The Impact of Climate Change on Danish Agriculture*

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Abstract

New and unique climate prediction data show the regional effect of climate change for weather outcomes in Denmark. The present study utilizes this data to forecast and discuss the impacts of climate change on Danish agriculture, namely for the distribution of wheat yields. Using a large data set with farm-level information combined with data on local meteorological observations, a fixed effect panel data model for wheat yields is estimated, including a prior tobit model to correct for the selection bias from wheat production.

Climate change is found to a have strong negative impact on average yields under the current technological constraints on agriculture. This fall in yields is transformed into a net increase in mean yields once the impact of technological progress on yields is taken into account.

In a regionally differentiated analysis, the peninsular Jutland in the west experiences a larger decrease in mean yields than the eastern parts of the country. In this context I point to the need for further studies on the specific cause of the regional differences of the impact as well as the informational needs on climate change, in order to improve the understanding of potential adaptation strategies.

Keywords: Climate Change, Agriculture, Fixed effect selection model.

JEL classification: C23, C24, Q12

1 Introduction

The chapter studies the impact of climate change on Danish agriculture, and provides a discussion on the importance of disaggregated information. The specific context is the expected change in climate conditions over the coming centenary and in particular the changes in the full outcome space as opposed

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to the often quoted changes in averages. While earlier studies on the impact of climate change on agriculture and agricultural adaptation [Schneider et al., 2000, for instance] have primarily focused on the effects of changes in the averages of climate variables[1] on agricultural yields, it is the full distribution of weather variables over outcomes, space and time that is of interest to the farmer. In the present study I therefore put weight on the local disaggregation of the meteorological impacts as a tool to describe the full outcome space.

Agriculture has a number of unique production features. Agricultural production is a sequential process, where the inputs and timing of input responses at several stages of production are crucial for the harvest-outcome. It is the unpredictability and stochastic nature of weather at all stages of production that distinguishes agriculture from other production procedures. As an example of this I study the impact of meteorological variation and climate change on wheat yields in Denmark.

Through the use of observed data from privately-managed farms, as opposed to agronomic studies with experimental plots or calibrated simulation algorithms, the present study integrates the effects of the ecological system, indirect effects of climate on crop growth as well as management in the analysis. That is, the climate is seen as one input factor in the overall production frame for agriculture. The agronomic approach to yield modelling is a detailed description of biological systems, but to quote Landau et al. [1999], "It is the real-life yields and not the imaginary optimal yields that one would want to predict in most applications, including climate change". Suboptimal management as well as indirect effects of climate change are crucial for an economic description of the impact of climate change on agriculture in general.

A farm encompasses several parallel as well as sequential production processes. Several crops are grown to exploit advantages of crop rotation, capital inputs often exhibits several uses, and many farms exploit the synergies with husbandry. Agricultural production is therefore often modelled in a multi-output setting, see e.g. Arnberg [2002] for an overview. Nevertheless, to simplify the analysis the present study nevertheless concentrates on wheat yields, employing a selection model to account for the allocated of farm acreage to wheat. The yield model is set up as a fixed effect model, as correlation between farm-level unobservable effects and inputs into wheat production are highly likely[2]. I find a good fit of the econometric model to 12 years of agricultural panel data combined with local weather observations.

Mendelsohn et al. [1994] applied a regression approach to study the determinants of net rent and farmland value, there among climatic outcomes. The value of farmland is based on the present value of possible future returns from the land. It is however highly affected by the vicinity of the land to an economic hub, the administrative definition and future plans for the area as well

[1] I here use the distinction between 'climate' and 'weather' stated by the Danish Meteorological Institute, which defines climate to be the mean weather at a location over a longer period, typically 30 years. 'meteorological' will in the present study thus refer to observed weather data.

[2] For a similar approach, albeit with a random effects model under the dubious assumption of zero correlation, see e.g. the study of Heshmati [1994].

as the credit and commodity markets. And most of all land prices in Europe are driven by agricultural quotas on livestock as well as subsidies of crops and acreage. In the present study I see an advantage in using direct crop yields as the dependent variable, to gain an unadulterated and more disaggregated assessment of the effect of climate change on agriculture.

The following section will describe the climate data and prediction to be used, and document the regional disparities in climate change for Denmark. After reviewing general findings for the impact of climate change on agriculture and in particular on wheat, I proceed to describe the agricultural as well as the meteorological data on which the model for wheat yields is calibrated, and to characterize the production of wheat. The latter gives evidence of differences between the wheat and no-wheat producing farms. This motivates the use of a selection correction model and section 5 discusses modelling approaches to agricultural production and lays out the fixed effect panel data model for wheat yields with a tobit selection model for wheat acreage. Section 6 then reports the estimation results for the selection model, followed by two different specifications of the yield model. In the first estimation I assume homogeneity in the response of yields to weather across the country, while the second estimation introduces regional differentiation. The selection correction is found to be significant in both models, as is the regional differentiation in the second model. Section 7 utilizes the two calibrated models to forecast the impact of climate change on wheat yields. The prior expectation that increase in temperatures will lead to a fall in yields is confirmed, while the western parts of the country are forecasted to suffer a relatively larger fall in the mean yield. The forecasts lead to a discussion of adaptation options and suitable policy environment in section 8, before section 9 concludes.

2 Documenting Climate Change

2.1 Climate Data and Forecasts

For the study of regional climate change over Denmark and subsequent simulations of wheat yields as a function of meteorological forces, the present research makes use of new and extensive climate data produced by the Danish Meteorological Institute in the framework of the PRUDENCE-project[3]. The project has provided a series of high resolution climate data scenarios for the years 2071 to 2100 and the work has explicitly been built around regional climate models (RCM). The climate models were calibrated on a *control* between 1961 and 1990, and the *scenario* forecast for 2071 to 2100 is based on the SRES A2 greenhouse-gas scenario[4] as specified by the Intergovernmental Panel on Climate Change (IPCC).

[3]See appendix A for a description of PRUDENCE, as well as `http://prudence.dmi.dk/`.

[4]"The A2 storyline and scenario family describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing population. Economic development is primarily regionally oriented and per capita economic growth and technological change more fragmented and slower than other storylines." [IPCC, 2001a, p.18]. See appendix B for details on all the IPCC scenarios.

The work has produced climate simulations down to a 25km-resolution, supplying a invaluable tool to assess detailed consequences of climate change on human systems. Earlier work only produced coarser global circulation models with a maximum resolution of approximately 300km. The present work will focus on monthly data of 2-meter-temperature and precipitation, as these are seen as the most decisive for biomass production and agriculture under Danish conditions [Olesen & Bindi, 2002].

2.2 Changes in Climate Distributions over Denmark

Overall mean differences between distributions can be tested using a Kolmorgorov-Smirnov-test or a t-test for equality of means. A more sensitive indicator of distributional discrepancies is achieved by using the quantiles of distributions, as argued by Wilk & Gnanadesikan [1968]. Quantile analysis is a non-parametric method that is more resistant to outliers and other disturbances to the underlying probability model than parametric models. See Lazante [1996] for an illustrative discussion.

The q%-quantile is defined as the value x^q in the empirical distribution of the data that solves $\mathrm{P}(x \leq x^q) = F(x) = q\%$, where $F(x)$ is the cumulative distribution function of x.. Reporting x^q for various values of $0 \leq q \leq 100$ can give a description of individual parts of a distribution, for instance the upper tail or the middle range. Two distributions F_A and F_B can equally be held up against each other by comparing their quantiles x_A^q and x_B^q for several values of q.

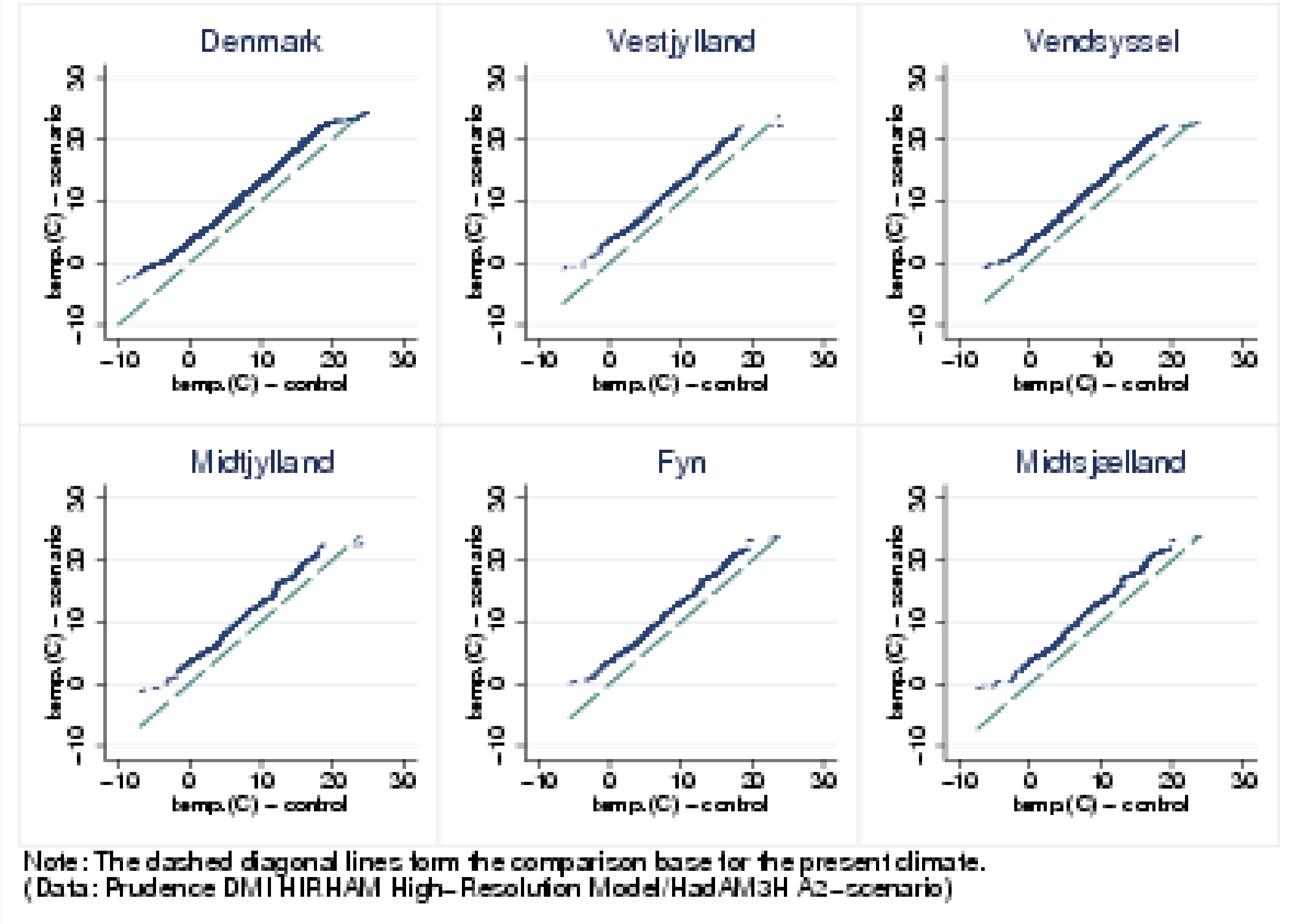
Ferro et al. [2004] apply this idea to evaluate changes in climate distribution data. They argue that (functions of) quantiles can capture changes in the location (represented by the median m) as well as the scale (interquartile range $s = x^{75} - x^{25}$) and the shape (skewness $a = [x^{75} - 2 \cdot x^{50} - x^{25}]/s$). Below the difference between climate distributions under the control and the scenario will be explored using quantile-quantile plots. A Q-Q-plot plots the order values of a distribution F_A against the ordered values of a distribution F_B. If the two distributions are identical, the plot should align along the straight diagonal line. A change in location would result in a parallel shift of the plot against the diagonal, while a change in scale would tilt the plot against the diagonal.

Figure 1 and 2 plot quantiles of the *scenario* against quantiles of the *control* for temperature and precipitation, respectively. The data consists of monthly means (and per day for precipitation) . To document regional differences, the analysis is done for Denmark as well as for five regions of the country.

Overall, the plots for temperature indicate a change in location, where the prediction of the scenario distribution are above the control distribution. There is a slight indication of a higher (lower) increase in the lowest (highest) region, compared to the middle of the distribution. While quantile-plots have less power in the tails of a distribution, where the densities are sparse, this signals a narrower distribution in the scenario.

