A Structural Land-Use Analysis of Agricultural Adaptation to Climate Change: A Proactive Approach

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Abstract

This article proposes a proactive approach for analyzing agricultural adaptation to climate change based on a structural land-use model wherein farmers maximize profit by allocating their land between crop-technology bundles. The profitability of the bundles is a function of four technological attributes via which climate variables' effect is channeled: yield potential; input requirements; yields' sensitivity to input use; and farm-level management costs. Proactive adaptation measures are derived by identifying the technological attributes via which climate variables reduce overall agricultural profitability, despite adaptation by land reallocation among bundles. By applying the model to Israel, we find that long-term losses stem from yield potential reductions driven by forecasted increases in temperature, implying that adaptation efforts should target more heat-tolerant crop varieties and technologies.

Keywords: adaptation; agricultural land use; climate change; crop-technology bundles

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This article proposes a proactive approach to agricultural adaptation to climate change. So far, the economic literature has taken a positive approach to evaluating farm losses resulting from climate change. The main debate in most studies is the methodology used to evaluate this loss. Studies conducted in the US illustrate these methodologies' evolution. Adams (1989) developed the production function approach whereby climate change's impact on various crops' yields affects farm profits. Mendelsohn et al. (1994) proposed the Ricardian (hedonic) approach, suggesting that farmers adapt by switching crops. Due to adaptation, the damages they predicted were much smaller than Adams' (1989). By applying the hedonic approach, Schlenker et al. (2005) demonstrated the importance of assessing separately climate change's economic effects on agriculture in both dry land and irrigated farmland. Deschênes and Greenstone (2007) used variations of weather conditions over time in order to avoid the possible bias stemming from omitted relevant variables embedded in the hedonic approach. Their findings predicted smaller yet more robust climate-change adverse impacts than did the preceding papers. Based on these studies, it is clear that climate change affects farm profits, whereas the magnitude of forecasted losses depends on methodological choices.

A positive approach was also employed for investigating farm adaptation strategies. Studies conducted in various parts of the world show that farmers invest in irrigation and switch crops or livestock species (Mendelsohn and Dinar, 2003; Kurukulasuriya and Mendelsohn, 2006; Seo and Mendelsohn, 2008a and 2008b). Fleischer et al. (2011) show that farmers adapt to climate change by changing their choices of crop-technology bundles.

Consistent with their positive approach, the aforementioned studies generally do not provide farmers and policymakers with tools to minimize the damage by using a more efficient adaptation process. This passive tendency implicitly assumes the existence of perfectly functioning markets for the development of new adaptation technologies and methods. However, such markets might suffer from market failures, which might be due to the free-riding phenomenon associated with the public-good nature of knowledge in general, and more specifically to the uncertainties associated with long-term climate predictions. Moreover, governments intervene heavily in the agricultural sector through policies that seek to internalize externalities and support farm incomes; as well as by designing and financing infrastructures such as roads, water networks, and research and development. Hence, governments actually play a key role in adaptation to climate change. For these reasons, unlike the case of the positive analyses, this article stresses the need for a more proactive approach. To this end, we develop a structural model providing farmers and policymakers with an understanding of how to improve adaptation in order to reduce climate-driven damages to agriculture.

Our methodology rests on land-use decisions. Following McGuirk and Mundlak (1992), we assume a recursive nature of decisions on a farm. First, land is allocated among those variables the selection of which concerns land allocation. As in Fleischer et al. (2011), land is simultaneously allocated among those crop-production input bundles characterized by limited short-term mobility, such as irrigation systems and greenhouses. Once land allocation is accomplished, profit is affected only by intra-growing-season applications of inputs and farm management, during which we assume optimality. That is, when contemplating land allocation in the first stage, farmers take into account their ability to alter profits in the second stage. This ability in turn relies on the available farm technologies' attributes, which are exogenous to the farmers. These technological attributes include the performance of crop varieties and the productivity of agronomic machinery and inputs, which themselves depend on climate conditions and other environmental factors. Under climate change, farmers ordinarily react by reallocating their land at the land-allocation stage while taking into account climate's impact on farm profits through its impact on these technological attributes. Thus, if adaptation through land reallocation fails, the failure is attributed to the existing technologies' characteristics. Our proactive approach is based on identifying both the climate variables to which land allocation fails to adapt, and the attributes of the technologies responsible for this failure. This approach enables us to recommend the specific features of the existing technologies that merit further efforts in order to improve their adaptation to the forecasted climate conditions.

In order to derive such adaptation recommendations, farm profit can no longer be treated as an unspecified reduced-form function; instead, it needs to be broken down into its structural components. In our land-use structural model, we consider three levels of profit decomposition. The upper level incorporates profitability (defined as profit per land unit) associated with each land-allocation decision variable, i.e., the crop-technology bundles. Following the "cost function" approach proposed by Letort and Carpentier (2009), bundle land-shares receive the flexible and easily estimable multinomial logit (MNL) functional form, which is structurally derived from bundles' profitability functions. These profitability functions incorporate technological attributes, which constitute the second level of profit decomposition. Four technological attributes are considered: yield potential; production-input requirements; yields' sensitivities to inappropriate applications of inputs; and farm-level constraints and managerial factors. At the third level of profit decomposition, these four technological attributes are treated as functions of exogenous variables, among which are the climate variables. This three-level structural framework enables elicitation of each climate variable's impact on each technological attribute associated with each crop-technology bundle, thereby allowing us to identify further adaptation efforts that should be made as per the forecasted climate conditions.

Our structural approach has a few advantages over previous studies. Firstly, its novel advantage over non-structural estimations of land-share functions (e.g., Lichtenberg et al., 1989; Wu and Segerson, 1995; Hardie and Parks, 1997; and Miller and Plantinga, 1999) is the information obtained on technological attributes' responses to climate-change variables. Secondly, its advantage over hedonic evaluations stems from its reliance on land-use data rather than on profit records. Unlike land-use data, which are readily available from official acreage reports, reliable profit data are scarce and suffer from measurement errors. As noted by Deschênes and Greenstone (2007), the use of land value as a proxy for profit can result in biased estimates due to omitted variables. Moreover, farmland value does not accurately reflect long-term profits when land markets are heavily regulated, as in Israel, our illustrative case study. Lastly, land-use data are less sensitive than are profits to the effects of unpredictable events such as pest outbreaks, sudden fluctuations of output and input prices, and extreme weather conditions. With respect to the latter, since the information at planting time does not include weather conditions along the growing season, farmers can only rely on their long-term experience with weather when allocating land to bundles, i.e., they rely on past climate conditions. Hence, observed spatial variation of land allocation represents farmers' revealed preferences with respect to adaptation to spatially distributed climate conditions.

Israel, chosen as a case study in order to illustrate the proposed model's performance, has a few advantages for the purpose of this study. Firstly, although small, it is characterized by a spatial climate gradient throughout, varying from Mediterranean climate in the north to arid conditions in the south (Dayan & Koch, 1999). Secondly, with respect to adaptation, Israel is known as a leader in agricultural innovations, and its agricultural sector generally employs state-of-the-art technologies. Thirdly, a panel of detailed bundle-acreage data on both regional and annual bases is accessible from official sources. Finally, daily weather data are available from a high spatial-resolution model (Krichak et al., 2010), which reproduces past climate conditions and simulates future climates under the IPCC A1B (IPCC, 2001) scenario. This rich weather dataset allows us to account not only for changes in temperature and precipitation levels, but also for their intra- and inter-annual volatility. This is a key feature, since there is a growing consensus that climate change is going to be characterized by extreme events, wherein variability is found to be as important as are absolute values (Katz and Brown, 1992). Our weather data also incorporate additional variables that are barely considered in the literature (Kaufmann and Snell 1997 being a notable exception): wind and solar radiation, the latter enables distinguishing between temperature and radiation effects.

Our profit decomposition framework enables both positive and proactive analyses. Following the positive approach, our results illustrate farmers' adaptation to changing climate conditions by reallocating their land among bundles. In general, temperature increase causes a shift toward protected farming or away from farming altogether, whereas a decline in precipitation causes farmers to shift to irrigated bundles. In response to increase in the inter-annual variability of both temperature and precipitation patterns, farmers are expected to let larger portions of their land lie fallow. On the other hand, most of the bundles benefit from larger intra-annual variability of both temperature and precipitations. Increase in radiation seems to be favorable for rain-fed bundles. Our long-run forecasts based on the IPCC A1B future climate scenario show that farmers in Israel are expected to react to these climate trends by substituting rain-fed bundles with more technology-intensive bundles. However, total cultivated land is expected to decline, implying overall decline in profitability. The unique contribution of this study lies in the further analysis of these results, allowing identification of the proactive measures to improve adaptation.

We show that most of the changes in land use are attributable to the impact of temperature, indicating that temperature is the climate factor to which land allocation, at current production technologies, does not provide efficient adaptation. An in-depth look into the bundles' technological attributes reveals that these climate effects are mainly channeled through their impacts on yield potentials, which are therefore identified as the main target of further adaptation efforts. This means that in our specific case study, the best strategy to minimize future loss to farmers is investment in breeding more heat-tolerant crops and in developing more heat-resistant technologies.

