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Climate change and food consumption: Is home-induced food a source of resilience and vulnerability?

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Abstract

Global warming-induced climate change presents a significant threat to agriculture and food security, particularly in vulnerable regions like India. This study explores whether home-produced food can act as a source of resilience or vulnerability in the face of climate change. Using comprehensive national data from the National Sample Survey (NSS) 68th round and the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), the paper quantifies the food consumption and security role of home-produced food across various Indian regions and examines the implications of climate-induced yield changes on food security. The study employs a deep learning approach to model the complex, non-linear relationships between climate change, agricultural yields, and household food consumption. Preliminary findings suggest that home-produced food plays a critical role in food consumption and security, especially in rural areas. However, increased dependence on home production could heighten vulnerability to climate anomalies. While home-produced food has the potential to enhance resilience, its role must be carefully supported through policies that provide tools and knowledge for better agricultural practices. Conversely, if market participation increases, ensuring effective market functioning and affordable nutritious food becomes crucial. The study findings provide valuable insights for policymakers on balancing home production and market reliance in the context of climate change.

JEL Codes: Q18, Q54, D13, O13, C45, E21

1. Introduction

Global warming-induced climate change poses a significant threat to humanity. Manifestations of climate change include rising temperatures, unprecedented changes in rainfall patterns, frequent floods, declining groundwater levels, soil erosion, prolonged dry spells, droughts, hailstorms, and rising sea levels due to melting glaciers (Kumar et al., 2013; Hussain A. et al., 2016). These changes are expected to severely affect agriculture and water resources, thereby affecting food security and health. Climate change disrupts various aspects of food security, leading to reduced access to food, which in turn diminishes dietary quality and diversity (Sibhatu et al., 2015; Behera et al., 2023).

India is particularly vulnerable to these climatic aberrations (Singh et al., 2020). Despite its economic progress, India struggles with malnutrition, which hinders socioeconomic development and exacerbates poverty. Approximately a quarter of the world's undernourished population resides in India, which ranks 111th out of 125 countries in the Global Hunger Index (GHI) 2023 (Citation). Addressing hunger necessitates progress in food and nutrition security; however, even minimal warming in a tropical country like India can lead to significant crop yield losses (Parry et al., 2007). The country's diverse geography and varying climatic conditions mean that regional impacts will differ, and some regions will be affected more than others. Research by the Indian Agricultural Research Institute (IARI) suggests a potential loss of 4–5 million tons in wheat production for every 1°C rise in temperature during the growing season (Citation). Future yields of wheat, soybean, mustard, groundnut, and potato are expected to decline by 3–7% with a 1°C increase in temperature (Aggarwal, 2009). Additionally, erratic monsoons could severely impact rain-fed agriculture, reducing the productivity of crops such as rice, maize, and sorghum, especially in regions like the Western Ghats, Coastal areas, and northeastern region, as well as apples in the Himalayan region (Kumar et al. 2011).

To enhance resilience to food insecurity in the face of climate change, households adopt and practice various measures. Among these measures, home-produced food through own farm production and homestead farming or rooftop agriculture remains vital for food and nutrition security despite rapid commercialization of smallholder farming and urbanization. Own-farm production and homestead farming systems involve the cultivation of diverse crop species and offer significant livelihood, nutrition, and health benefits to rural households.

These self-sustaining systems can enhance households' resilience to climate change and food insecurity, allowing the households to adapt their cropping patterns and to introduce more climateresistant crops based on their local conditions (Hussain A. et al., 2016). However, a significant portion of rural households comes from food purchases (Sibhatu and Qaim, 2018). Hence, when larger shares of food consumption come from own production, diets become highly dependent on local agricultural yield, and this dependence could increase vulnerability in case of adverse climate events. The dual nature of home-produced food as a source of resilience or vulnerability in the context of climate change remains unknown. This study aims to address this gap in literature.

In particular, this paper has two primary objectives. First, it quantifies the food security roles of home-produced food across various regions in India using comprehensive national data from the National Sample Survey (NSS) 68th round and the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). Second, it examines the implications of climate-induced yield changes on food security by specifically considering home production. Despite the promotion of home gardens as tools for enhancing resilience and nutrition, the significance of home-grown food has often been overlooked in policy and public discourse. If the importance of home-produced food increases with climate change, policies must support households with necessary tools and knowledge to improve their agricultural practices. Conversely, if the role of home production diminishes, there will be a need for effective market functioning, affordable prices, and the availability of nutritious foods. Hence, this study also aims to determine whether home production complements or replaces market-purchased food in the context of climate change.

In this study, the effect of climate change on agricultural households is captured by examining the effect of changes in the main crop yield that result from climate anomalies, accounting for the complex pathways through which lower yields affect food consumption. Household decisions on resource allocation aim to maximize revenue for food and non-food consumption. Given the complexity and multidirectional nature of these relationships, this study employs a deep learning method that offers flexibility in predicting nonlinear relationships with explanatory factors. The hidden layers of the network are expected to account for unobservable steps and trade-offs that influence household food consumption.

The remainder of this paper is organized as follows. Section 2 provides an overview of climate change projections in India, examining their effects on Indian agriculture, and the role of home-produced food in ensuring food security and nutrition. Section 3 outlines the conceptual framework linking climate change-induced shifts in agricultural production to food security, along with the identification strategy. Section 4 details the data sources and empirical methodology employed in this study. Section 5 presents and discusses the results. Section 6 concludes the study, discusses the policy implications, and suggests areas for future research.

2. Context

2.1. Climate change projections for India

Climate change projections for India paint a scenario of considerable environmental, economic, and social challenges that could intensify in the coming decades (Kumar et al., 2013; Sharmila et al., 2015; Yaduvanshi et al., 2019). Forecasts suggest a marked increase in temperature across the subcontinent, with a potential rise in the average temperature by 1.7°C to 2°C by 2030, relative to the baseline figures from the latter half of the 20th century (Yaduvanshi et al., 2019). This warming is expected to be more pronounced in food-producing agricultural areas, transforming climate patterns and exacerbating heatwaves, which are already a significant cause of climate anomalies (Kumar et al., 2013; Sharmila et al., 2015; Yaduvanshi et al., 2019). Moreover, the retreat of Himalayan glaciers, which are vital sources of water for perennial rivers in the Indian subcontinent, is set to impact water availability across the entire region, not only in India.

The implications of these temperature increases have been far reaching. India is projected to witness alterations in monsoon patterns, leading to erratic and unpredictable rainfall. While some areas may experience increased rainfall, leading to floods, others may suffer from reduced rainfall, exacerbating drought conditions for decades (Kumar et al., 2013; Sharmila et al., 2015; Yaduvanshi et al., 2019). Such variability poses a severe risk to agriculture, which remains a mainstay of the Indian economy and a primary source of livelihood for more than half of the country's population. Changes in monsoon patterns can severely disrupt agricultural cycles, affecting crop yields and threatening food security for millions.