To examine the change precipitation pattern, a distinction between rain and drizzle/dew has to made. In figure 2 I therefore truncate the distribution of

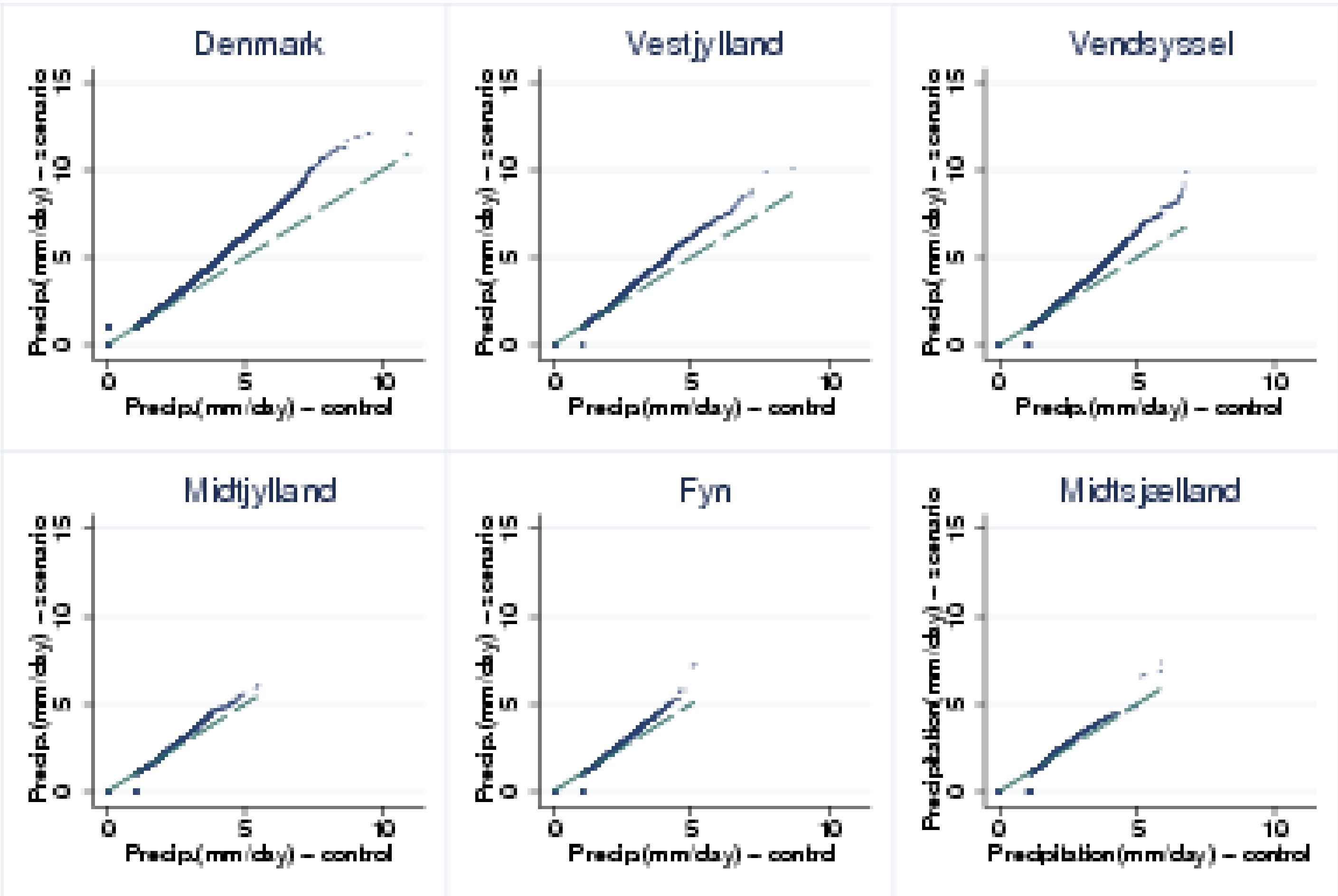
Figure 1: Q-Q-plots of temperature in control and scenario



precipitation at 1 mm/day, and solely examine the change in precipitation patterns over 1mm/day. The rain plots show a very different picture from the temperature plots. For the full country there is a clear anti-clockwise tilt of the plot relative to the diagonal. This documents a change in the shape of the distribution, where the lower tail of the distribution remains unchanged, while high-precipitation outcomes become more frequent. The regional disaggregation shows clear differences from west to east. It is mainly the west of Denmark (Vendsyssel, Vestjylland) that will experience more frequent high-precipitation events. The predicted changes in precipitation distribution for the central (Fyn) and eastern regions (Midtsjælland) are far less pronounced. These changes in distributions thus follow the present-time differences in the level of precipitation across the country, where the amount of rainfall decreases from west to east.

This comparison of the control period with the predicted scenario period yields two conclusions. The Q-Q plots firstly show the shifts in temperature and

Figure 2: Q-Q-plots of precipitation in control and scenario



Note: The dashed diagonal lines form the comparison base of no climate change.
(Data: Prudence DMI HIRHAM High-Resolution Model/HadAM3H A2-scenario)

precipitation levels. As it was argued above it is not so much the changes in the climate variables but rather the changes in derived outcomes that affect human systems that are of interest. The documented climate shifts therefore motivate the study of changes in wheat yields as a consequence of climate change. A second conclusion from the disaggregated climate change plots are the apparent differences in the changes of the climatic distributions across regions of Denmark. PRUDENCE took its starting point from the lack of regional detail in earlier climate change studies using global circulation models. Even though Denmark in general is a homogenous country in terms of agro-climatic conditions, the results above show heterogenous changes in the climate variables. This proves the importance of disaggregated analyses of climate change.

The present study investigates the regional differences in the impact of climate change on wheat yields, as an example of a factor in the human management system affected by climate and its changes.

3 Agriculture and Climate Change

Intensive arable and livestock farming dominate agriculture in Denmark. Photosynthesis is the source of growth for biological systems, and the growing season is restricted by low temperatures in early spring and low solar radiation in the autumn [Olesen, 2000]. Precipitation is necessary for plant growth, but the amount of rainfall also directly affects the handling of the soils. Proper farming of the land is inhibited both by too wet and too dry soils.

Climate therefore has a complex impact on agriculture, where the volume distribution as well as the temporal distribution of meteorological outcomes matter. The broad pattern of a local climate is shaped by the total volume of radiation, precipitation and temperature over a certain period, typically a year. The distinctions between ecological zones are evidence of this. The temporal dimension matters, as plant growth is a process with several stages and climate affects all stages distinctly. During the earlier stages, cereals need sufficiently of soil water. During the final ripening and harvest however, crops require mainly radiation.

It is therefore not enough to only examine the broad trends for climate change in terms of mean annual temperature change, mean annual precipitation change, etc., in order to see the effects on agriculture. On the contrary, it is essential to take the distributions of climatic variables and namely the changes in distributions into consideration.

3.0.1 Winter wheat

The present study focuses on the effect of climate change on the yield of winter wheat. Winter wheat is the highest yielding cereal and thus most attractive crop in the Danish climatic context, and the decision to plant wheat in a rotation of crops determines the share of other crops as well.

The duration from sowing to maturity for winter wheat depends on temperature and in many cases length of the day. An increase in temperature will therefore, *ceteris paribus*, shorten the period in which the crop can accumulate biomass. This reduces yields, if the management is not adapted to the change in circumstances [Olesen, 2000]. But the reduction in yields from temperature increases will be countered by another factor. A higher content of CO_2 in the atmosphere increases the resource-use efficiency for radiation, water and nitrogen [Olesen & Bindi, 2002].

And the climate - and changes therein - does not only affect grain yields directly through temperatures, precipitation and CO_2, but also through a number of indirect channels. The same factors that affect crop growth also affect weed growth, although the impact can be different and change the competitive balance between the crop and the weeds [Olesen, 2001]. A change in humidity and temperature also affects diseases. Warmer conditions are more favourable to insect pests as insects proliferate. Climate change is therefore also likely to increase the pressure of diseases and pests on wheat production. In modern agriculture with the use of large machinery, the workability of the plots as determined mainly by the water content of the soil is also crucial for an optimal management strategy. All these indirect factors from climate to crop growth are not fully or jointly describable in laboratory tests. I will discuss the capture of these effects by different approaches to yield modelling in further detail in section 5.

4 Data Description

To assess the interplay of agriculture and climate, data on agricultural performance are combined with detailed meteorological data as well as the described long-term climate forecasts produced in PRUDENCE. As the latter data was discussed above, the next two sections will describe the agricultural data, with emphasis on the characteristics of wheat production, and the contemporaneous meteorological data.

4.1 The Agricultural Data

The agricultural data used in the present study stems from a yearly survey undertaken by the Danish Research Institute of Food Economics to ground national statistics on agriculture. The survey is a representative sample from the total population of agricultural enterprises in Denmark, stratified according to full-time/part-time, size of the enterprise, focus of production, acreage, age of farmer and location. The population is made up of 42,873 enterprises (2002) and the sample consists of 4.6% of the total population.

The sample is managed on a rotating scheme, in order to keep the sample representative of Danish agriculture and reduce the sampling burden on the single farmer. Every year approximately one third of the farming enterprises are dropped from the survey, while other are introduced to complete the sample.

The farm-level data cover the years between 1992 and 2003 with 1,600 to 1,900 farms sampled yearly. This yields a total of 7,330 individual farms and 22,332 observations over a 12 year period. Table 1(a) documents the number of times the individual farms have been surveyed in the present sample. On average the farms were sampled trice during the period. The farms cover between 117,639 and 215,100 hectares every year, see table 1(b), with an overall median acreage of 61 hectares, but as a number of large estates are included the average land holding is 83 hectares. Table 1(b) also documents the gradual increase in the land holdings per farm, a development driven by both economies of scale as well as by regulatory measures requiring acreage corresponding to livestock holdings. The latter has led especially to an increase in the acreage of hog farms.

4.1.1 A Characteristic of wheat cultivation

The present study focuses on wheat yields, as wheat is a cornerstone in the crop rotations of most Danish farms with crops. The acreage of wheat in-

Table 1: Number and Acreage of Farms

(a) Sampling frequency

Times obs.	N
1	2580
2	1447
3	939
4	756
5	487
6	350
7	212
8	218
9	116
10	88
11	46
12	91
Total	7330

(b) Pattern of rotation

Year	N farms	Acreage, ha		
		Total	Mean	Median
1992	1878	117781	63	46
1993	1855	117639	63	45
1994	1873	122519	65	48
1995	1898	131101	69	51
1996	1910	137661	72	55
1997	1869	142276	76	59
1998	1616	127532	79	62
1999	1893	160224	85	65
2000	1867	178705	96	75
2001	1897	193491	102	80
2002	1918	209465	109	85
2003	1858	215100	116	92
Total	22332	1853494	83	61

creased from 3% of the total agricultural area in 1971 to 25% in 1997 [Olesen et al., 2000]. The following paragraphs and statistics therefore characterize the production of wheat in the sample in terms of which farms cultivate wheat and what differences there are in the wheat yields across groups of farms.

In the full sample two-thirds of all farms cultivated wheat, and table 2(a) shows that this fraction has been constant over the 14 years of the survey. But disaggregating the sample by counties to gain an impression of regional differences yields a different picture, with the frequency of wheat cultivation ranging from a low 37% in Ringkøbing to a high 92% on the island of Bornholm. This contrast follows from the different agro-climatic conditions and the derived differences in the composition of farming in the different regions. The western parts of the country - for instance Ringkøbing, Sønderjylland and Nordjylland - are mainly built on sandy soils and show a higher proportion of cattle and dairy farming in contrast to the more clayey soils of the eastern regions - for instance Vestsjælland and Storstrøm.