Structural Framework

Consider a representative, risk-neutral farmer acting in a small, open economy. Agricultural land is a fixed yet allocatable input, exhibiting constant returns to acreage. The farmer maximizes his/her expected profit from a representative land unit by choosing the optimal land allocation among *J* bundles, together with optimal input use for each bundle. The problem can be stated thusly:

$$\max_{\mathbf{x},\mathbf{s}} E\Pi = \sum_{j=1}^{J} s_j E\pi_j\left(\mathbf{z},\mathbf{m},x_j\right) - Ec\left(\mathbf{s},\mathbf{z},\mathbf{m}\right)$$
$$= \sum_{j=1}^{J} s_j\left[Ep_j Ey_j\left(\mathbf{z},\mathbf{m},x_j\right) - Ewx_j\right] - Ec\left(\mathbf{s},\mathbf{z},\mathbf{m}\right) \text{ subject to } \sum_{j=1}^{J} s_j = 1 \qquad (1)$$

In Eq. (1), s_j is the land share devoted to bundle j, $j = 1,\dots, J$; x_j are an aggregate quantity index of variable inputs applied per unit of land devoted to bundle j, including pesticides, seed, and fertilizers; the vectors $\mathbf{s} = \left(s_1,...,s_J\right)$ and $\mathbf{x} = \left(x_1,...,x_J\right)$ are defined accordingly; $E\pi_j\left(\cdot\right)$ is the expected gross profit per unit of land of bundle j that does not incorporate the expected farm-level management cost, $Ec(\cdot)$; Ep_j is the farmer's expected output price vis-à-vis the crop associated with bundle j; Ey_j is the crop yield;[1] $\mathbf{z}$ is a vector of exogenous climate variables; the vector $\mathbf{m}$ stands for exogenous farm characteristics; and Ew is the expected aggregate input price index.

Following Anderson et al. (1992), a specification for the cost function consistent with the

MNL functional form, is:

$$Ec(\mathbf{s},\mathbf{z},\mathbf{m}) = A + \sum_{j=1}^{J} s_j Ec_j(\mathbf{z},\mathbf{m}) + \frac{1}{a}\sum_{j=1}^{J} s_j \ln s_j \tag{2}$$

In Eq. (2), A is an unidentified fixed cost that needs to be calibrated, and $Ec_j(\mathbf{z},\mathbf{m})$ is the expected fixed cost per unit of land specific to bundle j, which represents explicit costs. The last element stands for implicit management costs, reflecting the constraints on farmers' acreage decisions as motives for bundle diversification, i.e., unfeasible rotation / associations of some crops; irrelevant crop-technology bundles; and limiting quantities of quasi-fixed inputs such as labor, machinery, or water quotas. Such a cost function includes the shadow costs of all binding constraints on acreage choices, as well as representing the allocative input **s**'s non-linear effects on farm's profits, a fundamental feature in the positive mathematical programming approach (Howitt, 1995). It is formulated as the opposite of the allocative vector **s**'s entropy function, wherein the a parameter, measured in land per money unit and therefore assumed positive, reflects the "weight" of the implicit management costs in the profit function. This term is negative, and attains a minimal value at $s_j = 1/J$ for all $j = 1,\ldots, J$, which implies that A can be chosen so as to ensure positive costs. According to Letort and Carpentier (2009), this cost function obtains a minimum value when the land-share for every bundle j, $j = 1,\ldots, J$, is given by:

$$s_j = \frac{\exp\left(-aEc_j(\mathbf{z},\mathbf{m})\right)}{\sum_{j=1}^{J}\exp\left(-aEc_j(\mathbf{z},\mathbf{m})\right)} \tag{3}$$

As a goes to infinity, the farmer specializes in the most profitable bundle. When a goes to zero, acreage shares minimize the cost function and obtain optimal values following Eq. (3).

The optimization process includes the aforementioned two stages, wherein the optimal intra-growing-season activities at Stage 2 are taken into account when land is allocated at Stage 1. Thus, farmers choose $\mathbf{x}^*$, the set of aggregated intra-season variable-input quantities that maximizes the gross profitability of each bundle j, $E\pi_j(\cdot)$; then, they choose the optimal land allocation, $\mathbf{s}^*$. Assuming internal solutions with respect to all x_i, using Eq. (1), the optimal land shares are given by:

$$s_j^* = \exp(a\left[E\pi_j(\mathbf{z},\mathbf{m},x_j^*) - Ec_j(\mathbf{z},\mathbf{m}) - \lambda\right] - 1); \quad i = 1,...,J \tag{4}$$

where λ is the Lagrangian multiplier of the land additivity linear constraint. Summing (4) over the J bundles, and employing the land constraint in (1), we get:

$$s_j^* = \frac{\exp\left(a\left[E\pi_j(\mathbf{z},\mathbf{m},x_j^*) - Ec_j(\mathbf{z},\mathbf{m})\right]\right)}{\sum_{j=1}^{J}\exp\left(a\left[E\pi_j(\mathbf{z},\mathbf{m},x_j^*) - Ec_j(\mathbf{z},\mathbf{m})\right]\right)} \quad \forall\, j = 1,...,J \tag{5}$$

wherein the optimal land share of each bundle j is explicitly formulated as a function of the J-bundles' optimized profits, thereby constituting the backbone of the structural analysis and following the MNL functional form.

Consider panel data wherein i and t respectively denote farmers and years. Let $j = J$ denote a reference bundle, representing non-cultivated agricultural areas. Using Eq. (5), the optimal land-share of bundle j vis-à-vis bundle J, is:

$$\ln\left(\frac{s_{ijt}^*}{s_{iJt}^*}\right) = a_i\left[E\pi_j\left(\mathbf{z}_i,\mathbf{m}_{it},x_{ijt}^*\right) - \pi_J\left(\mathbf{m}_{it}\right) - \left(Ec_j\left(\mathbf{z}_i,\mathbf{m}_{it}\right) - c_J\left(\mathbf{m}_{it}\right)\right)\right] + u_{ijt} \tag{6}$$

where u_{ijt} is the error term, normally distributed, and i.i.d, among individuals and over time, yet with possible correlation across bundle equations. This equation is thus linear in bundle-profitability elements (gross profits and explicit management costs per land unit), and can be easily estimated through a multiple-equation estimation procedure.

Note that being representative of farmers' expectations for weather conditions based on long-run experience, climate variables in Eq. (6) are time-invariant, i.e., they represent spatial climate variations across individuals and thereby explain spatial heterogeneity in land-use patterns only. However, the error terms may well represent deviations from expected climate such as weather shocks and unexpected agro-climatic events over the estimation period, in addition to other unobserved time-varying and individual-specific variables, e.g., prices and farm characteristics.

Up to this point, our bundle-profitability functions incorporate expected gross profits and costs per land unit. To accomplish the second level of profit decomposition, we express the bundles' expected gross profitability, $E\pi_j(\cdot)$, as a function of three technological attributes. Following Pope and Just (2003), we specify an expected per-hectare yield function:

$$Ey_{ijt} = \alpha_{ijt} - \frac{1}{2\gamma_{ijt}}[\beta_{ijt} - x_{ijt}]^2 \tag{7}$$

where α_{ijt} is the expected yield potential, β_{ijt} is the expected optimal usage of the aggregated variable inputs required to reach this yield potential, and γ_{ijt} is the inverse-sensitivity of production with respect to inputs use. Based on Eqs. (7) and (1), one can derive the first-order conditions for optimal gross profits, which yields the demands for aggregated variable inputs:

$$x^*_{ijt} = \beta_{ijt} - \gamma_{ijt}\frac{Ew_t}{Ep_{jt}} \tag{8}$$

where output and input prices are assumed to be homogeneous among farmers.[2] The resultant expected optimal per land unit gross-profit function is:

$$E\pi^*_{ijt} = \alpha_{ijt}Ep_{jt} + \frac{\gamma_{ijt}}{2}\frac{Ew_t^2}{Ep_{jt}} - \beta_{ijt}Ew_t \tag{9}$$

and by incorporating Eq. (9) into Eq. (6), we get:

$$\ln\left(\frac{s^*_{ijt}}{s^*_{iJt}}\right) = A_J + a_i\left[\alpha_{ijt}Ep_{jt} + \frac{\gamma_{ijt}}{2}\frac{Ew_t^2}{Ep_{jt}} - \beta_{ijt}Ew_t - Ec_j\left(\mathbf{z}_i, \mathbf{m}_{it}\right)\right] + u_{Jt} + u_{ijt} \tag{10}$$

where A_J is the reference-bundle's average net profit per unit of land over time and across farms, and u_{Jt} is a random effect due to the time-varying profitability of the reference bundle. The term u_{ijt} can be considered as the error terms pertaining to the per land unit gross-profit technological attributes α, β, γ, and the cost function, all of which may depend on climate and other exogenous variables; this leads us to the third level of profit decomposition.

We introduce the following linear specifications for the four technological attribute functions:

$$\alpha_{ijt} = \alpha_{0j} + \boldsymbol{\alpha}_{1j}\mathbf{z}'_i + \boldsymbol{\alpha}_{2j}\mathbf{m}'_{it} + \boldsymbol{\alpha}_{3j}\mathbf{zm}'_{it} + \mu^{\alpha}_{ijt} \tag{11}$$

$$\beta_{ijt} = \beta_{0j} + \boldsymbol{\beta}_{1j}\mathbf{z}'_i + \boldsymbol{\beta}_{2j}\mathbf{m}'_{it} + \boldsymbol{\beta}_{3j}\mathbf{zm}'_{it} + \mu^{\beta}_{ijt} \tag{12}$$

$$\gamma_{ijt} = \gamma_{0j} + \boldsymbol{\gamma}_{1j}\mathbf{z}'_i + \boldsymbol{\gamma}_{2j}\mathbf{m}'_{it} + \boldsymbol{\gamma}_{3j}\mathbf{zm}'_{it} + \mu^{\gamma}_{ijt} \tag{13}$$

$$Ec_{ijt} = c_{0j} + \mathbf{c}_{1j}\mathbf{z}'_i + \mathbf{c}_{2j}\mathbf{m}'_{it} + \mathbf{c}_{3j}\mathbf{zm}'_{it} + \mu^{c}_{ijt} \tag{14}$$

where **zm** is a vector incorporating the products of all the elements in **z** and **m**; the random terms μ^{α}_{ijt}, μ^{β}_{ijt}, μ^{γ}_{ijt} and μ^{c}_{ijt} are centered in zero and normally i.i.d. across farms and over time; and all other elements are vectors of parameters arranged so as to be consistent with the dimensions of **z**, **m**, and **zm**. By invoking Eqs. (11)-(14) into Eq. (10), and assuming $a_i = a$ for all farmers, we obtain a system of $J-1$ equations:

$$\ln\left(\frac{s^*_{ijt}}{s^*_{iJt}}\right) = A_J + \begin{bmatrix} Ep_{jt} & Ew_t & \dfrac{Ew_t^2}{Ep_{jt}} & 1 \end{bmatrix} \begin{bmatrix} A^{\alpha}_j & \mathbf{A}^{\alpha}_{zj} & \mathbf{A}^{\alpha}_{mj} & \mathbf{A}^{\alpha}_{zmj} \\ A^{\beta}_j & \mathbf{A}^{\beta}_{zj} & \mathbf{A}^{\beta}_{mj} & \mathbf{A}^{\beta}_{zmj} \\ A^{\gamma}_j & \mathbf{A}^{\gamma}_{zj} & \mathbf{A}^{\gamma}_{mj} & \mathbf{A}^{\gamma}_{zmj} \\ A^{c}_j & \mathbf{A}^{c}_{zj} & \mathbf{A}^{c}_{mj} & \mathbf{A}^{c}_{zmj} \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{z}'_i \\ \mathbf{m}'_{it} \\ \mathbf{zm}'_{it} \end{bmatrix} + u_{Jt} + \varepsilon_{ijt} \tag{15}$$

where

$$\begin{bmatrix} A^{\alpha}_j & \mathbf{A}^{\alpha}_{zj} & \mathbf{A}^{\alpha}_{mj} & \mathbf{A}^{\alpha}_{zmj} \\ A^{\beta}_j & \mathbf{A}^{\beta}_{zj} & \mathbf{A}^{\beta}_{mj} & \mathbf{A}^{\beta}_{zmj} \\ A^{\gamma}_j & \mathbf{A}^{\gamma}_{zj} & \mathbf{A}^{\gamma}_{mj} & \mathbf{A}^{\gamma}_{zmj} \\ A^{c}_j & \mathbf{A}^{c}_{zj} & \mathbf{A}^{c}_{mj} & \mathbf{A}^{c}_{zmj} \end{bmatrix} \equiv a \begin{bmatrix} \alpha_{0j} & \boldsymbol{\alpha}_{1j} & \boldsymbol{\alpha}_{2j} & \boldsymbol{\alpha}_{3j} \\ -\beta_{0j} & -\boldsymbol{\beta}_{1j} & -\boldsymbol{\beta}_{2j} & -\boldsymbol{\beta}_{3j} \\ \frac{1}{2}\gamma_{0j} & \frac{1}{2}\boldsymbol{\gamma}_{1j} & \frac{1}{2}\boldsymbol{\gamma}_{2j} & \frac{1}{2}\boldsymbol{\gamma}_{3j} \\ -c_{0j} & -\mathbf{c}_{1j} & -\mathbf{c}_{2j} & -\mathbf{c}_{3j} \end{bmatrix} \tag{16}$$

is the matrix of parameters of interest, and

$$\varepsilon_{ijt} = a\begin{bmatrix} Ep_{jt} & Ew_t & \dfrac{Ew_t^2}{Ep_{jt}} & 1 \end{bmatrix} \begin{bmatrix} \mu^{\alpha}_{ijt} \\ \mu^{\beta}_{ijt} \\ \mu^{\gamma}_{ijt} \\ \mu^{c}_{ijt} \end{bmatrix} + u_{ijt} \tag{17}$$

Expected prices Ep_{jt} and Ew_t are assumed known by all farmers at the time of acreage decision-making; hence ε_{ijt}, as a linear combination of normally and i.i.d.-distributed terms centered in zero, is also normally and i.i.d distributed. Due to the linear constraint in Eq. (1), we allow for correlation of these error terms across the *J* equations such that $E\left(\varepsilon_{ijt}\varepsilon_{ij^{'}t}\right) \neq 0$ for all $j \neq j'$, and $E(\varepsilon_{ijt}\varepsilon_{i^{'}jt}) = E(\varepsilon_{ijt}\varepsilon_{ijt^{'}}) = 0$ for all $i \neq i'$ and $t \neq t'$.

A fully estimable system should include *J*-1 land-share equations, *J*-1 input-supply functions, and *J*-1 input-demand functions. However, having only the *J*-1 land share equations, the various impact channels of climate and farms‘ heterogeneity are identifiable only up to the constant *a*, i.e, only within the parameters of Eq. (16)'s LHS matrix, not within those of the RHS matrix. Note also that the constants A_j^{α}, A_j^{β}, A_j^{γ}, and A_j^{c} are unidentifiable, since their estimates in Eq. (16) are summed with A_J, which is common across bundles.

Data and Construction of Variables

Our analysis is based on Israel‘s 54 natural regions, determined according to topographical, climatic, demographic, and historical criteria (ICBS, 2010). The average area of the regions is 416 square kilometers, each of which is considered as a representative farm, and each is spatially represented by a single point, corresponding to the locus of the region's farmland; the coordinates of these centroids were derived from GIS-based land-use data.

The agricultural land-use dataset is a panel from 1992 to 2001 (with 1999 missing) of acreage reports provided by the ICBS. In addition to land allocations to crops, these reports contain sub-divisions into production technologies, indicating irrigated and covered areas of each crop, allowing us to specify a choice of 12 relevant crop-technology bundles, and to obtain their regional annual land shares. Our main crops are vegetables, field crops, flowers, and orchards. Vegetables are subdivided into covered (denoted VCI) and open-space areas, where the latter is split further into irrigated (VOI) and rain-fed (VOR); field crops are all grown in open spaces and are subdivided into irrigated (FCI) and rain-fed (FCR); flowers are all irrigated, and subdivided into covered (FLOC) and open-space types (FLOO); orchards are not protected,[3] and are classified into sub-groups with specific climate requirements: citrus (CIT), which is sensitive to extreme cold events; deciduous (DEC), which need cold doses to produce fruit; and sub-tropical trees (SUBT), which are tolerant to hot conditions — all irrigated; all other types of orchards were assigned to irrigated (OTHI) and rain-fed (OTHR) groups. A 13th land-use category encompasses all the non-cultivated (NC) agriculture-related land, including grazing areas, access roads, and uncultivated farmland. The aforementioned constitutes our reference bundle. The sample averages of the observed bundles' land shares are shown in the first column of Table 4. Also shown is the share of total cultivated land (TCL), which, as will be explained later, plays a key role in our proactive analyses. On average, the sample covers 463,000 hectares of land (4,630 square kilometers), or about a quarter of Israel's surface.

Table 1 presents a summary statistics of all the explanatory variables.

[Table 1 here]

The climate variables were derived from data produced by RegCM3, a high-resolution, 25-kilometer climate simulation model (Krichak et al., 2010) specially designed for the eastern Mediterranean region, covering the area of Israel and the adjacent parts of its neighbors. The model provides daily data covering the period 1960-2060, i.e., weather data, including ground temperature, precipitation, wind, and solar radiation. While RegCM3 does not claim to accurately predict these weather variables on a daily basis, it does reproduce and forecast changes in the moments of their temporal and spatial distributions, exactly the climate-change information required for our analysis. The simulation for the period 1960-2005 was successfully validated by actual climate data. Projections for the years 2006-2060 were computed by assuming carbon emissions as per the IPCC's A1B scenario (IPCC, 2001), which forecasts rapid economic growth and technological progress along with reduction of worldwide spatial income inequality.

To study the effect of climate-change trends, we consider four periods of 20 years each. The first is 1981-2000, which is considered to incorporate the climate conditions that have affected agricultural land use during our sample period of 1992-2001. The successive three 20-year periods are used for simulations based on our estimated structural model. The inverse-distance-weighting (IDW) method was employed for assigning the climate variables from the 25-km resolution points of the RegCM3 model to our 54 natural zones, using the power 1 IDW specification due to its robustness superiority (Kurtzman and Kadmon, 1999).

To represent long-term impacts of climate change, the explanatory climate variables were constructed so as to reflect the main moments of the daily weather data distributions produced by RegCM3. Following Kaufman and Snell (1997), Deschênes and Greenstone (2007), and Schlenker et al. (2007), temperature impact was estimated based on degree-days,[4] annual sums of which were calculated for each resolution point of the model, as well as standard deviations, decomposed into intra- and inter-annual standard deviations. Similarly, the total annual precipitations (mm / year) and their intra- and inter-annual standard deviations were computed. The incorporation of these standard deviations allows us to capture the impact of changes in the volatility of weather conditions. Our data also include average solar radiation (W / m^2) and wind speed (m / sec) as additional variables, the impact of which has been barely studied in the literature. The effect of solar radiation may differ from that of temperature, particularly under cloudy, foggy, and hazy conditions. Wind influences irrigation and evaporation, and may damage plants, greenhouses, and other production equipment under storm events.

[Figure 1 here]

Figure 1 presents the future trends simulated by RegCM3 for the climate variables, at their average nationwide level, as per their reported values (Table 1) during the sample period. Overall, climate will be hotter and drier in the long run, while more precipitation and fewer degree-days are expected in the very short run. The model forecasts slight increases of degree-days' intra-annual variability, as well as reductions in inter-annual variability in both the short and long runs; while reverse patterns hold for precipitations. Regarding solar radiation and wind, average values do not follow any clear sequence. These unclear trends at the nationwide level might be due to the considerable heterogeneity across the natural regions (not shown).

Control variables are included in order to net out the climate-driven effects. The social organization of a village may be an important determinant of its farming costs through management and scale effects. We therefore account for the share of cooperative villages (kibbutzim) in each natural region. Additional scale effects and constraints on access to land are controlled for by the region's total agricultural land. As farmland is mostly owned by the state, and managed by the Israel Land Authority, variation in the total agricultural land is restricted, and thus considered exogenous. Soil type, measured in terms of the region's share of heavy soils, may account for differences in crops' productivities and cultivation requirements. Incorporation of water quotas, as shown by Fleischer et al. (2008), is essential to isolate the effect of precipitations. Quotas are administratively allocated to consumers in the agricultural sector and non tradable, and hence they constitute an exogenous variable. The distance from greater Tel Aviv stands for spatial differences that may affect production costs, e.g., through transportation and human capital. While prices are assumed not to vary spatially, this is not a strong assumption, since Israel is too small to induce spatial variations in market prices of outputs and purchased input factors, as evident from official data (IMARD 2011).

