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Assessment of climate change impacts on agriculture using farm level panel data of Austria

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Vienna, 30 April 2020 Abdul Quddoos

DECLARATION OF AUTHORSHIP

I hereby declare that I am the sole author of this work; no assistance other than that permitted has been used and all quotes and concepts taken from unpublished sources, published literature or the internet in wording or in basic content have been identified by footnotes or with precise source citations.

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ABSTRACT

In the last decade, econometrics has been established as a useful method to assess the impacts of climate change on agriculture. Nevertheless, it has mostly been applied to cross-sectional data using aggregated units of analysis (county, district, …). This is one of the initial studies to use a large farm-level panel dataset to assess the impacts of climate change on agriculture. Employing a dataset from Austria, this study demonstrates that: 1) panel data methods help to reduce a potential omitted variable bias; 2) controlling for sunshine duration does not alter the estimated coefficients of temperature and precipitation, but allows for alternative bio-physical model specifications to be explored; 3) it is important to consider endogeneity due to measurement errors in meteorological variables in such micro level studies; 4) farms with slopped land respond differently to climatic shocks than farms with flat land; 5) using growing season averages instead of seasonal (spring, summer, …) averages results in estimated coefficients according to theoretical expectations; 6) uncertainty analysis using multiple climate and econometric models facilitates predicting climate induced distributions of farm-level profit changes. Based on Austrian data and two climate scenarios for 2040 (RCP 4.5 and RCP 8.5), we estimate the profits of farms to decline on average in both emission scenarios. Without adaptations, profits will reduce by 4.4% (RCP 4.5) and 10% (RCP 8.5). Adaptation options help to ameliorate the adverse effects slightly as profits decrease by 2.5% (RCP 4.5) and 7.1% (RCP 8.5). Uncertainty analysis shows predicted impacts of climate change are more certain for alpine regions. Results thus stress the need for mitigation and adaption to climate change.

KURZFASSUNG

Die Ökonometrie hat sich im letzten Jahrzehnt zu einer nützlichen Methode zur Abschätzung der Auswirkungen des Klimawandels auf die Landwirtschaft entwickelt. Jedoch wurden bisher fast ausschließlich Querschnittsdaten aggregierter Einheiten (Gemeinden, Bezirke, …) dazu verwendet. Diese Arbeit ist einer der ersten, die ein großes Paneld von Einzelbetriebsdaten zur Schätzung der Auswirkung des Klimawandels auf die Landwirtschaft verwendet. Mit diesen österreichischen Betriebsdaten ist es möglich zu zeigen, dass: 1) Paneldaten mögliche Verzerrungen durch unbeobachtete Variablen reduzieren; 2) die zusätzliche Berücksichtigung der Sonnenscheindauer die geschätzten Koeffizienten von Temperatur und Niederschlag nicht verändert, aber alternative Formulierungen des bio-physikalischen Zusammenhangs ermöglicht; 3) Es wichtig ist die Endogenität durch Messfehler in den meteorologischen Daten zu berücksichtigen; 4) Betriebe im Bergland anders auf Klimaschocks reagieren als jene im Flachland; 5) bei Verwendung von Mittelwerten über die Vegetationsperiode statt über Jahreszeiten die geschätzten Koeffizienten den theoretischen Erwartungen entsprechen; 6) die Verwendung unterschiedlicher Klimamodelle und ökonometrischer Modelle es erlaubt, eine Verteilung der prognostizierten Auswirkungen des Klimawandels auf die Gewinne für Einzelbetriebe zu berechnen. Basierend auf den österreichischen Daten und zwei Klimaszenarien für 2040 (RCP 4.5 und RCP8.5) zeigt sich, dass sich in beiden Szenarien die durchschnittlichen Gewinne reduzieren werden. Ohne Adaption sinken die Gewinne um 4,4% (RCP 4.5) bzw. 10% (RCP 8.5). Adaption hilft die negativen Auswirkungen auf 2,5% (RCP 4.5) bzw. 7,1% (RCP 8.5) zu reduzieren. Die Unsicherheitsanalyse zeigt, dass die Auswirkungen des Klimawandels im alpinen Raum mit größerer Sicherheit vorhergesagt werden können. Die Ergebnisse lassen die

Schlussfolgerung zu, dass sowohl Vermeidung von, als auch Adaption an den Klimawandel notwendig sind.

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1. Introduction

Econometrics is now an established method to assess the impact of climate change on agriculture (Blanc & Schlenker, 2017). However, panel data econometric approaches have mostly been used to assess large area average effects which comprise average effects from many farms in each area (Burke & Emerick, 2016; Moore & Lobell, 2014; Schlenker & Roberts, 2009). Small area impact assessment has primarily been conducted with integrated bio-economic simulation models. There are only a few farm-level based econometric estimates of climate change on farm profits, all using cross-sectional data (Bozzola et al., 2018; De Salvo et al., 2013). To our knowledge, this is one of the initial studies to use a large farm-level *panel data* set to assess the impact of climate change on agriculture. In this monograph we discuss the econometric issues involved, when going from aggregated to individual farm level analysis in a small study area. Moreover, we perform uncertainty analysis of the predicted climate change impacts using different econometric specifications and split the uncertainty into the sources. Comparing the uncertainty of predicted impacts from different econometric climate change models has, to the best of our knowledge, not been done before.

Mendelsohn et al. (1994) introduced the so-called Ricardian approach, based on cross-sectional data, and showed that land values, accruing from discounted net revenues of farm, inherently reflect long-run climatic conditions. As land values incorporate all the adaptation possibilities which a farmer can take with given endowments at that piece of land, therefore Ricardian approach encompasses adaptations implicitly (unless some future adaptation comes to surface). For example, if an irrigation system is installed and irrigation water is used as an adaptation on that piece of land in the future this will moderate the impact of climate change and hence the land price (Carter et al., 2018; Kurukulasuriya et al., 2011). According to Mendelsohn and Massetti (2017) the Ricardian approach has been applied in 46 countries since it was introduced by Mendelsohn et al. (1994). Some recent examples from Europe using cross-sectional data are Bozzola et al. (2018), Van Passel et al. (2017) and Vanschoenwinkel et al. (2016). Besides few farm level studies, researchers used aggregate units of analysis e.g. provinces, counties, districts etc.

Similar to the standard Ricardian approach, another strand of literature relies on the panel data analysis where farm profits, net revenues or yields are regressed on climatic variables (Fisher et al., 2012; Schlenker & Roberts, 2009; Tack et al., 2015; Welch et al., 2010). Mendelsohn and Massetti (2017) name them 'Panel Weather Studies' while Blanc and Schlenker (2017) call them Panel Data Models (PDMs). The PDM harnesses the repeated observation of a region (farm) to remove time-invariant unobserved heterogeneity which may cause an omitted variable bias in the cross-sectional approach (Blanc & Schlenker, 2017). Therefore, Carter et al. (2018) argues that the PDMs capture unobserved heterogeneity better than cross-sectional Ricardian approach in the context of missing information (at least for time invariant factors e.g. altitude, distance from nearby cities etc.).

Both of these econometric approaches share similar criticism (Auffhammer & Schlenker, 2013; Seo, 2013). Due to naïve simplicity of the econometric approaches over bio-economic models, strong assumptions are borrowed; for example, competitive markets are assumed for both inputs and outputs. Moreover, the constant input-output price assumption is mostly criticised with respect to performing future predictions based on the econometric approaches. The criticism seems valid however, other alternate approaches like bio-economic models rely also on strong assumptions like the representation of sector by a representative farmer, assumptions on the behaviour of farmers, complex parametrization of for example crop models (Jones et al., 2017) or predictions of future input and output prices. We therefore opine that the input-output price ratio is though a strong assumption and it limits the future prediction based on the econometric approaches. Yet, this could still be a fairly possible guess with some naïve simplicity. After all, predicted future input-output ratios are highly uncertain themselves. Moreover, this assumption does hinder the predictions coming out of econometric models about far-future, but near future prediction and uncertainty analysis can still be justified.

Comparing econometric cross-sectional approaches to PDMs, the former approaches capture long-term climate response, while the latter are usually criticized for depicting weather instead of climate responses. However, a couple of authors showed ways to exploit time dimensions of longitudinal data and capture long-term responses with PDMs as well (Burke & Emerick, 2016; Moore & Lobell, 2014). Moore and Lobell (2014) introduced annual shocks and long-term climatic variables in a panel data settings to explicitly capture adaptation in PDM which is considered implicitly in the cross-sectional Ricardian approach. They used NUTS-3 regions as a unit of analysis for 11 European countries. The NUTS-3 aggregates administrative units for statistical purposes (Lippert et al., 2009) and varies a lot in terms of size among European countries (Min: 13 km^2 to Max: 98,249 km^2 (Statistical Office of the European Communities & European Commission, 2008)).

Both of the econometric approaches (Ricardian approach and PDM) have mostly used aggregate unit of analysis e.g. provinces, counties, districts, NUTS-3 etc. In case of Ricardian approach, even the studies, which directly use farm level observations employed climate data from centroid of spatially coarser resolution (examples of studies in EU: Bozzola et al. (2018) and Chatzopolous and Lippert (2015) used community centroid, Van Passel et al. (2017) used centroid of NUTS-3, Fezzi and Bateman (2015) used 10x10 km^2 grid, Lippert et al. (2009) and Lang (2007) used centroid of districts, etc.). The importance of spatially suitable climate data has been mentioned by De Salvo et al. (2014) as a possible improvement avenue in the econometric literature on climate change agriculture. De Salvo (2013) is an exception in cross-sectional Ricardian studies as it used 126 permanent crop farm data from northern Italy and merged with interpolated climate data based on 40 meteorological stations.

While, the PDM studies also mostly employed aggregate unit of analysis (e.g. county level (Burke & Emerick, 2016; Chen et al., 2016; Schlenker & Roberts, 2009), district level (Taraz, 2018), NUTS-3 level (Moore & Lobell, 2014), department level (Gammans et al., 2017), country level (Schlenker & Lobell, 2010)). Few farm level PDM studies (Tack et al., 2015; Welch et al., 2010) are exceptions however, these studies used experimental station data (crop field trials) from few and specially chosen farms, and only witnessed climate change impacts on crop yields pertaining to particular crop.

When aggregate units of analysis are used, a large study area is chosen to capture climate change impact on agriculture. Either this large study area comes from vast spatial variation as in studies for US (Burke & Emerick, 2016; Schlenker & Roberts, 2009), for EU (Moore & Lobell, 2014), for China (Chen et al., 2016) or large time dimensions like Schlenker and Lobell (2010) studied African countries, Taraz (2018) studied India, Gammans et al. (2017) studied France over a long period of time.

A spatially vast study area may represent more diverse climatic conditions which are good for identification, but more heterogeneity makes exogeneity of climate variables more difficult to achieve. Lengthy time dimension may represent historical trends better, however, technological advancements and policy decisions over time challenge exogeneity.

Besides these large scale applications, De Salvo et al. (2013) argues that econometric analysis may also be performed for small study areas, given sufficient variation in meteorological variables. Moreover, using a panel data Ricardian approach, Fezzi and Bateman (2015) found that aggregate units of analysis bias overall results. Similar to the analysis presented here, Fezzi and Bateman (2015) used the farm as unit of analysis and only one country (UK) as study area. However, they merged farm level data with courser resolution of climate data than the resolution we used. Moreover, Fezzi and Bateman (2015) followed the standard Ricardian approach and used land values as an explained variable. For PDM, so far, there are no publications explaining profits on farm level.

It is surprising, there are not more farm-level based studies, because there are several advantages of using individual farm observations instead of regional averages (De Salvo et al., 2013; Fezzi & Bateman, 2015). First, aggregation influences the estimated coefficients (Briant et al., 2010; Gerlt et al., 2014) by size and shape of the area: an estimated coefficient depends on how farms are aggregated (by administrative units, by agricultural zones, in grids, …). Moreover, average climatic conditions for an aggregated area may not be representative for the conditions where individual farms are located: for example, agricultural land is not located on high mountains or in urban areas where temperature and precipitation is typically different than in agricultural areas. Furthermore, it is not straightforward to aggregate some of the variables which moderate the impact of climate change. For example, the use of irrigation, which is endogenous to climate variables (Kurukulasuriya et al., 2011), may not be straightforward aggregated for the unit of aggregation. Another example are storage facilities, which can be helpful to mitigate the adverse climatic effects on market. The slope of the land is also difficult to average for aggregated units of analysis (Lippert et al. 2009).

Second, the variance of average values declines with increasing (spatial) aggregation. The variance in climatic stimuli, though, is an important source of information to identify the impact of changes in temperature and precipitation. Therefore, the variance in climate stimuli at the farm level helps to identify the climate impact within regions. Fezzi and Bateman (2015) pointed out that aggregation diminishes the variation and therefore attenuated coefficients show up in estimated models.

Third, climate change impacts in agriculture can vary depending on farm types and institutional conditions (Reidsma et al., 2010). These factors can be highly diverse even within a small area. It is thus generally not possible to predict effects of climate change on individual farms based on coefficients estimated with average regional values. For example, wheat yield variability at the farm level can be different from wheat yield variability on the regional level (Reidsma et al., 2007).

However, there are also several challenges related to climate change econometrics on farm level which were hardly addressed explicitly in the literature so far. First, exogeneity of weather variables is the key assumption for climate change econometrics. This assumption of exogeneity, as discussed by Blanc and Schlenker (2017), must be re-assessed for farm level data. Second, moving from regional to farm level analysis requires detailed farm and higher resolution meteorological data to correctly cover the climatic conditions at the farm level. Such data are typically interpolated which raises issues of accuracy. Third, moving to farm level data, issues typical to micro data analysis arise including unbalanced panels, negative profits and missing data.

Next to mapping the impacts of climate change, uncertainty analysis is pivotal in global climate change research and policy making (Burke et al., 2015). In fact, uncertainty analysis has emerged as a research topic in itself (Asseng et al., 2013; Bregaglio et al., 2017; Kassie et al., 2015; Wesselink et al., 2015). Studies lacking proper uncertainty analysis can lead to poor public policy guidelines regarding climate change economics (Pindyck, 2011; Weitzman, 2011). For agriculture, which is heavily reliant on climatic conditions, there are hardly any doubts that climate changes will have an impact.

More than one econometric model (and hence identification strategies) to estimate the climate change impact will culminate into a more reliable policy advice (just as using means of climate-model-ensemble is better than using individual climate model (Asseng et al., 2013; Bregaglio et al., 2017)). For climate change impact studies based on bio-economic model, a few studies have used more than one bio-economic model to assess climate change impacts on the same study area and extract uncertainties (Asseng et al., 2013; Bregaglio et al., 2017; Kassie et al., 2015). However, this has not been done with the econometric approaches so far.

We therefore not just use one econometric model to estimate the effect of climate on agriculture, but add a second econometric model. With two econometric identification strategies, we show the similarities and dissimilarities in predicted impacts for the study region. We identify areas with more certain impacts of climate in near future in the study region.

1.1. Problem statement

Using farm level econometric analysis to assess the impact of climate change has many advantages compared to using aggregate units of analysis. Still, farm level data has so far rarely been used. While several studies used cross-sectional data (Bozzola et al., 2018; De Salvo et al., 2013; Lang, 2007; Lippert et al., 2009; Van Passel et al., 2017; Vanschoenwinkel et al., 2016) there is only one study using panel data on farm level to explain land values (Fezzi & Bateman, 2015). No study has used farm level panel data to explain farm profits. Furthermore, no farm level data has so far explicitly modelled adaptation as done by (Moore & Lobell, 2014). Furthermore, a thorough assessment of econometric issues when moving from aggregated to farm level data is also needed.

Moreover, a comprehensive uncertainty analysis is also missing in the econometric approaches: Burke et al. (2015) reported that on average only two future scenarios are used in econometric studies. Bio-economic modellers instead typically use an ensemble of available climate model outputs combined with several bio-economic model outputs for their future scenarios. Multi-model uncertainty analysis and split-up of uncertainty is used by bio-economic modellers to put more faith in predicted changes. For econometric studies this has so far been applied only rarely and not comprehensively (Burke et al., 2015; Moore & Lobell, 2014).

In addition, climate change impact assessment on Austrian agriculture has only been studied with bio-economic models which predict positive impacts of climate change for the year 2040 (Schönhart et al., 2014) whereas, econometric studies show negative impact on the adjoining areas of Austria especially Alpine region (Lippert et al., 2009). So, a thorough farm-level econometric level analysis is required to supplement the already existing literature, and an econometric assessment for Austria will add additional insights.

1.2. Research Objectives and possible outcomes

Our study has four main contributions: First, to the best of our knowledge, we are the first to apply farm-level panel data to assess the impact of climate change on farm profits with an explicit adaptation option approach. We discuss the advantages and challenges of using the econometric approach at the farm level and how climate change econometric analysis can be modified to be applied to farm level data. This includes issues of exogeneity of explanatory variables in farm-level data, heterogeneity of farm responses to weather shocks and measurement errors in meteorological variables. Second, by adopting the seminal model of Moore and Lobell (2014), who used panel data econometrics on sub-national level (NUTS-3), to farm-level data, we can compare our estimated parameters to their results. This is the first time the method of Moore and Lobell (2014) has been replicated.

Third, we derive estimates of the impact of climate change on profits of Austrian farms in 2040 for the two most discussed global future emission scenarios from the International Panel of Climate Change (IPCC). Several predictions from integrated bio-economic simulation models for Austria have been published (Kirchner et al., 2015; Schönhart et al., 2014; Schönhart et al., 2018). These studies, though, do not use IPCC scenarios but rely on statistical predictions of temperature trends. The scenarios analysed there show heterogeneity in future profits within Austria and on average increased profits for constant input-output ratios. Econometric studies on areas adjoining Austria (De Salvo et al., 2013; Van Passel et al., 2017) however, predict negative impacts. Though, all these scenarios are not completely comparable because they differ in time period analysed, climate change scenario and policy assumptions, still applying the first farm-level data analysis in Austria, we add additional evidence on the effect of climate change on Austrian agriculture.

Fourth, we compare the results from two different econometric specifications for the same study region with farm-level analysis. Both specifications are derived from the literature and are based on the constructs of climatic variables. Moore and Lobell (2014) used long-term climate for growing season to estimate impacts of climate on agriculture (ML from now on), whereas Van Passel et al. (2017) used seasonal a split-up of meteorological variables in a cross-sectional analysis (VP from now on). We predict climate change impacts at the farm level and explore the congruence or conflict between the predicted impacts of ML and VP approach with the aim to explore the reason behind it. This multi-model assessment has previously been done with crop growth models only. With these predicted impacts, we can identify relatively certain impacts versus uncertain impacts in the study region and their spatial distribution. A comprehensive uncertainty measure will make climate change impact assessment complete and reveal the differences in predictions. We split the uncertainty into different sources to show which of the sources make the predicted impacts differ and uncertain. Finally, we also discuss limitations of the (farm level) econometric approach.

1.3. Structure of the manuscript

This manuscript is organised as follows. Section 2 has three subsections which describe the methods (theoretical and empirical model) and data for our study. Econometric issues for application of farm level panel data are also discussed. After introducing the specification of the empirical models, the descriptive statistics are used to describe the sample and climate change in the observed period. Section 3 presents results. Section 4 discusses the results with reference to existing literature and draws some conclusions.

2. Material and Methods

2.2. Conceptual model

Following Moore and Lobell (2014), we define long-run profits as profits resulting from complete adaptation to climatic condition. In contrast, short-run profits are defined as profits when the climatic conditions deviate from the long run and farmers have not adapted so far. Thus, climatic conditions may be split up in two components. One is the long-term climatic condition which captures cross-sectional variation. The other component is the annual deviation (‘shocks’) from the long-term climatic condition which farmers cannot adapt to. Difference between the impact of the long-term conditions and the shocks combined with scenarios for future climatic conditions allows to estimate the adaptation potential of a farm.

More formally, assume farmers are profit maximizers and they choose production practices constrained by quality of soil, climate and subsidies. Production practices include the choice of crop mix, crop varieties and other inputs.

$$\max_{Prod.practices} \Pi = p'_{output}\, f\,(W, Soil, Inputs, Varieties) - p'_{inputs} Inputs + Subsidies \qquad \textbf{(1)}$$

where Π is profit per hectare, p_{output} and p_{input} are prices, $f(\cdot)$ is a production function and W represents climate variables (‘W‘ from weather). We assume, farmers are fully informed and anticipate subsidy policies. With constant relative prices of outputs and inputs over time, farmers adjust production practices (inputs, varieties) to long-term climatic conditions to acquire maximum profits. Hence, optimised (long-run) profits (Π^*) are determined by long-term climate and soil quality. Actual profits (Π) depend on the weather in addition. So, actual profits can be expressed as the sum of optimal profits and a function of the deviations from long-term climatic conditions. Given soil quality does not change over time, only deviations of climatic conditions from their long-term averages determine actual profits.

$$\Pi = \Pi^* + f_1\big(W - E(W)\big) \tag{2}$$

where $f_1(\cdot)$ represents some functional form and $E(W)$ is the expected value of weather (long-term climate conditions pertaining to the farm). Changes in long-run ($\Delta\Pi_{LR}$) and short-run profits ($\Delta\Pi_{SR}$), i.e. long-run and short-run response curves to climate change, are

$$\Delta\Pi_{LR} \approx \frac{\partial\Pi^*}{\partial W}\,\Delta E(W) \tag{3}$$

$$\Delta\Pi_{SR} \approx \frac{\partial\Pi}{\partial W}\,\Delta E(W) \approx \Delta\Pi_{LR} + \frac{\partial f_1}{\partial W}\,\Delta E(W) \tag{4}$$

The term $\frac{\partial f_1}{\partial W}\Delta E(W)$ in the short-run response curve represents the deviation from the optimised profits and is expected to be negative whenever there is an adverse weather shock and positive in case of a favourable weather shock. Hence, this difference between long-run and short-run response curves represents the adaptation potential of farmers.

2.3. Empirical model

The starting point for the development of the empirical model is the pooled OLS model from the reduced form of theoretical model

$$\pi_{it} = \beta_0 + W_{it}\,\beta_1 + (W_{it})^2\,\beta_2 + Ws_{it}\beta_3 + X_{it}\beta_X + A_i\beta_A + \gamma_t + \varepsilon_{it} \tag{5}$$

where π_{it} is the logarithm of farm profit per ha of farm i in year t, measured by revenues less expenditures and depreciation of machinery. The long-term climate W_{it}, its square term $(W_{it})^2$, and weather-shocks Ws_{it} each contain a set of c meteorological variables. Therefore, W_{it}, $(W_{it})^2$ *and* Ws_{it} are '$it \times c$' matrices and their coefficients are of dimension $c \times 1$.

The long-term climatic variables W_{it} include 20-years temporal average of daily temperatures and similarly 20-years average for precipitation sums of the growing season (March to September). The quadratic form for long-term climatic conditions $(W_{it})^2$ is employed because climatic effects on farm yields are most likely non-linear (Lobell et al., 2011). Weather shocks, Ws_{it}, represents a squared difference between the current year weather average minus long-term climatic rolling averages prevailing at each farm: $Ws_{it} = (W_{it} - w_{it})^2$ where w_{it} is the weather at a particular farm in a particular year. We use small notation (w_{it}) for contemporary weather values and capital notation (W_{it}) for long-term past climate values. These weather shocks capture the "penalty" on the farm for ignoring adaptation to climate change and thus explain the influence of meteorological variables on farm performance without adaptation.

The long-term climatic variables W_{it} captures the cross-sectional differences in climatic conditions across the study region. It shows the expectation of farmers about the climatic conditions on their land for which he/she is prepared and has adjusted production practices accordingly. Moore and Lobell (2014) used rolling means of climate variables to represent this because a farmer may update his/her expectation about this long-term climate on his/her farm from time to time. A fixed window, instead, may bias the coefficient of weather shocks downward because of a changing climate in the study area over time.

