

Kodama, Wataru et al.

Working Paper

Adaptation Decisions under Climate Change Uncertainty and Weather Extremes

Suggested Citation: Kodama, Wataru et al. (2025) : Adaptation Decisions under Climate Change Uncertainty and Weather Extremes, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/330341>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Adaptation Decisions under Climate Change Uncertainty and Weather Extremes

Wataru Kodama^{1*}, Petra Friederichs², Amin Nematbakhsh¹,
Martin Odening³, Svenja Szemkus², Stefan Seifert¹, Silke Hüttel¹

¹University of Göttingen

²University of Bonn

³Humboldt-Universität Berlin

Abstract

Farms and landowners seem reluctant to invest in climate change adaptation despite socio-economic benefits. However, a dynamic economic model suggests that under uncertain future climate change, observed adaptation “reluctance” may be in fact optimal from the decision-makers’ perspective. This is because decision-makers consider the value of waiting to gather information about future climate and weather before committing to investment. To investigate how future climate change shapes adaptation behavior, this study presents an analytical framework that integrate scenario-based climate model projections into a dynamic economic model of the adaptation decision. Using adaptation decision of the Austrian farms as a case example, we use projections of temperature and precipitation under the Shared Socioeconomic Pathways (SSP) scenarios from Coupled Model Intercomparison Project Phase 6 (CMIP6) simulations. The future projections are used to calibrate the climate change parameters within the economic model to analyze adaptation responses. We find that adaptation reluctance intensifies particularly in response to revenue downside shocks induced by weather extremes, and due to increased uncertainty in future climate change the likelihood of adaptation under severe climate change scenarios is not necessarily higher than under mild scenarios. We also find that adaptation subsidies can enhance the likelihood. These results suggest that with increasing frequency and intensity of extreme events in future, the expected loss without adaptation will increase while the reluctance will also increase, and the adaptation investment timing will appear even more *delayed*. Such delays may incentivize policymakers to provide public interventions such as subsidies to induce adaptation investment. However, they should carefully compare the value of adaptation reluctance and the social costs of the reluctance (e.g., negative externalities) to justify the interventions.

Keywords: climate change adaptation, real options approach, climate change projection, weather extremes, Shared Socioeconomic Pathways

JEL codes: D25, D81, Q54

Acknowledgement: Kodama, Friederichs, Szemkus, Seifert and Hüttel gratefully acknowledge funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – through CRC (SFB) 1502/1–2022 – project id: 450058266.

* Corresponding author: wataru.kodama@outlook.jp

Climate change poses a major challenge to humanity, threatening industries operating with the social-ecological environment such as agri-food and forest sectors. Studies document considerable private and public net gains from climate change adaptation (Moore and Lobell, 2014; Zeilinger et al., 2023; OECD, 2024; Duan et al., 2025). However, decision-makers such as farms, landowners, and local governments appear reluctant to invest in climate change adaptation to adapt their systems to climate change (IPCC, 2022). For example, increased drought risks in central Europe negatively impacts agricultural producers and sometimes market prices; yet, a majority of farmers do not invest in irrigation infrastructure despite its expected net returns exceeding the investment costs (Ihli et al., 2014; OECD, 2025).

Against this background, IPCC reports (IPCC, 2022; Voelz and Hinkel, 2023) and academic literature (Toman, 2006; Pollack et al., 2025) argue that the adaptation is *delayed* or *insufficient* due to financial, institutional, behavioral factors and call for public policy and investment. However, is the observed adaptation timing sub-optimal? As a dynamic economic model, the real options approach (ROA) suggests that under uncertain future climate, the observed adaptation *reluctance* may be in fact optimal from the decision-makers' perspective. Climate change adaptation requires substantial sunk investment costs under uncertainties in future returns and decision-makers consider value of waiting to collect information on uncertain future climate in their dynamic investment decision (Pindyck, 2022). The ROA has thus been widely applied to explain observed reluctance to adaptation investments (e.g., Carey and Zilberman, 2002; Ihli et al., 2014; Narita and Quaas, 2014; Kim et al., 2017; Kind et al., 2018; Eisenack and Paschen, 2022).

This study aims to present the direct linkage between climate change uncertainties and decision-makers' adaptation reluctance. We develop a new analytical framework that integrates scenario-based climate model projections into an ROA adaptation decision model. We simulate temperature and precipitation under the scenarios of the Shared Socioeconomic Pathways (SSP), and rely on climate change parameters in the ROA model corresponding to each SSP. Climate models offer the most reliable projections of climate change and inform policy decisions (Baumberger et al., 2017). Hence, integrating the climate model projections into the adaptation investment decision model provides the most probable predictions on future adaptation patterns from the decision-makers' perspectives. The current study is one of the first to make this attempt to obtain policy implications on public adaptation investments.

Our adaptation decision model closes gaps in the literature, where existing models are “*limited to decisions taken by individual risk neutral profit maximizers*” and fail to account for “*the complex nature of uncertainties associated with climate change*” (Ginbo et al., 2021, p. 229). We model adaptation decisions of risk aversion decision-makers facing climate change uncertainties related to future climate patterns and frequency of weather extremes, with parameters quantified through climate model predictions. The consideration of weather extremes is particularly important because the future extreme weather patterns are hard to predict in climate models compared to gradual change in climate, making the importance of uncertainties even higher in the adaptation decision (Lee and Zhao, 2021).

Analytical Framework

We consider the dynamic adaptation investment decision. The decision-makers face negative impacts of climate change on their payoff (e.g., revenue, return) from their conventional (non-adapted) production system. To mitigate the climate change impacts, they have an option to invest in adapted system by bearing one-time sunk investment costs.² This adaptation investment is irreversible and its return is uncertain and largely determined by the future climate change patterns and realizations (Pindyck, 2022). One way to anticipate the future climate change patterns, hence investment returns and uncertainties, is to refer to the scenario-based climate model predictions.

Figure 1 summarizes our analytical framework. First, we use climate model data to derive climate change patterns (temperature and precipitation) under the SSP scenarios. Second, we quantify three *climate change parameters* that define expected and uncertain returns from adaptation investment in the real options approach (ROA) adaptation investment model. Parameters reflecting a negative payoff trend due to gradual change in climate, return volatility under climate change, and the frequency of downside shocks induced by extreme weather are quantified using climate model projections. We estimate the first two parameters with the climate response function (Moore and Lobell, 2014; Zeilinger et al., 2023) to translate climate change projections into future payoff streams of the decision-makers and the third parameter with the

² Examples of such adaptation decision includes farms’ investment in irrigation infrastructure and local governments’ investment in disaster prevention facility.

simulated extreme event index based on climate change projections. For each scenario, projections from model ensembles are used to quantify the climate change parameters, i.e., variations in climate projections across model ensembles enter to the ROA model as a major source of uncertainty. Finally, we plug the quantified climate change parameters for each SSP scenario into the real options approach (ROA) model, which reflects the dynamic adaptation decision. For each SSP scenario, we simulate the adaptation patterns of a representative decision-makers and investigate their response to climate change parameters.