Prices were obtained from the ICBS, which reports national yearly price indices for vegetables, field crops, flowers, citrus, and other plantations, as well as a cost index of agricultural inputs. In order to reflect prices expected by farmers in their land-use choices, we calculated moving averages over the period covered by our panel data. Since field crops, flowers, and vegetables can be adjusted from year to year, their price indices were constructed based on the two previous years; for orchards, the previous four years were taken.[5]

Estimation Results and Simulations

This section presents our estimation results and simulations which will be further discussed in the following sections. Equation System (15) was estimated by Zellner's SUR estimation method, which strategy is fully detailed in the Appendix. Table 2 presents the estimated coefficients of the variables in the four technological attribute functions associated with the 12 bundles.

[Table 2 here]

Exogenous variables' impact on bundles' land shares represents the variable's integrated effect on the bundles' four technological attributes, in addition to standing for the land-adaptation responses to a change in the variable. To obtain these land-allocation responses, the parameters in Table 2 were used to derive land-share marginal effects and elasticities. The method suggested by Wu and Segerson (1995) was employed for this purpose.[6] For a specific climate component z_i of the climate variables vector $\mathbf{z}_i$, the marginal land-share effect takes the form

$$\begin{aligned}\frac{\partial s_{ijt}}{\partial z_i} = s_{ijt}\Bigg\{&\begin{bmatrix} Ep_{jt} & Ew_t & \dfrac{Ew_t^2}{Ep_{jt}} & 1 \end{bmatrix}\begin{bmatrix} A_{zj}^{\alpha} & \mathbf{A}_{mzj}^{\alpha} \\ A_{zj}^{\beta} & \mathbf{A}_{mzj}^{\beta} \\ A_{zj}^{\gamma} & \mathbf{A}_{mzj}^{\gamma} \\ A_{jz}^{c} & \mathbf{A}_{mzj}^{c} \end{bmatrix}\begin{bmatrix} 1 \\ \mathbf{m}'_{it} \end{bmatrix} \\ &- \sum_{j=1}^{12} s_{ijt}\begin{bmatrix} Ep_{jt} & Ew_t & \dfrac{Ew_t^2}{Ep_{jt}} & 1 \end{bmatrix}\begin{bmatrix} A_{zj}^{\alpha} & \mathbf{A}_{mzj}^{\alpha} \\ A_{zj}^{\beta} & \mathbf{A}_{mzj}^{\beta} \\ A_{zj}^{\gamma} & \mathbf{A}_{mzj}^{\gamma} \\ A_{jz}^{c} & \mathbf{A}_{mzj}^{c} \end{bmatrix}\begin{bmatrix} 1 \\ \mathbf{m}'_{it} \end{bmatrix}\Bigg\}\end{aligned} \tag{18}$$

The same can be applied to the components of $\mathbf{m}_{it}$, the vector of farm-specific variables. Table

3 reports the 12 bundles' land-share elasticities, as well as the elasticity of the total cultivated land. Significance levels were computed by the Fisher test, using standard errors calculated by the Delta Method.

[Table 3 here]

The elasticities in Table 3 reveal how farmers adapt to a change in each of the climate variables by reallocating their land among bundles. This reallocation expresses a variety of adaptation strategies: Farmers can switch crops, change the technology used (irrigation and / or cover), or change the size of the land they farm. The coefficients of the technological attributes in Table 2 enable us to elaborate on the profitability drivers behind these adaptation steps. These coefficients should be interpreted in view of their settings in Eq. (15), i.e., a positive-value parameter indicates that *ceteris paribus*, an increase in the parameter's associated explanatory variable leads to a change in the value of the related technological attribute of the corresponding bundle, which in turn corresponds to a rise in the bundle's profitability, and is therefore translated into an increase in its land share. Specifically, positive A^{a} parameters point to an increase in yield potentials, positive A^{β} coefficients mean more efficient use of inputs (less input requirement), positive values of A^{γ} stand for a decrease in the sensitivity of yields to inefficient use of inputs, and positive A^{c} parameters imply a decrease in the explicit management cost.

In order to simulate future scenarios, we used Eq. (15) to calculate land shares under the regional climate conditions as forecasted by RegCM3 for the aforementioned three 20-year future periods (Figure 1). All other variables were held at their observed levels during the sampled period. Table 4(a) reports the simulated land allocations among bundles at the nationwide level for each period.

[Table 4 here]

Based on the simulated changes in land allocation, the total effect of climate change on each bundle's profitability can be computed. Let τ and τ' stand for two distinct time periods. Assuming that reference bundle *J*'s profitability is unaffected by climate change, a given bundle's acreage ratio over time is:

$$\frac{s_{ij\tau}}{s_{ij\tau'}} = \frac{\exp\left(a\left[\pi_j\left(\mathbf{z}_{i\tau},\mathbf{m}_i,x_{ij}^*\right)-c_j\left(\mathbf{z}_{i\tau},\mathbf{m}_i\right)\right]\right)}{\exp\left(a\left[\pi_j\left(\mathbf{z}_{i\tau'},\mathbf{m}_i,x_{ij}^*\right)-c_j\left(\mathbf{z}_{i\tau'},\mathbf{m}_i\right)\right]\right)}\cdot\frac{s_{iJ\tau}}{s_{iJ\tau'}}$$

Hence, an indicator for net profitability changes of each bundle between two time periods is:

$$a\underset{\tau,\tau'}{\Delta}\left[\pi_j\left(\mathbf{z}_{it},\mathbf{m}_i,x_{ij}^*\right)-c_j\left(\mathbf{z}_{it},\mathbf{m}_i\right)\right]=\ln\left(\frac{s_{ij\tau}}{s_{ij\tau'}}\cdot\frac{s_{iJ\tau'}}{s_{iJ\tau}}\right) \tag{19}$$

Table 4(b) reports this indicator's value computed for every pair of succeeding periods. These unitless values indicate directions and magnitudes of net-profitability changes in relation to the *a* parameter. The product of a bundle's indicator and its corresponding land share, in period τ', say, represents the bundle's contribution to the cultivated lands' overall profitability change as expressed by the TCL's profitability-change indicator.

The *a* parameter should be estimated in order to express profit changes in monetary terms. As aforementioned, the data required for a fully estimable system is unavailable. We therefore propose a calibration procedure based on additional data available at the nationwide level. Detailed per-hectare profit calculations provided by IMARD (2004) for 42 crops were used to compute net profitability levels of the main crop groups — vegetables, field crops, and orchards[7] — for the year 2001. Based on Kislev and Vaksin's (2003) price and cost indices, these profitability values were calculated for each year in our sample period, and multiplied by their corresponding land shares to obtain annual TCL profitability estimates. The *a* parameter was calibrated by applying Eq. (19) to the nationwide average profitability and land shares in the periods 1992-1996 and 1997-2001, resulting in *a*=0.002 . Nationwide profits were then calculated for each of the three simulated future periods. The results are presented in Table 5 in terms of 2002 dollars.

[Table 5 here]

Discussion of Estimation Results and Simulations

In this section, we discuss the estimation results presented in the previous section and their use for simulation of future scenarios. We apply a positive economic approach in describing climate variables' impact on farmers' land allocation decisions. In the next section, we further analyze these results, and by anticipating the changes, suggest proactive measures to improve adaptation.

Estimation Results

We begin our discussion with the various temperature variables. Elasticities of degree-day levels in Table 3 are negative for all bundles, except for greenhouse vegetables, and are statistically significant for most of them. This means that a rise in temperatures induces farmers to move away from most of the bundles to vegetables grown in greenhouses. The overall effect of temperature on TCL is negative (elasticity is -1.34), indicating that farmers let their land lie fallow in response to a temperature rise. Table 2 presents the underlying coefficients of these elasticities. Most of the estimated coefficients of degree-days presented in the table suggest that higher temperatures entail a loss in the yield potential of most bundles; a decrease in input requirements to attain that potential; an increase in the yield sensitivity to inputs' use; and a rise in the management costs for most bundles, excluding vegetables. The final result of negative elasticity for most of the bundles means that the negative effects on the technological attributes dominate, while the reverse holds for vegetables.

Larger inter-annual temperature fluctuations push farmers away from rain-fed bundles, yet without switching to other bundles (Table 3). An increase in intra-annual degree-days variability exhibits a differing effect, inducing farmers to downsize their irrigated field crops and flowers and mainly favor plantations, as well as vegetables to a lesser extent. This might be consistent with the temperature peaks required by many fruit trees to yield.

Regarding precipitation levels, land-share elasticity estimates indicate that a decline in precipitation induces farmers to move away from rain-fed bundles. Increase in inter-annual variability in precipitation has a negative effect on most of the bundles, whereas intra-annual variability in precipitation is beneficial to all of them except rain-fed orchards. Table 2 suggests that the negative effect of increase in inter-annual precipitation, especially on rain-fed bundles, is mainly driven by an increase in management costs. This phenomenon may be explained by the increasing need to accumulate and convey water from wet to dry years. The rest of the technological attributes are less sensitive to precipitation variability, which might indicate that Israeli farmers have already internalized the precipitation conditions.

Increases in solar radiation entail a substitution from irrigated bundles to rain-fed ones. Wind is beneficial to citrus and deciduous plantations, yet detrimental to rain-fed vegetables.

