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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

This paper combines a structural estimation of vegetative-agriculture supply, based on a farmland-allocation model, with a market-level partial equilibrium demand model, to simulate the effects of climate change on agricultural production and food prices. The supply estimation accounts for corner solutions associated with disaggregate land-use data, enabling the treatment of prices as exogenous. The explicit formulation of production and output prices enables linkage to the demand, as well as the exploitation of market-level data so as to assign production interpretation to the estimated coefficients of the land-use model. We use the model to assess climate-change impacts in Israel, where agriculture is protected by import tariffs. We find that the projected climate changes are 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 becomes positive only under scenarios of large climate change.

Key words: climate change; adaptation; agricultural land use; structural analysis; agricultural support policy

JEL Codes: Q15, Q18, Q11

Owing to their ability to capture economic interactions among quantities and prices of multiple products and regions, general and partial equilibrium models have become powerful tools for assessing climate-change effects on agriculture. Such market-level models are frequently linked with micro-level agricultural production models to represent farmers' optimal responses to changes in exogenous variables, including climate, prices and policy instruments. These micro-level models are often based on the mathematical programming approach, in which agricultural production is represented explicitly, enabling integration with the market-level equilibrium models to reflect price-feedback effects on supply changes (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, Willenbockel, and Strzepek 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 not capture the sample heterogeneity present in the data with regard to farmers' productivity and their decisions on cropland allocation, adoption of new production technologies and protocols, R&D investments, etc. (Costinot, Donaldson and Smith, 2016; McCarl, Thayer, and Jones 2016). This paper addresses this gap by developing a structural econometric framework for estimating a micro-level crop-supply model which is consistently linkable to a partial equilibrium model of an agricultural produce market. Specifically, our suggested approach allows simulation of the impacts of changes in output prices and climate variables on crop productivity and profitability, and consequently on adaptation through cropland allocation decisions.

The econometric models usually applied in economic analyses of climate change rely on the notion that observed farm-management practices and profits reflect farmers' optimal responses to external factors, including climate. One group of models can be referred to as land-use models, utilizing spatial variability in climate conditions to explore climate-change-adaptation measures (e.g., Mendelsohn and Dinar 2003; Kurukulasuriya and Mendelsohn 2008; Seo and Mendelsohn 2008; Fleischer, Mendelsohn, and Dinar 2011; Etwire, Fielding and Kahui, 2018). A second group of econometric models employs the Ricardian or Hedonic approach (Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fischer 2005; Deschênes and Greenstone 2007), 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 climate (McCarl, Villavicencio, and Wu 2008; Schlenker and Roberts 2009; Attavanich and McCarl 2014), as well as models estimating climate effects on other farm-management practices (Chen and McCarl 2001; Koleva, Schneider, and Tol 2010; McCarl, Thayer, and Jones 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).

The structural model developed in this paper builds on the approach suggested by Kaminski, Kan and Fleischer (2013). This approach relies on a recursive decision-making process (McGuirk and Mundlak 1992), in which farmers allocate land across crop bundles (i.e., fruit, vegetables and field 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 during the growing season; that is, based on climate. Hence, spatial variation in climate conditions leads to spatial variation in the anticipated relative optimal profitability of bundles, which in turn dictates the observed spatial variation in land allocation across crop bundles. The structure of the profit function enables us to use disaggregated crop-acreage 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-use data as opposed to land values allows us to avoid making assumptions regarding the presence of perfect markets for land and other inputs, which are common in applications of the Ricardian/Hedonic approach. More importantly, for the purpose of this study, agricultural production and output prices are expressed explicitly in the estimated 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 model, such that the aggregate output-value shares of the various crops derived from the model will be equal to the observed output-value shares. 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 Kaminski, Kan and Fleischer (2013) in two important aspects. First, we use disaggregated land-allocation data at the community level, whereas Kaminski, Kan and Fleischer (2013) used regional data. This allows us to treat output prices as exogenous in the estimation of the supply model. However, it also requires an estimation strategy that controls for the presence of a non-negligible number of observations with corner solutions (land shares of 0 or 1). 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. Thus, prices are exogenous in the estimation of micro-level production decisions, but become endogenous in the simulations under partial equilibrium conditions. These price-feedback effects were ignored in Kaminski, Kan and Fleischer (2013). The importance of allowing prices to be endogenous in the assessment of climate-change impacts has been highlighted by Fernández and Blanco (2015).

Miao, Khanna and Huang (2016) showed that ignoring the price effects of climate change may lead to an overestimation of the yield effects.

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. 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 price of some crop bundles 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. In addition, our methodology can be used to derive local impacts of climate change, which could be useful for spatially targeted policy responses (De Pinto, Wiebe, and Rosengrant 2016).

We illustrate our approach using Israeli data, assessing the impact of protective tariffs on the Israeli vegetative-agriculture markets 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 1.2% of Israel's NDP (Israel Central Bureau of Statistics 2017), Israeli agriculture is technologically advanced, and has enjoyed decades of experience 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, Rapaport-Rom and Shechter (2007) applied the mathematical programming technique to regional data from Israel, whereas Fleischer, Lichtman and Mendelsohn (2008) applied the Ricardian approach to micro-level data. The impact of climate change on agricultural decisions in Israel was further analyzed by Fleischer, Mendelsohn and Dinar (2011), using a discrete-choice model in which farmers choose among a set of crop-technology bundles, and by Kaminski, Kan and Fleischer (2013) based on their aforementioned structural model. 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 (OECD 2010); hence, many crop prices are determined within local markets. Therefore, a partial equilibrium model, in which prices are determined endogenously, is more suitable for assessing the ramifications of climate-change effects in the case of Israel. Furthermore, this also reveals a public economic perspective of the distribution of climate-change effects 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 potentially harmful climate-related impacts on economic activities.

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 farming sector, attributed to increased production of vegetables and field crops. On the other hand, fruit production is expected to shrink, entailing price increases to a level that will render protection by import tariffs ineffective. Consequently, local consumers of agricultural products face losses of surplus. However, the overall benefits to farmers exceed the losses to consumers, implying social welfare gain. We find that the forecasted sharp temperature rise drives these results, with moderate counterbalance by the projected slight decline in precipitation.

We compare the above results to the case where import tariffs are abolished. This policy transfers surpluses from producers to consumers, and we find that social welfare increases only under sufficiently large climate changes. 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 reduced 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 micro-level supply model and the link to the market-level partial equilibrium model. We then present the data and the empirical results, including the estimation of the land-use supply model and the simulations of climate-change impacts on profits and consumer surplus. The final section discusses policy implications and potential extensions.

Supply Model

We model a vegetative agricultural sector that operates 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*, $i = 1,\ldots,I$, can grow *J* potential bundles of crops (i.e., groups of field crops, vegetables, etc.). Let s_{ji} be the land share of crop bundle *j*, $j = 1,\ldots,J$, in farm *i*. The objective of some farmer *i* is to choose the vector of land shares $\mathbf{s}_i$, $\mathbf{s}_i = (s_{1i},\ldots,s_{Ji})$ at the onset of the growing season so as to maximize the farm's anticipated end-of-season profit:

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

$$\text{s.t.} \quad \sum_{j=1}^{J} s_{ji} = 1 \text{ and } s_{ji} \geq 0 \;\; \forall\, j = 1,\ldots,J$$

where Π_i is farm *i*'s economic profit (normalized to per-one-hectare profit), ρ_j is the bundle'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 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 the implicit production and management-cost function, representing costs that are neither bundle-specific nor independent across bundles; for example, $c(\mathbf{s}_i)$ incorporates risks, the costs associated with non-feasible production of certain crop bundles in rotating systems, and the allocation of quasi-fixed inputs such as labor and machinery across crop bundles with different patterns and cultivation timing. The function $c(\mathbf{s}_i)$ captures the constraints on farmers' acreage decisions as motives for bundle diversification, and represents the non-linear effects of the allocative land-use variables **s** on farm profits—a pivotal feature in positive mathematical programming (Howitt 1995).

