Agroforestry Adoption in the Face of Regional Weather Extremes

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Contributed Paper prepared for presentation at the 96th Annual Conference of the Agricultural Economics Society, K U Leuven, Belgium

4 – 6 April 2022

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Abstract

The cultivation of agroforestry systems is regarded as an effective strategy to synergistically mitigate and adapt to climate change in the face of an increased occurrence of regional extreme weather events. This study addresses the question if and under what conditions farmers are likely to adopt agroforestry and wood-based land-use systems in response to regional weather extremes. We conducted a discrete choice experiment to elicit farmers preferences for - and willingness to adopt - agroforestry and wood-based land use systems and combined the results with geo-spatial weather data. Assuming adaptive weather expectations, we regionally simulate land users' dynamic response to extreme weather years in terms of adoption probabilities. We find that farmers in our case study region in Southeast Germany have a negative preference for alley cropping and short rotation coppice compared to an exclusively crop-based land use system. However, the results from the simulation of a 2018-like extreme weather year show that alley-cropping systems (i.e. agroforestry) might have a very high probability of being adopted in the medium to long-run under different scenarios, thus enhancing farmers' resilience to climate change.

Keywords Climate change, extreme weather, land use, agroforestry, discrete choice experiment

JEL code Q23, Q24, Q15

1 Introduction

The latest assessment report of the Intergovernmental Panel on Climate Change (IPCC) reiterates the fact that climate change poses exceptional challenges to various sectors on a global scale (IPCC, 2021). The World Economic Forum (WEF), in its 2020 Global Risks Report, listed climate-related concerns as the top-five long-term risks for the first time (WEF, 2019). Beside affecting annual mean temperatures and precipitation, climate change also increases the number of occurrences of regional extreme weather events such as droughts, heat waves, heavy rain and floods (IPCC, 2021; Lüttger and Feike, 2018; Mann et al., 2018; Westra et al., 2014). In this context, agriculture is often seen as one of the most susceptible sectors to such changes (IPCC, 2007), which negatively affect, e.g., crop yields (e.g. Lesk, Rowhani, and Ramankutty, 2016; Schlenker and Roberts, 2009; Haqiqi et al., 2021), total factor productivity (e.g. Chambers, Pieralli, and Sheng, 2020; Chambers and Pieralli, 2020; Stetter, Mennig, and Sauer, 2021), and ultimately farm income (e.g. Kawasaki and Uchida, 2016; Dell, Jones, and Olken, 2014; Dalhaus et al., 2020). Prime examples for extreme weather years that heavily impacted agriculture are the 2003 European heat wave, the 2018 European drought and heat wave, or the 2010–2013 Southern United States and Mexico drought. However, agriculture is also regarded as one of the most important anthropogenic contributors to climate change (Lynch et al., 2021). All in all, farmers need effective adaptation and mitigation strategies to tackle the challenges of climate change.

One major channel through which agriculture can actively tackle climate change is land use (Pielke, 2005). A promising pathway in this direction could be the adoption of agroforestry and wood-based land-use systems, which are recognized to play a key role in approaching adaptation and mitigation synergistically (Verchot et al., 2007; Cardinael et al., 2021; Van Noordwijk, Hoang, and Neufeldt, 2011; Duguma, Minang, and Van Noordwijk, 2014; Van Noordwijk et al., 2014). Agroforestry systems are defined as a land-use systems where woody perennials are deliberately integrated with agricultural crops and/or livestock on a piece of land, either in some sort of spatial arrangement or temporal sequence (Nair, 1985; Leakey, 2017; Cardinael et al., 2021). Such systems mitigate climate change through their carbon sequestration potential aboveground, belowground and in the soil (e.g. Albrecht and Kandji, 2003; Schroeder, 1993; Oelbermann, Paul Voroney, and Gordon, 2004; Cardinael et al., 2017). There are also indirect mitigation effects in that the planting of wood on agricultural land might effectively reduce deforestation (Schroeder, 1993; Verchot et al., 2007) and help replace fossil fuels by fuelwood (Kuersten and Burschel, 1993). At the same time, the positive regulation effects on hydrological cycles, soil, and the microclimate lead to more climate change resilient agricultural production (Lasco et al., 2014). Furthermore, agroforestry and its provision of multiple ecosystem services (Brown et al., 2018; Wolz et al., 2018) is also seen as a main component in the realm of ecosystem-based climate change adaptation (Pramova et al., 2012; Hernández-Morcillo et al., 2018).

Provided the various merits of agroforestry systems, there is still huge potential for the introduction and expansion of agroforestry areas around the globe (Van Noordwijk et al., 2014). This might be of particular importance in the face of increased occurrence of regional extreme weather events (Duguma, Minang, and Van Noordwijk, 2014; van Noordwijk et al., 2021). This paper addresses the question if and under what conditions farmers are likely to adopt agroforestry and wood-based land-use systems in response to regional weather extremes. To this end, we conducted a discrete choice experiment to elicit farmers preferences for and willingness to adopt alley cropping and short rotation coppice and combined the results with geo-spatial weather data. Assuming adaptive weather expectations, we locally simulate their dynamic land-use response to extreme weather years in terms of adoption probabilities based on the approach of Ramsey, Bergtold, and Heier Stamm (2020). We then discuss these land-use responses in a wider climate change resilience context (see OECD, 2020; Meuwissen et al., 2019).

We find that farmers in our case study region in Southeast Germany have a negative preference/WTA for alley cropping and short rotation coppice compared to an exclusively crop-based land use system. However, the results from the simulation of extreme weather under different scenarios show that alley-cropping systems (agroforestry) might have a very high probability of being adopted in the medium to long-run and thus strengthening farmers' resilience to extreme weather.

The elicitation of farmers' preferences for agroforestry and woody perennials have been the subject of multiple studies. E.g., Gillich et al. (2019) and Pröbstl-Haider et al. (2016) analyze farmers' preferences for short rotation coppice in Germany and Austria using discrete choice experiments. Other studies focus on the adoption of agroforestry systems, mostly in the context of the Global South (Bayard, Jolly, and Shannon, 2007; Amusa and Simonyan, 2018; Beyene et al., 2019; Schaafsma, Ferrini, and Turner, 2019; McGinty, Swisher, and Alavalapati, 2008; Dhakal, Cockfield, and Maraseni, 2015). None of these studies, however, examine the effects of climate and (extreme) weather in this context. Furthermore, multiple authors have simulated the (economic) potential for agroforestry cultivation under different circumstances (e.g Paul, Weber, and Knoke, 2017; Frey et al., 2013). Lasch et al. (2010) and Gomes et al. (2020) project the cultivation potential for SRC in Eastern Germany and coffee-agroforestry in Brazil taking account of climate change scenarios until 2050. The problem with such scenarios is that they are usually on a global scale and likely do not represent local farmers actual and perceived experiences with extreme weather and climate change, which is why they are not well-suited for farm-level based simulations (Morton et al., 2015; Ramsey, Bergtold, and Heier Stamm, 2020). Overall, studies on the effect of weather shocks on land-use change are scarce (Girard, Delacote, and Leblois, 2021). To fill in this gap, Ramsey, Bergtold, and Heier Stamm (2020) develop a novel framework to simulate how farmers dynamically adjust their cropping decisions in response to specific weather patterns.

This study contributes to the literature in several ways. Firstly, we quantify the link between adverse weather and farmers' preferences for agroforestry and short rotation coppice accounting for short- to long-run adaptation responses. While many of the aforementioned studies are concerned with why integrating woody perennials into farms' cultivation plan might be useful in terms of mitigation and adaptation, they usually ignore whether and how farmers respond to weather patterns. Establishing this link is particularly important in light of the increased occurrence of extreme weather events due to climate change. Furthermore, by combining a discrete choice experiment, geo-spatial weather information and the simulation framework of Ramsey, Bergtold, and Heier Stamm (2020), we are able to provide novel insights into farmers' responses and resilience to climate change. Extending the work of Ramsey, Bergtold, and Heier Stamm (2020), our approach allows to take choice-specific attributes into account. Hence, we can develop multiple scenarios reflecting the role of legislation, market conditions and technological progress. What is more, our empirical case study on Southeast Germany sheds more light on the adoption potential of agroforestry in an industrialized country context. Much of the work on this topic has been done in a developing country context so far.

The remainder of the article is structured as follows. First, we provide a short description of agroforestry and wood-based agricultural land use systems before presenting our conceptual framework (Sec. 2). In section 3, we present our data collection and empirical strategy. Section 4 describes the result from the discrete choice experiment and the weather simulations, followed by a discussion of the most important finding (Sec. 5). The paper closes with a summary and several concluding remarks in Sec. 6.

2 Background and conceptual framework

2.1 A short description of agroforestry and wood-based agricultural land use systems

As mentioned above, agroforestry systems are land-use systems where woody perennials are integrated with agricultural crops and/or livestock on a piece of land, either in some sort of spatial arrangement or temporal sequence (Nair, 1985; Leakey, 2017; Cardinael et al., 2021). This definition includes a wide range of diverse systems including silvopastoral (the combination of trees with livestock), silvoarable (planting crops between rows of trees), forest farming (food, herbal, botanical, or decorative crops under a forest canopy), home gardens, as well as hedge, windbreak and riparian buffer strip systems and many more (Pantera et al., 2021; USDA, 2019). Agroforestry is not a new concept and goes back a very long time in many regions of the world (Pantera et al., 2021).

In regard to the integration of trees on agricultural land, short rotation coppices (SRC) have been identified as an attractive land use alternative from an economic and ecological perspective (Wolbert-Haverkamp and Musshoff, 2014; Baum et al., 2009). SRCs usually consist of fast-growing tree species such as poplar, willow, paulownia, robinia, or eucalyptus with short rotation periods and frequent harvests (every 3–5 years) (Rödl, 2019). Other than agroforestry, SRCs are usually bound to a single use on the same field.

More recently, alley cropping (AC) systems that integrate strips of short rotation coppices into agricultural fields have been receiving increasing attention (Tsonkova et al., 2012). In such a system, farmers produce crops and woody biomass on the same field at the same time, which can lead to multiple advantages across several domains.

For instance, Paul, Weber, and Knoke (2017), Gosling et al. (2020) and Schoeneberger, Bentrup, and Patel-Weynand (2017) show that AC can generate higher economic returns than single crop land-uses. Furthermore, diversifying production output can raise economic stability (Tsonkova et al., 2012). What is more, ACs can contribute to a more sustainable bio-based economy by simultaneously providing food and renewable raw materials (Gillich et al., 2019). Numerous studies have also found positive effects on crop yield and land-use efficiency (see e.g. Schoeneberger, Bentrup, and Patel-Weynand, 2017).

Alley cropping also provides a range of environmental services due to its multifunctional nature. It can break up large-scale structures, increase biodiversity through increased habitat and species diversity and their connectivity across agricultural landscapes, reduce soil erosion as well as nutrient leaching (Langenberg, Rauert, and Theuvsen, 2018; Tsonkova et al., 2012; Schoeneberger, Bentrup, and Patel-Weynand, 2017).

Finally, agroforestry systems as well as short rotation coppices to a certain degree can play an important role in approaching climate change mitigation and adaptation synergistically. In terms of mitigation, AC and SRC systems can store large amounts of carbon in aboveground and belowground biomass (Albrecht and Kandji, 2003) as well as in soil (Cardinael et al., 2017), thus reducing atmospheric carbon dioxide (CO_2) concentration (Cardinael et al., 2021; Tsonkova et al., 2012; Schroeder, 1993). Regarding adaptation, the intergration of trees on agricultural land provides a buffer to weather extremes through regulating hydrological cycles, improving nutrient- and water-use efficiency, and modifying microclimates (Wolz et al., 2018; Ashraf et al., 2019; Pramova et al., 2012). Agroforestry can also diversify income to hedge financial risk (Wolz et al., 2018), and make production more resilient to climatic change (van Noordwijk et al., 2021).

