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The impacts of climate change on cropland allocation, crop production, output prices and social welfare in Israel: A structural econometric framework

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ABSTRACT

We propose a model that simulates climate change impacts on crop production and food prices under partial equilibrium. Our model incorporates a system of Laspeyres price and quantity indices that link structurally estimated community-level produce supply functions to market level demand functions. The supply estimation accounts for corner solutions associated with disaggregate land use observations and is constrained to reproduce aggregate supply data. We use the model to assess climate change impacts in Israel, which protects local agriculture by import tariffs and quotas. The simulation results vary greatly when we allow prices to change as a response to supply changes, highlighting the importance of endogenizing prices in climate change simulations. The results imply that climate changes projected for Israel are expected to be beneficial to farmers, particularly due to the positive impact of the forecasted large temperature rise on field crop production. Fruit outputs are projected to decline, and reduce consumer surplus, but to a lower extent than the increase in total agricultural profits. Nearly 20% of the profit rise is attributed to farmers' adaptation through land reallocation. Adaptation to the projected reduction in precipitation by increasing irrigation is found to be warranted from the farmers' perspective; however, it is not beneficial to society as a whole. Abolishing import tariffs effectively transfers surpluses from producers to consumers, but the impact of this policy on social welfare is relatively modest.

"In reality, projecting impacts is the most difficult task and has the greatest uncertainties of all the processes associated with global warming" (Nordhaus, 2019, p. 1998).

1. Introduction

Climate changes pose significant threats to food security, both locally and globally. Agricultural production, which requires significant intensification due to the steady increase in world population and the associated increase in the scarcity of land, water and other agricultural inputs, faces additional challenges presented by projected climate changes. Numerous studies have shown that higher temperatures and lower precipitation are expected to decrease yields of important staple crops such as maize, rice, soybeans and wheat in many regions (e.g., Moore et al., 2017). Less attention has been given to the impact of climate changes on the production of fruits and vegetables, despite the fact that these crops are not less important to food security than staple crops (Krebs-Smith et al., 1987; Guenther et al., 2008; Hertel and de Lima, 2020). In addition, given the worldwide prevalence of agricultural protectionist policies, the impact of climate changes on agriculture in a particular country depends on the country's international trade policy, which determines the extent to which local prices of agricultural products react to variations in local and international food supply. This paper contributes to the broad literature on climate change and agriculture by integrating fruit and vegetable production into the analysis and by evaluating the economic impacts of climate change under alternative trade policy scenarios. We focus our analysis on the case of Israel, which is characterized by a spatial variability in climate conditions and projections for significant future climate changes. Moreover, due to its

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shortage in arable land and water, and a protectionist agricultural trade policy that favors local production of fruits and vegetables, Israel relies almost entirely on domestic supply of fruits and vegetables. These features, together with the availability of detailed agricultural land-use data and demand functions, make Israel an interesting case study from an international perspective.

This paper offers an innovative methodology for linking models of agricultural production and market equilibrium. The methodologies currently used for assessing the impacts of climate changes on agriculture vary considerably and often generate conflicting results (Carter et al., 2018). In particular, general and partial equilibrium models have become powerful tools to analyze those impacts due to their ability to capture economic interactions among quantities and prices of multiple products and regions. Such market level models are frequently linked with micro level agricultural production models to represent farmers' optimal responses to changes in exogenous factors, including climate conditions, prices and policy instruments. These micro level models are often based on the mathematical programming approach, in which the agricultural production function is specified explicitly, enabling integration with the market level equilibrium models to reflect feedback effects of prices on agricultural supply (e.g., Howitt, Tauber and Pienaar, 2003; Parry et al., 2004; Nelson et al., 2010; Arndt et al., 2011, 2012; Palatnik et al., 2011; Robinson et al., 2012; Shrestha et al., 2013). The agricultural production functions in such micro level models are usually calibrated or derived from estimates external to the model (Michetti, 2012). That is, there is no direct linkage between the market level equilibrium model and the dataset used to derive the agricultural production functions in the micro level model. Consequently, the analysis may overlook the heterogeneity in the farming sector, which is captured in the sample data with regard to farm productivity and farmers' decisions on cropland allocation, adoption of new production technologies and protocols, R&D investments, etc. (Costinot et al., 2016; McCarl et al., 2016). We address this gap by developing a structural econometric framework for estimating a micro level agricultural supply model, which is linked to a partial equilibrium model of produce markets. As a result, our approach allows simulation of the impacts of changes in output prices and climate variables on agricultural productivity and profitability, and consequently on adaptation through cropland allocation decisions (Arora et al., 2020; Gouel and Laborde, 2021; Aragón et al., 2021).[1]

The econometric models usually applied in economic analyses of the impacts of climate changes on agriculture rely on the notion that observed farm management practices and profits reflect farmers' optimal responses to external factors, including climatic conditions. One subgroup of these models can be referred to as land use models, utilizing spatial variability in climatic conditions to explore measures of adaptation to climate changes (e.g., Mendelsohn and Dinar, 2003; Kurukulasuriya and Mendelsohn, 2008; Seo and Mendelsohn, 2008; Fleischer et al., 2011; Etwire et al., 2019). A second subgroup of econometric models employs the Ricardian or hedonic approach (Mendelsohn et al., 1994; Schlenker et al., 2005; Deschênes and Greenstone, 2007; Mendelsohn and Massetti, 2017), in which spatial variation in farm profits or land values are explained by economic and environmental variables. Other approaches include the estimation of yield responses to spatial or temporal variability in climatic conditions (McCarl et al., 2008; Schlenker and Roberts, 2009; Attavanich and McCarl, 2014; Deschênes and Greenstone, 2011), as well as models estimating climate effects on other farm management practices (Chen and McCarl, 2001; Koleva et al., 2010; McCarl et al., 2016). Nevertheless, these types of models are based on a reduced form approach; that is, they do not explicitly estimate production functions, and therefore can only be linked to market level models implicitly (e.g., Mendelsohn and Nordhaus, 1996).

[1] The importance of accounting for price changes and adaptation has been highlighted by Blanc and Reilly (2017).

The structural model developed in this paper builds on the approach suggested by Kaminski et al. (2013), hereafter denoted as KKF (2013). This approach relies on a recursive decision-making process (McGuirk and Mundlak, 1992), in which farmers allocate land across different crops at the beginning of the growing season based on their anticipated end-of-season optimal per-hectare profits. The latter are based on farmers' long-term experience with weather events in their farms during the growing season; that is, based on climatic conditions. Hence, spatial variation in climatic conditions leads to spatial variation in the anticipated relative optimal profitability of the different crops, which in turn dictates the observed spatial variation in the land allocated to the different crops. The assumed structure of the profit function enables us to use disaggregated land allocation data in combination with aggregate production quantities to estimate per-hectare production and cost functions, as well as test whether the estimated profit functions comply with economic theory. Utilizing land allocation data as opposed to land values allows us to abstract from the assumption of perfect markets for land and other inputs, which is commonly made in applications of the Ricardian/hedonic approach. At least for Israel, the assumption of a functioning land market is far from reality. More importantly for the purpose of this study, agricultural production and output prices are expressed explicitly in the model; this key property is exploited to consistently link this structural econometric micro level supply model with a market level demand model. Consistency between the models is achieved by constraining the estimated coefficients of the micro level supply model, such that the aggregate output value shares of the various crops derived from the model will be equal to the output value shares observed in the market. Then, in simulations of exogenous changes, the supply and demand models feed into each other to determine the equilibrium quantities and prices of agricultural products, while capturing the heterogeneous supply responses in the entire sample used to estimate the supply model.

Our analysis deviates from the modeling strategy suggested by KKF in two important aspects. First, we use land allocation data at the village level, whereas KKF used regional data. This, however, requires an estimation strategy that accounts for the presence of corner solutions, due to the fact that not all crops are grown in all villages. Second, we account for responses of output prices to changes in supply by linking the micro level supply model to a market level demand model and simulating partial equilibria. These price feedback effects were ignored in KKF. The importance of allowing prices to be endogenous in the assessment of the impacts of climate changes on agriculture has been highlighted by Fernández and Blanco (2015) and Blanc and Reilly (2017), and by Miao et al. (2016) who showed that ignoring the price effects of climate changes may lead to an overestimation of the yield effects.

The suggested methodology can be applied at various spatial scales, can employ either partial or general equilibrium frameworks, and can consider the prices of different crops to be either exogenous or endogenous in the simulations. This feature enables using the model to analyze the impacts of agricultural support policies, particularly those affecting international trade, that are the topic of continuous debate (see Matthews, 2014): in countries employing trade barriers such as import tariffs, the prices of certain crops may be determined by equilibrium conditions in the local market, whereas in small open economies, prices are set in the global markets and hence are exogenous to the local market. Endogenizing price effects is also relevant in the context of developing countries where local markets are not fully integrated (Barrett, 2008; Blanc and Reilly, 2017). In addition, our methodology can be used to derive local impacts of climate changes, which could be useful for spatially targeted policy responses (De Pinto et al., 2016).

There are several policy contributions of the suggested methodology. First, it allows accounting for both, farmers' mitigation through land reallocation and partial-equilibrium price effects in the analysis of climate change impacts on farmers and consumers, which is especially relevant for agricultural products that are traded across regions and across borders. As such, it is useful for decomposing the contribution of land reallocation and other mitigation strategies to the alleviation of climate change impacts, which is important for policy actions aimed at enhancing the mitigation potential of farmers, such as developing new crop varieties and cultivation techniques, investing in irrigation infrastructure, and other technological advances. This is especially important given the worldwide food security threats implied by climate changes and the need for policies to alleviate these threats. Finally, our methodology is useful for evaluating the potential of reducing the negative welfare impacts of climate change through trade reforms.

We apply our approach to Israeli data, assessing the impact of protective tariffs on the fruit and vegetable markets in Israel under climate change. Israel is particularly suitable for studying the impact of climate change on agriculture because of its diversified climate conditions within a relatively small area, from subtropical in the north to arid in the south. In addition, while contributing only 1.3% of Israel's GDP, Israeli agriculture is technologically advanced, and is extremely experienced in adapting to unfavorable climate conditions. Not surprisingly, previous studies of the impact of climate change on Israeli agriculture cover the entire range of methodologies described above. For example, Kan et al. (2007) applied the mathematical programming technique to regional data from Israel, whereas Fleischer et al. (2008) applied the Ricardian approach to micro level data. The impact of climate change on agricultural decisions in Israel was further analyzed by Fleischer et al. (2011), using a discrete choice model in which farmers choose among a set of crop-technology bundles, and by KKF (2013) based on their structural model described above. In all of these studies, agricultural output prices were assumed constant and exogenous in the simulations of climate change. This assumption is particularly problematic in the case of Israel, and might lead to considerable biases, even if global food prices are stable. This is because the Israeli government limits imports of many agricultural products through import tariffs, quantity limitations, and other institutional means (Organization for Economic Co-operation and Development, 2019); consequently, many prices of agricultural products are determined within the local market. Therefore, a partial equilibrium model, in which prices are determined endogenously, is more suitable for assessing the impacts of climate change on Israeli agriculture. Furthermore, this also highlights a public economic perspective of the distribution of the damages caused by climate change between producers and consumers (since the latter are affected by climate driven price changes), with both efficiency and equity concerns as to which public policies could better mitigate the potentially harmful impacts of climate changes on economic activities.

After estimating the model using baseline data, we use changes in precipitation and temperature as projected under the various climate change scenarios adopted by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2014) to simulate changes in farmland allocations, agricultural production, output prices and producer and consumer surpluses. Our results indicate positive impacts of the projected climate changes on the Israeli farm sector, attributed to increased production of vegetables and field crops. On the other hand, fruit production is expected to decline sharply, entailing price increases to a level that will render the current level of protection by import tariffs ineffective. Consequently, local consumers of agricultural products see their consumer surpluses decline. However, the overall benefits to farmers exceed the losses to consumers, implying an increase in overall social welfare, although the welfare gain is not large. We find that the forecasted sharp temperature rise drives these results, with moderate counterbalance by the projected moderate decline in precipitation.

In order to evaluate the importance of endogenizing prices, we compare the above results to an alternative simulation that assumes exogenous prices. The changes in land shares, output supply and agricultural profits under exogenous prices are much more extreme than under endogenous prices. This result is expected, but the magnitude of the differences attests to the importance of allowing prices to change with changes in the supply.

We also evaluate an alternative scenario in which import tariffs are abolished. Compared to the restricted trade scenario, this policy change transfers surpluses from producers to consumers, as expected, but we find that this has only minor effects on overall social welfare. We further show how the model can incorporate farmers' adaptation through changes in input application, as well as account for changes in prices and availability of inputs. Specifically, we find that offsetting the effect of the projected decline in precipitation by increasing irrigation is an optimal strategy from the farmers' perspective, but not from that of society as a whole.

In the next two sections, we describe the conceptual micro level supply model, the econometric methodology and identification strategy, and the link of the supply model to the market level partial equilibrium model in the simulation of climate change. We then present the data and the results of the estimation of the farmland allocation model. After that we discuss the results of the climate change and trade reform simulations. The penultimate section summarizes the findings and suggests potential extensions, and the final section discusses the policy implications.