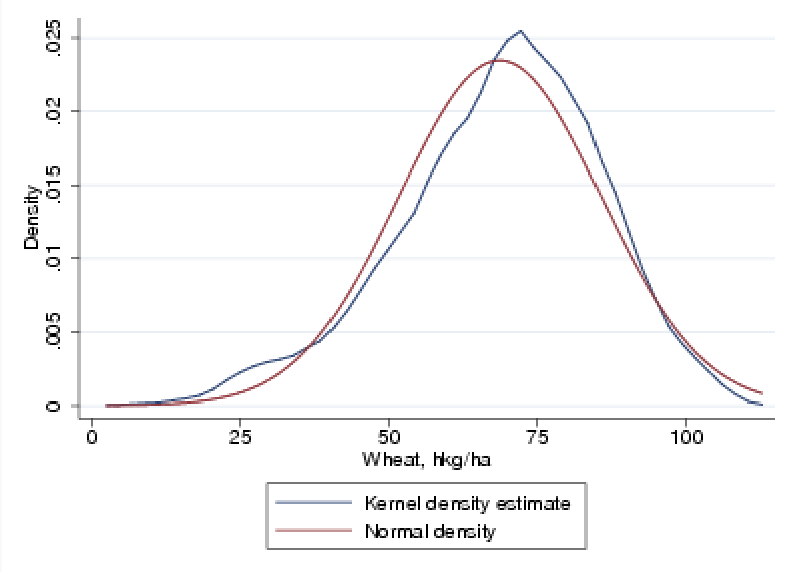
The yield for wheat (hkg pr. hectare) over all farms (with wheat production) and years is approximately normally distributed, see figure 3(a). But the scatter plot of county averages in yield in figure 3(b) shows a clear variation between the regional units. I will elaborate on these regional differences in the subsequent empirical analysis. Even though the sample only covers 12 years, the fitted quadratic function as well as a median spline function reveal a slight upward trend in the wheat yield over time.

Crop-producing farms and hog farms[5] show the highest wheat yields with a mean of 69 hkg/ha, while cattle farms on average only harvest 63 hkg/ha, see table 3. The third column also shows that only 45% of all cattle farm(-

[5] The definition of the production categories of crop-producing, hog and cattle farms is based on the main focus of the holdings in terms of gross margins. For further information see Pedersen [2003].

Figure 3: Wheat yields

(a) Distribution of wheat yields



(b) Development of wheat yields over time

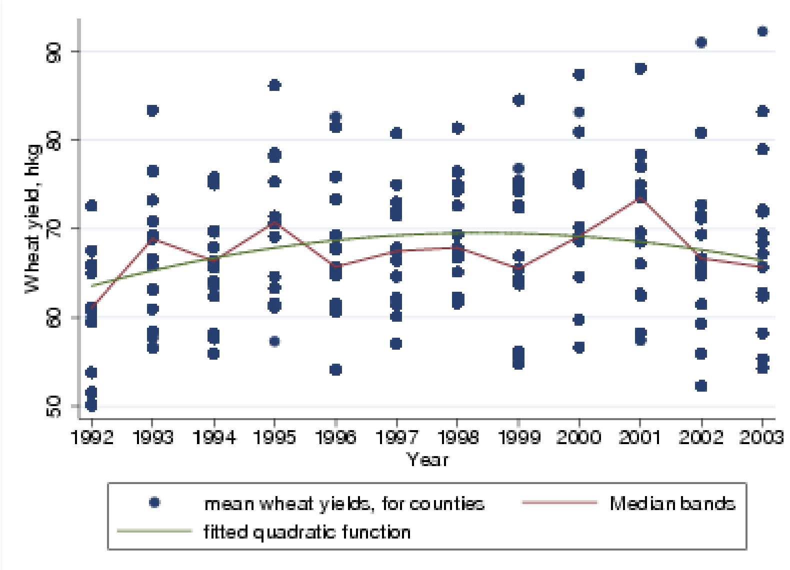


Table 2: FREQUENCY OF WHEAT CULTIVATION BY FARMS

(a) Over time

Year	Freq. (%)
1992	67
1993	70
1994	69
1995	67
1996	69
1997	68
1998	69
1999	60
2000	63
2001	66
2002	62
2003	64
Total	66

(b) Over space

County	Freq. (%)
København	84
Frederiksborg	81
Roskilde	80
Vestsjælland	86
Storstrøm	89
Bornholm	92
Fyn	85
Sønderjylland	64
Ribe	36
Vejle	67
Ringkøbing	37
Århus	79
Viborg	62
Nordjylland	65
Total	66

observations) cultivated wheat, while over three-quarter of the other groups had wheat acreage. The same distinction applies when studying the percentage of a farms acreage with wheat in column 4, and cattle farms also harvest a lower yield. This effect is partly due to the greater focus of cattle farms on coarse fodder and partly due to the higher prevalence of cattle farms in western Denmark with relatively poorer sandy soils. There is thus a clear difference in the likelihood of observing wheat cultivation among the production foci.

Table 3: WHEAT PREVALENCE AND YIELD BY PROD. CATEGORY

Prod. category	Obs.	Percentage of farms	Percentage of acreage	Wheat yield mean	Wheat yield std.dev.
Crops	5457	76	28	69	17
Cattle	3654	45	8	63	16
Pork	5805	80	31	69	15
Total	14916	64	22	68	16

As a consequence, it is mainly the larger farms that cultivate wheat. But this consequence can simply be a proxy for the effect of the production category, where crop and hog farms cultivating more wheat, as these groups on average are also made up of larger farms.

The management of a farm as a full-time or part-time job does not give rise to an overall difference in the cultivation of wheat. Table 4 distinguishes between these two groups, and shows no distinction in either the percentage of farms with wheat or the average percentage of acreage with wheat.

Organic farms are managed in order to let nutrients cycle between crops and livestock through the cultivation of fodder crops and extensive (and exclusive)

Table 4: Full-time vs. Part-time farming

	Obs.	Percentage of farms	land
Full-time	16953	68	21
Part-time	5647	60	23
Total	22600	66	21

use of manure as fertilizer. Conventional farms can add additional inputs into the system through e.g. mineral fertilizer. Organic farms therefore have to plant clover grass and pulses to restore the nitrogen content in the soil, and their rotation of crops has to pay closer attention to the control of pests by suitably sequencing their crops. These factors imply that fewer organic farms cultivate wheat and they on average also have a significant lower share of acreage with wheat than conventional farms, see table 5.

Table 5: Wheat by organic/conventional holdings

	Obs.	Percentage of farms	acreage	Mean yield (hkg/ha)
Conventional	15368	69	23	69
Organic/under change[a]	1586	27	5	43
Total	16954	65	22	68

[a]Not recorded in the data before 1995.

This section has documented some clear determinants of wheat cultivation, and I will in the following empirical analysis build on this.

4.2 The Meteorological Data

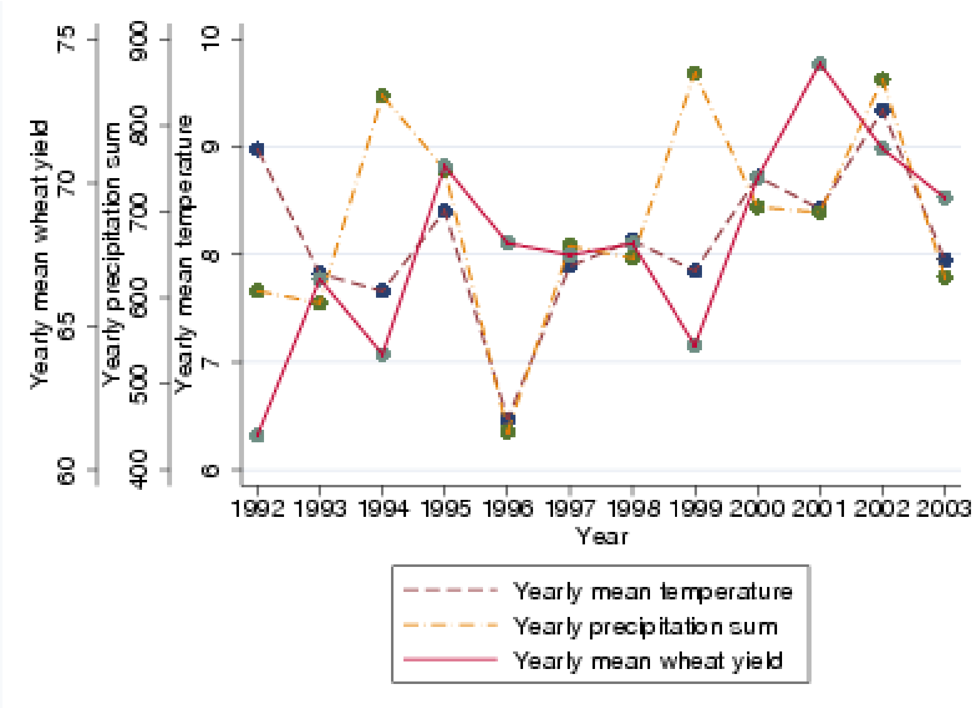
The direct agricultural inputs are supplemented by meteorological data to explain the regional and temporal differences in wheat yields documented in figure 3(b). The Danish Meteorological Institute (DMI) collects meteorological observations from local weather stations around Denmark, where information on temperature, precipitation and wind speed are recorded. As these stations are dispersed irregularly, I use interpolated values for a 10*10km grid calculated by the Danish Meteorological Institute. Here the information from the individual stations are inversely weighted by distance, and the transition between land- and sea-climates is handled. This interpolation obtains more smooth and complete data and lets the observations be less influenced by local, station-specific characteristics. See Scharling [1999b] and Scharling [1999a] for more detailed information on the climate grid, the calculations and the data.

From these meteorological grid observations the monthly temperature, precipitation and potential evaporation are derived and used to represent the weather impact on agricultural production during the yearly production cycle. The meteorological data is combined with the agricultural data by allocating the geographical location of the gridpoints to the municipalities the farms are located in. In case where there are several gridpoints in one municipality the values are averaged. With optimal sowing of winter wheat in September and a typical harvest in August the meteorological information from September to August are used to explain yields.

A decomposition of the variation in the meteorological data over space and time shows that the variation for temperature as well as for rain is dominated by the variation over time rather than variation over space. This was to be expected, given the geographically small area of Denmark, but stresses the importance of analyzing time series rather than only cross-sectional data to gain efficient estimates.

In figure 4 I have plotted yearly figures for temperatures, precipitation and yields over the observed years. Here as well the seeming upward trend in yields is conspicuous. Different combinations of temperature and precipitation determine the variation in yields, and a certain pattern is discernable. If temperature and rain move in unison, yields remain rather stable around the average yield at 69 hkg pr. hectare. When there is very high or low rain or temperature[6], yields typically fall. The years 1996 and 1999 are examples for.

Figure 4: Weather and Yield



But these general traits do not nearly explain the variation in yields over the years, and figure 3(b) also showed considerable variation in yields over space, adding a further dimension in variation to be explained. I will therefore

[6]Average overall temperature and precipitation in the observed period is 8.2 °C and 689mm, respectively.

proceed to build a model for wheat yields conditional on local weather as well as farm-specific input factors and determinants.

5 A Model for Wheat Yields

This section will outline the econometric model used for the description of wheat yields. The model of yields conditional on a range of farm-level human as well as ecological production factors is an economic view of wheat cultivation, and the focus of the present research is on the impact of climate change on human systems rather than on the intermediate environment.

Agronomic descriptions of crop growth by data from experimental plots and calibrated mechanic simulation algorithms give detailed analyses of the biological processes and stages. However, neither simulation algorithms nor experiments can account for the additional variation and (downward) bias in the yield outcome that stems from suboptimal farm management. This is at odds with the finding that the major part of the inter-annual variation in grain yields of winter wheat can be attributed to variation in stress conditions and management [Olesen et al., 2001].
Olesen & Bindi [2002] compare the yield gap, defined as the difference between yields in 1995-99 and the obtainable wheat yields in simulated optimal management scenarios, with the impact of climate change on yields. They conclude that for northern Europe the yield increase due to climate change is of the same magnitude as the yield gap. This substantiates the importance of managerial bias. For a further discussion of the proper modelling of yields see the discussion by Landau et al. [1998], Jamieson et al. [1999] and Landau et al. [1999].

Also indirect impacts of environmental factors on yields through the differentiated impact on soil texture, pests, weeds and diseases are only imperfectly and sporadically captured by models or experiments. A study that tries to introduce some of these factors into experimental designs is Olesen et al. [2000]. In the present approach this line of impact is taken into account as I study the impact of weather on the final yields, thus allowing for indirect positive as well as negative effects. A factor we cannot integrate in the present approach is the positive effect of CO_2 on crop growth, as we do not have the suitable data on CO_2 and the variation in CO_2-concentrations over the 13 years would not necessarily be large enough to even measure its impact on yields. As such the study is a contribution to the overall examination of the effects of climate change on agriculture, with a special emphasis on the study of real-world outcomes and managerial bias.