2.2. Effects of climate change on Indian agriculture

The agrarian landscape of rural India is currently at a crossroads, and climate change is posing new challenges. Rural agriculture, which is primarily rainfed, is extremely vulnerable to such changes (Pathak, 2022). Monsoons, which are vital to Indian agriculture, are becoming more erratic, causing droughts in some areas and floods in others (Kumar et al., 2013; Pommier et al., 2018; Saryal, 2018; Yaduvanshi et al., 2019). These anomalies disrupt planting seasons and affect crop growth and yield, thereby threatening food security (Rodthong et al., 2020).

Warming temperatures are expected to hasten crop maturation, shorten the growing season, and potentially reduce the yields of key staples, such as wheat and rice (Datta et al., 2022). For example, wheat, which requires a cooler growing season, may experience lower yields due to heat stress, especially in the already warm northern plains (Singh et al., 2023). A simulation study showed that a 2 °C increase in temperature reduced potential wheat yields in most places in India (Agarwal et al., 1993). Similarly, for rice, a rain-fed crop with a decrease in rainfall resulted in yield loss of about 8 % in a simulation model for the tropical Indian state, Kerela (Saseendran et al., 2000). A 1°C increase in temperature led to about 6% decline in the simulated yield of rice. This is especially concerning for rural populations, where dietary variety is limited and reliance on staple grains is high.

The consequences for rural food systems will be significant. As staple crop yields decline and nutritional content shifts, the risk of malnutrition is likely to rise, particularly among vulnerable populations (Chattopadhyay, 2011).

2.3. Food security role of home-produced food in rural India

Overall, Indian households draw non-negligible shares of their nutritional needs from non-market resources, such as own-production. This takes the form of farming households and workers who retain shares of cash crop production for their own consumption, or kitchen gardens specifically designed to procure households with varieties of fruits and vegetables for their own consumption. In both cases, own-produced food fulfills specific nutritional needs that complement those of foods purchased from markets.

In addition, home-produced food is not only a source of sustenance in rural India but also an important part of its cultural identity and nutritional autonomy. Rural households have developed intimate knowledge of food cultivation, which they use to feed their families and improve their health (Hudson et al., 2016). Agricultural practices are not only a source of income in rural India but also a repository of traditional ecological knowledge. Family farms and smallholdings use time-tested methods passed down through generations to maximize crop yields while working within the constraints of local climate and soil conditions (Cheek et al., 2023; Hudson et al., 2016).

Despite these advantages, the nutritional potential of home-grown food has not been fully realized, owing to a variety of constraints. Market access to surplus produce is frequently limited, reducing the incentive for domestic food production diversification and innovation (Gruère et al., 2009).

Furthermore, nutritional knowledge — understanding how to use a diverse range of available foods for a balanced diet — is sometimes insufficient (Cheek et al., 2023). Extension services and community education programs aimed at improving nutritional knowledge can be transformed in this context.

3. Conceptual framework

Overall, this paper is focused on the effect of agricultural yields on the quantities of own and purchased food by farming households, where yield is of interest as it is expected to lower as a result of climate change. Other pathways of climate change on food consumption are beyond the scope of this analysis. The following sub-sections explain the choice of yield as determinant of interest, and the complex relationship between yield and food consumption choices.

3.1. Climate change and agriculture

Complex interactions exist between agricultural productivity and climatic factors such as temperature, rainfall, and carbon dioxide levels. As stated above, climate change is expected to disrupt farming, resulting in crop cycle changes, increased pest and disease outbreaks, and altered land suitability for certain crops. Section 2 establishes that lower yields are a major aggregate consequence of climate change on farming households, as it integrates most of the effects of climate change on agriculture (through soil quality, crop growth, etc.). Given this context, we hypothesize that the multiform effects of climate change on agricultural activities are funneled into lower agricultural output.

In this framework, agricultural output is captured by average yield per hectare at the district level, where "yield" is the expected production per unit of land given its physical characteristics, including climate, and factors common to all farmers in the area (soil quality, technology, extension services, policies …). However, indirect effects of climate change on yield through migration, adaptation, price fluctuations, and the availability of farming inputs, though present on the long-term, are not explicitly accounted for.

3.2.Agricultural yields and food consumption

Our working hypothesis posits that yields affect food consumption through two pathways: monetary and non-monetary resources. First, yield, together with the size of land available, labor, and productivity, as well as market prices for harvested crops determine how much monetary value crop growers can expect to draw from the sale of the products to the market. This monetary resource is available for food and non-food consumption. Second, when farmers maintain a share of their production for their own consumption, this generates an in-kind resource that is available for their family's food consumption. Of course, the two pathways are interdependent, as a higher share of crops sold in the market results in smaller quantities available for their own consumption. Together, these monetary and non-monetary resources make the aggregate amount available for food consumption. Therefore, yields are expected to affect food consumption through both the monetary and non-monetary pathways.

More precisely, let us first consider households' endowment in labor and land, which households can exploit to generate revenue. According to the productivity of these factors (yield for land, labor productivity for labor) and their remuneration (expected harvest price for agricultural production, and off-farm wage for labor), households decide the labor allocation between their on- and off-farm activities (Nakajima, 1986; Von Braun and Kennedy, 1994**)**. This determines the level of agricultural production obtained by the household and monetary income obtained from off-farm activities. Regarding agricultural production, households then decide the portion to be sold on the market and the portion to keep for own consumption. This decision essentially depends on the gap between sale price and shadow price (Janvry et al., 1991**,** de Janvry & Sadoulet, 2011). The effects of these decisions are ambiguous and complex (Janvry et al., 1991; Sadoulet and de Janvry, 1995; Ravallion, 2000; Taylor and Adelman, 2003; Gillespie et al., 2012). Together, the endowments and decisions maximize aggregate household resources, which are then allocated by each household between food and non-food consumption. Food consumption thus consists of purchases from the market made with off-farm monetary income and monetary revenue from the sale of agricultural products, and from in-kind food production from agricultural production. Thus, food security is a function of both market purchases and own-produced food, both of which are affected by lower yields due to climate anomalies.