Other covariates include time and cross-sectional varying variables (X_{it} includes land use and subsidies received per hectare), time constant and cross-sectional varying variables (A_i includes regional dummies, farmer's education and soil quality) as well as yearly dummies which captures time fixed effects (γ_t) e.g. long-term trends in farm profits due to technological progress or CO_2 fertilization and other price or policy effects. One might be concerned that the yearly dummies also act as a 'false control' which leads to a downward bias in coefficients of meteorological variables. However, given the very heterogeneous climatic conditions between e.g. the alpine regions and continental regions (e.g. climate in the Pannonian Basin) in Austria, this seems of limited relevance for our study.

Several authors (Auffhammer et al., 2013; Blanc & Schlenker, 2017; Briant et al., 2010; Cai et al., 2014; Schlenker & Roberts, 2009) have discussed econometric issues while estimating the impact of climate change on agriculture. These issues have been discussed in the context of aggregated and/or cross-sectional data or in yield based weather response function. Here we provide a detailed discussion of econometric problems relevant for going from aggregated to farm level panel data analysis which includes omission of time constant and time varying variables, short-term adaptations, heterogeneous responses by farmers to weather shocks, measurement errors in meteorological variables, aggregation related biases, validity of the model and different constructs of climate variables.

2.3.1. Omission of time-constant variables

One frequent difficulty of (Ricardian) cross-sectional models is the omission of unobserved time-constant variables. Panel data models, instead, control for all time-constant variables whether we observe them or not (e.g. soil attributes important in production, farm specific (dis)advantages, production techniques native to a particular region or farm, etc.) via fixed effects at the unit of analysis. This is the case for aggregated and farm level data alike. In addition to the pooled OLS estimations (Equation **(5)**) we therefore estimate a fixed-effects model, where α_i captures all time constant effects, those which are observed (A_i) and others which are not included in the cross-sectional specification in equation **(5)**. Time fixed effects γ_t which are constant across all cross-section for a particular point in time but vary over years, has been explained before.

$$\pi_{it} = \alpha_i + W_{it}\,\beta_1 + (W_{it})^2\,\beta_2 + Ws_{it}\beta_3 + X_{it}\beta_k + \gamma_t + \varepsilon_{it} \tag{6}$$

This general form of a fixed effects equation is estimated by demeaning of all variable which renders the observed and unobserved time constant effects disappear from the regression and hence

$$\ddot{\pi}_{it} = \ddot{W}_{it}\beta_1 + \left(\ddot{W}_{it}\right)^2\beta_2 + \ddot{W}s_{it}\beta_3 + \ddot{X}_{it}\beta_k + \gamma_t + \varepsilon_{it} \tag{7}$$

where each double dotted accent mark shows demeaned variable e.g., $\ddot{\pi}_{it} = \pi_{it} - \bar{\pi}_i$ where $\bar{\pi}_i = T^{-1} \sum_{t=1}^{T} \pi_{it}$.

2.3.2. Omission of time varying variables

If there are unobserved time-varying variables (e.g. sunshine duration, humidity or wind) which influence profits and are also correlated with the 20-years average meteorological variables used as explanatory variables (typically, temperature and precipitation), this induces a bias in the estimated meteorological coefficients. Limited data availability precludes us including all time-varying weather and environmental variables. However, in a separate regression, we add sunshine duration as additional variable. We check for the influence of the omitted variable by including the annual sunshine duration and its square to equation **(6)**. Alternatively, it is also possible to extend the matrices of W_{it} and Ws_{it} by sunshine duration (i.e., include sunshine duration in the same functional form as temperature and precipitation). Given the correlation of the meteorological variables, it will yield coefficients different from those in equation **(6)**.

The input-output ratio of prices is another time varying variable. Ratios determined by global price level changes are controlled by yearly dummies. The part of price ratio variability not covered by yearly dummies, is assumed to be uncorrelated with the meteorological variables we use. In assuming constant price ratios also for our predictions, we follow the majority of publications of climate change impacts on agriculture.

2.3.3. Short-term adaptation

Coefficients of ‘weather shocks’ (deviations from 20-years averages), are typically not correlated with unobservable farm production decisions before the weather is observed, because they are not foreseeable by farmers and therefore not correlated with long-term meteorological variables. If short term-adaptation to weather shocks is possible (e.g., using pesticides during weather conditions conducive to plant disease or use of irrigation water), though, this will influence estimated coefficients. However, if profits and not yields are the outcome of interest (as in this analysis), all short term adjustments causing costs (e.g. increased expenditures for pesticides), automatically reduce profit (Blanc & Schlenker, 2017) and are (at least to some extent) internalised. We therefore do not control for short term adaptation. Moreover, controlling for short term adaptation is only relevant if the research question is about climate change impact in conditions where short term adaptation is not possible for all farms (e.g. some use irrigation and can adopt to water shortage, but others cannot). However, if controlling for short-term adaptations is necessary (which is not the case in our study), it is more straightforward on farm level compared to aggregated units containing more than one farm.

2.3.4. Measurement error

Measurement errors related bias can be exacerbated in panel data (Wooldridge, 2010, p. 365). Schlenker and Roberts (2009) refer that it may become a more pronounced problem in data where spatial fixed effects absorb a lot of variation (i.e. 'between variability') leaving only small 'within variability' of climate data. Meteorological variables at farm-level can be obtained through interpolation: meteorological measurements are observed at meteorological stations and then interpolated – be it regional or farm-level. At regional-level, the climatic variables show an average of the whole area which may be erroneous depending on the interpolation strategy. Coarser resolution reports less variability and shows an average temperature over the whole unit of resolution despite the fact that climate may vary within that unit. Therefore, coarser resolution will have less 'signal' (i.e. true variation) in the presence of climatic variability within an aggregated unit. Similarly, for farm-level data, interpolation may lead to measurement with error, depending on the interpolation strategy. However, there will be more variability in the climatic variables given the finer resolution. Estimation bias in case of measurement error comes from the 'noise' to 'signal' ratio. Going from the regional aggregated level to the farm-level increases 'signal' on one hand but may also increase 'noise' (i.e. error-related variation) on the other. Without knowing this ratio, the measurement error related effect of going from aggregated to farm level data is unknown.

Our temperature and precipitation data are measured at weather stations and need to be interpolated to match the required grid points. Moreover, interpolated grid points are typically not exactly where the farm is located. Therefore, there can be a difference between the true value and the interpolated value in our data. Economists call this 'measurement error' while meteorologists call this 'conditional bias' (Hiebl & Frei, 2017). For point estimates, as in our dataset, 'measurement error' can be assessed by comparing the values at a particular weather station to the interpolated value when leaving out this weather station for interpolation ('leave-one-out cross-validation'). For temperature and precipitation Hiebl and Frei (2016, 2017) reported a tendency for small precipitation intensities and low temperatures to be overestimated and for large precipitation intensities and high temperatures to be underestimated in the case of Austria. The conventional way to address measurement error issues is to use Two Stage Least Square (2SLS) regressions (Wooldridge, 2010, p. 112). It is applicable if, next to the variable with measurement error, there is a second measure available for the same variable which has a measurement error as well. The two measurement errors need to be independent from each other. If so, one measure can be instrumented with the other measure. For instrument in spatial data, spatial lags may make a good instrument (Anselin et al., 2008). Since, we have detailed climatological spatial data, we used spatial lags for temperature and precipitation variables.

Theoretically, long-term climatic variables W_{it} (20-years average temperature and precipitation) as well as weather-shocks Ws_{it} (temperature and precipitation shocks) could all be affected by measurement errors. However, weather shocks are in deviations form and are unlikely to be affected. For long-term climatic variables W_{it} and their squares, we used spatial lags as instruments for each of temperature and precipitation: two different spatial lags were constructed for temperature and two for precipitation.

For long-term temperature, we constructed a spatial lag in the following way: we take the mean from the 3000 nearest neighbouring grid points (what translates to a 62 km diameter), but exclude grid points with more than ±50 m difference in altitude to the central grid point (the nearest to a farm). Our spatial-means are correlated with the temperature at the central grid-point but do not suffer from the central point specific conditional bias. To instrument long-term temperature square, we follow a procedure described by Wooldridge (2010, p. 268): the ideal choice in such case is to use the squares of exogenous variables (already appearing in the structural equation) and to add interaction variables to capture non-linearities. Consequently, we used the square of an already available exogenous variable (e.g. the square from precipitation shock). We also used an interaction variable between altitude of farm and square of long-term temperature from spatial means of 1500 neighbouring grid points of a farm. Hence, we used two different spatial lags and squares of shocks as additional instrument. These instruments enabled us to over-identify the model. First stages of the fixed-effect 2SLS can be written with the help of notation in equation **(7)** as following:

$$\ddot{W}_{it_1} = \ddot{Z}_{it}\mathit{O}_1 + \ddot{W}_{it_2}\mathit{O}_2 + \ddot{W}_{it_2}^2\mathit{O}_3 + \ddot{W}s_{it}\mathit{O}_4 + \ddot{W}s_{it}{}^2\mathit{O}_5 + A\ddot{S}_{it}^2\mathit{O}_6 + \ddot{X}c_{it}\mathit{O}_7 + t\mathit{O}_t + \emptyset_{it} \qquad \textbf{(8)}$$

$$\ddot{W}_{it_1}^2 = \ddot{Z}_{it}\delta_1 + \ddot{W}_{it_2}\delta_2 + \ddot{W}_{it_2}^2\delta_4 + \ddot{W}s_{it}\delta_5 + \ddot{W}s_{it}{}^2\delta_6 + A\ddot{S}_{it}^2\delta_3 + \ddot{X}c_{it}\delta_7 + t\ \delta_t + \vartheta_{it} \qquad \textbf{(9)}$$

If subscript 1 shows long-term climate variable for temperature and subscript 2 for precipitation, then $\ddot{W}_{it_1}$ depicts past 20-year average temperature at the nearest grid points to the farm in deviation form. Coefficients to be estimated in first stage of 2SLS are Os and δs. The set of additional instruments include the spatial lag of the long-term temperature $\ddot{Z}_{it}$, interaction between altitude and spatial lag of long-term temperature $A\ddot{S}_{it}^2$ and $\ddot{W}s_{it}^2$ containing squared shock variables of precipitation. Similarly, for long term precipitation, we used spatial lag of precipitation, square from another spatial lag of precipitation and squares of temperature shocks.

For instrumenting long-term precipitation and its square, we use a disjoint donut made up of 80 grid points with 20 km radius around the farm. A second spatial lag was constructed from long-term precipitation squared average of 1500 near neighbours of a farm excluding the farm grid point. Yet another instrument for long-term precipitation is the square of the temperature shock variable already appearing in the model. We also tried alternative definitions (diameter, altitude restrictions) of spatial lags. They lead to similar results. First stages for precipitation case can also be written on the same format as in equation **(8)** and equation **(9)** where subscript *1* will change to *2* and vice versa. Moreover, spatial lags of precipitation and squared shock variables of temperature will replace additional instrument variables $\ddot{Z}_{it}$, $A\ddot{S}_{it}^{2}$ and $\ddot{W}s_{it}^{2}$ in the list of instruments.

2.3.5. Heterogenous response

Another issue is heterogeneity of farm responses to climate change. Blanc and Schlenker (2017) discuss that one of the assumptions underlying panel models is that the response to fluctuations in the exogenous variables is the same for all farms. Bozzola et al. (2018) have therefore analysed sub-samples based on farming types. However, they discuss that farm types might change due to climate change. Instead, in our study we distinguish farms by the steepness of their field-slopes (which is correlated with temperature but does not change with climate change). For example, in Austria farms in lowlands with typically flat areas have a different production focus (e.g. crops) than farms in mountains, i.e. at a higher altitude with slopped fields (e.g. livestock). Temperature may correlate with altitude and slope of the farm. Assuming homogenous responses to changes in temperature would mean that changes in temperature have the same impact on profits irrespective of the area in which a farm is situated and hence production orientation. If there is an interaction between temperature and for example steep-slope, not including steepness of field-slope results in a functional form misspecification. We investigate this issue by adding cross-terms of temperature and precipitation shocks with a dummy indicating if a farm is operating on steeply slopped land. This 'slopped farm' dummy is based on a farm's average slope gradient of its plots. The dummy is '1' for the farms where tractors or other farm machinery and equipment is difficult to use, i.e. on a slope gradient of more than 18%. In total 24.72% of the farms are categorized as 'slopped farms'. Lippert et al. (2009) argued that the slope of farm land may hinder a complete shift of production focus, for example, from grassland to crop land. Because, after a certain threshold, farm machinery may not work well. Therefore, a sloped land dummy may very well capture heterogeneous response. Since, Lippert et al. (2009) employed German districts as a unit of analysis, they could not employ farm slope whereas, we have farm level data. Cai et al. (2014) exploited spatial information in the data set to capture heterogeneous response of climate on US corn yield with panel data analysis.

2.3.6. Aggregation bias

Ecological fallacy says aggregated level results may not always represent individual results. Fezzi and Bateman (2015) concluded that a significant bias occurs with aggregation and identification at the micro level helps to eliminate this bias. For the UK, they find farm-level based effects of climate change to be less positive than estimates based on aggregated data. Similarly, Briant et al. (2010) show that spatial aggregation influences the estimated coefficient. Gerlt et al. (2014) show how farm yield estimates can be biased if based on county level yields. While working with farm-level data, there is only an issue of spatial aggregation to the extent that a farm may have different plots. However, for all plots, there will be one manager and thus farm level unit is a reasonable aggregation especially in models explaining profits. Farm-level data, as available for the EU, allow more precise farm-level profit calculations than spatially aggregated data. As regard to the aggregation of meteorological data, we are using 1x1 km^2 resolution data from Hiebl and Frei (2016, 2017) compared to other studies who used farm-level data, merged it with 5x5 km^2 gridded data and used 10x10 km^2 grids (Fezzi & Bateman, 2015).

2.3.7. Validity of the model

Another advantage of panel models is the possibility of applying out-of-sample forecasts as suggested by Blanc and Schlenker (2017). We validate the out-of-sample forecasts for equation **(6)** by using all years except one (i.e., 13 years). The forecast for the excluded year is then compared to the actual realization and measured against a 'naïve' forecast of profits, which are the same as in the year before as defined by the Theil's UII statistic (Bliemel, 1973).

2.3.8. Seasonal construct of the meteorological variables

Meteorological variables are typically available with daily or even hourly recordings. Such detailed recordings facilitate the use of many different constructs of the meteorological variables. Therefore, the constructs of meteorological variables in econometric assessment of climate change impacts on agriculture vary across different studies. Carter et al. (2018) reviewed studies on climate change econometrics and classified the construction of meteorological variables in three groups: cumulative averages, growing degrees days and different threshold bins.

In our study we only employ cumulative averages constructed in two ways. First, in the models specified above, growing season averages (March to September) of meteorological variables are used. Furthermore, meteorological variables are split up in past long-term averages (W_{it}) and weather shocks (Ws_{it}) of growing season. This construct of meteorological variables is borrowed from Moore and Lobell (2014). We can represent this construct of meteorological variables used in equation **(5)** with a general notation of $\omega_{it}\beta_k$ as follows:

$$\omega_{it}\beta_k \cong W_{it}\beta_1 + (W_{it})^2\beta_2 + Ws_{it}\beta_3 \quad \textbf{(10)}$$

where, ω_{it} represents all meteorological variables and the subscript k equals 1, 2, 3. Using this construct of climate variables leads us to the same equation as in equation **(5)** where each coefficient vector ($\beta_1, \beta_2, \beta_3$) is *c x 1*. For two meteorological variables (i.e. temperature and precipitation), *c* equals 2 and all of the βs here are *2 x 1*. Thus the OLS model from equation **(5)** can be re-written with the general notation for construct of meteorological variables (ω_{it}) as

$$\pi_{it} = \beta_0 + \omega_{it}\beta_k + X_{it}\beta_X + A_i\beta_A + \gamma_t + \varepsilon_{it} \quad \textbf{(11)}$$

and the panel data fixed effect model from equation **(6)** as

$$\pi_{it} = \alpha_i + \omega_{it}\beta_k + X_{it}\beta_X + \gamma_t + \varepsilon_{it} \quad \textbf{(12)}$$

Here, the regression equation links log farm profits π_{it} at farm *i* in time *t* to the construct of meteorological variables represented with ω_{it}. All of the variables and coefficient stay the same except that metrological variables are described with a more general notation now compared to equation **(5)** and equation **(6)**. This general form will be helpful to introduce, another construct of meteorological variables. Second construct of meteorological variables we are using in this study is borrowed from Van Passel et al. (2017). In this construct seasonal averages are used for each of the *c* meteorological variables instead of using the whole growing season averages. Massetti et al. (2016) criticised the aggregated measure of climate for the whole year and stressed the importance of split-up by seasons. Contrarily, Schlenker et al. (2006) showed that seasonal split up may be beneficial for individual crops however for agriculture activity as a whole growing season is suitable. We remain agnostic about the superiority of one specification over the other.

Van Passel et al. (2017) is not the only one using seasonal averages of meteorological variables. In fact, most of the researchers employing cross-sectional Ricardian approach use a seasonal construct of meteorological variables, while only few used seasonal averages with panel data models (Tack et al., 2015; Welch et al., 2010). We refer to Van Passel et al. (2017) because, their study included Austria and is therefore assumed to be suitable to the Austrian conditions. Van Passel et al. (2017) used cross-sectional Ricardian approach for EU at NUTS-3 level including Austria (whereas we employ farm level panel data for only Austria) and used the following construct for their meteorological variables.

To indicate contemporary seasonal averages of meteorological variables as an alternative specification of meteorological variables in equations **(11)** and **(12)**, we use w_{it_s}. For example, if w_{it_s} are seasonal averages of temperature in the current year for winter, spring, summer, autumn, then, *s* equals 1 to 4. If we use two meteorological variables (e.g., temperature and precipitation), then *k* in equations **(11)** and **(12)** equals 1 to 2.

$$\omega_{it}\beta_k \;\cong\; \sum_{s=1}^{4}\left(\beta_{1_s} w_{it_s} + \beta_{2_s}\left(w_{it_s}\right)^2\right) \tag{13}$$

where all the βs are *2 x 1* vectors just like in equation **(10)** above. While this construct uses seasonal averages (winter, spring, fall and winter) and their squared terms it does not include rolling long term averages and weather shocks.

We use these above mentioned two constructs of meteorological variables to access the impact of climate change on farm profits in Austria. These two regression models are referred to as model-I when talking about the specification of meteorological variable as in equation **(10)** and as model-II when talking about the specification as in equation **(13)**. We use both constructs to estimate predicted impacts of climate change on farm profits for Austria and see; whether different regression specification (response models) imparts dominant variation in predicted impacts or it is the climate models who dominate.

2.4. Predictions and uncertainty analysis

Finally, predictions inform us about changes in farm profits due to future (expected) changes in climatic conditions in comparison to a given base year and conditioning that other variables remain unchanged. These predicted impacts of climate change have uncertainty attached to them. Analysing the sources and magnitude of this uncertainty helps to draw clear inference and policy making.

Principally, there are two components, we need for obtaining estimates of predicted impacts of climate change on agriculture. First, the estimated coefficient from regression model represents the sensitivity of farm profits to changes in climate. We compute two regression models; thus we have two sets of response model sensitivities. The second component is the future climate conditions which comes from different climate model simulations. The Global Climate Models (GCMs) are used to predict future climate with complex mathematical models to mimic geo-physical process taking place on earth. These GCMs usually produce coarse resolution climate values which are downscaled to local levels with the help of Regional Climate Models (RCMs). As an input, these climate models take emission scenarios which are linked to different socio-economic pathways. For our study, we use two Representative Concentration Pathways (RCP 4.5 (Effective Measure) and RCP 8.5 (Business as Usual) described in Moss et al. (2010) in the fifth International Panel on Climate Change Report (IPCC, (2013)).

Based on these predicted impacts of climate change, we do an uncertainty analysis which tells, how unanimous predicted impacts are across future climate values coming from different climate models and across different response models based on regression specifications in our case. This uncertainty analysis is essential for sound agriculture policy regarding climate change adaptation and mitigation (Burke et al., 2015). We decompose the uncertainty about predicted impacts into its sources: climate models, response model specifications and response model parameters. This split-up not only helps to identify congruence and divergence between predicted impacts across different studies, it also serves to pinpoint future course of action for improved and more precise predicted impacts of climate change (Ruiz-Ramos & Mínguez, 2010).

When estimated climate response sensitivities are multiplied with future climate data coming from more than one climate model, uncertainty related to the climate model can be derived. Whereas, using an ensemble mean from all these climate models along with estimated climate response sensitivities from multiple response models (i.e. different regression specifications in our case and different crop growth models in case of Bregaglio et al. (2017) and Assenge et al. (2013)) yields uncertainty related to response models. A third source of uncertainty emanates from the standard errors of response model parameters, in our case given by the standard errors of the estimated parameters.

To derive sectoral level impacts, all of the predicted profits, adaptation potential and uncertainty estimates, are weighted to be representative for Austria. The inverse sampling probability of each farm in total population is used for weighting. For details on weighting, see appendix A.1.

2.4.1. Predicted impacts of climate change

The predicted impacts of climate change on farm profit ($\Delta\pi_{it}$) are derived by keeping other variables constant while changing the climate variables ($\Delta\omega_{it}$). The simulated climate coming from climate models for a future year (say 2040) is inserted in lieu of ω_{it} while other control variables (X_{it}, technology and time trend etc.) are kept unchanged. The predicted change in profits is relative to a base year (say 2016 in our case). Using equation **(6)** above, we can depict the predicted change in farm profits ($\Delta\pi_i$) dependent on the change in climate variables ($\Delta\omega_i$). As we fixed the prediction to a particular future year, the subscript *i* shows that there is a different predicted impact of climate change for each farm. Moreover, the change in the climate variables ($\Delta\omega_i$) is derived in the same construct of meteorological variables as used in estimation of response sensitivities.

Auffhammer et al. (2013) discuss that the change in climate variables ($\Delta\omega_i$) should come from two parts. First, the climate variable in the base year from observed dataset plus the difference in future and base year values from simulated data set (all following the same construct). We followed this recommendation and applied it in analogy to Moore and Lobell (2014) to derive the change in farm profits

$$\Delta\pi_{i.2040} \approx \Delta\omega_{i\times k} \, . \;\; \hat{\beta}_{k\times 1} \qquad \textbf{(14)}$$

where $\hat{\beta}_k$ represents the respective parameters estimated from equation **(6)** with two regression specification based on the construct of meteorological variables in equation **(10)** (model-I) and in equation **(13)** (model-II).