In the following I will first discuss the special characteristics of agricultural production and the derived model for wheat yields, before estimation issues are examined and an econometric model is outlined.

5.1 A Model of Agricultural Production

Agricultural production is a production with several stages, from sowing, the sprouting of the seeds, ripening and harvesting. The crop yield y is therefore modelled as

$$y = f[f_1(x^1), \ldots, f_m(x^m)|\alpha] \quad , \tag{1}$$

where superscripts $1, \ldots, m$ indicate production stages up to the harvest at m, x^t is the input vector in stage t, and $f_i(\cdot)$ are separable production functions for the intermediate 'output' y_i [Just & Pope, 2001]. The wheat production is moreover conditional on farm-specific effects α that include factors such as soil conditions and skills of the farmer.
The sequential specification points to an important distinction of agricultural production from other production processes. In order to gain a high yield, the farmer has to acquire information on partly unobservable intermediate outputs, such as the first seedlings and stands. Through experience, external information from extension services and monitoring the farmer has to deduce the optimal input strategy for the following stage of production. This process can be made clear by rewriting equation (1) as

$$y = f[f_1(x^1, y_0), \ldots, f_m(x^m, y_{m-1})|\alpha] \quad , \tag{2}$$

expressing the dependence of the production process[7] in stage i on the state of plant growth in the preceding stage $i-1$. y_0 constitute the initial conditions for crop growth, such as soil types.

Agricultural production is also characterized by the high importance of unpredictable and stochastic external factors, namely weather. The local temperature, moisture and wind speed constitute impacts on plant growth that cannot be fully countervailed by technological inputs, have impacts in all stages of production. Too wet conditions in early soil preparation stages can lead to a reduced airing of the top soil layers and reduce the germination capacity for newly sown seeds. Too dry conditions, on the other hand, do not give the seeds the necessary resources for growth and impede the development of stands. A combination of radiation, rain and temperature over the several distinct stages of the growing season determine the size and quality of the harvest. Too wet conditions during harvest lead to high energy consumption both for the harvest and subsequent drying of the crop yield. Weather characteristics at all stages of the growth cycle are thus significant determinants of the final yield, and have to be included in a descriptive model of crop yields. Equation (2) is therefore restated as

$$y = f[f_1(x^1, y_0, \epsilon^1), \ldots, f_m(x^m, y_{m-1}, \epsilon^m)|\alpha] \quad , \tag{3}$$

where ϵ^i represents the impact of weather on the intermediate production process f_i.

[7] The notation in equation (2) is a more convenient way of writing $y = f_m(x^m, f_{m-1}[x^{m-1}, f_{m-2}(x^{m-2}, \ldots, f_1(x^1, y_0) \ldots))|\alpha]$

The econometric model for wheat yield will follow these main structural characteristics, incorporating initial conditions, deterministic inputs and the stochastic impacts of weather on yields from several stages in the vector of explanatory variables. In the following two sections I will discuss estimation issues and outline the econometric model, before I proceed with the estimation.

5.2 Econometric Modelling Issues

For the calibration of a model for wheat yields on the farm-level data several issues have to be taken into account in the choice and design of an econometric model. Though discussed earlier, I will repeat the issues here for clarity and state them in terms of the econometric modelling to follow.

Firstly, individuals with differing skills, knowledge and experience manage a farm. As these factors are hard to quantify but do affects yields and other inputs, a farm-level analysis incurs an unobserved farm-specific effect. This effect is mostly thought of as the managerial skills, motivation and drive of the farmer, which are hard to capture quantitatively, as discussed by Rogour et al. [1998]. And in agricultural management of crops, correlation between this farm-specific effect and explanatory variables representing inputs in the growth process is likely. For instance, the application of fertilizer will most likely be correlated with a farmer's knowledge and experience. An estimation using e.g. pooled OLS would therefore yield inconsistent estimates. But given the repeated sampling of most farms in the present study we can deal with the unobserved effect as well as the correlation with the explanatory variables by a fixed effect specification of the yield model.

Secondly, there is a potential selection bias in the estimation of a conditional distribution of wheat yields. In the sample we only observe wheat cultivation for two-third of the observation in any survey round. The wheat yields for the sub-sample of farms with wheat cultivation do not give a reliable estimate of the wheat yields of the other farms, had they decided to cultivate yield. Typically, a farmer decides what crops to grow given the characteristics of the farm in terms of other fixed production lines on the farm, available fixed capital inputs, soil quality, the predominant weather pattern and the expected output and input prices. Section 4.1 gave evidence of the differences and determinants of wheat production. The sub-sample of wheat-cultivating farms is therefore not a random sample of the population, but rather endogenously determined by farm characteristics and potential yields. An estimation on the sub-sample therefore does not give consistent estimates for the population of farms, as it was initially shown by Heckman [1979]. And an estimation on the full sample would lead to inconsistent estimates, as these are confounded with parameters determining the probability of cultivating wheat in the first place. To deal with this non-random selection, I will apply a two-stage selection model, where the entry of the farms into wheat cultivation is explicitly modelled.

Thirdly, the survey is managed as a rotating panel, where approximately a third of the farms are dropped from the survey in every round and replaced by others. Farms are therefore observed for between 1 and 12 time periods, both continuously and sporadically.

5.3 An Econometric Model

The current section outlines a two-stage Tobit selection model based on Wooldridge [1995] to take account of the raised issues, namely the non-random selection of wheat production, the rotating sampling scheme and the correlated farm-specific effect in the yield model.

Based on equations (1) to (3), wheat yield for farm i in year t is modelled as

$$y_{it} = \alpha_i + \mathbf{x}_{it}\beta + u_{it} \quad , \tag{4}$$

where α_i is the farm-specific effect expressing the conditioning factors for wheat growth. $\mathbf{x}_{it}$ is a vector of explanatory variables for wheat yields, and u_{it} a residual term. The sequential nature of the wheat production model in equations (1) to (3) will be captured by the inclusion of seasonal weather observations in the explanatory vector $\mathbf{x}_{it}$.

The observations of wheat yields are conditional on the cultivation of wheat. Acreage of wheat, h_{it}, is therefore modelled as a left-censored tobit model

$$h_{it} = \max[0; \mu_i + \mathbf{z}_{it}\delta + v_{it}] \quad \text{and} \quad w_{it} = \mathbf{1}[h_{it} > 0] \quad , \tag{5}$$

where $v_{it} \sim N(0, \sigma_t^2)$ and v_{it} is independent of $\mathbf{z}_{it}$ and μ_i. The tobit-specification utilizes more information than a probit selection rule, which was used by Heshmati [1994]. The vector of explanatory variables z_{it} can be overlapping with x_{it}, but for identification we have to have an exclusion restriction on x_{it}. This condition will not be too difficult to fulfill for wheat production, as the decision to grow wheat is determined partly by fixed characteristics that do not affect yields directly, an issue I will come back to. To reflect the rotational sampling, I define $r_{it} = 1$ if farm i is surveyed in time t.

For equation (4) the strict exogeneity assumption

$$\mathrm{E}(u_{it}|\alpha_i, \mathbf{x}_i, r_{it}) = 0 \quad \forall t \tag{6}$$

is invoked. The conditioning on r_{it} implies that the rotation in and out of the sample is assumed to be exogenous to (deviations in) the wheat yield, a plausible assumption. The rotation of the sample is undertaken to keep the sample up to date with the overall structure of Danish agriculture. Any correlation of r_{it} will thus rather be with structural characteristics of the farm, and assumption (6) does not restrict the correlation of r_{it} with α_i and $\mathbf{x}_i$.

To correct for the selection bias in equation (4) the expectation of the yield residual has to be conditioned on both components of the error term, v_{it} and μ_i, in the selection model (5) [Wooldridge, 1995].

As it is standard in two-stage selection models, the residual of the yield equation is conditioned on the residual in the selection equation as

$$\mathrm{E}(u_{it}|\mathbf{v}_i) = \rho v_{it} \quad . \tag{7}$$

The time-invariant effect μ_i in the selection equation (5) constitutes a general predisposition of farm i to cultivate wheat. This effect will depend on the general characteristics of the farm in terms of other fixed production lines on the farm, available fixed capita inputs and soil quality. I therefore specify a Mundlak [1978]-type decomposition of μ_i as

$$\mu_i = \bar{\mathbf{z}}_i\gamma + c_i \qquad ,$$

where $\bar{z}_i$ are time constant farm characteristics and $c_i \sim N(0, \sigma_c^2)$. Inserting this expression for μ_i into the selection model (5) yields

$$h_{it} = \max[0; \bar{\mathbf{z}}_i\gamma + \mathbf{z}_{it}\delta + c_i + v_{it}] \quad . \tag{8}$$

Assuming now that (u_{it}, v_{it}) are independent of $(\alpha_i, \mu_i, x_i, z_i)$, the conditional expectation (7) can be extended to

$$\mathrm{E}(u_{it}|\alpha_i, c_i, \mathbf{x}_i, r_{it}, \mathbf{z}_i, \mathbf{v}_i) = \mathrm{E}(u_{it}|c_i, \mathbf{v}_i) = -\rho c_i + \rho v_{it} \quad . \tag{9}$$

The first equality restates the orthogonality assumption (6) that α_i, x_{it} and r_{it} are strictly exogenous, conditional on c_i and v_{it}.
The second equality makes the residual u_{it} in the yield equation a (linear) function of the full error term in the selection equation to correct for the selectivity bias, and states the mean independence of u_{it} from $v_{ir}, r \neq t$, conditional on the latent variable c_i. Assumption (9) thus excludes serial correlation in v_{it}. With a correctly specified selection model (8) for the acreage of wheat, we should not observe serial correlation in v_{it}. Any latent effect in the selection should be captured by $\bar{\mathbf{z}}_\mathbf{i}$.

These assumptions do not put any conditions on the correlation between the farm-specific effect α_i and the explanatory variables x_{it} in equation (4). Other possible estimation approaches, such as SUR, pooled OLS and GLS require (at least) contemporary exogeneity of α_i and $\mathbf{x}_{it}$. This is, as discussed above, implausible for the model for wheat yields.

This allow us to restate the model for wheat yields in a fixed effect specification as

$$\begin{aligned} \mathrm{E}(y_{it}|\alpha_i, c_i, r_{it}, \mathbf{x}_i, \bar{\mathbf{z}}_\mathbf{t}, \mathbf{z}_\mathbf{it}, \mathbf{v}_\mathbf{i}) &= \alpha_i + \mathbf{x}_{it}\beta - \rho c_i + \rho v_{it} \\ &= \eta_i + \mathbf{x}_{it}\beta + \rho v_{it} \quad . \end{aligned} \tag{10}$$

As the selection in equation (5) is fully determined by $\mathbf{z}_\mathbf{it}$, $\bar{\mathbf{z}}_\mathbf{it}$ and v_{it}, we can by the law of iterated expectations condition on w_{it}, and we can state the expectation of wheat yields for the sub-sample of surveyed farms with wheat as

$$\mathrm{E}[y_{it}|\eta_i, r_{it}, \mathbf{x}_i, \mathbf{v}_i, w_{it}] = \eta_i + \mathbf{x}_{it}\beta + \rho v_{it} \quad . \tag{11}$$

This allows us to estimate the panel-data model

$$y_{it} = \eta_i + \mathbf{x}_{it}\beta + \rho v_{it} + \epsilon_{it} \quad , \tag{12}$$

using a within-estimator on the sample of wheat-cultivating farms. The selection bias correction term, v_{it}, is not directly observable, but can be estimated consistently by cross-sectional tobit regressions of model (8) for each t.

A significance test for $\mathrm{H}_0 : \rho = 0$ in model (12) also offers a direct testing strategy for the occurrence of sample selection.

6 Estimation Results

Based on the discussion in the previous section of the model for agricultural production and the econometric estimation strategy, the present section will present a range of estimation results. First the estimation of the selection model (8) is reported. The estimated tobit residuals are used to correct for the selectivity bias in the subsequent discussions of yields estimation results. I here present a number of different specifications and show the corresponding simulations or wheat yields under the PRUDENCE *scenario* forecast described in section 2.

6.1 Selection equation

In the first stage of the outlined econometric strategy, the selection equation (8) has to be estimated in order to find estimates for $\hat{v}_{it}$.

The decision to grow wheat is a function of structural farm characteristics that are not variable in the short-term as well as year-specific factors that may change. Table 6 in the appendix reports the estimation of the selection model for all rounds separately.