We further specify the expected optimal per-hectare output of each bundle *j* by the linear function $y_{ji} = \mathbf{b}_j \mathbf{x}_i$, 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.[1] The expected optimal bundle-specific economic costs are specified by $c_{ji} = \boldsymbol{\gamma}_j \mathbf{w}_i$, where $\mathbf{w}_i$ is a vector of cost-attributable exogenous variables and $\boldsymbol{\gamma}_j$ is the corresponding vector of coefficients. Thus, the expected maximum per-hectare economic profit of bundle *j* is:

$$y_{ji}\rho_j - c_{ji} = \mathbf{b}_j \mathbf{x}_i \rho_j - \boldsymbol{\gamma}_j \mathbf{w}_i \equiv \mathbf{v}_j \mathbf{z}_{ji} \qquad (2)$$

where $\mathbf{v}_j = (\mathbf{b}_j, -\boldsymbol{\gamma}_j)$ and $\mathbf{z}_{ji} = (\mathbf{x}_i \rho_j, \mathbf{w}_i)$. Note that since $\boldsymbol{\gamma}_j \mathbf{w}_i$ incorporates the shadow values of constrained factors, it expresses the per-hectare economic costs rather than the explicit costs reported in bookkeeping records; hence, $\mathbf{v}_j \mathbf{z}_{ji}$ represents the per-hectare economic profit rather than the accounting profit. Also note that the vector of exogenous variables $\mathbf{z}_{ji}$, being bundle-specific due to the multiplication of the variables in $\mathbf{x}_i$ by the respective output price ρ_j, is crucial for the identification of the production-function coefficients, 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. Carpentier and Letort (2014) and Kaminski, Kan and Fleischer (2013) assumed the opposite-entropy function:

$$c(\mathbf{s}_i) = \frac{1}{a} \sum_{j=1}^{J} s_{ji} \ln(s_{ji}) \tag{3}$$

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 negative, non-monotonic convex function with respect to s_{ji}. The non-monotonicity implies that, ceteris paribus, the implicit costs decline with s_{ji} for $\exp(-1) \geq s_{ji} \geq 0$, and increase with s_{ji} when $1 \geq s_{ji} > \exp(-1)$. 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 $j = 1, \ldots, J$.

Deriving the optimal solution to problem (1) above, given the per-hectare optimal expected profit specification (Eq. (2)) and the opposite-entropy specification (Eq. (3)) for

$c(\mathbf{s}_i)$, yields the following multinomial logit functional form for the optimal land shares (see Appendix A):

$$s_j^*(\mathbf{z}_i) = \frac{\exp(a\mathbf{v}_j\mathbf{z}_{ji})}{\sum_{j=1}^{J}\exp(a\mathbf{v}_j\mathbf{z}_{ji})} \tag{4}$$

where $s_j^*(\mathbf{z}_i)$ is the profit-maximizing land share of bundle *j*, and $\mathbf{z}_i \equiv (\mathbf{z}_{1i},...,\mathbf{z}_{Ji})$.

The land constraint implies that the parameters of only $J-1$ bundles can be identified; we specify bundle *J* as the reference bundle. As will be shown later, to simulate partial equilibrium, one must identify the parameters of the linear yield function $\mathbf{b}_j$ for all *J* bundles. 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. 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, $\mathbf{b}_J = 0$. We divide and multiply s_{ji}^* in Eq. (4) by $\exp(a\mathbf{v}_J z_{Ji})$ to obtain

$$s_{ji}^*(\mathbf{z}_i) = \exp(\mathbf{V}_j\mathbf{z}_{ji})\left(\sum_{j=1}^{J}\exp(\mathbf{V}_j\mathbf{z}_{ji})\right)^{-1} \tag{5}$$

where $\mathbf{V}_j = (a\mathbf{b}_j, -a(\boldsymbol{\gamma}_j - \boldsymbol{\gamma}_J)) \equiv (\mathbf{B}_j, \mathbf{G}_j)$; this implies that we cannot identify a or $\mathbf{v}_j$, but only the coefficients $\mathbf{B}_j$ and $\mathbf{G}_j$ in $\mathbf{V}_j$.

One could use Eq. (5) to obtain a system of $J-1$ linear land-share regression equations.[2] 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, McCarl, and Mendelsohn 2010; Mu, McCarl, and Wein 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 aggregated data at the regional level, where zero land-share observations are rare; however, at this level of aggregation, prices may be endogenous. Our community-level land-use dataset discards the endogeneity of prices,[3] but on the other hand, may involve a non-negligible number of observations with corner solutions. Hence, we estimate Eq. (5) by employing the quasi-maximum-likelihood approach to the fractional multinomial logit likelihood function (Papke and Wooldridge 1996; Buis 2010):

$$\ln\left(L\right)=\sum_{i=1}^{I}\sum_{j=1}^{J}s_{ji}\ln\left(s_{ji}^{*}\left(\mathbf{z}_{i}\right)\right) \tag{6}$$

where s_{ji} is the observed land share, and $s_{ji}^{*}\left(\mathbf{z}_{i}\right)$ is as specified in Eq. (5).[4]

The land-use model developed thus far can be transformed into a supply model using the per-hectare profit-maximizing yield function $y_{ji}=\mathbf{b}_{j}\mathbf{x}_{i}$, such that the predicted total production of bundle *j* by farm *i* is $l_{i}s_{ji}^{*}\left(\mathbf{z}_{i}\right)\mathbf{b}_{j}\mathbf{x}_{i}$, where l_{i} is the total land area of farm *i*. Two obstacles emerge: first, output data are frequently available only at the macro-level (e.g., for the entire country); second, the coefficients $\mathbf{b}_{j}$ cannot be separated from the *a* parameter.[5] We handle these limitations by referring to production outputs in relative terms and by utilizing aggregate information as a constraint in the estimation of the land-use model. Let the sample's total production value of bundle *j* be

$$A_{j}\left(\mathbf{z}\right)=a\rho_{j}\sum_{i=1}^{I}l_{i}s_{j}^{*}\left(\mathbf{z}_{i}\right)\mathbf{b}_{j}\mathbf{x}_{i} \tag{7}$$

where $\mathbf{z} \equiv (\mathbf{z}_1, ..., \mathbf{z}_I)$. Let bundle 1 be the reference, and let us denote by r_j the observed ratio of the aggregate countrywide production values of bundles *j* and 1. We estimate Eq. (6) subject to the set of constraints

$$\frac{A_j(\mathbf{z})}{A_1(\mathbf{z})} = r_j \ \ \forall\, j = 2, ..., J-1 \tag{8}$$

The parameter *a* in Eq. (7) is canceled out in Eq. (8). The additional benefit is that we can now use the aggregate information embedded in the ratios r_j, $j = 2, ..., J-1$, to assign a meaningful production interpretation to the coefficients $\mathbf{b}_j$.