Simulations

Our simulations are based on the future scenarios provided by RegCM3 for the expected changes in the climate variables for the three periods (Figure 1). The simulations presented in Table 4 reflect the full impact of expected future changes in the climate variables. An overall long-run (2021-2060) declining trend in cultivated land is anticipated (Table 4a), implying a reduction in the average profitability of agricultural bundles (Table 4b). The harshest climate conditions predicted for the 2021-2040 period lead to large decreases in rain-fed bundles' land shares and more contained decreases for the more protected bundles, notably vegetables. This prediction implies that farmers will adapt by moving from rain-fed production to the more technology-intensive ones. The slight climate recovery in the fourth period, mainly related to reductions in the inter-annual variability of precipitations and temperatures, causes farmers to return rapidly to rain-fed vegetables and field crops. The rain-fed orchards are less sensitive to these climate changes, probably due to their longer life cycle and differing physiology. Open-field flowers are expected to vanish in the long run, after a sharp increase in the 2021-2040 period; only covered flowers subsist under the 2041-2060 climate forecasts.

With respect to crops in general, our results predict a switch from vegetables, field crops, and flowers to orchards regardless of the production technology, pointing out a relative advantage of orchards over other crops under the predicted future conditions. In the long term, only citrus acreage increases, consistent with its tolerance to drier and hotter conditions under the current technologies. Vegetables and field crop areas are expected to be substantially reduced.

Table 5 depicts a considerable long-run decline in the profitability of agriculture in Israel, as well as in overall profits. These evaluations differ from those of Fleischer et al. (2008) mainly due to the fact that the latter applied the Ricardian model to cross-sectional data and performed profit simulations under a differing set of future climate scenarios.

Proactive Analyses

This section presents an application of our unique contribution to the relevant literature, wherein not only do we describe farmers' adaptation measures to climate change, but also provide actual tools to improve these measures. The specific adaptation directives are derived from the coefficients in Table 2. This is due to the fact that they represent climate variables' impacts on the technological attributes, which are exogenous to the farmers and are the drivers of their land-use responses, as reported in Table 3.

To elucidate, consider when land reallocation would no longer be employed by farmers as an adaptation strategy: It might occur if alternative adaptation steps, such as crop breeding, production input development, and management practices improvements would render all technological attributes unresponsive to climate changes. Thus, Table 2 constitutes a guidebook for such further adaptation efforts. The information it provides enables us to identify adaptation directions that, if implemented as per forecasted climate changes, might augment the profit of agriculture overall. To illustrate the directive formation procedure, we consider adaptation of citrus (CIT) production to anticipated changes in precipitations. We first analyze impacts from a positive point of view, and then deduce the proactive measures based on the objective of maximizing cultivated lands' profits.

According to Table 3, farmers are expected to react to precipitation increases by reducing citrus land shares. Table 2 points out two statistically significant drivers for this response. The first is a positive impact on input efficiency (A_{zj}^{β} Precip), indicating that precipitations are a substitute for production inputs. The second is negative, involving increased sensitivity to input use (A_{zj}^{γ} Precip), because precipitation may reduce fertilizers' and pesticides' efficacy, possibly through increased risk of pest contamination. These impacts' magnitude attenuates on heavier soils, as can be learned from A_{zmj}^{β} Precip×Soil's and A_{zmj}^{γ} Precip×Soil's coefficients. Citrus's negative land-share response in Table 3 indicates that the negative effect of increased sensitivity to inputs overrides the positive effect of reduced input requirements. Since precipitations are expected to decline in the long run (Figure 1), yields will be less sensitive to inadequate applications of inputs, whereas more inputs will be required to achieve citrus's potential yield. Thus, the following proactive measure emerges: Adaptation efforts should aim at moderating the negative effect of precipitations' decline on input requirements in citrus production. These measures may include input subsidies, breeding less input-intensive citrus varieties under dry conditions, and developing water-saving irrigation systems.

By conducting a similar analysis for each bundle as per each climate variable, we can identify the technological attributes that, regarding future climate conditions, will negatively affect the bundle’s profitability. Accordingly, one can infer about the need for further improvement of these technological attributes. If these adaptation efforts should successfully turn positive all the currently negative responses of all the technological attributes, the profitability of cultivated land as a whole would increase. This increased profitability would in turn be reflected by an increase in the share of TCL out of total farmland. Thus, the response of TCL’s share, translated into TCL's profit based on Eq. (19) and the calibrated a parameter, can be used to evaluate each adaptation move’s profitability contribution, which can then be confronted with its corresponding adaptation cost. Such cost-benefit analyses can be used for ranking adaptation measures in order to facilitate their selection under budget constraints.

As aforementioned, TCL’s profit can be used to reveal the impact of climate changes on the profitability of agriculture, i.e., the remaining impact post-adaptation by land reallocation. In order to identify the impact of a given climate variable on each of the technological attributes, we would have to conduct a large number of simulations, changing only the variables in question and holding the rest constant. This procedure can be used to compute the specific contribution of each variable to the total residual impacts, separated into bundles and technological attributes. Since such a detailed analysis is too lengthy for this article, we illustrate it for changes in groups of variables and present the results graphically. The results of this exercise draw a comprehensive picture of climate variables’ impacts and their corresponding adaptation strategies. This information can be used by policymakers to design overall long-run adaptation plans.

Figure 2 presents the residual TCL's profit effects of (a) the major groups of climate variables, (b) the temperature variables, (c) the precipitation variables, and (d) the technological attributes through which the impacts of all variables are channeled.

[Figure 2 here]

Figure 2a indicates that the remaining long-run negative effect of climate change on TCL's profit is mostly attributable to the damaging impact of temperature changes. Although in the mid-term, precipitation variables — first positively, then negatively — affect agricultural profitability, their effect is not significant in the long run. Radiation and wind play a minor role relative to temperature and precipitations. These findings support the fact that while Israeli agriculture is already adapted to a drier climate, it nevertheless will be significantly affected by increased temperatures over time. Extra-adaptational efforts should therefore be mainly devoted to moderating these harmful effects of temperature variables.

Figure 2b shows that via land reallocation, farmers can effectively adapt to the predicted changes in temperature-variability variables, yet not to the anticipated increase in absolute temperature levels; the latter would drive them away from farming unless further adaptation means should be developed. This is not the case for precipitation, where the residual effect is driven largely by changes in the inter-annual variability, and precipitation levels and intra-annual variability offset one another (Figure 2c). This long-run negative impact of reduced intra-annual variability of precipitation calls for additional adaptation attention. For example, increasing spatial and temporal flexibility of intra-seasonal irrigation might be considered.

With regard to the particular technological attributes (Figure 2d), the long-run decline in total profit is mostly driven by the effect on yield potential, and to a lesser extent by the effect on yields' sensitivity to inputs' use. Note that there is a slight positive effect on input efficiency, which attenuates the two former negative ones. In the long run, the explicit management costs channel significant negative climate-change impacts on profits, meaning that farmers' adaptation to future climates by reallocating land among crop-technology bundles is expected to drive up management costs.

Conclusions

In this study, we propose a new approach toward understanding and taking proactive measures in farmers' adaptation to climate change. Specifically, we introduce a structural model wherein farmers maximize profits by allocating their land between crop-technology bundles in view of climate variables' impact on profitability, as channeled through climate's impact on attributes of production technologies. The model allows us to provide policymakers not only with estimates on expected land-use changes and evaluations of losses in agricultural profits driven by climate change, but also with recommendations as to which and how these technological attributes should be further developed in order to minimize these losses. We applied the model to the case study of Israel based on the long-run IPCC A1B climate scenario, and forecast a considerable profit loss in the long run. We show that the sensitivity of yields' potential to high temperature is the main cause thereof, and therefore identify this vulnerable point as the main target of further adaptation efforts.

Our proactive analysis is based on the objective of minimizing profit losses of cultivated farming. From a societal standpoint, however, proactive measures should be designed based on a more comprehensive normative approach, which accounts for climate impacts on non-market environmental services of farmland such as landscape and biodiversity. For instance, the move toward protected bundles is expected to decrease landscape amenities, whereas switching to orchard bundles is expected to increase landscape value (Fleischer and Tsur, 2009). In addition, while our model explicitly incorporates output and input price indices, following the assumption of a small open economy, these are all assumed fixed throughout the simulations; see Cline (1996) for criticism. This assumption may be relaxed if trade barriers could be accounted for by a nationwide partial equilibrium model, wherein functions of local demand for agricultural outputs and supply of farming inputs are integrated into our structural model. All these extensions are left for future research.

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Appendix - Estimation Strategy

In this part, we discuss the main econometric issues raised by the estimation of Eq. (15) and heretofore explored in the literature of multi-crop acreage MNL models, such as in Wu and Segerson (1995). The multinomial acreage model is convenient for econometric purposes because it ensures interior solutions for optimal bundles' acreage due to its functional form. In our estimations, the MNL model is used not only for its non-linear mathematical convenience, but also because it enables us to estimate the structural parameters of the underlying production function and implicit management cost. However, one of its drawbacks is that it does not deal with corner solutions. Thus we chose to work with regional data wherein nearly all bundles appear in each region over the considered time period.

Following Wu and Segerson (1995), for the cases wherein we had corner solutions (44 observations for VCI; 3 for VOI; 77 for VOR; 17 for FCI; 11 for FCR; 91 for FLOC; 98 for FLOO; 14 for CIT; 35 for DEC; 9 for SUBT; 13 for OTHI; and 102 for OTHR), we assigned an infinitesimal value (1E-12) so that the logarithm of relative shares with respect to the reference bundle can be defined in the system of estimable Eq. (15); sensitivity analysis indicates that the results are not significantly sensitive to the chosen value.

An important issue is the slope heterogeneity of climate effects on profits, such as stressed by Schlenker et al. (2005), who ran separate regressions between irrigated and non-irrigated counties in the US. We have no such heterogeneity problem in our case, since all regions use irrigation, irrigated bundles are already specified, and we control for the exogenous water quotas.