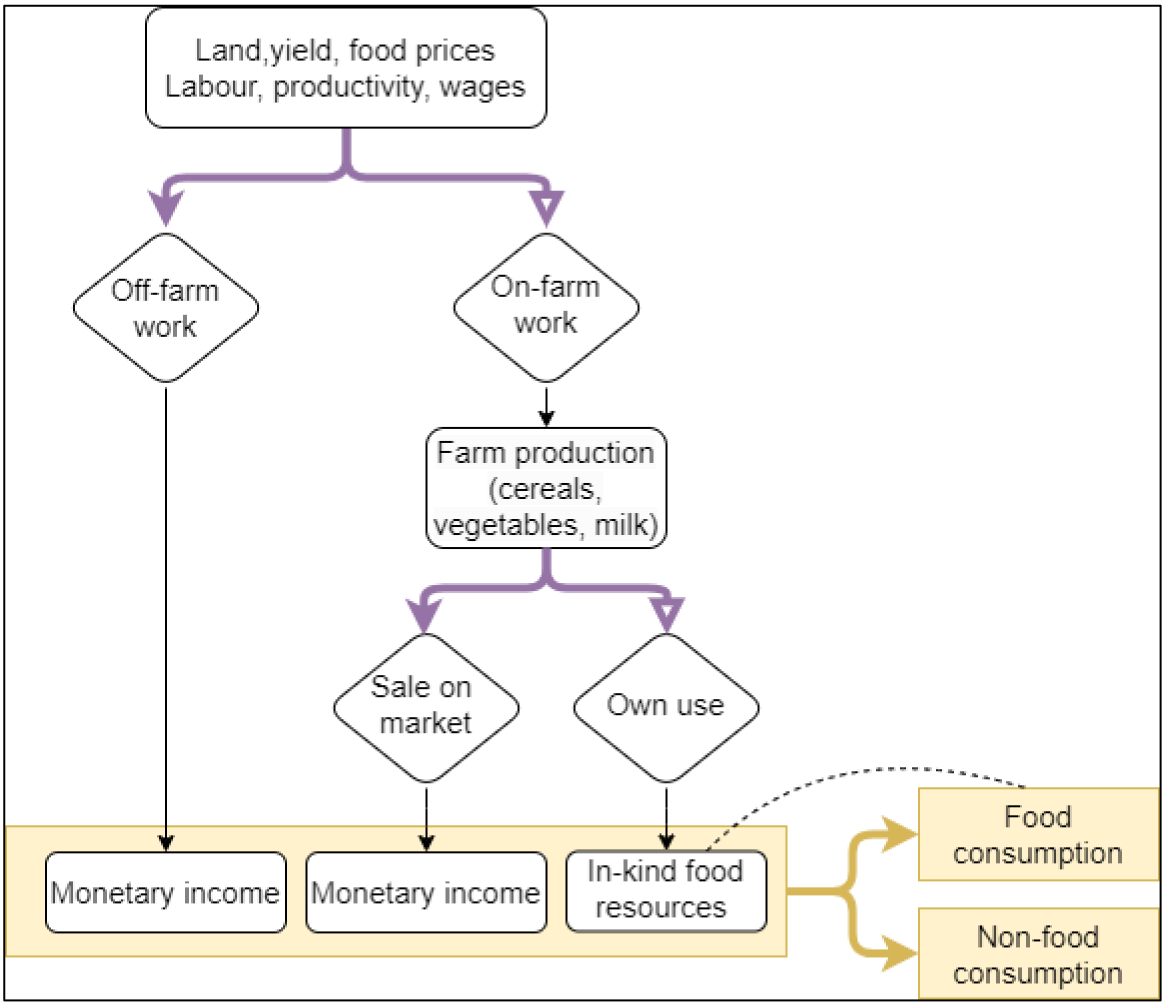

Figure 1: Linkages between food production and food consumption, in household production model (own design)

3.3. Identification

The identification of the effect of yield on food choice is based on the assumption that yield affects food consumption through several intermediate variables that result from household decisions and additional determinants, which in turn do not affect district level yield.

Yield is expected to change how households allocate their labor between on- and off- farm employment, as well as the share of agricultural production sold to the market. In turn, these decisions affect earned resources (monetary and non-monetary), and, in the end, the chosen quantities of purchased and in-kind foods consumed by the household. These production and consumption decisions (labour allocation, market participation, income allocation) have a mediating effect on how yield translate into food consumption decisions. To guarantee the correct evaluation of the effect of yield on food choice, these mediating variables are not included in the analysis

(Cinelli et al, 2022). By allowing them to vary with yield, the internal and complex adaptation of households to changing yield is captured, and its effect on food consumption reflected. Of course, these underlying household decisions are made simultaneously and are prone to endogeneity. However, they are not established or estimated formally in the model, and therefore do not prevent us from empirically establishing the overarching relationship of the model between yield and food consumption. Nevertheless, exogenous determinants that affect these mediating variables and/or the outcome food consumption, are included in the model as controls. Households' socio-demographics, agricultural product prices, and infrastructure are expected to influence the mediating decisions, and to influence the outcome, and are therefore included in the model. As described in Cinelli et al (2022), these are expected to be neutral with respect to bias of the effect, but to render more precise estimations of the effect.

Importantly, we consider that changes in yield are exogenous to the intermediate household decision and resulting food consumption, as yield is only affected by climate change and other factors (state of technological progress, soil quality, etc.) that are not directly influenced by households. To ensure this, the measure of yield is taken as the average of the district level and does not reflect the individual decisions of households. Yield represents the average level of production a household may expect, independently of its specific productivity level, farming practice, exploitation size, etc. The large geographical area covered in the data, spanning several states and agro-ecological zones, provides a source of exogenous variation to identify the effect of yield. In addition, district fixed effects capture unobserved confounders of yield, the intermediate decisions, and the outcome. Similarly, intermediate households' decisions are considered exogenous to food consumption, at least in the short term. Of course, the long-term effects of better food consumption affect productivity and earned resources. For example, the decreasing diversity of home-grown food due to climate change may impair nutritional status, which in turn may reduce the availability of agricultural labor, potentially triggering a cycle of vulnerability. However, these indirect long-term effects are not accounted for explicitly in the model.

Finally, when lowering yield to account for effect of climate change, we assume that no factor that affects consumption, other than yield, has been affected by climate change. Therefore, indirect effects of climate change are excluded from the analysis. For example, households' demographics likely affect both production and consumption decisions; however, they are assumed to be unaffected by lower yields or climate change, at least in the short term. Therefore, in the model there are no pathways other than lower yields in which climate change affects the production and consumption decisions of households.

4. Empirical methods and data

4.1. Data

Data for India for food consumption, household demographic and socio-eco characteristics come from the 68th round of the National Sample Surveys (NSS)[1] on Household Consumer Expenditure, carried out in 2011-2012. The subset retained consists of rural households that cultivate some land and include some of their own products in their diet, or close to 60 percent of all rural households. Observations with missing values for the variables of interest are excluded from the analysis. Income and food consumption are measured per capita, and food consumption per capita is adjusted for demographics of household composition: age, sex, and days away for each member, as well as for meals taken outside the home and meals served to guests. Market price data of food items are computed from survey data by dividing expenditures by consumed quantities at the household level and aggregating this at the district level and food category level (cereals, pulses, milk and dairy products, oils, egg, and animal proteins, vegetables, and fresh fruits) using weights that correspond to district average shares of items in their food category.