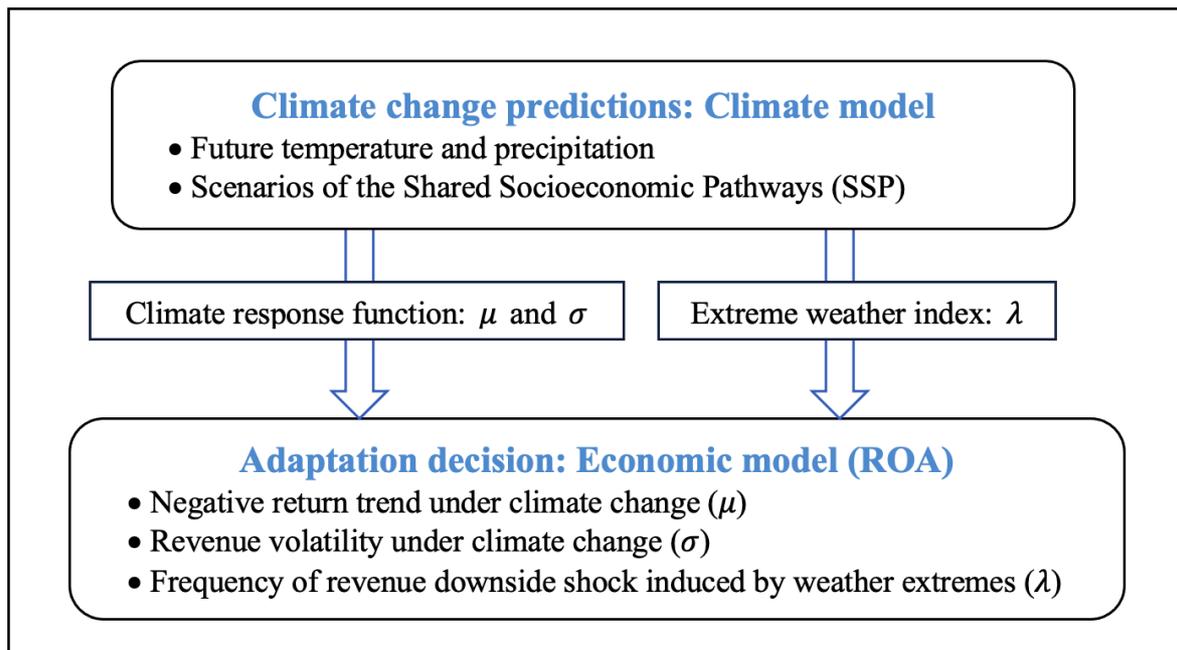


Figure 1. Analytical Framework of Adaptation Decision to Climate Change

Scenario-based climate change predictions: We rely on multimodal global climate projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016), coordinated by the World Climate Research Programme (WCRP), as the most significant sources of information regarding the potential future development of the climate system. The simulation data are generated using various numerical models of the global climate system under different possible future emission scenarios from the Shared Socio-economic Pathways (SSP, Riahi et al., 2017). The CMIP6 simulations provide possible future developments in temperature and precipitation (Tebaldi et al., 2021). Ensemble simulations enable the consideration of numerous potential future developments, accounting for the internal variability of the climate system and the uncertainties inherent in global climate model formulation.

Adaptation decision model: In our ROA model, we consider risk-averse and risk-neutral decision-makers who maximize a constant relative risk aversion (CRRA) utility with a risk preference parameter ε . They receive an uncertain payoff x_t^c in each period t under a conventional production system; once adapted by an investment with sunk costs I , they receive the less risky payoff x_t^a . Normalizing the payoff under the conventional system $x_t (= x_t^c/x_t^a)$, the payoff under the adapted system becomes numéraire, and their adaptation investment decision can be viewed as an exit problem (Dixit and Pindyck, 1994). The decision-makers expect negative effects of (future) climate change on the normalized payoff x_t ; they have an incentive to invest in adaptation to receive a constant payoff.

We assume that the uncertain normalized payoff x_t follows a mixed geometric Brownian Motion and Poisson jump process characterized by three key climate change parameters:

- Drift rate μ : negative payoff trend due to gradual change in climate. The normalized payoff reduces by $100\mu\%$ in each period.
- Volatility σ : payoff volatility under climate change. A fluctuation of the normalized payoff follows a normal distribution with mean zero and variance σx_t in each period.
- Frequency λ : frequency of downside shock induced by extreme event. A fixed magnitude of a downside shock to normalized payoff occurs with probability λdt .

The decision-maker considers the current value of investment $V_t(\mu, \sigma, \lambda, \varepsilon)$, the current value of sunk costs $V_t(I, \varepsilon)$, and the current value of waiting $VW_t(\mu, \sigma, \lambda, \varepsilon)$ in their adaptation decision. While traditional valuation approaches, such as the expected present value approach (EPVA), simply compare expected returns and investment costs, the ROA incorporates the value of waiting or flexibility to avoid investment under the future realizations of negative or insufficient investment returns. The adaptation investment decision rule under the EPVA and ROA are:

$$\text{EPVA: } V_t(\mu, \sigma, \lambda, \varepsilon) - V_t(I, \varepsilon) > 0;$$

$$\text{ROA: } V_t(\mu, \sigma, \lambda, \varepsilon) - V_t(I, \varepsilon) > VW_t(\mu, \sigma, \lambda, \varepsilon).$$

The ROA may better explain the observed patterns of the adaptation investment than the EPVA (e.g., Ihli et al., 2014; Kim et al., 2017; Kind et al., 2018); the EPVA serves as a reference to understand the value of waiting or the investment reluctance decision-makers face.

Solving the ROA investment decision is equivalent to finding an adaptation threshold x^* that triggers the investment. The decision-maker invests in the adapted system when the current payoff is lower than an adaptation threshold x^* :

$$x_t < x^*(\mu, \sigma, \lambda, \varepsilon, I). \quad (1)$$

Intuitively, this is the case where the current payoff is low enough compared to the counterfactual payoff under adaptation and sunk investment costs. The adaptation threshold is a function of three climate change parameters (μ, σ, λ) . Note that due to the value of waiting induced by uncertainties, the ROA threshold is lower than the EPVA threshold. Based on the threshold, we estimate the adaptation likelihood by a given period T :

$$P(\exists t \leq T | x_t < x^*). \quad (2)$$

These adaptation threshold and likelihood are used to evaluate the future adaptation patterns under future climate change patterns and scenarios.

Case example and parametrization: We take Austrian farms' adaptation decision as a case study. We rely on climate projections for 2025-2050 considering average temperature anomalies ($^{\circ}\text{C}$) relative to the 1950–2000 baseline from historical simulations and monthly precipitation sum (mm) during the growing season (May to August) over Austria (see Materials and methods). To quantify the climate change parameters, we use estimates of the climate response function of Austrian farmers by Zeilinger et al. (2023) based on 2003-2016 farm-level data. This climate response function returns the farm net revenue with and without adaptation from growing season temperature and precipitation. We quantify farmers' future net revenue with and without adaptation under various climate projections. Assuming that the expected farm revenue follows geometric-Brownian motion, we estimated the drift rate and volatility with maximum likelihood estimation (MLE).

While there are various extreme weather extreme that may affect farm revenue, drought is a major and increasing threat to crop production in Austria and Central Europe (Schmitt et al., 2022; e.g., Zeilinger et al., 2023). Therefore, we use the Standardized Precipitation Evapotranspiration Index (SPEI, Vicente-Serrano et al., 2014) as a dimensionless measure of drought conditions to model extreme weather events. The SPEI combines both precipitation and potential evapotranspiration (PET) capturing not only water supply but also the influence of temperature and atmospheric water demand. With negative values indicating drier conditions relative

to the historical baseline, we use $SPEI \leq -1.5$ as the threshold for “drought” to estimate drought frequency, and thus downside shock frequency (see *Materials and Methods* for details).

Results

The scenario-based climate projections for Austria and respective quantified parameters values based on the projections (Table 1, top) indicate higher uncertainties in the high-emission scenarios SSP5-8.5 and SSP3-7.0. Temperature shows comparatively stronger trends across all scenarios, with average anomalies between 1.3 °C and almost 1.8 °C. Average monthly precipitation during the growing season decreases in all scenarios compared to the historical average for 1950-2000 (79.28 mm/month) with a substantially weaker magnitude than for temperature. These results are consistent with the IPCC Sixth Assessment Report (Lee et al., 2023).

Climate change parameters (Table 1, bottom) quantified for each ensemble under a given SSP scenario show higher negative drift rates under the severe climate change scenarios (SSP3-7.0 and SSP5-8.5) compared to the mild and optimistic climate change scenario (SSP1-1.9 and SSP2-4.5). This is similar for the frequency of downside shock, but SSP2-4.5 scenario presents the highest value. The volatility is also highest under the SSP2-4.5 scenario followed by SSP3-7.0 and SSP5-8.5 scenarios, implying that the former scenario present higher uncertainties in model projection.