Despite these manyfold advantages, silvoarable agroforestry systems are still not very widespread in Europe (den Herder et al., 2015; Langenberg, Rauert, and Theuvsen, 2018). Van Noordwijk et al. (2014) notes that there is huge potential for the introduction and expansion of agroforestry areas around the globe.

2.2 Land Use, Random Utility Maximization and Weather Expectations

Given the large potential for the introduction and expansion of agroforestry, this study seeks to elicit farmers' preferences for agroforestry and short rotation coppice in comparison to conventional crop farming against the background of a changing climate. The theoretical basis for our analysis is based on random utility maximization (RUM) following Lancaster (1966) and McFadden (1973). When it comes to planning the usage of their land, farmers face a choice among a set of alternative land uses in one or more decision situations under varying conditions. Each farmer obtains a certain level of indirect utility from a land-use alternative. In a given decision situation t, she will select alternative i if and only if $U_{it} > U_{jt}, j \neq i$. The indirect utility of an alternative cannot be directly measured but it can be expressed by a systematic (deterministic) component V, reflecting specific characteristics as well as farmers' individual and location-specific features and a random component ϵ, representing unobserved decision-relevant elements (Mariel et al., 2021). A farmer n obtains a certain level of of indirect utility U_{njt} from a land use alternative j in a choice situation t.

$$U_{njt} = V_{njt} + \epsilon_{njt} \tag{1}$$

As is standard, we assume farmers utility for a land use alternative to vary with a set of decision-relevant characteristics (x, see Sec. 3.2.1). Furthermore, as agricultural land use is heavily dependent on weather (c), we assume that farmers' utility also depends on expected weather at the time of the planting decision:

$$V_{njt} = f(x_{njt}, c_{nt}; \beta, \gamma) \tag{2}$$

where β and γ are coefficients to be estimated. Following Nerlove (1958) and Ramsey, Bergtold, and Heier Stamm (2020), we assume that farmers have adaptive weather expectations that are based on past local weather history, where both short-term and long-term trends might affect land use choices. What is more, it is realistic to assume that farmers do not assign equal importance on each past weather event, which is why a simple average of past weather would not properly reflect farmers' expectations. Ramsey, Bergtold, and Heier Stamm (2020) express the expected-weather-formation-process as follows:

$$c_{nkt} = \omega_0 + \omega_s\, W(\ddot{c}_{nkt-1}, \ldots, \ddot{c}_{nkt-r}) + \omega_l\, W(\ddot{c}_{nkt-r-1}, \ldots, \ddot{c}_{nkt-R}) \tag{3}$$

where $\ddot{c}_{nkt-r}$ are actual past weather events. ω_0 is a reference expectation, ω_s reflects a farmer's weight assigned to the recent past, ω_l is the weight assigned to the more distant past, and $W(\cdot)$ is a weighting function (e.g. annual mean). Hence, weather expectations are formed by two components, one reflecting longer term weather patterns ("signal") and one reflecting short term weather variations ("noise"). In terms of climate change adaptation (i.e. the adoption of novel land use options), one would presume that the signal plays the dominant role in decision making. However, especially with respect to severe, more tangible weather shocks, the noise component might be more important because of its immediate negative effect on production Ramsey, Bergtold, and Heier Stamm (2020), while such an experience might level off with ordinary weather events in the longer run.

In light of these theoretical considerations, we expect that past (extreme) weather events are likely to influence farmers' decisions to adopt more climate change-robust and mitigating land-use options such as agroforestry or short rotation coppice by affecting farmers' weather expectations, which ultimately influence farmers' preferences for selected options.

3 Material and methods

We first provide information on the case study region, Bavaria, before describing the discrete choice experiment (DCE) setup we used to collect data on farmers' preferences. We then present the data that are used to describe weather. By combining the experimental with the weather data and utilizing a correlated random parameter logit model (RPL) approach, we estimate farmers' preferences and probabilities for the cultivation of each land-use option and retrieve coefficient estimates reflecting the influence of land use characteristics and (anticipated) weather. Finally, we describe the simulation approach used to model the adaptive adjustment behavior of farmers in response to an extreme weather year based on the estimates from the RPL model.

3.1 Study area

We conducted our DCE in Bavaria, a federal state of Germany in Central Europe. Located in the southeast of Germany, Bavaria belongs to the core regions of agricultural production within the European Union (EU). It reflects the variety of European farming (conditions) to a high extent, which is why we selected this site for conducting our study. In terms of natural conditions, farming takes place along an elevational gradient of 1500m (from 100m in Northwest Bavaria to 1600m in Southeast Bavaria) and a macroclimatic gradient with a mean annual temperature range between 3 and 10 °C and an annual precipitation of 470–1592 mm (from 1960 to 2020). Its natural conditions, ranging from pre-alpine and alpine areas with high precipitation and rather clayey, limestone and dolomite based soils to regions with flat land and fertile loess soils to dry, marlstone, limestone and dolomite based hillside locations, are well-suited for various agricultural production systems including crop farming, intensive and extensive dairy farming, pig and cattle fattening and breeding, poultry farming, vegetable farming, orcharding, hop production and viticulture. This heterogeneity is to a certain degree reflected in Bavaria's seven administrative districts (figure 1), which will be analyzed individually in addition to the entire region in the results section.

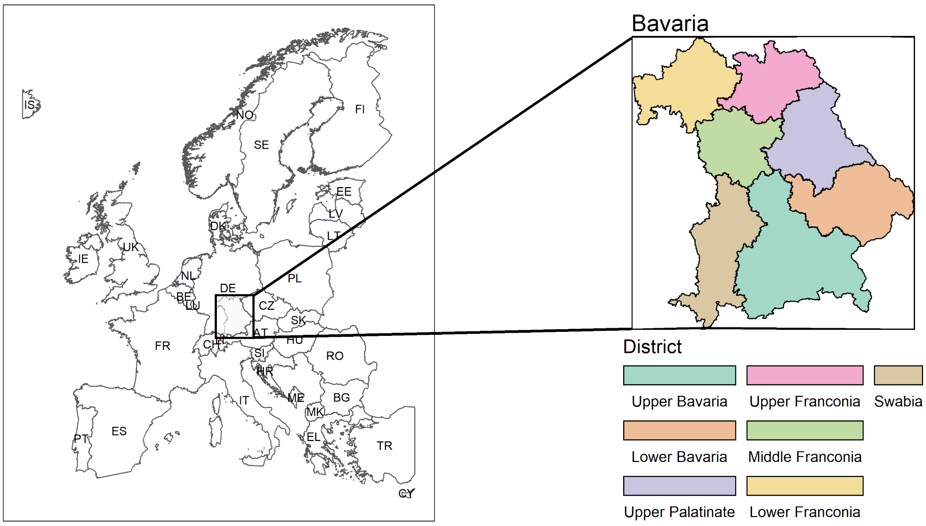

Figure 1: The case study region Bavaria is a federal state of Germany and lies in Central Europe. It is comprised of seven administrative districts.

3.2 Choice Experiment Setup

A discrete choice experiment was used to elicit the influence of land use characteristics on farmers' decision on whether or not to cultivate agroforestry. Each farmer was repeatedly confronted with a choice situation, in which the attributes of three land-use alternatives (namely short rotation coppice, alley-cropping, and status quo crop farming) varied.

3.2.1 Attribute Selection and Levels

Following a careful literature search and the feedback from agricultural experts, the attributes we use to describe the land-use alternatives are: Average yearly margin contribution, yearly margin contribution variability, minimum useful lifetime, payments for ecosystem services and a dummy if the alternative qualifies as ecological priority area.

Our primary monetary attribute, the margin contribution, measures yearly revenues (yield times price), minus variable cost. Fixed cost and subsidies are not considered in this measure. Moreover, because revenues and costs are spread over the entire production period of short-rotation coppice and alley cropping, a margin contribution equivalent is introduced, which corresponds to the annualized form of the net present value.

Previous studies show that uncertainty play an important role when it comes farmers' decision making in general (see e.g. Menapace, Colson, and Raffaelli, 2013) and land allocation in particular (El-Nazer and McCarl, 1986; Knoke et al., 2015). We express outcome uncertainty in terms of gross margin fluctuations. Given that farmers are predominantly risk-averse (Menapace, Colson, and Raffaelli, 2013), we expect an increase in variability to negatively affect preferences.

The minimum useful lifetime of a land-use alternative is closely related to the entrepreneurial flexibility of farm businesses. Being longer tied to one land-use type means a loss of flexibility (Musshoff, 2012), which is expected to negatively affect farmers' preferences.

Since SRC and AC provide a wide range of environmental services, payments for ecosystem services could provide a positive incentive for farmers to cultivate one of these land-use options (e.g. Layton and Siikamäki, 2009).

Finally, Langenberg, Rauert, and Theuvsen (2018) find that one major driver for farmers to engage in alley-cropping might be the qualification as "ecological priority area". Farmers have to attribute a certain amount of land to ecological priority areas (which are considered environmentally-friendly) to receive area based "greening" payments, which account for approximately 30% of the farmers' total basic payment.

We aimed for realistic levels of each attribute based on official databases (e.g. StMELF, 2018; LfL, 2018), previous studies (e.g. Gillich et al., 2019; Pröbstl-Haider et al., 2016; Langenberg and Theuvsen, 2018; Hauk, Knoke, and Wittkopf, 2014), expert consultation and plausibility considerations. Table 1 summarizes the attributes and attribute levels.

Table 1: Description of attributes and levels

Attribute	Description	Attribute levels
MC	Margin contribution (equivalent) (€/ha)	400[a], 600, 800
MCV	Margin contribution variation (%)	15[a], 30
MUL	Minimum useful lifetime (years)	3[a,b], 16, 20, 24
PES	Payment for environmental services (€/ha)	0[a], 100, 200
Green	Qualification as ecological priority area	Yes, No[a]

[a] Fixed attribute levels for the status quo alternative.
[b] Attribute level that only applies for the status quo alternative.

3.2.2 Conducting the Choice Experiment

After having determined choices, attributes and corresponding levels followed the actual choice experiment. We created a choice experiment with three labeled alternatives, namely "Short Rotation Coppice", "Agroforestry", and "Status Quo". Given its labeled nature, we followed Viney, Savage, and Louviere (2005) and created an L^{MA} design for our DCE, that resulted in 36 choice cards. To reduce the psychological burden of answering all choice tasks we randomly blocked them into three sets of twelve choice cards. An exemplary choice card can be found in the appendix A.1. Each respondent was then randomly assigned to one of the three blocks. Before the participants started the choice experiment, we explained how the DCE would work and provided descriptions of the alternatives and attributes relevant for the task (see appendix A.2). To tackle hypothetical bias, we used "cheap talk" (Landry and List, 2007) and reminded the participants about the danger of hypothetical bias and that they should answer truthfully.

Our survey consisted of several parts. After some general information and the respondents' consent to participate, we asked for general (socioeconomic) characteristics of their farm, which was followed by the DCE. Finally, the participants were asked to give further information on their local climate change perception and several character traits.

After an extensive pre-test phase in the early summer, the survey was conducted online in October 2020. Respondents from Bavaria were recruited through a large panel of farmers provided by an agricultural market research platform called agriEXPERTS and through multiple outlets of a specialist publishing house for agriculture (`Deutscher Landwirtschaftsverlag, dlv`). The survey included an invitation to take part in a lottery to win one of ten vouchers for a popular agricultural clothing shop worth 50 EUR each. It took around twelve minutes to complete the questionnaire.