There are also three specification issues in this empirical methodology. The first is the possible contemporaneous correlation between residual terms of Eq. (15) due to the joint and simultaneous nature of the bundles' acreage decision made by farmers. Using Zellner's seemingly unrelated regressions (SUR) allows us to estimate a system of 12 equations for which explanatory variables are not necessarily the same and errors are correlated over time. In order to ensure this specification's relevance, a Breush-Pagan test of independent equations was performed; it was rejected at a highly significant level.

Error terms may be autocorrelated over time because disturbances that affect one bundle or one crop in one year may affect these in the future unless our explanatory variables provide sufficient control. If this is the case, and since the residual autocorrelation is not accounted for by the Zellner's technique, we needed to correct therefor using another technique (such as the Kmenta technique). We thus performed a Breush-Godfrey test for autocorrelated errors for each residual term of each equation in System (15). The test statistic is a chi-square statistic that takes the form $\chi^2(p) \approx nR^2$, where p is the number of lags for which the Breush-Godfrey test has to be performed, $n = T-p$, where T is the number of periods of observations (here $T = 9$), and R^2 is the usual statistic calculated for the (auxiliary) autoregressive model that estimates contemporaneous predicted errors with p lags AR(p) and that also contains the explanatory variables used in System (15). We calculated the chi-square statistic value for each residual term of each equation of System (15) for the case of one lag: $p = 1$, and $n = 8$. We then compare the computed values to the critical value of the chi-square test with 10% significance (3.84). In none of the 12 equations of System (15) was the computed chi-square value greater than this critical value, meaning that "no error autocorrelation" is not rejected (the computed chi-square statistic values are: 0.14 for VCI; 0.02 for VOI; 0.17 for VOR; 0.48 for FCI; 1.38 for FCR; 0.24 for FLOC; 0.18 for FLOO; 0.37 for CIT; 0.88 for DEC; 1.45 for SUBT; 0.08 for OTHI; and 0.36 for OTHR). Therefore, we do not need to correct for possible autocorrelated errors in our SUR estimation procedure. This may be due to the fact that our explanatory variables convey enough control on residual serial correlation.

The last specification issue lies in residual heteroskedasticity (or groupwise heteroskedasticity) due to regional unobserved cross-heterogeneity in many factors and geographical size. Groupwise heteroskedasticity is tested in the SUR model estimation by a Lagrange multiplier test applied to each of the 12 equations of System (15). The null hypothesis of homoskedasticity is not rejected for all equations up to 10% of significance. We thus do not need to generalize the likelihood function of Zellner for robust standard errors (by iterating the generalized least-square function).

Table 1. Summary statistics of explanatory variables[a]

Variable	Description	Sample average	Sample Std. Dev.
Precip	Annual precipitations (mm / year)	398.6	91.0
IntraPp	Intra-annual standard deviation of precipitations (mm / day)	3.82	0.80
InterPp	Inter-annual standard deviation of precipitations (mm / year)	123.1	29.93
DegDay	Annual sum of degree days (C^o / year)	4,381	270.5
IntraDD	Intra-annual standard deviation of degree days (^oC / day)	5.51	1.09
InterDD	Inter-annual standard deviation of degree days (^oC / year)	197.3	28.76
Rad	Average daily solar radiation (watts / m^2)	242.4	4.05
Wind	Average daily wind speed (km / h)	25.28	1.37
DistTel	Distance from Tel Aviv (km)	75.56	42.80
Coop	% of income-sharing communities (kibbutzim)	49.43	30.22
Soil	% of heavy soils	39.57	33.41
WatQuota	Water quotas ($10^6 \times m^3$ / year)	19.19	17.15
Land	Total agricultural lands (10^3 hectare)	85.51	63.15
FcPrice	National price index of field crops	254.7	52.28
VegPrice	National price index of vegetables	247.5	40.49
CitrPrice	National price index of citrus plantations	217.0	41.68
FruitPrice	National price index of non-citrus fruit plantations	207.9	41.15
FlowPrice	National price index of flowers	253.4	44.94
InputPrice	National price index of agricultural inputs	285.6	65.13

a. All variables are at the regional level except for price indices, which are at the nationwide level. Climate variables are for the period 1981-2000, calculated at the regional centroids. The base period for the prices and costs' indices is 1986 (100 = 1986).

Table 2. Estimated coefficients of the structural model

		Coefficient	VCI	VOI	VOR	FCI	FCR	FLOC	FLOO	CIT	DEC	SUBT	OTHI	OTHR
Yield potential	$A_j^{\propto}$	Constant	-0.456	-1.019	4.4487	0.9598	3.9485	-3.225	-5.526*	-5.582**	2.1238	-7.73**	3.8572	4.3882
	$A_{zj}^{\propto}$	Precip	0.0039	-0.004	-0.013*	0.0068	0.0035	0.0167	-0.053**	-0.006	0.0041	-0.004	-0.004	0.0296*
	$A_{zj}^{\propto}$	IntraPp	0.0916	0.1291	-0.059	-0.227	0.0561	-0.088	-0.119	-0.009	0.3371	-0.074	-0.072	-1.005*
	$A_{zj}^{\propto}$	InterPp	-0.007	-0.002	0.0144**	0.0005	1×10^{-4}	-0.042	0.133*	-0.001	-0.007	0.0006	-0.002	0.0206*
	$A_{zj}^{\propto}$	DegDay	-0.009*	0.0005	-0.003	0.0033	0.0011	0.0015	-0.008**	0.005*	-0.006	-0.002	-0.008	0.0304**
	$A_{zj}^{\propto}$	IntraDD	-0.133	-0.124**	-0.328**	0.1307*	0.0863	-0.05	-1.143	0.2577**	0.1781	0.0889	0.3427***	0.5061**
	$A_{zj}^{\propto}$	InterDD	-0.07*	-0.024	-0.007	0.0258	0.0118	0.0424	-0.008	0.0503	0.0033	0.0203	-0.044	0.2513*
	$A_{zj}^{\propto}$	Rad	0.0032*	-0.003	0.0041	-0.013	-0.003	0.0226	0.1334***	0.0171	-0.02	0.0115	-0.015	0.0101
	$A_{zj}^{\propto}$	Wind	0.1395	-0.427**	0.0179	0.0197	-0.003	0.4147	0.0301	0.005	-7×10^{-4}	-0.003	0.0242	-0.063
	$A_{mj}^{\propto}$	Coop	-1.468*	-0.892**	-1.13	-1.429	0.3021	0.0828	-0.112	-2.31***	-2.859	0.0194	-0.362	4.1523
	$A_{mj}^{\propto}$	Soil	-6.346*	-4.37***	-4.046	5.1991**	5.811***	-7.436	-10.79	-1.312	11.975**	4.0702*	9.8937***	9.1475
	$A_{mj}^{\propto}$	WatQuota	2×10^{-5}	6×10^{-6}	8×10^{-6}	1×10^{-5}	3×10^{-7}	-2×10^{-5}	3×10^{-5}**	2×10^{-5}	-4×10^{-5}	-2×10^{-5}	2×10^{-5}	-2×10^{-5}
	$A_{mj}^{\propto}$	Land	-4×10^{-8}	6×10^{-9}	-4×10^{-7}*	-5×10^{-8}	-1×10^{-7}*	1×10^{-7}	-4×10^{-8}	2×10^{-7}**	-2×10^{-7}	1×10^{-7}	-1×10^{-8}	-9×10^{-8}
	$A_{zmj}^{\propto}$	Precip×Soil	-.035***	0.008	0.0101	-0.012	0.0016	-0.002	-0.015	0.0382***	-0.035	0.0145	0.02	0.0408
	$A_{zmj}^{\propto}$	IntraPp×Soil	-0.127	-0.237	0.1511	0.3265	0.2087	0.0403	2.1509*	0.1942	0.4596	0.2903	0.2287	-0.052
	$A_{zmj}^{\propto}$	DegDay×Soil	0.0011	-4×10^{-4}	-2×10^{-4}	-9×10^{-4}	-6×10^{-4}	0.0024*	0.0015	-5×10^{-4}	0.0025	-5×10^{-4}	-8×10^{-4}	-0.003
	$A_{zmj}^{\propto}$	IntraDD×Soil	2.580***	0.5625	-0.17	0.2784	-1.102	-0.258	0.4198	-2.096***	-1.155	-1.383	-2.38*	-2.986
Yield sensitivity to inputs use	A_j^{γ}	Constant	0.5379	0.6275	-3.33	-0.651	-3.091	2.5891	4.6887**	2.87**	-1.117	4.1093**	-1.776	-2.417
	A_{zj}^{γ}	Precip	0.0018	-0.002	-0.004	0.0028	0.0029	0.0063	-0.052***	-0.006**	0.0027	-0.003	-0.004	0.0116
	A_{zj}^{γ}	IntraPp	-0.027	-0.051	0.0168	0.1507	0.0248	0.0674	0.0825	0.0189	-0.052	0.0423	-0.018	0.442*
	A_{zj}^{γ}	InterPp	0.003	0.0012	-0.004	-1E-03	0.0004	-0.027	0.0995*	0.0004	0.0017	-0.002	0.0023	-0.007*
	A_{zj}^{γ}	DegDay	-0.006**	0.0007	-0.001	0.0022	0.0006	0.0002	-0.008***	0.0021	-0.004	-0.001	-0.005*	0.0152**
	A_{zj}^{γ}	IntraDD	0.0532	0.0473**	0.1682***	-0.076*	-0.036	-0.395	-1.524	-0.115**	-0.072	-0.05	-0.115***	-0.153*
	A_{zj}^{γ}	InterDD	-0.053*	-0.02	-0.012	0.0225	0.0121	0.03	-0.002	0.032*	0.002	0.0114	-0.02	0.1414*
	A_{zj}^{γ}	Rad	-4×10^{-4}	0.001	0.0038	0.0066	0.0028	-0.013	-0.068***	-0.009*	0.0092	-0.008*	0.0041	-0.001
	A_{zj}^{γ}	Wind	0.1277	-0.321*	-0.05	-0.012	0.0027	0.2264	0.0524	0.005	-0.002	0.0018	-0.002	0.0176
	A_{mj}^{γ}	Coop	-1.099*	-0.629**	-0.784	-1.238*	0.1429	0.2894	0.1118	-1.323***	-1.501	-0.02	-0.225	2.175
	A_{mj}^{γ}	Soil	1.9463	1.825***	1.1269	-2.35*	-1.923	3.1146	4.3847	0.475	-5.14**	-1.784*	-2.847**	-3.236
	A_{mj}^{γ}	WatQuota	2×10^{-5}	4×10^{-6}	4×10^{-6}	1×10^{-5}	8×10^{-7}	-1×10^{-5}	2×10^{-5}**	1×10^{-5}	-2×10^{-5}	-1×10^{-5}	9×10^{-6}	-1×10^{-5}

