and internal displacement, which elevate the risk of conflict. Integrating climate adaptation measures into peacebuilding and development strategies is therefore critical, especially in regions where agriculture is the backbone of livelihoods.

Future work should expand this framework to incorporate additional structural factors, such as governance capacity, infrastructure access, and population dynamics, which may further shape the climate-agriculture-conflict nexus. The use of real-time, high-resolution data, combined with the continued application of interpretable ML methods, can further enhance prediction accuracy and policy relevance. Ultimately, interdisciplinary approaches combining climate science, economics, and conflict research are essential for developing effective and sustainable responses to the growing challenges posed by climate-induced instability.

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Appendix

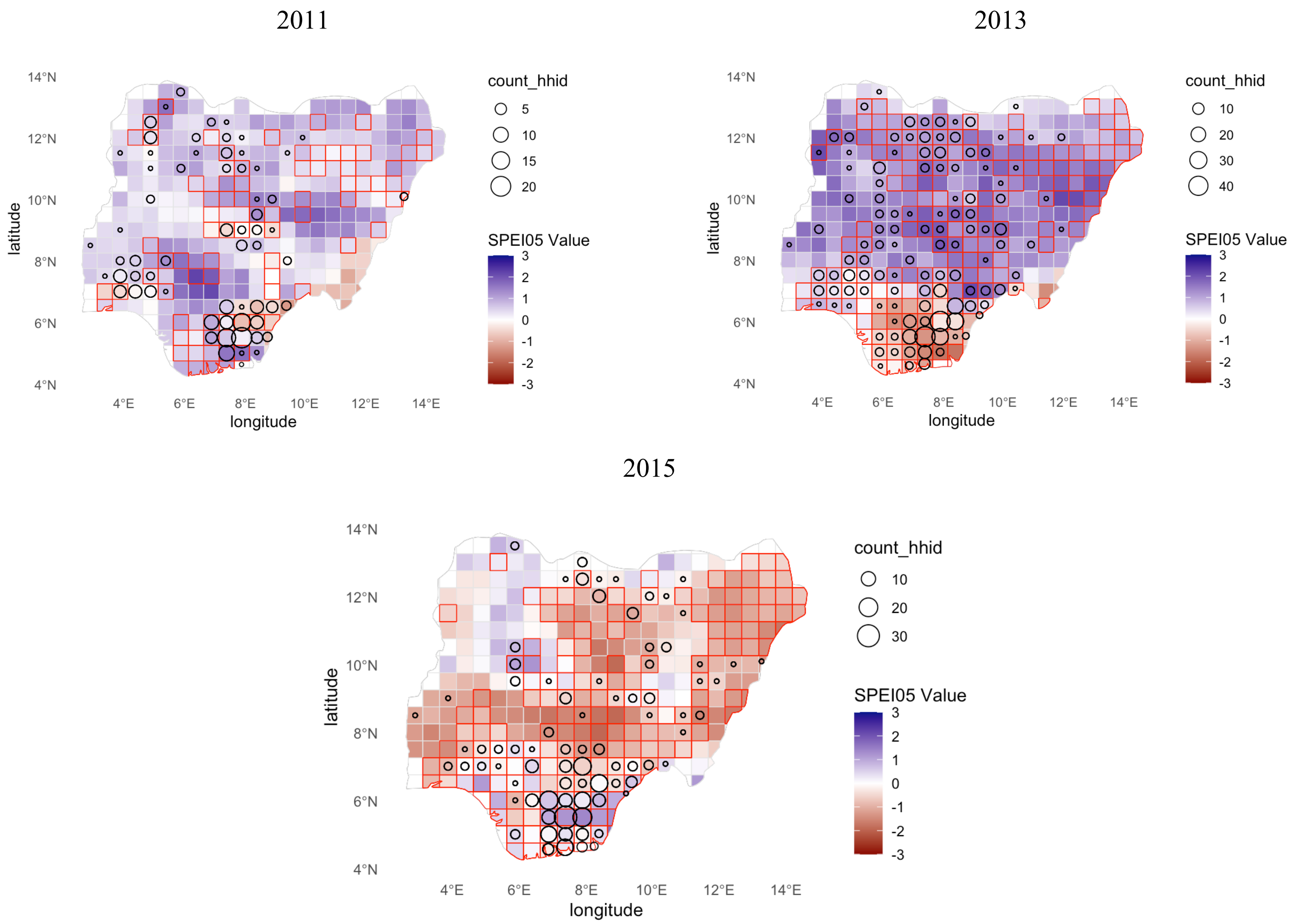

Figure A.1. Household Count, SPEI Crop Values, and Conflict Presence.