3.3 Weather variables

To accurately describe the local weather history of farms, we selected five common weather indicators, namely average temperature, precipitation sum, number of dry days, number of hot days and the number of heavy rain days during the local growing season (Mar–Oct). The variables are derived from 0.1 degree gridded daily data from the European Climate Assessment & Dataset (ECA&D) project (Cornes et al., 2018). Following ETCCDI (2018) and DWD (2022), dry days are days with precipitation of < 1mm and hot days are defined as days with maximum temperature > 30°Celsius. On heavy rain days precipitation exceeds 20mm (DWD, 2022). The weather indicators were aggregated at the municipality level (2031 municipalities) and linked to the responses from the questionnaire via zip codes.

As outlined in section 2.2, farmers form their weather expectations based on historical weather, which can be distinguished between short-term and longer-term weather patterns. To capture this distinction, we define short-term and long-term weather variables by different lag structures. In our base specification short-term weather patterns for our five indicators are based on the average of years $t-1$ to $t-3$ (more recent past) and longer-term weather patterns are based on the average of years $t-4$ to $t-10$ (more distant past). Fig. 2 summarizes these variables. Further lag structures were computed reflecting multiple candidate time horizons of expectation formation, which were later tested against the base structure (sec. 4.2). All weather variables are mean-centered. This will later be useful for the interpretation of the alternative-specific constants in the RPL model and the corresponding willingness to adopt measures.[1]

[1]Mean-centering the weather variables will allow to directly interpret these measures, as the intercepts will be evaluated at the average weather (for which all weather variables take on a value of zero.)

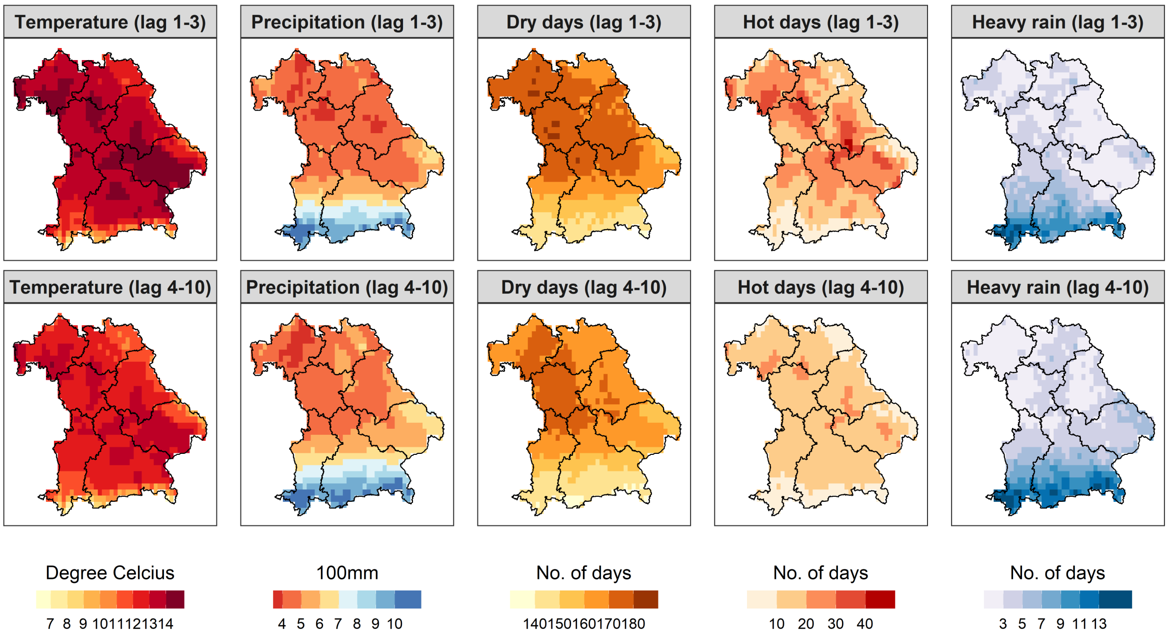

Figure 2: Summary of the weather variables used for the estimation of our baseline model with lag structure 1-3 and 4-10.

3.4 Econometric Approach

For our econometric analysis, we use the random parameter logit model to account for preference heterogeneity in the utility function of the investigated sample (Hensher, Rose, and Greene, 2015; Train, 2009). We parametrize the utility function (2) with alternative specific constants (α_{ji}), land-use specific attributes (X) and individual-specific weather parameters (C):

$$V_{ij} = \alpha_{ji} + \beta_i X_{jt} + \delta_{ij} C_i + \epsilon_{ijt} \tag{4}$$

The model formulation is a one level multinomial logit model, for individuals $i = 1, \ldots, N$ in choice setting t alternatives j. Assuming a Gumbel distribution of the error term ϵ_{ijt}, the probability of each choice j is (Hensher, Rose, and Greene, 2015):

$$Prob(y_{it} = j) = \frac{\exp \alpha_{ji} + \beta_i X_{jt} + \delta_{ij} C_i}{\sum_j (\exp \alpha_{ji} + \beta_i X_{jt} + \delta_{ij} C_i)} \tag{5}$$

In the random parameter logit framework, the coefficient vectors α_{ji}, β_i, and δ_{ij} are considered random draws from a distribution whose parameters need to be estimated. Under this assumption, we can use maximum simulated likelihood estimation to obtain coefficient estimates for α_{ji}, β_i, and δ_{ij} (Train, 2009). We use a total of 1000 Halton draws for each model estimation. As for the parameter distributions, we assume:

$$(\alpha_{ji}, \beta_i) = (\alpha_j, \beta) + \Gamma\ \nu_{(j)i} \tag{6}$$

$$\delta_{ji} = \delta_{ji} + \Omega\ \upsilon_{ji} \tag{7}$$

where $\nu_{(j)i}$ and υ_{ji} describe random unobserved preference variation, with mean zero and covariance matrix with known values on the diagonal, fixed by identification restrictions. Γ is a lower triangular matrix that allows correlation across the attribute-related random parameters and $\Omega = diag(\sigma_1, \ldots, \sigma_k)$.

With this specification we follow Hess and Rose (2012) and Hess and Train (2017), who show that only by allowing for correlation across attribute-related random parameters, it is possible to capture scale heterogeneity alongside heterogeneity in utility coefficients. According to Hess and Rose (2012, p.9): "Such correlations can be expected in any setting: they simply reflect that respondents' preferences for one attribute are related to their preferences for another attribute". Ignoring this correlation could severely bias parameter estimates. One reason why this specification is only rarely observed in the literature might be its significantly higher computational burden (Mariel and Meyerhoff, 2018).

We assume all random parameters to be normally distributed except for the coefficient of the contribution margin, which we assume to be log-normally distributed. We do this for two reasons. First, economic theory states that the sign for the profit attribute should always be positive. Second, we assure finite moments for the willingness to adopt values (Daly, Hess, and Train, 2012), which are defined as the change in one attribute with respect to the return margin. Hence they are the ratio of each parameter estimate and the parameter estimate of the marginal contribution:

$$WTA = \frac{(\widehat{\alpha}_{ji}, \widehat{\beta}_i)}{\widehat{\beta}_{i,\text{contribution margin}}} \tag{8}$$

By mean-centering the weather variables we can make direct use of the estimated ASCs.

Dividing them by the individual-specific coefficient estimate on the return margin gives us the marginal willingness to adopt at mean weather because all mean centered weather variables in C are zero at their means (see also Iacobucci et al., 2016).

3.5 Post-Estimation Simulation

To evaluate the short- and longer-term adjustment dynamics to an extreme weather period, we simulate farm-level responses to one to five-year weather shocks over a period of 10 years following the approach by Ramsey, Bergtold, and Heier Stamm (2020). The simulation is based on the estimated parameters from the fitted random parameter logit model in sec. 3.4. Our simulations are primarily based on the 2018 drought year, which caused severe damages in German crop farming (Webber et al., 2020). Following the reasoning of Girard, Delacote, and Leblois (2021), that different weather shock have different impacts on land-use responses, we will also present simulation results for a 2003-like heatwave (Ciais et al., 2005).

Given the lag structure of the weather variables, we can simulate farmers' adoption probabilities in response to an extreme weather period each year during and after the weather shock based on the formula for land use probabilities (Eq. 5). In the baseline scenario, we replace the values of the weather variables C for every farm in years 0–10 with their respective (sub-)sample longterm averages (LTA) over the 20-year period 1991–2020. For a one-year shock scenario, the 2018 (2003)-like event is assumed to occur in period $t = 0$, and then weather returns to the LTA. This shock will affect the values for the short-term weather variables (lags 1–3) in periods 1–3, and then they return to the LTAs. The longer-term weather variables (lags 4–10) remain at the LTAs for periods 1–3 before changing to a "shocked" level in years 4–10 after the shock (compare Ramsey, Bergtold, and Heier Stamm, 2020, p.13). Fig. 3 illustrates the composition of each weather variable over time for a one-year, a two-year and a three-year weather shock as they enter equation 5 in the simulation.

We ran simulations for the full sample as well as for each district separately to explore more regional adaptation paths. Table 2 summarizes the respective values used for the

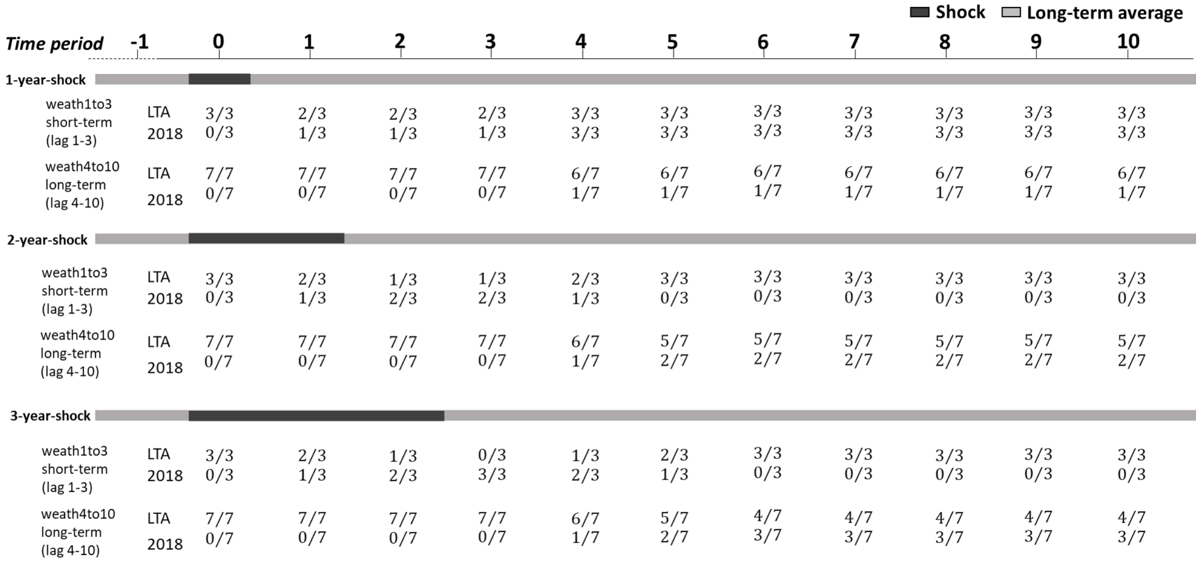

Figure 3: Illustration of the composition of the weather variables as they enter the simulation scenarios and replace the original weather variables used for the RPL estimation. The replacement procedure is demonstrated of a one-year, two-year and three-year shock scenario. Longer-term shocks change accordingly.

construction of the weather variables.

Regarding the levels of the land-use attributes X, we constructed several scenarios, reflected by different attribute levels used in the simulations. The respective levels and scenarios are summarized in table 3.