	Coefficient		VCI	VOI	VOR	FCI	FCR	FLOC	FLOO	CIT	DEC	SUBT	OTHI	OTHR
	A^{γ}_{zmj}	Precip×Soil	-0.03***	0.0021	0.0114	-0.001	0.0069	-0.002	0.0094	0.0248***	-0.013	0.0119*	0.0155*	0.0253
	A^{γ}_{zmj}	IntraPp×Soil	-0.012	0.0855	-0.266	-0.396*	-0.361*	-0.072	-1.093*	-0.185	-0.125	-0.161	-0.195	-0.136
	A^{γ}_{zmj}	DegDay×Soil	-2×10^{-4}	-0.001***	-9×10^{-4}	0.0003	0.0007	0.0002	-0.001	-5×10^{-4}	0.0033***	0.0004	0.0009	-3×10^{-4}
	A^{γ}_{zmj}	IntraDD×Soil	1.665***	0.2658	-0.292	0.4535	-0.64	-0.363	0.2501	-1.253***	-0.242	-0.634	-0.961	-1.495
Optimal variable inputs use	A^{β}_{zj}	Precip	-0.005	0.0049	0.0134	-0.009	-0.007	-0.02	0.1082***	0.0122*	-0.007	0.0074	0.0094	-0.037*
	A^{β}_{zj}	DegDay	0.0146**	-0.001	0.0037	-0.005	-0.001	-0.001	0.016***	-0.006	0.0098	0.003	0.0136*	-0.043**
	A^{β}_{zj}	InterDD	0.1211*	0.0448	0.0217	-0.048	-0.024	-0.07	0.0077	-0.08*	-0.006	-0.03	0.0595	-0.382*
	A^{β}_{zj}	Wind[a]	-0.274	0.7465**	0.0632	-	-	-0.59	-0.092	-	-	-	-	-
	A^{β}_{mj}	Coop	2.573*	1.5021**	1.8679	2.6512*	-0.415	-0.455	-0.067	3.4774***	4.168	0.0011	0.5974	-5.976
	A^{β}_{mj}	WatQuota	-4×10^{-5}	-1×10^{-5}	-1×10^{-5}	-3×10^{-5}	-1×10^{-6}	3×10^{-5}	-6×10^{-5}**	-2×10^{-5}	6×10^{-5}	3×10^{-5}	-3×10^{-5}	3×10^{-5}
	A^{β}_{zmj}	Precip×Soil	0.0661**	-0.008	-0.021	0.0133	-0.008	0.0053	-0.002	-0.061***	0.0414	-0.027	-0.036*	-0.063
	A^{β}_{zmj}	DegDay×Soil	-3×10^{-4}	0.002**	0.0017	0.0002	-8×10^{-4}	-0.002	0.0007	0.0011	-0.007*	-2×10^{-4}	-0.001	0.0024
	A^{β}_{zmj}	IntraDD×Soil	-4.02***	-0.75	0.5952	-0.823	1.6109	0.6919	-0.621	3.249***	1.1313	1.8647	2.9384	4.2032
Management cost	A^{c}_{zj}	Precip	-0.096	0.15	0.7592*	-0.183	0.2343**	-0.499	-0.69*	-0.09	0.1587	-0.137	-0.122	-0.012
	A^{c}_{zj}	IntraPp	-3.836	-12.46	14.917	6.4147	-20.33	16.804	4.8343	-2.557	-40.86*	-2.304	25.114	38.471
	A^{c}_{zj}	InterPp	0.3435	0.0791	-2.712***	0.3483	-0.23	0.2441	-0.393	0.1014	0.5892	0.5378*	-0.535*	-1.406**
	A^{c}_{zj}	DegDay	0.0591*	0.0467***	0.1199**	-0.043***	-0.055***	-0.062	-0.097*	-0.041**	-0.091***	-1×10^{-3}	-0.093***	-0.057
	A^{c}_{zj}	IntraDD	14.38	16.572**	23.105	-12.74***	-10.48*	-25.71	-58.23**	-12.4	-15.54	1.0761	-26.39***	-47.07***
	A^{c}_{zj}	InterDD	0.0776	-0.308	-0.51	0.0938	0.0267	-0.458	0.5295	-0.105	0.2465	0.0183	-0.162	1.2518*
	A^{c}_{zj}	Rad	-0.885	0.4188	-1.746	1.1482	0.0625	-1.606	-11.59***	0.1206	0.9946	0.4188	1.4717*	-1.096
	A^{c}_{zj}	Wind	2.0009	-0.958	-8.283	-1.289	0.5132	-9.65*	1.2293	-2.36	2.0085	0.0651	-4.454**	6.1148
	A^{c}_{mj}	DistTel	-0.01	-0.005	0.0392*	0.0268**	-0.012	-0.019	0.0109	-0.006	-0.008	0.0119	-0.002	0.0128
	A^{c}_{mj}	Coop	-8.769*	0.0971	3.7101	5.0103*	-4.628**	12.987*	8.8193	6.9481***	-8.635*	4.423*	-7.41**	-15.66**
	A^{c}_{mj}	Soil	819.92*	530.19**	444.02	-652.9***	-943.7***	693.44	1156.2	-5.772	-742.7*	-148.4	-999***	-828.9
	A^{c}_{mj}	WatQuota	0.0001	3×10^{-5}	-3×10^{-4}*	2×10^{-5}	6×10^{-5}	1×10^{-4}	0.0001	8×10^{-5}	-2×10^{-4}*	1×10^{-5}	0.0001*	7×10^{-5}
	A^{c}_{mj}	Land	3×10^{-5}	-2×10^{-6}	0.0001*	2×10^{-5}	3×10^{-5}*	-1×10^{-5}	2×10^{-5}	-4×10^{-5}*	7×10^{-5}**	-2×10^{-5}	5×10^{-6}	5×10^{-5}
	A^{c}_{zmj}	Precip×Soil	-0.318	-0.464	-0.495	-0.337	-0.464	-0.109	1.2825	-0.26	0.5944	-0.043	0.0533	-0.121
	A^{c}_{zmj}	IntraPp×Soil	27.788	37.287	62.623	58.738	70.609**	0.5571	-181.2	35.046	-54	11.984	27.796	39.946
	A^{c}_{zmj}	DegDay×Soil	-0.13*	-0.09**	-0.077	0.1068***	0.1618***	-0.14	-0.215*	-0.006	0.14**	0.0255	0.1553***	0.1461**
	A^{c}_{zmj}	IntraDD×Soil	-39.13**	-16.57*	-26.66	16.826*	26.972***	-8.889	-4.831	0.6236	19.674**	1.394	34.118***	13.922
		R^2	.246	.263	.323	.340	.386	.659	.657	.348	.317	.353	.327	.292

Notes: *** implies 1% significance level; ** implies 5%; and * implies 10%; a. 'Wind' was omitted in some of the regressions due to multicolinearity

Table 3. Climate variables' elasticities of bundles' land shares

Variable	VCI	VOI	VOR	FCI	FCR	FLOC	FLOO	CIT	DEC	SUBT	OTHI	OTHR	TCL
Precip	0.94*	-0.43	1.33*	-1.65**	-0.20	0.62	0.95*	-1.01*	0.04	-1.64**	-0.92	0.75*	-0.62
IntraPp	1.09*	0.80	1.79***	0.20	0.67*	1.87***	0.80*	1.06**	1.14**	0.55	0.57	-1.24*	0.58*
InterPp	-2.27*	-0.92*	-2.90**	0.63	-0.81*	-11.7***	40.2***	-0.23	-1.41*	0.15	-0.41*	-0.19	0.16
DegDay	1.69**	-1.36*	0.01	-2.10***	-1.01	-1.61**	-1.20*	-0.24	-2.29***	-1.15*	-1.22	-2.56***	-1.34***
IntraDD	0.13	0.37*	0.20	-0.90**	0.58**	-4.46***	-23.00***	1.02**	-0.26	0.56**	0.95*	1.09**	-0.69*
InterDD	0.20	-0.37	-1.50***	0.59	-0.47*	-0.98**	-0.43*	-0.51**	0.39	-0.66**	-1.32**	-1.60***	-0.27
Rad	-3.86***	-2.16*	5.07***	-1.35*	0.66*	-0.57	2.42***	1.97*	2.82***	-4.60***	-2.30***	3.10***	-0.32
Wind	0.22	0.80	-2.80**	-0.26	0.59	-0.17	-0.75	1.05*	1.64*	0.54	-0.03	0.35	0.37

Note: *** implies 1% significance level; ** implies 5%; and * implies 10%

Table 4. (a) Observed and simulated land shares at the nationwide level; (b) Bundles' profitability changes between periods

		(a) Land shares				(b) Profitability change between periods[a]		
Bundles		Observed 1992-2001	2001-2020	2021-2040	2041-2060	1992-2001 to 2001-2020	2001-2020 to 2021-2040	2021-2040 to 2041-2060
VCI	Vegetables, Covered, Irrigated	0.004	0.006	0.001	0.002	0.56	-2.14	0.75
VOI	Vegetables, Open field, Irrigated	0.098	0.128	0.037	0.048	0.44	-1.73	0.36
VOR	Vegetables, Open field, Rain-fed	0.014	0.023	0.002	0.011	0.67	-3.08	1.92
FCI	Field Crops, Irrigated	0.122	0.108	0.093	0.096	0.05	-0.63	0.12
FCR	Field Crops, Rain-fed	0.177	0.207	0.128	0.154	0.33	-0.97	0.28
FLOC	Flowers, Covered	0.003	0.006	0.000	0.006	0.96	-6.81	6.56
FLOO	Flowers, Open field	0.002	0.001	0.011	0.000	-0.51	2.17	-6.93
CIT	Citrus	0.034	0.035	0.038	0.041	0.19	-0.42	0.17
DEC	Deciduous plantations	0.018	0.017	0.012	0.012	0.14	-0.85	0.10
SUBT	Subtropical plantations	0.027	0.036	0.014	0.019	0.45	-1.47	0.42
OTHI	Other plantations, Irrigated	0.009	0.013	0.003	0.004	0.52	-1.95	0.47
OTHR	Other plantations, Rain-fed	0.020	0.022	0.016	0.018	0.24	-0.82	0.22
TCL	Total Cultivated Land	0.528	0.602	0.353	0.411	0.30	-1.02	0.24
NC	Non-Cultivated agricultural areas	0.472	0.398	0.647	0.589	-	-	-

a. Values displayed in these columns are computed according to the indicator of profitability changes in Eq. (19).