2.3.1.1 Predictions based on model-I:

The estimated vectors of coefficients of the meteorological variables, $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ are used to predict short-run and long-run response curves. The divergence between these response curves depicts the adaptation potentials for temperature and precipitation. The change in long-run profits at each farm *i* due to climate change ($\Delta\hat{\pi}_{LRi}$) is computed as the sum of the long-run response from temperature and precipitation:

$$\Delta\hat{\pi}_{LRi} = \sum_{c=1}^{2} \Delta\hat{\pi}_{LRi_c} = \sum_{c=1}^{2} \left(\hat{\beta}_{1_c} \left(\overline{W}_{Bi_c} + \overline{W}_{\Delta i_c} \right) + \hat{\beta}_{2_c} \left(\overline{W}_{Bi_c} + \overline{W}_{\Delta i_c} \right)^2 - \hat{\beta}_{1_c} \overline{W}_{Bi_c} - \hat{\beta}_{2_c} \overline{W}_{Bi_c}{}^2 \right) \qquad \textbf{(15)}$$

$$\Delta\hat{\pi}_{LRi_c} = \hat{\beta}_{1_c}\,\overline{W}_{\Delta i_c} + \hat{\beta}_{2_c}\left\{\left(2\overline{W}_{Bi_c}\overline{W}_{\Delta i_c}\right) + \left(\overline{W}_{\Delta i_c}\right)^2\right\} \quad \textbf{(16)}$$

where *c* indicates temperature and precipitation, respectively. Subscript *B* is the long-term climate value of the base year (in our case the last observed year, 2016) and the subscript Δ is the change in long-term climatic condition of the predicted year (i.e. 2040) to the base year. For example, we may use 20-years average temperature from observed data (Hiebl & Frei, 2016) as a base temperature value while, the change in the 20 years averages can be obtained from meteorological model predictions of climatic conditions (Chimani et al., 2016). The long-run change describes the full adaptation case captured by the coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$. In the short-run, there is no adaptation and therefore a 'penalty' for unexpected changes is added using $\hat{\beta}_3$ to capture the change in short-run (SR) profits for each climate variable *c*.

$$\Delta\hat{\pi}_{SRi_c} = \hat{\beta}_{1_c}\left(\overline{W}_{Bi_c} + \overline{W}_{\Delta i_c}\right) + \hat{\beta}_{2_c}\left(\overline{W}_{Bi_c} + \overline{W}_{\Delta i_c}\right)^2 - \hat{\beta}_{1_c}\overline{W}_{Bi_c} - \hat{\beta}_{2_c}{\overline{W}_{Bi_c}}^2 + \hat{\beta}_{3_c}\left(\overline{W}_{\Delta i_c}\right)^2 \quad \textbf{(17)}$$

$$\Delta\hat{\pi}_{SRi_c} = \hat{\beta}_{1_c}\,\overline{W}_{\Delta i_c} + \hat{\beta}_{2_c}\left\{\left(2\overline{W}_{Bi_c}\,\overline{W}_{\Delta i_c}\right) + {\overline{W}_{\Delta i_c}}^2\right\} + \hat{\beta}_{3_c}\left(\overline{W}_{\Delta i_c}\right)^2 \quad \textbf{(18)}$$

The last component ($\hat{\beta}_{3_c}\left(\overline{W}_{\Delta i_c}\right)^2$) of equation **(17)**, thus captures the adaptation potential with respect to each meteorological variable.

2.3.1.2 Prediction based on the model-II:

For model-I it was shown how to derive the adaptation potential and predict short-run as well as long-run responses separately. In case of model-II one can predict one response only. According to Mendelsohn and Massteti (2017) and many others this response is the short-run response. However, most of the PDM literature argues that a quadratic response function may also capture the long-run response because the quadratic term can capture the long-term trend (Carter et al., 2018). The advantage with model-II is that we may find different climate sensitivities for agriculture in different seasons instead of one whole growing season sensitivity. The change in profits ($\Delta\hat{\pi}_i$) with model-II at each farm *i* due to climate change is therefore computed as the sum of the responses from temperature and precipitation:

$$\Delta\hat{\pi}_i = \sum_{c=1}^{2}\sum_{s=1}^{4}\Delta\hat{\pi}_{i_{s_c}} = \widehat{\beta_1}_{s_c}\left(\overline{w}_{Bi_{s_c}} + \overline{w}_{\Delta i_{s_c}}\right) + \widehat{\beta_2}_{s_c}\left(\overline{w}_{Bi_{s_c}} + \overline{w}_{\Delta i_{s_c}}\right)^2 - \widehat{\beta_1}_{s_c}\overline{w}_{Bi_{s_c}} - \widehat{\beta_2}_{s_c}\overline{w}_{Bi_{s_c}}{}^2 \quad \textbf{(19)}$$

$$\Delta\hat{\pi}_{i_c} = \sum_{s=1}^{4}\left[\widehat{\beta_1}_{s_c}\,\overline{w}_{\Delta i_{s_c}} + \widehat{\beta_2}_{s_c}\left\{\left(2\overline{w}_{Bi_{s_c}}\overline{w}_{\Delta i_{s_c}}\right) + \left(\overline{w}_{\Delta i_{s_c}}\right)^2\right\}\right] \quad \textbf{(20)}$$

where $\Delta\hat{\pi}_i$ represents the cumulative effects of all climate variables i.e. temperature and precipitation, we used for our analysis and $\Delta\hat{\pi}_{i_c}$ represents the combined effect of all seasonal changes related to one particular climate variable. Individual response curves may be derived for each season and each climate variable separately in case of the model-II. A small $\overline{w}$ notation represents contemporary seasonal construct of meteorological variable. Subscript B is the seasonal average of a particular meteorological variable of the base year (in our case the last observed year, 2016). The subscript Δ represents the change in seasonal average for a particular meteorological variable of the predicted year (i.e. 2040) to the base year. For example, we use spring temperature average from observed data (Hiebl & Frei, 2016) as $\overline{w}_{Bi}$, which is base spring temperature value. The change in the spring temperature, instead, is obtained from meteorological model predictions of climatic conditions (Chimani et al., 2016).

2.4.2. Uncertainty and its sources

Uncertainty in estimates of climate change impacts on agriculture comes from different sources (Katz, 2002). First source of uncertainty emanates from climate model uncertainty, i.e. differences in the predictions of future climate from different climate models (Katz, 2002; Moore & Lobell, 2014). These Global Climate Models (GCM) or Regional Climate Models (RCM) simulate future climatic conditions differently. Even after using uniform RCPs (emission scenarios) as an input, these climate models present a set of future climatic conditions. These sets of values make up an ensemble for future climatic conditions. Recent literature either uses averages from this ensemble to derive predictions or uses all of the predicted climate conditions and derives many predicted impacts. Here, we use 13 bias corrected future climatic conditions derived from climate models using each of the emission scenario. This makes a total of 26 future climate values for each farm in our case because we use two emission scenarios (RCP 4.5 and RCP 8.5). Thus, we have a range of predicted impacts ('m' prediction of $\Delta\hat{\pi}_i$ in each RCP) at each farm. The variance in predicted impacts of climate change is calculated for each farm from regression model-I and regression model-II and noted as $Var(\Delta\pi_{i.m.I})$ and $Var(\Delta\pi_{i.m.II})$, respectively. Climate uncertainty comes from weighted average of the variance in these predictions at each farm. As weights the inverse sampling probability (P_i) of each farm in total population is used. The climate model uncertainty is calculated for each of the two RCPs separately:

$$Climate\ Model\ Uncertainty = \frac{1}{2}\left\{\frac{1}{\Sigma \mathrm{P}_i}\sum_{i=1}^{n} \mathrm{P}_i.Var(\Delta\pi_{i.m.I}) + \frac{1}{\Sigma \mathrm{P}_i}\sum_{i=1}^{n} \mathrm{P}_i.Var(\Delta\pi_{i.m.II})\right\} \qquad \textbf{(21)}$$

The second source of uncertainty is due to standard errors of the estimated parameters in the response models (i.e. regression model-I and regression-II in our case). We call it responses model uncertainty. This uncertainty is easier to capture with the econometric approach as compared to crop models which have to produce a great number of simulations starting from many different combinations of parameter first (Pindyck, 2011; Weitzman, 2011). We computed this second source of uncertainty using the variance of the parameters estimated from our two econometric models i.e. the model-I and the model-II. The estimated parameters from each econometric model are combined with the ensemble mean changes from 13 climate models ($\widetilde{\Delta\omega}_i$) to predict one mean prediction at each farm (i.e. $\widetilde{\Delta\pi}_i$) for each of the two RCPs. Thus, we hold the simulated climate constant at each farm and predict mean climate change impact using one of the two econometric models. This mean change can be written as

$$\widetilde{\Delta\pi}_i \;=\; \widetilde{\Delta\omega}_i \,.\, \hat{\beta}_k. \tag{22}$$

Applying the variance operator gives the variance in prediction at each farm coming from the response model parameters.

$$Var\left(\widetilde{\Delta\pi}_i\right) = \left(\widetilde{\Delta\omega}_i\right) .\; Var\left(\hat{\beta}_k\right) . \left(\widetilde{\Delta\omega}_i\right)' \tag{23}$$

This is summed up over all farms with inverse probability sampling weights (P_i). The average from both response models gives the response model uncertainty.

$$Response\ Model\ Uncertainty = \frac{1}{2}\left\{\frac{1}{\Sigma\mathrm{P}_i}\sum_{i=1}^{n}\mathrm{P}_i . Var\left(\widetilde{\Delta\pi}_{i,I}\right) \;+\; \frac{1}{\Sigma\mathrm{P}_i}\sum_{i=1}^{n}\mathrm{P}_i . Var\left(\widetilde{\Delta\pi}_{i,II}\right)\right\} \tag{24}$$

Where $Var\left(\widetilde{\Delta\pi}_{i,I}\right)$ and $Var\left(\widetilde{\Delta\pi}_{i,II}\right)$ are the farm specific variance in predicted impacts using regression model-I and regression model-II are respectively. The response model uncertainty is calculated for each of the two RCPs separately.

Predicted impacts of climate change are also uncertain because of the response model used to study climate change impacts on agriculture. These research tools or response models capture climate change impact on agriculture with different underlying assumptions and simplifications, therefore tend to differ in predicted impacts. Researchers tend to project one response model results and neglect others (Asseng et al., 2013). However, George Box says “all models are wrong, but some are useful”. Multiple response model based prediction of climate change impacts is popular in bio-economic modellers (Asseng et al., 2013; Bregaglio et al., 2017; Iizumi et al., 2011; Kassie et al., 2015). With econometric literature this multi-model impact assessment and related uncertainty is still to be explored rigorously. We use two regression specification to model climate change impacts for Austria. This is called here as regression model uncertainty.

We have used two econometric models, therefore variance between the two predictions at each farm may underestimate this uncertainty compared to an approach where more econometric models are used. To derive the regression model uncertainty We use a method adapted from Moore and Lobell (2014).

$$Regression\ Model\ Uncertainty = \frac{1}{2}\sum_{i=1}^{n} \mathrm{P}_i . Var\left(\widetilde{\Delta\pi}_{i,I}\ , \widetilde{\Delta\pi}_{i,II}\right) \tag{25}$$

Yet another source of uncertainty, as Kundzewics et al. (2018) write, comes from vast collection of unknown-unknowns or unknown-knowns of socio-economic factors linked to climate change impacts in agriculture. We do not further investigate these uncertainties here.

All data analysis in this study is done with the statistical software ‘R’ (2017) using the packages ‘plm’ (Croissant & Millo, 2008) and standard error bootstrapping package (Esarey & Menger, 2019).

2.5 Data descriptive statistics

Farm level panel data econometric analysis of climate change requires data about the farm and its performance, meteorological data and some additional control variables (e.g. soil quality) on farm level. Since meteorological data are typically grid based, farms need to be merged to the closest grid point. We merged farms to the closest grid point from a 1x1 km^2 grid. This study used following four kinds of data sets for Austria.

First, profits, inputs and farm characteristics are taken from the ‘Farm Accountancy Data Network’ (FADN) data, which is available for each EU country. We obtained this data from the Federal Ministry of Sustainability and Tourism. The data set is based on farm accounts from a representative sample of farms across whole Austria (i.e. 2% of total farms) for each year. The stratum covers farms with respect to production focus (e.g. dairy, cereals, permanent crops) and economic size of farms (European Commission, 2019). Our data set includes the years 2003 to 2016 and consists of 31,876 observations (on average 2,277 per year). We use 82.35% of these observations as the locations of some farms could not be identified (8.7%), because slope information was missing (3.26%) or profits were negative and therefore not suitable for log-transformation (5.7%). *Table 1* shows descriptive statistics of our sample.

FADN and meteorological data variables	**Mean**	**Min**	**Max**	**Median**	**SD**
Observations used = 26248; years = 14	(sample with positive profits, spatial and slope information)				
Profit (Euro/ha/year)	925.92	0.08	22492.53	646.62	1161.49
Altitude (meter)	514.90	113	1600	460	270.9
Farm area (ha)	54.78	0.9	470.45	42.80	45.14
Arable land (%)	42.94	0.00	100	39.43	35.63
Grass land (%)	26.09	0	100	20.56	25.26
Subsidy (€/ha)	473.41	0	4148.91	470.8	210.59
Family labour (%)	95.3	0.00	100.00	100.00	11.66
Meteorological data growing season					
Temperature: 20 years average (°C)	13.7	6.63	16.83	14.01	1.49
Precipitation: 20 years average (mm/month)	88.51	47.8	200.17	85.76	25.04
Temperature: shock (°C²)	0.63	0	6.39	0.22	0.84
Precipitation: shock ((mm/month)²)	259.76	0	7938.69	101.94	405.51
Sunshine duration (annual in hours)	8.42	4.27	11.75	8.41	1.1
Meteorological data seasonal split-up					
Temperature winter: contemporary (°C)	-0.28	-6.612	5.43	-0.45	2.05
Temperature spring: contemporary (°C)	9.54	1.36	13.83	9.69	1.72
Temperature summer: contemporary (°C)	18.78	10.47	23.48	18.90	1.77
Temperature autumn: contemporary (°C)	9.58	2.65	13.86	9.69	1.50
Precipitation winter: contemporary (mm/month)	49.21	7.33	354.90	42.01	29.31
Precipitation spring: contemporary (mm/month)	66.52	14.06	244.19	62.84	25.42
Precipitation summer: contemporary (mm/month)	112.51	24.64	366.36	108.96	40.94
Precipitation autumn: contemporary (mm/month)	66.83	10.30	322.33	61.78	30.42

Notes: The number of observations per year varies (unbalanced panel). Profits per ha are gross value added including subsidies but without energy expenses. Climatic variables are for the growing seasons (March to September) at the grid points closest to the farms. Temperature is the yearly mean of minimum and maximum and precipitation aggregated yearly sums. Temperature and precipitation shocks are squared deviation of current year's temperature from 20 years average values.

Table 1: Descriptive statistics of the sample from FADN and meteorological data from year 2003-2016.

The mean profit per ha is 925.92 Euros per year and varies from essentially zero to above 22.000 Euros. The farms are located between 113 and 1600 meters above sea level. This variation in altitude is the reason for much of the variance in cross-sectional climatic conditions. The average farm area in our sample is 54.78 ha. The share of grassland is on average 26.09% and the share of arable land is 42.94%. Other land uses include forest, horticulture, permanent culture and unused land. Subsidies per ha are on average 473.41 Euros per year and therefore account, on average, for more than half of profits. Family labour accounts for 95% of total labour.

Second, our meteorological data are all based on meteorological spatial interpolation and kriging developed by the Austrian governmental agency for meteorology and geodynamics 'Zentralanstalt für Meteorologie und Geodynamik'. All data are available at a 1 x 1 km^2 grid for the whole area of Austria and in daily resolution. The model for close to surface daily minimum and maximum temperatures is based on 115 weather stations and the model for daily precipitation sums on 520 weather stations (Hiebl & Frei, 2016, 2017). Both variables are available from 1961 to 2016. The sunshine duration interpolations are based on 53 to 148 stations and are available from 1980 to 2016. Topology as well as overcasting are used in spatial interpolations (Olefs & Koch, 2013).

The second panel of *Table 1* describes the distribution of the meteorological data for the years 2003 to 2016 during the growing season (March to September) at the grid points closest to the farms. The yearly temperature values are derived from daily means of minimum and maximum values at each grid point. The variable shown in the table are averages for past 20 years annual growing seasons. Precipitation is shown in average monthly sums during past 20 years. The observed variance of 20-years averages between grid points are important to estimate the effect of climate on profits when farms adapt to the climate. The shocks are yearly deviations from the 20-years averages and help to identify the effect of climate change without adaptation. Sunshine duration is measured in hours of sunshine at each particular grid point. Comparing our meteorological values in lower panel of *Table 1* to those of Moore and Lobell (2014), we find that mean temperature (15.2 °C), mean precipitation (60.9 mm/month) and standard deviation of precipitation (24.0 mm/month) are very similar while the standard deviation of temperature (2.7°C) is higher in their case. The higher standard deviation is not surprising given that Moore and Lobell's area covers 11 EU countries at

NUTS-3 level: Belgium, Germany, Greece, Spain, France, Ireland, Italy, Luxemburg, the Netherlands, Portugal and the United Kingdom.

The third panel of *Table 1* describes the distribution of the meteorological data for the years 2003 to 2016 during different seasons at the grid points closest to the farms. The whole year is categorized into four seasons comprising three months each. Meteorological conditions averaged over December, January and February represent winter weather conditions. Similarly, March, April and May represent spring, June, July and August represent summer and, finally, September, October and November describe autumn. The contemporary seasonal temperature is derived from daily means of minimum and maximum values at each grid point. The variables shown in the table are seasonal averages for contemporary year. Precipitation is shown in average monthly sums during a particular season. This average is also derived from daily precipitation values.

Comparing our meteorological values in third panel of *Table 1* to those of Van Passel et al. (2017), we find that mean spring temperature (9.54 °C) and summer temperature (18.78 °C) for Austria are almost similar to the long-term seasonal averages of EU-15 member states used by Van Passel et al. (2017). Winter (-0.28 °C) and autumn temperature (9.58 °C) describe that Austria is on average colder than EU-15 member states. In case of precipitation, winter (49.2 mm/month) and autumn (66.8 mm/month) months in Austria are drier compared to EU-15 averages, whereas, spring (66.5 mm/month) and summer (112.5 mm/month) months are wetter. In fact, summers are twice as rainy as the average of EU-15 member states. However, standard deviations for EU-15 member states for both temperature and precipitation are of course higher than in Austria only. These higher standard deviations are due to vaster spatial coverage. The EU-15 countries comprise of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and UK.

In the appendix we also provide descriptive statistics for the data before dropping the observations with negative profits (*Table A 1*) and those without slope information (*Table A 2*). Dropping those with negative profits increases the mean profits as expected, but other descriptive statistics remain almost unchanged. Most importantly, the weather variables hardly change because of spatial randomness of dropped observations (see *Figure A 1* in the appendix). Temporally, dropped observations belong to every observed year. However, dropping farms with negative profits may under report negative impacts because negative profits might partly be due to weather shocks.

For illustration of past trends of climate change in Austria, we show trends and changes in climate from three NUTS-3 regions (using all grid points within each of them) of Austria. One from the centre (Pinzgau-Pongau), east (Vienna) and west (Bludenz-Bregenzer Wald) of Austria, respectively. The figure for Vienna is presented here, the other two have similar temperature increasing trends and are presented in the appendix (see *Figure A 2*, *Figure A 3*).

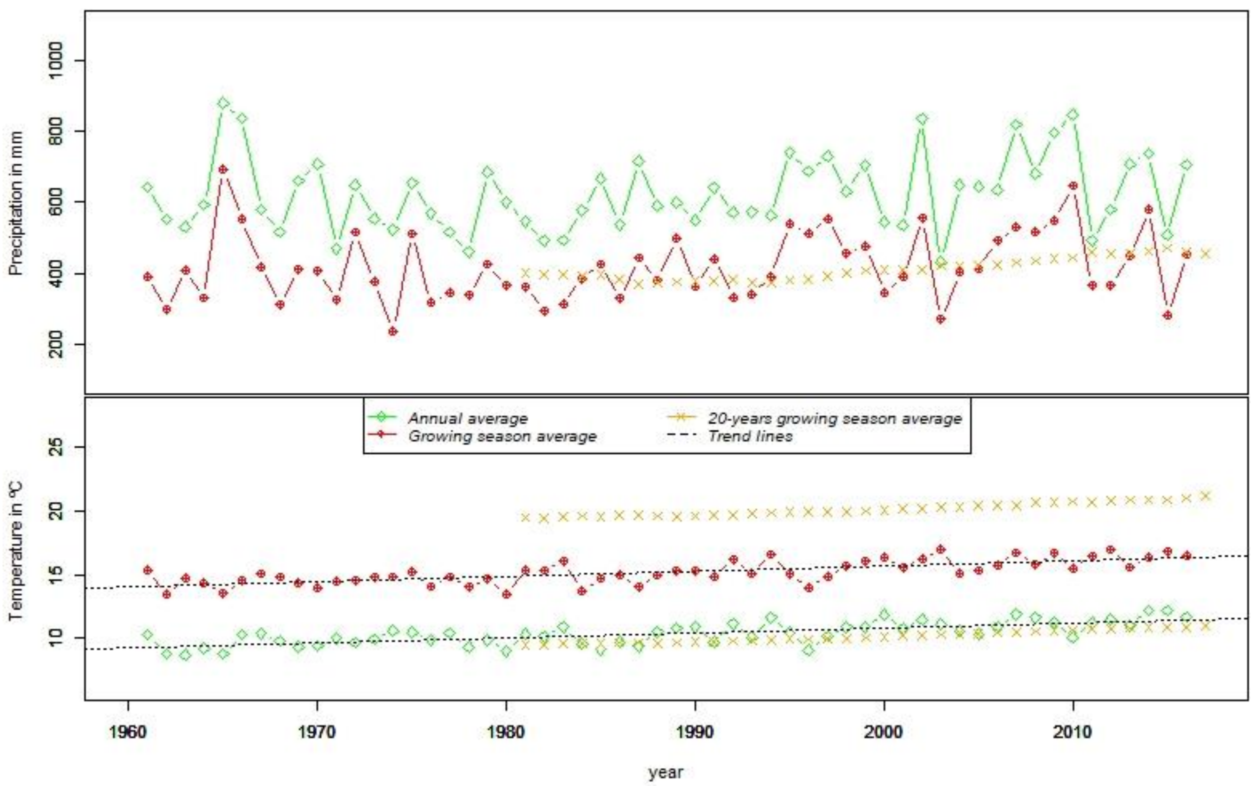


Figure 1: Past Precipitation and Temperature trend in Vienna (a region in the east of Austria) from Jan 1, 1961 to 31 Dec, 2016.

Description: Climate data here presents spatial averages from all 1x1 km grid points in Vienna. Past 20-years averages represent long-term precipitation and temperature conditions for growing season. In temperature plot, long term averages for growing season contains temporal averages over past 20 years for night and day temperatures.

Third, data on future climatic conditions with different scenarios are obtained from the ’ÖKS15 – Klimaszenarien für Österreich‘ project (Chimani et al., 2016) which contains 13 bias-corrected climate model predictions for Austria (till 2100) with different emission scenarios. These 13 climate model predictions come from five Global Climate Models (GCMs) namely, CNRM-Cerfacs, EC-EARTH, IPSL-CM5A, HadGEM and MPI-ESM coupled with different Regional Climate Models (RCMs) named as CLMcom, ALADIN, SMHI, KNMI, DMI, INERIS. These climate models (GCMs and RCMs) map different geophysical processes of earth differently and simulate these processes in order to predict future climatic conditions with different emission scenarios. The GCM works at global scale and usually predict future climate at coarser resolution since they cannot capture local phenomenon effectively. To down scale these future climate predictions, say to *1x1* Km^2 resolution, Regional Climate Models are employed which can represent local geophysical processes more effectively. All of these climate models take human activity as given and predict future climate based on the emission scenarios. For our study, we use two Representative Concentration Pathways (RCP 4.5 (Effective Measure) and RCP8.5 (Business as Usual) described in Moss et al. (2010) in the fifth International Panel on Climate Change Report (IPCC, (2013)). All these predictions make up a set of values depicting possible future climate conditions for any location under a particular emission scenario. Most recent literature either uses several climate predictions to show a complete range of future possibilities or uses a mean of these predictions which are termed as ensemble mean predictions. Since, we are interested to split up the variance in predicted impacts of climate change, we used all predictions individually as well as their ensemble means for each emission scenario.

Here we present future climate conditions (ensemble means) constructed in exactly the fashion as the variables we used in our empirical model and meteorological data (observed) described above. We use long-term growing season meteorological variables and seasonal meteorological variables. Hence, our future climate variables depict the average of 13 climate model predictions at the grid point closest to a farm in each of the two emission scenarios RCP 4.5 and RCP 8.5.