Under the parameter values of the SSP3-7.0 scenario, we find the ROA thresholds of 0.687, 0.689, and 0.692 for $\varepsilon = (0, 0.5, 2)$, respectively. This means that a decision-maker adapts to climate change when their normalized payoff with initial value of 1 hits these thresholds. The EPVA thresholds are above 1 (1.176, 1.266, and 1.398, respectively), considerably higher than the ROA thresholds, and would imply immediate adaptation. In both ROA and EPVA, more risk-averse decision-makers have lower thresholds implying earlier adaptation; differences in ROA are trivial and less significant than those in EPVA. This suggests the adaptation reluctance induced by uncertainties is particularly high for risk-averse decision-makers.

Table 1: Climate Change Projections (2025–2050) and Model Parameters under SSP Scenarios; Mean values and 10% and 90% percentiles in brackets

Scenario	SSP1-1.9	SSP2-4.5	SSP3-7.0	SSP5-8.5
Climate Change Projection: Growing Season (2025–2050)				
Temperature (°C)	1.34 [1.05,1.66]	1.60 [1.23,1.87]	1.70 [1.46,1.96]	1.76 [1.43,2.09]
Precipitation (mm)	80.80 [77.86,83.90]	80.04 [77.33,83.07]	79.85 [75.28,83.12]	79.64 [75.88,82.56]
Climate Change Parameters				
Neg. drift rate (μ)	0.0081 [0.000, 0.0317]	0.0106 [0.000, 0.0373]	0.0125 [0.001, 0.0653]	0.0115 [0.001, 0.0337]
Volatility (σ)	0.0578 [0.012, 0.165]	0.0577 [0.012, 0.164]	0.0681 [0.011, 0.224]	0.0672 [0.012, 0.199]
Frequency (λ)	0.0646 [0.000, 0.154]	0.0877 [0.000, 0.192]	0.0785 [0.000, 0.154]	0.0808 [0.000, 0.175]

Notes: Climate change parameter values based on 2025–2050 temperature and precipitation projections for Austria. Temperature refers to temperature anomalies relative to the 1950-2000 historical baseline; Precipitation refers to the expected monthly precipitation in mm/month in the growing season.

Figure 2 shows the ROA adaptation thresholds and likelihoods as functions of the climate change parameters (μ, σ, η) under the SSP3-7.0 scenario for different levels of risk aversion. Higher (negative) **drift rate** μ increases the adaptation threshold, i.e., higher rates of unfavorable and/or gradual changes in climate induce higher adaptation incentives due to lower expected payoffs (utility) from the non-adapted system. Higher drift rate also leads to higher likelihood of adaptation. Overall, as expected, unfavorable gradual changes in climate leads to higher adaptation incentives and likelihood.

In contrast, higher **volatility** σ decreases the adaptation threshold (lower adaptation incentives). Although it reduces the expected utility of risk-averse decision-makers (higher adaptation incentives), it also increases the value of waiting (lower adaptation incentives), and the latter effect dominates the former effect. Because the risk-averse decision-makers have adaptation incentives with the former effect, their threshold is higher than the risk-neutral decision-makers. Interestingly, higher volatility decreases the adaptation likelihood in a certain range,

which may sound counter-intuitive because the risk mitigation is seen as one of the key benefits of adaptation. Similar to the case of adaptation threshold, this result can be explained by the effect of increased value of waiting that makes decision-makers more reluctant to adapt. The marginal effect of the volatility on the likelihood turns into positive when the volatility is around 0.05–0.06. This means that an average volatility that decisionmakers face is in fact within the range that minimize the adaptation likelihood (see Table 1). Overall, the results show that higher volatility provide significant incentives for decision-makers to become reluctant to adapt.

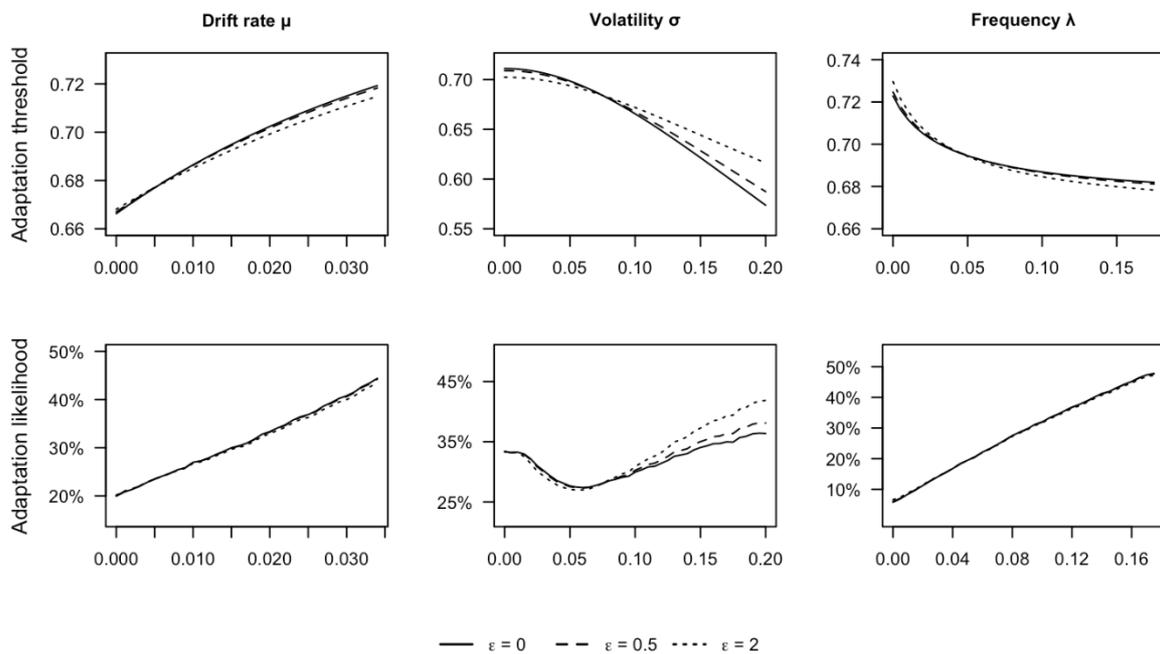


Figure 2 Climate Change Parameters and Adaptation Threshold and Likelihood for SSP3-7.0

Notes: Parameters are set as follow: Magnitude of downside shock $\eta = 0.300$ (Slijper et al., 2022); relative risk aversion coefficient $\varepsilon = (0, 0.50, 2)$ following Iyer et al. (2020); Interest rate $r = 0.10$; Initial normalized payoff $x_0 = 1$; Sunk investment cost $I = 2$. Initial normalized payoff is 1. See *Materials and Method* for detailed parameter definitions and estimation methodologies.

Higher **frequency of a downside shock** λ decreases adaptation threshold (lower adaptation incentives). Although the expected return from adaptation becomes higher with higher likelihood of downside shock, it also increases the value of waiting, where the latter effect overweighs. When decision-makers expect a higher likelihood of weather extremes, they are incentivized to delay the investment so that they can wait to see if the weather extremes really occur

in their area of production. Indeed, evidence suggests that decision-makers adapt only after experiencing damages and losses from extreme events (e.g., Reilly and Schimmelpfennig, 2000). The adaptation likelihood increases with frequency as downside shock makes the payoff becomes more likely to hit the threshold. Nonetheless, an increased frequency of downside shocks induced by weather extremes enhances the adaptation reluctance, restraining an increase in adaptation likelihood.

Finally, we estimate Austrian farmers' 5-year adaptation likelihood based on the climate change parameters corresponding to each SSP scenario and their sensitivity to an adaptation investment subsidy (Figure 3). For the selected parameter values, all EPVA thresholds exceed 1 suggesting an immediate adaptation. In contrast, adaptation likelihood is about 21–27% under the ROA decision rules. Such difference reflects the seemingly delayed adaptation from the EPVA perspective.

The optimistic scenario SSP1-1.9 shows the lowest adaptation likelihood. Interestingly, adaptation likelihood under severe climate change scenarios (SSP3-7.0 and SSP5-8.0) is not necessarily higher than that under mild climate change scenarios (SSP2-4.5). That is, high future climate uncertainty under severe climate change does not necessarily induce widespread adaptation; rather, its timing appears to be *delayed* (Hawkins and Sutton, 2009).