As the dependent variable in the selection model, I use the relative share of wheat of farm acreage, instead of the absolute acreage with wheat. Using the percentage of wheat lets us distinguish economies of scale from the simple effect that larger farms can allocate more hectares to wheat.

The focus of production on a farm is a rather stable characteristic, as farmers often have tied considerable amounts of capital in stables and specialized machinery. Here the indicator for cattle farms is highly significant over all estimations in table 6, reflecting the earlier stated fact that cattle farms show a lower proportion of wheat cultivation than hog farms or crop-producing farms. Hog farms do not show any significant difference in their choice of wheat compared to the base group of crop-producing farms.

Another structural characteristic is whether the farm is organically managed. To become organically certified, farmers have to go through a transition period over which they have to manage their activities organically but cannot obtain the higher or subsidized output prices. This makes the change rather costly, inducing sunk costs and thus a reluctance to change on short notice. The discussed features of organic farms in terms of crop rotation and pest control mean that wheat is less attractive for them. This is reflected in the significant negative impact of the organic indicator on the acreage of wheat.

To control for the yield potential of the farm in the decision of the farmer, I use soil type and general weather patterns. Winter wheat is best grown on clayey soils, which is clearly reflected in the coefficient of the percentage of clay soils on the farm. In addition, the seasonal means[8] over precipitation and temperature show a high joint significant, confirming the anticipation that

[8]The seasons are defined as; autumn: September, October, November; winter: December, January, February; spring: March, April, May; Summer: June, July, August

farmers plant wheat if wheat is suited in the specific context. Here a certain degree of interdependence cannot be ruled out, as the composition and local practices of agricultural production are adapted to the local conditions. The positive effect of clay on wheat cultivation can therefore partly stem from the higher prevalence of cattle farms on sandy soils in western Denmark. A similar mechanism can also work for the weather patterns, as the main focus of production is obviously adapted to the specific climatic conditions.

6.2 Yield estimation I

Equipped with the first stage tobit-residuals $\hat{v}_{it}$, the second-stage fixed effect model (12),

$$y_{it} = \eta_i + \mathbf{x}_{it}\beta + \rho\hat{v}_{it} + \epsilon_{it} \quad ,$$

can be estimated. Table 7 (in the appendix) reports the estimation results for a first model of wheat yields.

As for the selection bias, a joint test on the included (but not reported) tobit-residuals from the first stage are highly significant, thus reconfirming the earlier discussion and empirical justification of a selection correction approach.

The explanatory variables $\mathbf{x}_{it}$ for wheat yields can be sorted into 3 categories - the initial conditions for plant growth, the deterministic inputs by the farmer, and the meteorological outcomes as stochastic inputs to plant production.

Soil types - i.e. different blends of sand, clay and humus particles - constitute the conditioning factors for plant growth and gain their importance through their ability to store and release nutrients and water. Clay can hold more water than sandy soil and wheat generally does better on clayey soil. But the percentage of clay soil on the farm is not significant in the present yield regression. This has two explanations. If there is sufficient precipitation, the soil type is less crucial, and on modern non-organic, intensive farms the management effects dominate the effects of the soil type. A consequence of this is that the absolute increase in wheat acreage in Denmark between 1971 and 1997 was largely driven by a relative increase in wheat on sandy soils [Olesen et al., 2001]. Besides this natural explanation, the econometric specification may give another clue. The farm-specific effect is likely to capture the effect of the soil type on yield, and leave the percentage of clay soils without explanatory power. Further studies would have to shed light on these two explanations.

The next four coefficients reflect the managed inputs or yearly decisions by the farmer. Pesticides (expressed in 1000dkr) have a small but significant effect on the yield, as they keep pests and diseases at bay. Mineral fertilizer does not show any significant impact on yields, but this may partly be a result of the econometric specification with a farm-specific effect. The amount of mineral fertilizer is to a large extend determined by the soil type, as different soil types have varying requirements on supplementary minerals. The farm-specific effect will capture the mixture of soil types on the farm, and thereby also 'explain' a large part of the fertilizer-effect on yields.

While the coefficient for pesticides and fertilizer express linear and continuous effects, the organic indicator exhibits a threshold effect, as organic farms cannot use either mineral fertilizer or pesticides. The estimation result here reproduces the significantly lower yield - 15 hkg less per hectare on average - that organic farmers have to tolerate when cultivating without pesticides and mineral fertilizers. But this fall in yield is usually offset by higher prices and subsidies for organic products.
The fifth coefficient in this group - lagged percentage of grain acreage - displays the effect of crop rotation on the yield. All crops utilize a certain bundle of nutrients in the soil and subsequent cultivation of similar crops on the same plot reduces the potential yield. A high percentage of grain crops in year $t-1$ should therefore have a negative impact on yields in year t, which is confirmed in the present regression.

Even though the data used only cover 12 years, the descriptive evidence in section 4.1 indicated an increase in yields over time. This finding is here confirmed by the positive and significant trend that indicates an average increase of 0.8 hkg in yields per year due to better technology, more knowledge and improved management practices..

Following the preceding discussion and model (3) the vector of climatic variables consists of observations on temperature, precipitation and potential evaporation over several stages $1, ..., m$ of the growth process of wheat, from sowing in September till harvesting in August. This group of meteorological controls shows a high joint significant, thus substantiating the impact of the weather for the cultivation of crops. I have chosen a second-order specification of the meteorological effects, as there is a natural saturation of wheat growth with respect to both precipitation and temperature. The regression indicates that the weather, especially in the autumn and winter, determines the yield. Both temperature and precipitation show hump shaped effects on yields in the first 6 month of wheat's growing season. This reflects that high precipitation in the autumn can hinder the optimal sowing and postpone it. The seedlings are therefore smaller when the winter starts and take longer in the spring to regain the lost growth, reducing overall growth. These results broadly confirm findings in Olesen et al. [2000].

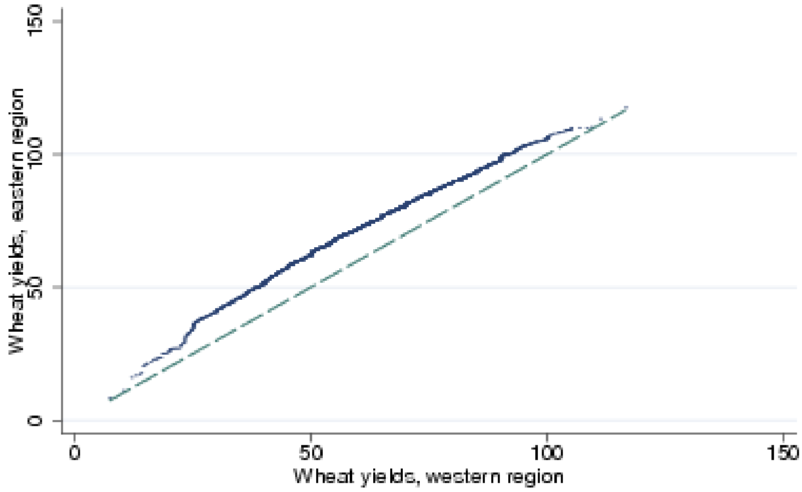
6.3 Yield estimation II

In the data descriptive part above I gave some evidence of regional differences in wheat production, e.g. the variation in yields in the single years across counties in figure 3(b). This is followed up by a regionally differentiated model for wheat yields, where I use the unique local dimension of the data assembled in the present study.

For this purpose, Denmark is divided into 2 regions. The peninsular Jutland in the west with rather sandy soils and higher precipitation figures forms the one region of analysis, while the islands in the eastern part of the country with their rather loamy soils and less precipitation form the other region. The regional differences are also substantiated by a quantile-quantile-plot of wheat yields in eastern Denmark against wheat yields in western Denmark, see figure

5. The plot indicates an upward shift in location from west to east Denmark, as soils in the eastern parts are overall more fertile than soils in Jutland.

Figure 5: Regional differences in observed yields



Note: The dashed diagonal lines indicates the comparison base of no differences in the yield distributions. (Data: Representative farm data from the Danish Research Institute of Food Economics

These regional differences are caused by different environmental compositions and thus we should expect a differentiated impact of weather on wheat yields. Tabel 8 (in the appendix) reports the estimation results for this model, where I use bimonthly data for temperature and precipitation instead of tri-monthly/seasonal data as in the previous model. The meteorological data has been differentiated by regions, which here are defined as Jutland on the one hand and the islands on the other hand[9].

The impact of non-weather variables was discussed above and is roughly unchanged, but overall the model shows a better fit than the previous one. The variables '..., east' denote the additional impact of temperature or rain for the eastern region, and the better fit of the model is confirmed by the clear significance of the regional differentiation in table 8. We can therefore conclude that there are regional differences in the sensibility of wheat yields to weather and climate change. I will use this to analyze regional differences in the effect of climate change on agriculture.

7 Yield Simulations

The present section uses the estimation results from the previous section to simulate wheat yields under the climate forecast scenario discussed in section 2.

[9]A further regionalisation into 5 regions was tested, but the results were not as clear-cut as the east-west divide and fit the data worse.

We have repeatedly stressed the importance of using local and intra-year-differentiated weather data to model agricultural production, as the harvested yield will depend on the local weather conditions, for instance in October and in July. This fits with the scenario data, where we have monthly means of precipitation and temperature for a 25×25km grid for the years 2070 to 2100, but the issue at hand is to decide how to use this data to forecast. For a start, I will use monthly means in temperature and precipitation over all 29 years[10], as a central estimate of the full distribution of monthly measures. Alternatives to use in future work are the median and other quantiles of the meteorological distributions to assess more extreme weather outcomes.

I will first present a simulation using the overall model from estimation I, without any regional distinctions, before I apply estimation II to gain information on the regional differences in yield changes.

7.1 Forecast with overall seasonal-means - Estimation I

Figure 6(a) plots several nonparametric yield distributions. As a base for comparison, the distribution of observed yields from the agricultural data has been plotted. To test the fit of the estimated model for wheat yields, the model is first applied to the observed agricultural and meteorological data 1992-2003. The estimated distribution of wheat yields can be seen to fit the original overall distribution of wheat yields reasonably well. The estimates seem to be a little more centered with lower tails, which is probably the result of the estimation using an expected means-model. To do better on these details, one could apply quantile regressions in the second step. Bushinsky [1998], for instance, has applied quantile methods in a selection context.

The third distribution in figure 6(a) shows the distribution of forecasted yields, which have been generated by inserting the predicted monthly means of temperature and precipitation into the estimated model from regression I (table 7). The other production factors are kept unchanged.

It is seen that the mean of the forecasted yields is significantly lower than the mean of the presently observed yields. This is in line with other findings for wheat yields in a Danish climate, that a higher temperature *ceteris paribus* leads to faster ripening of the crop and therefore a lower yield [Olesen et al., 2000, for instance].

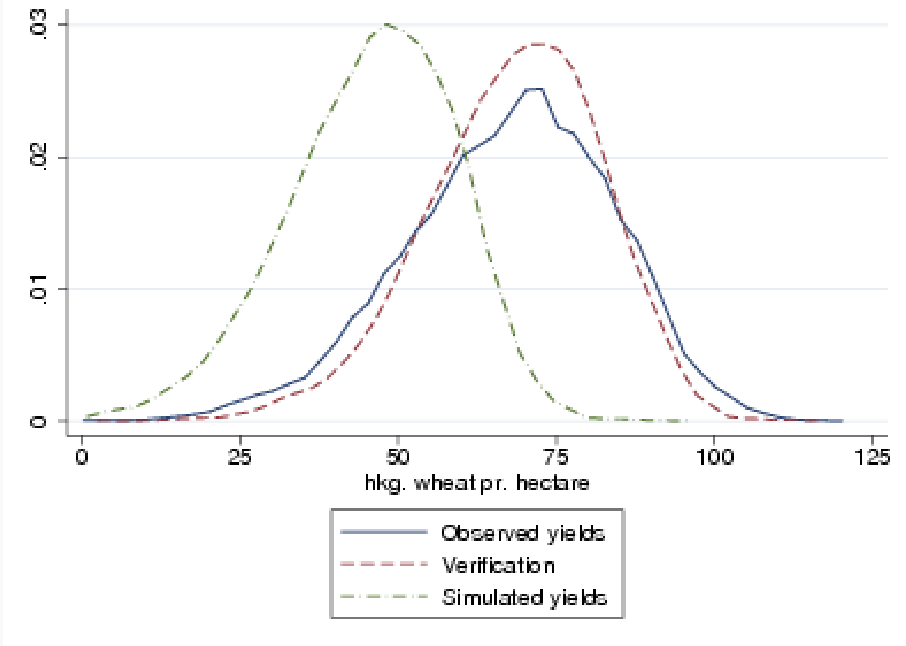
To compare not only the change in location, as represented by the mean, but also the change in dispersion, figure 6(b) presents a quantile-quantile plot of the present yields against the forecasted yields. The decrease in the location of the distribution is confirmed by the - in relation to the diagonal - downward shifted quantile-quantile plot. But moreover the q-q-plot is slightly tilted clockwise compared to the diagonal, indicating a small reduction in the overall variance of yields.