Linking Micro- and Market-Level Models

The aggregate production value of bundle *j*, $A_j(\mathbf{z})$, also serves as the link between the micro-level supply model and the market-level demand model. Let $\phi_{jt}^p = \rho_{jt} / \rho_{j1}$ denote the simulated output-price index of crop bundle *j* in some year *t* relative to year 1 (the base year), so that ϕ_{j1}^p is normalized to 1. We define a vector of price indices $\boldsymbol{\phi}_t^p = (\phi_{1t}^p, ..., \phi_{J-1t}^p)$, and the corresponding set of explanatory variables $\mathbf{z}_{ijt} = (\phi_{jt}^p \rho_{j1} \mathbf{x}_{it}, \mathbf{w}_{it})$ for every farm $i = 1, ..., I$, bundle $j = 1, ..., J-1$, and year *t*, where $\mathbf{x}_{it}$ and $\mathbf{w}_{it}$ incorporate the values (observed for $t = 1$, forecasted for $t > 1$) of farm *i*'s variables in year *t*. Accordingly, $\hat{s}_j^*(\mathbf{z}_{it})$ is the predicted land share calculated by Eq. (5) given year *t*'s set of variables $\mathbf{z}_{it} = (\mathbf{z}_{ijt}, ..., \mathbf{z}_{iJ-1t})$ and the estimated coefficients $\hat{\mathbf{B}}_j$ and $\hat{\mathbf{G}}_j$. Then, the aggregate optimal output value for each bundle *j* is predicted by $\hat{A}_j(\mathbf{z}_t) = \phi_{jt}^p \rho_j \sum_{i=1}^{I} l_i \hat{s}_j^*(\mathbf{z}_{it}) \hat{\mathbf{B}}_j \mathbf{x}_{it}$, where $\mathbf{z}_t = (\mathbf{z}_{1t}, ..., \mathbf{z}_{It})$. We use the Laspeyres quantity index to derive the change in the output of crop bundle *j* supplied by local producers in response to changes in the prices and exogenous variables between base-year 1 and some year *t*. The local-supply quantity index is:

$$\phi_j^y\left(\mathbf{z}_t\right)=\frac{\hat{A}_j\left(\mathbf{z}_t\right)}{\hat{A}_j\left(\mathbf{z}_1\right)} \tag{9}$$

The quantity index $\phi_j^y\left(\mathbf{z}_t\right)$ depends on the output-price index ϕ_{jt}^p directly through the impact on the output value $\hat{A}_j\left(\mathbf{z}_t\right)$, as well as indirectly through the effect on $\mathbf{z}_t$, which entails land-use adaptation responses. Note that the parameter *a* vanishes in Eq. (9) as well, thereby enabling the simulation of changes in the supply index based on $\hat{\mathbf{B}}_j$ without the need to identify *a* (i.e., $\mathbf{b}_j$).

We now turn to the demand side. Similar to the supply side, we formulate a bundle-quantity index as a function of price indices, which is based on aggregate countrywide data on individual crops within each bundle. To simplify the notation, and without loss of generality, assume that the number of different crops in each bundle *j*, $j=1,...,J-1$, is identical and equal to *K*. Denote the price of crop *k*, $k=1,...,K$, of bundle *j* in year *t* as p_t^{kj}, and the aggregate quantity of this crop demanded by local consumers as Q_t^{kj}. Also assume that the countrywide aggregate demand function is of the constant-elasticity form:

$$Q_t^{kj}=h^{kj}\cdot\left(p_t^{kj}\right)^{\beta^{kj}} \tag{10}$$

where β^{kj} is a known demand elasticity and h^{kj} is a calibrated parameter. Assume further that all crops in each bundle *j* satisfy the criteria of a composite commodity; that is, their prices change proportionately.[6] Define the Laspeyres demanded-quantity index, ϕ_{jt}^q, which based on Eq. (10) becomes a function of the simulated price index ϕ_{jt}^p, as:

$$\phi_j^q\left(\phi_{jt}^p\right)=\frac{\sum_{k=1}^{K}p_1^{kj}h^{kj}(\phi_{jt}^p p_1^{kj})^{\beta^{kj}}}{\sum_{k=1}^{K}p_1^{kj}Q_1^{kj}} \tag{11}$$

If the markets for bundle-j products are in equilibrium in the base period ($t=1$), then $\phi_j^q\left(\phi_{j1}^p\right)=\phi_j^y\left(\mathbf{z}_1\right)=1$. In future years, $\mathbf{x}_t$ incorporates the modified values of all climate variables in relation to the base year, such that plugging $\mathbf{x}_t$ into the supply-quantity index in Eq. (9) breaches the equilibrium. Without trade restrictions, prices change only if world prices change,[7] and the gap between the demand-quantity index $\phi_j^q\left(\phi_{jt}^p\right)$ and the supply-quantity index $\phi_j^y\left(\mathbf{z}_t\right)$ represents the change in import or export of bundle j's products. If trade is restricted by import tariffs, the set of local price indices $\boldsymbol{\phi}_t^p$ will change to meet equilibrium conditions in the local markets, unless price changes are large enough to render import-tariff restrictions ineffective. Let $\bar{\boldsymbol{\phi}}^p=\left(\bar{\phi}_1^p,...,\bar{\phi}_{J-1}^p\right)$ be the set of import prices, each equals the world price plus the respective country’s import tariff. We simulate partial equilibrium by solving

$$\begin{aligned}&\min_{\boldsymbol{\phi}_t^p}\sum_{j=1}^{J-1}\left(\phi_j^q\left(\phi_{jt}^p\right)-\phi_j^y\left(\mathbf{z}_t\right)\right)^2\\&s.t.\ \boldsymbol{\phi}_t^p\le\bar{\boldsymbol{\phi}}^p\end{aligned}\tag{12}$$

Eq. (12) links the supply-quantity index, which incorporates all of the sample data points, to the demand-quantity index, which is based on aggregate data, while taking into account trade restrictions through the implementation of import tariffs.

The model provides the information required to calculate changes in welfare elements. The change in consumer surplus from the base period to some year $t, \Delta CS_{jt}$, is computable for every bundle j, $j=1,...,J-1$, based on Eq. (10): $\Delta CS_{jt}=\sum_{k=1}^{K}\frac{h^{kj}}{\beta^{kj}+1}\left[(\phi_{jt}^p)^{\beta^{kj}+1}-1\right](p_1^{kj})^{\beta^{kj}+1}$.