The RCP 4.5 is a scenario with a certain degree of CO_2 emission reduction efforts where the emissions in 2070 are below today’s emissions and CO_2 concentration stabilizes in 2100. The RCP 8.5 is a scenario where economic growth continues to be mainly based on fossil fuels and CO_2 concentration continues to grow beyond 2100. We took 2040 as the future year for our predictions. *Table 2* describes average temperature and precipitation for farms in 2040 as compared to their 2016 climatic conditions. In case of temperature, both emission scenarios are showing an increase in temperature for the year 2040 compared to the base year 2016. Except for spring temperature in RCP 4.5 which shows a drop in spring temperature for the future year compared to 2016. However, RCP 8.5 is hotter than RCP 4.5 in the long-term construct as well as the seasonal construct of meteorological variables. In case of precipitation, RCP 4.5 is slightly drier as compared to both RCP 8.5 in 2040 and RCP 4.5 in the base year 2016 except for winter precipitation however, precipitation on average increases for RCP 8.5 at an increased variance.

Variable	**RCP**	**Change from 2016 to 2040**	**Mean**	**Min**	**Max**	**Median**	**SD**
Temperature	4.5	Long-term average	0.66	0.60	0.92	0.65	0.05
		Winter average	1.86	1.43	2.29	1.89	0.16
		Spring average	-0.45	-0.88	0.32	-0.45	0.25
		Summer average	0.24	-0.03	0.87	0.23	0.13
		Autumn average	0.57	0.42	0.82	0.56	0.06
	8.5	Long-term average	0.92	0.84	1.28	0.89	0.08
		Winter average	0.99	0.36	1.47	0.99	0.22
		Spring average	0.51	0.22	1.29	0.47	0.15
		Summer average	0.48	0.09	1.23	0.44	0.18
		Autumn average	1.26	1.03	1.59	1.26	0.10
Precipitation	4.5	Long-term average	-1.03	-4.45	1.92	-1.03	1.04
		Winter average	9.97	-6.19	39.29	8.95	6.33
		Spring average	-6.93	-34.48	7.52	-7.19	6.85
		Summer average	-5.29	-22.42	34.85	-5.97	6.19
		Autumn average	-14.55	-45.19	7.00	-13.41	6.90
	8.5	Long-term average	2.02	-2.80	6.58	2.17	1.01
		Winter average	1.35	-32.60	30.80	0.56	7.04
		Spring average	-5.94	-23.88	17.96	-5.33	6.85
		Summer average	3.29	-32.47	27.11	4.51	9.09
		Autumn average	-2.19	-46.04	19.97	-3.12	7.54

Note: Temperature averages are in degree Celsius and precipitation averages are in mm/month for the year 2040. Long-term changes depict change in 20-years growing season average at 2040 from base year of 2016. Seasonal variations depict changes in seasonal average of 2040 from seasonal average of 2016. All changes are based on Chimani et al. (2016) and show differences in long-term and seasonal averages for both years with simulated data. These values come from averaging 13 bias corrected climate models for Austria.

Table 2: Future climatic conditions at farms in Austria based on simulated data for 2881 grid points closest to the farms.

Fourth, farm related soil information on soil-texture and soil-quality attributes were acquired from the digital soil map of the ’Bundesforschungszentrum für Wald‘ (BFW, 2016). This data is available for the whole of Austria with 1 x 1 km^2 resolution. We only used grid points nearest to farms with one cross-sectional soil quality value for whole of the FADN data set from 2003-2016, assuming that soil properties did not change within this period. Soil data set show that most of the productive soil in Austria contains high values of PH, lime share and silt share and clay share.

soil quality value	NOM (%)	PH value	lime (%)	sand (%)	silt (%)	clay (%)
Low	3.48	5.45	1.31	44.19	43.33	11.85
low to medium	3.62	5.30	1.77	36.28	48.47	15.25
Medium	3.26	5.67	2.23	33.66	50.92	14.36
medium to high	3.26	6.32	3.37	31.84	51.50	15.23
High	2.66	6.48	5.07	21.10	59.26	18.74

Notes: Soils have been categorized from low to high soil quality in BFW soil dataset. Above table shows soil quality attributes (organic matter in mass percent, PH value, contents of lime, sand, silt and clay in percentage) against each class of soil. NOM = organic matter

Table 3: Soil quality and texture of farms in the sample.

3. Results

In section 3.1 econometric estimates of climate change impacts on agriculture using Austrian farm level panel data, are presented. Moreover, different econometric aspects are discussed in detail, one by one as discussed in methods section. In section 3.2 we present predicted impacts of climate change on Austrian agriculture. Uncertainty analysis of predicted impacts is carried out using two identification strategies i.e. model-I and model-II. We also split-up uncertainty into its sources as introduced in method section. Moreover, we show the spatial distribution of the adaptation potential of Austrian farms using model-I.

3.1. Results of econometric model

3.1.1. Estimated coefficients of the basic model-I

The pooled linear OLS regression as specified in equation **(5)** is the most basic model estimated. The first column of *Table 4* shows the results of this model with agricultural production area dummies, soil and farmer's education variables, altitude and livestock share dummies. The second and third columns show the results of the fixed-effects model (equation **(6)**) with unbalanced and balanced panel, respectively. The coefficients between the pooled OLS and fixed-effects model differ substantially as the former is susceptible to the omission bias from farm specific (i.e. time-constant) effects. In particular, the coefficients of the average 20-years temperature and precipitation are affected: farms adapt to these long term values and in the pooled OLS model it is not possible to control for all differences between farms. The coefficients of the fixed-effects model suggest an inverted u-shaped effect of long-term temperature and precipitation. The Wald test for joint significance shows temperature variables are jointly significant with an F-statistics value of 8.78 (p-value of 8.07E-6). The long-term precipitation variables are individually significant. The profit maximizing average growing season temperature is 11.1°C and precipitation is 145 mm/month for an average Austrian farm using linear and quadratic coefficients of long-term variables. Profit maximizing temperature of Moore and Lobell (2014) is four degrees higher (i.e. 16.4°C) and their precipitation is 162 mm/month.

	Pooled			Fixed effects unbalanced			Fixed effects balanced		
	Est.	St. error		Est.	St. error		Est.	St. error	
Temp. longterm	0.0618	(0.1378)		0.5693	(0.3992)		0.7116	(0.5001)	
Temp. longt. squ.	0.0002	(0.0054)		-0.0256	(0.0100)	**	-0.0238	(0.0125)	*
Temp. shock	-0.0384	(0.0207)	*	-0.0644	(0.0153)	**	-0.0807	(0.0174)	**
Preci. longt.	0.0115	(0.0046)	**	0.0654	(0.0108)	**	0.0577	(0.0126)	**
Preci. longt. squ.	-3.5E-05	(2.0E-05)	*	-0.0002	(4.9E-05)	**	-0.0002	(0.0001)	**
Preci. Shock	-4.1E-05	(1.6E-05)	**	2.2E-06	(1.1E-05)		5.9E-06	(1.3E-05)	
Land: 'arable'	-0.0120	(0.0007)	**	-0.0059	(0.0013)	**	-0.0067	(0.0017)	**
Land: 'grass'	-0.0139	(0.0008)	**	-0.0006	(0.0008)		-0.0008	(0.0011)	
Subsidies	0.0010	(0.0001)	**	0.0002	(4.1E-05)	**	0.0001	(4.5E-05)	

R^2	0.3777	0.7578	0.7754
Observations	26248	26248	11662
No. of farms	2881	2881	833

Notes: Robust standard errors in parenthesis. Significance: * =10%, **=5% or less. Dummies for years have not been shown in all three models. Whereas for pooled regression other variables i.e. regions, farmer's education, soil type, soil quality, altitude, livestock intensity and constant are not shown.

Table 4: Results of pooled and fixed effects for basic models.

The coefficient for temperature shocks (i.e. deviations from the long term mean) has negative signs what implies a penalty on the profits of a farm for ignoring climate change altogether. A year that is 1°C warmer or cooler induces an average profit reduction of 6.4%. This is considerably higher than the effect estimated by Moore and Lobell (2014). For precipitation shocks, the average effect on profits of a one standard deviation change (24.7mm/month) is 0.12%, where Moore and Lobell (2014) find 4.2%, but the coefficients are not significantly different from zero in both studies.

Finally, the coefficients of the farm specific, time-varying variables of arable land share and ‘subsidy per ha’ are significant. The coefficients of land use shares (arable land and grass land) are both negative which suggests that other uses (horticulture, permanent crops and forestry) have on average higher per ha profits. In our model, subsidies are part of profit. Hence, it is expected that more subsidies received per hectare have a positive impact on profits per hectare.

The third column shows results from a fixed-effects model with a balanced panel. The number of observations reduces from 26,248 to 11,662. The coefficients in this model are not statistically different from the unbalanced panel model (for all coefficients the interval [estimated coefficient± 1.96* standard error] includes the coefficient of the unbalanced model) except for subsidies. We are cognizant of the possible shortcomings in fixed effects with unbalanced panel as discussed by Wooldridge (2010, Chapter 19). Since, the results from the unbalanced model are based on more than twice as many observations than the balanced model, the unbalanced data are used for all following calculations.

3.1.2. Omitted variables

Results for the effect of omission of sunshine duration on our main coefficients are summarized in *Table 5*. We include average annual and average annual squared contemporary values (column 1) as well as past 20 years-average and deviations from the 20-years average (i.e. shocks) values (column 2). There are no statistically significant changes in the estimated coefficients of temperature and precipitation in the model we extended by contemporary values (first column). It suggests, while sunshine is significant, it would not lead to a bias when not included. Extending the model by a variable for sunshine duration constructed in the same fashion as temperature and precipitation substantially changes the coefficients of temperature and standard errors (column 2). This is not surprising, given the correlation coefficient between 20-years average sunshine and temperature being 0.54 and between shocks of sunshine and temperature being 0.83. It suggests alternative meteorological variables could be used to construct the biophysical part of the model. However, it is difficult to include all meteorological variable (Zhang et al., 2017) due to lack of data on the one hand and due to potential multi-collinearity problems associated with strongly correlated meteorological variables on the other hand (Carter et al., 2018).

	FE model with average annual sunshine			FE model with 20 year averages sunshine and shocks		
	Est.	St. error		Est.	St. error	
Temp. longterm	0.5778	(0.3985)		0.2444	(0.4266)	
Temp. longt. squ.	-0.0221	(0.0100)	**	-0.0126	(0.0119)	
Temp. shock	-0.0537	(0.0153)	**	-0.0731	(0.0153)	**
Preci. Longterm	0.0602	(0.0108)	**	0.0713	(0.0110)	**
Preci. longt. Squ	-0.0002	(4.9E-05)	**	-0.0003	(0.0001)	**
Preci. Shock	3.2E-06	(1.1E-05)		2.1E-06	(1.1E-05)	
Land: 'arable'	-0.0061	(0.0013)	**	-0.0063	(0.0013)	**
Land: ‘grass’	-0.0010	(0.0008)		-0.0011	(0.0008)	
Subsidies	0.0002	(4.1E-05)	**	0.0002	(4.1E-05)	**
Sunshine annual	-0.3764	(0.0564)	**			
Sunshine ann. squ.	0.0199	(0.0032)	**			
Sunshine longterm				-1.0673	(0.4655)	**
Sunshine longt. squ.				0.0474	(0.0250)	*
Sunshine shock				0.0368	(0.0079)	**

R^2	0.7583	0.7582
Observations	26248	26248
No. of farms	2881	2881

Notes: Robust standard errors in parenthesis. Significance: * =10%, **=5% or less. Dummies for years are not shown.

Table 5: Unbalanced fixed effects (FE) model extended by sunshine duration to check omission related to sunshine.

3.1.3. Measurement error

A 2SLS regression is used to check for measurement error induced biases. To be consistent with Moore and Lobell (2014), we stick to the model without sunshine duration. We categorise our 2SLS models with respect to variables potentially with measurement error. Consequently, we estimate a model where we instrument 1) long-term temperature and long-term temperature squared, 2) long-term precipitation and long-term precipitation squared. A third option (instrumenting long-term temperature and precipitation as well as temperature and precipitation shocks) did not lead to substantially different results, but substantially increases in complexity.

Table 6 shows the second stage results when temperature or precipitation are instrumented by their spatial lags (appendix contains first stage results as in *Table A 3* and *Table A 4*). As we computed both stages of 2SLS separately, clustered bootstrap standard errors with 1000 repetitions were drawn for robust inference making.

Following the Sargan-Hansen over-identifying restriction test, the H_0 that the over identifying restriction holds is not rejected in both cases (p-values: 0.84, 0.83). F-statistics in each of the first stage (long-term temperature and long-term precipitation) is indicating that instruments are not weak. This makes sense as these spatial lags are strongly correlated to long-term temperature and precipitation at the grid point nearest to a farm (i.e. instruments are relevant). We also tested for measurement error related endogeneity (see *Table A 5* for endogeneity test). Test results support the absence of any pronounced endogeneity in temperature whereas long-term precipitation is endogenous (p-values: 0.46, 0.001). This is not surprising, as the leave-one-out cross-validation (*Figure A 4* and *Figure A 5* in the appendix) already shows almost no systematic error for temperature and a slight downward bias for summer precipitation.

Coefficients from 2SLS estimates (*Table 6*) are smaller as compared to unbalanced panel results in *Table 4*. A large difference in coefficients means that measurement error may pose a problem in micro level studies. In our case, coefficients have the same sign and slightly different magnitudes (comparing coefficients in *Table 4* to *Table 6*). Since our endogeneity test is only significant for precipitation, in the following model extensions, we used the unbalanced panel model like in column 2 of *Table 4* for temperature and 2SLS instrumenting for precipitation like in column 2 of *Table 6*.

	Temperature instrumented			Precipitation instrumented		
	Est.	St. error (Bootstr.)		Est.	St. error (Bootstr.)	
Temp. longterm+	0.4109	(0.5279)		0.5288	(0.4429)	
Temp. longt. squ. +	-0.0217	(0.0137)		-0.0230	(0.0112)	**
Temp. shock	-0.0654	(0.0170)	**	-0.0629	(0.0168)	**
Preci. longt. +	0.0644	(0.0117)	**	0.0631	(0.0155)	**
Preci. longt. squ. +	-0.0002	(0.0001)	**	-0.0002	(0.0001)	**
Preci. Shock	2.0E-06	(1.4E-05)		-2.1E-06	(1.3E-05)	
Land: 'arable'	-0.0059	(0.0020)	**	-0.0058	(0.0020)	**
Land: 'grass'	-0.0005	(0.0011)		-0.0005	(0.0012)	
Subsidies	0.0002	(0.0001)	**	0.0002	(0.0001)	**
R^2	0.7579			0.7579		
Observations	26,248			26,248		
No. of farms	2881			2881		
		p-value			p-value	
Weak instrument test		2.2E-16			2.2E-16	
Over-identification test		0.8367			0.8274	
Endogeneity test (F-test significance of all residuals)		0.4579			0.0013	

Notes: Clustered bootstrap standard errors with 1000 repetitions in parenthesis are given for robust inference. Significance: * =10%, **=5% or less. Dummies for years are not shown.

Table 6: Second stage of unbalanced fixed effects model with Two Stage Least Square (2SLS) estimates.

3.1.4. Heterogeneous response

To check for differing responses of farms at different gradient of field-slopes, we estimated heterogeneous response model in two ways. The first one is a fixed effects unbalanced panel estimation, the second one contains fixed effects 2SLS panel estimation where long-term precipitation is corrected for measurement error bias. In both specification climate shock variable is interacted with field-slope dummy for a farm. *Table 7* shows that in both heterogeneous response models, the interaction terms with shock variables are statistically significant. This means that farms on slopped land respond differently to climate anomalies than those on flat land. We find long-term temperature jointly significant with squared, shock and crossed terms for the heterogeneous response model without 2SLS in column 1 (p-value 1.9E- 15) and the heterogeneous response model with 2SLS in column 2 (p-value 5.99e-16). First stage of the 2SLS can be found in *Table A 6* and endogeneity test results in *Table A 7* in appendix.

	Heterogeneous response to climate shocks			Heterogeneous response to climate shocks (2SLS)		
	Est.	St. error (Robust)		Est.	St. error (Bootstr.)	
Temp. longterm	0.3903	(0.4012)		0.3623	(0.4792)	
Temp. longt. squ.	-0.0197	(0.0101)	*	-0.0178	(0.0118)	
Temp. shock	-0.0420	(0.0156)	**	-0.0413	(0.0169)	**
Preci. longt. +	0.0638	(0.0108)	**	0.0625	(0.0151)	**
Preci. longt. squ. +	-0.0002	(5.0E-05)	**	-0.0002	(0.0001)	**
Preci. Shock	-2.9E-05	(1.4E-05)	**	-3.0E-05	(1.4E-05)	**
Land: 'arable'	-0.0061	(0.0013)	**	-0.0059	(0.0020)	**
Land: 'grass'	-0.0009	(0.0008)		-0.0008	(0.0012)	
Subsidies	0.0002	(4.1E-05)	**	0.0002	(0.0001)	**
Temp.shock: slopped.land	-0.0715	(0.0104)	**	-0.0694	(0.0122)	**
Preci.shock: slopped.land	0.0001	(2.2E-05)	**	0.0001	(2.5E-05)	**
R^2	0.7583			0.7583		
Observations	26,248			26,248		
No. of farms	2881			2881		
		p-value			p-value	

Weak instrument test	---	2.2E-16
Over-identification test	---	0.7733
Endogeneity test (F-test significance of all residuals)	---	0.0038

Notes: Clustered bootstrap standard errors with 1000 repetitions in parenthesis are given for robust inference. Significance: * =10%, **=5% or less. Dummies for years are not shown.

Table 7: Heterogeneous response by farmers to climate shocks: without and with 2SLS.

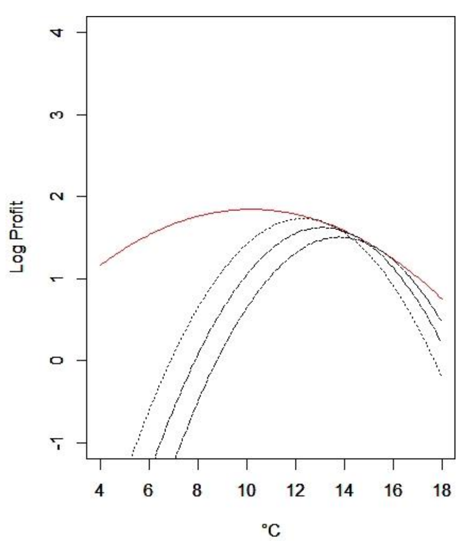
Results based on both heterogeneous response model estimates lead to the same qualitative results, but the 2SLS results (column 2 of *Table 7*) have slightly lower coefficients for meteorological variables than the model without 2SLS (column 1 of *Table 7*). Individual coefficient for residuals in endogeneity-check are insignificant (see online appendix) however, joint significance test shows otherwise. As both of the columns have similar results, we used 2SLS heterogeneous response model results for further prediction. Results show that a year that is one standard deviation (1.46°C) warmer or cooler than past average induces an average profit reduction of 6.03% in average profits of farms with flat land and an additional 10.13% reduction for farms with slopped land. Putting it another way, this means that farms on slopped land possess more adaptation potential to climate change induced temperature increase as compared to farms on flat land.

In case of precipitation, adaption potential in the short run is smaller than in the long run for flat land farms as we would expect (i.e., a negative sign of precipitation shock): one standard deviation (24.7 mm/month) drier or wetter growing season induces a reduction of 0.07% in profits on average. For farms on slopped land, the overall effect of precipitation anomaly is positive like in Moore and Lobell (2014). This is true for both estimates in *Table 7*. Low adaptation potential of farms on slopped land with respect to precipitation might make sense as they are solely relying on rain fed area and they focus on activities which are not affected as much by precipitation shocks (e.g. livestock rearing).

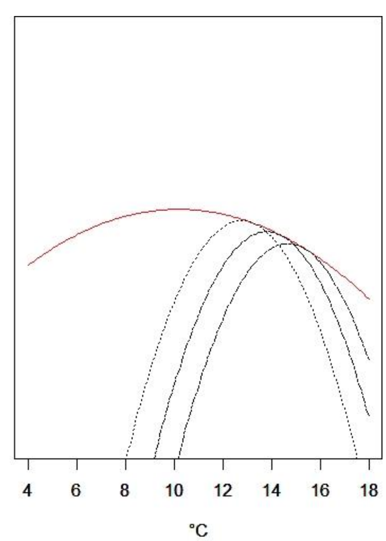
Figure 2 shows long run and short run response curves for temperature and precipitation. These curves have been computed on the basis of heterogeneous response model in *Table 7* column 2. The short-run response curves show the short-run profit without adaptation at the 25th, 50th and 75th percentile. Solid lines are long-term profits curve, say for temperature. The long-term curve describes the relationship between temperature and profits with farmers using their full adaption potential. Dotted lines describe the short run profits curves for different quantiles of farmer (with respect to temperature they are facing). For example, a farmer facing a median value of temperature (long-run) will have short run profit curve in the middle (out of three dotted lines). The point where the long-term and the short-term curves converge depicts the situation with a zero temperature shock. As the shock increases, the difference between long-term and short-term profits, i.e. the vertical difference between the two lines (solid and dotted), increases.

Short run profits are always lower than long run profits for temperature and for farms (with flat land) in case of precipitation (panel A, B and C). However, profits from farms (with slopped land) in the long run are below their short run profits in case of precipitation (panel D). This “over-adaptation” is difficult to explain but has likely to do with farms (with slopped land) not having a lot of option of adapting to precipitation shocks. Over-adaptation is severe though, only for very high precipitation values (the 75th percentile of precipitation is 103.8 mm/month) and may indicate a major change in agricultural activity.

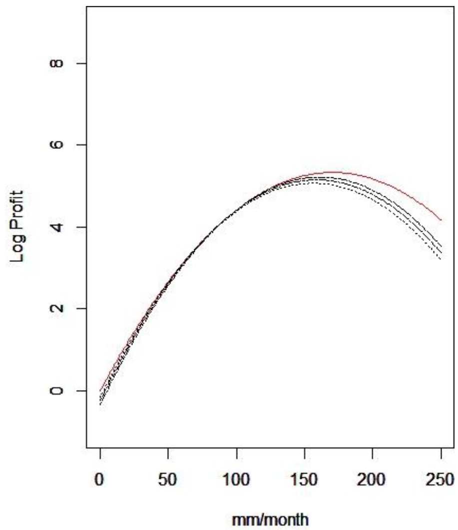
A: Temperature response curves for farms with flat land



B: Temperature response curves for farms with slopped land



C: Precipitation response curves for farms with flat land



D: Precipitation response curves for farms with slopped land

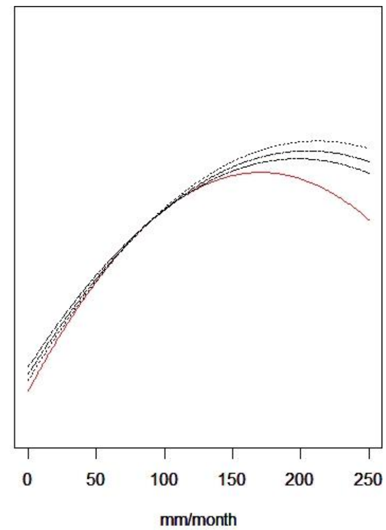


Figure 2: Long-run (red line) and short-run response curve at 1st, 2nd and 3rd quartiles of growing season temperature and precipitation.