2. Conceptual modelling

We model a crop production sector in a small economy where all goods are freely traded, except for a subgroup of agricultural products that are subject to import tariffs. Consider a sample of I farms, where each farm $i, i = 1, ..., I$, allocates its land among J potential crop bundles (a bundle is an aggregate of crops, i.e., field crops, fruits, vegetables, etc.). Let s_{ji} be the land share of bundle j, $j = 1, ..., J$, in farm i. The objective of each farmer i is to choose at the onset of the growing season the vector of land shares $\mathbf{s}_i = (s_{1i}, ..., s_{Ji})$ that maximizes the farm's anticipated end-of-season per-hectare profit:[2]

$$\max_{\mathbf{s}_i} \quad \Pi_i = \sum_{j=1}^{J} s_{ji}\left(\rho_j y_{ji} - c_{ji}\right) - c(\mathbf{s}_i) \tag{1}$$

$$\boldsymbol{s.t.} \sum_{j=1}^{J} s_{ji} = 1 \ \boldsymbol{and} \ s_{ji} \geqslant 0 \ \forall \ j = 1, ..., J$$

where Π_i is farm i's per-hectare economic profit, ρ_j is bundle j's expected output price, y_{ji} is the farm-specific expected end-of-season per-hectare optimal yield of bundle j, and c_{ji} stands for the expected end-of-season bundle-specific per-hectare optimal explicit economic costs. Both y_{ji} and c_{ji} are anticipated by the farmer while accounting for bundle-specific per-hectare profit maximization measures that he/she expects to apply during the growing season (i.e., irrigation, fertilization, pesticides, herbicides, etc.) in response to foreseen exogenous events, the likelihood of which depends on various conditions, including climate.

The function $c(\mathbf{s}_i)$ is an implicit cost function, representing unobservable costs that are neither bundle-specific nor independent across bundles. For example, $c(\mathbf{s}_i)$ includes the certainty equivalent associated with risks entailed by assigning a larger land share to a particular bundle (e.g., due to sensitivity to specific extreme weather conditions, market price volatility, and other uncertain events during the growing season). It also includes the costs associated with non-feasible production of certain crop bundles in rotating systems, and costs of allocating the quasi fixed inputs such as labor and machinery across crop bundles with different patterns and cultivation timing (see KKF, 2013, and Carpentier and Letort, 2014). Thus, $c(\mathbf{s}_i)$ stands for the constraints on farmers' acreage decisions that lead to bundle diversification, and represents the nonlinear effects of the land shares $\mathbf{s}_i$ on farm economic profits – a pivotal feature in positive mathematical programming (Howitt, 1995).

[2] It is assumed that the total land of each farm is fixed, and therefore maximizing per-hectare profit is equivalent to maximizing total profit.

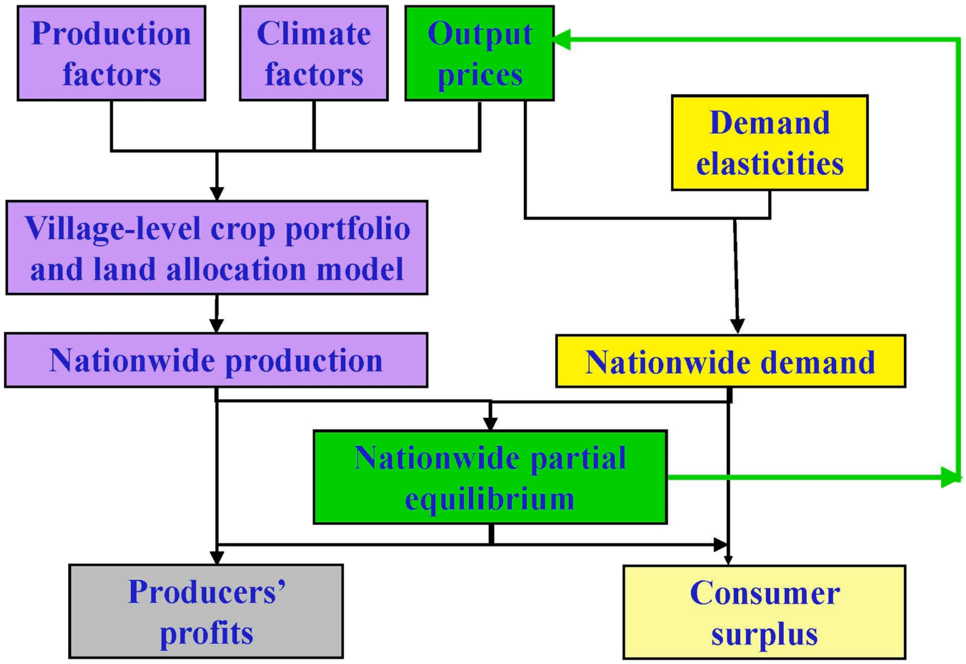

Fig. 1. Illustration of the conceptual model. Note: Changes in production and climate factors lead to changes in village-level land allocations and thereby alter nationwide production; in parallel, nationwide demand responses lead to new prices, which in turn affect farmers' land-allocation decisions. This process continues until a new equilibrium is reached, with new producers' profits and consumers' surpluses.

The importance of this nonlinear component of the objective function is that linear optimization problems tend to lead to corner solutions, unless they are performed under constraints. In the current case, they are likely to lead to specializing in the most profitable (in terms of expected profit) crop bundle. The implicit cost function represents the unobserved costs in a flexible way that enables reproducing the observed land allocation patterns.

Our first objective is to estimate the functions representing the impact of climate variables on the expected end-of-season yield y_{ij} and cost c_{ji} for the J bundles. To this end, we utilize spatial climate variability across farms in Israel. In this micro level analysis we assume that the land allocation observed at any farm i,s_i, constitutes the solution to the optimization problem in Eq. (1), where y_{ij} and c_{ji} of each bundle j reflect decades of experience through which farmer i has adapted to the climate conditions prevailing at her specific location during the period relevant for our sampled farms.

Our second objective is to use the micro level estimated functions y_{ij} and c_{ji} in simulations of climate change, while taking output price feedback effects at the market level into account. For this purpose, we use calibrated demand functions based on demand elasticities estimated elsewhere. Our model integrates, for every bundle j, a market level demand function with the sample's aggregate supply, $\sum_{i=1}^{I} l_i s_{ji} y_{ij}$, where l_i is farm-i's total cultivable land. Thus, by affecting individual farms, climate change alters the cumulative local supply of each bundle j at the market level. As this aggregate supply change interacts with aggregate consumer demand (subject to exogenous import tariffs, if prevail), a new output price ρ_j emerges. This new price, in turn, affects land allocation of each farm, leading to further changes in aggregate supply, and so on until convergence to a new equilibrium. We simulate the new equilibrium under the climate conditions projected for future periods; that is, after each farmer has adapted to the updated climate at her farm, and the J markets have converged to new equilibrium prices.[3] The outcomes of these simulations are, then, the simulated equilibrium prices.

The simulations under the different scenarios and the estimated coefficients allow us to compute changes in (a) the land allocated to each crop bundle; (b) the quantity produced; (c) the market price; (d) individual and aggregate farm profits; and, using the calibrated demand functions, (e) consumer surplus. The sum of (d) and (e) constitute the change in overall social welfare. Fig. 1 summarizes and illustrates the conceptual modelling approach.

3. Empirical strategy

We develop our econometric framework with the aim of identifying climate impacts on farm profit attributes, based on observed micro level land use data, as well as linking the micro and market levels in the simulation of equilibrium under alternative climate change and trade policy scenarios. Appendix A provides the detailed formulation of this framework, while here we describe its principles more briefly. To simplify the estimation while still being able to identify the main parameters of interest, we linearize the per-hectare production and explicit cost functions. We adopt an opposite entropy formulation of the implicit cost function, as in KKF (2013) and Carpentier and Letort (2014).[4] This

[3] Our estimated y_{ji} and c_{ji} functions reflect the outcome of adaptation, not the adaptation process itself. The latter may depend on farmers' perceptions of climate change forecasts (Arbuckle et al., 2013), their ability to practically identify climate change (Bradshaw et al., 2004) and foresee related macro trends of prices and agricultural protection policies, and the extent to which farmers adopt ex-ante or ex-post adaptation measures (Burke and Lobell, 2010, Kurukulasuriya, 2013).

[4] The implicit cost function is common in multi-crop optimization models. The advantage of the opposite entropy functional form of the implicit cost function is that it directly leads to the fractional multinomial model of land shares. Other researchers have used quadratic functions, but when we adopted these we obtained a very complicated semi-structural empirical model that did not comply with profit-maximization principles and therefore did not yield reasonable results.

Table 1
Observations and land shares in crop production portfolios.

Portfolio	Number of observations	Land shares[a] Vegetables	Field crops	Fruits	Not cultivated
Fruits	608	0.000	0.000	0.830	0.170
Field crops	44	0.000	0.963	0.000	0.037
Field crops & Fruits	1173	0.000	0.606	0.343	0.050
Vegetables	53	0.800	0.000	0.000	0.200
Vegetables & Fruits	817	0.319	0.000	0.543	0.138
Vegetables & Field crops	158	0.182	0.794	0.000	0.024
Vegetables & Field crops & Fruits	4716	0.181	0.532	0.241	0.046
Total	7569	0.150	0.547	0.260	0.043

[a] Weighted by communities' total agricultural land.

formulation leads to a solution of the profit maximization problem in the form of a set of optimal land shares, each of which depends on all model coefficients. These coefficients can be estimated using a fractional multinomial logit model (Papke and Wooldridge, 1996; Buis, 2010). Since our disaggregate data include corner solutions (i.e., not all crop bundles are cultivated in all farm communities), we estimate the model using the quasi-maximum likelihood approach. In Appendix A we show how predicted aggregate supply is derived from the estimated equations.

After estimating the supply parameters using base-period data, we turn to the derivation of equilibrium prices, in both the base period and future periods, based on simulations. Appendix B provides the full specification of this procedure, while here we outline the main points. Let t index periods with distinct climate conditions, where $t = 1$ marks the sample period. We assume that equilibrium conditions hold under the observed sample period conditions, and simulate the equilibrium to which the economy converges where, ceteris paribus, period t's climate conditions prevail. To this end, we link the market level demand functions and the estimated total local supply, where the latter aggregates micro level supplies over the sample of I farms.

For the modelling of the demand side, we formulate a Laspeyres index of the economy-wide demanded quantity of bundle j's crops, as an aggregate of crop-specific demand functions. To simplify the notation, and without loss of generality, assume that the number of different crops in each bundle $j, j = 1, \ldots, J-1$, is identical and equal to K. Denote the price of crop k, $k = 1, \ldots, K$, of bundle j under period t's conditions as p_t^{kj}, and the aggregate quantity of this crop demanded by local consumers as Q_t^{kj}. Also, assume that the aggregate demand function is of the constant elasticity form:

$$Q_t^{kj} = h^{kj} \cdot \left(p_t^{kj}\right)^{\beta^{kj}} \tag{2}$$

where β^{kj} are known demand elasticities, and h^{kj} are calibrated parameters. To overcome scale differences between the sample aggregate supply and market demand (because they are derived from different sources), our simulation model employs a system of Laspeyres price and quantity indices, each expresses the situation under period t's conditions in relation to those under period 1. Appendix B shows how these indices are used to simulate agricultural profits and consumer surplus.

4. Data and variables

Our dataset for estimating the micro level land allocation model is a panel of 7,569 observations, encompassing 743 agricultural villages (about 85% of all agricultural villages in Israel) over the years 1992–2002, provided by the Israeli Ministry of Agriculture and Rural Development (IMARD).[5] Altogether, the sample covers 264,000 ha per year, more than 60% of the agricultural land in Israel. The land allocated to each crop bundle is reported for the village as a whole. Thus, our analysis reflects only the aggregate village level outcomes of the individual farmers' decision making, which may vary with the village's internal economic structure. Forty percent of the villages in our sample are Kibbutzim (collective farms), in which all economic activities, including agriculture, are managed collectively. Another 9% of the sample are private villages, wherein agricultural decisions of the different farmers are completely independent of each other. The remaining 51% of the sample villages are Moshavim (cooperative villages with 70 individual farms on average), where each Moshav member can make his/her own land allocation decisions, subject to some institutional constraints (Kimhi, 1998).

Our data comprise aggregate land shares of four crop bundles: vegetables, field crops, fruits, and the reference bundle of non-cultivated land.[6] In Table 1, we present the number of observations and average land shares (weighted by total village agricultural land) of the eight different crop-bundle portfolios, where a portfolio indicates which and how many of the three crop bundles are cultivated. For example, the portfolio that includes all three crop bundles (bottom line of Table 1) is observed in 62% of the observations; this highlights the need to account for corner solutions in the estimation procedure. As expected, the land share of field crops is the largest with 54.7%, ahead of fruits (26.0%), then vegetables (15.0%), and non-cultivated areas (4.3%); the latter varies across portfolios between 20% in the communities that produce vegetables only, and 2% when production of vegetables is combined with field crops.