The data are merged with data from the District Level Data for India (DLD) platform[2] developed by ICRISAT and its partners, using district census codes and names. The DLD data provide district-level information on yield, agricultural profile (areas of cultivation for main crops, harvest prices), general infrastructure (roads, number of banks, agricultural credit, etc.), and economic situation (wages). This allows us to model the production components of the model. Variables with more than half of the missing values are excluded from the analysis. For the remaining variables, missing values in this dataset are replaced by average state values. The final sample consists of 28282 observations, as ICRISAT data are not available for all states and districts; therefore, not all selected

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[1] Household Consumer Expenditure: NSS 68th Round, NSSO, Ministry of Statistics & Programme Implementation, Government of India, http://microdata.gov.in/nada43/index.php/catalog/1

[2] District Level Database (DLD) for Indian agriculture and allied sectors, http://data.icrisat.org/dld/src/about-dld.html

NSS observations can be used. Descriptive statistics for variables entered in the model are shown in table Appendix A.

The effect of extreme climate events is worse than the effect of mean climate change, and the importance of considering climate variability in the effect of climate on food security (Hasegawa, 2021). To model the effect of future climate events on food consumption, we compute district-level projected climate anomalies from a high-resolution dataset for the South Asian region from the Center for Climate Change Research at the Indian Institute of Tropical Meteorology (CCCR-IITM) Climate Data Portal (see detail in Appendix C). The effect of climate anomalies on various crops in India agriculture is estimated by Gupta et al (2022).

4.2. Empirical strategy

In order to model the consequences of a change in yield on food security using existing data, we implement a model that reports the baseline relationship between yield and aggregate food consumption. Then, the values for yield are altered according to the projected scenarios of climate change to observe changes in food consumption. A neural network is employed that connects a series of inputs to a designated output through a series of hidden layers, where each layer represents a vector of nodes, and each node is the result of a combination of inputs. In short, employing deep learning allows to map inputs to responses while accounting for several layers of complexity and non-linearity, which is appropriate given the complex mediating decisions of the model. Full details on training are available Appendix B. A semiparametric neural network is implemented using TensorFlow in RStudio (TensorFlow Authors and RStudio, 2015-2022).

4.2.1. Predictors and outputs

The model aims to predict the quantities of food consumption, focusing on cereals, that come from monetary resources and from in-kind resources. Predictions are made from a set of inputs that include district level yield, as well as additional controls.

Data on labor allocation, market participation are not available and not necessary as they should remain flexible to allow to household's adjustment to changing yield. However, information on household endowments (labour force, land size), their expected return (wage at district level and gate prices of agricultural products) is known and is expected to affect the households' intermediate decisions, while being exogenous to yield. Thus, controlling for theses helps reduce variability of the effects of yield on food consumption. Similarly, other factors expected to influence both household decisions and food consumption are included. Given the availability of data, we include market food prices, remoteness in the form of travelling time to cities with at least 50 000 inhabitants (Weiss *et al*., 2015), number of banks, and amount of agricultural credit at the district level; as well as socio-demographic information at household level. Descriptive statistics for all variables are available in Appendix A.

Thus, we can map the effect of changes in yields on household cereal food consumption and assess the specific role of home food. Section 3.2 showed how varying yields the structure of food consumption between a market-purchased portion derived from monetary income, and an in-kind portion obtained from the own production of agricultural products. To reflect this, we adopt a multi-dimensional output which consists of the quantity of monthly cereal consumption per capita purchased from store, and derived from own-production.

4.2.2. Semi-parametric neural network

Even in the presence of sufficient data, exactly mapping out the decisions and their consequences is an arduous and uncertain task, as decisions are likely to be taken simultaneously and to have endogeneity issues. As the internal mechanism of how endowments are turned into resources is complex, and would not be established firmly with linear relationships, we adopt a neural network approach to map out the overarching effects. The structure in several hidden layers allows high levels of non-linearity and can capture the sub-levels of decision making that we are unable to model explicitly due to endogeneity, in order to recreate the connection between endowments and household food consumption, for which data are available.

Nevertheless, certain robust relationships between production factors, household resources, and consumption have been strongly established by prior research, and should be used to inform the model. Therefore, we turn to a semiparametric methodology developed by Crane-Droesch (2018) to predict crop yields for the US using climate variables, which combines the flexibility of a neural network to build highly non-linear relationships with the predictive power of known linear relationships. This approach is based on a set of layers and nodes that form a neural network to establish nonlinear combinations of the variables. The innovation lies in the inclusion of a set of linear terms in the last layer, intended for factors known to have a linear effect on the outcome. This semiparametric version of a neural network models an OLS type of relationship between the target variables and variables known to affect it linearly, but also allows for additional nonlinear effects and interactions with other variables that are unknown or unobservable. This approach fits the data and problem particularly well as it makes use of the relationships that have been extensively researched and robustly established in prior research, while it allows space for multidirectional and interaction effects that we know exist but are unable to disentangle and quantify precisely. The structure of the model, showing how the parametric layer (right-hand side) is combined with the last non-parametric layers (left-hand side), is shown in Figure 2. In parentheses are the number of nodes, starting with a layer of all 36 inputs entered non-parametrically (left), and a layer of seven of these inputs entered linearly (right), which makes the prediction of a single value (bottom), the value of the total household resources available for consumption.