Figure 2 show that adaptation potentials are much higher for temperature and less for precipitation as short run curves sharply fall apart from long run curve within the climate ranges for Austrian farm. Our results are in line with Moore and Lobell (2014) in regard to the inverse U-shaped response curves for farm profits (see *Figure 3*). But our individual farm level data shows a much more sensitive relationship between climate change and farm profits: all of the coefficients of meteorological variables have higher magnitudes. This was expected because Moore and Lobell (2014) used NUTS-3 averages whereas we used farm level data. Reidsma et al. (2010) showed individual level results may vary from aggregated level results because aggregation leads to loss of heterogeneity within aggregated unit and this may lead to weaker relationships. Moreover, Fezzi and Bateman (2015) also argues that individual farm values show more sensitive relationship to climate as compared to aggregated unit of analysis. Additionally, values for Austria can, indeed, be different than for the countries analysed in Moore and Lobell (2014).

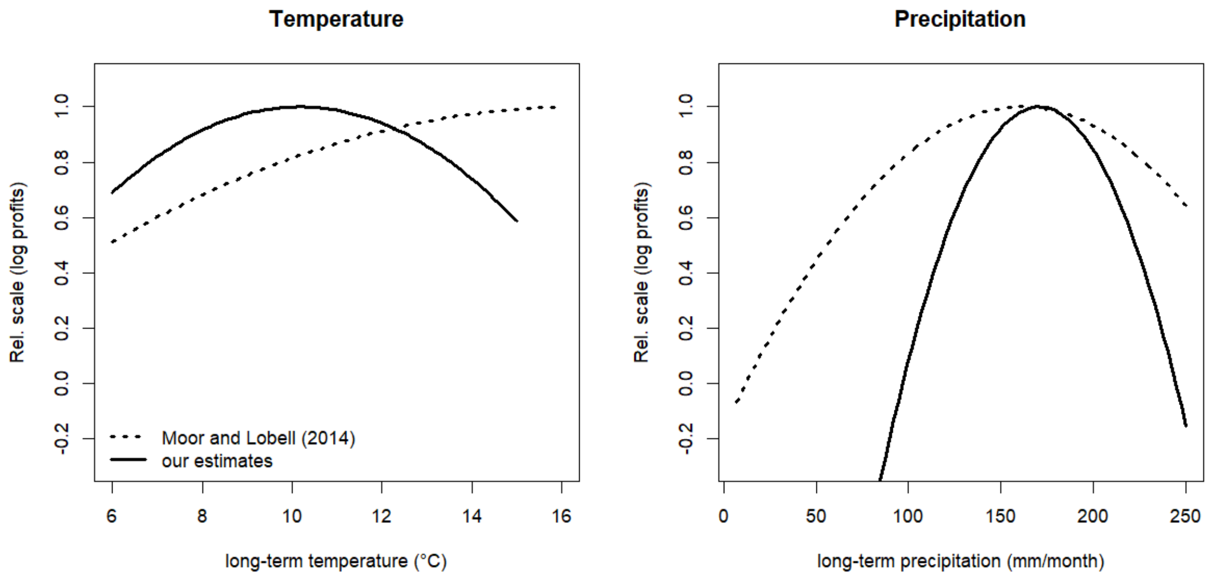


Figure 3: Comparing our long run response curves with results from Moore and Lobell (2014).

Description: Curves are scaled to have a maximum at 1. In both climatological variables, the response curves for individual farm level analysis for Austria are more sensitive compared to subnational level analysis covering 11 other EU countries.

3.1.5. Out-of-sample testing

As Blanc and Schlenker (2017) mentioned that out of sample accuracy may easily be computed with panel data models, so we checked for the out of sample accuracy of our regression model results in *Table 7* by keeping one year out, and predicting dependent variable for left out year. *Table 8* shows Theil's UII coefficients for the past 13 years. We find that in 12 out of 13 predictions, the model performs better than a naïve prediction (the profit does not change from one year to the next), as Theil's UII value is below 1. On average, Theil's UII coefficient is 0.78. Additionally, the predictions do not include the time-fixed effects and thus the Theil's UII measure underestimate the accuracy of our model.

Year	Theil's UII
2016	0.83
2015	0.71
2014	0.81
2013	0.70

2012	0.77
2011	0.75
2010	1.05
2009	0.53
2008	0.67
2007	0.78
2006	0.97
2005	0.61
2004	0.99

Table 8: Leave-one-out model validation with Theil's UII values.

3.1.6. Seasonal construct of metrological variables

So far regression results from model-I have been presented. In this sub-section, we present results related to model-II which uses seasonal averages instead of averages of the growing season. The first column of the *Table 9* shows the pooled regression results for the specification in equation **(11)** using seasonal averages of meteorological variables (model-II) defined in equation **(13)**. Similar to the pooled regression results for model-I in *Table 4* column 1, it is controlled only for the observed variables: agricultural production area dummies, soil and farmer's education variables, altitude and livestock share dummy. Therefore, omitted variables may bias the coefficients of climate variables. The second column of *Table 9*, shows the fixed effect regression and therefore it is controlled for all (observed and unobserved) time constant effects just like column 2 of *Table 4*. The coefficients of explanatory variables differ between column 1 and column 2 with respect to magnitude. However, the sign stays the same for most of the variables except for precipitation. As previously seen in *Table 4*, the coefficient of cross-sectional regression may be biased, therefore we interpret the fixed effect regression coefficients, only.

	Pooled			Fixed effects		
	Est.	St. error		Est.	St. error	
Temp. winter	-0.0001	(0.0207)		-0.0459	(0.0112)	**
Temp. winter. squ.	-0.0034	(0.0017)	**	0.0001	(0.0012)	
Temp. spring	0.2699	(0.0519)	**	0.0257	(0.0353)	
Temp. spring. squ.	-0.0032	(0.0023)		-0.0036	(0.0016)	**
Temp. summer	-0.3634	(0.0889)	**	-0.2782	(0.0636)	**

Temp. summer. squ.	0.0100	(0.0024)	**	0.0053	(0.0016)	**
Temp. autumn	0.1806	(0.0605)	**	0.1443	(0.0395)	**
Temp. autumn. squ.	-0.0138	(0.0028)	**	-0.0095	(0.0019)	**
Preci. Winter	0.0006	(0.0009)		-0.0002	(0.0005)	
Preci. winter. squ.	-3.8E-06	(4.0E-06)		2.7E-07	(2.3E-06)	
Preci. Spring	0.0058	(0.0013)	**	-0.0026	(0.0008)	**
Preci. spring. squ.	-1.9E-05	(7.0E-06)	**	1.6E-05	(4.0E-06)	**
Preci. Summer	0.0009	(0.0009)		-0.0026	(0.0005)	**
Preci. summer. squ.	-7.5E-07	(3.2E-06)		6.8E-06	(2.0E-06)	**
Preci. Autumn	0.0023	(0.0010)	**	-0.0006	(0.0006)	
Preci. autumn. squ.	-1.6E-05	(4.2E-06)	**	3.9E-06	(2.4E-06)	
Land: 'arable'	-0.0101	(0.0008)	**	-0.0068	(0.0013)	**
Land: 'grass'	-0.0091	(0.0010)	**	-0.0022	(0.0008)	**
Subsidies	0.0009	(0.0001)	**	0.0002	(4.2E-05)	**
R^2	0.2848			0.7585		
Observations	26248			26248		
No. of farms	2881			2881		

Notes: Robust standard errors in parenthesis. Significance: * =10%, **=5% or less. Dummies for years have not been shown in all three models. Whereas for pooled regression other variables i.e. regions, farmer's education, soil type, soil quality, altitude, livestock intensity and constant are not shown.

Table 9: Results of pooled and fixed effects for model-II (using seasonal construct of meteorological variables).

The second column of *Table 9* shows that the seasonal variation of temperature and precipitation have heterogeneous effects on profits with respect to direction and magnitude. Based on the joint significance of the linear and the squared terms (not shown), all coefficients are significant. The only exception is precipitation in winter. Interestingly, for most seasons the inverse u-shaped form, as found in model-I, cannot be confirmed. Only for spring and autumn temperature an inverse u-shaped form is confirmed: the maxima are 3.58 °C for spring and 7.59 °C for autumn. The median values for the sample of Austrian farms show hotter conditions i.e. 9.54 °C and 9.58 °C (see *Table 1*). This confirms results found in model-I (compare coefficients with *Table 4*) where a further increase (beyond the median for all farms) in long-term temperature tend to have profit decreasing effects. U-shaped relationships are difficult to interpret: there is no temperature or precipitation to maximize profits but just a minimum. It is note-worthy that in the OLS model an inverse u-shape is observed in two out of eight seasons constructs. Deschênes and Greenstone have rightly pointed out that in a model with farm fixed effect, random variation in seasonal weather at each farm over a year is responsible for identification of parameter (Deschênes & Greenstone, 2007). Since Van Passel et al. (2017) also find some seasons with u-shaped parameters this could be an explanation for this phenomenon.

The coefficients of the farm specific, time-varying variables of arable land share and 'subsidy per ha' are significant and almost identical to model-I in tables *Table 4*, *Table 5*, *Table 6* and *Table 7* except for grass share which is insignificant in model-I. The coefficients of land use shares (arable land and grass land) are both negative as in all estimates of model-I. The almost similar R^2 in all regression specifications and *Table 4*, *Table 5*, *Table 6*, *Table 7* and *Table 9* indicates that fixed effects are explaining a considerable part of the variance of the explained variable. Measurement related bias may be pronounced in such cases (Fisher et al., 2012).

Given the identification issue pointed out by Deschênes and Greenstone (2007) future estimates of climate change impacts using out of sample predictions too far into the future may be questionable when using model-II. We used estimated coefficients from model-II (and model-I) to predict change in Austrian farm profits for 2040 as compared to 2016. In fact, inherent shortcomings of econometric estimation methodologies (first of all the influence of prices), hinder predicting impacts of climate change too far in future like 2100.

3.2. Results of uncertainty analysis

3.2.1 Predictions for climate change impacts

After identifying the influence of climate on profits, the estimated coefficients along with future climate data are used to predict changes in farm profits. We used estimated coefficients from model-I (based on Moore and Lobell (2014) methodology) and model-II (based on seasonal construct of meteorological variable as used in Van Passel et al. (2017)). We use the simple specification of model-I as described in and *Table 4* column 2 to remain comparable to Moore and Lobell (2014). However, predicted impacts based on different specifications of model-I (for example, heterogeneous response) yield similar results. In case of model-II, we use the specification in and *Table 9* column 2 for predicting climate change impacts and their uncertainty analysis.

Figure 4 shows the boxplot of predicted change in profits of 2881 farms in Austria for 2040 compared to the base year of 2016. We use estimated coefficients from both regression models (model-I and model-II) along with future climate values from 13 climate models for two emission scenario. Emission scenario RCP 8.5 is based on “business as usual” whereas RCP 4.5 is based on a moderate CO_2 emission reduction. This gives $13×2×2=52$ predictions of climate change impacts at each farm. Predictions have been grouped with respect to five GCMs namely, CNRM-Cerfacs, EC-EARTH, IPSL-CM5A, MOHC-HadGEM and MPI-ESM. RCMs are used to downscale predicted climate to finer resolution. The predictions based on regional models also differ greatly in between as can be seen from different impacts using the same GCM combined with different RCM. MPI-ESM and HadGEM show extreme shifts in impact using the same emission scenario but with different RCM (i.e. CLMcom, INERIS and SMHI).

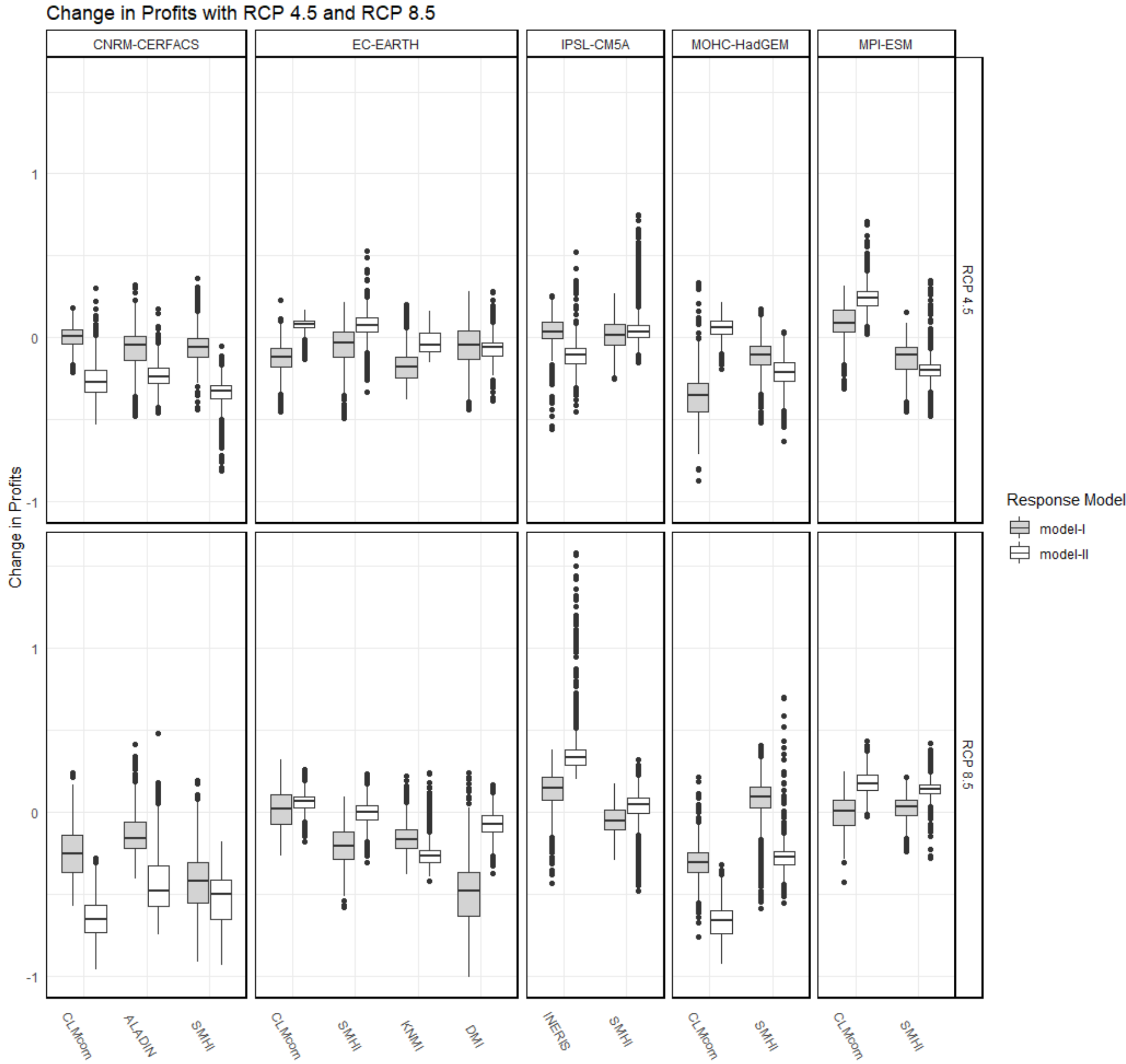


Figure 4: Boxplot of predicted impacts with the model-I and the model-II using different GCMs and RCMs for Austria.

Both models predict an on average negative effects of climate change on Austrian farms for both emission scenarios. For most of the climate models, predictions based on seasonal variation (model-II) are more pronounced compared to the long-term variation method (model-I). As expected, profit losses are lower in RCP 4.5. The averages of the mean prediction (i.e. $\widetilde{\Delta y_i}$) for Austrian farms with model-I and model-II show a decrease of 6.5% and 10.6% in farm profits respectively in case of RCP 4.5. Employing RCP 8.5, averages from mean prediction are -11.6% and -16.8% with the model-I and the model-II respectively. Considering the assumptions of the model, the predictions only inform about the changes in profits due to change in climate variables keeping the input-output price ratios constant.

3.2.2. Uncertainty analysis of predictions:

Although the average of the mean prediction (i.e. $\widetilde{\Delta y_i}$) from Austrian farms is negative with both econometric models, there are individual farms which may gain i.e. farms have predicted positive impacts of climate change with one climate model. Using model-I or model-II, there are 13 predictions of climate change impacts on individual farm in each emission scenario. To look at the direction and precision of these predicted impacts, we counted number of positives (when predicted change is greater than zero) and spatially display them with the variance based on all 13 predictions at each farm. This spatial distribution of the predicted impacts tells us that the number of positive predictions from both econometric models tend to partially agree, especially for the alpine regions. We present here RCP4.5 case (see *Figure A 6* for RCP 8.5 case). The number of prediction which are greater than zero (positives for one farm) varies across Austria: predictions based on model-I have relatively higher positives compared to predictions based on model-II. Colour gradient in *Figure 5* represents number of positives and size of the dot represents variance based on all 13 predictions.

Based on model-I, minimum number of positive predictions for a farm is 0 and maximum is 13 whereas for model-II the minimum is 1 and maximum is 8. Similarly, variance in the predicted impacts has a range of 5 to 608 for model-I and 81 to 2259 for model-II. To keep the figure simple and comprehendible, we group number of positive predictions into four classes i.e. 2 or less, 3 to 4, 5 to 6 and 7 or more. Similarly, the variance of predicted impacts has also been categorised into three different levels where lower variance means more precise predicted impacts. The variance of prediction in model-II is substantially higher than in model-I. This is true for RCP 4.5 and RCP 8.5. The variance in predicted impacts of climate change shows similar spatial distributions in model-I and model-II. The variance is lowest along the Alpine ridge, in particular in central Austria and to a lesser extent in the alpine regions towards the west. The highest number of negative predicted farm profits is observed for farms in the north of the alpine ridge (nördliches Alpenvorland) as well as on the southern board of Austria in Carinthia and Styria.

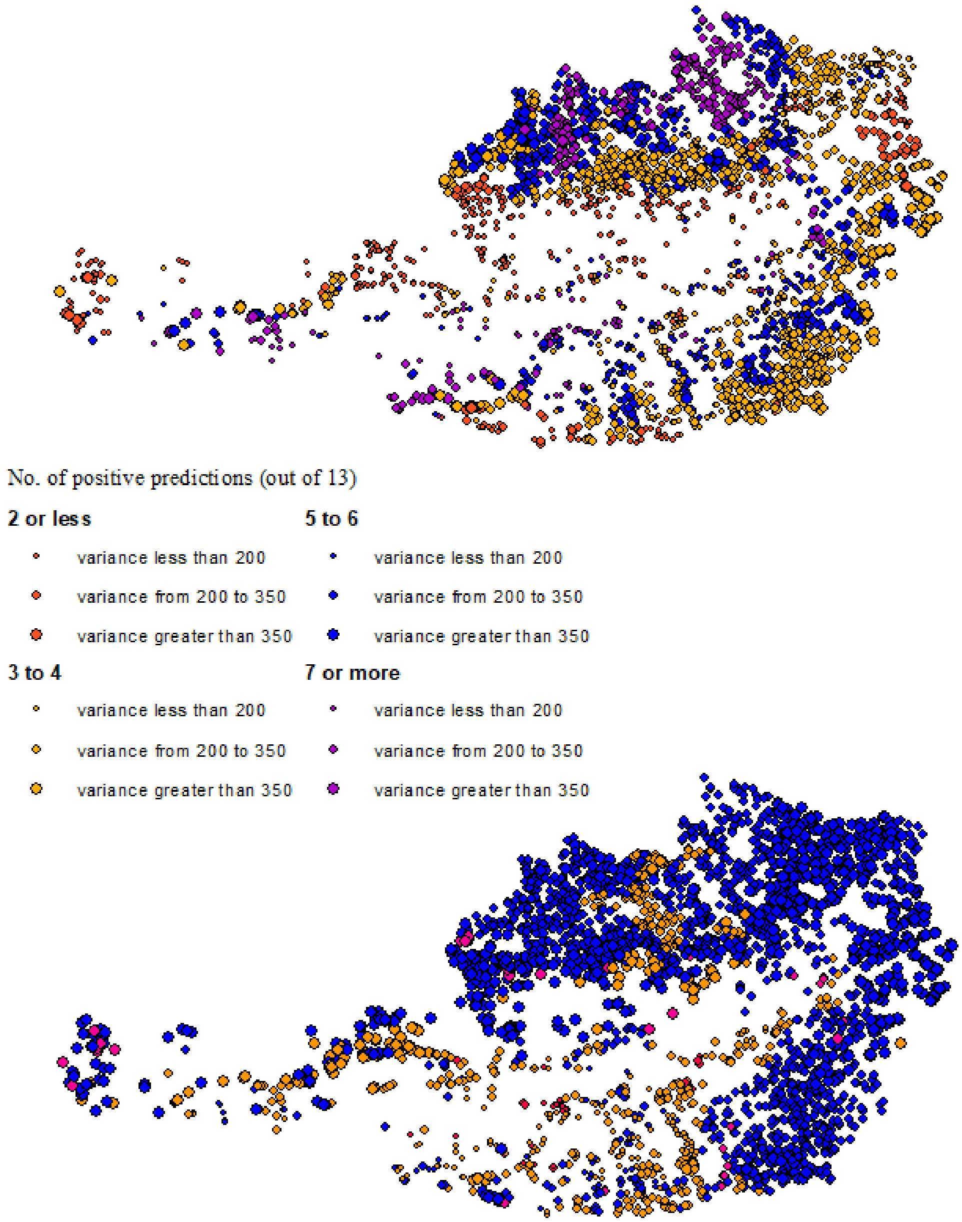


*Figure 5: Number of positive predictions and variance of predicted impacts at each farm using all of the 13 climate models with RCP 4.5 based on the model-I (**top**),model-II (**bottom**).*

Obviously, this count measure does not give any information on the magnitude of losses. This can be a reason why the East of Austria, which is often considered as being particularly susceptible to climate change, does not seem to be that affected according to this way or representing climate change impact. Given the large difference in different predictions shown in *Figure 4* and the higher variance of predictions in the East this seems likely and is also confirmed by the figures about spatial distribution of losses below (*Figure A 8*).

To answer which meteorological variable makes the predicted impacts negative or positive, we look at the density plot of all the predictions with respect to meteorological variables and their total (sum) impacts. We split up the predicted impacts of climate change to its parts i.e. temperature related impact and precipitation related impact. *Figure 6* demonstrates the influence of each meteorological variable on overall sign of the predicted impact. We find that predicted impacts caused by temperature changes are dominant in deciding the direction of total impact for both econometric models and are mostly negative. In case of model-I, precipitation impacts tend to partly offset temperature effects. Predictions based on the model-II almost entirely come from temperature changes (*Figure 6*).