Aggregate local farming revenues and imports at time t are given by $\phi_j^y\left(\mathbf{z}_t\right)\sum_{k=1}^{K}p_1^{kj}Q_1^{kj}$ and $\left[\phi_j^y\left(\mathbf{z}_t\right)-\phi_j^q\left(\phi_{jt}^p\right)\right]\sum_{k=1}^{K}p_1^{kj}Q_1^{kj}$, respectively. To compute local aggregate accounting profits, one needs to subtract the explicit costs from the production value. However, as already noted, the estimated economic-cost function $\mathbf{G}_j \mathbf{w}_i$ 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 $\mathbf{w}_i^e = \left(w_i^{1e},...,w_i^{Ne}\right)$ as a subset of $\mathbf{w}_i$ that incorporates those variables associated with explicit costs (e.g., purchased production factors). Accordingly, farm *i*'s predicted total explicit cost at time *t* is

$$C_{it}\left(\mathbf{z}_{it}\right) = \sum_{j=1}^{J-1} l_i s_{ji}^*\left(\mathbf{z}_{it}\right) C_j\left(\mathbf{w}_{it}^e\right) \tag{13}$$

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

$$C_j\left(\mathbf{w}_{it}^e\right) = L_j^{-1} \sum_{k=1}^{K} L^{kj} C^{kj} \sum_{n=1}^{N} \alpha_n^{kj} \frac{w_{it}^{ne}}{w_{i1}^{ne}} \tag{14}$$

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_n^{kj} is the share of explicit-cost item n , $n = 1,...,N$, in C^{kj}, and w_{it}^{ne} is the level of farm *i*'s explicit-cost variable *n* at time *t*. Note that the explicit costs can serve as an additional link between the micro-level supply model and market-level input-demand model so that input prices can be treated endogenously.

Data and Variables

Our dataset for estimating the micro-level land-allocation model is a panel of 7,569 observations, encompassing 743 agricultural communities (about 85% of all agricultural communities in Israel) over the years 1992–2002, provided by the Israeli Ministry of Agriculture and Rural Development (IMARD).[8] Altogether, the sample covers 264,000 hectares per year—more than 60% of the agricultural land in Israel. The land allocated to each crop bundle is reported for the community as a whole, so we must treat each community as if it was a single decision-making unit. This is in fact true for about 40% of the sample communities, which are Kibbutzim, in which all economic activities, including agriculture, are managed collectively. Another 51% of the sample communities are Moshavim (cooperative villages with individual farms). While each Moshav member can make his/her own land-allocation decisions, being a member of a cooperative imposes some constraints on those decisions (Kimhi 1998). In only 9% of the sample (private communities), agricultural decisions of the different farmers are completely independent of each other.

Our data comprise aggregate land shares of four crop bundles: vegetables, field crops, fruit, and the reference bundle of non-cultivated land. In table 1, we present the number of observations and average land shares (weighted by total community agricultural land) of the eight different crop-bundle portfolios. Land is allocated to all three crop bundles in only 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 fruit (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.

Table 1 about here

Table 2 reports sample means and standard deviations of the explanatory variables used in the estimation of the production value (**x** and ρ_j for the three bundles) and cost (**w**) functions. As noted, the interaction of **x** with ρ_j enables identifying the production and cost impacts of variables that appear in both **x** and **w**; however, prices vary only with time, and due to the small number of periods, multicollinearity emerges.[9] Herein we assign variables to either **x** or **w** based on our preliminary expectations of their dominant impact, where climate variables are assumed to affect end-of-season expected profit-maximizing outputs. Thus, the output coefficients incorporate both the climate variables' direct impact on yields and their indirect effects on damage-prevention activities by profit-maximizing farmers.[10]

Table 2 about here

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. We assign the data from station locations to the coordinates of each agricultural community in our sample using the inverse distance weighting (IDW) method. We choose the power 1 IDW specification due to its superior robustness (Kurtzman and Kadmon 1999). The climate variables are annual average temperature and cumulative annual precipitation. For each year in the sample, we consider the average temperature and precipitation for the previous 10-year period as those that have been considered by farmers in their agricultural land-use decisions.

In the simulations of climate conditions in 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); 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). Table 3 presents the statewide average of the forecasted climate variables. The three models generally predict a considerable increase in average temperature throughout Israel for both future periods, from 19^{o}C up to 25^{o}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 base-period level).

Table 3 about here

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), representing the production impacts of the decision-making process and level of 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 19 ecological regions (as defined by the Israel Central Bureau of Statistics (ICBS)) 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, $\overline{p}_1^j = \sum_{k=1}^{K} p_1^{kj} Q_1^{kj} \Big/ \sum_{k=1}^{K} Q_1^{kj}$ (recall p_1^{kj} and Q_1^{kj} in Eq. (11)), where p_1^{kj} is taken from cost-and-return studies (IMARD) and Q_1^{kj} is the ICBS data on the crop's countrywide annual output in 2002 (see Appendix B; all monetary values are in US dollars in 2000). Following Kaminski, Kan and Fleischer (2013), we use lagged moving averages to reflect price expectations that farmers use when making land-use decisions. Since land shares of field crops and vegetables can be adjusted from year to year, their price indices were constructed based on the two previous years, whereas the previous four years were used for fruit.[11]

The production-value ratios r_j used in Eq. (8) are computed by $r_j = \sum_{k=1}^{K} p_1^{kj} Q_1^{kj} \Big/ \sum_{k=1}^{K} p_1^{k1} Q_1^{k1}$, where field crops is used as the reference bundle ($j = 1$).

For the per-hectare cost functions, 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 non-farm 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 vegetative sector (Kislev and Vaksin 2003); this variable represents the explicit costs $C_j\left(\mathbf{w}^e\right)$ (recall Eq. (13)). To reflect explicit cost differences across bundles, we multiply this price-input index by a bundle-specific factor, which is computed by $\sum_{k=1}^{K} L^{kj}C^{kj} \Big/ \sum_{k=1}^{K} L^{kj}$ (recall Eq. (14)), where L^{kj} is countrywide agricultural lands (IMARD) and C^{kj} is the per-hectare costs[12] 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} (Eq. (10)). Israel is a net exporter of vegetables and fruit, 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 fruit 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 fruit, respectively (Finkelshtain, Kachel, and Rubin 2011).[13] For the local markets of vegetables and fruit, we adopt demand-elasticity parameters from Hadas (2001) (Appendix B). Both growers and consumers of field crops face the world prices of field crops; hence, 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, Nicita and Olarreaga (2008), and import quantities of field-crop products were obtained from the ICBS (Appendix B). We substitute these elasticities and import values into Eq. (11), and then employ Eq. (12) to simulate import response to price changes. 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. Figure 1 presents the resultant demand curves based on the calibrated $\phi_j^q\left(\phi_j^p\right)$ functions.

Figure 1 about here

As already noted, our analysis is based on the assumption that markets were in equilibrium in the base period (represented by the year 2000). According to Finkelshtain, Kachel and Rubin (2011), the local prices of vegetables and fruit are generally similar to their corresponding world prices. Therefore, imports of vegetables and fruit to Israel are negligible due to the presence of high import tariffs (reported in Appendix B). We calculate the average import price for the bundles of vegetables and fruit, weighted by crop-production quantities, and use these averages as the upper limit of prices ($\bar{\phi}_t^p$) in the simulation of the restricted-trade scenario (Eq. (12)). The calculated average import prices (world prices + import tariffs) are higher by 36% and 23% than the average local prices for vegetables and fruit, respectively. As to forecasts of world prices, we take the trends projected by Eboli, Parrado and Roson (2010) using a global CGE model.[14]

Estimation Results

We use the Stata fractional multinomial logit command (fmlogit) to estimate the coefficients $\mathbf{V}_j$ for the three crop bundles, through maximization of the quasi-likelihood function in Eq. (6) subject to the constraints in Eq. (8). We control for potential spatiotemporal autocorrelations in the residuals by clustering observations according to years and 60 *natural* regions.[15] We include quadratic levels of the precipitation, temperature, agricultural land and water-quota variables to capture non-linear responses. The estimated coefficients are reported in table 4.[16, 17]

Table 4 about here

Interpretation of the estimation results is facilitated by table 5, where we present the marginal effects of the explanatory variables on optimal land shares and economic profits. These marginal effects are defined as $\frac{\partial s_j^*(\mathbf{z}_i)}{\partial \mathbf{z}_i}$ for the land-share marginal effects (left four columns in table 5), and as $\frac{\partial\left(s_j^*(\mathbf{z}_i)\cdot V_j\mathbf{z}_i\right)}{\partial \mathbf{z}_i}$ for the economic-profit marginal effects (right four columns in table 5). Standard errors were estimated using the bootstrap procedure.