Appendix Table A1 reports per-community sample means and standard deviations of the explanatory variables used in the estimation of the production value (x_i and ρ_j in equation A1) and explicit cost (c_i) functions. As noted in Appendix A, the interaction of x_i with ρ_j enables identifying the production and cost impacts of variables that appear in both x_i and c_i; however, prices in our data vary only with time, and due to the small number of years in the sample, multicollinearity emerges.[7] Herein we assign variables to either x_i or c_i based on our presumption about their dominant impact, where climate variables are assumed to affect the end-of-season expected profit maximizing outputs, $x_i b_j$, in which b_j is the set of output coefficients. Accordingly, b_j incorporates the climate variables' direct impact on expected yields, as well as their indirect effects on expected damage prevention activities that farmers

[5] These data were not collected in later years.

[6] Note that we do not consider the livestock sector here. This is because in Israel, livestock farms are not using farmland directly. Rather, most of them buy their feed from others (among them, field crop farms, which are included in our data). The land that is used for farm buildings is included in our reference bundle of non-cultivated land.

[7] We test for multicollinearity using an OLS regression; when both price-interacted and non-interacted climate variables are incorporated in the regression, all the variance inflation factors of the climate variables exceed 10.

employ during the growing season in attempt to maximize per-hectare profits.[8]

Precipitation and temperature data are from reports by the Israeli Meteorological Service (IMS) for 594 and 70 meteorological stations, respectively, covering the entire state of Israel during the years 1981–2002 (Appendix Fig. A1). We assign the data from station locations to the coordinates of each agricultural community in our sample using the inverse distance weighting (IDW) method, using the power 1 IDW specification (see Kurtzman and Kadmon, 1999). The climate variables are annual average temperature and cumulative annual precipitation.[9] For each year in the sample, we consider the average temperature and precipitation for the previous 10-year period as those that have shaped farmers' expectations with respect to bundles' per-hectare profits while deciding on agricultural land allocation.

In the simulations of predicted climate conditions for future periods, we use forecasts provided by three global circulation models (GCMs): CCSM4 (Gent et al., 2011), MIROC5 (Watanabe et al., 2010) and NorESM1-M (Bentsen et al., 2013).[10] Each GCM provides projections for a representative year in two future periods (2040–2060 and 2060–2080) under each of the four Representative Concentration Pathways (RCP2.6, RPC4.5, RPC6 and RPC8.5) adopted by the IPCC for its fifth assessment report (IPCC, 2014).[11] We retrieved these forecasts for Israel at a 285-coordinate-grid level (see Zelingher, 2017) and assigned it to each agricultural community using the IDW method. Appendix Table A2 presents the country-wide averages of the forecasted climate variables. The three models generally predict a considerable increase in average temperature throughout Israel for both future periods, from 19 °C up to 25 °C. Annual precipitation is expected to slightly decline during 2040–2060, and then decline more sharply during 2060–2080 (by about 14% relative to the sample period level).

In addition to the climate variables, we explain production by dummy variables for the type of community (Moshav and private communities; Kibbutz is the reference category), capturing implicitly the impact of internal economic organization and cooperation within each community (Kimhi, 1998). A dummy variable, indicating whether agricultural land is dominated by light soils, stands for the suitability of farmland to the different crop bundles. We also include dummy variables for Israel's 20 ecological regions (as defined by the Israeli Central Bureau of Statistics (ICBS, 2010)) to capture spatial differences that may affect outputs (e.g., topographic and additional climate variables).

Output prices (ρ_j) are almost homogeneous across Israel, as evidenced by official data (IMARD, 2013). Hence, we use countrywide annual output price indices reported by the ICBS for each bundle over the sample years. To reflect price differences between bundle outputs, we multiply each bundle's price index by the average price of its main crops, $\overline{p}_1^j = \sum_{k=1}^K p_1^{kj} Q_1^{kj} / \sum_{k=1}^K Q_1^{kj}$, where p_1^{kj} is the price of crop k of bundle j in the base period, and is taken from cost-and-return studies (IMARD), and Q_1^{kj} is quantity demanded of that crop in the base period, and is taken from the ICBS data on the crop's countrywide annual output in 2002.[12] Following KKF (2013), we use lagged moving averages of wholesale price indices to represent the end-of-season prices that farmers might have considered when making land use decisions at the onset of the growing season. The number of lags for each bundle was determined based on ARIMA estimations using R^2 and Akaike–Schwarz information criteria, resulting with an average of two previous years for field crops and vegetables, and four previous years for fruits.[13,14]

The production value ratios r_j, which are defined as the observed ratio of the aggregate countrywide production value of bundle j relative to that of bundle 1, are computed by $r_j = \sum_{k=1}^K p_1^{kj} Q_1^{kj} / \sum_{k=1}^K p_1^{k1} Q_1^{k1}$, where the field crops bundle is used as the reference ($j = 1$). For the per-hectare cost function variables c_i, we use the distance to Tel Aviv to represent peripheral effects, such as transportation costs and availability of purchased inputs and services, as well as alternative nonfarm employment opportunities (Kimhi and Menahem, 2017). Water resources are officially controlled by the state in Israel, and per-village total irrigation water quotas are set administratively by the authorities; these quotas are introduced to capture the impact of water availability on production costs. Land assignment to farming is also centrally managed in Israel. The total agricultural land owned by the community represents potential diseconomies of land fragmentation and economies of scale. Finally, we include the previous year annual price index of purchased agricultural inputs that are relevant for the crop sector (Kislev and Vaksin, 2003); this variable represents the explicit costs $C_j(c^e)$(see Appendix B). To reflect explicit cost differences across bundles, we multiply this price input index by a bundle-specific factor, which is computed by $\sum_{k=1}^K L^{kj} C^{kj} / \sum_{k=1}^K L^{kj}$, where L^{kj} is countrywide agricultural lands (IMARD) and C^{kj} is the per-hectare costs[15] taken from cost-and-return studies (IMARD) (Appendix B).

In addition to the already mentioned data on L^{kj},C^{kj}, Q_1^{kj} and p_1^{kj}, the market level model requires the demand elasticities β^{kj} (see Eq. (2)). Israel is a net exporter of vegetables and fruits, whose imports are constrained by import tariffs, and a net importer of field crop products, which are traded freely. Hence, the output prices faced by growers of vegetables and fruits are affected by both the local and international markets. As our micro level disaggregated land-use data do not enable distinguishing between production for the local and international markets, we assume constant export shares of 29% and 22% of the total production value of vegetables and fruits, respectively (Finkelshtain and Kachel, 2009; Finkelshtain et al., 2011).[16] For the local markets of vegetables and fruits, we adopt demand elasticity parameters from

[8] For example, larger precipitation levels can directly augment yields through increased transpiration, but may also aggravate pest damage (Koleva et al., 2010), which the farmer may alleviate by applying pesticides up to the level at which the associated marginal expenses equal the marginal avoided output-value loss.

[9] Israel has a (short) rainy season and a longer completely dry season. Our crop bundles are aggregates of crops grown in one of the seasons or both. Therefore, there was no point in differentiating our climate data by seasons. We did try to use more time-disaggregated climate data, but this did not lead to different insights.

[10] For a description of GCMs, and the advantages and disadvantages of using them, see Auffhammer et al. (2013).

[11] A Representative Concentration Pathway (RCP) is a greenhouse gas concentration (not emissions) trajectory adopted by the IPCC. Four pathways were used for climate modeling and research for the IPCC fifth Assessment Report (AR5) in 2014. The pathways describe different climate futures, all of which are considered possible depending on the volume of greenhouse gases (GHG) emitted in the years to come. The RCPs – originally RCP2.6, RCP4.5, RCP6, and RCP8.5 – are labelled after a possible range of radiative forcing values in the year 2100 (2.6, 4.5, 6, and 8.5 W/m^2, respectively) (Stocker et al., 2013).

[12] The full list of crops can be seen in Appendix Table A.3. These crops cover roughly 95% of total crop production. All monetary values are in US dollars at 2000 values.

[13] We include lagged climate variables in the ARIMA analysis to check whether there is correlation between output prices and climate that farmers might have foreseen when designing land use. None of the variables was found to have a statistically significant effect.

[14] Prediction of expected output prices based on future prices (e.g., Taylor et al., 2006) is impossible in our case, because the analysis incorporates numerous crops for which future prices are unavailable.

[15] For consistency with the estimated coefficients$V_j = (b_j, G_j)$, we computed c^{kj} while subtracting the overhead assigned in the cost-and-return studies to the non-cultivated agricultural lands (the reference bundle).

[16] The allocation of products between the local and international markets frequently occurs in the wholesale markets; that is, beyond the control of farmers (Kachel, Y., personal communication, May 2014). Forecasting changes in the export shares is quite impossible, as these are determined much more by global market conditions (competition from other countries, exchange rate fluctuations, etc.) than to the local supply conditions.

Table 2
Estimated coefficients of the land share equations.[a]

Log likelihood	−7657.6		
Wald $\chi^2(91)$	29144.1		
Variable	**Vegetables**	**Field crops**	**Fruits**
Production ($\widehat{b}_j$)			
$\rho_j \times$ Precipitation	0.008**	0.002	0.008***
$\rho_j \times$ Precipitation^2	-1.53×10^{-5}***	1.17×10^{-6}	-4.96×10^{-6}*
$\rho_j \times$ Temperature	−4.615**	−0.622	−0.557
$\rho_j \times$ Temperature^2	0.125**	0.027	0.015
$\rho_j \times$ Moshav[b]	−2.019***	−2.917***	−1.032***
$\rho_j \times$ Light soil	−0.661***	−0.511***	0.171***
ρ_j	47.683**	3.310	5.831
Costs ($\widehat{G}_j$)			
Distance to Tel Aviv	−0.006***	−0.011***	0.005***
Water quota	0.546***	0.441***	0.105
Water quota^2	−0.147***	−0.113***	−0.103***
Agricultural land	0.096***	0.132***	0.090***
Agricultural land^2	−0.002***	−0.002***	−0.002***
Input price index	−1.750***	0.780***	−1.547***
Constant	−0.293	1.370***	0.604***

Note: *** indicates significance at 1%, ** indicates significance at 5%, * indicates significance at 10%.
[a] Coefficients for Ecological Regions are not reported.
[b] The dummy variable for private communities was omitted due to collinearity.

Table 3
Marginal effects of explanatory variables on land shares and agricultural profits.

	Land share				Per-hectare economic profit (elasticity)			
Variable	**Vegetables**	**Field crops**	**Fruits**	**Total cultivated**	**Vegetables**	**Field crops**	**Fruits**	**Total**
Production								
Precipitation	−0.001***	3.23×10^{-4}***	4.35×10^{-4}***	6.46×10^{-5}**	−0.537***	0.328***	0.402***	0.501***
Temperature	−0.007	0.062***	−0.047***	0.008**	0.166***	2.388***	−0.902**	2.086***
Moshav	0.033***	−0.294***	0.192***	−0.069***	−0.069***	−0.389***	0.036***	−0.481***
Light Soil	−0.027***	−0.076***	0.093***	−0.010***	−0.045***	−0.084***	0.065***	−0.063***
Vegetable price index (ρ_v)	0.455***	−0.245***	−0.179***	0.03***	0.515*	−0.129	−0.094***	0.052***
Field-crop price index (ρ_f)	−0.020***	0.068***	−0.042***	0.007***	−0.013***	0.085***	−0.028***	0.067***
Fruit price index (ρ_p)	−0.102***	−0.300***	0.439***	0.037***	−0.067**	−0.196***	0.528***	0.271
Costs								
Distance to Tel Aviv	-3.3×10^{-4}	−0.003***	0.003***	-2.3×10^{-4}***	−0.092**	−0.388***	0.297***	−0.221***
Water quota	0.002***	0.005***	−0.007***	-1.06×10^{-4}	0.054	0.107	−0.139***	0.018
Agricultural land	−0.001	0.011***	−0.005***	0.004***	0.063	0.205*	0.045***	0.337***
Input price index	−0.205***	0.552***	−0.372***	−0.024*	−0.23	0.353***	−0.323***	−0.042

Note: *** indicates significance at 1%, ** indicates significance at 5%, * indicates significance at 10%.

Hadas (2001) (Appendix Table A3). Both growers and consumers of field crops face the world prices of field crops; therefore, the demand elasticity equals the sum of import demand and local supply elasticities, weighted by the relative import and local production quantities. Import demand elasticities were taken from the World Bank (2012), where they were estimated based on the methodology developed by Kee et al. (2008), and import quantities of field crop products were obtained from the ICBS (Appendix Table A3). We substitute these elasticities and import values into equation (B2), and then employ equation (B3) to simulate import response to price changes (see Appendix B). This exercise yields an import demand elasticity of −1.60 for field crops. To calculate the local supply elasticity, we use our estimated micro level supply model to simulate field crop production response to a price change, obtaining a supply elasticity of 0.55. As local production of field crops constitutes 24% of the total consumption, the demand elasticity equals −1.08. Appendix Fig. A2 illustrates the resultant demand curves based on the calibrated functions $\phi_j^q\left(\phi_j^p\right)$, in which $\phi_j^q(\cdot)$ and ϕ_j^p represent Laspeyres demand quantity and price indices, respectively (see Appendix B).