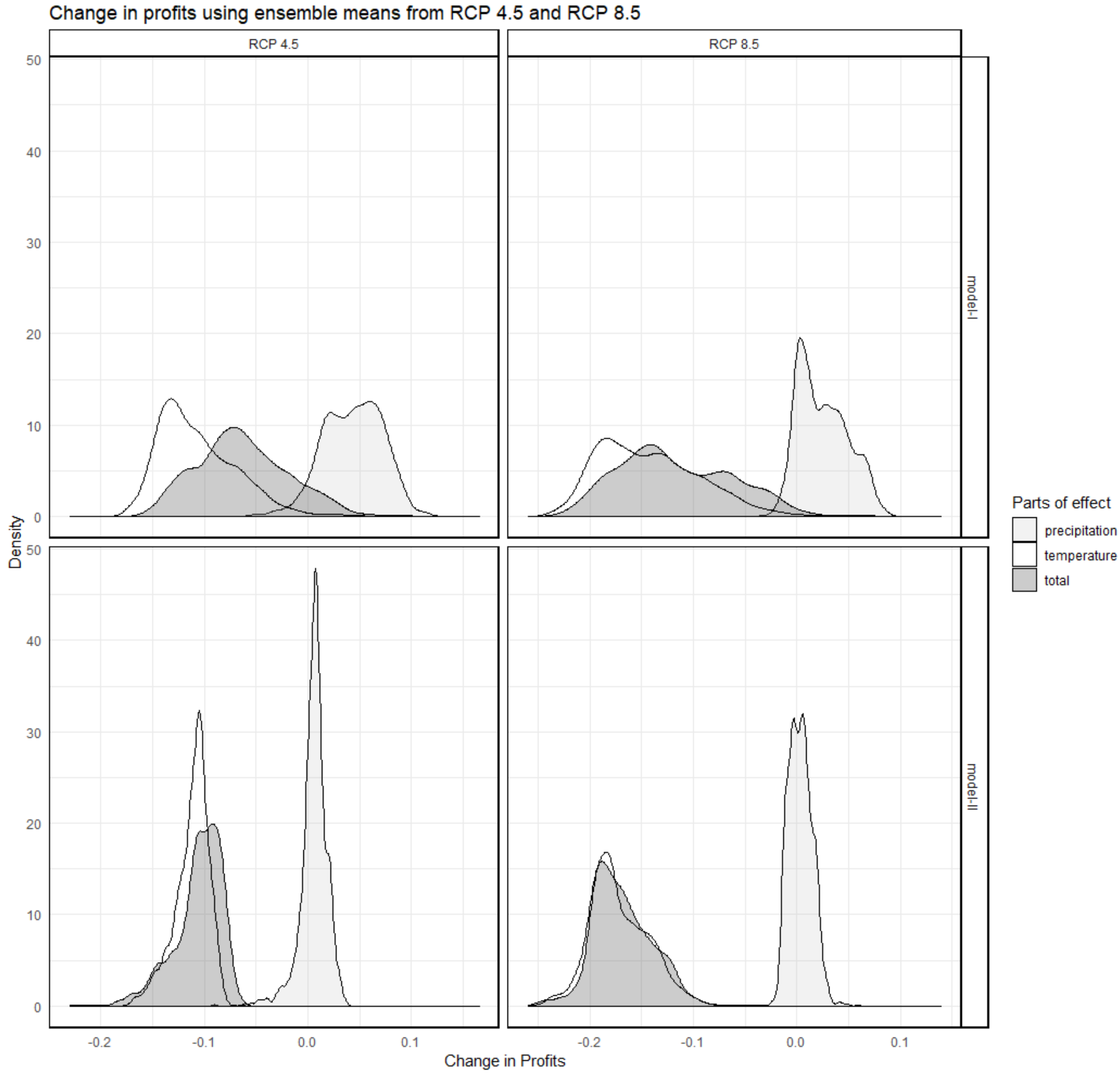


Figure 6: Density plot of predicted impacts with both econometric models under two emission scenarios.

3.2.3. Uncertainty split up

Figure 7 shows the decomposition of the uncertainty using both econometric models and 13 climate models under two emission scenarios each. We decompose the total variance of predicted impacts into three sources i.e. climate model related uncertainty, regression specification related uncertainty and response model related uncertainty.

In our case the contribution of uncertainty is as follows: in the predicted impacts based on the RCP 4.5, the climate model uncertainty constitutes 67.15% of the total uncertainty. In RCP 8.5 this share is even higher with 78.54%. This is probably due to a greater uncertainty from the climate models in the "business as usual" scenario. Clearly, the climate model related uncertainty drives the impact. Using multiple bio-economic models, Bregaglio et al. (2017) find similar results. In contrast, Iizumi et al. (2011) and Assenge et al. (2013) find that the uncertainty in response models (bio-economic models in their case) drives the uncertainty in predicted impacts.

The second source of uncertain impacts is the regression specification i.e. the model choice. It accounts for smallest share of total uncertainty in our case i.e. 4.43% in the RCP 4.5 and 3.07% in the RCP 8.5. However, we might underestimate this uncertainty because we only included two model specifications.

The third source of uncertainty is the standard errors of the estimated parameters in regression models. The response model uncertainty contributes to 28.4% of the total variance in the RCP 4.5 based predictions and a major share (28.1%) comes from the higher standard error of the temperature coefficients. In the RCP 8.5 based prediction, the uncertainty from climate models takes higher share and therefore, the share of response model uncertainty shrinks. As *Figure 6* and *Figure 7* depict, predicted impacts rely more on future temperature as compared to precipitation which may be due to higher coefficients of temperature and more significant change in the simulated climate.

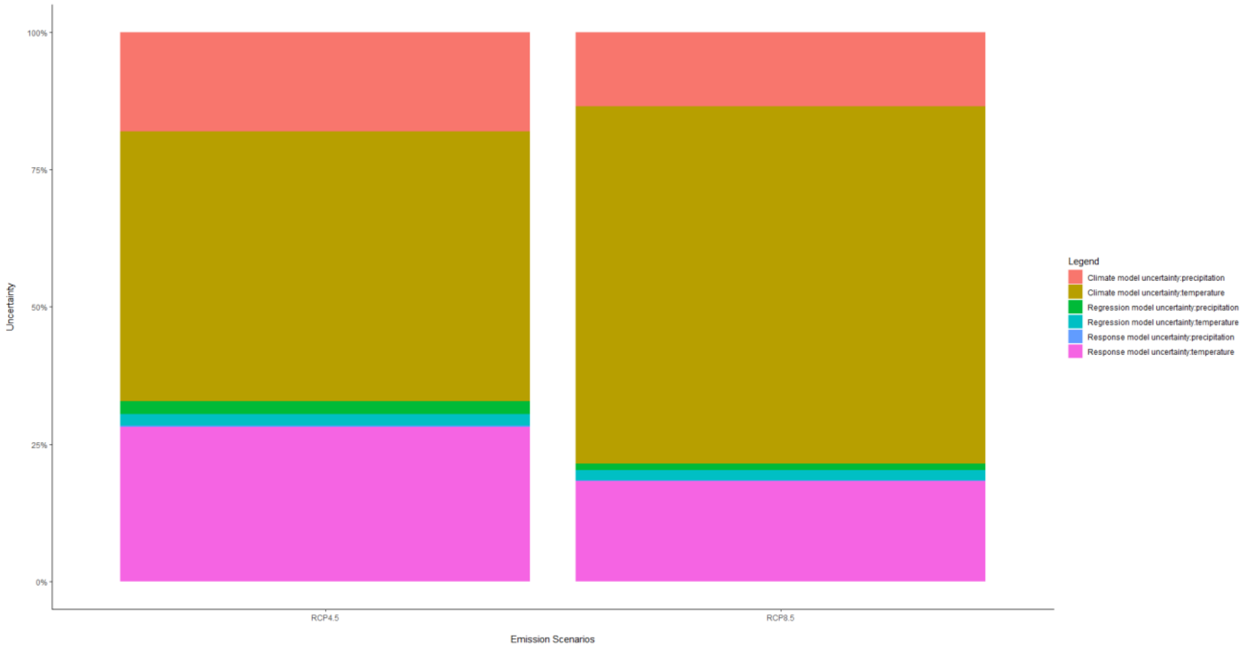


Figure 7: Uncertainty split-up for predicted impacts of climate change on agriculture in Austria based on estimated sensitivities in second columns of Table 4 and Table 9 along with future climate conditions in Table 2.

3.2.4. Adaptation potential

One of the advantages in using the Moore and Lobell (2014) approach (specified as model-I) is that it allows to estimate the adaptation potential of farms. The adaptation potential of Austrian farms is computed from the difference between long-term predicted impacts as in equation **(16)** and short-term predicted impacts as in equation **(17)**. The difference between long-term and short-term impacts comes from weather shock coefficients i.e. the last term of equation **(17)**. We use the estimated coefficients of the heterogeneous effect model from *Table 7* column 1 to compute adaptation potential of Austrian farms.

Using the coefficients from *Table 7*, ensemble means from all of the 13 future climate models and the two emission scenarios RCP 4.5 and RCP 8.5 a change in profits and adaptation potentials for the year 2040 are computed. As a base year for comparison, we use the 2016 observational data from Hiebl and Frei (2016, 2017). The change in climatic conditions for future year (2040) is based on simulated data from Chimani et al. (2016).

For both RCPs, farm profits are predicted to decline. Boxplots for changes in profits using column 1 of *Table 7* are shown in appendix *Figure A 7*. The ensemble means from future scenario for RCP 4.5 predicts hotter and relatively wetter climatic conditions for the growing season in Austria, therefore, negative effects on farm profits are less severe compared to business as usual emission scenario with even hotter growing season of RCP 8.5. The vast majority of the 2,881 farms included in the analysis are going to lose without adaptation (see *Figure A 8*) from climate change under RCP 4.5 (compare *Table 2*): the average profit decreases by 4.4%, the median by 4.5%. This is mainly due to the increase in the long-term growing season temperature (mean: +0.55°C) while the increase in precipitation (mean: 1.95 mm/month) plays a secondary role. With adaptation majority of farms gain due to climate change though slightly. However, the mean change is still negative. The mean profits decrease by 2.5% and the median by 2.6% with adaptation in RCP 4.5.

In the RCP 8.5 the majority of farms will lose profits and losses are higher: without adaptation the average loss is 10% and the median loss is 10.7%. With adaptation the mean loss is 7.1% and the median is 7.9%. Compared to RCP 4.5, losses are higher because the temperature raise (mean: +0.61°C) is accompanied by a lesser increase in precipitation (mean: +0.93 mm/month). The adaptation potential in RCP 8.5 is slightly higher than in RCP 4.5 because the long-term changes are higher in this scenario. The estimated adaptation potential is in the range of the estimates by Moore and Lobell (2014) even though it is not directly comparable since their base year is 1975 and they used 11 EU countries other than Austria. Finally, the impacts of RCP 8.5 are more uncertain as compared to RCP 4.5 (the boxplots of RCP 8.5 in *Figure A 7* have a wider spread).

Spatial distribution of climate change impacts with adaptation and without adaptation in both of the emission scenarios (i.e. RCP 4.5 and RCP 8.5) are given in appendix (see *Figure A 8*). Spatial distribution of adaptation potential in case of RCP 8.5 is presented in *Figure 8*. Adaptation potential of 1.5 to 7.6 percentage points may slightly attenuate the negative impacts of climate change overall (average losses reduces from 10% to 7.1% as mentioned above). However, it does not convert all loosing farms to profiteering farms. As expected, adaptation potential is higher for those farms which are situated on high elevation. However, this result must be seen in light of the limitation of the econometric approach: as high elevation farms (mostly grasslands livestock) cannot be readily converted to crop farms due to steepness of the slope of a farm.

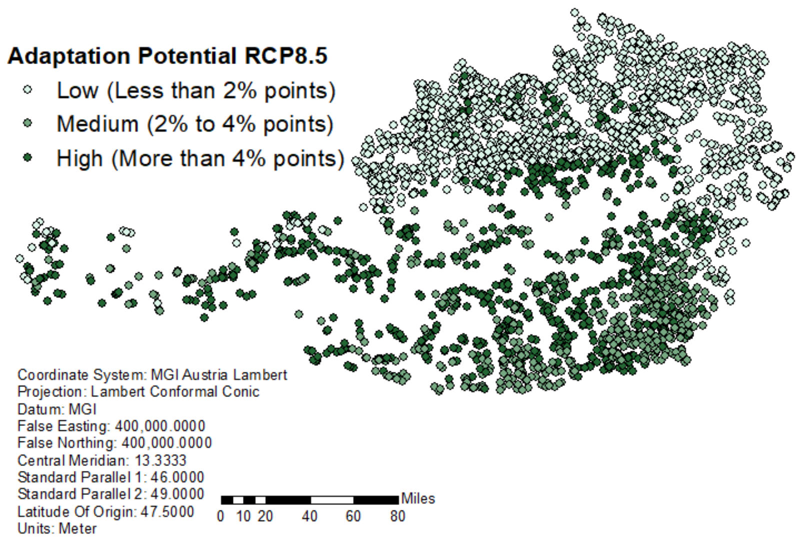


Figure 8: Adaptation potential for Austrian farmers based on RCP 8.5 emission scenario and results from estimates in Table 7. The adaptation potential has been categorized into three parts. It ranges between 1.5% to 7.6%-points.

4. Discussion and conclusion

Climate change econometrics based on farm level panel data has the advantage in accounting for farm heterogeneity (e.g., climatic conditions, farm management, subsidies and workforce) as opposed to aggregated 'unit of analysis' which uses districts, counties or NUTS-3 averages. Moreover, this kind of analysis may reveal the within region heterogeneity of climate change impacts and is therefore complementary to econometric climate change impact assessment based on regional data and comparative to small area impact assessment based on integrated bio-economic simulation models.

To fully benefit from the advantages of farm-level studies, detailed data are necessary. We have demonstrated for Austria how farm accounting data, interpolated meteorological data and climate scenarios can be combined to access climate impact on the farm level. Similar farm accounting data is usually available for most countries. For our data and the model applied, we were able to demonstrate that: 1) omission bias in pooled OLS regression is evident and fixed effects can control for time invariant factors involved; 2) including sunshine duration, in our case does not significantly change the estimated impact of temperature and precipitation, but modelling the biophysical aspects of the response models with alternative / additional variables is an option for future research; 3) endogeneity due to measurement errors in temperature and precipitation variables (with finer resolution) must be considered for such micro level studies; 4) heterogeneous response of agricultural farms towards climate change is an issue, especially for countries (regions) with heterogeneous farming patterns. In our case farms with slopped land respond differently to climatic shock compared to farms with flat land; 5) using a model with seasonal contemporary meteorological averages (as opposed to long term averages combined with weather shocks) resulted in difficult to interpret coefficient which suggests shortcomings in the strategy; 6) similar to bio-economics simulation models, econometric models can be used to decompose uncertainty in the predicted impact of climate change what is key for better policy guideline; and 7) we complemented the existing climate change impact estimates for Austria which have previously been undertaken with bio-economic simulation approaches only or with aggregated units of analysis in econometric approaches.

Omission bias in the econometric studies on climate change impact assessment has been already researched by many authors (Blanc & Schlenker, 2017; Deschênes & Greenstone, 2007; Fezzi & Bateman, 2015; Fisher et al., 2012; Zhang et al., 2017). Carter et al. (2018) concludes that panel data models have a clear advantage by being able to control for time constant unobserved heterogeneity. They are superior to cross-sectional estimations which are sensitive to the choice of control variables (Deschênes & Greenstone, 2007). However, most of the panel data models are only able to capture short-term weather effects (Blanc & Schlenker, 2017; Deschênes & Greenstone, 2007; Hsiang, 2016). Following Moore and Lobell (2014) (our model-I), we found different coefficients with pooled regression as compared to panel regression model. This difference may indicate omitted variable bias problem associated with cross-sectional approaches or sensitivity in selecting control variables (Deschênes & Greenstone, 2007).

Omission of time varying variable is one reason why estimated coefficients could be biased in a panel data model as has been discussed elsewhere (Zhang et al., 2017). We found that omission of sunshine duration does not bias coefficients of long-term climate variables. However, inclusion of sunshine duration provides the opportunity to model the bio-physical part of the model differently. Other climate variables could also be used to access omitted time varying variables, for example, humidity, air pressure, wind speed, soil moisture, evapotranspiration etc. However, including more explanatory variables may pose multi-collinearity issues (Carter et al., 2018).

Another aspect which needs attention is that the inclusion of fixed effects implies that estimated coefficients are identified by the variation in climate variables conditioned on fixed effects leaving the model more prone to measurement error biases (Auffhammer et al., 2013). Therefore, accuracy of explanatory variables especially meteorological variables becomes important. Especially, considering that meteorological data comes from meteorological stations which may be situated at different place than the observed agriculture data. Blanc and Schlenker (2017) compared different types of climate data and find that interpolated data is less prune to measurement error bias in panel data models. We also used interpolated climate data for Austria (Hiebl & Frei, 2016, 2017; Olefs & Koch, 2013) and we employed 2SLS method to potentially solve the problem of measurement error related bias. Results found that no measurement bias exist in case of temperature however, precipitation was found to be endogenous in one of the models. Applying 2SLS using spatial lags as instruments (Anselin et al., 2008), we find estimated coefficients to be very similar to those estimated without 2SLS.

In their review on econometric impact assessment of climate change, Blanc and Schlenker (2017) pointed out one of the prospects for future research with panel data model will be the estimation of heterogeneous effects. Cai *et al.* (2014) used geographically weighted panel data regression to see heterogeneous impact of climate change on yield of maize in the US. Van Passel et al. (2017) used farm types to capture heterogeneous impacts of climate with a caution that the farm type may be endogenous. Lippert et al. (2009) note that slope of a farm land decides the production focus and is also correlated to climate variables for Germany. It is a time constant factor which makes it a good variable to capture heterogeneous impacts of climate on farms with different focus. We found heterogeneous impact of weather shock on farms with differently slopped land. Our slope variable is independent of weather shocks which makes it exogenous contrary to farm types utilized by Van Passel et al. (2017). Furthermore, we also used this heterogeneous response of weather shock to compute adaptation potential of Austrian farms on the lines of the Moore and Lobell (2014) methodology.

Massetti et al. (2016) and Schlenker and Roberts (2009) studied the effects of seasonal averages versus growing season averages in the context of climate change impacts on agriculture. Both of them find that seasonal climatic conditions differently capture climate change impacts on agriculture. We used seasonal construct of meteorological variables (our model-II) in addition to growing season averages (our model-I). We found that seasonal variables capture climate-agriculture response relationship differently. Our estimated coefficients form the fixed effects model, though, were difficult to interpret. This observation has previously also been made by Van Passel et al (2017). It is likely related to the joint use of seasonal averages and yearly time fixed effects as has been discussed by Deschênes and Greenstone (2007).

We also used the predicted impacts of climate change based on model-I and model-II to analyse the influence of the modelling decisions on predictions and on uncertainty of estimated impacts. Such a multiple model impact assessment is a norm in bio-economic model studies and a priority of the large agricultural climate research initiative AgMIP (Agriculture Model Inter-comparison and Improvement Project). On one hand, multiple model impact assessment provides the opportunity to analyse the uncertainty attached to predicted impacts of climate change for better policy making. On the other hand, it is easy to compare predictions of climate change impacts across different models. We present two econometric response models to show congruence and divergence in predicted impacts of climate change. Therefore, our work with panel data econometrics contributes to the research agenda of the AgMIP initiative which works on multi-model impact assessment and aggregation issues for bio-economics simulation models.

Our predicted impacts of climate change are derived from estimated regression coefficients and future climate scenarios for Austria. Comprehensive future climate information is required for reliable inference in climate change impact studies to avoid the reliance on some outlier climate model outcome. Burke et al. (2015) discussed the shortcomings of earlier well cited studies who predicted impacts of climate change with 2 climate models on an average. This over reliance on few climate models puts less faith in predicted impacts and may lead to poor policies. We employed 13 bias corrected climate model outputs (Chimani et al., 2016) for predicting the future climate for Austrian farms. These climate model outputs were built from 5 Global Climate Models (GCMs) downscaled with 6 Regional Climate Models (RCMs) to the same resolution of observed meteorological data, as we have. For our study, we only used two Representative Concentration Pathways (RCP 4.5 (Effective Measure) and RCP 8.5 (Business as Usual) described in Moss et al. (2010) in the fifth International Panel on Climate Change Report (IPCC, (2013)).

Inherent limitation of the econometric approaches, hinders them to be used for predicting climate change impacts too far in future and with too big changes in climate compared to observed changes in climate (Blanc & Schlenker, 2017; Deschênes & Greenstone, 2007). We used 2040 as a future year for our climate change impact estimates (predictions) compared to the base year 2016. Both models (model-I and model-II) predicted negative impacts of climate change on Austrian agriculture. In the RCP 4.5 (moderate reduction of CO_2 emission), model-I predicts on average 6.5% loss in profits while model-II predicts 10.6%. The situation with the RCP 8.5 (business as usual emission scenario), is even more severe with a decline of on average 11.6% and 16.8% of profits using model-I and model-II respectively. The losses under both emission scenarios occur due to temperature increase on average. A slightly higher increase in precipitation compensate losses in case of RCP 4.5 as compared to RCP 8.5.

Using 26 predictions (13 climate model and 2 sets of regression model coefficients) of climate change impacts at each farm, we are also able to conduct an uncertainty analysis and decompose the uncertainty into its different sources (temperature vs. precipitation as well as climate model vs. econometric model specification vs. standard error of estimated coefficients). The RCP 8.5 predictions of climate change impacts on Austrian agriculture are more uncertain compared to the RCP 4.5. This was expected because of the climate being more uncertain with business as usual emission scenario (RCP 8.5) compared to the case of radiative enforcing to control emission (RCP 4.5). Temperature variation in future climate condition is more influential than precipitation and leads the direction of predicted impacts on farms. This may either be due to bigger temperature changes in future compared to precipitations changes or changes in temperature are more important to the outcome as of precipitation are. We decompose the uncertainty of predicted impacts of climate change with respect to different sources i.e. uncertainty contributed by climate models, uncertainty related to standard errors of response models (regression models in our case) and uncertainty related to choice of regression model. climate model related uncertainty, standard.

Using econometric models for climate change impact assessment, we find that climate model related uncertainty outweighs the other sources of uncertainty (67% to 79%, depending on the emission scenario). Bregagglio et al. (2017) also find similar results using bio-economic models. Standard error of the estimated coefficients of the response model (i.e., our econometric models) contribute second largest and a significant contribution in the uncertainty of predicted impacts (28% to 9%). The choice of the response model (model-I vs. model-II) contribute 3% to 4% to uncertainty. Obviously, adding more econometric models would change these relative shares of uncertainty.

Using our model-I, it is also possible to derive the adaptation potential of Austrian farms. Here, we used the estimates from the heterogeneous response model (farms on flat vs slopped land) to predict mean changes in profits and the adaptation potential for two emission scenarios (RCP 4.5 and RCP 8.5), based on average values from the ensemble of 13 climate models for the year 2040. Under both scenarios we reveal an adaptation potential: under RCP 4.5 (moderate CO_2 emission reduction) the adaptation potential is 1.9% points (as average profits decreases by 4.4% without adaptation and 2.5% with adaptation) and under RCP 8.5 (business as usual) the adaptation potential is 2.9% points (as average profits decrease by 10% without adaptation and 7.1% with adaptation). Our estimated adaptation possibilities are a lower bound, as dropping negative profits (necessary because profits are logarithmically transformed) likely biased the adaptation potential downward. While it might be surprising that the climate change impact in RCP 4.5 and RCP 8.5 does not look so different, this could change when looking at the year 2100 instead of 2040 or an alternative base year (e.g. 1975 instead of 2016).

Ricardian econometric climate change studies mostly find positive effects of climate change in Europe: For Austria, Van Passel et al. (2017) find a 1°C increase in annual temperature to increase land values on average by 9.4% and an increase of precipitation (100mm/month) increases land values by 6.5% (results based on NUTS-3 level data with a quantile regression). For Germany, Lang (2007) finds profits of farms to increase when the temperature increases by 0.6°C but impacts become negative if temperature increases by more than 1°C. For Alpine regions bordering Austria, Lang (2007), finds climate change to reduce land values between 30% and 60%. Similarly, Lippert et al. (2009) find German farm profits to increase by 5-6% if temperature increases by 1.5°C, but expect losses for more severe changes in temperature and precipitation. While they find effects to be positive in almost all regions and scenarios, the Alpine regions bordering Austria have lower gains than other regions. For Italy Bozzola et al. (2018) find the average effect of climate change on land value, depending on the scenario, ranging from +1.5 to -15.8%. Interestingly the NUTS-3 region bordering Austria (Alto Adige) is predicted to suffer negative impacts (–65% to –10% depending on the scenario). For Trentino, the Italian NTUS-3 region neighbouring Alto Adige, De Salvo et al. (2013) also predicted negative impacts of climate change based on 126 apple and grape farms using a cross-sectional Ricardian approach: for an average increase in temperature of 1.4°C and an average decrease in precipitation of 4.81mm/month precipitation, they find profit reduction between 0.7 and 6.2%. Their farms though, are all irrigated and may be more resilient to climate change, while irrigation in Austria is (yet) not common.