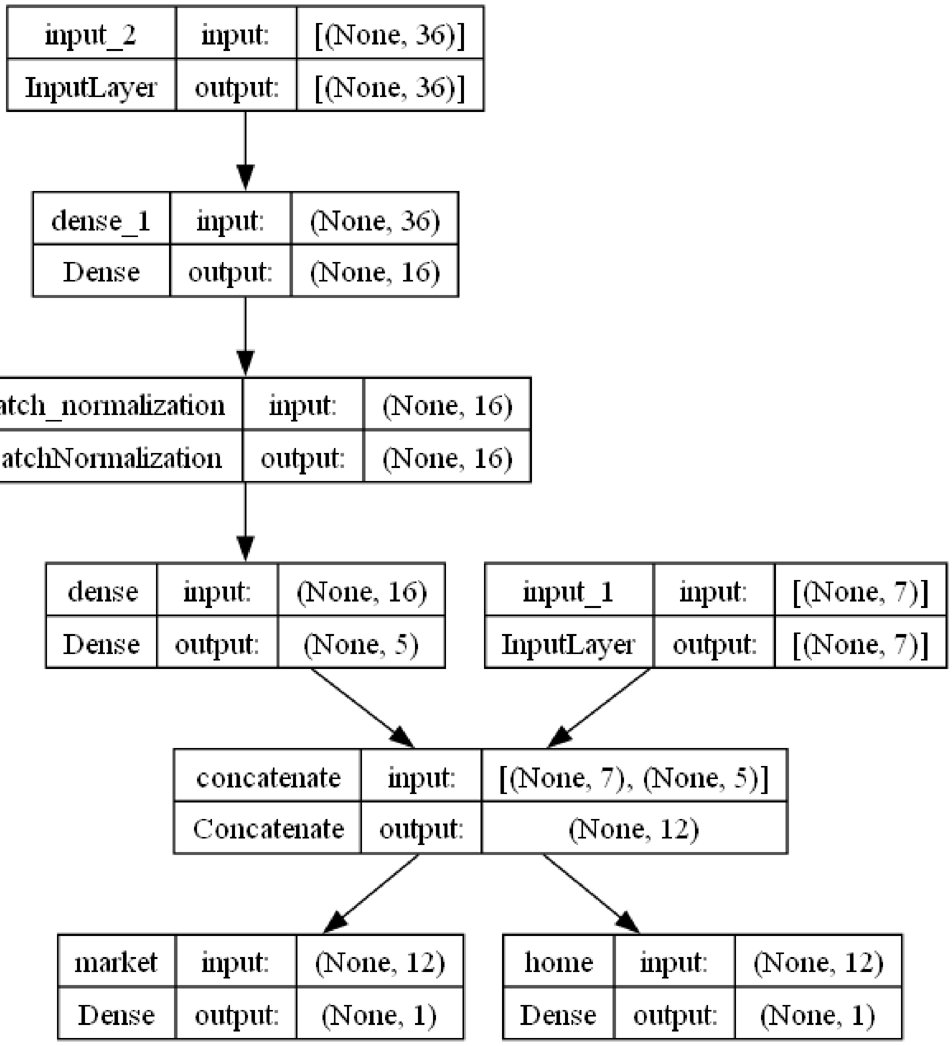

Figure 2: Semi-parametric neural network architecture

Specifically, the factors expected to affect resources linearly in the model and entered parametrically at the last layer are the size of cultivated land, district male field labor, paddy harvest price, wheat harvest price, groundnut harvest price, chickpea harvest price, and travel time to cities with at least 50000 inhabitants. All variables entered parametrically are also present in the non-parametric layer of the model, allowing these factors to have both linear and non-linear effects.

5. Results and Discussions

5.1. Relevance of home-produced food for basic nutrition

Two main observations can be drawn from preliminary observations of the data. First, home-produced food plays a non-negligible role in nutrition, in particular in fulfilling basic caloric needs, as the contribution of home-produced food is mostly found in grains. Second, a strong regional pattern of home-grown consumption indicates reliance of households on one primary cereal, drawn from their own production according to their regions, as opposed to a balanced mix of cereals. This double dependency reinforces the threatening effects of lower yields due to climate change.

We compute the share of home production within the total food consumed for rice and wheat, using the NSS 68th round data. From the initial sample of about 100,000 households, 40% have a share of their food consumption that comes from home-produced food. 86% of households who consume home products reside in rural areas and cultivate land. Table 1 shows that among households that consume some level of home products, cereals and milk products are the food groups where home consumption is most important (44% and 51.4%, respectively), followed by vegetables and fresh fruits, representing nearly 20% of the average food consumption in these categories. Figure 3 shows the average consumption of various grain types in India.

Table 1: Percentage of food coming from home production (sub-sample of NSS households that consume some home-products)

Selected Food Groups	Home production (%)
Cereals	44.0%
Cereals Substitutes	14.3%
Pulses	13.2%
Milk and dairy Products	51.4%
Oil	4.9%
Egg, Fish, Meat	8.9%
Vegetables	18.3%
Fruits Fresh	19.9%
Dry Fruits	7.0%
Total	41.3%

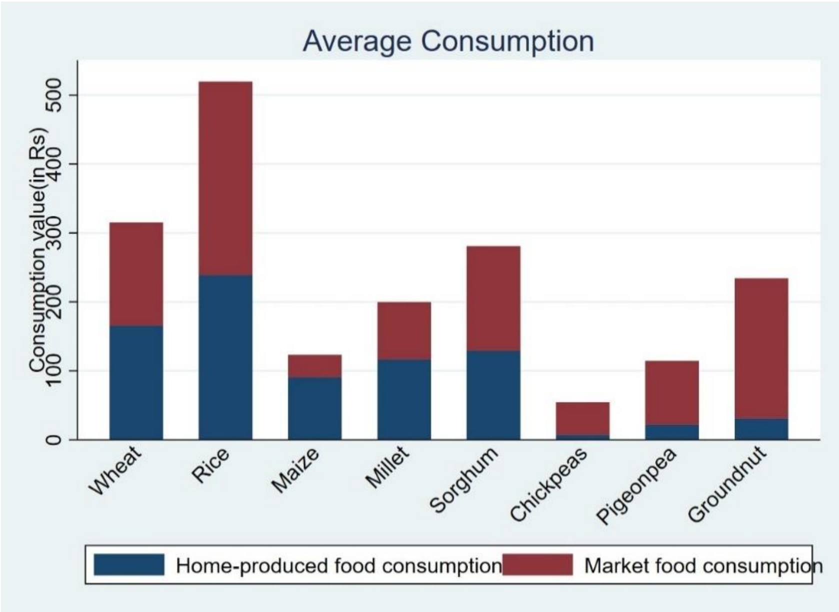

Figure 3: Average grain consumption and share of home-production in consumption, in India, from NSS 2012 data (sub-sample of NSS households that consume some home-products)

Among cereals, the highest shares and quantities of home-produced food consumption were found for rice and wheat. Therefore, home production plays an important role in fulfilling basic nutritional requirements with calorie-rich foods. This is consistent with existing literature that observed households using market purchases to diversify their diets and rely on home-produced staples for calorie-rich foods (Von Braun et al., 1991, Sibhatu and Qaim, 2017, Ogutu et al., 2020).