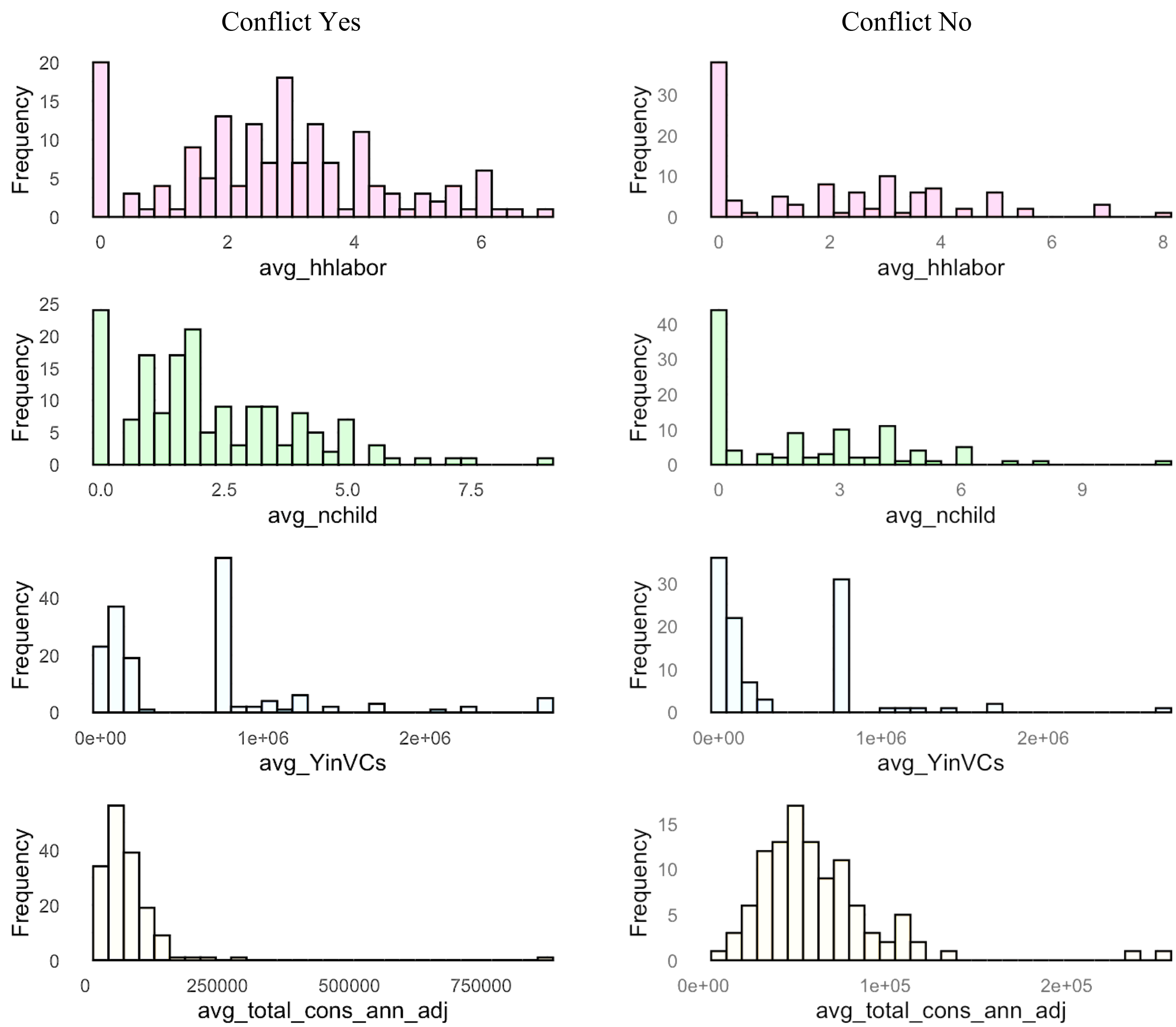

Figure A.2. Descriptive Statistics by Conflict Type

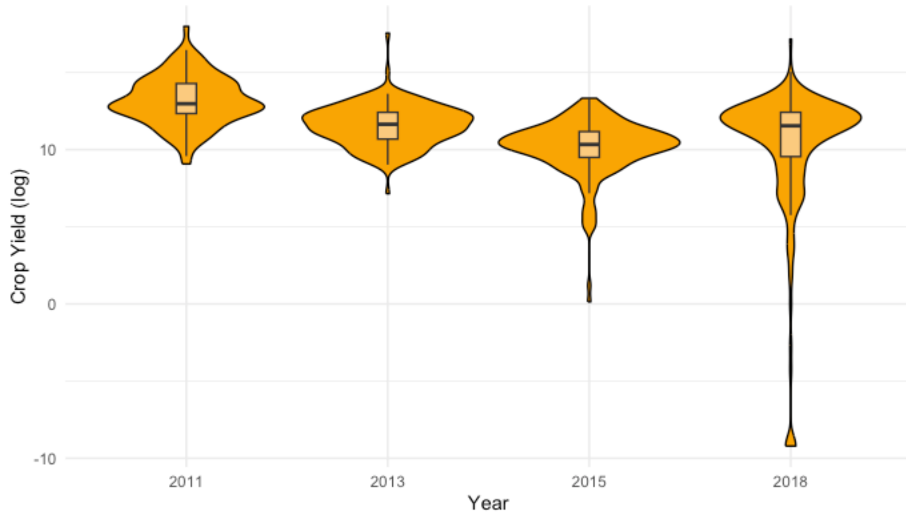

Figure A.3. Violin Plots for Crop Yield

Table A.1. Logit vs GAM – SPEI.

	Logit	**GAM**
SPEI	-0.2421	-0.0878
avg_YinVCs	0.5182+	0.2884
avg_total_cons_ann_adj	0.4740**	0.3044+
HHs Control Variables	YES	YES
Year FE, Grid FE, HHs per Grid	YES	YES
Intercept	-0.0888	-0.5002
Training observations (70% split)	189	189
Accuracy	0.6202	0.6835
Precision	0.5	0.5862

Signif. codes: *** *p<0.01,* ** *p<0.05,* * *p<0.1,* $^{+}$*p<0.15.*

Table A.2. Logit vs GAM – SPEI Crop.

	Logit	GAM
SPEI	-0.0084	0.2115*
avg_YinVCs	0.3501**	0.0969
avg_total_cons_ann_adj	0.2139**	0.0727**
HHs Control Variables	YES	YES
Year FE, Grid FE, HHs per Grid	YES	YES
Intercept	-0.3685	-0.7868**
Obs. Train Data (Split at 0.7)	732	732
Accuracy	0.6512	0.7160
Precision	0.5477	0.6697