Table 5 about here

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. Farmers in higher-precipitation areas benefit from growing field crops and fruit more than vegetables; this result is congruent with the relative advantage of the southern arid part of Israel for vegetable production, as mentioned by Fleischer, Lichtman and Mendelsohn (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). Farmers may apply costly protective inputs so as to obtain profit-maximizing per-hectare yield levels that are lower than those obtainable in the drier regions. Higher temperatures increase field-crop profitability, but reduce profits in fruit cultivation, which may be explained by the deciduous trees' chilling requirements to bloom.

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 fruit 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 statistically significant 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, Gadish and Mishaeli (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 fruit and vegetables, and is a complement to precipitation in field-crop production; this finding coincides with the fact that, while vegetables and fruit are usually irrigated, the field-crop bundle includes both rain-fed 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 production-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.

Simulations

Using the estimated model, we simulate production of the three crop bundles where, ceteris paribus, climate variables change as reported in table 3,[18] and world prices vary according to Eboli, Parrado and Roson (2010). That is, we assess the impact of changes in climate conditions and the associated world prices as if they had occurred in the base period, where all other factors (e.g., population and technological level) are fixed. We study the consequences of these changes under six scenarios with respect to policies and farming-adaptation strategies. Specifically, we solve Eq. (12) for each scenario, where $\phi_j^y\left(\mathbf{z}_t\right)$ and $\phi_j^q\left(\phi_{jt}^p\right)$ are as defined in Eq. (9) and Eq. (11), 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 6 and 7 report the results in terms of changes relative to the base-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 6) exhibit similar trends under all four RCPs, for the two future climate periods. The supplies of vegetables and field crops increase, whereas that of fruit declines. Local output prices of vegetables decline, while those of fruit rise to their respective upper bound, $\bar{\phi}_{jt}^p$; consequently, the demanded quantity of fruit exceeds the local supply and import emerges. The prices of field crops change marginally with world prices; hence, the demanded quantity remains stable, and the increased supply of field-crop outputs may reduce the import of field-crop products.

Table 6 about here

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 field-crop productivity is predicted to increase more than twofold, which in turn leads to expanding the land allocated to field crops by about 10% at the expense of vegetables and fruit. Per-hectare production of vegetables also increases, but to a lower extent than that of field crops; therefore, the land allocated to vegetables declines. Fruit production declines sharply by about 40–60%, leading to a land-share reduction of about 25%.

Table 7 about here

Table 7 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 farms also benefit from climate change, but to a much lower extent, whereas fruit farms suffer losses. Taken together, the Israeli vegetative agricultural sector is expected to enjoy an increase of about 7% in its accounting profits. Surpluses of local consumers are projected to decline moderately, particularly due to the increase in fruit prices. 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).

We turn to a study of the trade-policy implications. According to OECD (2014), the *producer support estimate* measure for Israel indicates that the overall support to farmers is lower than in 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 abolishment of tariffs such that import prices of all vegetative agricultural products equal their world-price counterparts, as forecasted based on Eboli, Parrado and Roson (2010). Table 8 reports the results of Scenario 2; that is, the simulated climate-change effects on the welfare measures under the free-trade scenario.

Table 8 about here

To comprehend the impact of the free-trade policy, compare tables 8 and 7. The accounting profits of vegetable and field-crop growers increase slightly under the free-trade scenario, whereas fruit growers face a considerable drop in profits, particularly because fruit imports climb to more than 50% of local consumption compared to a mere 20% under the prevailing constrained-trade regime (Scenario 1). Consumer surpluses associated with vegetables rise more than under the current trade barriers, whereas the surplus associated with fruit drops much more moderately. Figure 2 summarizes the effect of removing import tariffs by depicting the difference it makes to the accounting profit, consumer surplus and social welfare (i.e., the values in table 8 minus their counterparts in table 7). In general, 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), the benefits to consumers from removing the import tariffs exceed the losses to producers, and therefore social welfare increases.[19]

Figure 2 about here

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 (table 9) reveals that the aforementioned climate-change-driven welfare benefits stem from the considerable rise in temperature, as forecasted by all GCMs (table 3). 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.[20]

Table 9 about here

Under each of the latter four scenarios, 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. This scenario is equivalent to Scenario 4, except that the input-price index varies according to the costs associated with changing the irrigation so as to compensate for the change in precipitation. The share of irrigation costs in the total explicit costs of each crop in each bundle (α_n^{kj} in Eq. (14)) is computed using cost-and-return studies (IMARD).[21] 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, we find water quotas ineffective, and assume that this is also the case under the simulated change. Comparing Scenario 5 (table 9) to Scenario 1 (table 7) shows that offsetting the precipitation changes by increasing irrigation is socially non-beneficial. Nevertheless, from the farmers' point of view, this adaptation strategy is warranted.

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 ($\sum_{i=1}^{I}\sum_{j=1}^{J} s_{jit}^{*}\left(\mathbf{z}_{it}\right)\mathbf{V}_j\mathbf{z}_{jit}$) 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 base-period land shares). Based on comparison to the economic profits without land responses ($\sum_{i=1}^{I}\sum_{j=1}^{J} s_{ji1}\mathbf{V}_j\mathbf{z}_{jit}$), we attribute about 18% of the overall profit increase stemming from climate change ($\sum_{i=1}^{I}\sum_{j=1}^{J} s_{jit}^{*}\left(\mathbf{z}_{it}\right)\mathbf{V}_j\mathbf{z}_{jit} - \sum_{i=1}^{I}\sum_{j=1}^{J} s_{ji1}\left(\mathbf{z}_{i1}\right)\mathbf{V}_j\mathbf{z}_{ji1}$), to land adaptation.[22]

Conclusion

Summary and Policy Implications

This paper develops a structural econometric model to assess climate-change impacts on vegetative agricultural production under equilibrium in the food 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 micro-level agricultural production and market-level demand is particularly important as governments and international organizations alike are being called upon to revise current policies in order to provide adaptation options 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 food prices into consideration is extremely important given their relevance to the critical issues of poverty, food security and malnutrition worldwide.

Indeed, our empirical analysis of the Israeli case study yields different simulation results when import tariffs are abolished compared with the more realistic case of restricted trade. Our results suggest that, under restricted trade, Israeli farmers will generally benefit from the predicted climate changes, especially from the rise in temperatures. Abolishing import tariffs effectively transfers surpluses from producers to consumers, but the overall welfare effect of this policy change varies across climate scenarios. We also find that adaptation through land reallocation contributes nearly 20% of the simulated rise in agricultural profits, and that adaptation through increased irrigation in response to the predicted decline in precipitation is beneficial to farmers, but not to consumers.