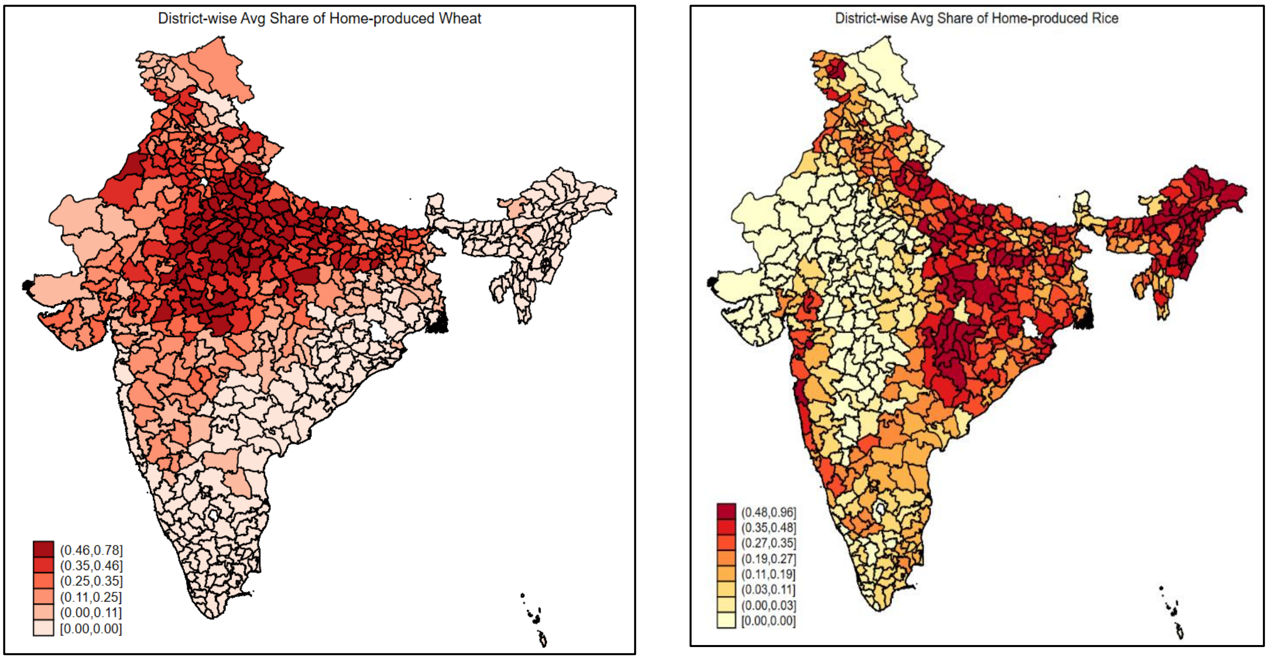

Figure 4: Geographical variation in consumption of home-produced crops, India, NSS 2012 data

Figure 4 illustrates the geographical variation in the average share of home-produced rice and wheat in different districts of India. Regions in Eastern India rely the most on home production for their consumption of rice, which covers more than half of the rice consumption in many districts. The northern and northwestern Indian regions use home production the most to cover their consumption of wheat, often for more than 50% of their wheat consumption. This fragmentation matches the major rice and wheat growing regions. The southern states, which are more developed and urbanized, rely less on home-produced food for consumption, although this persists. Thus, households seem to select one major cereal for their own consumption, whereas other cereals play marginal roles.

5.2. Baseline model of yields, income and food consumption

Performance of the model is shown in Table 2. To verify how well the model generalizes to new, unseen data, the prediction ability is calculated for a portion of the data not included in the training (i.e., the test data). At this point in the preliminary analysis, the loss is relatively large compared to the outcome variable. This indicates that the fit of the model can be improved. Thus, the basic model needs to be further developed in the next steps of this project to achieve a better ability to make correct predictions. The error on test set being not larger than on train indicates there is no overfitting.

Table 2: Model performance

	Neural Network			Fully Linear Model		
RMSE	**Train**	**Test**	**Mean target**	**Train**	**Test**	**Mean target**
Entire model	43.9	44.4	-	60.2	60.9	-
Market-purchased food	28.4	29.1	32.13	47.0	48.6	32.13
Home-produced food	33.5	33.5	27.63	37.5	36.7	27.63

The results of the semi-parametric approach can be compared to those of a fully linear approach in the form of a neural network with a single layer of all parameters and a linear activation function, similar to OLS. The results are presented in the last 3 columns of Table 2. Considering the current network architecture, the semi-parametric approach adds a small gain in prediction precision compare to a fully parametric approach.

To verify the role of yield on household resources and of household resources on food consumption patterns, it is possible to use the Shapley value method (Sundararajan and Najmi, 2020), which computes the importance of each variable to the predictions. Computing Shapley values that are compatible with the semiparametric approach will be performed in the near future and integrated with these results.

5.3. Projections of diets vulnerability due to climate change

In this step, we update the yield with the projected values that account for climate change available in Gupta et al. (2022). They compute the impact of projected hot and dry anomalies for 12 major crops grown in India using comprehensive historical data at the district level for the period 1966-2017. They generally find that rainfall extremes (wet or dry) and extreme heat events reduce average crop yields, although effects are heterogeneous across crops. Yield projections for the horizon 2030 (946.3 mm and 25.23 C°) and 2050 (927.5 mm and 26.06 C°) are done based on Word Bank's SSP 2-4.5 scenario of climate change in India that presents a "middle of the road" scenario in which emissions remain around current levels. Therefore, projected yields are available for each crop, but only at the national level. Compared to normal levels, rice yield is expected to change by -6,2% and -9,2%, and wheat by -4,9% and -7,3%, in 2030 and 2050, respectively.

Predictions for household food consumption (for rice at this stage) are obtained using a model trained with baseline data. Preliminary results (Table 3) indicate, on average, a moderate decrease in household revenues, a decrease in the value of rice consumed, and no change in the balance between market purchase and home-produced rice consumption.

Table 3 : Preliminary results for baseline and projections to 2030

Preliminary model: Value of monthly rice consumption, in Rs per capita						
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Actual	4.00	108.00	270.00	367.14	514.00	6780.00
Baseline	-24.72	264.47	350.11	435.45	567.03	2359.56
2030 Prediction	-24.71	264.47	350.44	435.51	567.04	2359.50
Diff. 2030-Baseline	-0.46	0.01	0.02	0.06	0.06	11.22

A sensibility analysis with the results for various income groups and regions will be carried out to uncover heterogeneity.

6. Conclusion and Policy Implications

Climate change poses a significant threat to agriculture and food security in rural India. While home-produced food provides an important share of household basic calories, it is unclear whether it will be a tool for enhancing resilience or vulnerability in the face of climate change. This analysis revisits household production models with deep learning to shed light on the reaction of households to reduced crop yields caused by extreme climate conditions, with explicit attention to the role of in-kind resources in the form of home-produced food.

Specifically, yield affects several decisions of households, which are typically made simultaneously and have ambiguous consequences, but which affect food consumption. The neural network approach builds a connection between inputs and outputs as a succession of layers, which we expect can reflect the several sub-instances and complexity of decision-making. For example, the arbitrage between job market participation or staying at the farm depends on the household's endowment in labor and land, their productivity, and the possibility of off-farm employment. The decision to sell or maintain agricultural production depends on market access, prices, the need to generate monetary income for non-food expenses, and preferences for time, food safety, culture, household demographics, and women's empowerment, which are all difficult to model precisely. Finally, the decision to purchase food or consume own-production also depends on household demographics, access to markets, and market prices.

Overall, the model builds the overarching relationship between district level yield and quantity of food consumption coming from purchase and home production, given available data for India, using a national survey of household consumption in 2012 and ICRISAT data for the district-level context. In addition, the semi-parametric approach allows for the reconciliation of high non-linearity and accounts for known linear relationships that have been strongly established in prior literature. This takes the form of an added layer of linear inputs entered in the last layer of the neural network.