We note that estimates of the likelihood are sensitive to an adaptation investment subsidy. The results suggest that subsidies of 20% and 40% of the initial investment costs increase the adaptation likelihood by 17–18% and 35–37%, respectively.

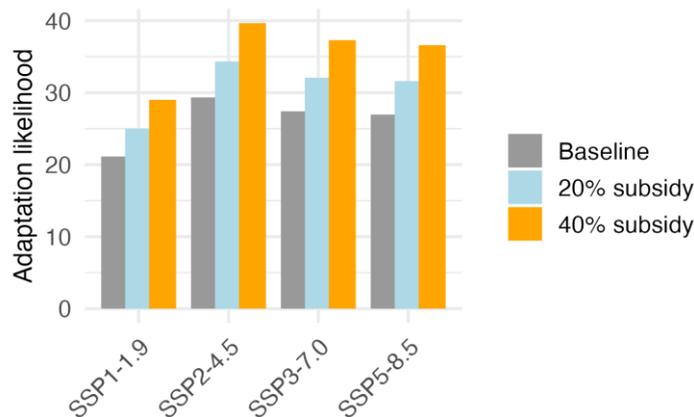


Figure 3 Adaptation Likelihood under Climate Change Scenarios

Notes: Drift rate, volatility, and frequency of downside shock corresponding to each SSP scenario projections (2025-2050) are used to simulate adaptation probability (see Table 1). Relative risk aversion rate is set $\varepsilon = 2$.

Discussion

Our analytical framework for adaptation decision and empirical application to Austrian farms shows several interesting results: First, adaptation threshold and a likelihood indicate a considerably delayed adaptation compared to the EPVA benchmark, even though it is optimal from the decision-makers' perspective. This reflects observed *reluctance* to invest in adaptation. Second, adaptation reluctance particularly intensifies in response to downside revenue shocks induced by weather extremes. Increasing frequency of extreme weather events under climate change will further increase adaptation reluctance. Third, because uncertainty about future climate increases, the likelihood of adaptation under severe scenarios is not necessarily higher than under mild ones. This counter-intuitive result implies possible production losses due to under-adaptation under severe climate change. Finally, adaptation investment subsidies may enhance the likelihood of adaptation. Together, these results have policy-relevant implications.

Although decision-makers already seem reluctant to invest in adaptation (IPCC, 2022), this reluctance is likely to intensify as climate change progresses. One key channel is downside shocks induced by weather extremes. With increasing frequency and intensity of extreme events, the expected loss without adaptation investment will increase; at the same time, the option value of waiting also increases for decision-makers. As a result, the adaptation investments will be further *delayed*.

Such delays may incentivize policymakers to provide public interventions to enhance the adaptation investment (e.g., investment subsidy). Member states of the European Union in fact supports investments into irrigation and in water-savings measures according to the CAP strategic plans, usually aimed at modernization and increasing efficiency of irrigation systems (European Commission, 2023). However, according to the ROA, adaptation timing is only seemingly delayed and optimal from the decision-makers' perspective; thus, unnecessary public investments in adaptation may lead to inefficient resource allocations.

Nonetheless, policymakers can justify the public investments when the adaptation reluctance has some negative externalities. One prominent example is staple cereal price. Demand for most staple cereals (e.g., wheat, maize, rice) are relatively inelastic, and a negative supply shock (e.g., production loss) can sharply rise its price (e.g., Khalfaoui et al., 2024). Therefore,

reducing expected production loss by earlier adaptation through public investment may predict future cereal price surge, enhancing future social welfare.

Another perspective of justifying the public interventions is imperfect financial market. When the decision-makers faces borrowing constraints, their real investment sunk costs are higher than the nominal one. In this case, investment subsidy or concessional loans can compensate the additional costs of to the borrowing constraints on the investment sunk costs. Some adaptation programs target disadvantaged groups (e.g., smallholder farmers) because these groups tend to face borrowing constraints for the adaptation investment.

Overall, careful considerations are required for the public intervention to induce adaptation investment. The policymakers should compare the value of adaptation reluctance with *social costs* of the reluctance.

Materials and methods

Climate model: The climate projections and historical simulations analyzed in this study are based on the MPI-ESM1-2-LR model (Wieners et al., 2019), which is part of the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016). All simulations, including the 50 ensemble members for both historical and future scenario experiments, are publicly available through the Earth System Grid Federation (ESGF) data portal (<https://esgf-node.llnl.gov/projects/cmip6/>).

Calculation of climate variables: The model output was processed to derive temperature and precipitation values as follows: Temperature anomalies were derived from monthly mean temperature fields by subtracting the corresponding 1950–2000 climatological baseline, calculated from the historical simulations. Precipitation was taken as monthly precipitation totals. Both variables were averaged over the planting season (March–August) and spatially across Austria, defined by the domain 8° E–17° E and 45° N–50° N.

The Standardized Precipitation-Evapotranspiration Index (SPEI) accounts for both precipitation and potential evapotranspiration (PET). PET was estimated using the Thornthwaite method (Thornthwaite, 1948), which is temperature-based and commonly applied when only temperature and precipitation data are available. The SPEI was calculated on a 6-month aggregation scale during the planting season (March–August), following Vicente-Serrano et al. (2014), with standardization relative to the 1950–2000 baseline period using a log-logistic

probability distribution and historical simulations. As with temperature anomalies and total precipitation, the resulting SPEI values were spatially averaged over Austria (8° E–17° E, 45° N–50° N).

Downside shock parametrization: We consider downside shocks as a result of a Poisson process (Lee and Zhao, 2021) and consider cases with $SPEI < -1.5$ as droughts (e.g., Wang et al., 2021). We obtain an estimate of the downside shock frequency (λ_E) for each SSPs through maximum likelihood estimation (MLE) for each ensemble member. SSP-specific λ s are calculated as arithmetic mean over the ensemble members.

Drift rate and volatility parametrization: To parametrize drift rate and volatility under the five SSP climate change scenarios, we use the short-run (SL) and long-run (LL) response functions of weather and climate effects on agricultural outcomes from existing studies (McIntosh and Schlenker, 2006; Moore and Lobell, 2014; Mérel and Gammans, 2021; Zeilinger et al., 2023). That is, we use spatial and temporal variations of weather realization to estimate the response function:

$$\text{SL: } y_{it} = \alpha + f(\bar{W}_{it}; \beta) + g(|W_{it} - \bar{W}_{it}|; \gamma) + \delta_i + \delta_t + \varepsilon_{it}$$

$$\text{LL: } y_{it} = \alpha + f(\bar{W}_{it}; \beta) + \delta_i + \delta_t + \varepsilon_{it},$$

where y_{it} is agricultural outcome, W_{it} denotes weather variables, \bar{W}_{it} denotes the moving average of weather variables in the last 20-30 years representing long-run climate conditions, and (δ_i, δ_t) are farm- and time-fixed effects. The error term ε_{it} is orthogonal to weather and climate variables. The deviation from long-term climate, $W_{it} - \bar{W}_{it}$ only affects the short-run response function. Assuming that farms adapt their production systems to climate change in the long-run, $g(|W_{it} - \bar{W}_{it}|; \gamma)$ in the short-run response function describes the “adaptation potential”, or an “expected loss” without adaptation (Moore and Lobell, 2014; Zeilinger et al., 2023).