The empirical finding that climate change will be beneficial to Israel should be interpreted with caution, for several reasons. First, 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). Second, 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). Third, 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). Had we been able to account for these factors, our results could change in either direction. Hence, we do not assign much importance to the finding that Israel will benefit from climate change. Rather, we emphasize the findings that cropland reallocation is an important component of adaptation strategies, that ignoring output price changes may lead to different conclusions, and that trade policy changes may also affect farmers' adaptation strategies.

Agricultural adaptation to climate change calls for government intervention because of equity concerns and prioritization (e.g., Lobell et al. 2008); however, such interventions obviously need to focus on adaptation strategies with a public-good nature (McCarl, Thayer, and Jones 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 base-year conditions, consumers are adversely affected whereas producers benefit from the projected future climate changes. Under removal of import tariffs, climate change becomes beneficial to both producers and consumers with minor effect on total welfare, implying that this policy could be politically acceptable.

Second, as improved adaptation technologies require R&D investments with a public-good component (Pardey, Alston, and Chan-Kang 2012), identification of the technological channels through which projected consumer and producer surpluses change is useful for promoting a “directed technological change” with a higher benefit–cost ratio and more effective public and private spending. For example, our simulations predict that the surpluses of both producers and consumers of fruit 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 Kaminski, Kan and Fleischer (2013).

Further Research and Extensions

The results also indicate several directions for further research and extensions. First, our empirical framework can be generalized to derive a broader and integrated assessment of agricultural-related impacts of climate change on social welfare by considering agricultural amenities and environmental externalities in the simulations. Upon availability of sufficient valuation studies and applicability of benefit-transfer methods, the impact of climate change on ecosystem services and landscape values through agricultural productivity adjustments and land-use adaptation (e.g., Kan et al. 2009) could also be assessed (e.g., Bateman et al. 2013). This would also require a refinement of the econometric model to enable estimation of intra-growing season input applications and environmental effects, such as polluting effluents. In turn, this could alter the conclusions about the efficiency and equity of agricultural policies and public investments targeted at climate-change adaptation, since total climate-driven effects on overall social welfare may significantly differ from the effects on private consumers and producer surpluses. For instance, the projected conversion of land planted with fruit orchards and vegetables into land used for field-crop production presumably comes with benefits in agricultural amenities such as landscape and recreational services (open fields versus greenhouses and protected crops), as well as changes in the use of polluting inputs and irrigation water.

As mentioned above, our analysis is restricted by the data available for the sample period. Thus, an extension of the paper might account for (i) a wider range of climate variables, such as the Palmer Drought Severity Index (Palmer 1965), maximum and minimum temperatures, incidence of extreme events and CO_2 levels, all of which have been found to affect productivity (McCarl, Thayer and Jones 2016); and (ii) a more detailed level of crop-mix adaptations (i.e., disaggregating the crop bundles to smaller bundles or specific crops).

Finally, as noted, the model can be linked to input-supply models through the cost variables. For example, integrating the agricultural supply model into a hydro-economic model (e.g., Reznik et al. 2017) would enable considering water prices endogenously. Moreover, applying the model in conjunction with more sophisticated macro-models such as CGE can be used to assess a range of additional issues associated with agricultural production and policies; for example, the development of production-supportive infrastructures and changing other agricultural protection policies, such as subsidies.

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Table 1. Observations and Land Shares in Crop-Production Portfolios

Portfolio	Number of observations	Land shares[a] Vegetables	Field crops	Fruit	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 & Fruit	1,173	0.000	0.606	0.343	0.050
Vegetables	53	0.800	0.000	0.000	0.200
Vegetables & Fruit	817	0.319	0.000	0.543	0.138
Vegetables & Field crops	158	0.182	0.794	0.000	0.024
Vegetables & Field crops & Fruit	4,716	0.181	0.532	0.241	0.046
Total	7,569	0.150	0.547	0.260	0.043

a. Weighted by communities' total agricultural land.

Table 2. Descriptive Statistics of the Explanatory Variables

Variable	Units	Mean	Std.
Production (x)			
Precipitation	mm/year	449.8	87.83
Temperature	C^o	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 (w)			
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

Table 3. Future Forecasts of State-Wide Average Climate Variables

Climate period	RCP	Climate model	Precipitation (mm/year)	Temperature (C°)
Base			450	19
2040–2060	2.6	CCSM4	463	22
		MIROC5	424	23
		NorESM1	464	23
		Average	450	23
	4.5	CCSM4	443	23
		MIROC5	439	24
		NorESM1	387	23
		Average	423	23
	6	CCSM4	428	23
		MIROC5	433	23
		NorESM1	500	23
		Average	454	23
	8.5	CCSM4	381	24
		MIROC5	406	24
		NorESM1	395	24
		Average	394	24
	Average		430	23
2060–2080	2.6	CCSM4	423	23
		MIROC5	426	23
		NorESM1	397	23
		Average	415	23
	4.5	CCSM4	421	23
		MIROC5	398	25
		NorESM1	336	23
		Average	385	24
	6	CCSM4	401	24
		MIROC5	399	24
		NorESM1	381	23
		Average	393	24
	8.5	CCSM4	367	25
		MIROC5	360	25
		NorESM1	334	25
		Average	353	25
	Average		387	24

Table 4. Estimated Coefficients of Land-Share Equations (Eq. (6))[a]

Log likelihood	-7657.6		
Wald $\chi^2(91)$	29144.1		
Variable	**Vegetables**	**Field crops**	**Fruit**
Production			
$\rho_j \times$ 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	-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			
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. The dummy variable for private communities was omitted due to collinearity.

Table 5. Marginal Effects

	Land share				Economic profit			
Variable	**Vegetables**	**Field crops**	**Fruit**	**Total cultivated**	**Vegetables**	**Field crops**	**Fruit**	**Total**
Production								
Precipitation	-0.001***	3.23×10^{-4}***	4.35×10^{-4}***	6.46×10^{-5}**	-0.001***	0.002***	0.002***	0.002***
Temperature	-0.007	0.062***	-0.047***	0.008**	0.009	0.260***	-0.084**	0.185***
Moshav	0.033***	-0.294***	0.192***	-0.069***	-0.131***	-1.499***	0.118***	-1.512***
Light Soil	-0.027***	-0.076***	0.093***	-0.010***	-0.082***	-0.314***	0.204***	-0.191***
Vegetable price index (ρ_v)	0.455***	-0.245***	-0.179***	0.03***	1.005***	-0.515***	-0.321***	0.168***
Field-crop price index (ρ_f)	-0.020***	0.068***	-0.042***	0.007***	-0.020***	0.269***	-0.075***	0.174***
Fruit price index (ρ_p)	-0.102***	-0.300***	0.439***	0.037***	-0.105***	-0.631***	1.445***	0.709***
Costs								
Distance to Tel Aviv	-3.3×10^{-4}	-0.003***	0.003***	-2.3×10^{-4}***	-0.001***	-0.011***	0.007***	-0.005***
Water quota	0.002***	0.005***	-0.007***	-1.06×10^{-4}	0.004***	0.016***	-0.018***	0.002
Agricultural land	-0.001	0.011***	-0.005***	0.004***	0.010***	0.069***	0.013***	0.093***
Input price index	-0.205***	0.552***	-0.372***	-0.024*	-0.482***	1.517***	-1.181***	-0.147