Signif. codes: *** *p<0.01,* ** *p<0.05,* * *p<0.1,* $^{+}$*p<0.15.*

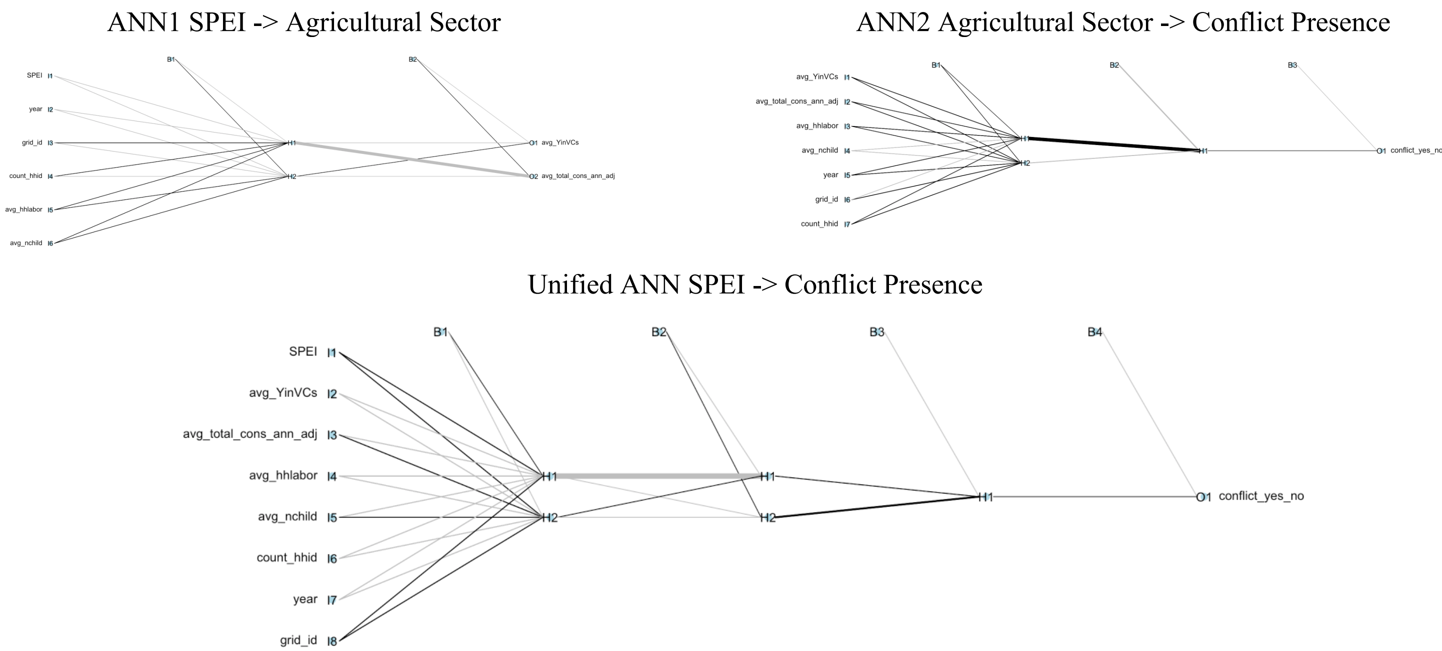

Figure A.4. ANN SPEI -> Agricultural Sector SPEI Crop

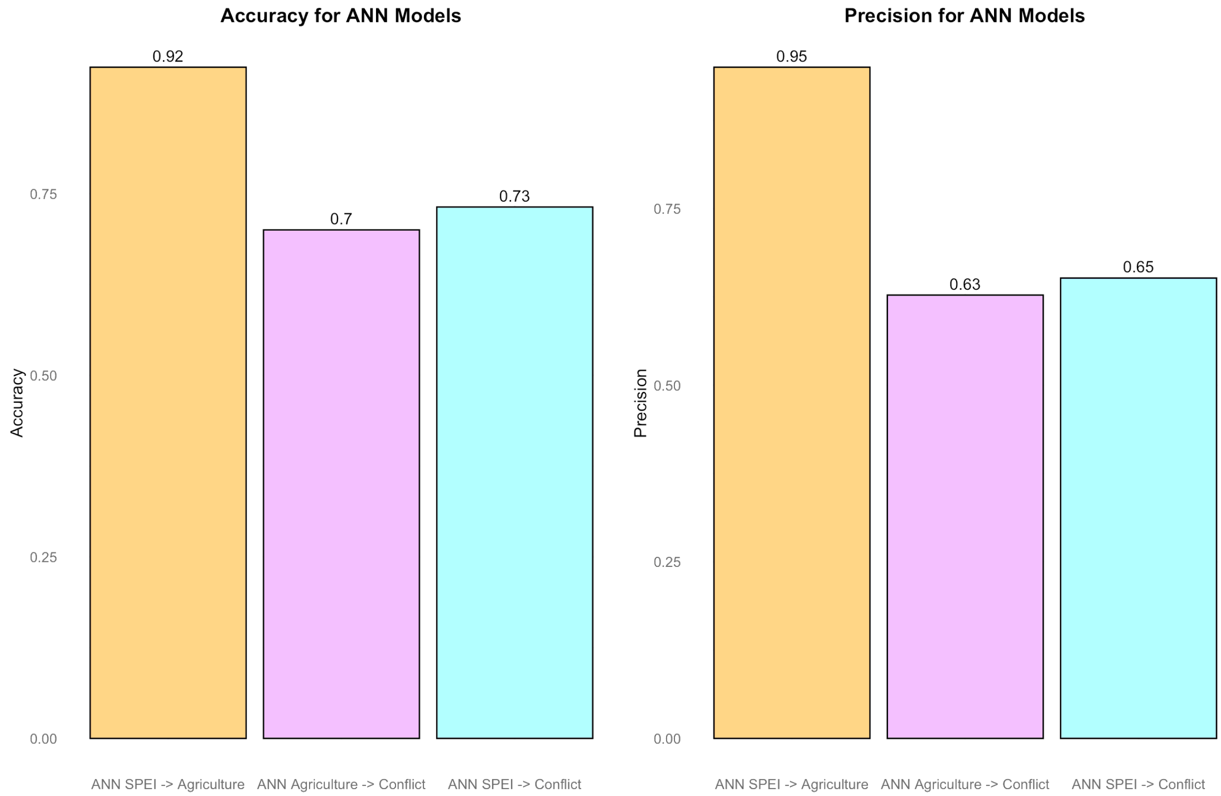

Figure A.5. Performance Metrics ANN Models – SPEI Crop