Table 5. Nationwide profit evaluations of the total cultivated land

	Observed 1992-2001	2001-2020	2021-2040	2041-2060
Agricultural profitability ($ / ha-year)	2,192	2,342	1,832	1,952
Total cultivated land (ha)	326,091	371,793	218,012	253,832
Cultivated lands' profit (10^6×$ / year)	714.8	870.6	399.3	495.4
Change in profit relative to the sample period (%)	-	21.8	-44.1	-30.7
Change in profit relative to the previous period (%)	-	21.8	-54.1	24.1

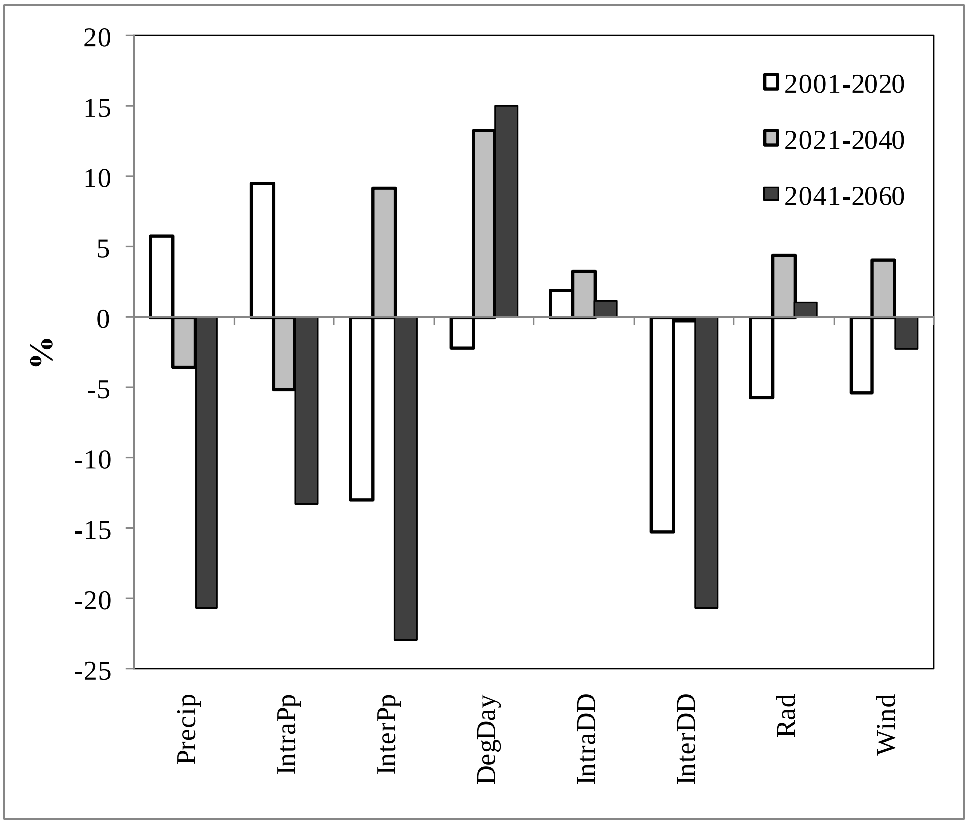

Figure 1. Forecasted changes in sample-averaged climate variables, in percentage relative to the 1981-2000 period

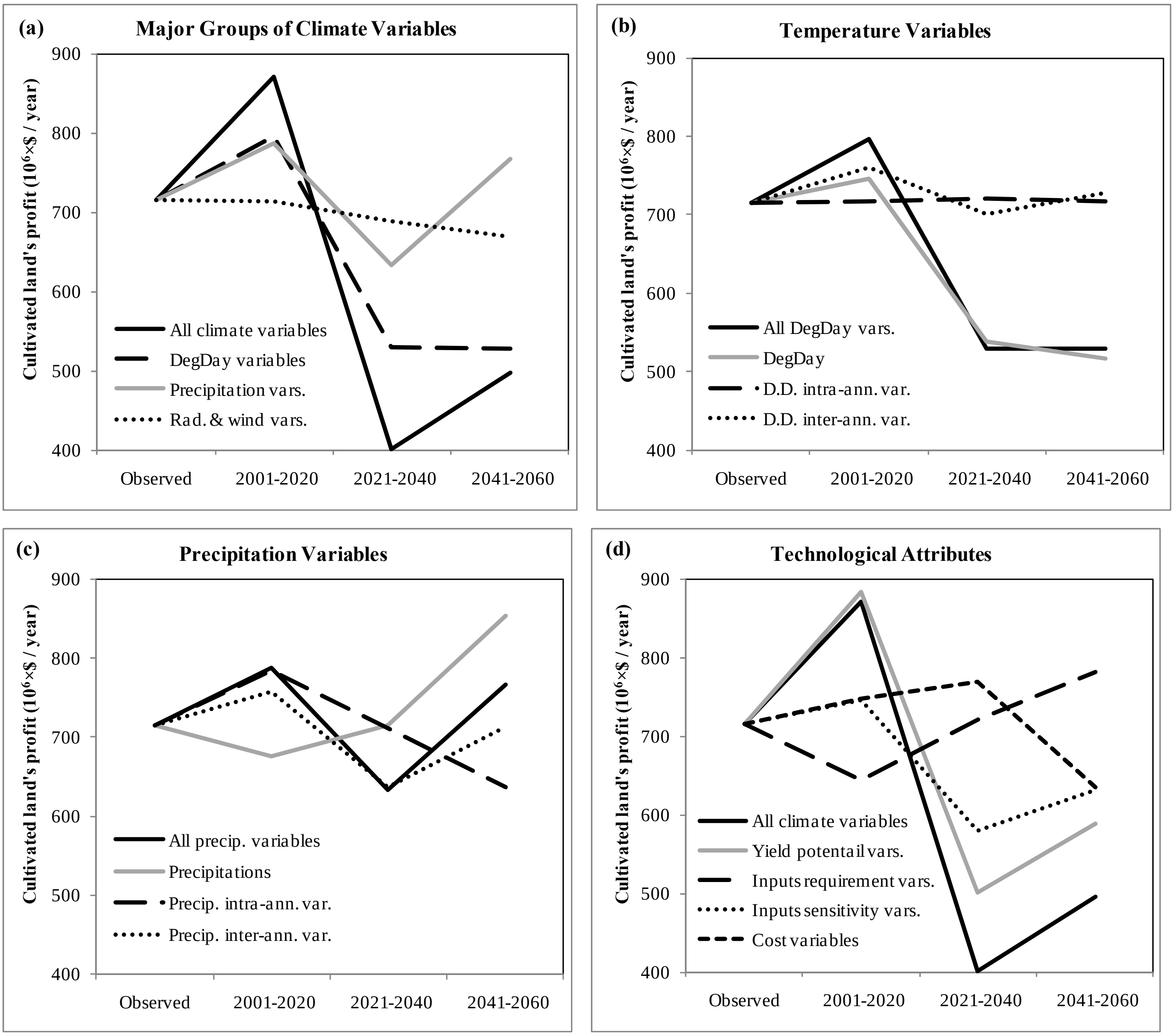

Figure 2. Assessment of residual effects of climate variables and technological attributes on the profit of total cultivated agricultural land

Notes

[1] Orthogonal crop prices and individual yields are assumed.

[2] In our application to the case of Israel, output prices are spatially homogenous (IMARD, 2011), and other spatial variations are controled for by the distance from Tel Aviv.

[3] The use of net-houses was negligible at the data collection period.

[4] Degree-days are a temperature measurement of the cumulative number of daily Celsius degrees between 8° to 32°C over a given number of days. This temperature measurement makes more sense from an agronomic physiological standpoint, since the growth of the plant is, among others, determined by the number of degree-days rather than by absolute temperatures (Richie and NeSmith, 1991).

[5] We re-estimated the econometric model with other price indices that we constructed based on ARIMA estimation with the number of lags determined by the partial autocorrelation-coefficient method, as suggested by Judge et al. (1988) and already used by Wu and Segerson (1995). The selected models for all crops except field crops are AR(2)I(1), and AR(1)I(1) for field crops. The estimates of these price indices do not significantly differ from the calculated moving average price ones (based on the Hausman statistic).

[6] Since the climate conditions act in our analysis as fixed effects, an estimation procedure allowing cross-regional parameter heterogeneity (Plantinga and Miller, 1999) is redundant.

[7] While unavailable, flower data constitute a minor portion of total profits of vegetative farming.