We refer to the response function from Zeilinger et al. (2023), where the short-run response function is:

$$\begin{aligned} V_{it} = & \alpha + \beta_1 \bar{W}_{it} + \beta_2 \bar{W}_{it}^2 + \gamma_1 (W_{it} - \bar{W}_{it})_{<0} + \gamma_2 (W_{it} - \bar{W}_{it})_{<0}^2 \\ & + \gamma_3 (W_{it} - \bar{W}_{it})_{>0} + \gamma_4 (W_{it} - \bar{W}_{it})_{>0}^2 + \delta_i + \delta_t + \varepsilon_{it}, \end{aligned}$$

with V_{it} as net revenue per hectare (EUR/ha) of an Austrian farm; W_{it} denotes the average temperature and precipitation during the growing season. Plugging the projected growing-sea-

son temperature and precipitation during 2025–2050 under different SSP scenario into the response function, we quantify the farm net revenue during 2025–2050 for each set of scenario and ensemble. We assume that the net revenue follows a Geometric Brownian motion (GBM) and quantify drift rate and volatility for each scenario and ensemble member by Maximum Likelihood Estimation.

Adaptation decision model: In our adaptation decision model, the decision-makers face a dynamic adaptation investment decision where in each time period they have an option to invest in adaptation technology with sunk investment costs. We formally present our model with following assumptions:

Assumption 1. A risk-averse decision-maker maximizes their expected utility with the constant relative risk aversion (CRRA) utility

$$u(x) = \frac{x^{1-\varepsilon}}{1-\varepsilon} \quad (\varepsilon \geq 0, \varepsilon \neq 1), \quad (3)$$

where ε denotes a relative risk aversion parameter. This utility function is tracable in a ROA framework with the advantage to nest the standard model. For a risk-neutral decision-maker $\varepsilon = 0$, utility reduces to $u(x) = x$ and the expected utility maximization problem is equivalent to the expected payoff maximization problem.

Assumption 2. A normalized payoff under the conventional system ($x_t = x_t^{\text{conv}}/x_t^{\text{adapt}}$) is uncertain and follows a mixed GBM and Poisson jump process:

$$x_0; dx_t = \mu x_t dt + \sigma x_t dz_t - \eta x_t dq_t, \quad (4)$$

where $x_0 > 0$ is the initial payoff, μ is the drift rate, σ is the volatility, and dz_t is an increment of the Wiener process. The (negative) drift rate represents negative return trend under the unfavorable and gradual changes in climate. The volatility represents fluctuations in the payoff streams. The discontinuous downside jump process dq_t is

$$dq_t = \begin{cases} 1 & \text{with probability } \lambda dt \\ 0 & \text{with probability } 1 - \lambda dt \end{cases},$$

where λ is the jump frequency or the mean arrival rate of the Poisson process and $\eta \in (0,1)$ denotes the jump size. In the time interval dt , the payoff discontinuously declines by $100 \cdot \eta\%$ with probability λdt . We assume the Wiener and the jump process are independent.

Assumption 3. A decision-maker receives normalized payoff x_t in each period t under a conventional production system, while once adapted by paying irreversible fixed switching costs

I they receive numéraire payoff. They find an optimal adaptation time t^* by solving the following maximization problem:³

$$\max_t E \left[\int_0^t u(x_s) e^{-rs} ds + \int_t^\infty u(1 - rI) e^{-rs} ds \right]. \quad (5)$$

Our proposed model departs from the standard ROA models in several ways. First, we consider not only gradual and unfavorable effects of climate change changes but also the negative effects of climate extremes on the downside shocks. As outlined in Assumption 2, we implement a mixed geometric Brownian motion (GBM) with a Poisson jump process based on recent models that relax the continuous stochastic payoff function assumption (Guthrie, 2019; Lee and Zhao, 2021; Guthrie, 2023). In addition, we incorporate a risk utility function into the value function (e.g., Mense, 2018) of our model in order to understand the interplay between risk preference of decision-makers and uncertainties related to weather extremes (Assumption 1 and 3). CRRA utility is used for the sake of analytical tractability.

The dynamic investment problem above is equivalent to finding an adaptation threshold x^* that triggers adaptation investment. To find the adaptation threshold x^* under the ROA model proposed in equation (3)-(5), we use dynamic programming techniques (see Appendix 1). We numerically estimate the threshold x^* for a given set of parameters based on the following proposition that summarizes the model result.

Proposition: *The decision-maker switches to the adapted system if and only if the current payoff is below adaptation threshold x^**

$$\begin{aligned} u(x^*) &= \frac{\delta}{r} \left(\frac{\beta^*}{\beta^* - 1} \right) u(y_0 - rI). \\ \Leftrightarrow x^* &= (y_0 - rI) \left[\frac{\delta}{r} \left(\frac{\beta^*}{\beta^* - 1} \right) \right]^{\frac{1}{1-\varepsilon}}. \end{aligned} \quad (6)$$

The convenience yield δ is given by

³ We model switching cost I as an annuity instead of a one-time cash payment and assume no borrowing constraint.

$$\delta = r - \tilde{\mu} + \lambda\tilde{\eta},$$

where $\tilde{\mu} = \mu(1 - \varepsilon) - \frac{\sigma^2}{2}\varepsilon(1 - \varepsilon)$ and $\tilde{\eta} = 1 - (1 - \eta)^{1-\varepsilon}$.

- If $0 < \varepsilon < 1$: β^* is a unique negative root of the polynomial equation (4).
- If $\varepsilon > 1$: β^* is a unique positive root of the polynomial equation (4) and greater than 1.

$$\frac{1}{2}\tilde{\sigma}^2\beta(\beta - 1) + \tilde{\mu}\beta - \lambda[1 - (1 - \tilde{\eta})^\beta] - r = 0,$$

where $\tilde{\sigma} = \sigma(1 - \varepsilon)$.

Proof: See Appendix A1.

In addition to the threshold, we also estimate the adaptation likelihood, i.e., probability of investing on adaptation by a given period (cf., equation 2). The explicit form of the adaptation likelihood can be solved if the payoff follows a continuous stochastic process (cf. Sarkar, 2000), though not for our extension by the jump component due to the “undershoot” problem (Lee and Zhao, 2021). We therefore use Monte-Carlo simulation techniques to estimate the adaptation probability: For a given set of parameters or stochastic process s , we simulate a payoff realization $x_t(s)$ for N times, count the number of times it hits the numerically obtained adaptation threshold $\hat{x}^*(s)$ by time T , and denote the number with $n_T(s)$, to estimate the likelihood by $\hat{P}(t^* \leq T|s) = n_T(s)/N$. We set $N = 100,000$ and $T = 5$.

References

- Baumberger, C., Knutti, R., Hirsch Hadorn, G., 2017. Building confidence in climate model projections: an analysis of inferences from fit. *WIREs Clim Change* 8 (3).
<https://doi.org/10.1002/wcc.454>.
- Carey, J.M., Zilberman, D., 2002. A Model of Investment under Uncertainty: Modern Irrigation Technology and Emerging Markets in Water. *Am J Agric Econ* 84 (1), 171–183.
<https://doi.org/10.1111/1467-8276.00251>.
- Dixit, A.K., Pindyck, R.S., 1994. *Investment under uncertainty*. Princeton University Press, Princeton, New Jersey, Chichester, West Sussex, 468 pp.

- Duan, L., Carlino, A., Caldeira, K., 2025. Near-term benefits from investment in climate adaptation complement long-term economic returns from emissions reduction. *Commun Earth Environ* 6 (1). <https://doi.org/10.1038/s43247-024-01976-6>.
- Eisenack, K., Paschen, M., 2022. Adapting long-lived investments under climate change uncertainty. *Journal of Environmental Economics and Management* 116, 102743. <https://doi.org/10.1016/j.jeem.2022.102743>.
- European Commission, 2023. Approved 28 CAP Strategic Plans (2023-2027): Summary overview for 27 Member States. <https://agriculture.ec.europa.eu/system/files/2023-06/approved-28-cap-strategic-plans-2023-27.pdf>.
- Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., Taylor, K.E., 2016. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.* 9 (5), 1937–1958. <https://doi.org/10.5194/gmd-9-1937-2016>.
- Ginbo, T., Di Corato, L., Hoffmann, R., 2021. Investing in climate change adaptation and mitigation: A methodological review of real-options studies. *Ambio* 50 (1), 229–241. <https://doi.org/10.1007/s13280-020-01342-8>.
- Guthrie, G., 2019. Real options analysis of climate-change adaptation: investment flexibility and extreme weather events. *Climatic Change* 156 (1-2), 231–253. <https://doi.org/10.1007/s10584-019-02529-z>.
- Guthrie, G., 2023. Optimal adaptation to uncertain climate change. *Journal of Economic Dynamics and Control*, 104621. <https://doi.org/10.1016/j.jedc.2023.104621>.
- Ihli, H.J., Maart-Noelck, S.C., Musshoff, O., 2014. Does timing matter? A real options experiment to farmers' investment and disinvestment behaviours. *Aust J Agric Resour Econ* 58 (3), 430–452. <https://doi.org/10.1111/1467-8489.12028>.
- IPCC, 2022. Summary for policymakers. *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.
- Khalifaoui, R., Goodell, J.W., Mefteh-Wali, S., Chishti, M.Z., Gozgor, G., 2024. Impact of climate risk shocks on global food and agricultural markets: A multiscale and tail connectedness analysis. *International Review of Financial Analysis* 93, 103206. <https://doi.org/10.1016/j.irfa.2024.103206>.