As already noted, our analysis is based on the assumption that markets were in equilibrium in the sample period (represented by the year 2000). According to Finkelshtain et al. (2011), the local prices of vegetables and fruits during 2000–2009 were generally similar to their corresponding world prices. Therefore, imports of vegetables and fruits to Israel are negligible due to the presence of high import tariffs (reported in Appendix Table A3). We calculate the average import price for the bundles of vegetables and fruits, weighted by crop production quantities, and use these averages to compute the upper limit of price indices (denoted $\bar{\phi}^p{}_t$) in the simulation of the restricted trade scenario (equation (B3)). The calculated average import prices (world prices + import tariffs) are higher by 220% and 83% than the average observed local prices for vegetables and fruits, respectively. As to forecasts of world prices under future climates, we take the trends projected by Eboli et al. (2010) using a global CGE model.[17]

5. Estimation results

We use the Stata fractional multinomial logit command (fmlogit) to estimate the coefficients of the micro-level land allocation model

[17] These projections represent the effect of climate change in comparison to a baseline scenario without the climate-change impact. In our case, we simulate changes in climate variables and prices where all other elements of the economy are assumed to remain at their sample-period levels.

Table 4
Climate change impact on partial equilibrium indices under restricted trade policy (Scenario 1).

		Price index (φ^{p}_{jt})			Demand quantity index (φ^{q}_{jt})			Supply quantity index (φ^{Y}_{jt})			Land share index (s_{jt}/s_{j1})		
Climate period	RCP	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits
2040–2060	2.6	0.855	1.033	1.340	1.200	0.997	0.710	1.200	2.242	0.710	0.949	1.075	0.854
	4.5	0.793	1.033	1.421	1.312	0.997	0.671	1.312	2.347	0.671	0.947	1.080	0.844
	6.0	0.845	1.033	1.361	1.216	0.997	0.699	1.216	2.346	0.698	0.946	1.079	0.846
	8.5	0.691	1.033	1.558	1.546	0.997	0.615	1.546	2.669	0.615	0.941	1.090	0.822
	Average	0.796	1.033	1.420	1.319	0.997	0.674	1.319	2.401	0.674	0.946	1.081	0.841
2060–2080	2.6	0.811	1.057	1.426	1.273	0.995	0.667	1.273	2.225	0.667	0.949	1.076	0.850
	4.5	0.701	1.057	1.598	1.535	0.995	0.604	1.535	2.627	0.604	0.942	1.089	0.824
	6.0	0.718	1.057	1.557	1.477	0.995	0.615	1.477	2.561	0.615	0.942	1.088	0.827
	8.5	0.578	1.057	1.806	1.953	0.995	0.544	1.953	3.169	0.544	0.933	1.104	0.795
	Average	0.702	1.057	1.597	1.559	0.995	0.608	1.559	2.645	0.608	0.942	1.089	0.824

(denoted V_j for crop bundle j), through maximization of the quasi-likelihood function in equation (A9) subject to the constraints in equation (A11). We control for potential spatiotemporal autocorrelations in the residuals by clustering observations by years and by 60 *natural* regions.[18] We include quadratic levels of the precipitation, temperature, agricultural land and water quota variables to capture nonlinear responses. The estimated coefficients are reported in Table 2.[19,20]

Interpretation of the estimation results is facilitated by Table 3, where we present the marginal effects of the explanatory variables on optimal land shares and economic profits. These marginal effects are defined as $\frac{\partial s_j^*(z_i)}{\partial z_i}$ for the land share marginal effects (left four columns in Table 3), and as $\frac{\partial\left(s_j^*(z_i)\cdot V_j z_i\right)}{\partial z_i}$ for the per-hectare economic profit marginal effects (expressed in terms of elasticities in the right four columns in Table 3). Standard errors were estimated using the bootstrap procedure (50 replications, clustered at the natural region and year levels).[21]

On the production side, both precipitation and temperature have positive and significant marginal effects on the overall cultivated land, implying that farmers in wetter and warmer regions benefit from devoting more arable land to agricultural production. These climate variables also positively affect the total economic profit, but with different impacts across bundles. Profits of field crops and fruits are higher in higher precipitation areas, while profits of vegetables are lower in those areas. This result is congruent with the relative advantage of the southern arid part of Israel for vegetable production, as mentioned by Fleischer et al. (2008). Recall that the per-hectare expected outputs in our model are associated with anticipated optimal responses of farmers to various events during the growing season. A possible explanation for the relative disadvantage of vegetables in the wetter areas is the enhancement of plant disease by rainfall (see Agrios, 2005; Burdman and Walcott, 2012). These may adversely affect vegetable yields and/or force farmers to apply costly protective inputs, so that profits per-hectare are lower than those obtainable in the drier regions. Higher temperatures increase profitability of field crops and vegetables, and this is a likely result of expanding the cultivation season. Also, vegetables in warmer areas tend to be grown in greenhouses and other protected constructions, which provide more favorable growing conditions, under which the plants can benefit from higher temperatures. Higher temperatures reduce profits in fruit cultivation, which may be explained by the deciduous trees' chilling requirements to bloom, and by the higher need for expensive pest control materials because of the lower exposure to low night temperatures.[22]

Moshavim tend to allocate less land to field crops than Kibbutzim and private communities, and their total economic profits in field crops are lower. Light soils are associated with more farmland allocated to fruits and less to vegetables and field crops, and this is also reflected in the profit differentials associated with soil type. Regarding output prices, as expected theoretically, all bundles exhibit marginal positive own price impacts and negative cross bundle impacts on economic profits.

The marginal effects of the cost variables on total economic profits also exhibit expected signs. Peripheral communities face lower profits, which can be explained by the higher transportation costs and lower availability of production factors. Larger irrigation water quotas increase profitability. However, the effect is statistically insignificant, indicating that water quotas do not constitute effective constraints; this matches the conclusion of Feinerman et al. (2003) that, since the early 1990s, agricultural water consumption in Israel has been dictated by water prices rather than water quotas. By examining the water quota effects in relation to those of precipitation, we find that irrigation water is a substitute for precipitation in the production of fruits and vegetables, and is a complement to precipitation in field crop production; this finding coincides with the fact that, while vegetables and fruits are usually irrigated, the field crop bundle includes both rainfed and irrigated crops. The positive sign of the community's total agricultural land indicates the presence of economies of scale. Finally, the marginal effects of input prices vary across crop bundles, where the overall impact on economic profits is negative (although not statistically significant). Thus, the effect of both input and output prices on economic profits complies with economic theory.

6. Simulations

We simulate local production of the three crop bundles under equilibrium in the respective markets, where, ceteris paribus, climate vari-

[18] These regions were determined by the ICBS (2010) based on criteria such as topography, climate, demography and history, each includes on average 12.4 (std = 8.2) sampled communities. Thus, the clusters capture those spatial autocorrelations of measurement errors in the dependent and independent variables between communities of the same region that are not necessarily diminishing with Euclidean distance (e.g., as assumed by the Moran's I statistic). For example, due to the presence of topographic (and therefore climatic) boundaries (e.g., between valleys and highlands) and intra-regional processing and marketing cooperatives, the correlation in measurement errors between two adjacent communities from different regions may be considerably lower than the correlation of each one of them with remote communities within the region.

[19] We omit a time-trend variable from the estimation due to multicollinearity considerations, as reported in Footnote 7.

[20] Marginal productivity effects are zeroed at an annual precipitation of 261.5 mm and temperature of 18.5°C for vegetable production, and at an annual precipitation of 806.5 mm for fruit production.

[21] We run the procedure with 100 replications and the results were practically similar.

[22] One should also recall that the three crop bundles we defined are aggregates of many different crops that could be affected differently by climate change, and hence the effect of climate change on the aggregate bundle is not always easy to explain with agronomic arguments.

Table 5
Climate change impact on aggregate welfare measures under restricted trade policy (Scenario 1), (10^6 \$/year).

		Accounting profit[a]				Consumer surplus				Social welfare			
Climate period	RCP	Vegetables	Field crops	Fruits	Total	Vegetables	Field crops	Fruits	Total	Vegetables	Field crops	Fruits	Total
2040–2060	2.6	38	251	−4	284	85	−26	−184	−125	122	225	−187	160
	4.5	46	271	−1	317	126	−26	−220	−119	172	246	−220	197
	6.0	40	271	−2	309	91	−26	−193	−128	131	245	−196	181
	8.5	66	335	8	409	202	−26	−278	−102	267	309	−270	307
	Average	47	282	0	330	126	−26	−219	−118	173	256	−218	211
2060–2080	2.6	42	258	−2	297	113	−44	−223	−154	155	213	−225	143
	4.5	65	339	10	414	196	−44	−292	−141	260	295	−282	273
	6.0	60	326	7	392	181	−44	−277	−141	240	281	−270	251
	8.5	100	449	29	578	306	−44	−371	−109	406	405	−342	469
	Average	67	343	11	420	199	−44	−291	−136	265	299	−280	284

[a] Accounting profits in the base period amount to \$119, \$656, \$2,146 and \$2,921 million/year for vegetables, field crops, fruits and overall, respectively.

Table 6
Climate change impact on partial equilibrium indices under abolishment of import tariffs (Scenario 2).

		Price index (φ_{jt}^{p})			Demand quantity index (φ_{jt}^{q})			Supply quantity index (φ_{jt}^{y})			Land share index (s_{jt}/s_{j1})		
Climate period	RCP	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits
2040–2060	2.6	0.855	1.033	1.340	1.200	0.997	0.710	1.200	2.242	0.710	0.949	1.075	0.854
	4.5	0.793	1.033	1.421	1.312	0.997	0.671	1.312	2.347	0.671	0.947	1.080	0.844
	6.0	0.845	1.033	1.361	1.216	0.997	0.699	1.216	2.346	0.698	0.946	1.079	0.846
	8.5	0.689	1.033	1.514	1.551	0.997	0.631	1.551	2.683	0.592	0.939	1.093	0.817
	Average	0.796	1.033	1.409	1.320	0.997	0.677	1.320	2.404	0.668	0.945	1.082	0.840
2060–2080	2.6	0.811	1.057	1.426	1.273	0.995	0.667	1.273	2.225	0.667	0.949	1.076	0.850
	4.5	0.698	1.057	1.507	1.545	0.995	0.634	1.545	2.653	0.563	0.939	1.094	0.814
	6.0	0.716	1.057	1.528	1.480	0.995	0.625	1.480	2.570	0.600	0.941	1.090	0.823
	8.5	0.570	1.057	1.532	1.990	0.995	0.624	1.989	3.251	0.427	0.927	1.117	0.766
	Average	0.699	1.057	1.498	1.572	0.995	0.638	1.572	2.675	0.564	0.939	1.094	0.813

ables change as reported in Appendix Table A2,[23] and world prices vary according to Eboli, Parrado and Roson (2010). That is, we assess the impact of the climate conditions predicted for a future period (which are incorporated in x_t, $t > 1$) and the associated world prices as if they had occurred in the sample period ($t = 1$), where all other factors (e.g., population and technological level) are fixed. We study the consequences of these changes under five scenarios with respect to policies and agricultural adaptation strategies. Specifically, we solve equation (B3) for each scenario, where the Laspeyres indices $\phi_j^y(z_t)$ and $\phi_j^q\left(\phi_{jt}^p\right)$ are as defined in equations (B1) and (B2), respectively, thus capturing the supply and demand responses to changes in the relevant variables, as depicted by each scenario.

Scenario 1 simulates shifts in the climate variables under the prevailing policy of constraining trade by use of import tariffs. Tables 4 and 5 report the results in terms of changes relative to the sample period climate, averaged across the three GCMs. Changes in output prices (φ_{jt}^p), quantities demanded (φ_{jt}^q) and supplied (φ_{jt}^y), and land shares (s_{jt}/s_{j1}) (Table 4) exhibit similar trends under all four RCPs, for the two future climate periods. The supplies of vegetables and field crops increase, whereas the supply of fruits declines. Local output prices of vegetables decline, while those of fruits rise, but not to the level of the import price (international price + tariffs), and therefore there is no import of fruits under this scenario. The prices of field crops increase marginally with world prices; hence, the demanded quantity remains relatively stable, and the increased supply of field crop outputs may reduce the import of field crop products.

By comparing the local supply indices (φ_{jt}^y) to the land share indices (s_{jt}/s_{j1}), one can assess the role played by the changes in per-hectare production versus changes in land allocation. The simulations indicate that the share of land devoted to fruits declines, but the production of fruits declines even more, indicating a decline in the per-hectare productivity of fruits. Similarly, the per-hectare productivity of field crops and vegetables is predicted to increase sharply, making them more attractive than fruits. The share of land allocated to vegetables declines slightly, probably due to the lower price, which in turn leads to an expansion of the share of land allocated to field crops.