4 Results

4.1 Sample Summary Statistics

In total, we received 210 responses. We deleted twelve responses after a series of plausibility checks. Our analysis is thus based on the responses of 198 farmers. In Table **4**, summary statistics for key farm characteristics in our sample are described and compared with the population means for Bavaria (mostly stemming from official census data). Approximately half of our sample are full-time farmers, which is only slightly higher than the Bavarian average (45%). Several characteristics of our sample are on average similar to the Bavarian average, namely cropland and grassland shares, farmers' age and the participation rate in agri-environmental programs. At the same time, our sample farms

Table 2: Description of the weather indicators as they enter the 2018-like shock simulations.

	Precipitation (mm/year)	Average Temp. (°C)	Dry days	Heavy rain days	Hot days
Bavaria (full sample)					
Long-term average (baseline)	610.21	12.39	156.35	4.92	12.36
Extreme weather year (2018)	421.52	13.93	181.14	3.75	24.63
Difference	-188.70	1.53	24.79	-1.17	12.26
Upper Bavaria					
Long-term average (baseline)	778.48	12.27	147.98	7.77	11.14
Extreme weather year (2018)	583.21	13.70	170.29	6.23	17.99
Difference	-195.27	1.44	22.32	-1.54	6.85
Lower Bavaria					
Long-term average (baseline)	601.28	12.57	156.37	4.48	13.09
Extreme weather year (2018)	421.10	14.27	180.66	3.34	26.73
Difference	-180.18	1.70	24.29	-1.14	13.64
Upper Palatinate					
Long-term average (baseline)	509.76	12.30	160.66	3.09	12.52
Extreme weather year (2018)	327.00	13.97	184.70	1.97	29.04
Difference	-182.75	1.67	24.04	-1.12	16.52
Upper Franconia					
Long-term average (baseline)	525.48	12.13	158.80	3.40	11.58
Extreme weather year (2018)	302.93	13.72	185.51	1.60	25.63
Difference	-222.55	1.59	26.70	-1.80	14.05
Middle Franconia					
Long-term average (baseline)	474.35	12.85	164.70	2.91	15.00
Extreme weather year (2018)	316.06	14.39	193.00	2.93	31.40
Difference	-158.29	1.54	28.30	0.02	16.40
Lower Franconia					
Long-term average (baseline)	463.42	12.90	163.59	2.54	15.41
Extreme weather year (2018)	304.78	14.57	192.77	2.54	35.61
Difference	-158.64	1.67	29.18	0.00	20.20
Swabia					
Long-term average (baseline)	721.56	11.93	152.09	6.98	9.54
Extreme weather year (2018)	506.23	13.17	174.49	4.94	14.21
Difference	-215.33	1.24	22.41	-2.03	4.68

Table 3: Description of the simulation scenarios and corresponding attribute values.

	Alley-Cropping					Short Rotation Coppice					Status Quo				
Scenario	MC	MCV	MUL	PES	Green	MC	MCV	MUL	PES	Green	MC	MCV	MUL	PES	Green
1. Regular-case	400	30.0	24	0	No	400	30.0	24	0	No	400	15	3	0	No
2. Regular-case w/ policy support	400	30.0	24	200	Yes	400	30.0	24	200	Yes	400	15	3	0	No
3. Regular-case w/ technological improvement	400	30.0	16	0	No	400	30.0	16	0	No	400	15	3	0	No
4. Better-case for agroforestry	600	22.5	20	100	Yes	600	22.5	20	100	Yes	400	15	3	0	No
5.Ideal-case for agroforestry	800	15.0	16	200	Yes	800	15.0	16	200	Yes	400	15	3	0	No

Note: MC = Margin contribution (Euro), MCV = margin contribution variation (%), MUL = Minimum useful lifetime (years), PES = Payments for environmental services (Euro), Green = Cultivated area eligible for greening premium

Table 4: Sample description and comparison with the population mean.

	Sample			Bavaria
	Mean	Median	SD	Population Mean
Full-time farming (1 if yes, 0 otherwise)	0.49	0	0.5	0.45[c]
Utilized area (ha)	69.79	40.5	89.84	36.66[c]
Share of cropland (%)	59.57	64.55	27.13	65.18[c]
Share of grassland (%)	34.07	30	22.9	34.37[c]
Share of forested land (%)	10.19	5	12.37	–
Share of rented land (%)	31.13	20	30.71	51.0[c]
Workforce (AWU[a])	0.1	0	0.3	0.12[c]
Full-time farming (1 if yes, 0 otherwise)	1.63	1.25	1.29	2.27[c]
Farmer's age (years)	48.34	50	12.42	50.3[d]
Higher education (1 if yes, 0 otherwise)[b]	0.24	0	0.43	–
Participation in agri-environmental program (1 if yes, 0 otherwise)	0.73	1	0.44	0.68[e]

Note: Number of observations = 198; a AWU denotes annual working units. b Higher education refers to having a university degree. Sources: c Destatis (2021b), d LfL (2015), e Destatis (2021a)

manage more land on average, have a smaller share of rented land and a smaller workforce than the population mean. Also, the sample share of organic farms with 10% is very similar to the population share (12%). Overall, the descriptive statistics show that our sample reflects the Bavarian farmer population reasonably well, except for a few dimensions including farm size and labor. These deviations from the population mean are not necessarily negative in light of a dynamic trend toward fewer but larger farms in the EU (Wimmer and Sauer, 2020). Nearly all farmers stated they had already experienced negative consequences a climate change related extreme weather events in particular in the form of yield and quality losses.

4.2 Model Estimates and Willingness to Accept

4.2.1 Model estimates

The model estimation results are summarized in Table A1. In a first step, we compared the model of our choice – the correlated random parameter logit (RPL) model – to a multinomial logit model (Model 1) and an uncorrelated RPL model with weather variables (Model 2). Likelihood-ratio tests show that the correlated RPL model has a significantly better fit to the data than the alternative models, which is why this model is our preferred choice. Table A2 shows the parameters' correlation structure. What is more, from these tests we empirically confirm that the weather (history) variables have jointly a significant impact on farmers' land use decision as assumed in theory section. From Table A1 (Model 3), we can see by the attribute specific constants (ASC) that crop farming is preferred to both SRC and AC at average weather conditions. We also find preference heterogeneity (indicated by the estimates of the standard deviation of the random parameters) for most choice attributes except for margin contribution variability.

4.2.2 Willingness to adopt

To obtain further insights into farmers' land-use preferences, we calculated farmers' willingness to adopt based on the individual coefficient estimates from the correlated RPL with weather variables. Figure 4 presents the results separately for both the full sample as well as regional districts. Panel A shows that farmers have a negative general WTA with respect to agroforestry (median value of −€123 for Bavaria) and short rotation coppice (median value of −€513 for Bavaria) evaluated at average weather conditions. These values can be interpreted as the farmers' *ceteris paribus* compensations to cultivate the corresponding alternative in addition to the contribution margin from the status quo crop rotation. SRC is valued more negatively and has a larger heterogeneity than AC (and crop farming), a pattern that is consistent across regional districts. Median WTA values for AC range from −€83 in Lower Bavaria to −€132 in Central Franconia, and for SRC from −€286 in Lower Bavaria to −€544 in Central Franconia. Hence, on average, farms in Central Franconia seem to be most adherent to status quo crop farming, while farms in Lower Bavaria seem to be most prone to switch to agroforestry and SRC.

As for the land use characteristics (Fig. 4 panel B), an increase in the contribution margin variability (i.e. higher economic risk) as well as an increase in the minimum useful lifetime (i.e. lower entrepreneurial flexibility) decrease the willingness to adopt a land use option, which is the case for all regions to varying extents. This also means a reduction in these variables could lead to a higher willingness to cultivate agroforestry and SRC. For instance, the negative WTA for agroforestry in the Lower Franconia subsample (median: −€128) could potentially be offset by a *ceteris paribus* reduction of the minimum useful lifetime (median WTA: −€33.4) by 4 years. Furthermore, offering payments for ecosystem services (PES) lead to an increase in the willingness to accept, e.g. for the full sample, every extra PES Euro leads to an €0.53 increase. While this value varies across observations and regions, the increase in ecosystem payments is in many cases underproportional to the increase in the WTA (< 1) and thus quite inefficient. As already evident from Table A1, accepting land as ecological priority area is not a useful lever to increase farmers willingness to cultivate AC and SRC.

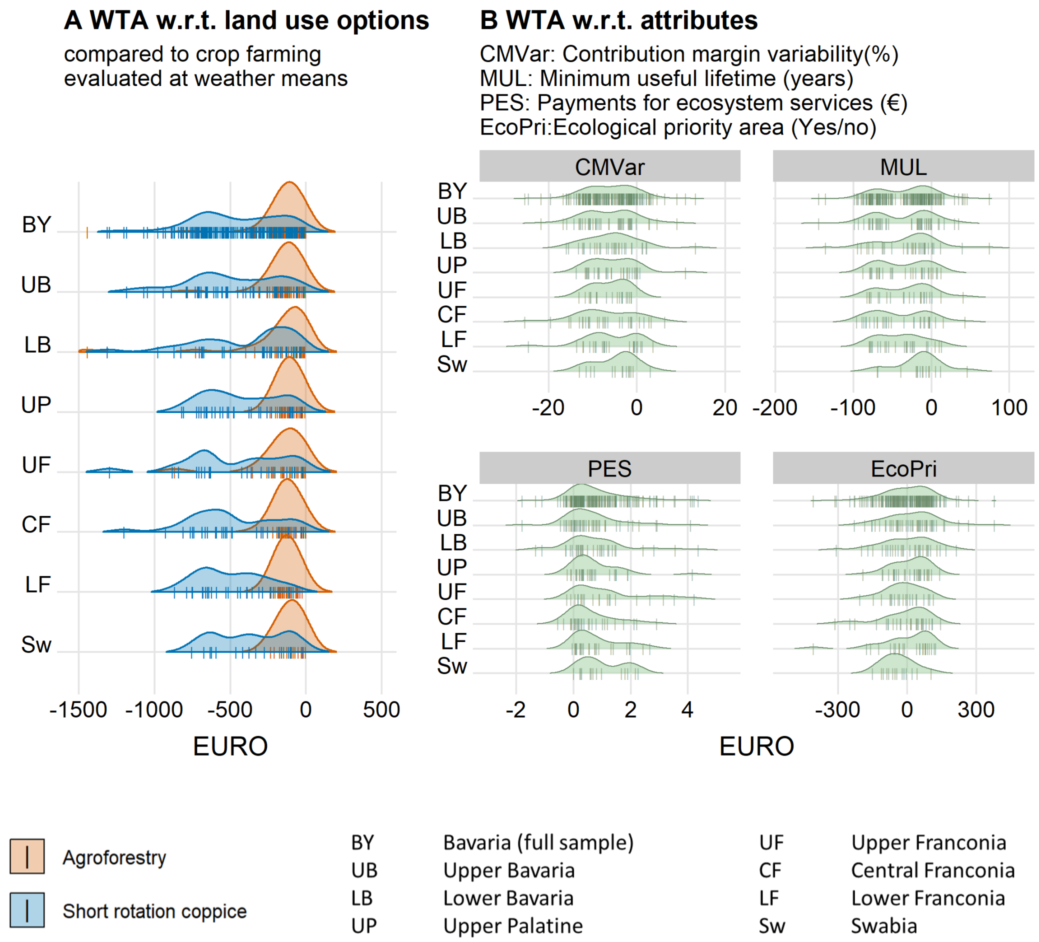

Figure 4: Summary of individual-specific willingness to adopt (WTA) estimates expressed as EUR/ha.

We refrain from analyzing the coefficient estimates of the weather variables individually because they are likely suffer from a certain degree of multicollinearity, which is not a problem *per se* but makes *ceteris paribus* statements very difficult. We return to this issue in Sec. 5.