Under climate scenarios for 2030 and 2050, projections of food consumption are generated for the anticipated values of lower yields. While the study requires further development, preliminary results indicate a moderate reduction in household resources and a moderation reduction in the consumption of rice. Detailed implications for home-produced food are still under development.

This study contributes to the existing literature by integrating in-kind revenues generated from farming aimed at own-consumption for projections of food consumption under climate change, recognizing that consumption of own-grown food products remains an essential part of households' nutrition in rural India.

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Appendix A: Descriptive statistics of independent and dependent variables

Panel I: Independent Variables					
Variable	Observation*	Mean	Std. Dev.	Min	Max
ICRISAT Data (District averages)					
Area under Rice cultivation	28052	90.44	103.47	0	655.68
Area under Wheat cultivation	28052	51.46	68.24	0	394
Area under Chickpea cultivation	28052	14.09	34.82	0	319.45
Area under Groundnut cultivation	28052	11.69	54.81	0	753.84
Rice Yield	28052	2063.25	973.94	0	5422
Wheat Yield	28052	1978.62	1322.76	0	5675
Chickpea Yield	28052	762.57	533.6	0	4500
Groundnut Yield	28052	907.1	863.19	0	5633
Rice Harvest Price	28052	1117.73	284.19	514	3062
Wheat Harvest Price	23803	1235.21	179.85	800	2150
Chickpea Harvest Price	23864	3373.57	645.01	1875	6500
Groundnut Harvest Price	23101	3598.37	889.04	1322	6300
Wage of male field labour	26931	230.17	106.28	73.33	836.67
Total agricultural credit	28052	8191804.7	9049470.6	18358	53595204
Banks	28052	57.85	17.83	17.8	94.3
NSS Data					
Agriculture characteristics					
Area of land cultivated/capita	28052	1392.54	2410.22	1	60702
Price of cereal	28052	.02	0	.01	.03
Price of pulse	28052	.06	.01	.04	.07
Price of milk	28052	.05	.02	.02	.19
Price of oil	28052	.08	.01	.05	.1
Price of egg	28052	.97	.6	.13	4.32
Price of vegetables	28052	.06	.03	.01	.2
Price of fresh fruits	28052	2.43	1.76	.22	9.6
Household characteristics					
Household size	28052	5.21	2.44	1	32
Age of household head	28052	48.82	13.03	16	102
Working age female share	28052	.51	.18	0	1
Non-durable ownership	28052	12.86	4.75	1	29
Religion (%)					
Hinduism	24072	85.81			
Islam	2566	9.15			
Christianity	664	2.37			
Sikhism	550	1.96			
Jainism	22	0.08			
Buddhism	85	0.30			
Others	93	0.33			
Possess Ration Card (%)					
Yes	24860	88.62			
No	3192	11.38			
Type of land owned (%)					

Homestead only	1635	5.83			
Homestead and other land	26297	93.74			
Other land only	120	0.43			
Social group (%)					
ST	3387	12.07			
SC	3932	14.02			
OBC	12393	44.18			
Others	8340	29.73			
Sex of household head (%)					
Female	2199	7.84			
Male	25853	92.16			
Primary education (%)					
No	23600	84.13			
Yes	4452	15.87			
Secondary education (%)					
No	10995	39.20			
Yes	17057	60.80			
Higher education (%)					
No	22764	81.15			
Yes	5288	18.85			
Young kids (%)					
No	18395	65.57			
Yes	9657	34.43			
Other source					
Travel time to cities	28052	42.46	60.42	2.41	653.65

Panel II: Dependent Variables (NSS Data)					
Variable	Observation*	Mean	Std. Dev.	Min	Max
Home share Rice	28052	.34	.45	0	1
Home share Wheat	28052	.29	.44	0	1
Home share Chickpeas	28052	.06	.24	0	1
Home share Groundnut	28052	.06	.24	0	1
Home share Maize	28052	.05	.22	0	1
Home share Millet	28052	.04	.19	0	1
Home share Sorghum	28052	.04	.18	0	1
Home share Pigeon pea	28052	.09	.28	0	1
Home value Rice	25641	239.02	419.18	0	9780
Market value Rice	25641	280.33	375.91	0	10390
Total value Rice	25641	519.35	466.68	4	10390
Home value Wheat	24022	165.54	288.19	0	3600
Market value Wheat	24022	149.39	216.58	0	5900
Total value Wheat	24022	314.93	302.6	3	5900
Home value Chickpeas	16019	7.24	29.94	0	1750
Market value Chickpeas	16019	47.36	53.11	0	1875
Total value Chickpeas	16019	54.6	55.22	2	1875
Home value Groundnut	16019	31.03	128.31	0	7500
Market value Groundnut	16019	202.95	227.62	0	8035.71
Total value Groundnut	16019	233.98	236.64	8.57	8035.71
Home value Maize	2282	90.89	143.97	0	1440
Market value Maize	2282	32.12	85.45	0	1480
Total value Maize	2282	123.01	149.83	3	1480
Home value Millet	1892	116.79	209.88	0	4500
Market value Millet	1892	82.75	165.36	0	1800
Total value Millet	1892	199.55	231.7	4	4500
Home value Millet	1892	116.79	209.88	0	4500
Market value Millet	1892	82.75	165.36	0	1800
Total value Millet	1892	199.55	231.7	4	4500
Home value Sorghum	2428	129.27	248.26	0	3000
Market value Sorghum	2428	151.36	224.41	0	3200
Total value Sorghum	2428	280.63	271.56	5	3200
Home value Pigeon pea	17462	22.03	70.14	0	1200
Market value Pigeon pea	17462	92.45	97.4	0	3000
Total value Pigeon pea	17462	114.48	101.95	3	3000

*Samples with valid observations only.

Appendix B: Training parameters of neural networks

Neural network is trained to minimize a loss function that represents the difference between the actual and predicted values (mean squared error for continuous variables, accuracy for categories). The leaky ReLU, a piece-wise linear function and a popular choice for training, is adopted as activation function, which defines how nodes are activated to map data to the next layer. During training, weights and biases are adjusted at regular intervals to make the most accurate predictions possible using the Nadam optimizer, which is one of the most popular methods for its performance and efficiency. We use 50 epochs, and keep 20% of the initial data for the testing. Two hidden layers are chosen for each model, with the number of nodes shown in the table below. The choice of the number of nodes and layers is driven by the rule of thumb that it is better to have deeper than wider layers, as more layers are able to handle more levels of complexity. However, as some of the variables are already included linearly, the remaining part is not expected to be highly complex so that only a small number of layers are deemed necessary. Table 4 displays the parameters across the various layers.