Table 5 reports changes in aggregate agricultural accounting profits, consumer surplus and their sum (i.e., social welfare) under Scenario 1. Apparently, climate change is generally beneficial to Israeli farmers, particularly to field crop growers. Vegetable producers also benefit from climate change, but to a much lower extent, whereas the profit of fruit producers does not change much. Taken together, the Israeli crop growers are expected to enjoy an increase of about 14% in their accounting profits. Local consumers are expected to benefit from the higher supply and lower price of vegetables, but suffer because of the lower supply and higher prices of fruits. Altogether, the surpluses of local consumers are projected to decline moderately. Thus, the overall expected welfare change is positive. This result prevails under both future climate periods and the four RCPs, with the largest (lowest) change under RPC8.5 (RCP2.6).

In order to evaluate the importance of allowing prices to reach a new equilibrium as a result of climate changes and farmers' adaptation, we repeat the previous simulation while not allowing prices to change. We have found that under endogenous prices, climate changes are expected to lead to a higher price of fruits and a lower price of vegetables (the price of field crops was assumed to be equal to the import price). Here

[23] The predicted responses to temporal changes in climate variables are based on the spatial variations of these variables across communities in the sample period. Hence, the larger the spatial variability in comparison to the temporal variation, the larger the validity of the simulation predictions for changed climate conditions; in our case, the spatial variance among communities captures 96% and 69% of the total spatiotemporal variance of precipitation and temperature, respectively.

Table 7
Climate change impact on aggregate welfare measures under abolishment of import tariffs (Scenario 2), (10^6 \$/year).

		Accounting profit[a]				Consumer surplus				Social welfare			
Climate period	RCP	Vegetables	Field crops	Fruits	Total	Vegetables	Field crops	Fruits	Total	Vegetables	Field crops	Fruits	Total
2040–2060	2.6	38	251	−4	284	85	−26	−184	−125	122	225	−187	160
	4.5	46	271	−1	317	126	−26	−220	−119	172	246	−220	197
	6.0	40	271	−2	309	91	−26	−193	−128	131	245	−196	181
	8.5	67	338	−31	374	203	−26	−260	−82	270	312	−291	291
	Average	47	283	−9	321	126	−26	−214	−114	174	257	–223	207
2060–2080	2.6	42	258	−2	297	113	−44	–223	−154	155	213	−225	143
	4.5	66	344	−63	347	199	−44	−257	−103	265	300	−320	245
	6.0	60	327	−19	369	181	−44	−266	−128	242	283	−284	241
	8.5	106	465	−179	393	314	−44	−267	3	420	421	−446	395
	Average	69	349	−66	352	202	−44	−253	−96	270	304	−319	256

[a] Accounting profits in the base period amount to \$119, \$656, \$2,146 and \$2,921 million/year for vegetables, field crops, fruits and overall, respectively.

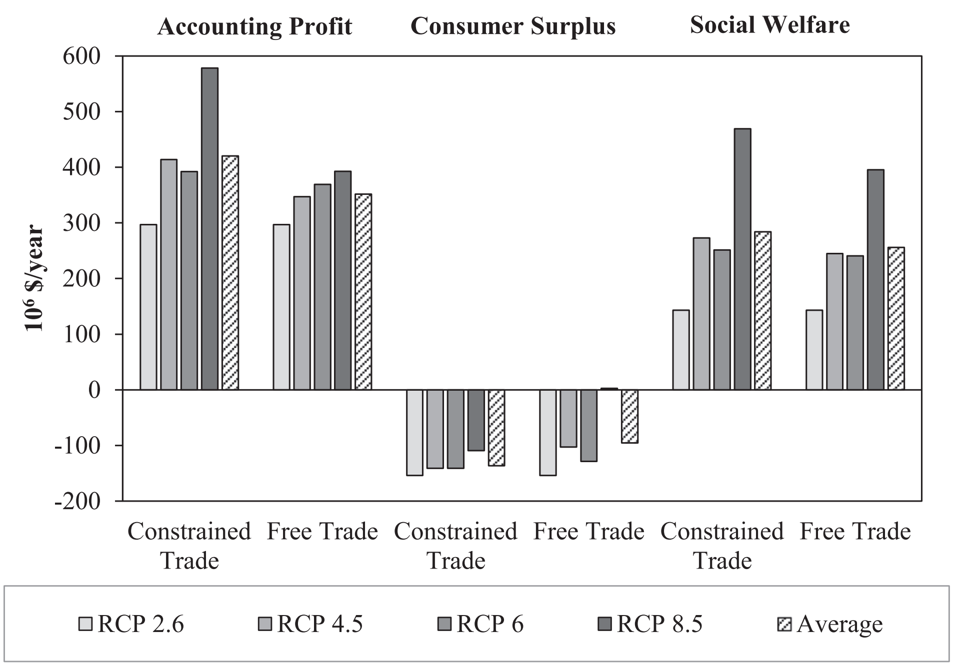

Fig. 2. Climate change impacts under the free trade (Table 7) and restricted trade (Table 5) scenarios (10^6 \$/year, 2060–2080 climate period).

we keep all prices constant at their base-period level. Appendix Tables A4 and A5 provide the simulation results. Comparing Appendix Table A4 to Table 4, we find that, as expected, not allowing the price of fruits to increase leads to a larger reduction in the share of land devoted to fruits and in the fruit output. In parallel, not allowing the price of vegetables to decline leads to a smaller reduction in the share of land devoted to vegetables and a larger increase in the vegetable output.

Appendix Table A5 shows the welfare impacts of climate change under the fixed price constraint. Compared to Table 5, we do not find a decline in consumer surplus, because nothing changed on the demand side. Agricultural profits increased much more sharply than in Scenario 1, to practically unreasonable levels, mostly because both price and output of vegetables are higher compared to the endogenous-prices scenario. Altogether, social welfare increased much more than in Scenario 1. This comparison highlights the importance of allowing prices to change as a response to climate changes in such simulations.

We now turn to study trade policy implications. According to Organization for Economic Co-operation and Development, 2019, the *producer support estimate* measure for Israel indicates that the overall support to farmers is close to the average OECD country, but the fraction of trade-distorting support policies, particularly the *market price support* measure, is considerably larger; hence, compliance with World Trade Organization rules requires removing import tariffs. This policy is examined in Scenario 2, where we simulate the abolishment of tariffs such that import prices of all crop products equal their world price counterparts, as forecasted based on Eboli et al. (2010). Tables 6 and 7 report the results of Scenario 2. Effectively, the only expected change in the parameterization of the simulations is in the price of fruits, because the equilibrium price of vegetables turned out to be lower than the import price in Scenario 1, and free trade of field crops was allowed throughout. Imports of fruits are more likely under Scenario 2 because the effective import price does not include tariffs. Comparing the simulated increases in the quantity demanded and quantity supplied of fruits, we find that there will be imports of fruits in 2040–2060 only under the most extreme RCP. Averaging over the four RCPs, fruit imports are projected to account for a small fraction of local consumption. However, the simulation for 2060–2080 shows fruit imports in three of the four RCPs, with an average import of 11.5% of local consumption. As a comparison of Table 6 and Table 4 shows, the fact that fruit growers face lower prices leads to a stronger decline of the share of land devoted to fruits, mostly in favor of field crops. In addition, the output of fruits declines more sharply, while the output of vegetables and field crops increases further, compared to Scenario 1.

Table 7 shows the welfare impacts of climate change under free trade. Comparing Table 7 to Table 5, we find that the accounting profits of vegetable and field crop growers increase slightly under the free trade scenario, whereas fruit growers face a more substantial drop in profits, particularly because of the emergence of fruit imports and the lower price compared to constrained trade regime (Scenario 1). Consumer surpluses associated with vegetables rise more with climate change than under the current trade barriers, whereas the surplus associated with fruits drops by a lesser amount than it does under free trade.

To comprehend the impact of the free trade policy, Fig. 2 summarizes the effect of removing import tariffs by depicting the accounting profit, consumer surplus and social welfare simulation results under both trade regimes (i.e., the values in Table 7 and their counterparts in Table 5).[24] Recall that under the relatively large climate change scenarios, which are driven by large CO_2 concentrations (i.e., RCP 8.5 in 2040–2060 and RCPs 4.5, 6 and 8.5 in 2060–2080), local fruit prices reach the (lower) import price. As a result, farmers' profits are lower under these RCPs, while consumer surpluses are higher. However, in all cases the benefits to consumers from removing the import tariffs are lower than the losses to producers, and therefore social welfare declines.[25] The explanation is that fruit growers lose twice: they get relatively lower prices for their output, and the quantity declines as well because of the imports. Still, the overall welfare losses are not large, and hence the impact of removing import tariffs are mostly redistributive, from farmers to consumers.

In Scenarios 3 and 4, we isolate the effects of changes in precipitation and temperature, respectively. To this end, we rerun Scenario 1 while changing only one of the two climate variables. This exercise (Appendix Table A6) reveals that the aforementioned welfare benefits of climate change stem from the considerable rise in temperature, as forecasted by all GCMs (Appendix Table A2). The changes in precipitation lead, in most cases, to welfare losses that are much smaller in magnitude than the welfare benefits of the temperature changes.[26]

Under each of the four scenarios examined up to now, farmers adapt to the changes in climate conditions by reallocating their land across the three crop bundles. In Scenario 5, we assume that farmers also adapt by offsetting the change in precipitation by applying additional irrigation water.[27] This scenario is equivalent to Scenario 4, where precipitation remained at its base-period level, except that the input price index varies according to the additional costs associated with irrigation that compensate for the change in precipitation (i.e., higher c_{it}^{ne} for the irrigation cost item n in equation B5). The share of irrigation costs in the total explicit costs of each crop in each bundle (α_n^{kj} in equation B5) is computed using cost-and-return studies (IMARD).[28] Note that increasing irrigation implies higher agricultural water consumption, which is possible if water quotas are not binding, or otherwise they should be extended. As already noted, our results imply that water quotas are not binding in the base period, i.e., farmers do not use their entire quotas, and we assume that this is also the case under the simulated change. Comparing Scenario 5 (Appendix Table A6) to Scenario 1 (Table 5) shows that offsetting the decline in precipitation by increasing irrigation decreases both farmers' profits and consumer surplus, implying a lower social welfare. Comparing the results (Appendix Table A7) to Scenario 1 (Table 4), we find that while land allocation is expected to change only slightly, the supply of fruits is expected to increase, and the price of fruits is expected to decline. However, the supply of vegetables is expected to decline more sharply and their price is expected to rise, implying a lower consumer surplus. It turns out that the loss in consumer surplus related to vegetables is larger (in absolute value) than the gain related to fruits, and this is the main reason for the result that this policy is not expected to improve social welfare.

Our last issue is the role played by land reallocation in the adaptation to the projected climate changes. In this case, rather than the accounting profit, the economic profit.

($\sum_{i=1}^{I}\sum_{j=1}^{J}s_{jit}^{*}(\mathrm{z}_{it})\mathrm{V}_j\mathrm{z}_{jit}$) is the appropriate measure, as it dictates land use adaptation. Scenario 6 imitates Scenario 1, but without allowing for land adaptation (i.e., retaining the sample period land shares). Based on comparison to the economic profits without land responses ($\sum_{i=1}^{I}\sum_{j=1}^{J}s_{ji1}\mathrm{V}_j\mathrm{z}_{jit}$), we attribute about 16% of the overall profit increase stemming from climate change (i.e., $\sum_{i=1}^{I}\sum_{j=1}^{J}s_{jit}^{*}(\mathrm{z}_{it})\mathrm{V}_j\mathrm{z}_{jit} - \sum_{i=1}^{I}\sum_{j=1}^{J}s_{ji1}(\mathrm{z}_{i1})\mathrm{V}_j\mathrm{z}_{ji1}$), to land adaptation.[29]

7. Summary and discussion

Hertel and de Lima (2020) claim that there is a significant knowledge gap pertaining to climate change impacts on crops other than staples, that are not less important for food security and perhaps even more important in providing essential micronutrients. This paper contributes to narrowing this knowledge gap by giving equal attention to all types of crops. It develops a structural econometric model to assess climate

[24] The figure includes the projections for the 2060–2080 climate period only, because they were not very different in the two scenarios for the earlier climate period.

[25] This result is consistent across the three GCM models used to predict climate change.

[26] Kawasaki and Uchida (2016) also found that a rise in temperature benefits farmers by increasing crop yields. However, they also found that at the same time, crop quality may decline. While we cannot directly account for this effect with our data, our analysis captures it indirectly provided that farmers are aware of the decline in quality and take it into account in their cropland allocation decisions. A number of recent articles (e.g., Salazar-Espinoza et al., 2015; Khanal and Mishra 2017) have focused on climate uncertainty rather than climate trends. However, Yang and Shumway (2016) found that farmers' adjustment to climate change is not affected much by ignoring climate uncertainty.

[27] Israeli farmers operate under irrigation water quotas, but, given the high price of water, these quotas are mostly ineffective in the relevant period (Feinerman et al., 2003). Since the use of desalinated water for irrigation is expensive, reduced precipitation is likely to have a negative effect on crop profitability. If farmers do not increase irrigation, yields would be lower. If they do increase irrigation, costs would be higher. In our simulations, we assume the latter, and adjust the cost of irrigation water accordingly.