4.2.3 Further robustness checks

As mentioned before, there are multiple possibilities for the empirical specification of the lag structure of the weather history reflecting longer term weather patterns (”signal”) and short term weather variations (”noise”). Therefore, we tested a series of alternative weather variable specifications and re-estimated the correlated RPL model and compared the model fit with our selected model (lags 1-3 and lags 4-10) (Tab. A3). We can see that our preferred model fits the data best followed by models with lag structures 1/2-15 and 1-3/4-15.

4.3 Weather Simulations

To examine farmers' agroforestry adoption in response to more extreme and adverse weather patterns, that are predicted to occur more often and last longer, we simulate a 2018-like (and 2003-like) extreme weather year at the regional level and observe the deviations of land-use probabilities from the average thirty-year baseline weather considering multiple socioeconomic scenarios. We further simulate the same weather events lasting for three and five years, respectively. Furthermore, we developed an interactive simulation tool that allows to flexibly adjust and combine the simulation settings according to one's individual needs. This tool is available at: `https://ge36raw.shinyapps.io/main_dashboard/`.

Turning to our pre-defined scenarios in Figure 5, for a one-year 2018-like weather shock, we can see that in the regular-case scenario (all land-use options at their base levels), farms' land use probabilities remain – after an adjustment period – close to their baseline levels. In all regions except Swabia is crop farming the preferred land-use type. However, if we change the setting such that AC and SRC experience policy support

("Regular-case w/ policy supp"). Alley-cropping becomes at least equally likely to be adopted as crop farming in Upper and Lower Bavaria. This is even more pronounced if the minimum useful lifetime of wood-based cultivars is reduced to sixteen years. From the scenarios with more preferential conditions for the wood-based land uses, we can see that farmers in Upper Palatinate and Middle Franconia are quite reluctant to adopt these land use types. We can observe an interesting pattern across all scenarios and regions. In the first years after a one-year shock, farmers tend to prefer status quo crop farming, indicated by an increasing adoption probability. We find similar outcomes for a 2003-like weather event (Table A1), although we can observe less adjustment movement in terms of crop farming but more pronounced adjustment in terms of SRC. Also, we find that alley-cropping becomes also more likely to be adopted in Swabia.

Concerning a longer shock duration, Table 6 shows the simulation results for a three-year 2018-like extreme event. Over all, we find very similar patterns as before. Nevertheless, following the more pronounced extreme weather event (in terms of its duration) the farms' adaptation path following such an event becomes also more marked. For instance in Lower Bavaria, the probability of cultivating crops only reaches nearly 100% in scenarios one and three following the extended weather shock before falling considerably below the baseline level (and the probability of adopting AC). We also find that without policy intervention or the shortening of the minimum useful lifetime, AC becomes the preferred land use option in Upper and Lower Bavaria. In the case of a 2003-like extended weather event (Fig. A2) and looking at the full sample, alley cropping becomes the preferred land-use choice regardless of the scenario. What is more, the adaptation path regarding crop farming becomes considerably more volatile.

Finally, looking at an even more extensive weather shock spanning five years (Fig 7), we can see that alley cropping eventually becomes the preferred land-use type in almost all instances (except for Swabia and Middle Franconia), which holds also true for a 2003-like weather period (Fig A3). However, in case of a 2003-like five-year weather period, alley cropping is also preferred in Swabia.

Overall, we find that farmers in Lower and Middle Franconia are most reluctant to

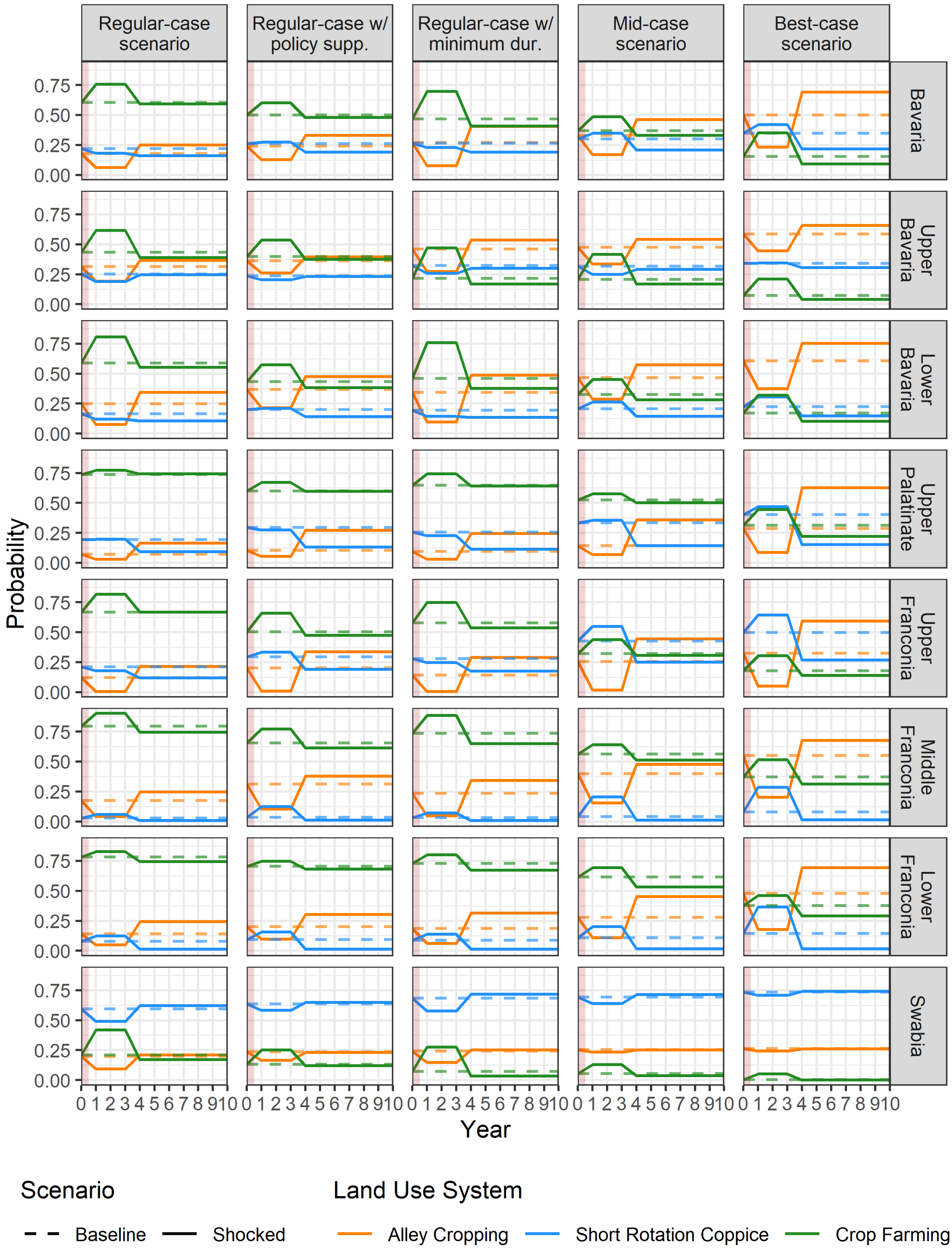

Figure 5: Summary of the propensity scores obtained from the step-1 propensity forest

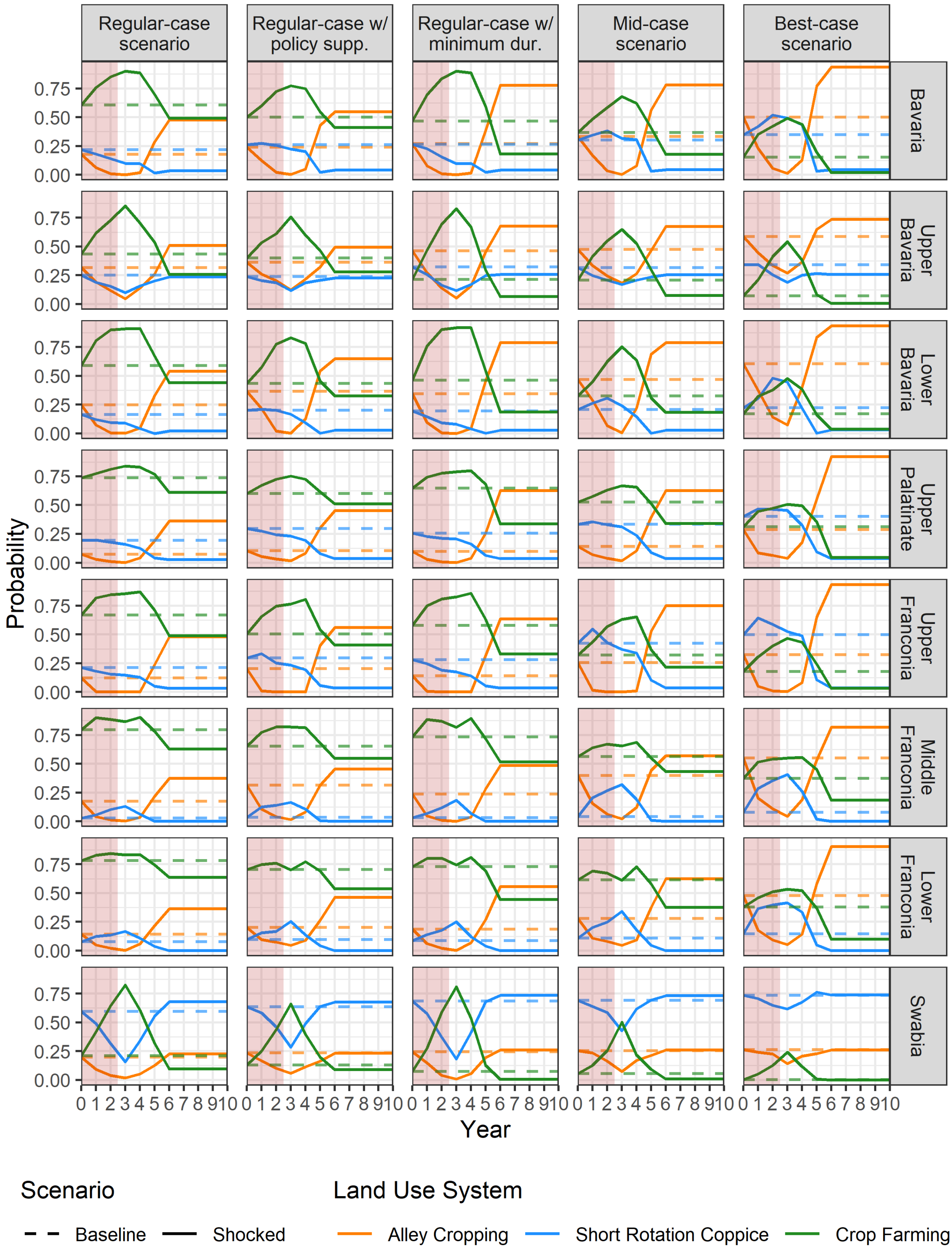

Figure 6: Summary of the propensity scores obtained from the step-1 propensity forest