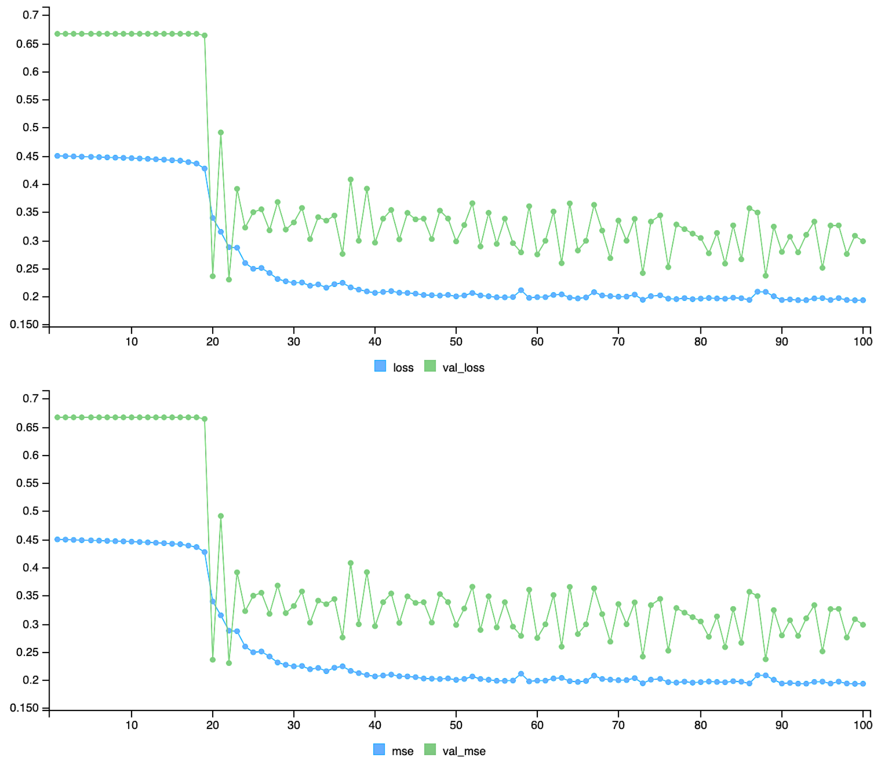

Figure A.6. ANN Keras SPEI-Conflict

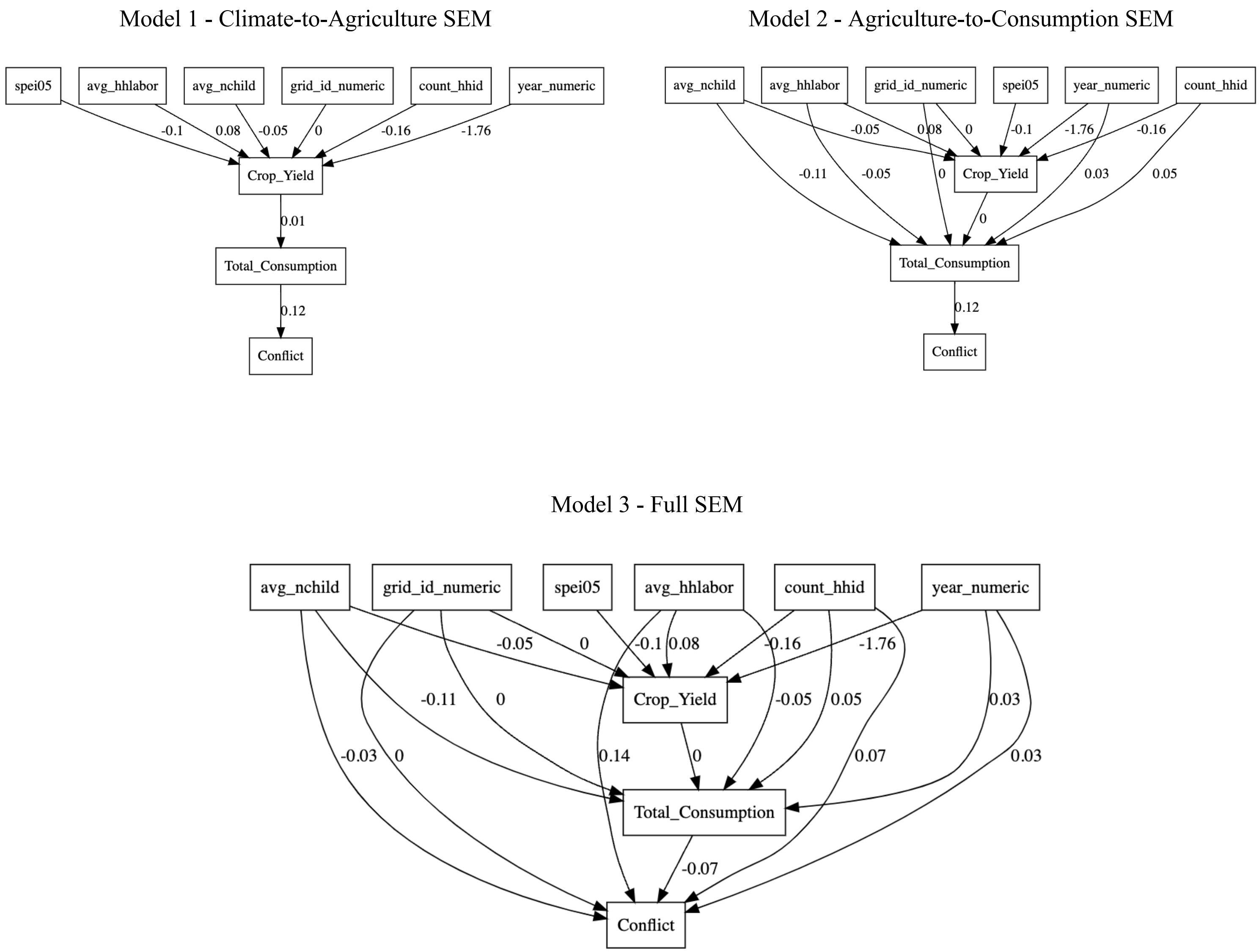

Figure A.7. SEM Plots.