[28] Irrigation constitutes 9%, 38% and 17% of the total explicit costs of vegetables, field crops and fruits, respectively.

[29] While this seems to be a small number, farmers can adapt in other ways, in addition to land reallocation. Burke and Emerick (2016) found that the adaptation capacity of US farmers is quite limited. However, Miao et al. (2016) found that the price responsiveness of land allocation is larger than that of yield. Moreover, Trapp (2014) found that farm-level adaptation, especially cropland expansion and crop-portfolio adjustments, can largely mitigate the negative impacts of climate change on regional crop production in the EU.

change impacts on crop production and produce prices under equilibrium between supply and demand in the relevant markets. The suggested methodology can be applied to various spatial scales, employing partial or general equilibrium frameworks, wherein the prices of different crop bundles can be considered either exogenous or endogenous in the simulations. The linkage between a micro-level crop production model and a market-level demand model is particularly important as governments and international organizations alike are being called upon to revise current policies in order to provide adaptation solutions to climate change, and to integrate agricultural policies within a broader set of policies targeting sustainable development and natural resource management (Howden et al., 2007). Taking produce prices into consideration is extremely important given their relevance to the critical issues of poverty, food security and malnutrition worldwide. Moreover, this paper highlights farmer adaptation to climate change through land reallocation, which has been indicated by Carter et al. (2018) as "perhaps the area of research that is most in need of development.".

Indeed, our empirical analysis of the Israeli case study yields substantially different simulation results when prices are allowed to reach a new equilibrium following the changes in supply stemming from both climate change and farmers' adaptation. This is consistent with the conclusion of Gouel and Laborde (2021) that the production adjustments to climate changes are mostly driven by price changes, and indicates that ignoring potential price adjustments may lead to severely biased projections of the impact of climate change on agriculture. Our analysis also yields different results when import tariffs are abolished compared with the current situation of restricted trade, allowing for a welfare evaluation of trade policies. Our results suggest that, under restricted trade, Israeli farmers are expected to benefit (and consumers are expected to lose) from the predicted climate changes, especially from the rise in temperatures. This result is opposite to what Reilly et al. (2003) found for the US, and it mostly stems from the increased supply of vegetables and field crops. The increased supply is in part due to the shift of farmland from fruits and vegetables to field crops, but also to higher output per hectare for vegetables and field crops, possibly as a result of longer cropping seasons for these crops (Ortiz-Bobea, 2021). Another possible reason is that some crops could benefit from higher temperatures if they move into greenhouses and other protected constructions and provided sufficient irrigation. Fruit production, on the other hand, is expected to suffer because of the deciduous trees' chilling requirements to bloom, and because of the potentially higher need for expensive pest control materials due to the lower exposure to low night temperatures.

Our simulation results also show that nearly 20% of the rise in agricultural profit is attributed to farmers' adaptation through land reallocation. The combined impact of land reallocation and other mitigation measures, which we do not explicitly observe, is most likely even greater. This result is consistent with the findings of Costinot et al. (2016), that production adjustments substantially mitigate the ill effects of climate change. For example, Ortiz-Bobea and Just (2013) and Kawasaki and Uchida (2016) found that adapting planting dates can substantially reduce the negative impact of climate change, while Jagnani et al. (2021) found that farmers respond to temperature changes by adapting other cultivation practices.

In the Israeli case study, abolishing import tariffs mostly transfers surpluses from producers to consumers, and the overall welfare effect of this policy change is quantitatively small. This is similar to the finding of Costinot, Donaldson and Smith (2016) that trade adjustments play little role in explaining the magnitude of climate change impacts on agricultural markets worldwide, and to that of Gouel and Laborde (2021) that production adjustments are more important than trade adjustments in reducing the expected welfare losses resulting from climate change. With import tariffs, the tariffs become effective only for fruits, as the equilibrium price of fruits is found to be lower than the import price in some of the (less extreme) climate models. Abolishing the tariffs, then, hurts the local fruit growers. As a result, this leads to a stronger decline in the share of land devoted to fruits, mostly in favor of field crops. In addition, the output of fruits declines more sharply than under import tariffs, while the output of vegetables and field crops increases further.

While the somewhat surprising result that climate changes can be welfare-enhancing is plausible for the case of Israeli agriculture for the reasons described above, it must be interpreted with caution, for several reasons. First, our analysis relies on relatively strong functional form assumptions. Second, it may suffer from omitted variables bias, as our climate variables are limited to temperature and precipitation, and do not include other climatic conditions such as, for example, CO_2 levels in the atmosphere (Baldos and Hertel, 2014; Zelingher et al., 2019). The effects of CO_2 levels are theoretically ambiguous, so the bias could go either way. Still, Moore et al. (2017) conclude that CO_2 fertilization fully offsets negative impacts of warming on crop yields. Third, we do not account for the fact that future climatic conditions will include higher within-year variability and more extreme weather events such as droughts and flooding (Baldos and Hertel, 2015). This is likely to reduce farm profits and consumer welfare compared to our simulation results. Fourth, our analysis focuses on climate changes only, and does not take into account possible future changes in important factors such as crop technology (Delzeit et al., 2018), which are likely to improve social welfare. Finally, we abstract from losses due to climate change impacts on agricultural inputs, such as the negative labor productivity implications of heat stress (Hertel and de Lima, 2020). Had we been able to account for all these factors, our results could change in either direction. Given the fact that the overall predicted change in social welfare is quantitatively small in absolute value in most simulations, the results could also change from positive to negative. Hence, we do not assign much importance to the finding that Israel's farm sector will benefit from climate change. In any case, these results may be specific to Israel, as previous research has shown that the effects of climate change on agriculture could be very different in different parts of the world (Carter et al., 2018). Rather, we emphasize the findings that cropland reallocation is an important component of adaptation strategies, that ignoring output price changes may lead to very different conclusions, and that trade policy changes may also affect farmers' adaptation strategies.

The methodology proposed in this paper has many potential extensions. Here are two major examples. First, climate change affects water demands for domestic, industrial and irrigation uses, as well as the recharge rate of natural water resources. Integration of our framework into a hydro economic model (e.g., Reznik et al., 2017) would allow us to account for climate change impacts on optimal water allocation policies and development paths of water infrastructure. Second, one may include valuations of agricultural external effects to assess environmental implications of climate change impacts on agricultural land use. For instance, our analysis projects conversion of fruit and vegetable lands into field crops (Table 4), which in turn increases landscape amenities (Kan et al., 2009).

8. Policy implications

Quantifying the welfare impacts of climate change that are related to agriculture is important for estimating the overall social cost of carbon, which is, in turn, important for designing appropriate mitigation strategies (Moore, Baldos and Hertel, 2017; Hertel and de Lima, 2020). In addition, the food security threats implied by climate changes for most world regions require effective agricultural adaptation strategies. These adaptation strategies require government intervention because of equity concerns (farmers vs. consumers) and the need to set priorities for policy-driven adaptation efforts to be focused on certain crops or regions (e.g., Lobell et al., 2008); however, such interventions obviously need to focus on adaptation strategies with a public good nature (McCarl et al., 2016). The results of this paper identify several policy interventions that are important for agricultural adaptation. First, heterogeneous impacts of climate change on both producer and consumer welfare may call for specific policy attention; e.g., under our specifications and given the sample period conditions, consumers are adversely affected (in most scenarios) whereas producer profits rise with the projected future climate changes. This calls for policies that put a higher weight on improving consumer welfare. An example of such policies is the removal of trade protections (Moore et al., 2017). The removal of import tariffs undoubtedly shifts welfare from farmers to consumers. The improved profitability of farmers with climate change could make such a policy more politically acceptable. This result may be relevant not only for countries that protect their local producers with trade barriers, such as Israel, but also for countries that are subject to relatively large transportation costs or other costs associated with imported produce. These policy conclusions could have been very different had we not allowed prices to change as a result of climate-driven changes in supply.

As mentioned above, improved adaptation technologies require R&D investments with a public good component (Pardey et al., 2012). Projections of the changes in consumer and producer surpluses could be useful for identifying technological improvements with higher benefit-cost ratios. This can lead to more effective public and private R&D spending. For example, our simulations predict that the surpluses of both producers and consumers of fruits in Israel will decline, whereas the surpluses associated with vegetables are projected to increase for both producers and consumers. Hence, within this context, proactive adaptation efforts would ideally be directed toward fruits. Similarly, specific technology attributes of the agricultural systems (e.g., inputs use and maximum potential outputs) could also be targeted, as done by KKF (2013).

Finally, our model emphasizes farmers' adaptation through changes in land allocation across different crops, and our results showed that this adaptation accounts for a sizeable fraction of the overall welfare changes resulting from climate change. Another role of the public system, including R&D, extension, regulation, etc., is to prepare the grounds (both literally and metaphorically) for faster and more efficient changes in farmland allocations.

CRediT authorship contribution statement

Iddo Kan: Conceptualization, Methodology. **Ami Reznik:** Data curation, Software. **Jonathan Kaminski:** Conceptualization, Methodology. **Ayal Kimhi:** Supervision, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Derivation of the land share estimation procedure

We specify the expected optimal per-hectare output of each bundle j as $y_{ji} = \mathrm{b}_j\mathrm{x}_i$, where $\mathbf{b}_j$ is a vector of coefficients, and $\mathbf{x}_i$ is a set of farm specific yield-related exogenous variables, including climate variables and farm characteristics.[30] The expected optimal bundle-specific economic costs are specified by $c_{ji} = \gamma_j\mathrm{c}_i$, where $\mathbf{c}_i$ is a vector of cost-related exogenous variables (e.g., purchased input prices and the distance to markets) and γ_j is the corresponding vector of coefficients. Thus, the expected end-of-season maximum per-hectare economic profit of bundle j is:

$$y_{ji}\rho_j - c_{ji} = \mathrm{b}_j\mathrm{x}_i\rho_j - \gamma_j\mathrm{c}_i \equiv \mathrm{v}_j\mathrm{z}_{ji} \tag{A1}$$

where $\mathrm{v}_j = \left(\mathrm{b}_j, -\gamma_j\right)$ and $\mathbf{z}_{ji} = \left(\mathbf{x}_i\rho_j, \mathrm{c}_i\right)$. Note that, since $\gamma_j\mathrm{c}_i$ incorporates the shadow values of constrained factors, it expresses the per-hectare economic costs rather than the explicit costs reported in bookkeeping records; hence, $\mathrm{v}_j\mathrm{z}_{ji}$ represents the per-hectare economic profit rather than the accounting profit. Moreover, the bundle-specific interaction $\mathrm{x}_i\rho_j$ enables to identify the production function coefficients b_j, which in turn allows linking the micro and market level models.

The function $c(\mathbf{s}_i)$ plays a key role in the econometric analysis, as its functional specification determines the attributes of the structural equations to be estimated, and therefore the required estimation procedure. KKF (2013) and Carpentier and Letort (2014) assumed the opposite entropy function:

$$c(\mathbf{s}_i) = \frac{1}{a}\sum_{j=1}^{J} s_{ji}\ln\left(s_{ji}\right) \tag{A2}$$

where the a parameter, measured in land-per-money units (and therefore assumed positive), reflects the "weight" of the implicit costs in the economic profit function. This is a non-positive, non-monotonic convex function with respect to s_{ji}. The non-monotonicity implies that, ceteris paribus, the implicit costs decline with s_{ji} for $\exp(-1) \geqslant s_{ji} \geqslant 0$, and increase with s_{ji} when $1 \geqslant s_{ji} > \exp(-1)$. Since land shares are negatively correlated among themselves through the land constraint, $c(\mathbf{s}_i)$ reaches its minimum value when $s_{ji} = 1/J$ for all $j = 1, \ldots, J$.

After using the parameterization in (A1) and (A2) in Eq. (1) in the main text, the farmer's profit-maximization problem becomes (we omit the farm index for notation brevity):

$$\max_{\mathbf{s}} \quad \Pi = \sum_{j=1}^{J} s_j\mathrm{v}_j\mathrm{z}_j - \frac{1}{a}\sum_{j=1}^{J} s_j\ln\left(s_j\right) \; s.t. \; \sum_{j=1}^{J} s_j \leqslant 1 \tag{A3}$$

Using the first order condition.