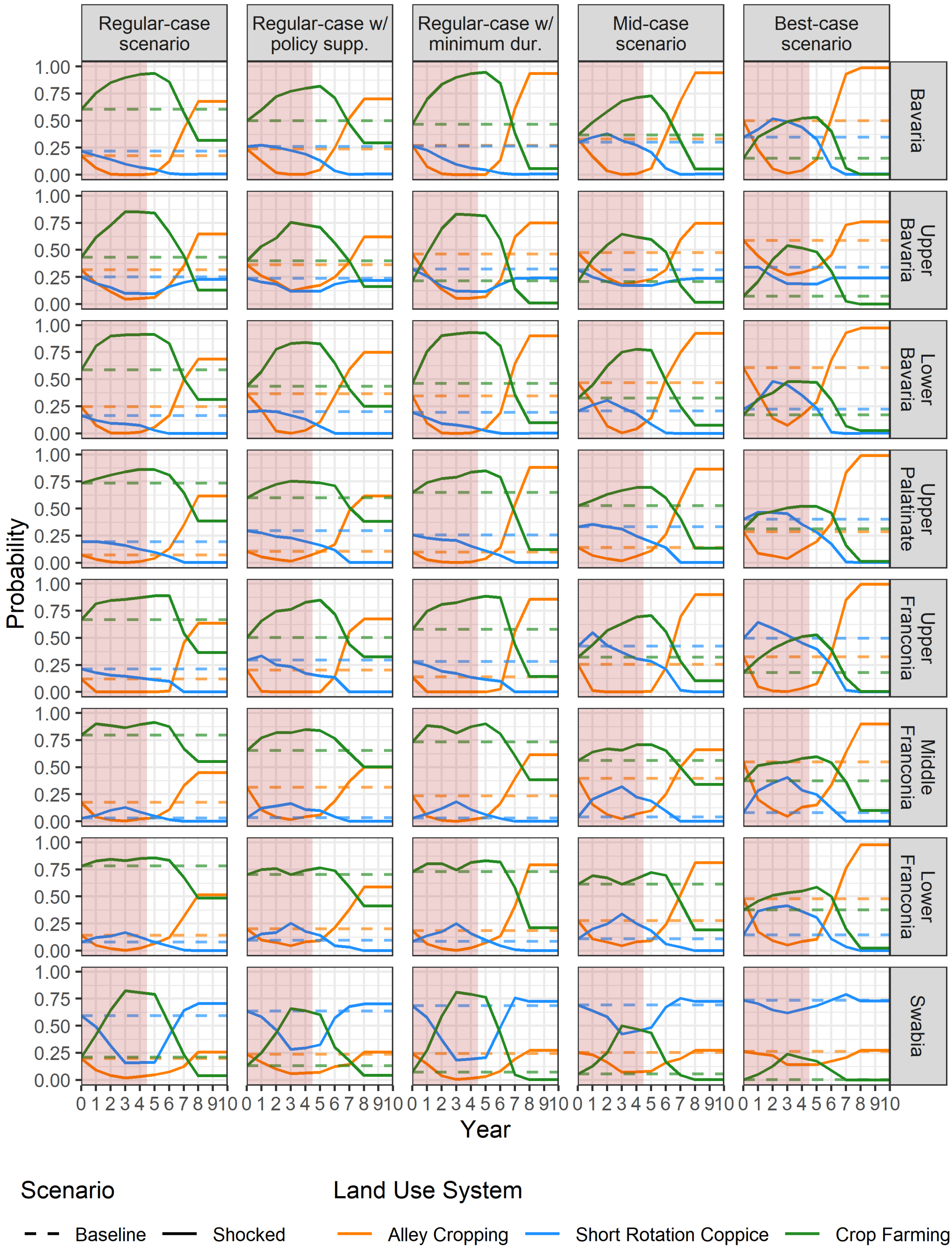

Figure 7: Summary of the propensity scores obtained from the step-1 propensity forest

transition away from status quo crop farming. Our results show that the socioeconomic conditions affect the land-use response of farmers to regional weather extremes. This involves policy support as well as technological progress. Furthermore, we find regional differences in farmers' willingness to adopt agroforestry and short-rotation coppice after an extreme weather event. Finally our results show that prolonged extreme weather periods lead to an increased probability of adopting climate-resilient agroforestry land-use systems in our sample.

5 Discussion

Weather resilience capacities

From the result section (4), we can observe a series of interesting patterns. Regarding farmers' dynamic land-use responses to extreme weather years (Section 4.3), we find characteristic response pathways that occur across farms and regions before reaching a (novel) equilibrium state. More specifically, these pathways can largely be divided into three phases: an absorption phase (during and directly after a shock, land-use probabilities move away from the baseline), a recovery phase (probabilities return to the initial levels), and an adaptation phase (probabilities move away from the initital level toward a (new) equilibrium). These phases reflect important resilience capacities in agricultural systems (OECD, 2020; Meuwissen et al., 2019).

As for the absorption phase, we find that the probability of status quo crop farming increases across all regions for a 2018-like weather shock. Since crop farming is also the most the land-use system with the highest probability in most scenarios and regions, we can conclude that farms adhere even stronger to their status quo in the direct aftermath of a shock than in the baseline. This might be surprising at first sight, because one would expect farms to turn to more weather-robust land-uses like AC and SRC (Ogunbode et al., 2019; Wilson et al., 2020). However, in the short-run, decisional factors are usually rigid, and production structures fixed, and thus limiting farmers' capacity to react (Girard, Delacote, and Leblois, 2021). Further barriers to transform their land-use directly after a (long-lasting) weather shock might lie in behavioral barriers such as farmers' perceived risk or their perceptions of the benefits and costs associated with more weather-robust land-uses (Dessart, Barreiro-Hurlé, and Van Bavel, 2019). Farmers might therefore be prone to only make adjustments within their familiar land-use system (i.e. crop farming). This trend intensifies with the duration of the weather shock.

Depending on the situation, the recovery phase can last between one and five years. We can see that independent of the scenario and region, the sample farms are able to recover from a weather shock in terms of their land-use probabilities (see also Béné et al., 2012; OECD, 2020). This might also be seen as a phase when the extreme weather period has settled and farmers are able to reconsider their initial land-use and prepare for transformative action.

In the adaptive phase, we find mixed effects regarding farmers' adaptive capacity (Smit and Wandel, 2006; Engle, 2011). If there is no monetary incentive or technological improvement in AC and SRC, which provide a comparative advantage over crop farming apart from its relative excellence with respect to climate robustness, farms are reluctant to transform and adopt these options. Although we find a certain degree of heterogeneity across shocks and regions, this trend is quite stable in our analyses. However, farmers appear to acknowledge the relative excellence of the agroforestry system, because irrespective of the scenario and region, the probability of adopting this system after a weather shock increases in the long-run. Especially, in the case of a very long-lasting extreme weather period (i.e. five years), agroforestry becomes the preferred land-use option.

What is more, our results empirically confirm the conceptual considerations by Meuwissen et al. (2019) that resilience and its capacities are shock- and context-specific.

Policy implications

Our results have also important implications for policy-makers. First, payments for ecosystem services increase farmers' probability of adopting wood-based and agroforestry land-use systems. They can therefore be an important lever to promote the cultivation of these climate-robust systems. While PES might be effective in promoting climate-robust land-use systems, they are not *cost-effective*. From Sec. 4.2.2, we learned that one extra Euro of such payments only increase the marginal willingness to adopt these system for most farms (approx. 67%) by less than a Euro (median: €0.54). This finding is in line with a series of previous studies finding low cost-effectiveness of PES and agri-environmental schemes (e.g. Chabé-Ferret and Subervie, 2013; Bartolini et al., 2021; Stetter, Mennig, and Sauer, 2022). However, there is within and across-region heterogeneity, e.g. the cost-effectiveness is on average highest in Upper (90%) and lowest in Central Franconia (28%). Accounting for such differences and offer environmental payments for the cultivation of agroforestry on a regional level could significantly increase the cost-effectiveness of such payments (Wünscher, Engel, and Wunder, 2008; Stetter, Mennig, and Sauer, 2022).

Another policy-relevant driver of agroforestry adoption is the minimum useful lifetime of the wood-based land use options. Farmers seem to assign a high value to their entrepreneurial flexibility (see also Musshoff, 2012). Rosenqvist and Dawson (2005), Avohou et al. (2011) and Londo et al. (2001) show that the useful lifetime of wood-based land uses is very important for their economic viability. To incentivise land-use change, legislators could establish a framework to encourage the development of coppices with reduced minimum useful lifetime but without reduced economic benefits. One way to do this might be the promotion of novel breeding methods, which have shown high innovation potential across several domains (Qaim, 2020).

Conceptual framework

Our analysis adds to a small but increasing body of studies that assess the link between climate variability and land-use change (Girard, Delacote, and Leblois, 2021). While most of these previous studies focus on established land use types and crops (Ramsey, Bergtold, and Heier Stamm, 2020; Salazar-Espinoza, Jones, and Tarp, 2015; He and Chen, 2022), our approach allows to *ex ante* assess the potential land-use of novel, not-established land-use types that could play an important role in the future.

Limitations

Finally, our study has some limitations that bear mentioning. For instance, we use cross-sectional weather data for the estimation of our econometric models. This means, we measure farmers' preferences only at one point in time (October 2020). This might be problematic under the assumption that preferences vary temporally (neglecting weather changes, which we account for in our model). However, several studies suggest that preferences are likely to be stable at least in the short- to medium-run (see e.g. Dasgupta et al., 2017; Doiron and Yoo, 2017; Andersen et al., 2008). Another weakness relates to the direct interpretation of the estimated weather coefficients in the RPL model. It is unlikely that any of the weather indicators changes in isolation, i.e. *ceteris paribus* statements are not valid. This is why we refrain from directly interpreting the estimated weather coefficients and instead focus on the weather simulations, which alleviate this problem to some extent (Ramsey, Bergtold, and Heier Stamm, 2020). Furthermore, we find multiple common characteristics of our sample and the underlying Bavarian farmer population, indicating reasonable representativeness. Although this is true for the full sample, it is likely not the case for our subsample analysis, which is why our results should be interpreted with care regarding their generalizability at the regional level (Pachali, Kurz, and Otter, 2020).

6 Summary and concluding remarks

Climate change poses exceptional challenges to farm businesses. Especially, the rising number of extreme weather events call for action in terms of climate change adaptation and mitigation. The cultivation of agroforestry and wood-based land-use systems could play a key role in making farms more climate resilient. This study analyzes farmers' dynamic willingness to adopt such systems in response to extreme weather periods. To this end, we integrate random utility theory with the concept of adaptive weather expectations. Methodologically, we combine a discrete choice experiment conducted with farmers in October 2020 in Bavaria, Germany with local weather data. For our analysis, we use a correlated random parameter model, which serves as a basis for regional weather simulations following Ramsey, Bergtold, and Heier Stamm (2020).

Our results indicate that farms are generally reluctant to adopt agroforestry and short-rotation coppice compared to crop farming but they are more likely to adopt these options after an extreme weather event in the medium- to long-run. Furthermore, we find characteristic weather response pathways that can be divided into three phases reflecting important resilience capacities, namely absorption, recovery, and adaptation. Moreover, our findings show that policy makers can effectively promote the adoption of agroforestry through payments for ecosystem services – although with low cost-effectiveness – and through fostering technological progress. Several robustness checks are conducted to assess the plausibility of our model. The paper also addresses important limitations concerning the underlying data, its representativeness and the model interpretation. Overall, our results show that farms might be increasingly likely to switch to agroforestry and wood-based systems in response to regional weather extremes.

Finally, we want to outline potential paths for future research. First, it would be interesting to assess the statistical uncertainty of the simulations. This could, for instance, either be done by means of a (computationally very expensive) nonparametric bootstrap procedure or by switching to a (hierarchical) Bayesian estimation framework. Furthermore, it would also be interesting to evaluate the appropriateness of our approach for other climate change adaptation strategies outside land-use. Last, we would appreciate similar studies in different regions around the world for to get an overall better understanding of the causal link between climate change and land-use.