We are, as noted before, not able to assess the positive effect of an increased CO_2-concentration into account. Olesen & Bindi [2002] quote experimental

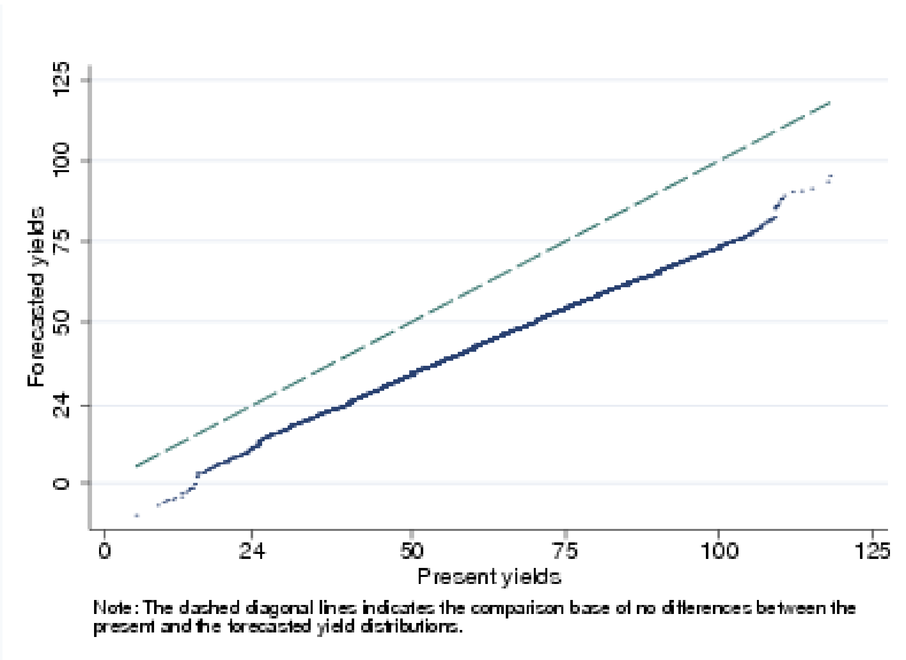
[10] The reorganization of the data into agricultural years September-August looses 1 year of the full 30-year time span.

Figure 6: Comparing present and forecasted wheat yield distributions

(a) Plot of distributions



(b) The distributional impact of climate change



results from Downing et al. [2000] that indicate a mean wheat yield increase of 28% from a doubling of the current CO_2-concentration in the atmosphere. This corresponds approximately to the lower bound in the prediction for CO_2-concentrations by IPCC [2001a] in the year 2070. But IPCC [2001b] mentions that productivity gains in crops as a response to increased CO_2-concentrations are smaller under field conditions than indicated by plant-pot experiments. With simulations of wheat yields in an integrated assessment model, Antle et al. [2004] find a decrease of between 20% and 40% in wheat yields without the CO_2-fertilization, while the inclusion of the CO_2-effect leads to an overall slight increase. While their first result thus lends support to our findings the latter points to the supplementarity of the present assessment and the agronomic approaches.

Technological change

A reservation to take to the presented forecast of the yield distribution is the long time span between on the one hand the base data on which we have estimated the models, and on the other hand the climate prediction that are inserted to form the forecasts. As the models are estimated in the data-specific context of the years 1992 to 2003, the estimated model parameters reflect the current technological restrictions on agricultural production. However, it is to be expected that agricultural technology will improve over the next 70 years in the form of higher-yielding and adapted seed corn as well as better cultivation techniques. Figures 3(b) and 4 already gave an indication that yields showed an increasing trend even over the 14 years of agricultural data analyzed. To capture this process a trend variable was inserted into the model and indicated an increase in yields over time, see table 7.

The predictions and illustrations above were undertaken in the present data-specific context, so no technological progress was assumed. In the following I will undertake a small sensitivity analysis to illustrate the impact of different scenarios for technological progress.

In figure 7 I have again plotted the present distribution of yields as the baseline, but now yields are forecasted with a linear trend under the present and predicted climate, respectively. Now the forecasted yields under the predicted climate scenario exhibit a higher mean than the present wheat yield distribution. The increase in yields from technological progress has undone the 'pure' fall in yields found above in figure 6(a). The combination of climate change and technological progress shifts the mean of the yield distribution approximately 39% up. However, the earlier documented fall in yields solely from climate change is still present, as technological progress would have increased yields far more under a continuation of the present climate. Kim & Chavas [2003] similarly find evidence for climate change, but also conclude that the impact of technological change dominated climate change for corn farmers in the corn belt of the United States.

The used linear specification of technological progress is only one scenario for future technological change. Figure 8 therefore reports the same results as in figure 7, but now with a logarithmic specification of the technological progress. As expected, this concave functional form reduces the increase in yields over the time span. Under the present climate regime, mean yields would increase by approximately 20% over the time span. But the earlier reported yield fall due to climate change undoes this technologically induce increase. The combined effect of climate change and technical change leads to small fall in mean yields, mainly due to a smaller right tail of the distribution. I will discuss the issue of technological adaptation to climate change in more detail in section 8.

7.2 Forecasts by regions - Estimation II

The estimation results in table 8 showed that there are clear regional differences in the sensibility of wheat yields to weather outcomes. This conclusion is here taken up to produce regionally distinct forecasting scenarios, illustrated in figure 9.

The model is shown to fit nicely to the observed distribution of current wheat yields, as the fitted distribution using the base data almost overlaps with the observed distribution, although the tails still seem a little lower. See the discussion on this issue in the previous section.

For the regional analysis, Denmark has been subdivided into an eastern region combining the islands of Denmark, and a western part with Jutland, as discussed above. The change to the new climate regime produces an overall leftward shift of the two regional distributions, in line with the earlier findings for the full sample. The disaggregation of the forecast by regions shows that the impact of climate change is predicted to be higher in Jutland than in the eastern parts of the country. This exacerbates the present regional differences in wheat yields, where yields on the eastern islands are overall higher than the yields on Jutland (figure 5). The intra-year variability of precipitation is predicted to increase, and the fall in yields could therefore be attributed to the lower capacity of sandy soils to hold water and act as a buffer against temporary precipitation surpluses and shortfalls.

For this forecast of course the same comments on the effect of CO_2 as well as on technological progress apply, as discussed above. However, these caveats have a more or less uniform impact on yields, and they will therefore not change the relative conclusion, that Jutland under the ecological as well as the present socio-economic conditions (e.g. the higher prevalence of cattle farms) will be harder hit by climate change. But the most important conclusion to draw from this result is the regional difference in the effect of climate change on agriculture. This gives better information to deal with climate change, especially for the specification of a suitable policy context, as I will discuss in the following section. Another conclusion from the regional disaggregation is that the source of the difference needs to be analyzed in more detail. It is namely of interest for a policy debate to see whether the difference is caused by ecological conditions for agriculture (e.g. sandy soils) or by the socio-economic context (for instance cattle rearing vs. hog farming), in order to improve the understanding of potential adaptation strategies.

Figure 7: Comparing present and forecasted wheat yields with linear technological progress

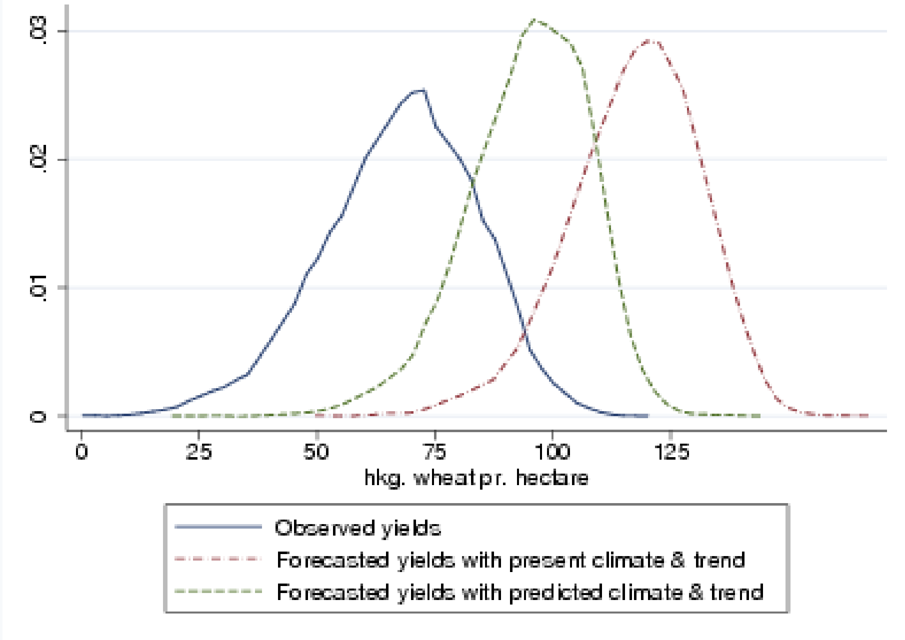
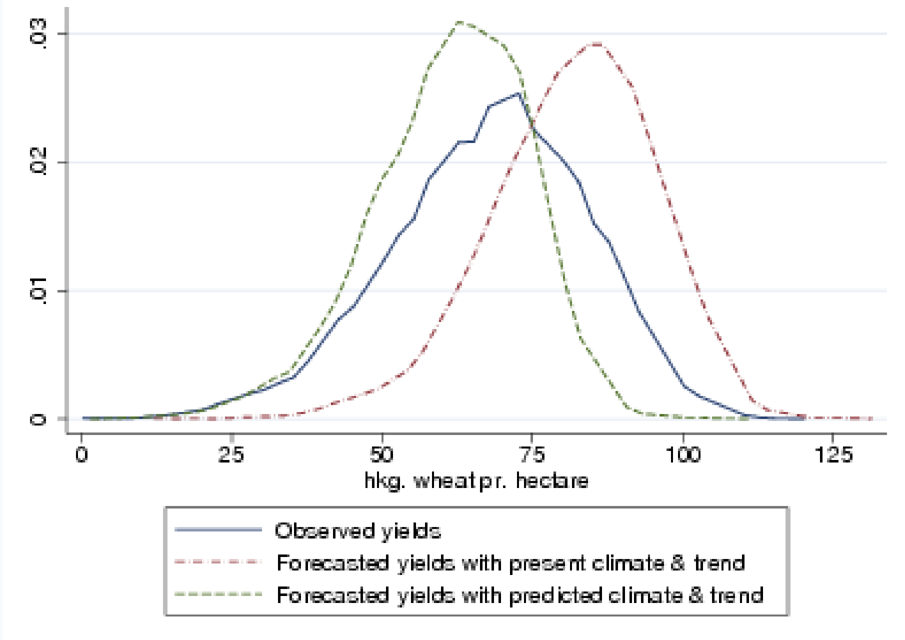