[30] While this linear yield function is adopted to facilitate the analysis, the model can be easily extended; for example, KKF (2013) specified y_{ji} as a quadratic function of per-hectare bundle-specific endogenous inputs with structural parameters, and thereby accounted for the impact of climate change through optimal input applications and identified the effect of climate variables on attributes of agricultural production technologies.

$$\frac{\partial \Pi}{\partial s_j} = \mathrm{v}_j \mathrm{z}_j - \frac{1}{a}\left(\ln(s_j) + 1\right) - \lambda = 0 \tag{A4}$$

we get the land share:

$$s_j = \frac{\exp\left(a\left(\mathrm{v}_j \mathrm{z}_j\right)\right)}{\exp(a\lambda + 1)} \tag{A5}$$

Substituting (A5) into the land constraint in (A3), we obtain:

$$\sum_{j=1}^{J} s_j = \exp(-a\lambda - 1)\sum_{j=1}^{J}\exp\left(a\left(\mathrm{v}_j \mathrm{z}_j\right)\right) = 1 \tag{A6}$$

Eq. (A6) can be solved to obtain the shadow value of the land constraint as:

$$\lambda = \frac{\ln\left[\sum_{j=1}^{J}\exp\left(a\left(\mathrm{v}_j \mathrm{z}_j\right)\right)\right] - 1}{a} \tag{A7}$$

This can be substituted back into the land share in (A5) to obtain the multinomial logit functional form for the optimal land shares:

$$s_j^*(\mathrm{z}_i) = \frac{\exp\left(\mathrm{v}_j \mathrm{z}_{ji}\right)}{\sum_{j=1}^{J}\exp\left(\mathrm{v}_j \mathrm{z}_{ji}\right)} \tag{A8}$$

where $s_j^*(\mathrm{z}_i)$ is the profit maximizing land share of bundle j, and $\mathrm{z}_i \equiv (\mathrm{z}_{1i}, ..., \mathrm{z}_{Ji})$. Note that the parameter a is canceled out, and therefore unidentifiable.[31] Moreover, since $c(\mathbf{s}_i)$ does not discriminate across farms and bundles, the land use in each farm i is determined merely by the relative expected per-hectare economic profit $\mathrm{v}_j \mathrm{z}_{ji}$ of the J bundles.

The land shares constraint $\sum_{j=1}^{J} s_{ji} = 1$ implies that the set of identifiable parameters comprises only $J-1$ bundles. Let J be the reference bundle, and define $\mathrm{V}_j \equiv \left(\mathrm{b}_j - \mathrm{b}_J, -\left(\gamma_j - \gamma_J\right)\right)$ for bundles $j = 1, ..., J-1$. However, linking the micro and market level models for simulation of partial equilibrium requires identification of b_j rather than $\mathrm{b}_j - \mathrm{b}_J$. We take advantage of the fact that farmers typically devote non-cultivated agricultural land to roads, storage lots and other uses that support production in the cultivated areas, and treat these supportive lands as the reference bundle J. As in crop cost-and-return studies (e.g., see studies by the University of California, Davis (2013)), the revenue contribution of the supportive lands is reflected only through the cultivated areas; that is,$\mathrm{b}_J = 0$. Hence, defining $\mathrm{G}_j \equiv -\left(\gamma_j - \gamma_J\right)$, our estimated coefficients are $\mathrm{V}_j \equiv \left(\mathrm{b}_j, \mathrm{G}_j\right)$ for all $j = 1, ..., J-1$.

One could use (A8) to obtain a system of $J-1$ linear land share regression equations of the form $\ln\left(s_{ji}^*/s_{Ji}^*\right) = \mathrm{V}_j \mathrm{z}_{ji} + u_{ji}$, where u_{ji} is an error term. Indeed, being conveniently estimable due to linearity, flexible, and ensuring that for each observation the predicted land shares are between 0 and 1, and add up to 1, the multinomial logit functional form was favored over alternative specifications in land use analyses in general (e.g., Wu and Segerson, 1995; Hardie and Parks, 1997; Miller and Plantinga, 1999; Marcos-Martinez et al., 2017), and with respect to climate change in particular (Seo et al., 2010; Mu et al., 2013; Cho and McCarl, 2017).

However, the set of linear regression equations derived by the multinomial logit specification cannot treat corner solutions (i.e., land shares of 0 or 1). This limitation may not emerge when estimation is based on agricultural land-use data aggregated over many farms, where zero land share observations are rare. Our analysis, however, is based on a community level land use dataset, which involves a non-negligible number of observations with corner solutions. Hence, we estimate the system of equations in (A8) by employing the quasi maximum likelihood approach to the fractional multinomial logit likelihood function (Papke and Wooldridge, 1996; Buis, 2010):

$$\ln(L) = \sum_{i=1}^{I}\sum_{j=1}^{J} s_{ji}\ln\left(s_{ji}^*(\mathrm{z}_i)\right) \tag{A9}$$

where s_{ji} is the observed land share, and $s_{ji}^*(\mathrm{z}_i)$ are the optimal land shares as specified in (A8).[32]

Estimation based on (A8) yields $J-1$ sets of production function coefficients b_j, which are deduced merely from land use observations. To improve supply predictions, we use additional information on bundle outputs; alas, these are available only at the state level in our case study. We therefore use them in the form of quantity index constraints. Let bundle 1 be the reference for this purpose, and denote by $r_j, j = 2,...,J-1$, the observed ratio of the aggregate countrywide production value of bundle j relative to that of bundle 1. Let the sample's total production value of bundle j be.

$$A_j(\mathrm{z}) = \rho_j \sum_{i=1}^{I} l_i s_j^*(\mathrm{z}_i)\mathrm{b}_j \mathrm{x}_i,\ j = 1, ..., J-1$$

where $\mathrm{z} \equiv (\mathrm{z}_1, ..., \mathrm{z}_I)$. We estimate the model in (A8) subject to the set of $J-2$ constraints.

$$\frac{A_j(\mathrm{z})}{A_1(\mathrm{z})} = r_j\ \forall\ j = 2, ..., J-1$$

The aggregate production value in (A10),$A_j(\mathrm{z})$, is also the link between the micro and market level models in the simulation of climate change

[31] KKF (2013) showed that a can be calibrated using panel data and additional information on crop profitability.

[32] The disadvantage of not using the linearized version of the multinomial logit model is the inability to account for spatial correlations and random effects, as in Marcos-Martinez et al. (2017).

scenarios, as we describe next.

Appendix B. Linking micro and market level models in climate change simulations

Let $\phi^p_{jt} = \rho_{jt}/\rho_{j1}$ denote the simulated output price index of bundle j under period t's climate relative to that of period 1. We define a vector of simulated price indices $\phi^p{}_t = (\phi^p_{1t}, ..., \phi^p_{J-1t})$, and the corresponding set of explanatory variables $z_{ijt} = \left(\phi^p_{jt}\rho_{j1}x_{it}, c_{it}\right)$ for every farm $i = 1,...,I$, bundle $j = 1,...,J-1$, and period t, wherein x_{it} and c_{it} incorporate the values (observed for $t = 1$, forecasted for $t > 1$) of farm i's variables under period t conditions. Accordingly, $\widehat{s}^*_j(z_{it})$ is the land share calculated by (A8), given period t's set of variables $z_{it} = \left(z_{ijt}, ..., z_{iJ-1t}\right)$ and the estimated coefficients $\widehat{b}_j$ and $\widehat{G}_j$. Using (A10), the sample aggregate optimal output value for bundle j in period t is $\widehat{A}_j(z_t) = \phi^p_{jt}\rho_{j1}\sum_{i=1}^{I} l_i\widehat{s}^*_j(z_{it})\widehat{b}_j x_{it}$, where $z_t = (z_{1t}, ..., z_{It})$. Then, the Laspeyres quantity index of the local supply of bundle j is:

$$\phi^y_j(z_t) = \frac{\widehat{A}_j(z_t)}{\widehat{A}_j(z_1)} \tag{B1}$$

Note that $\phi^y_j(z_t)$ depends on the simulated price indices $\phi^p{}_t$, all of them indirectly affect the micro level land uses through z_t, and bundle j's price index ϕ^p_{jt} also directly affects $\widehat{A}_j(z_t)$.

Assume further that all crops in each bundle j satisfy the criteria of a composite commodity; that is, their prices change proportionately.[33] Using equation (2), we formulate the Laspeyres demanded quantity index,ϕ^q_{jt}, as a function of bundle j's simulated price index ϕ^p_{jt}:

$$\phi^q_j\left(\phi^p_{jt}\right) = \frac{\sum_{k=1}^{K} p_1^{kj} h^{kj}\left(\phi^p_{jt}p_1^{kj}\right)^{\rho^{kj}}}{\sum_{k=1}^{K} p_1^{kj} Q_1^{kj}} \tag{B2}$$

Under the above settings, equilibrium in the sample period implies $\phi^q_j\left(\phi^p_{j1}\right) = \phi^y_j(z_1) = 1$ for all $j = 1, ..., J-1$. We simulate equilibrium under period t's conditions z_t by solving.

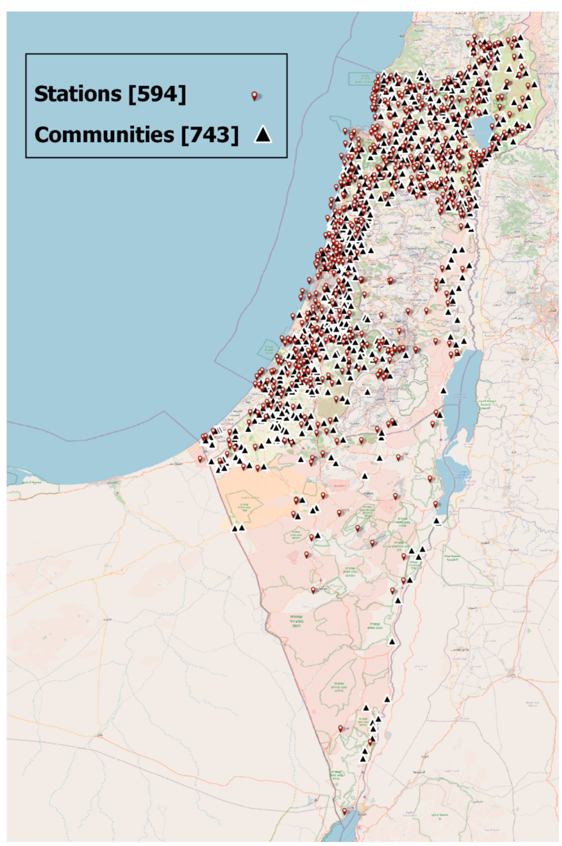

Fig. A1. Locations of agricultural villages and weather stations.

[33] We employ this assumption to derive bundle-level Laspeyres quantity indices, since the community-level land-use data are available only for bundles of crops, whereas market-level quantities and prices are available for the various crops in each bundle.

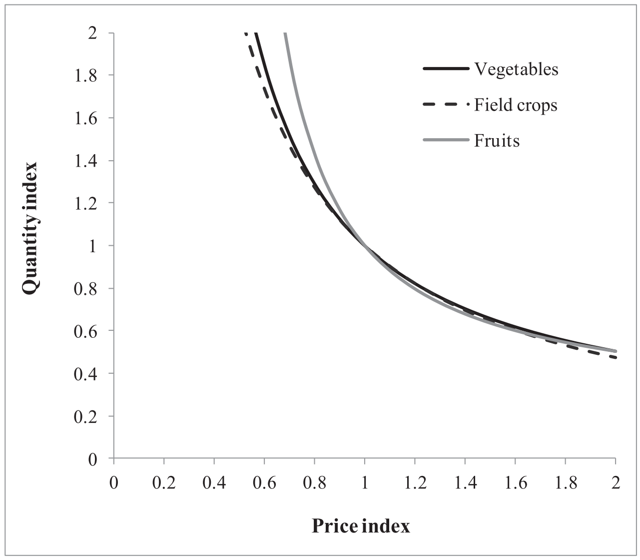

Fig. A2. Demand curves of the three crop bundles, formulated in terms of quantity and price indices.

Table A1
Descriptive statistics of the explanatory variables.

Variable	Units	Mean	Std.
Production (x)			
Precipitation	mm/year	449.8	87.83
Temperature	C°	19.29	0.546
Moshav	dummy	0.544	0.498
Private community	dummy	0.094	0.292
Light soil	dummy	0.566	0.496
Output price indices (ρ_j)			
Vegetable price index	index	0.526	0.068
Field crop price index	index	0.663	0.081
Fruit price index	index	0.654	0.127
Costs (c)			
Distance to Tel Aviv	km	71.79	41.45
Water quota	$10^6 \times m^3$/year	1.393	0.949
Agricultural land	$10^3 \times m^2$	6,217	5,963
Vegetable input price index	index	0.522	0.107
Field crop input price index	index	0.489	0.100
Fruit input price index	index	1.654	0.338

$$\min_{\phi^p{}_t} \sum_{j=1}^{J-1} \left(\phi_j^q\left(\phi_{jt}^p\right) - \phi_j^y(z_t)\right)^2 \quad s.t.\ \phi^p{}_t \leqslant \bar{\phi}^p \tag{B3}$$

where $\bar{\phi}^p = \left(\bar{\phi}_1^p, ..., \bar{\phi}_{J-1}^p\right)$ is the set of $J-1$ import price indices, each equals the sum of the world price and the respective country's import tariff, divided by the observed local price in the sample period. Eq. (B3) links the local supply quantity index, which incorporates all of the sample data points, and the demand quantity index, which relies on country level aggregate data, while taking trade restrictions (through the implementation of import tariffs) into account.