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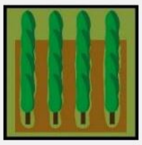
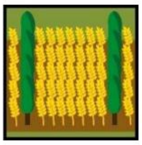
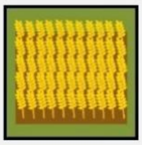
A Appendices

A.1 Description of the DCE alternatives

	Alternative 1: **Short Rotation Coppice**	This alternative relates to the cultivation of fast-growing tree species that are capable of sprouting, such as poplar, willow, locust and others. The trees are planted as a permanent crop on agricultural land and have a harvest cycle of several years. The cultivation is used for material utilization, for example in the paper, pulp and wood-based materials industries. However, the main focus is on generating energy from wood chips.
	Alternative 2: **Agroforestry**	This alternative corresponds to the strip-shaped cultivation of short rotation trees (poplar, willow, robinia and others) in combination with field crops. The distance between the rows of trees is created in such a way that the processing and harvesting of the field crops as well as the energy wood is possible without major restrictions and losses. The proportion of tree strips within the field is approx. 5 or 10%.
	Alternative 3: **Reference Crop Rotation**	This alternative corresponds to a standard crop rotation with the three crops maize, wheat and barley in conventional cultivation. The management requirements correspond to the legal minimum standards.

A.2 Description of the DCE attributes

	Eigenschaft	Beschreibung
	Margin contribution/ Margin contribution equivalent	The gross margin corresponds to the sum of the revenues minus the variable costs and is the contribution to covering the fixed and overhead costs. In the case of SRC and agroforestry, the relatively high initial investments are offset by only low expenditures for the management of SRC in the following years. Harvest costs and timber revenues are only incurred in years of harvesting activities. By means of dynamic investment calculation (or annuity calculation), the irregular payment flows can be converted into an annual margin contribution equivalent.
	Margin contribution variability	Corresponds to the average fluctuation in the margin contribution (equivalent).
	Minimum useful lifetime	The minimum useful lifetime of the corresponding alternative. For the reference crop rotation alternative, this corresponds to a three-year crop rotation.
	Agro-environmental premium per hectare and year	Annual premium per hectare for the cultivation of the respective land use alternative.
	Recognition as an ecological priority area (greening).	Is it possible to use the area as an ecological priority area?

A.3 Weather variable formulation for simulation

One year shock

$$weath1to3_t = \frac{1}{3} weath_{shock} + \frac{2}{3} weath_{lta} \text{ for } t = 1, 2, 3 \tag{9}$$

$$weath1to3_t = weath_{lta} \text{ for } t = 4, \dots, 10 \tag{10}$$

$$weath4to10_t = weath_{lta} \text{ for } t = 1, 2, 3 \tag{11}$$

$$weath4to10_t = \frac{1}{7} weath_{shock} + \frac{6}{7} weath_{lta} \text{ for } t = 4, \dots, 10 \tag{12}$$

A.4 Weather Simulations of a 2003-like extreme weather event

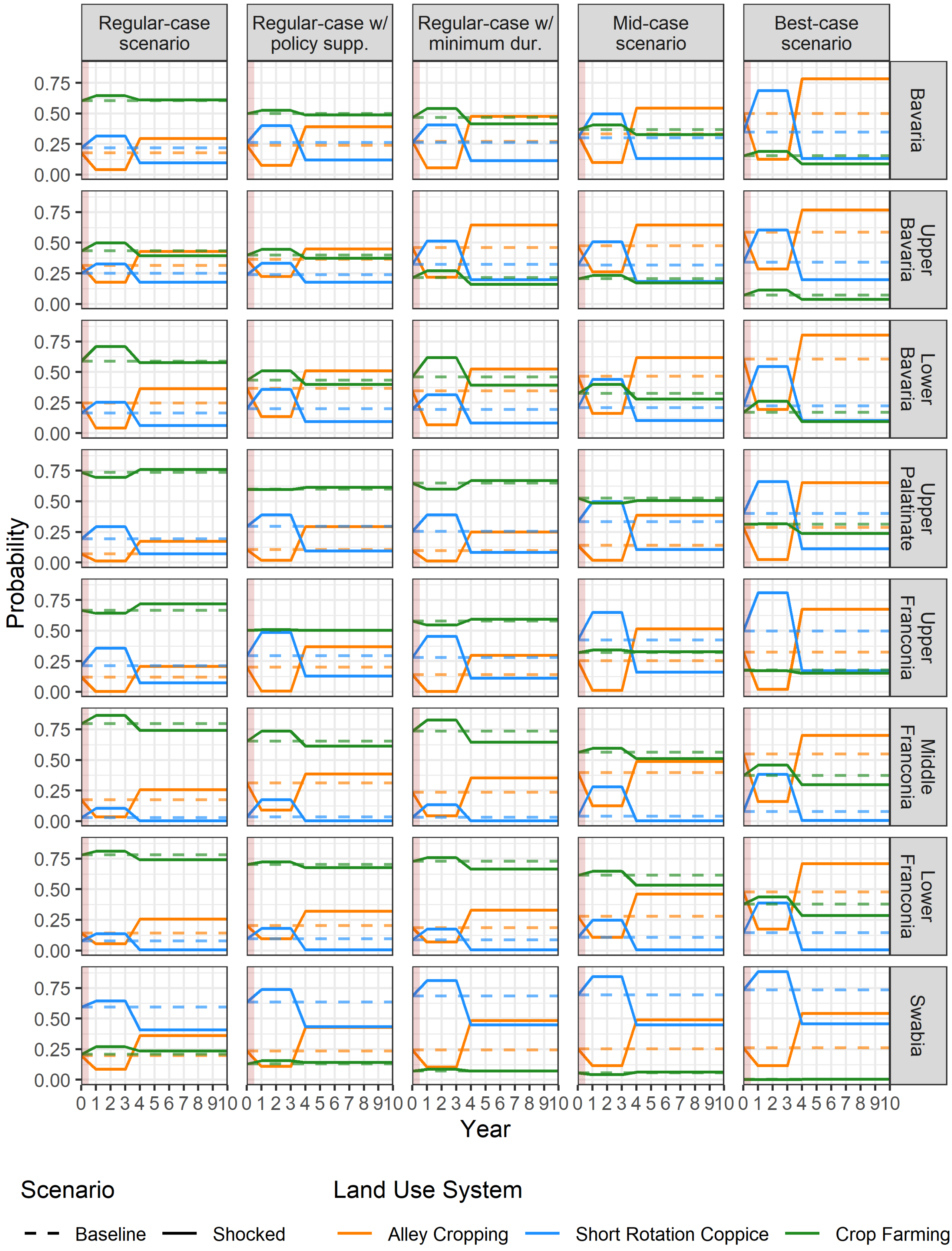


Figure A1: Summary of the propensity scores obtained from the step-1 propensity forest

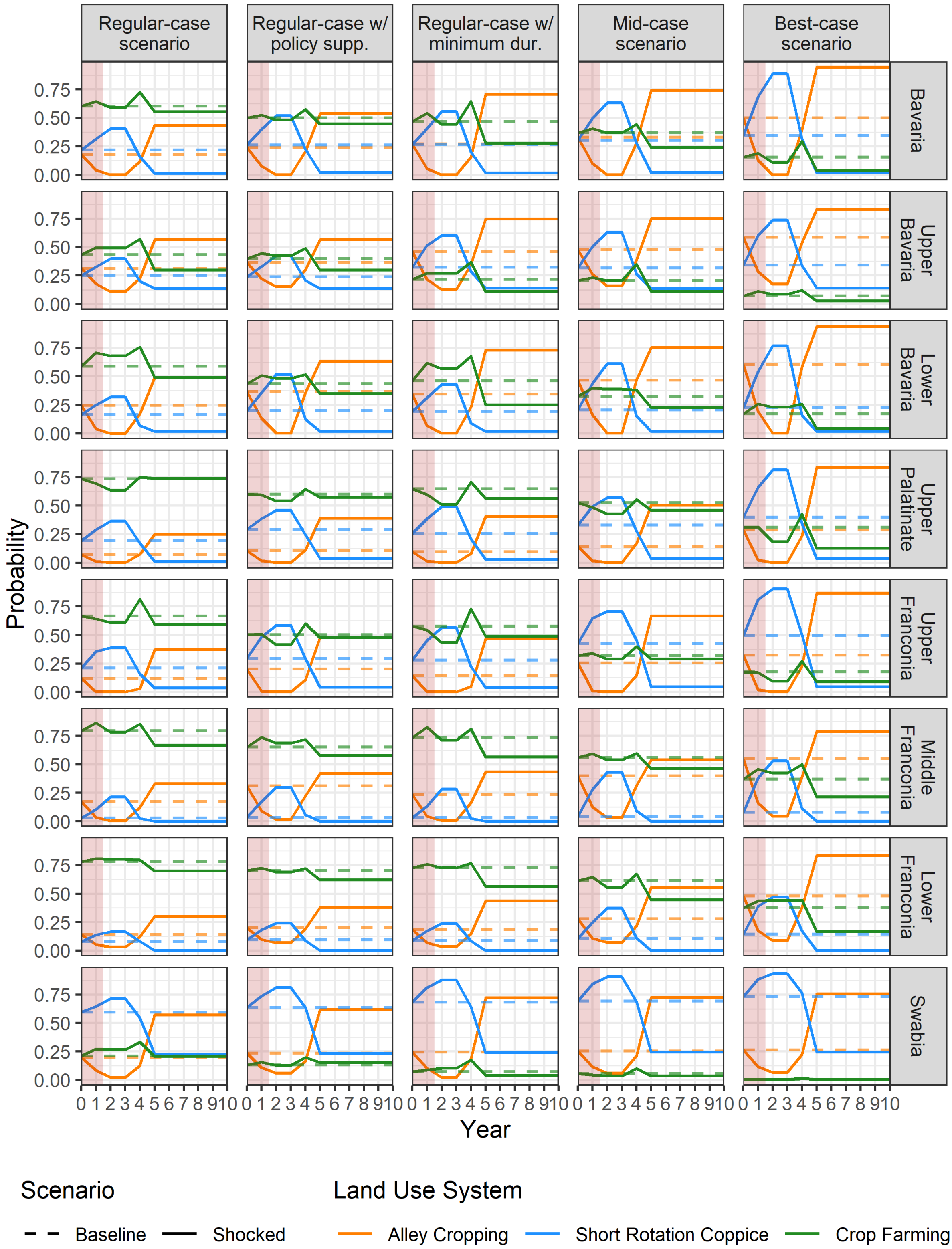


Figure A2: Summary of the propensity scores obtained from the step-1 propensity forest