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

Table 6. Climate-Change Impact on Partial Equilibrium Indices under Constrained-Trade Policy (Scenario 1)

		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**	**Fruit**	**Vegetables**	**Field crops**	**Fruit**	**Vegetables**	**Field crops**	**Fruit**	**Vegetables**	**Field crops**	**Fruit**
2040–2060	2.6	0.877	1.033	1.259	1.164	0.997	0.755	1.163	2.258	0.682	0.946	1.079	0.846
	4.5	0.822	1.033	1.259	1.254	0.997	0.755	1.253	2.387	0.603	0.941	1.088	0.826
	6.0	0.868	1.033	1.259	1.178	0.997	0.755	1.177	2.368	0.659	0.943	1.084	0.836
	8.5	0.733	1.033	1.259	1.435	0.997	0.755	1.433	2.750	0.489	0.931	1.106	0.790
	Average	0.825	1.033	1.259	1.258	0.997	0.755	1.257	2.441	0.608	0.940	1.089	0.824
2060–2080	2.6	0.837	1.057	1.281	1.226	0.995	0.742	1.225	2.258	0.609	0.944	1.084	0.835
	4.5	0.740	1.057	1.281	1.429	0.995	0.742	1.427	2.708	0.480	0.932	1.105	0.792
	6.0	0.755	1.057	1.281	1.386	0.995	0.742	1.385	2.632	0.502	0.933	1.102	0.798
	8.5	0.634	1.057	1.281	1.728	0.995	0.742	1.726	3.313	0.353	0.918	1.127	0.747
	Average	0.741	1.057	1.281	1.442	0.995	0.742	1.441	2.728	0.486	0.932	1.104	0.793

Table 7. 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**	**Fruit**	**Total**	**Vegetables**	**Field crops**	**Fruit**	**Total**	**Vegetables**	**Field crops**	**Fruit**	**Total**
2040-2060	2.6	36	253	-61	228	70	-26	-145	-101	107	228	-207	128
	4.5	44	279	-121	201	105	-26	-145	-66	150	253	-267	135
	6.0	39	275	-78	236	76	-26	-145	-95	115	249	-224	141
	8.5	62	350	-208	204	167	-26	-145	-3	230	325	-354	200
	Average	45	289	-117	217	105	-26	-145	-66	150	264	-263	151
2060-2080	2.6	41	263	-110	194	95	-44	-156	-105	136	219	-266	89
	4.5	61	354	-209	206	164	-44	-156	-36	225	310	-365	170
	6.0	57	339	-192	204	152	-44	-156	-48	209	295	-349	155
	8.5	90	477	-306	261	251	-44	-156	50	341	433	-463	312
	Average	62	359	-204	217	166	-44	-156	-34	228	314	-361	182

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

Table 8. Climate-Change Impact on Aggregate Welfare Measures under Abolishment of Import Tariffs (Scenario 2), (10^6 \$/year)

		Accounting profit				Consumer surplus				Social welfare			
Climate period	**RCP**	**Vegetables**	**Field crops**	**Fruit**	**Total**	**Vegetables**	**Field crops**	**Fruit**	**Total**	**Vegetables**	**Field crops**	**Fruit**	**Total**
2040–2060	2.6	40	266	-250	57	77	-26	-15	36	117	240	-265	93
	4.5	48	291	-289	49	112	-26	-15	71	160	265	-304	120
	6.0	43	288	-263	68	82	-26	-15	41	125	262	-277	110
	8.5	66	361	-346	82	174	-26	-15	133	239	336	-361	214
	Average	49	302	-287	64	111	-26	-15	70	160	276	-302	134
2060–2080	2.6	45	275	-281	39	102	-44	-26	32	147	231	-307	71
	4.5	65	365	-346	85	170	-44	-26	99	235	321	-372	184
	6.0	61	350	-335	77	158	-44	-26	87	219	306	-361	164
	8.5	94	487	-409	172	256	-44	-26	186	350	443	-435	358
	Average	66	370	-343	93	171	-44	-26	101	238	325	-369	194

Table 9. 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**	**Consumer surplus**	**Social welfare**	**Accounting profit**	**Consumer surplus**	**Social welfare**	**Accounting profit**	**Consumer surplus**	**Social welfare**
2040–2060	2.6	10	-11	-1	218	-106	112	222	-104	118
	4.5	-5	-13	-17	229	-88	141	212	-96	115
	6.0	12	-11	1	223	-96	127	230	-92	138
	8.5	-21	-19	-40	266	-43	223	227	-63	164
	Average	-1	-13	-14	234	-83	151	223	-89	134
2060–2080	2.6	-4	-35	-39	238	-134	104	214	-146	68
	4.5	-20	-48	-68	284	-81	204	239	-104	135
	6.0	-16	-40	-56	271	-90	181	232	-110	122
	8.5	-37	-60	-97	358	-11	347	292	-46	246
	Average	-19	-45	-65	288	-79	209	244	-102	143