Our results, thus predict higher losses for Austrian agriculture than other econometric studies for other regions. Differences between our panel data analysis and the Ricardian analysis may be due to difference in estimation method and model specification, the climate change scenarios and the region considered. Another reason could be that indeed moving from aggregated levels to farm-level data plays a key role in explaining lower profits as results by Fezzi and Bateman (2015) suggest. Our approach uses more variance in meteorological variables to identify the effect of temperature and precipitation than studies with aggregated data for our study region. Finally, a unique feature of our farm-level based results is the ability to make farm-level predictions. We can thus identify farms within Austria where losses due to climate change are highest. Results, obviously, are subject to the selected climate change scenario and demonstrate the usability of econometric farm-level data for climate change impact predictions.

There are several bio-economic simulations studies for Austrian agriculture (Kirchner et al., 2015; Schönhart et al., 2014, 2018). Although results from these models are based on different climate change scenarios, research focus, and time periods, it is interesting to compare the results. These studies show increased profits (0-5%) for Austrian agriculture in 2050 (Schönhart et al., 2014) and confirm the high impact of precipitation changes on regional heterogeneity in profit changes (Schönhart et al., 2018). In comparison to econometric studies, agricultural policy and ecosystem services are explicitly modelled (in particular in Kirchner et al. (2015)). As in the econometric approaches, estimates from bio- economic simulation models are also based on regional average values (NUTS-3) and farm type and are thus subject to the similar aggregation issues as comparable econometric studies – at least with respect to some of the modelled aspects (Hansen & Jones, 2000).

Using Austria as study area for farm level climate change econometric analysis, we benefit from the availability of detailed data on climate and farm accounts. Still, we could not account for certain aspects in our model which are partly associated to the unavailability of additional data e.g. further meteorological variables like wind speed, humidity or the limitations inherent to the econometric approaches for impact assessment. For example, it is difficult to capture CO_2 fertilization effects with the econometric approaches whether it be cross-sectional or panel data study. Schlenker and Roberts (2009) pointed that CO_2 quickly dissipate into the atmosphere which cause a gentle time trend and thus cannot be disentangled from technological time trend in statistical models. Although CO_2 concentration does not vary between locations within Austria, yet it will increase in the future, what will have an impact on agriculture. Newer crop varieties and adaptation measures (like irrigation) which have not been introduced so far, cannot be included in our analysis. Inclusion of such adaptation measures may ameliorate the pessimistic predicted impacts of climate change we found. Another limitation of this econometric approach is that subsidies are considered as part of farm revenues. Obviously, our estimates of susceptibility to climate change are influenced by the distribution of current subsidies. If subsidies change, different farms might be more susceptible to climate change. Moreover, our study like all other econometric studies borrowed the constant input-out price ratio which may not hold in the future. Price expectation and behavioural responses may change in future due to changing climatic conditions. We included 13 bias corrected future climate models available for Austria. Other climate models which have not been covered may also bring uncertainty in predicted impacts (Déqué et al., 2012; Déqué et al., 2017). These limitations are reflected in the above described results.

5. Literature

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Appendix

Appendix A.1: Weighting of predictions

The FADN sample is stratified by farm type and standard output. We use these strata to weight predicted log outputs for our RCPs: each of the prediction is weighted by the inverse of its sampling probability. As bases for the population distribution the year 2013 is used. See *Table A 8* for the strata, their population and their sample numbers.

In total, there are 3122 number of farms in our book keeping dataset from 2003 to 2016. Since we use an unbalanced panel, the predicted profits also include 1264 farms which dropped out of the panel already before 2013. For these farms, the last year of observation was used to determine their survey weight. The standard output we used to assign these to a category was adjusted according to older strata with respect to standard output (or standard gross margin for years before 2000). Since the sampling frame is for farms with standard output lower than 8.000€/year only, farms below this standard output (184 farms) are not taken in consideration. For 135 farms the stratum is unknown and they are therefore not used for the predictions. In total the summary statistics of the predictions are based on 2803 predictions.

Appendix: Tables

FADN and meteorological data variables	Mean	Min	Max	Median	SD
Observations used = 28300; years = 14 (sample with positive & negative profits, spatial and slope information)					
Profit (Euro/ha/year)	854.57	-3339.63	22492.53	595.85	1156.68
Altitude (meter)	525.46	113	1600	470	278.68
Farm area (ha)	53.84	0.9	491.39	42.09	44.96
Arable land (%)	41.96	0	100	37.77	35.67
Grass land (%)	26.73	0	100	21.17	25.65
Subsidy (€/ha)	472.87	0	4148.91	468.84	216.34
Family labour (%)	95.46	0	100	100	11.43
Meteorological data growing season					
Temperature: 20 years average (°C)	13.7	6.63	16.83	13.99	1.49
Precipitation: 20 years average (mm/month)	88.78	47.80	200.17	85.89	25.09
Temperature: shock (°C²)	0.62	0.00	6.39	0.22	0.83
Precipitation: shock ((mm/month)²)	259.69	0.00	7,938.69	101.61	406.91
Sunshine duration (annual in hours)	8.42	4.27	11.75	8.41	1.09
Meteorological data seasonal split-up					
Temperature winter: contemporary (°C)	-0.32	-7.16	5.43	-0.48	2.05
Temperature spring: contemporary (°C)	9.49	1.36	13.83	9.64	1.74
Temperature summer: contemporary (°C)	18.72	10.47	23.48	18.86	1.80
Temperature autumn: contemporary (°C)	9.55	2.65	13.86	9.67	1.52
Precipitation winter: contemporary (mm/month)	49.65	7.33	354.90	42.31	29.67
Precipitation spring: contemporary (mm/month)	67.00	14.06	244.19	63.20	25.58
Precipitation summer: contemporary (mm/month)	113.59	24.64	366.36	109.99	41.30
Precipitation autumn: contemporary (mm/month)	67.43	10.30	322.33	62.29	30.88

Notes: The number of observations per year varies (unbalanced panel). Profits per ha are gross value added including subsidies but without energy expenses. Climatic variables are for the growing seasons (March to September) at the grid points closest to the farms. Temperature is the yearly mean of minimum and maximum and precipitation aggregated yearly sums. Temperature and precipitation shocks are squared deviation of current year's temperature from 20 years average values.

Table A 1: Descriptive statistics of the sample from FADN and meteorological data from year 2003-2016.

FADN and meteorological data variables	Mean	Min	Max	Median	SD
Observations used = 29112; years = 14 (sample with positive & negative profits and spatial information but no slope information)					
Profit (Euro/ha/year)	858.21	-3339.63	22492.53	587.8	1235.29
Altitude (meter)	522.3	113	1600	465	278.3
Farm area (ha)	53.37	0.69	491.39	41.72	45.14
Arable land (%)	41.78	0	100	37.38	35.71
Grass land (%)	26.57	0	100	20.74	25.74
Subsidy (€/ha)	470.54	0	4148.91	467.17	218.78
Family labour (%)	95.38	0	100	100	11.62
Meteorological data growing season					
Temperature: 20 years average (°C)	13.74	6.63	16.83	14.02	1.46
Precipitation: 20 years average (mm/month)	88.16	47.80	200.17	85.62	24.7
Temperature: shock (°C²)	0.63	0.00	5.79	0.23	0.84
Precipitation: shock ((mm/month)²)	257.48	0.00	7,938.69	100.84	400.18
Sunshine duration (annual in hours)	8.44	4.27	11.75	8.43	1.09
Meteorological data seasonal split-up					
Temperature winter: contemporary (°C)	-0.32	-7.16	5.43	-0.49	2.05
Temperature spring: contemporary (°C)	9.50	1.36	13.83	9.65	1.73
Temperature summer: contemporary (°C)	18.74	10.47	23.48	18.88	1.80
Temperature autumn: contemporary (°C)	9.56	2.65	13.86	9.68	1.52
Precipitation winter: contemporary (mm/month)	49.49	7.33	354.90	42.14	29.49
Precipitation spring: contemporary (mm/month)	66.75	14.06	244.19	63.01	25.53
Precipitation summer: contemporary (mm/month)	113.24	24.64	366.36	109.59	41.28
Precipitation autumn: contemporary (mm/month)	67.11	10.30	322.33	61.97	30.83

Notes: The number of observations per year varies (unbalanced panel). Profits per ha are gross value added including subsidies but without energy expenses. Climatic variables are for the growing seasons (March to September) at the grid points closest to the farms. Temperature is the yearly mean of minimum and maximum and precipitation aggregated yearly sums. Temperature and precipitation shocks are squared deviation of current year's temperature from 20 years average values.

Table A 2: Descriptive statistics of the sample from FADN and meteorological data from year 2003-2016.

	First stage of linear term			First stage of squared term		
	Est.	St. error		Est.	St. error	
Temp. longterm (**SL-I**)	1.0128	(0.0009)	**	32.522	(0.0937)	**
Temp. longt. squ. (**SL-II**)	-4.0E-08	(1.8E-08)	**	-0.0005	(0.0000)	**
Temp. shock (C°)	0.0001	(0.0001)	**	-0.0001	(0.0078)	
Preci. longt.	7.6E-07	(3.7E-05)	**	0.0089	(0.0041)	**
Preci. longt. squ.	5.3E-07	(1.7E-07)	**	0.0000	(1.9E-05)	
Preci. Shock	5.1E-08	(7.4E-08)		1.7E-05	(8.1E-06)	**
Land: 'arable'	-1.5E-05	(4.8E-06)	**	-0.0066	(0.0005)	**
Land: 'grass'	-3.9E-06	(3.2E-06)		-0.0072	(0.0004)	**
Subsidies	1.1E-07	(1.7E-07)		6.7E-05	(1.9E-05)	**
Preci. shock squ.	-3.6E-12	(2.1E-11)		-5.0E-09	(2.3E-09)	**
R^2	0.99			0.99		
Observations	26248			26248		

Notes: Robust standard errors in parenthesis. Significance: * =10%, **=5% or less. Dummies for years are not shown. SL represent Spatial Lag for a variable. SL-I comes from long-term temperatures of near-similar-altitude grid points situated among nearest 3000 neighbours of a farm. SL-II comes from long-term temperatures squared of all nearest 1500 neighbours of a farm grid points multiplied by altitude of a farm.

Table A 3: First stages of 2SLS basic model with long term temperature and its square instrumented with spatial lags and squares of shocks.

	First stage of linear term			First stage of squared term		
	Est.	St. error		Est.	St. error	
Temp. longterm	1.1062	(0.2838)	**	-192.63	(80.730)	**
Temp. longt. squ.	-0.1596	(0.0069)	**	-44.983	(1.9597)	**
Temp. shock (C°)	0.0821	(0.0276)	**	30.335	(7.8439)	**
Preci. longt. (**SL-I**)	1.4497	(0.0073)	**	150.92	(2.0877)	**
Preci. longt. squ. (**SL-II**)	-0.0020	(3.5E-05)	**	0.3389	(0.0099)	**
Preci. shock	0.0001	(1.1E-05)	**	0.0310	(0.0030)	**
Land: 'arable'	-0.0005	(0.0010)		-0.8426	(0.2805)	**
Land: 'grass'	0.0011	(0.0007)	*	0.2487	(0.1888)	
Subsidies	4.9E-05	(3.5E-05)		0.0139	(0.0098)	
Temp. shock squ.	-0.0347	(0.0065)	**	-15.715	(1.8625)	**
R^2	0.99			0.99		
Observations	26248			26248		

Notes: Robust standard errors in parenthesis. Significance: * =10%, **=5% or less. Dummies for years are not shown. SL represent Spatial Lag for a variable. SL-I comes from long-term precipitation of continuous 1500 neighbours of a farm grid point. SL-II comes from squared long-term precipitation of a disjoint donut made of 80 grid points around a farm with 20Km radius.

Table A 4: First stages of 2SLS basic model with long term precipitation and its square instrumented with spatial lags and squares of shocks.

	Temperature instrumented			Precipitation instrumented		
	Est.	St. error (Bootstr.)		Est.	St. error (Bootstr.)	
Temp. longterm^{+}	0.4109	(0.5451)		0.5288	(0.4528)	
Temp. longt. squ. $^{++}$	-0.0217	(0.0141)		-0.0230	(0.0119)	*
Temp. shock (C°)	-0.0654	(0.0167)	**	-0.0629	(0.0167)	**
Preci. longt. $^{-}$	0.0644	(0.0117)	**	0.0631	(0.0150)	**
Preci. longt. squ. $^{--}$	-0.0002	(0.0001)	**	-0.0002	(0.0001)	**
Preci. Shock	2.0E-06	(1.4E-05)		-2.1E-06	(1.3E-05)	
Land: 'arable'	-0.0059	(0.0020)	**	-0.0058	(0.0021)	**
Land: 'grass'	-0.0005	(0.0012)		-0.0005	(0.0012)	
Subsidies	0.0002	(0.0001)	**	0.0002	(0.0001)	**
Residuals.1^{+}	2.5963	(2.3083)				
Residuals.2^{++}	-0.0135	(0.0270)				
Residuals.1^{-}				-0.0484	(0.0281)	*
Residuals.2^{--}				3.0E-05	(0.0001)	
R^2	0.76			0.76		
Observations	26,248			26,248		

Notes: Clustered bootstrap standard errors with 1000 repetitions in parenthesis are given for robust inference. Significance: * =10%, **=5% or less. Dummies for years are not shown. There are four residuals coming from first stage of 2SLS. Each residual and endogenous variable are marked with same superscript.

Table A 5: Results for test of endogeneity in 2SLS models for measurement error bias as suggested by Wooldridge (2009, p. 528).

	First stage of linear term for precipitation			First stage of squared term for precipitation		
	Est.	St. error		Est.	St. error	
Temp. longterm	1.1845	(0.2845)	**	-167.57	80.903)	**
Temp. longt. squ.	-0.1617	(0.0069)	**	-45.594	(1.9712)	**
Temp. shock (C°)	0.0837	(0.0276)	**	31.504	(7.8517)	**
Preci. longt. (**SL-I**)	1.4520	(0.0074)	**	151.73	(2.0903)	**
Preci. longt. squ. (**SL-II**)	-0.0020	(3.5E-05)	**	0.3338	(0.0099)	**
Preci. Shock	4.3E-05	(1.3E-05)	**	0.0180	(0.0037)	**
Land: 'arable'	-0.0004	(0.0010)		-0.8153	(0.2803)	**
Land: 'grass'	0.0014	(0.0007)	**	0.3501	(0.1894)	*
Subsidies	4.8E-05	(3.5E-05)		0.0134	(0.0098)	
Temp. shock squ.	-0.0372	(0.0066)	**	-16.601	(1.8672)	**
Temp.shock: slopped.land	0.0237	(0.0102)	**	6.4169	(2.8950)	**
Preci.shock: slopped.land	0.0001	(2.0E-05)	**	0.0315	(0.0056)	**
R^2	0.99			0.99		
Observations	26248			26248		

Notes: Robust standard errors in parenthesis. Significance: * =10%, **=5% or less. Dummies for years are not shown. SL represent Spatial Lag for a variable. SL-I comes from long-term precipitation of continuous 1500 neighbours of a farm grid point. SL-II comes from squared long-term precipitation of a disjoint donut made of 80 grid points around a farm with 20Km radius.

Table A 6: First stages of 2SLS heterogeneous response model with long term precipitation and its square instrumented with spatial lags and squares of shocks.

	Long-term precipitation and its square instrumented		
	Est.	St. error (Bootstr.)	
Temp. longterm	0.3623	(0.4604)	
Temp. longt. squ.	-0.0178	(0.0117)	
Temp. shock (C°)	-0.0413	(0.0168)	**
Preci. longt. +	0.0625	(0.0154)	**
Preci. longt. squ. ++	-0.0002	(0.0001)	**
Preci. Shock	-3.0E-05	(1.3E-05)	**
Land: 'arable'	-0.0059	(0.0021)	**
Land: 'grass'	-0.0008	(0.0012)	
Subsidies	0.0002	(0.0001)	**
temp.shock:slopped.land	-0.0694	(0.0126)	**
preci.shock:slopped.land	0.0001	(2.6E-05)	**
Residuals.1+	-0.0466	(0.0293)	
Residuals.2++	3.9E-05	(0.0001)	
R^2	0.76		
Observations	26,248		

Notes: Clustered bootstrap standard errors with 1000 repetitions in parenthesis are given for robust inference. Significance: * =10%, **=5% or less. Dummies for years are not shown. There are two residuals coming from two first stages of 2SLS. Each residual and endogenous variable are marked with same superscript.

Table A 7: Results for test of endogeneity in 2SLS for heterogeneous response model as suggested by Wooldridge (2009, p. 528).

Farm type	St. output (1000 €/year)	Population	Sample	Inv. sampling probability
Forestry	8-<15	4654	46	101.2
Forestry	15-<30	3494	50	69.9
Forestry	30-<50	1701	48	35.4
Forestry	50-<100	1107	34	32.6
Forestry	100-<350	272	7	38.9
Crop	8-<15	2945	47	62.7
Crop	15-<30	3292	71	46.4
Crop	30-<50	2229	94	23.7
Crop	50-<100	2253	130	17.3
Crop	100-<350	1130	61	18.5
Wine and Fruits	8-<15	1887	11	171.5
Wine and Fruits	15-<30	2082	15	138.8
Wine and Fruits	30-<50	1476	26	56.8
Wine and Fruits	50-<100	2168	63	34.4
Wine and Fruits	100-<350	2574	88	29.3
Cows and dairy	8-<15	9952	110	90.5
Cows and dairy	15-<30	13450	241	55.8
Cows and dairy	30-<50	11711	308	38.0
Cows and dairy	50-<100	11485	484	23.7
Cows and dairy	100-<350	3222	149	21.6
Pork and chicken	8-<15	201	5	40.2
Pork and chicken	15-<30	470	5	94.0
Pork and chicken	30-<50	662	15	44.1
Pork and chicken	50-<100	1622	64	25.3
Pork and chicken	100-<350	4550	180	25.3
Mixed agriculture	8-<15	1867	23	81.2
Mixed agriculture	15-<30	1949	26	75.0
Mixed agriculture	30-<50	1486	49	30.3
Mixed agriculture	50-<100	2132	84	25.4
Mixed agriculture	100-<350	1634	90	18.2
Any farm type	>350	1053	15	70.2
		100710	2639	38.2

Table A 8: Strata, sample and inverse sampling probability used for predictions. Source for Population values: Table appendix from "Der Grüne Bericht" (BMLFUW, 2014)

BMLFUW. 2014. 'Der Grüne Bericht 2014'. Vienna, Austria: Bundesministerium für Land- und Forstwirtschaft, Umwelt und Wasserwirtschaft, Abteilung II 5.

Appendix: Figures

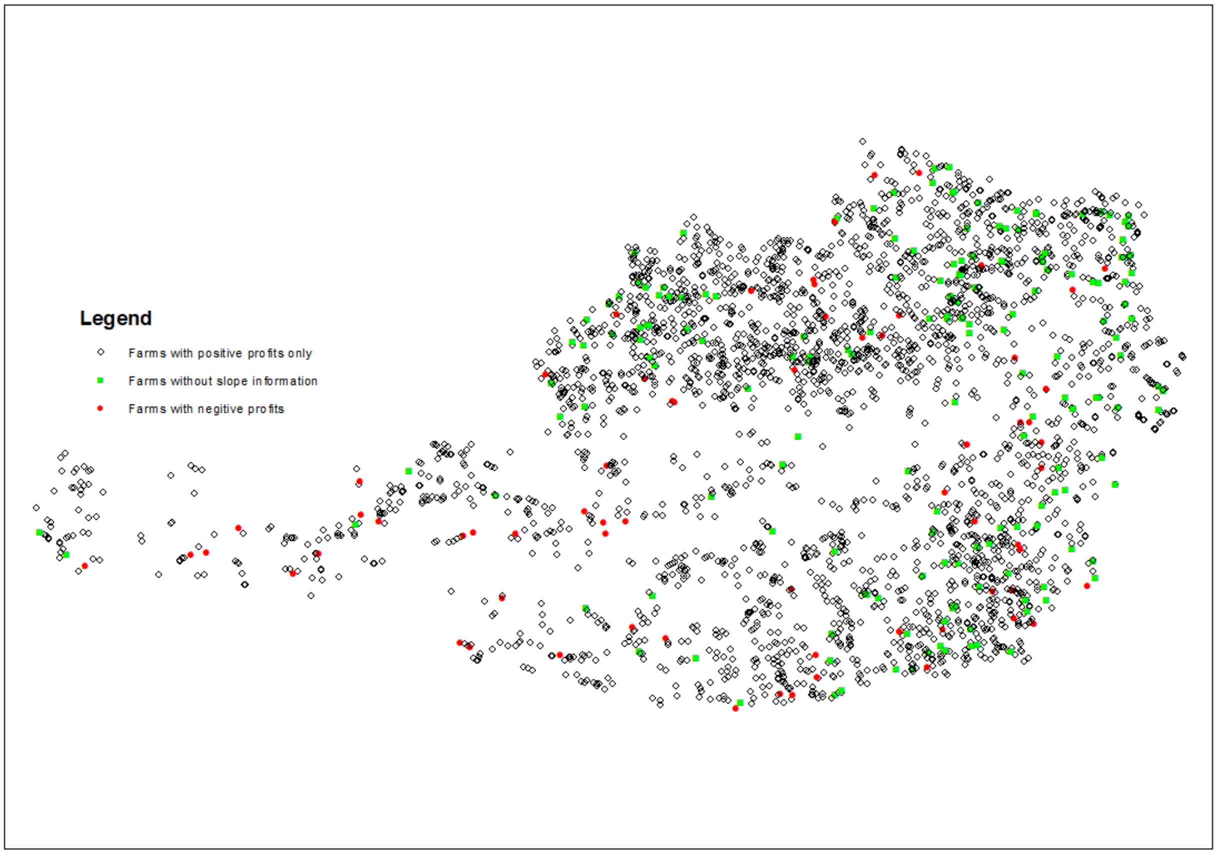


Figure A 1: Spatial distribution of dropped farms due to missing slope information (blue) and negative profits (pink) from the FADN sample.

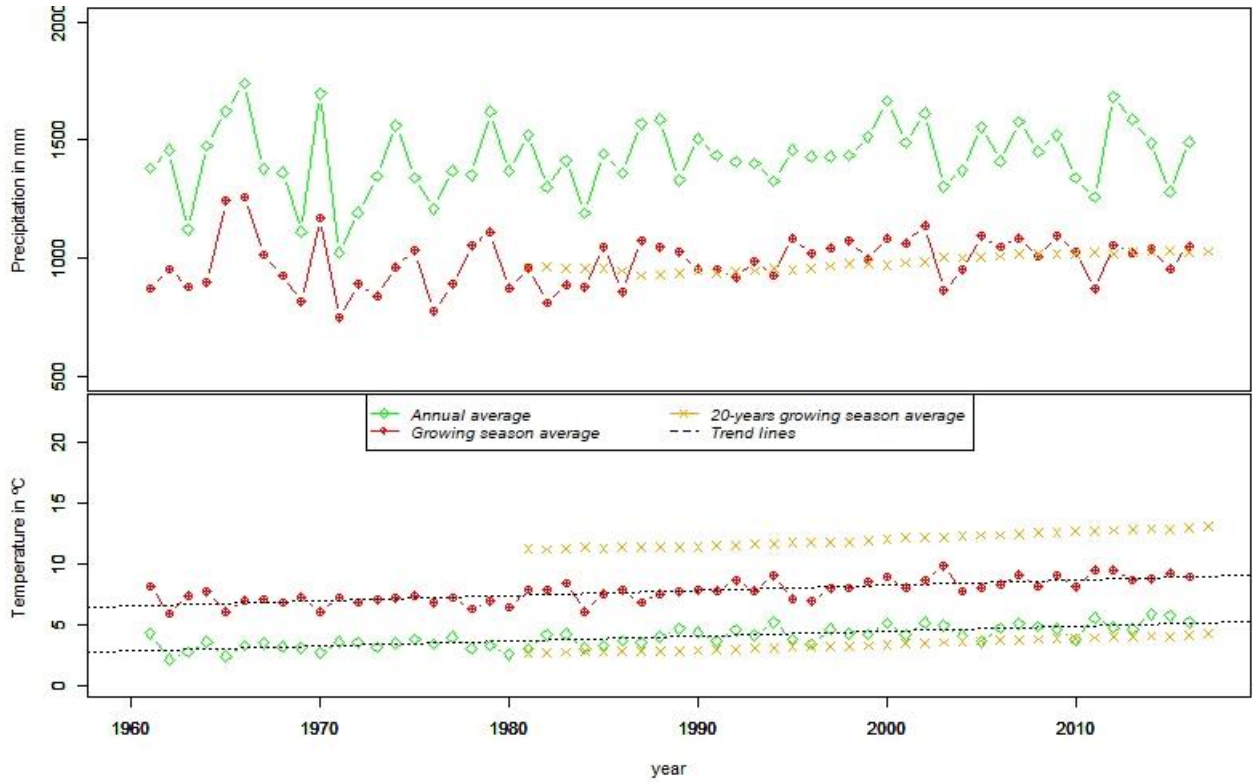


Figure A 2: Past Precipitation and Temperature trend in Pinzgau-Pongau, Austria from Jan 1, 1961 to 31 Dec, 2016.