- Kim, K., Ha, S., Kim, H., 2017. Using real options for urban infrastructure adaptation under climate change. *Journal of Cleaner Production* 143, 40–50. <https://doi.org/10.1016/j.jclepro.2016.12.152>.
- Kind, J.M., Baayen, J.H., Botzen, W.J.W., 2018. Benefits and Limitations of Real Options Analysis for the Practice of River Flood Risk Management. *Water Resour. Res.* 54 (4), 3018–3036. <https://doi.org/10.1002/2017WR022402>.
- Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P.W., Trisos, C., Romero, J., Aldunce, P., Barrett, K., Blanco, G., Cheung, W.W., Connors, S., Denton, F., Diongue-Niang, A., Dodman, D., Garschagen, M., Geden, O., Hayward, B., Jones, C., Jotzo, F., Krug, T., Lasco, R., Lee, Y.-Y., Masson-Delmotte, V., Meinshausen, M., Mintenbeck, K., Mokssit, A., Otto, F.E., Pathak, M., Pirani, A., Poloczanska, E., Pörtner, H.-O., Revi, A., Roberts, D.C., Roy, J., Ruane, A.C., Skea, J., Shukla, P.R., Slade, R., Slangen, A., Sokona, Y., Sörensson, A.A., Tignor, M., van Vuuren, D., Wei, Y.-M., Winkler, H., Zhai, P., Zommers, Z., Hourcade, J.-C., Johnson, F.X., Pachauri, S., Simpson, N.P., Singh, C., Thomas, A., Totin, E., Arias, P., Bustamante, M., Elgizouli, I., Flato, G., Howden, M., Méndez-Vallejo, C., Pereira, J.J., Pichs-Madruga, R., Rose, S.K., Saheb, Y., Sánchez Rodríguez, R., Ürge-Vorsatz, D., Xiao, C., Yassaa, N., Alegría, A., Armour, K., Bednar-Friedl, B., Blok, K., Cissé, G., Dentener, F., Eriksen, S., Fischer, E., Garner, G., Guivarch, C., Haasnoot, M., Hansen, G., Hauser, M., Hawkins, E., Hermans, T., Kopp, R., Leprince-Ringuet, N., Lewis, J., Ley, D., Ludden, C., Niamir, L., Nicholls, Z., Some, S., Szopa, S., Trewin, B., van der Wijst, K.-I., Winter, G., Witting, M., Birt, A., Ha, M., Kim, J., Haites, E.F., Jung, Y., Stavins, R., Orendain, D.J.A., Ignon, L., Park, S., Park, Y., Reisinger, A., Cammaramo, D., Fischlin, A., Fuglestvedt, J.S., Matthews, J.R., Péan, C., 2023. IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland.
- Lee, S., Zhao, J., 2021. Adaptation to climate change: Extreme events versus gradual changes. *Journal of Economic Dynamics and Control* 133, 104262. <https://doi.org/10.1016/j.jedc.2021.104262>.
- McIntosh, C.T., Schlenker, W., 2006. Identifying Non-linearities In Fixed Effects Models.

- Mense, A., 2018. A real options approach to amenity valuation: The role of uncertainty and risk aversion. *J Regional Sci* 58 (2), 315–329. <https://doi.org/10.1111/jors.12355>.
- Mérel, P., Gammans, M., 2021. Climate Econometrics: Can the Panel Approach Account for Long-Run Adaptation? *American Journal of Agricultural Economics* 103 (4), 1207–1238. <https://doi.org/10.1111/ajae.12200>.
- Moore, F.C., Lobell, D.B., 2014. Adaptation potential of European agriculture in response to climate change. *Nature Clim Change* 4 (7), 610–614. <https://doi.org/10.1038/nclimate2228>.
- Narita, D., Quaas, M.F., 2014. Adaptation to Climate Change and Climate Variability: Do It Now or Wait and See? *Clim. Change Econ.* 05 (04), 1450013. <https://doi.org/10.1142/S2010007814500134>.
- OECD, 2024. Climate Adaptation Investment Framework. OECD Publishing.
- OECD, 2025. Global Drought Outlook. OECD Publishing.
- Pindyck, R.S., 2022. Climate future: Averting and adapting to climate change. Oxford University Press, New York, NY, pages cm.
- Pollack, A.B., Santamaria-Aguilar, S., Maduwantha, P., Helgeson, C., Wahl, T., Keller, K., 2025. Funding rules that promote equity in climate adaptation outcomes. *PNAS* 122 (2), e2418711121. <https://doi.org/10.1073/pnas.2418711121>.
- Reilly, J., Schimmelpfennig, D., 2000. Irreversibility, uncertainty, and learning: Portraits of adaptation to long-term climate change. *Climatic Change* 45 (1), 253–278. <https://doi.org/10.1023/A:1005669807945>.
- Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O’Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change* 42, 153–168. <https://doi.org/10.1016/j.gloenvcha.2016.05.009>.

- Sarkar, S., 2000. On the investment–uncertainty relationship in a real options model. *Journal of Economic Dynamics and Control* 24 (2), 219–225. [https://doi.org/10.1016/S0165-1889\(99\)00005-6](https://doi.org/10.1016/S0165-1889(99)00005-6).
- Schmitt, J., Offermann, F., Söder, M., Frühauf, C., Finger, R., 2022. Extreme weather events cause significant crop yield losses at the farm level in German agriculture. *Food Policy* 112, 102359. <https://doi.org/10.1016/j.foodpol.2022.102359>.
- Slijper, T., Mey, Y. de, Poortvliet, P.M., Meuwissen, M.P.M., 2022. Quantifying the resilience of European farms using FADN. *European Review of Agricultural Economics* 49 (1), 121–150. <https://doi.org/10.1093/erae/jbab042>.
- Tebaldi, C., Debeire, K., Eyring, V., Fischer, E., Fyfe, J., Friedlingstein, P., Knutti, R., Lowe, J., O'Neill, B., Sanderson, B., van Vuuren, D., Riahi, K., Meinshausen, M., Nicholls, Z., Tokarska, K.B., Hurtt, G., Kriegler, E., Lamarque, J.-F., Meehl, G., Moss, R., Bauer, S.E., Boucher, O., Brovkin, V., Byun, Y.-H., Dix, M., Gualdi, S., Guo, H., John, J.G., Kharin, S., Kim, Y., Koshiro, T., Ma, L., Olivié, D., Panickal, S., Qiao, F., Rong, X., Rosenbloom, N., Schupfner, M., Séférian, R., Sellar, A., Semmler, T., Shi, X., Song, Z., Steger, C., Stouffer, R., Swart, N., Tachiiri, K., Tang, Q., Tatebe, H., Voldoire, A., Volodin, E., Wyser, K., Xin, X., Yang, S., Yu, Y., Ziehn, T., 2021. Climate model projections from the Scenario Model Intercomparison Project (ScenarioMIP) of CMIP6. *Earth Syst. Dynam.* 12 (1), 253–293. <https://doi.org/10.5194/esd-12-253-2021>.
- Thorntwaite, C.W., 1948. An Approach toward a Rational Classification of Climate. *Geographical Review* 38 (1), 55–94.
- Toman, M., 2006. Values in the Economics of Climate Change. *Environmental Values* 15 (3), 365–379. <https://doi.org/10.1177/096327190601500311>.
- Vicente-Serrano, S.M., Azorin-Molina, C., Sanchez-Lorenzo, A., Revuelto, J., Morán-Tejeda, E., López-Moreno, J.I., Espejo, F., 2014. Sensitivity of reference evapotranspiration to changes in meteorological parameters in Spain (1961–2011). *Water Resources Research* 50 (11), 8458–8480. <https://doi.org/10.1002/2014WR015427>.
- Voelz, V., Hinkel, J., 2023. Sea Level Rise Learning Scenarios for Adaptive Decision-Making Based on IPCC AR6. *EARTH'S FUTURE* 11 (9). <https://doi.org/10.1029/2023EF003662>.