Model

Layer (type)	Output Shape	Param#	Connected to	Trainable
input_2 (InputLayer)	[(None, 36)]	0	[]	Y
dense_1 (Dense)	(None, 16)	592	['input_2[0][0]']	Y
batch_normalization (BatchNormalizat ion)	(None, 16)	64	['dense_1[0][0]']	Y
input_1 (InputLayer)	[(None, 7)]	0	[]	Y
dense (Dense)	(None, 5)	85	['batch_normalization[0][0]']	Y
concatenate (Concatenate)	(None, 12)	0	['input_1[0][0]', 'dense[0][0]']	

Total params: 767 (3.00 KB)
Trainable params: 735 (2.87 KB)
Non-trainable params: 32 (128.00 Byte)

Table 4: model parameters

Figure 5 indicates the value of the error as training progresses along the number of epochs, and the number of times the entire dataset passes through the algorithm. A comparison of the two curves indicates that there is no overfitting, as a decreasing training loss with a similar or slightly increasing validation loss is a good sign of learning.

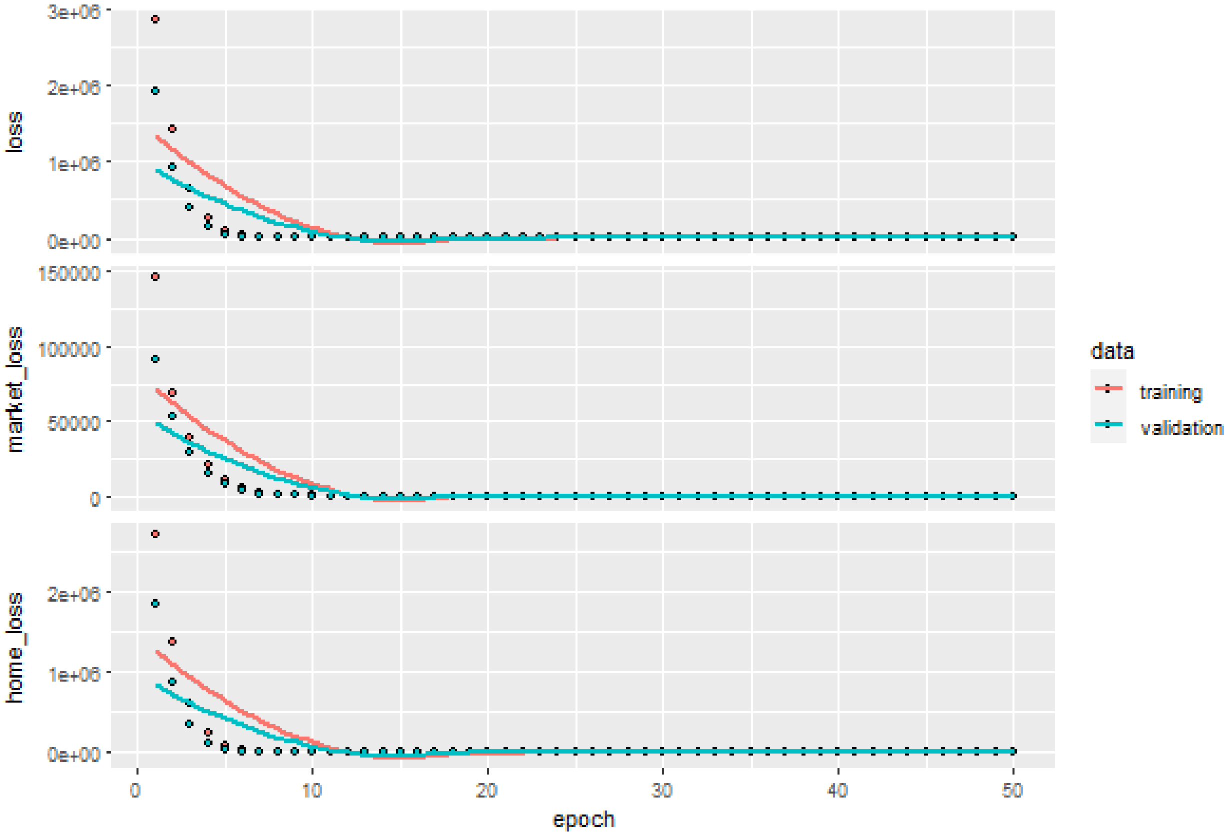

Figure 5: Learning of model on entire model (top), market quantities (middle), home-produced quantities (bottom)

Appendix C: Climate projection methodology and data

To assess the impact of climate change on consumption from home production, we use a high-resolution dataset for the South Asian region from the Center for Climate Change Research at the Indian Institute of Tropical Meteorology (CCCR-IITM) Climate Data Portal. The Centre for Climate Change Research at the Indian Institute of Tropical Meteorology Pune was launched in 2009 with the support of the Ministry of Earth Sciences (MoES), Government of India, to focus on the development of new climate modeling capabilities in India and South Asia and to address issues concerning the science of climate change. CCCR-IITM is the nodal agency coordinating the CORDEX modeling activity in South Asia. The dataset includes an ensemble of high-resolution 20th-century climatic variations and future climate projections using a global climate model with telescopic zooming (~ 35 km longitude × 35 km latitude) over the South Asian region. Monthly outputs of simulated rainfall and surface air temperature for the historical period (1951–2005) and 21st-century RCP4.5 scenario projection for the period 2006-2095 are available.

From the available dataset, we have used the data for the Indian subcontinent spanning between 8°4′N to 37°6′ N latitudes and 68° 7′ E to 97°25′ E longitudes. To do so, we have used the QGIS 3.14.16, where we layered the CCCR-IITM data on the Indian district shape file and cropped it. Our study consists of the historical period of 2000-2005 and the RCP 4.5 projected period of 2016-2050. The climate profile of the country consists of regional variations, with a tropical climate in the south, sub-humid tropical climate in the central, and temperate climate in the northern Himalayan region. Indian Meteorological Department (IMD) has categorized the Indian climate into four prominent seasons: i) Cold weather season (January–February), ii) Pre-monsoon season (March-May), iii) Southwest monsoon season (June–September) and iv) Post monsoon/Northeast monsoon season (October–December) (Attri and Tyagi, 2010). Similarly, the temperature profile of the country shows an extreme distribution ranging from below 0 °C in the northern region in winter to above 45 °C during May–June (Attri and Tyagi, 2010).

This study uses climate anomalies as independent variables in regression estimations. By considering climate anomalies, we can observe the effect of deviations from normal temperature and rainfall on agricultural yields and, in turn, how it affects their consumption from home production. Anomaly variables are created by taking the difference between the temperature or rainfall for year t and long-term climate normals (Gupta et al., 2022). Climate normals are defined as averages computed over a relatively long period of at least 30 years (World Meteorological Organization). The formulas for temperature and rainfall anomalies are as follows:

$$TA_{it} = T_{it} - \overline{T}_{i}$$

$$RA_{it} = R_{it} - \overline{R}_{i}$$

For our study, we have calculated the climate normal twice, first for 2030 considering the period (2000-2030) and second for 2050 considering the period (2020-2050). Analyzing decadal data shows that India will experience hotter temperatures and scarce rainfall in the coming years