Description: Climate data here presents spatial averages from all 1x1 Km grid points in Pinzgau-Pongau region of Austria. Past 20-years averages represent long-term precipitation and temperature conditions for growing season (March to September). In temperature plot, long term averages for growing season contains temporal averages over past 20 years for minimum and maximum temperatures.

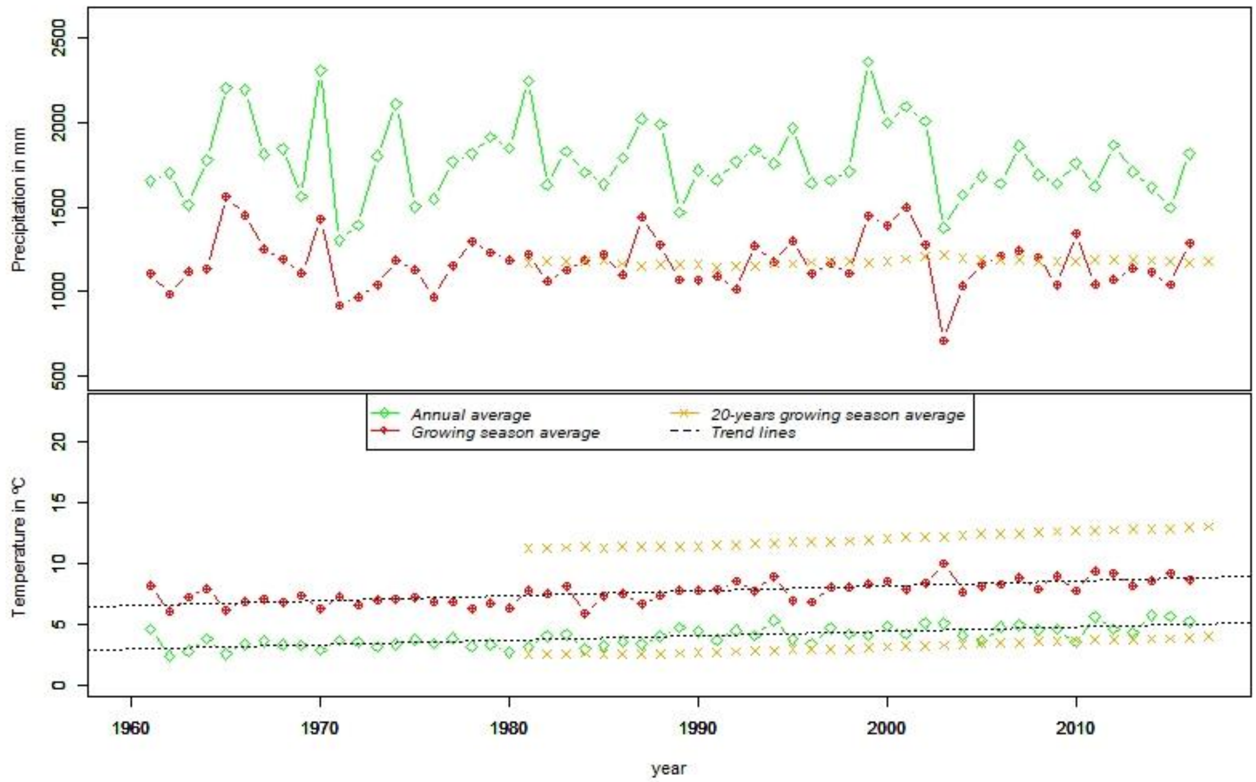


Figure A 3: Past Precipitation and Temperature trend in Bludenz-Bregenzer Wald(a region in the west of Austria) from Jan 1, 1961 to 31 Dec, 2016.

Description: Climate data here presents spatial averages from all 1x1 km grid points in Bludenz-Bregenzer Wald. Past 20-years averages represent long-term precipitation and temperature conditions for growing season. In temperature plot, long term averages for growing season contains temporal averages over past 20 years for night and day temperatures.

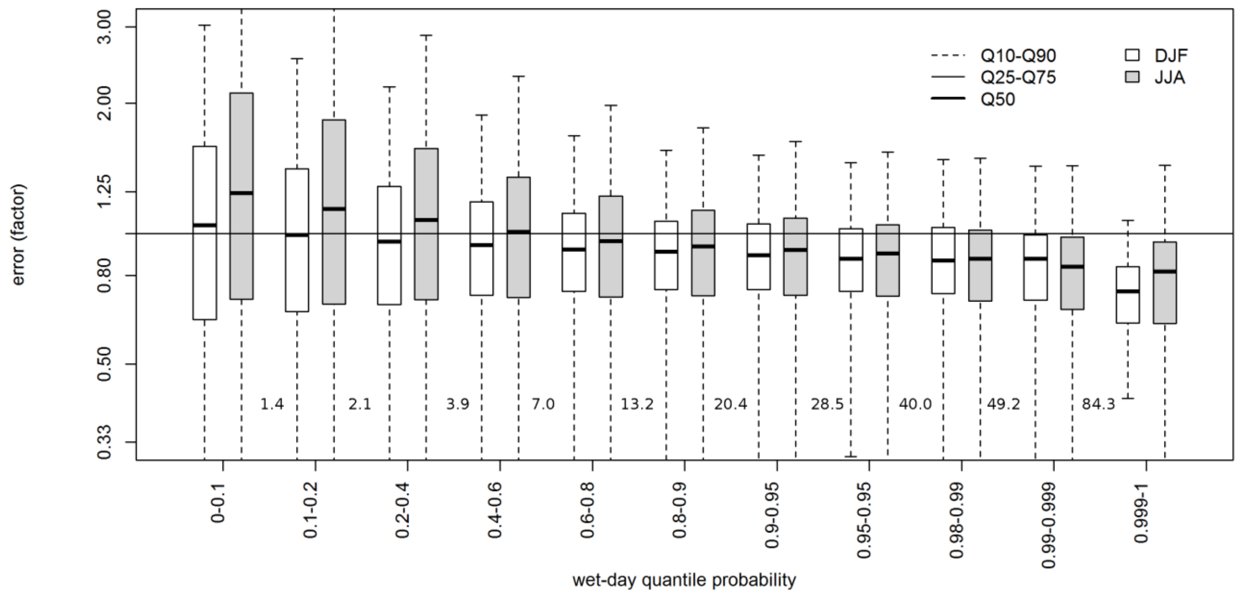


Figure A 4: Box plots of the interpolation error inferred from a systematic leave-one-out cross-validation.

Description: Errors are expressed as ratio between interpolated (at the location of the stations) and observed (at the stations) values. The sample errors are stratified into bins of precipitation intensity, which are defined in terms of quantiles. The sample includes only cases with estimated and observed precipitation ≥1 mm per day. Box plots represent the median (bold line), the interquartile range (box) and the 10-90% quantile range (whiskers) of the error distribution. Results are shown separately for winter (DJF) and summer (JJA). Figures between boxplots are precipitation sums defining classes. Source:

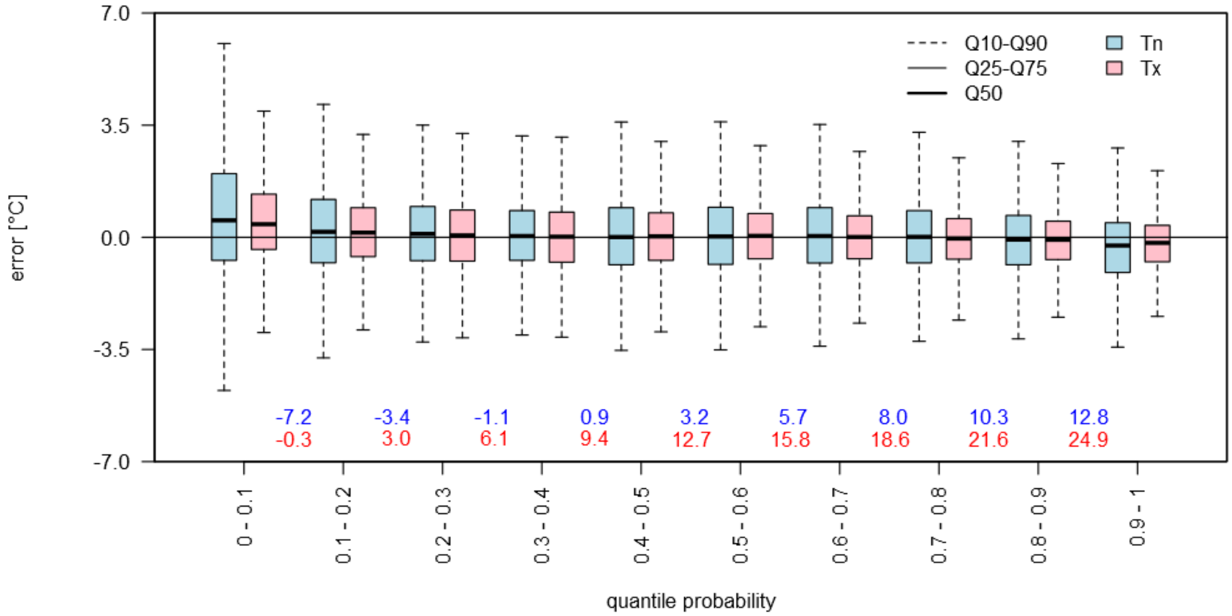


Figure A 5: Box plots of the interpolation error inferred from a systematic leave-one-out cross-validation.

Description: Errors are expressed as ratio between interpolated (at the location of the stations) and observed (at the stations) values. The sample errors are stratified into bins of temperature values, which are defined in terms of quantiles. Box plots represent the median (bold line), the interquartile range (box) and the 10-90% quantile range (whiskers) of the error distribution. Results are shown separately for temperature minimum (Tn) and maximum (Tx). Figures between boxplots are temperatures defining classes for minimum (blue) and red (maximum). Published with kind permission of Johann Hiebl. All Rights reserved.

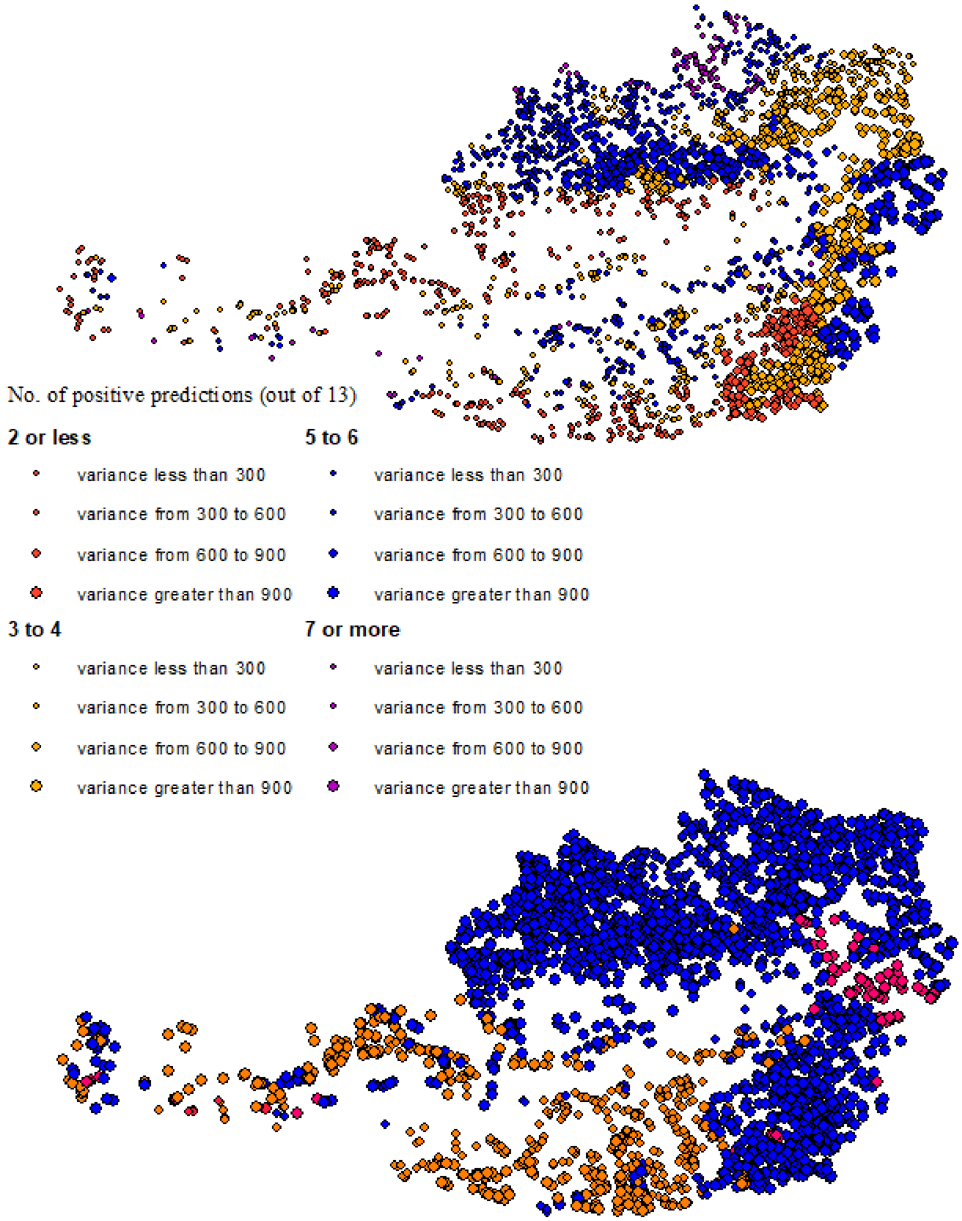


*Figure A 6: Number of positive predictions and variance of predicted impacts at each farm using all of the 13 climate models with RCP 8.5 based on the model-I (**top**),model-II (**bottom**)..*

Note: Future prediction comes from estimated coefficients in second columns of *Table 4* **(top)** & *Table 9* **(bottom)** and 13 bias corrected simulated changes in climate conditions. Therefore, each farm gets 13 future prediction for change in profits. Sign of the predictions are presented here with color scheme as positive predictions out of total 13 at each farm. Size of the dots represents the spread in prediction which comes from the variance of the 13 predictions at each farm.

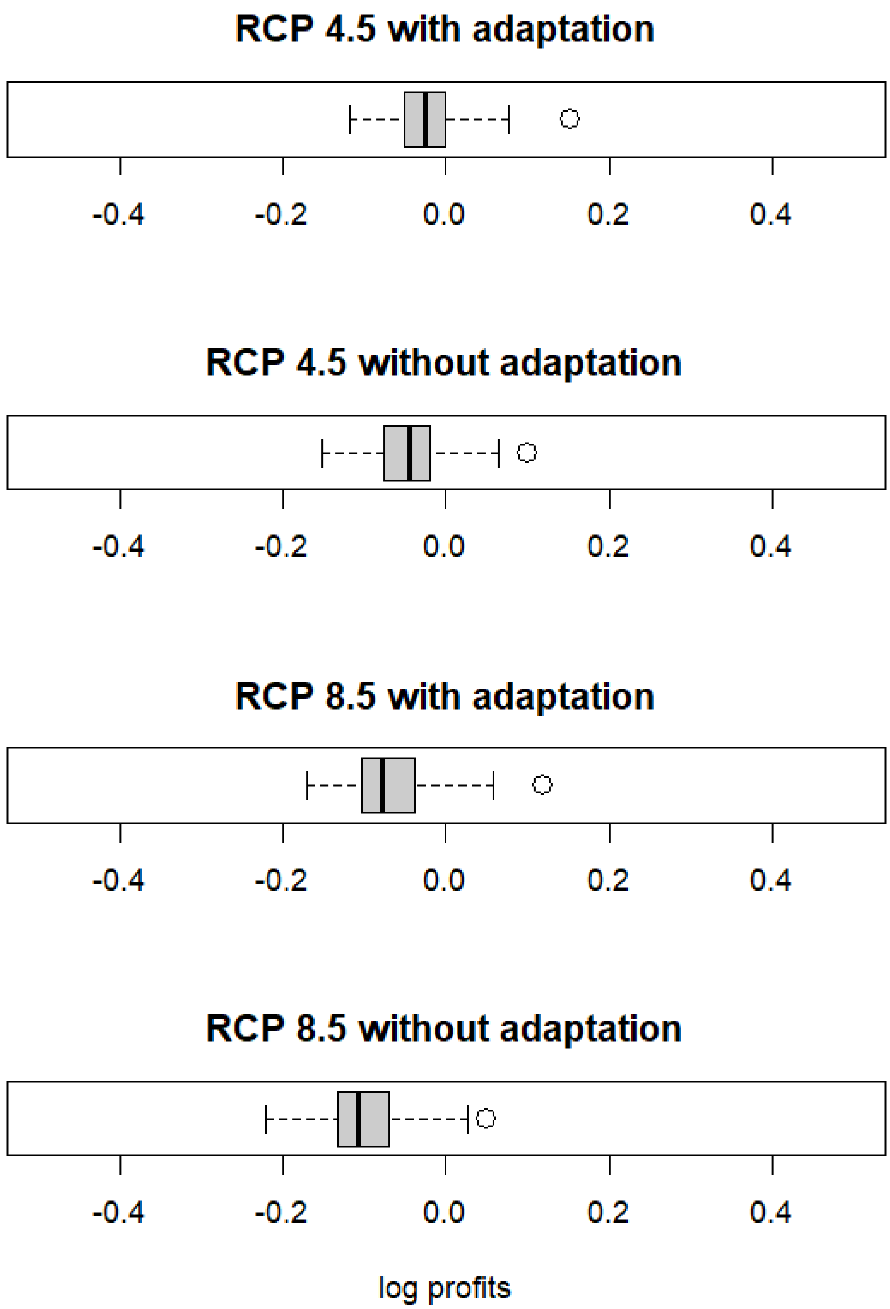
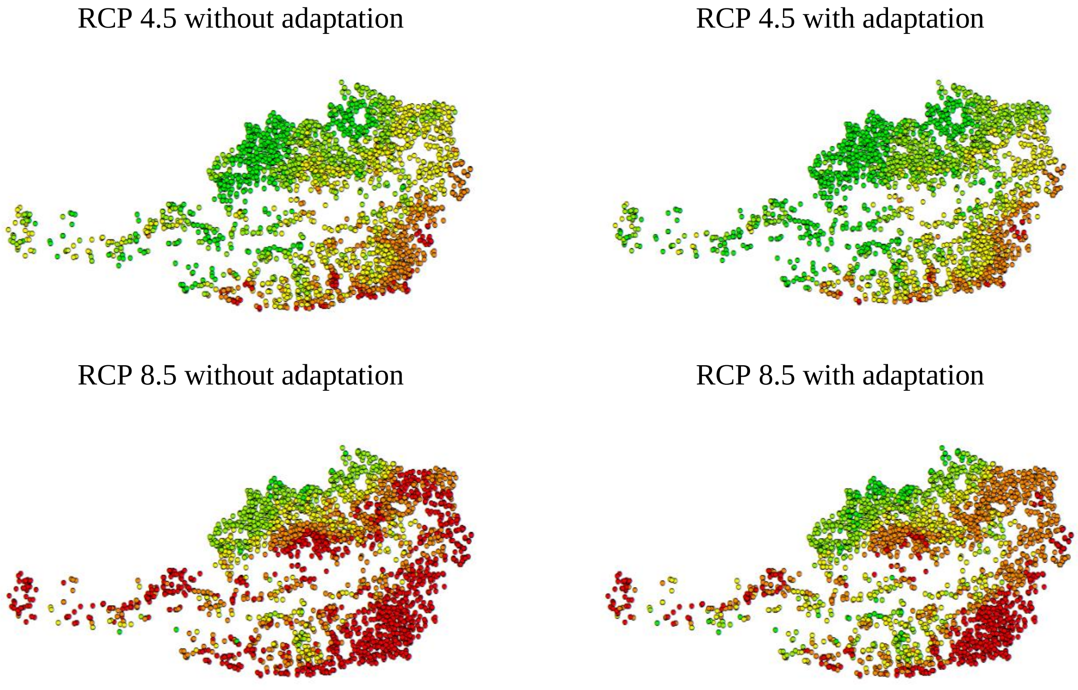


Figure A 7: Change in log profits due to climate under RCP 4.5 and RCP 8.5 based on results from estimates Table 7 first column.

Description: Results are weighted to be representative with respect to standard output and farming types. Whiskers extend to 1.5 interquartile range or to the most extreme point, whichever is shorter. Only the most extreme outlier is shown.



Coordinate System: MGI Austria Lambert
Projection: Lambert Conformal Conic
Dateum: MGI
False Easting: 400,000.0000
False Northing: 400,000.0000
Central Meridian: 13.3333
Standard Parallel 1: 46.0000
Standard Parallel 2: 49.0000
Latitude of Origin: 47.5000
Unit: Meter

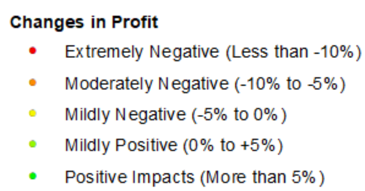


Figure A 8: Gaining and losing of profits due to climate change in RCP 4.5 and RCP 8.5 based on results from estimates in Table 7.

Description: The shown patterns results from climate change heterogeneity within Austria (climate change prediction differ for each grid point). Impacts are classified with respect to their intensities in extremely negative (< -10%), moderately negative (-10% to -5%), mildly negative (-5% to 0%), mildly positive (0% to +5%) and moderately or higher positive impacts (< +5%). In RCP 4.5 without adaptation, agricultural profits decline in most regions. Only in the northern parts of Austria (northern Upper and Lower Austria) and some parts of western Austria (parts of Tyrol and Carinthia) losses are less severe or positive. Little surprising, these are mostly areas in higher elevations and consequently lower temperature. In RCP 8.5 losses are generally higher, but we see a similar pattern: those farms in more elevated areas (in particular in the northern part of Austria but also in the south as in Carinthia and Western Styria) have mild losses or even gains. On the eastern fringe of Austria where the temperatures are generally higher and in the West, losses – again – are more pronounced. Adaptation can reduce the losses, in particular in the Alpine and southern regions (compare *Figure 8*). In RCP 8.5 adaptation renders profits of the most farms situated in the South (Carinthia and western parts of Styria) and the North (Mühlviertel) positive.