Wang, Q., Zeng, J., Qi, J., Zhang, X., Zeng, Y., Shui, W., Xu, Z., Zhang, R., Wu, X., Cong, J., 2021. A multi-scale daily SPEI dataset for drought characterization at observation stations over mainland China from 1961 to 2018. *Earth Syst. Sci. Data* 13 (2), 331–341. <https://doi.org/10.5194/essd-13-331-2021>.

Wieners, K.-H., Giorgetta, M., Jungclaus, J., Reick, C., Esch, M., Bittner, M., Legutke, S., Schupfner, M., Wachsmann, F., Gayler, V., Haak, H., Vrese, P. de, Raddatz, T., Mauritsen, T., Storch, J.-S. von, Behrens, J., Brovkin, V., Claussen, M., Crueger, T., Fast, I., Fiedler, S., Hagemann, S., Hohenegger, C., Jahns, T., Kloster, S., Kinne, S., Lasslop, G., Kornblueh, L., Marotzke, J., Matei, D., Meraner, K., Mikolajewicz, U., Modali, K., Müller, W., Nabel, J., Notz, D., Peters-von Gehlen, K., Pincus, R., Pohlmann, H., Pongratz, J., Rast, S., Schmidt, H., Schnur, R., Schulzweida, U., Six, K., Stevens, B., Voigt, A., Roeckner, E., 2019. MPI-M MPIESM1.2-LR model output prepared for CMIP6 CMIP.

Zeilinger, J., Niedermayr, A., Quddoos, A., Kantelhardt, J., 2023. Identifying under-adaptation of farms to climate change. *European Review of Agricultural Economics* 50 (2), 497–528. <https://doi.org/10.1093/erae/jbac025>.

Appendix A1. Optimality Condition

A1.1. Ito’s Lemma

Suppose

$$dx = a(x, t)dt + b(x, t)dz + c(x, t)dq,$$

where dz is a Wiener process and dq is a Poisson jump process with mean arrival rate λ . We assume that these two processes are independent each other and the jump size is deterministic, $c(x, t)$ in a time interval dt , $dq = 1$ with a probability of λdt and $dq = 0$ with a probability of $1 - \lambda dt$.

With a given function $H(x, t)$, we have (cf., Dixit and Pindyck, 1994):

$$dH = \frac{\partial H}{\partial t} dt + \frac{\partial H}{\partial x} dx + \frac{1}{2} \frac{\partial^2 H}{\partial x^2} (dx)^2 + \dots$$

For $(dx)^2$, we have:

$$(dx)^2 = b^2(x, t)dt + o(dt).$$

We can rewrite dH as:

$$\begin{aligned} dH &= \frac{\partial H}{\partial t} dt + \frac{\partial H}{\partial x} dx + \frac{1}{2} \frac{\partial^2 H}{\partial x^2} (dx)^2 + o(dt) \\ &= \left[\frac{\partial H}{\partial t} + a(x, t) \frac{\partial H}{\partial x} + \frac{1}{2} b^2(x, t) \frac{\partial^2 H}{\partial x^2} \right] dt + b(x, t) \frac{\partial H}{\partial x} dz \\ &\quad + \{H(x + c(x, t), t) - H(x, t)\} dq + o(dt), \end{aligned} \quad (A1)$$

which is a special case of Ito's Lemma. While Dixit and Pindyck (1994) shows:

$$dH = \left[\frac{\partial H}{\partial t} + a(x, t) \frac{\partial H}{\partial x} + \frac{1}{2} b^2(x, t) \frac{\partial^2 H}{\partial x^2} \right] dt + b(x, t) \frac{\partial H}{\partial x} dz + c(x, t) \frac{\partial H}{\partial x} dq + o(dt),$$

$c(x, t) \frac{\partial H}{\partial x} dq$ is an approximated expression of $\{H(x + c(x, t), t) - H(x, t)\} dq$. When the jump size is large enough, the approximated expression is inaccurate because the change of H due to the jump cannot be approximated by the first derivative.

A1.2. Value of the adaptation investment

Suppose that the stochastic process follows a mixed geometric Brownian motion (GBM) and Poisson jump process with the deterministic jump size:

$$dx = \mu x dt + \sigma x dz - \eta x dq,$$

where we assume $\mu < 0$, $\sigma > 0$, and $\eta \in (0, 1)$. Suppose we have a utility function:

$$u(x, t) = \frac{x^{1-\varepsilon}}{1-\varepsilon}.$$

From equation (A1) we have:

$$\begin{aligned} du &= \left[\mu x \frac{\partial u}{\partial x} - \frac{\sigma^2 x^2}{2} \frac{\partial^2 u}{\partial x^2} \right] dt + \sigma x \frac{\partial u}{\partial x} dz + [u(x - \eta x) - u(x)] dq + o(dt) \\ &= \left[\mu x^{1-\varepsilon} - \frac{\sigma^2}{2} \varepsilon x^{1-\varepsilon} \right] dt + \sigma x^{1-\varepsilon} dz + \left[\frac{(x - \eta x)^{1-\varepsilon}}{1-\varepsilon} - \frac{x^{1-\varepsilon}}{1-\varepsilon} \right] dq + o(dt) \\ &= \left[\mu(1-\varepsilon) - \frac{\sigma^2}{2} \varepsilon(1-\varepsilon) \right] u dt + [\sigma(1-\varepsilon)] u dz - [1 - (1-\eta)^{1-\varepsilon}] u dq + o(dt). \end{aligned}$$

Therefore, the utility also follows the GBM and Poisson jump process:

$$du = \tilde{\mu} u dt + \tilde{\sigma} u dz - \tilde{\eta} u dq, \quad (A2)$$

where $\tilde{\mu} = \mu(1 - \varepsilon) - \frac{\sigma^2}{2}\varepsilon(1 - \varepsilon)$ and $\tilde{\sigma} = \sigma(1 - \varepsilon)$ are the drift rate and volatility of the GBM, respectively, and $\tilde{\eta} = 1 - (1 - \eta)^{1 - \varepsilon}$ is a size of the Poisson jump.

The expectation of du is:

$$E[du] = (\tilde{\mu} - \lambda\tilde{\eta})udt,$$

because $E[dz] = 0$ and $E[dq] = \lambda dt$, which leads to the expected utility of continuing the conventional system:

$$E[u(x_t)] = u(x_0)e^{(\tilde{\mu} - \lambda\tilde{\eta})t}.$$

Since $y_t = y_0$, the value of the investment at the current time period $V(x_t, y_t)$ is:

$$\begin{aligned} V &= E \int_t^\infty [u(y_s - rI) - u(x_s)]e^{-rs} ds \\ &= \int_t^\infty [u(y_0 - rI)e^{-rs} - u(x_0)e^{-(r - \tilde{\mu} + \lambda\tilde{\eta})s}] ds \\ &= \int_0^\infty [u(y_t - rI)e^{-rs} - u(x_t)e^{-\delta s}] ds \\ &= \left[\left(-\frac{1}{r}\right)u(y_t - rI)e^{-rs} - \left(-\frac{1}{\delta}\right)u(x_t)e^{-\delta s} \right]_0^\infty \\ &= \frac{u(y_t - rI)}{r} - \frac{u(x_t)}{\delta}, \end{aligned} \tag{A3}$$

where δ is a convenience yield given by:

$$\delta = r - \tilde{\mu} + \lambda\tilde{\eta} > 0.$$

For the investment to be profitable, it is necessary that $r < \delta$ when $\varepsilon < 1$ and $\delta < r$ when $\varepsilon > 1$. This holds in our assumptions, i.e., $\mu < 0$ and $0 < \eta < 1$.