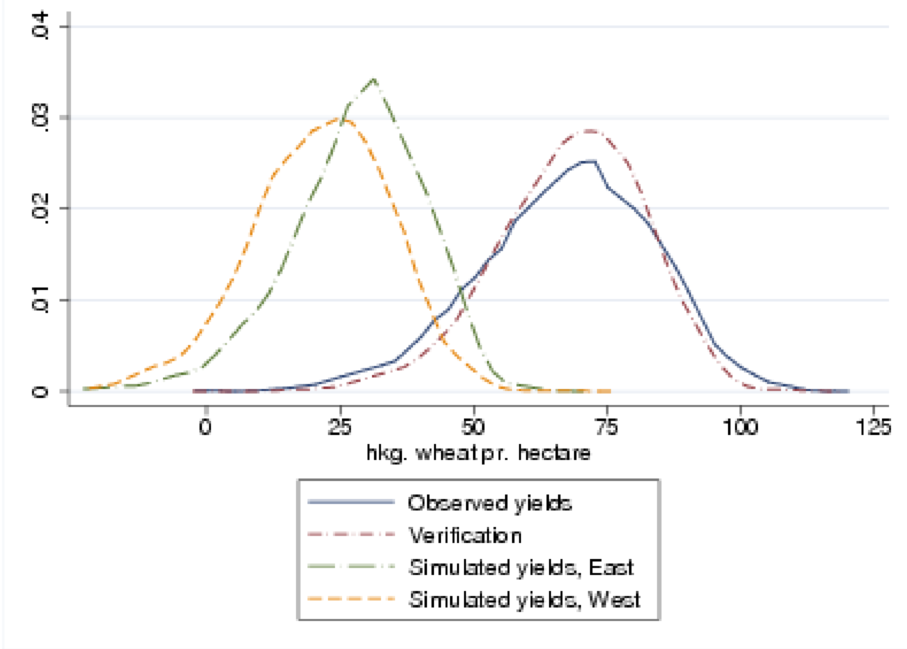
Figure 8: Comparing present and forecasted wheat yields with decreasing technological progress



8 Adaptation

With changes in the climate, adaptation to these changes will have to occur in agriculture, as the climatic input into production cannot be substituted on

Figure 9: Forecasted wheat yield distributions with regional differentiation



any reasonable scale. From ancient times, farming systems have adapted to changing economic conditions, technologies, resource availabilities and population pressure. The effects of climate change on agriculture will therefore in a similar spirit be met by changes in managerial decisions on crop choice, soil management and applied technologies. Changes in the climate can for instance be countered by changes to crop sorts that are better suited to the new climate regime. The frequency and timing of farm operations will be adapted to the changed growth pattern of the crops. An increase in temperatures and the following shorter duration from sowing to ripening will for instance lead to a change in the optimal sowing data, as documented by Olesen [2000]. Changes in the yearly distribution of precipitation can lead to moisture shortages for parts of the year, as it is also the case on some sandy soils in Denmark today. This is already today offset by irrigation, and extended moisture shortages could thus be met by the application of technology (if it is profitable to do so).

An important role in the adaptation to climate change will be assigned to technological developments. The past challenges to agricultural development have mostly been met by technological conquests of new technologies. In the present models used for forecasting wheat yields under the new climate regime the technological progress in agricultural production was modelled using a time trend. As noted, this specification might not be fully correct. Still, it gives an indication that technological developments have to be taken into account for the effects of climate change. In agricultural economics, the analysis of the generation and adoption of new technologies constitutes a large field, see for instance the review by Sunding & Zilberman [2001]. Adoption of new technologies in agriculture and thus technological adaptation to climate change is highly heterogeneous and depends on a number of factors. Firstly, agricultural technology is embodied both in physical capital such as buildings and machinery, as well as in variable inputs such as seeds, fertilizer and pesticides. These two classes of inputs into agricultural production are distinguished by their fixed nature, where the former requires long-term investments while the latter can be changed with short notice. Secondly, the decision to adopt new technology is highly dependent on individual abilities to learn and heterogeneous constraints on the access to information and to credit for investment.

8.1 The Policy Environment and Adaptation

Another major force on the structure of agricultural production and therefore the adaptation to climate change is the policy environment.

A general question for policy considerations with regard to climate change is the aim of the policies. Farming policies can on the one hand be used to support the existing (farming) structures, and can on the other hand be pro-active and back adaptive measures by individuals. The latter can happen through economic incentives or through the provision of a supportive infrastructure.

The common agricultural policy (CAP) for the European Union is a major determinant of the structure and development of European agriculture. Policy instruments can overrule necessary adaptation impulses and freeze a production set-up. In as far as subsidies, price stabilization programmes and regulatory policies dominate the incentives to adapt to a changing climate, a policy environment such as the CAP can counteract adaptation. But the costs of the common agricultural policy as well as demands through the World Trade Organization have over the last decades implied a trend towards more market-based price determination coupled with area-based income subsidies and structural programmes. This leaves the incentives of the single farmer for adaptation in place.

For the adaptation to climate change specifically the provision of information stands out as a possible supportive measure. Information about climate change and its (locally and regionally differentiated) consequences is the crucial factor for an efficient adaptation of agricultural structures to the changing environmental conditions. The adaptation of crop varieties to local climate and soils as well as the composition of fertilizer are based on agronomic models and/or experimental evidence. As climate change progresses, this information will increasingly have to be updated to suit a new climate regime at a certain location. Information shows public good characteristics, as the use of a piece of information by one person does not reduce the possible consumption of the same piece of information by another. The private provision of information is therefore inefficient, as the single agent does not take the full benefit for the others into account. There is therefore a role for social provision of information on the (local and regional) consequences of climate change.

9 Conclusion and Discussion

New and unique regional climate prediction data shows the regional effects of climate change for weather outcomes in Denmark. The present study has utilized these data to forecast and discuss the impacts of climate change on Danish agriculture, namely on the distribution of wheat yields. Using a large data set with farm-level information combined with data on local meteorological observations, a fixed effect panel data model for wheat yields is estimated, including a prior tobit model to correct for the selection bias from wheat production.

The model is estimated in two versions. In the first all farm observations are treated jointly. In the second the data is differentiated regionally to gain an insight into the regionally different impacts of climate on agriculture. Both models are seen to fit the observed distribution of wheat yields well, and climate change is found to have strong negative impact on the location of the distribution under the current technological constraints on agriculture. This fall in yields is transformed into a net increase in the location of the yield distribution once we take account of the impact of technological progress on yields.

For the regional analysis, Denmark has been subdivided into an eastern region combining the islands of Denmark, and a western part with Jutland. A difference is found in the effect of climate change for the two regions, where Jutland experiences a larger decrease in mean yields. In this context I point to the need for further studies on the specific cause of the regional differences of the impact as well as the informational needs on climate change, in particular with respect to these localized effects.

In the econometric approach and the use of data from privately managed farms, the study differs from agronomic approaches, which mainly use experimental data and crop growth simulation models for yield modelling. The present approach can integrate the indirect effect of climate on yields (for instance through its effect on pests and diseases), the real-life management bias as well as scenarios on technological progress. The agronomic approaches are better able to study the growth stages of crops and can simulate possible but yet unobserved changes, such as the impact of an increasing CO_2-concentration. As such, these approaches supplement each other, yielding specific information on a variety of issues for the impact of climate change on agriculture. The final prognosis on the effect of climate change on agriculture is a highly complex picture, and the different approaches can shed light on specific parts of it. And the inherent lack of knowledge on future technological development paths and possible adaptations through changes in agricultural practices and technological will remain.

The study has focused on the impact of climate change on one crop, winter wheat. Analysis along similar lines can be undertaken for other crops to gain profiles of climate change effects. Assembled, such studies can enter into farm-level multi-crop and -activities models[11] to predict changes in crop rotations

[11] For instance the econometric agricultural sector model ESMERALDA maintained by

and aggregated effects on agricultural supply.

We have focused on the changes in wheat yields from climatic conditions in real life settings for privately managed farms. To describe the final impact of climate change on agriculture and individual farmers, one needs to consider the income of the farmer, which is determined not only by the yields but simultaneously by the the price-profile of the crop.
The price variability in agricultural markets in Europe is expected to rise in the wake of reforms of the CAP and an increasing integration of EU-markets in the world trade of farm goods. If we describe the price of wheat over time by a probability distribution, the correlation between the yield at the single farm and the market price for wheat has to be taken into account to give a full picture of the uncertainty of income facing the farmer. With large-scale general climate outcomes, a negative correlation between yield and price can appear, and the variability of the economic return will be less than the variability of the wheat yields. But as the weather outcomes vary across the market space - for Denmark the European Union - a negative shock to yield in Denmark might as well be balanced by a positive shock to yields in other parts of Europe. We can thus not ex-ante conclude on the correlation of yield and prices, and the variability of income.

In the presented research a rich collection of data has been assembled combining agricultural farm-level data with detailed local meteorological data and supplemented with far-reaching forecasting data. This information will surely give rise to further studies on the effect of weather and climate change on agriculture.

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APPENDIX

A PRUDENCE

The PRUDENCE ("Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects")-project was a European-scale collaboration of 21 European research institution under the EU 5th Framework program for Energy, environment, and sustainable development between 2001 and 2004.

The following summary of PRUDENCE is taken from `http://prudence.dmi.dk/public/project_summary.html`.

A.1 project summary

Problem to be solved:

European decision-makers in government, non-governmental organisations (NGOs), and industry as well as the general public need detailed information on future climate. In this way it becomes possible to evaluate the risks of climate change due to anthropogenic emissions of greenhouse gases. Projections of future climate change already exist, but are deficient both in terms of the characterisation of their uncertainties and in terms of their regional detail. To date, the assessment of potential impacts of climate change has generally relied on projections from simple climate models or coarse resolution Atmospheric-Ocean General Circulation Models (AOGCMs), neither capable of resolving spatial scales of less than 300km. This coarse resolution precludes the simulation of realistic extreme events and the detailed spatial structure of variables like temperature and precipitation over heterogeneous surfaces e.g. the Alps, the Mediterranean or Scandinavia. Simple models include, at best, a limited physical representation of the climate system.

Scientific objectives and approach:

PRUDENCE is a European-scale investigation with the following objectives:

1. to address and reduce the above-mentioned deficiencies in projections;
2. to quantify our confidence and the uncertainties in predictions of future climate and its impacts, using an array of climate models and impact models and expert judgement on their performance;
3. to interpret these results in relation to European policies for adapting to or mitigating climate change.

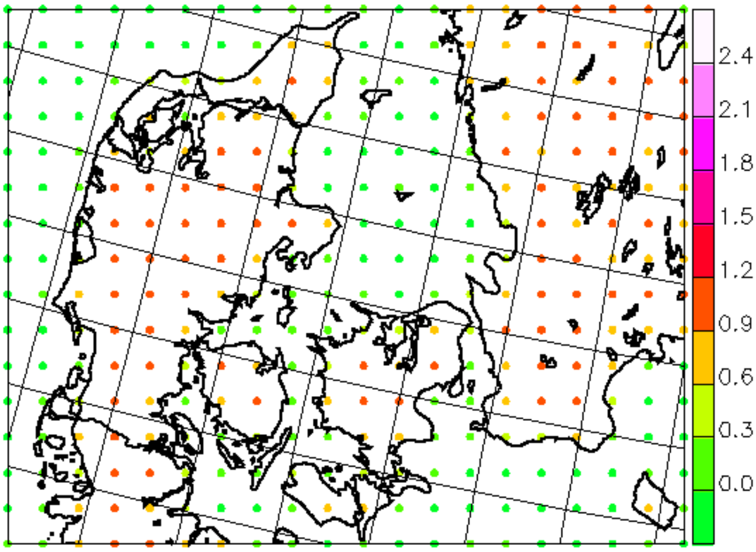
Climate change is expected to affect the frequency and magnitude of extreme weather events, due to higher temperatures, an intensified hydrological cycle or more vigorous atmospheric motions. A major limitation in previous studies of extremes has been the lack of: appropriate computational resolution - obscures or precludes analysis of the events; long-term climate model integrations - drastically reduces their statistical significance; co-ordination between modelling groups - limits the ability to compare different studies. These three issues are all thoroughly addressed in PRUDENCE, by using state-of-the-art high resolution climate models, by co-ordinating the project goals to address critical aspects of uncertainty, and by applying impact models and impact assessment methodologies to provide the link between the provision of climate information and its likely application to serve the needs of European society and economy.