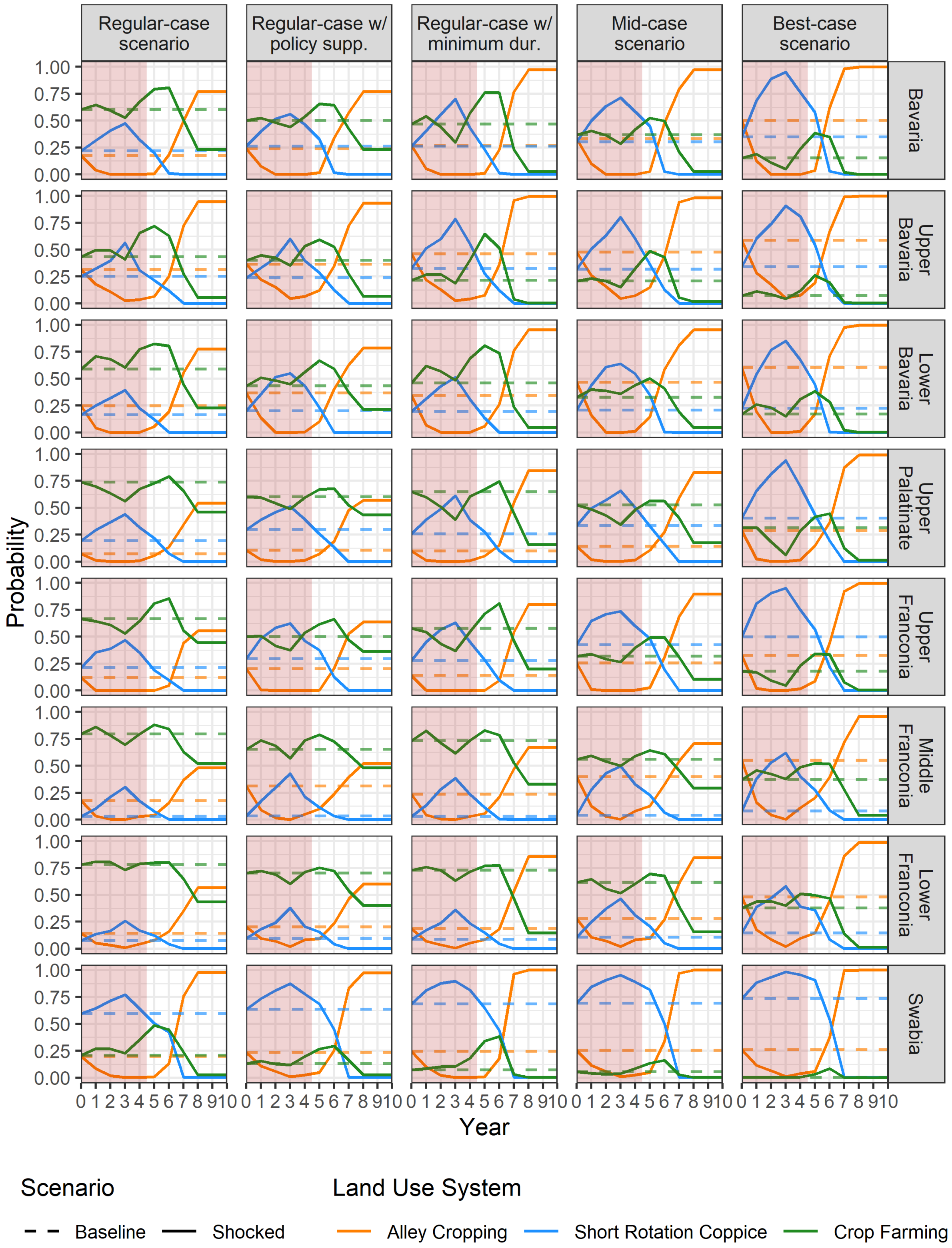


Figure A3: Summary of the propensity scores obtained from the step-1 propensity forest

Table A1: Estimation results summary

	MNL	uncor. RPL	cor. RPL
Means			
ASC: SRC	$-1.52\ (0.22)^{***}$	$-3.82\ (0.57)^{***}$	$-3.52\ (0.60)^{***}$
ASC: AC	$-0.98\ (0.22)^{***}$	$-2.04\ (0.53)^{***}$	$-0.89\ (0.53)^{\circ}$
Returns	$0.00\ (0.00)^{***}$	$-4.87\ (0.10)^{***}$	$-4.80\ (0.10)^{***}$
Returns variability	$-0.01\ (0.00)^{*}$	$-0.03\ (0.01)^{**}$	$-0.05\ (0.01)^{***}$
Min. useful lifet.	$-0.04\ (0.01)^{***}$	$-0.22\ (0.03)^{***}$	$-0.26\ (0.03)^{***}$
PES	$0.00\ (0.00)^{***}$	$0.01\ (0.00)^{***}$	$0.01\ (0.00)^{***}$
No greening	$-0.09\ (0.07)$	$-0.64\ (0.17)^{***}$	$-0.25\ (0.22)$
Rain 1-3:SRC	$0.01\ (0.00)^{*}$	$0.07\ (0.01)^{***}$	$0.10\ (0.02)^{***}$
Rain 1-3:AC	$0.01\ (0.00)^{*}$	$0.02\ (0.01)^{*}$	$0.04\ (0.01)^{***}$
Rain 4-10:SRC	$-0.02\ (0.01)^{*}$	$-0.20\ (0.03)^{***}$	$-0.09\ (0.03)^{***}$
Rain 4-10:AC	$-0.01\ (0.01)^{*}$	$-0.06\ (0.02)^{***}$	$-0.02\ (0.02)$
Temp. 1-3:SRC	$1.17\ (0.84)$	$-5.44\ (1.91)^{**}$	$-9.36\ (2.48)^{***}$
Temp. 1-3:AC	$-1.66\ (0.67)^{*}$	$-14.06\ (2.02)^{***}$	$-1.70\ (1.96)$
Temp. 4-10:SRC	$-1.29\ (0.86)$	$6.05\ (1.95)^{**}$	$8.21\ (2.54)^{**}$
Temp. 4-10:AC	$1.80\ (0.69)^{**}$	$14.25\ (2.00)^{***}$	$1.33\ (1.79)$
Dry days 1-3:SRC	$-0.05\ (0.04)$	$-0.30\ (0.13)^{*}$	$0.69\ (0.15)^{***}$
Dry days 1-3:AC	$-0.03\ (0.04)$	$0.18\ (0.10)^{\circ}$	$-0.04\ (0.11)$
Dry days 4-10:SRC	$-0.03\ (0.05)$	$-0.80\ (0.18)^{***}$	$-0.46\ (0.20)^{*}$
Dry days 4-10:AC	$-0.09\ (0.05)^{\circ}$	$-0.53\ (0.12)^{***}$	$-0.04\ (0.12)$
Heavy rain 1-3:SRC	$0.03\ (0.16)$	$-0.71\ (0.38)^{\circ}$	$-2.87\ (0.49)^{***}$
Heavy rain 1-3:AC	$0.11\ (0.13)$	$-0.27\ (0.34)$	$0.17\ (0.35)$
Heavy rain 4-10:SRC	$0.16\ (0.23)$	$5.48\ (0.92)^{***}$	$3.27\ (0.96)^{***}$
Heavy rain 4-10:AC	$0.02\ (0.20)$	$2.34\ (0.56)^{***}$	$-0.74\ (0.56)$
Hot days 1-3:SRC	$0.01\ (0.05)$	$0.88\ (0.18)^{***}$	$0.70\ (0.20)^{***}$
Hot days 1-3:AC	$0.13\ (0.04)^{**}$	$0.98\ (0.16)^{***}$	$-0.01\ (0.15)$
Hot days 4-10:SRC	$-0.10\ (0.11)$	$-2.01\ (0.36)^{***}$	$-1.75\ (0.40)^{***}$
Hot days 4-10:AC	$-0.18\ (0.09)^{\circ}$	$-1.75\ (0.30)^{***}$	$0.30\ (0.29)$
Standard deviations			
SD Rain 1-3:SRC		$0.06\ (0.01)^{***}$	$0.05\ (0.00)^{***}$
SD Rain 1-3:AC		$0.05\ (0.00)^{***}$	$0.02\ (0.00)^{***}$
SD Rain 4-10:SRC		$0.06\ (0.00)^{***}$	$0.05\ (0.00)^{***}$
SD Rain 4-10:AC		$0.05\ (0.00)^{***}$	$0.02\ (0.00)^{***}$
SD Temp. 1-3:SRC		$2.02\ (0.57)^{***}$	$-4.03\ (0.58)^{***}$
SD Temp. 1-3:AC		$2.28\ (0.44)^{***}$	$-0.74\ (0.48)$
SD Temp. 4-10:SRC		$0.02\ (0.33)$	$1.77\ (0.46)^{***}$
SD Temp. 4-10:AC		$-0.81\ (0.29)^{**}$	$-4.44\ (0.65)^{***}$
SD Dry days 1-3:SRC		$0.02\ (0.04)$	$0.09\ (0.04)^{*}$
SD Dry days 1-3:AC		$0.08\ (0.02)^{**}$	$0.00\ (0.04)$
SD Dry days 4-10:SRC		$-0.02\ (0.03)$	$-0.20\ (0.04)^{***}$
SD Dry days 4-10:AC		$0.12\ (0.04)^{**}$	$0.22\ (0.04)^{***}$
SD Heavy rain 1-3:SRC		$0.57\ (0.14)^{***}$	$0.10\ (0.18)$
SD Heavy rain 1-3:AC		$-0.24\ (0.15)$	$-0.37\ (0.20)^{\circ}$
SD Heavy rain 4-10:SRC		$0.08\ (0.11)$	$-0.08\ (0.17)$
SD Heavy rain 4-10:AC		$0.11\ (0.11)$	$0.17\ (0.11)$
SD Hot days 1-3:SRC		$0.09\ (0.05)$	$-0.30\ (0.06)^{***}$
SD Hot days 1-3:AC		$-0.25\ (0.04)^{***}$	$-0.28\ (0.04)^{***}$
SD Hot days 4-10:SRC		$0.50\ (0.09)^{***}$	$0.47\ (0.11)^{***}$
SD Hot days 4-10:AC		$-0.78\ (0.11)^{***}$	$-0.57\ (0.11)^{***}$
SD Returns		$1.08\ (0.07)^{***}$	$1.22\ (0.69)^{\circ}$
SD Returns variability		$0.07\ (0.01)^{***}$	$0.33\ (0.57)$
SD Min. useful lifet.		$0.25\ (0.02)^{***}$	$1.11\ (0.07)^{***}$
SD AES		$0.01\ (0.00)^{***}$	$0.10\ (0.02)^{***}$
SD No greening		$1.27\ (0.20)^{***}$	$0.28\ (0.03)^{***}$
SD ASC: SRC		$-2.38\ (0.32)^{***}$	$0.01\ (0.00)^{***}$
SD ASC: AC		$-0.33\ (0.23)$	$1.76\ (0.28)^{***}$
Correlation	-	No	Yes
logLik	-215604	-118413	-115521
Pseudo-R2	0.09	0.50	0.51
AIC	4366.09	2476.27	2460.43
Obs.	2376.00	2376.00	2376.00

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Table A2: Parameter correlation matrix of the RPL model.

	ASC: SRC	ASC: AC	Returns	Returns variability	Min. useful lifet.	PES	No greening
ASC: SRC	0.01	-0.45	0.51	0.29	0.46	0.26	0.57
ASC: AC	-0.45	1.76	0.08	0.11	-0.08	0.09	-0.34
Returns	0.51	0.08	1.22	0.88	0.67	-0.05	0.25
Returns variability	0.29	0.11	0.88	0.33	0.75	-0.43	-0.12
Min. useful lifet.	0.46	-0.08	0.67	0.75	1.11	-0.11	-0.14
PES	0.26	0.09	-0.05	-0.43	-0.11	0.10	0.23
No greening	0.57	-0.34	0.25	-0.12	-0.14	0.23	0.28

Table A3: Comparison different lag structures

	Log Likelihood	**McFadden Pseudo R2**	**Akaike Information Criterion**
Selected Model short-term: 1-3 years, long-term: 4-10 years	-1155.21	0.51	2460.43
Specification Alt. 1 short-term: 1 year, long-term: 2-10 years	-1389.99	0.41	2929.97
Specification Alt. 2 short-term: 1 year, long-term: 2-15 years	-1176.99	0.50	2503.98
Specification Alt. 3 short-term: 1 year, long-term: 2-20 years	-1400.24	0.41	2950.47
Specification Alt. 4 short-term: 1-3 year, long-term: 4-15 years	-1238.40	0.48	2626.81
Specification Alt. 5 short-term: 1-3 year, long-term: 4-20 years	-1382.27	0.42	2914.54
Specification Alt. 6 short-term: 1-5 year, long-term: 6-10 years	-1411.71	0.40	2973.42
Specification Alt. 7 short-term: 1-5 year, long-term: 6-15 years	-1398.10	0.41	2946.20
Specification Alt. 8 short-term: 1-5 year, long-term: 6-20 years	-1405.48	0.41	2960.97