The rest of this section describes the calculations of welfare elements. The difference in consumer surplus (CS) between the equilibria under period t's and period 1′s conditions, ΔCS_{jt}, is computable for every bundle $j, j = 1,...,J-1$, using (2): $\Delta CS_{jt} = \sum_{k=1}^{K}\frac{h^{kj}}{\beta^{kj}+1}\left[\left(\phi_{jt}^p\right)^{\beta^{kj}+1} - 1\right]\left(p_1^{kj}\right)^{\beta^{kj}+1}$. Aggregate local agricultural revenues and imports at period t are given by $\phi_j^y(z_t)\sum_{k=1}^{K} p_1^{kj} Q_1^{kj}$ and $\left[\phi_j^y(z_t) - \phi_j^q\left(\phi_{jt}^p\right)\right]\sum_{k=1}^{K} p_1^{kj} Q_1^{kj}$, respectively. To compute local aggregate accounting profits, one needs to subtract the explicit costs from the production value. However, as already noted, the estimated per-hectare economic cost function $\widehat{G}_j c_i$ differs from farm i's explicit costs by the presence of constrained factors multiplied by their respective shadow values. We distinguish between these two types of costs by defining $c_i^e = \left(c_i^{1e}, ..., c_i^{Ne}\right)$ as a subset of c_i that incorporates those variables associated with explicit costs (e.g., purchased production factors). Accordingly, farm i's predicted total explicit cost under period t conditions is.

$$C_{it}(z_{it}) = \sum_{j=1}^{J-1} l_i s_{ji}^*(z_{it}) C_j\left(c_{it}^e\right) \tag{B4}$$

Table A2
Forecasts of national average climate variables for Israel (change from base period).

RCP	Climate model	2040–2060		2060–2080	
		Precipitation (mm/year)	Temperature (C°)	Precipitation (mm/year)	Temperature (C°)
Base period		450	19.3	450	19.3
2.6	CCSM4	2.9%	3.2	−6.0%	3.3
	MIROC5	−5.8%	3.9	−5.3%	4.1
	NorESM1	3.1%	3.4	−11.8%	3.5
	Average	0.0%	3.5	−7.8%	3.6
4.5	CCSM4	−1.6%	3.4	−6.4%	4.1
	MIROC5	−2.4%	4.3	−11.6%	5.4
	NorESM1	−14.0%	3.9	−25.3%	4.2
	Average	−6.0%	3.9	−14.4%	4.5
6	CCSM4	−4.9%	3.6	−10.9%	4.2
	MIROC5	−3.8%	3.9	−11.3%	4.9
	NorESM1	11.1%	3.7	−15.3%	4.2
	Average	0.9%	3.7	−12.7%	4.4
8.5	CCSM4	−15.3%	4.4	−18.4%	5.5
	MIROC5	−9.8%	5.0	−20.0%	6.1
	NorESM1	−12.2%	4.6	−25.8%	5.5
	Average	−12.4%	4.7	−21.6%	5.7
Average		−4.9%	3.2	−10.9%	3.3

Table A3
Nationwide data in the base year for the crops in the three crop bundles.

Crop	Land (L^{kj}, hectares)	Quantity (Q_1^{kj}, ton/year)	Price (p_1^{kj}, \$/ton)	Demand elasticity (ρ^{kj})	Explicit cost (C^{kj}, \$/hectare)	Import tariff (% of world price)
Vegetables						
Watermelon	15,461	184,596	216	−0.7	8,917	29
Melon	2,888	48,993	654	−0.7	2,004	47
Tomato	4,291	288,621	1,178	−0.7	23,320	42
Strawberry	454	9,614	2,493	−0.7	66,511	35
Potato	12,742	196,680	461	−2.2	10,060	78
Cucumber	1,827	67,870	536	−0.3	35,211	12
Eggplant	798	28,517	423	−0.3	6,994	20
Pepper	2,475	50,946	818	−1.3	21,586	32
Zucchini	971	17,968	560	−1.1	2,059	17
Onion	3,210	53,860	313	−1.1	8,811	61
Carrot	1,265	50,938	332	−1.5	24,443	58
Lettuce	1,262	22,441	540	−1.1	26,771	10
Cabbage	1,980	37,082	292	−1.1	15,029	39
Cauliflower	1,579	18,177	413	−1.1	12,813	29
Celery	521	10,606	551	−1.3	5,357	19
Radish	415	7,243	421	−1.1	5,384	111
Field crops – local						
Cotton, raw	11,646	92,668	991	–	2,663	0
Chickpea	7,558	9,328	998	–	296	0
Corn	5,233	98,766	358	–	3,215	0
Pea	2,162	8,945	626	–	597	0
Peanuts	3,744	24,169	1,592	–	1,196	0
Sunflowers	7,680	19,447	1,340	–	994	0
Wheat	83,646	160,260	260	–	74	0
Barley	8,364	5,342	257	–	60	0
Hay	64,294	86,188	146	–	73	0
Field crops – import						
Cotton, lint	–	12,381	16,213	−0.06	–	–
Chickpea	–	8,000	998	−0.7	–	–
Corn	–	796,836	358	−1.6	–	–
Pea	–	2,400	626	−1.5	–	–
Peanuts	–	2,901	1,592	−0.3	–	–
Wheat	–	1,582,069	260	−2.0	–	–
Barley	–	233,808	257	−0.85	–	–
Fruits						
Apple	5,506	119,316	987	−1.9	6,186	39
Pear	1,676	25,055	1,190	−1.3	4,274	39
Peach	5,630	51,298	1,177	−0.7	7,839	21
Grapes	11,740	95,295	923	−1.0	5,959	31
Banana	2,382	94,590	762	−1.5	6,456	37
Avocado	5,709	69,157	1,180	−3.8	2,082	40
Dates	3,441	12,276	3,297	−5.3	6,640	48

(*continued on next page*)

Table A3 (*continued*)

Crop	Land (L^{kj}, hectares)	Quantity (Q_1^{kj}, ton/year)	Price (p_1^{kj}, \$/ton)	Demand elasticity (β^{kj})	Explicit cost (C^{kj}, \$/hectare)	Import tariff (% of world price)
Orange	3,303	376,476	377	−0.4	1,277	5
Grapefruit	7,763	520,864	343	−0.2	2,332	24
Lemon	1,726	45,122	432	−1.4	2,696	27
Olive	20,034	34,450	1,262	−1.7	1,664	49
Almond	2,979	4,086	2,110	−1.7	1,074	9

Table A4
Climate change impact on partial equilibrium indices under exogenous prices.

		Price index (φ_{jt}^{p})			Demand quantity index (φ_{jt}^{q})			Supply quantity index (φ_{jt}^{y})			Land share index (s_{jt}/s_{j1})		
Climate period	RCP	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits
2040–2060	2.6	1.000	1.000	1.000	1.000	1.000	1.000	1.684	2.294	0.551	0.951	1.089	0.815
	4.5	1.000	1.000	1.000	1.000	1.000	1.000	2.092	2.407	0.484	0.954	1.095	0.799
	6.0	1.000	1.000	1.000	1.000	1.000	1.000	1.741	2.403	0.529	0.949	1.094	0.806
	8.5	1.000	1.000	1.000	1.000	1.000	1.000	3.181	2.729	0.385	0.961	1.104	0.771
	Average	1.000	1.000	1.000	1.000	1.000	1.000	2.175	2.458	0.487	0.953	1.096	0.798
2060–2080	2.6	1.000	1.000	1.000	1.000	1.000	1.000	1.991	2.271	0.497	0.956	1.090	0.809
	4.5	1.000	1.000	1.000	1.000	1.000	1.000	3.336	2.670	0.385	0.965	1.101	0.775
	6.0	1.000	1.000	1.000	1.000	1.000	1.000	2.948	2.610	0.404	0.961	1.101	0.779
	8.5	1.000	1.000	1.000	1.000	1.000	1.000	6.303	3.163	0.271	0.992	1.107	0.741
	Average	1.000	1.000	1.000	1.000	1.000	1.000	3.645	2.678	0.389	0.968	1.100	0.776

Table A5
Climate change impact on aggregate welfare measures under exogenous prices, (10^6 \$/year).

		Accounting profit[a]				Consumer surplus				Social welfare			
Climate period	RCP	Vegetables	Field crops	Fruits	Total	Vegetables	Field crops	Fruits	Total	Vegetables	Field crops	Fruits	Total
2040–2060	2.6	393	246	−256	382	0	0	0	0	393	246	−256	382
	4.5	608	267	−296	579	0	0	0	0	608	267	−296	579
	6.0	424	267	−268	422	0	0	0	0	424	267	−268	422
	8.5	1187	329	−355	1161	0	0	0	0	1187	329	−355	1161
	Average	653	277	−294	636	0	0	0	0	653	277	−294	636
2060–2080	2.6	558	241	−290	510	0	0	0	0	558	241	−290	510
	4.5	1277	318	−356	1238	0	0	0	0	1277	318	−356	1238
	6.0	1070	306	−345	1031	0	0	0	0	1070	306	−345	1031
	8.5	2861	412	−424	2850	0	0	0	0	2861	412	−424	2850
	Average	1442	319	−354	1407	0	0	0	0	1442	319	−354	1407

[a] Accounting profits in the base period amount to \$119, \$656, \$2,146 and \$2,921 million/year for vegetables, field crops, fruits and overall, respectively.

Table A6
Impacts on welfare measures of changes in precipitation only (Scenario 3), temperature only (Scenario 4), and offsetting precipitation change by irrigation (Scenario 5) (10^6 \$/year).

		Scenario 3 Change in precipitation only			Scenario 4 Change in temperature only			Scenario 5 Offsetting precipitation change by irrigation		
Climate period	RCP	Accounting profit[a]	Consumer surplus	Social welfare	Accounting profit[a]	Consumer surplus	Social welfare	Accounting profit[a]	Consumer surplus	Social welfare
2040–2060	2.6	10	−9	1	283	−137	146	286	−134	152
	4.5	−4	−8	−13	323	−133	190	313	−148	164
	6.0	13	−10	3	306	−136	170	310	−129	181
	8.5	−21	−12	−32	421	−115	306	396	−151	245
	Average	−1	−10	−10	333	−130	203	326	−141	186
2060–2080	2.6	−4	−31	−34	307	−169	139	293	−190	103
	4.5	−19	−41	−61	428	−148	279	399	−190	209
	6.0	−16	−34	−50	406	−155	251	382	−191	191
	8.5	−36	−51	−86	590	−116	474	545	−179	366
	Average	−19	−39	−58	433	−147	286	405	−187	217

[a] Accounting profits in the base period amount to \$119, \$656, \$2,146 and \$2,921 million/year for vegetables, field crops, fruits and overall, respectively.

Table A7
Climate change impact on partial equilibrium indices under constrained trade policy and increased irrigation (Scenario 5).

		Price index (φ^{p}_{jt})			Demand quantity index (φ^{q}_{jt})			Supply quantity index (φ^{y}_{jt})			Land share index (s_{jt}/s_{j1})		
Climate period	RCP	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits	Vegetables	Field crops	Fruits
2040–2060	2.6	0.861	1.033	1.349	1.185	0.997	0.704	1.185	2.246	0.704	0.949	1.074	0.857
	4.5	0.849	1.033	1.399	1.207	0.997	0.680	1.207	2.411	0.680	0.944	1.081	0.844
	6.0	0.839	1.033	1.370	1.222	0.997	0.693	1.222	2.338	0.693	0.947	1.077	0.851
	8.5	0.790	1.033	1.497	1.315	0.997	0.637	1.315	2.804	0.637	0.935	1.094	0.818
	Average	0.835	1.033	1.404	1.232	0.997	0.679	1.232	2.450	0.679	0.944	1.081	0.843
2060–2080	2.6	0.890	1.057	1.394	1.144	0.995	0.682	1.144	2.306	0.682	0.945	1.078	0.849
	4.5	0.815	1.057	1.511	1.280	0.995	0.633	1.280	2.779	0.633	0.934	1.094	0.819
	6.0	0.823	1.057	1.494	1.252	0.995	0.639	1.252	2.696	0.639	0.936	1.092	0.823
	8.5	0.715	1.057	1.662	1.487	0.995	0.582	1.487	3.402	0.582	0.923	1.110	0.787
	Average	0.811	1.057	1.516	1.291	0.995	0.634	1.291	2.796	0.634	0.935	1.094	0.819

where $C_j\left(c^e_{it}\right)$ is a bundle-specific total per-hectare explicit cost function, which is derivable from state level information and cost-and-return studies. We specify.

$$C_j\left(c^e_{it}\right) = L_j^{-1}\sum_{k=1}^{K} L^{kj}C^{kj}\sum_{n=1}^{N}\alpha^{kj}_{n}\frac{c^{ne}_{it}}{c^{ne}_{i1}} \tag{B5}$$

where L^{kj} is the countrywide aggregate land allocated to crop k in bundle j; L_j is the aggregate land allocated to bundle j such that $L_j = \sum_{k=1}^{K} L^{kj}$; C^{kj} is the per-hectare production costs of crop k in bundle j; α^{kj}_n is the share of explicit cost item $n, n = 1, \ldots, N$, in C^{kj}, and c^{ne}_{it} is the level of farm i's explicit cost variable n under period t conditions. In the simulations, we use the explicit cost c^{ne}_{it} of irrigation to assess the impact of increasing irrigation water applications to compensate for projected reductions in precipitation .[34]

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