Expected impacts:

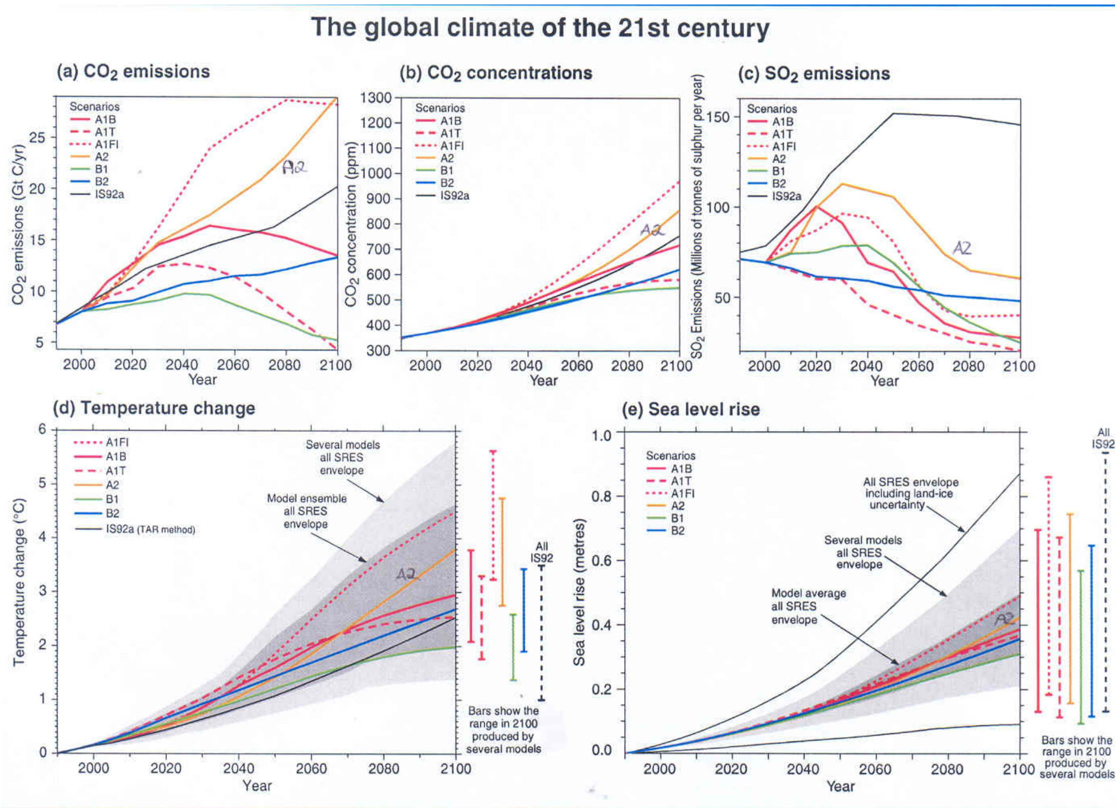
PRUDENCE will provide a series of high-resolution climate change scenarios for 2071-2100 for Europe, characterising the variability and level of confidence in these scenarios as a function of uncertainties in model formulation, natural/internal climate variability, and alternative scenarios of future atmospheric composition. The project will provide a quantitative assessment of the risks arising from changes in regional weather and climate in different parts of Europe, by estimating future changes in extreme events such as flooding and windstorms and by providing a robust estimation of the likelihood and magnitude of such changes. The project will also examine the uncertainties in potential impacts induced by the range of climate scenarios developed from the climate modelling results. This will provide useful information for climate modellers on the levels of accuracy in climate scenarios required by impact analysts. Furthermore, a better appreciation of the uncertainty range in calculations of future impacts from climate change may offer new insights into the scope for adaptation and mitigation responses to climate change. In order to facilitate this exchange of new information, the PRUDENCE work plan places emphasis on the wide dissemination of results and preparation of a non-technical project summary aimed at policy makers and other interested parties.

A.2 PRUDENCE grid-data

A number of participants in the PRUDENCE-project have completed RCM-simulations for all of Europe. The present study focuses on Denmark, corresponding to the grids defined by the rotated longitudes 79-98 and rotated latitudes 94-109. The figure below illustrates the 25km-gridnet covering Denmark.



B IPCC Scenarios for Climate Change



Source: IPCC [2001a]

C Estimation results

Table 6: ESTIMATION OF SELECTION MODEL, FOR EVERY t

Pct. wheat-acreage	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Cattle farm	-19.42***	-17.37***	-19.15***	-18.27***	-21.58***	-18.35***	-19.60***	-17.41***	-19.25***	-20.59***	-21.75***	-22.67***
	(1.26)	(1.29)	(1.34)	(1.33)	(1.40)	(1.43)	(1.61)	(1.61)	(1.45)	(1.42)	(1.44)	(1.53)
Hog farm	6.25***	5.29***	2.65**	4.12***	4.55***	6.78***	6.81***	8.28***	8.57***	7.78***	6.05***	7.93***
	(1.24)	(1.28)	(1.27)	(1.29)	(1.36)	(1.37)	(1.51)	(1.52)	(1.38)	(1.33)	(1.33)	(1.39)
Organic	-[a]		-	-	-22.92***	-24.85***	-19.84***	-19.32***	-21.90***	-21.72***	-16.11***	-16.33***
	(0.79)				(7.81)	(6.32)	(4.28)	(2.05)	(1.90)	(1.93)	(1.76)	(1.85)
Size	0.09***	0.06***	0.04***	0.04***	0.05***	0.06***	0.05***	0.05***	0.04***	0.04***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Pct. clayey soils	-	-	14.62***	19.90***	15.26***	17.07***	11.03***	16.99***	16.67***	18.63***	15.68***	22.88***
			(1.46)	(1.53)	(1.42)	(1.52)	(1.42)	(1.66)	(1.60)	(1.56)	(1.50)	(1.62)
rainA	-0.11***	-0.09***	0.08***	-0.05**	-0.02	-0.15***	-0.13***	-0.01	-0.04**	-0.04**	-0.11***	-0.08***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
tempA	12.18*	-4.69	2.69	-15.10*	-15.48***	-18.31***	2.74	12.17**	13.80**	-23.85***	-22.32***	0.92
	(6.31)	(6.54)	(3.75)	(7.99)	(3.09)	(5.00)	(4.65)	(4.78)	(5.46)	(4.62)	(5.43)	(5.13)
rainW	-0.03	-0.03	-0.05**	-0.00	0.11**	-0.17***	-0.15***	-0.16***	-0.09***	-0.16***	-0.08**	-0.08
	(0.05)	(0.04)	(0.03)	(0.02)	(0.05)	(0.04)	(0.04)	(0.05)	(0.02)	(0.04)	(0.03)	(0.05)
tempW	-10.39*	8.92	4.34	14.33**	18.66***	31.40***	9.72	-9.47***	-4.95	31.16***	34.04***	7.66
	(6.23)	(6.31)	(4.32)	(6.74)	(3.44)	(4.90)	(6.79)	(3.35)	(6.30)	(5.39)	(6.20)	(5.73)
rainSp	-0.09***	0.07	-0.18***	-0.01	-0.22***	-0.03	0.02	0.28***	0.04	0.09***	-0.18***	0.14***
	(0.03)	(0.07)	(0.04)	(0.04)	(0.05)	(0.03)	(0.05)	(0.05)	(0.04)	(0.03)	(0.05)	(0.04)
tempSp	7.08*	-5.91*	0.12	-12.05**	-16.74***	-5.99*	-10.94**	7.17***	1.62	-22.52***	-13.14***	-12.10***
	(4.21)	(3.41)	(4.06)	(4.98)	(3.67)	(3.44)	(5.29)	(2.75)	(3.22)	(4.48)	(3.51)	(2.91)
rainSu	-0.10***	-0.01	0.04	-0.02	0.09***	0.10***	0.06**	-0.01	-0.08**	0.05**	0.09***	-0.09***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
tempSu	11.46***	16.94***	3.40	22.87***	20.19***	3.12	11.15*	0.94	-11.39***	9.85***	0.29	5.42
	(5.71)	(4.17)	(2.81)	(5.53)	(3.64)	(5.28)	(5.78)	(3.23)	(3.15)	(3.74)	(3.04)	(5.51)
Constant	27.73***	-125.31***	-53.44	-175.94***	-12.71	183.51***	-83.56**	-153.79***	74.96	191.19***	294.32***	24.25
	(2.97)	(25.35)	(50.33)	(45.56)	(69.30)	(63.76)	(38.44)	(38.70)	(60.23)	(61.76)	(51.65)	(57.10)
Observations	1871	1851	1867	1894	1908	1867	1615	1891	1864	1884	1918	1858
Left-cens.	609	560	573	632	587	594	494	734	665	628	697	631
Uncens.	1262	1291	1294	1262	1320	1272	1121	1157	1199	1256	1219	1224
Pred. correctly	0.69	0.67	0.68	0.54	0.67	0.67	0.69	0.67	0.53	0.63	0.63	0.70

Significance levels : $*$: 10% $**$: 5% $***$: 1% Standard errors in parentheses

[a] Missing data

Table 7: Regression I - General

Wheat, hkg/ha	
Pct. clayey soils	-0.658
	(0.498)
Organic	-15.396***
	(1.804)
Pesticides	0.014***
	(0.005)
Mineral fertilizer	-0.002
	(0.006)
Pct. grain, lagged	-1.463***
	(0.399)
Full-/Part-time	0.079
	(0.788)
Trend	0.797***
	(0.084)
Rain, autumn	0.043***
	(0.012)
Rain, autumn, squared	-0.000***
	(0.000)
Rain, winter	0.039***
	(0.010)
Rain, winter, squared	-0.000**
	(0.000)
Rain, spring	0.013
	(0.020)
Rain, spring, squared	-0.000**
	(0.000)
Rain, summer	-0.012
	(0.011)
Rain, summer, squared	-0.000
	(0.000)
Temp., autumn	7.919***
	(1.697)
Temp., autumn, squared	-0.486***
	(0.095)
Temp., winter	1.438***
	(0.242)
Temp., winter, squared	-0.252***
	(0.057)
Temp., spring	-5.003**
	(2.424)
Temp., spring, squared	0.190
	(0.171)
Temp., summer	0.317
	(2.801)
Temp., summer, squared	-0.054
	(0.088)
Constant	59.762**
	(26.277)
Observations	14877
Farms	5112
F(34,9731), overall	27.64***
F(12,9731), tobit-res.[a]	8.24***
F(16, 9731), meteorol. var.	36.37***
R2 within	0.09
R2 between	0.13
R2 overall	0.09

Sign. levels: ∗: 10% ∗∗: 5% ∗ ∗ ∗: 1%
(Standard errors in parentheses)

[a] The estimates for the tobit-residuals are not reported.

Table 8: Regression II - Regional differentiation

hkg wheat pr. hectare	
Pct. clayey soils	-3.128*
	(1.842)
Pct. clayey soils, squared	1.568
	(1.770)
Organic	-14.163***
	(1.839)
Pesticides	0.015***
	(0.005)
Mineral fertilizer	0.000
	(0.006)
Pct. grain, lagged	-1.467***
	(0.404)
Trend	0.619***
	(0.085)
Rain Sept.-Oct.	-0.015***
	(0.005)
Rain Sept.-Oct., east	-0.001
	(0.009)
Rain, Nov.-Dec.	-0.009*
	(0.005)
Rain, Nov.-Dec., east	0.024*
	(0.012)
Rain, Jan.-Feb.	0.011*
	(0.006)
Rain, Jan.-Feb., east	-0.001
	(0.011)
Rain, March-April	-0.036***
	(0.005)
Rain, March-April, east	0.029***
	(0.009)
Rain, May-June	-0.011*
	(0.006)
Rain, May-June, east	0.042***
	(0.010)
Rain, July-Aug.	-0.017***
	(0.004)
Rain, July-Aug., east	0.015**
	(0.007)
Temperature, Sept.-Oct.	-0.682***
	(0.241)
Temperature, Sept.-Oct., east	0.374
	(0.330)
Temperature, Nov.-Dec.	0.804***
	(0.230)
Temperature, Nov.-Dec., east	1.373***
	(0.379)
Temperature, Jan.-Feb.	1.126***
	(0.256)
Temperature, Jan.-Feb., east	-1.832***
	(0.429)
Temperature, March-April	-0.349
	(0.447)
Temperature, March-April, east	1.952***
	(0.756)
Temperature, May-June	-2.135***
	(0.359)
Temperature, May-June, east	-0.529
	(0.521)
Temperature, July-Aug.	-0.213
	(0.153)
Temperature, July-Aug., east	-0.472**
	(0.228)
Constant	104.989***
	(3.885)
Observations: 14558; Farms: 5015	
R^2within: 0.10; R^2between: 0.25; R^2overall: 0.20	
F(42,9501), overall	25.02***
F(12,9501), tobit-res.[a]	7.84***
F(24, 9501), meteorol. var.	8.41***
F(12, 9500), reg. difference	7.86***

Sign. levels: ∗: 10% ∗∗: 5% ∗ ∗ ∗: 1%; Standard errors in parentheses)

[a] The estimates for the tobit-residuals are not reported.