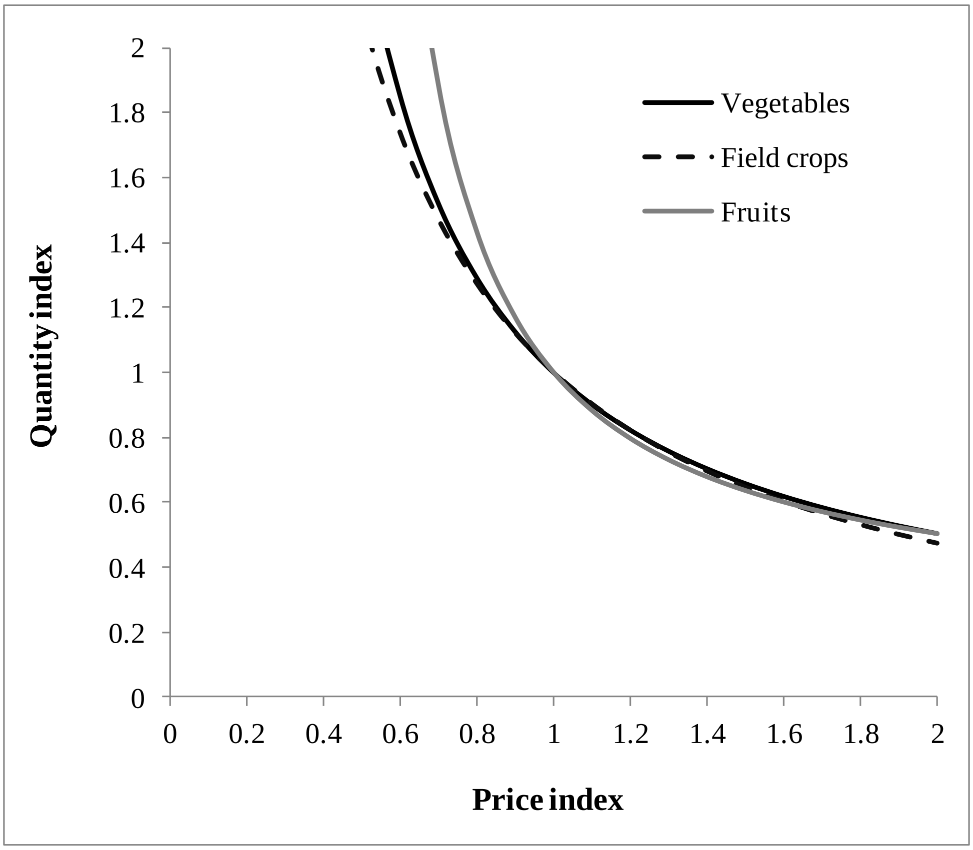

Figure 1. Demand curves of the three crop bundles

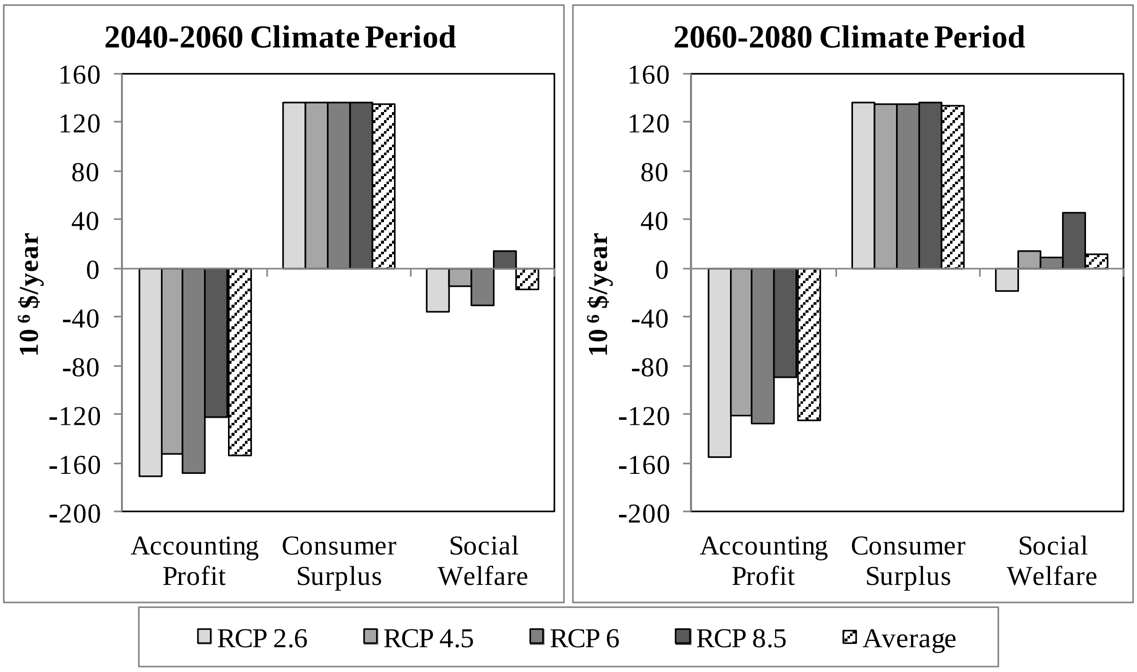

Figure 2. Difference in welfare elements between the free- and restricted-trade scenarios (free-trade (table 8) minus restricted trade (table7))

Appendix A – Derivation of the optimal land share in Eq. (4)

The farmer's problem is (we omit the farm index for notation brevity):

$$\max_{\mathbf{s}} \Pi = \sum_{j=1}^{J} s_j \mathbf{v}_j \mathbf{z}_j - \frac{1}{a}\sum_{j=1}^{J} s_j \ln\left(s_j\right) \quad s.t. \quad \sum_{j=1}^{J} s_j \leq 1 \tag{A1}$$

Using the first-order condition

$$\frac{\partial \Pi}{\partial s_j} = \mathbf{v}_j \mathbf{z}_j - \frac{1}{a}\left(\ln\left(s_j\right)+1\right) - \lambda = 0 \tag{A2}$$

we get the land share:

$$s_j = \frac{\exp\left(a\left(\mathbf{v}_j \mathbf{z}_j\right)\right)}{\exp\left(a\lambda + 1\right)} \tag{A3}$$

Substituting Eq. (A3) into the land constraint in (A1),

$$\sum_{j=1}^{J} s_j = \exp\left(-a\lambda - 1\right)\sum_{j=1}^{J} \exp\left(a\left(\mathbf{v}_j \mathbf{z}_j\right)\right) = 1 \tag{A4}$$

we get the shadow value

$$\lambda = \frac{\ln\left[\sum_{j=1}^{J} \exp\left(a\left(\mathbf{v}_j \mathbf{z}_j\right)\right)\right] - 1}{a} \tag{A5}$$

which we substitute back into the land share in Eq. (A3) to get Eq. (4).

Appendix B. 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 (β^{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	-	-
Fruit						
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
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

Notes

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[1] While the linear function is adopted to facilitate the analysis, the model can be easily extended; for example, Kaminski, Kan and Fleischer (2013) specified y_j 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.

[2] The resultant linear equations are of the form $\ln\left(s^*_{ji} / s^*_{Ji}\right) = \mathbf{V}_j \mathbf{z}_{ji} + u_{ji}$, where u_{ji} is an error term.

[3] Where only regional data are available, one may overcome endogeneity by employing simultaneous estimation of both prices and land shares; however, this poses two challenges: (i) an identification strategy and the availability of instrumental variables for regional prices in the micro-level estimations of the econometric model, (ii) a tractable partial or general equilibrium model with simultaneous and endogenous price determination adjusting with the outputs of the micro-level estimations.

[4] 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).

[5] Kaminski, Kan and Fleischer (2013) showed that, to enable identification of the parameters $\mathbf{v}_j$ for $j = 1,...,J-1$, a can be calibrated using panel data and additional information on crop profitability.

[6] We employ this assumption to derive bundle-level quantity indices, since disaggregated land-use data are usually available only for bundles of crops, whereas aggregated quantities and prices may be available for the various crops in each bundle.

[7] According to Finkelshtain and Kachel (2009), Israel's agriculture is small enough not to affect world food prices. While the methodology used herein can be employed in a world-level CGE model for simulating climate-change impacts on world prices under equilibrium, our analysis is limited to the case of Israel’s local market under partial equilibrium.

[8] Data were not available for later years due to changes in the data-collection procedure.

[9] 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.

[10] 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.

[11] The number of lags was determined after ARIMA estimations using R^2 and Akaike–Schwarz information criteria.

[12] For consistency with the estimated coefficients $\mathbf{v}_j = \left(a\mathbf{b}_j, -a\left(\boldsymbol{\gamma}_j - \boldsymbol{\gamma}_J\right)\right)$, we computed c^{kj} while subtracting the overhead assigned in the cost-and-return studies to the non-cultivated agricultural lands, i.e., the reference bundle.

[13] 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).

[14] 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 base-year levels.

[15] These regions were determined by the ICBS (2010) based on criteria such as topography, climate, demography and history. 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.

[16] We omit a time-trend variable from the estimation due to multicollinearity considerations, as reported earlier in footnote 8.

[17] 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.

[18] 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.

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

[20] 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. We cannot account for this effect with our data. A number of recent articles (e.g.,

Salazar-Espinoza, Jones, and Tarp 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.

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

[22] 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 at 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.