A1.3. Optimality condition

In the region with declining yet sufficiently high payoff under the conventional system, i.e., the decision-maker has an opportunity to invest, option value F holds the following the Bellman equation (cf., Dixit and Pindyck, 1994):

$$rF(u)dt = E[u + dF(u)],$$

which states that over the time interval dt , the expected return on the option value expressed in the decision-maker's utility is equal to its expected rate of payoff appreciation.

Let $v = |u|$ be the absolute value of the utility. That is, $v = u$ if $0 < \varepsilon < 1$ and $v = -u$ if $\varepsilon > 1$. The option value is thus revised as $F(v) = F(u)$ if $0 < \varepsilon < 1$ and $F(v) = -F(u)$ if $\varepsilon > 1$. The Bellman equation is also revised as: $rF(v)dt = E[v + dF(v)]$.

From equation (A2), v follows a mixed GBM and Poisson jump process:

$$dv = \tilde{\mu}vdt + \tilde{\sigma}vdz - \tilde{\eta}vdq,$$

where $\tilde{\mu} = \mu(1 - \varepsilon) - \frac{\sigma^2}{2}\varepsilon(1 - \varepsilon)$; $\tilde{\sigma} = \sigma(1 - \varepsilon)$; and $\tilde{\eta} = 1 - (1 - \eta)^{1-\varepsilon}$. With $[dz] = 0$ and $E[dq] = \lambda dt$ and equation (A1), we have:

$$E[dF] = E\left[\tilde{\mu}v\frac{\partial F}{\partial u} + \frac{1}{2}\tilde{\sigma}^2v^2\frac{\partial^2 F}{\partial u^2}\right]dt + \lambda E[F(v - \tilde{\eta}v) - F(v)]dt.$$

From the Bellman equation, we have

$$rF(v) = v + \tilde{\mu}E\left[v\frac{\partial F}{\partial u}\right] + \frac{1}{2}\tilde{\sigma}^2E\left[v^2\frac{\partial^2 F}{\partial u^2}\right] + \lambda E[F(v - \tilde{\eta}v) - F(v)].$$

When $x_t = 0$, the option value becomes zero, i.e., $F(v(0)) = F(0) = 0$. Thus, the general form of the differential equation above is

$$F(v) = Av^\beta + \frac{v}{\delta},$$

where δ is a convenience yield. Therefore:

$$rAv^\beta = \tilde{\mu}\beta Av^\beta + \frac{1}{2}\tilde{\sigma}^2\beta(\beta - 1)Av^\beta + \lambda[(1 - \tilde{\eta})^\beta - 1]Av^\beta.$$

Rearranging the equation:

$$\frac{1}{2}\tilde{\sigma}^2\beta(\beta - 1) + \tilde{\mu}\beta + \lambda[(1 - \tilde{\eta})^\beta - 1] - r = 0 \quad (A5)$$

is the fundamental polynomial equation that the option value should hold. Since there is no analytical solution for this equation, we need to find a numerical solution.

Let $g(\beta)$ be the left-hand side of equation (A5), we have:

$$g(\beta) = \left[\frac{1}{2}\tilde{\sigma}^2(\beta - 1) + \tilde{\mu}\right]\beta + \lambda[(1 - \tilde{\eta})^\beta - 1] - r$$

$$g'(\beta) = \tilde{\sigma}^2\beta - \frac{1}{2}\tilde{\sigma}^2 + \tilde{\mu} + \lambda\beta(1 - \tilde{\eta})^{\beta-1}.$$

(i) If $0 < \varepsilon < 1$, $\tilde{\mu} < 0$ and thus $g'(0) = -\frac{1}{2}\tilde{\sigma}^2 + \tilde{\mu} < 0$. Therefore,

$$\forall \beta \leq 0: g'(\beta) < 0 \text{ and } g(\beta) \rightarrow \infty (\beta \rightarrow -\infty).$$

Thus, g decreases monotonically in a range of $\beta \leq 0$. Since $g(0) = -r < 0$ and f diverges to infinity in this range, there is a unique negative root that satisfies $g = 0$.

(ii) If $\varepsilon > 1$, we have $\tilde{\mu} > 0$ and $1 - \tilde{\eta} = (1 - \eta)^{1-\varepsilon} > 0$, and thus $g'(1) = \frac{1}{2}\tilde{\sigma}^2 + \tilde{\mu} + \lambda(1 - \tilde{\eta}) > 0$. Therefore,

$$\forall \beta \geq 1: g'(\beta) > 0 \text{ and } g(\beta) \rightarrow \infty (\beta \rightarrow \infty).$$

Thus, g increases monotonically in a range of $\beta \geq 1$. Since $g(1) = -\delta < 0$ and f diverges to infinity in this range, there is a unique negative root that satisfies $g = 0$ and is larger than 1. Note that there is no root in a range of $\beta \in [0,1]$ because $g(0) < g(1) < 0$ and g increases monotonically in this range.

We let β^* be such a negative and positive unique root when $0 < \varepsilon < 1$ and $\varepsilon > 1$, respectively, i.e., $\beta^* < 0$ if $0 < \varepsilon < 1$ and $\beta^* > 1$ if $\varepsilon > 1$. At the adaptation threshold x^* , the option value satisfies the value matching condition and smooth pasting condition:

$$F(v) = \frac{v(y_t - rI)}{r}$$

$$\frac{\partial F}{\partial x}(v(x^*)) = 0.$$

Substituting $F(v(x^*)) = Av(x^*)^\beta + \frac{v(x^*)}{\delta}$ and its first derivative we have:

$$Av(x^*)^\beta + \frac{v(x^*)}{\delta} = \frac{v(y_t - rI)}{r} \quad (\text{A6a})$$

$$\beta Av(x^*)^{\beta-1} \frac{\partial v(x^*)}{\partial x} + \frac{1}{\delta} \frac{\partial v(x^*)}{\partial x} = 0$$

$$\Leftrightarrow Av(x^*)^\beta = -\frac{v(x^*)}{\beta\delta}. \quad (\text{A6b})$$

From equation (A6a), we have

$$Av(x^*)^\beta = \frac{v(y_t - rI)}{r} - \frac{v(x^*)}{\delta} = \begin{cases} \frac{u(y_t - rI)}{r} - \frac{u(x^*)}{\delta} = V & \text{if } 0 < \varepsilon < 1 \\ -\frac{u(y_t - rI)}{r} + \frac{u(x^*)}{\delta} = -V & \text{if } \varepsilon > 1 \end{cases}$$

where V is the (positive) value of the adaptation investment (cf., equation A3). Thus, for the investment to be profitable, it is necessary that $A \geq 0$ if $0 < \varepsilon < 1$ and $A \leq 0$ if $\varepsilon > 1$.

Given equation (A5b), therefore, β needs to be negative if $0 < \varepsilon < 1$ and positive if $\varepsilon > 1$. Thus, β^* ($\beta^* < 0$ if $0 < \varepsilon < 1$ and $\beta^* > 1$ if $\varepsilon > 1$) is a unique root of the polynomial equation (A4) that satisfies the boundary conditions.

From equation (A6a) and (A6b), the optimality condition is:

$$\begin{aligned} -\frac{v(x^*)}{\beta^* \delta} + \frac{v(x^*)}{\delta} &= \frac{v(y_t - rI)}{r} \\ \Leftrightarrow v(x^*) &= \frac{\delta}{r} \left(\frac{\beta^*}{\beta^* - 1} \right) v(y_t - rI) \\ \Leftrightarrow u(x^*) &= \frac{\delta}{r} \left(\frac{\beta^*}{\beta^* - 1} \right) u(y_t - rI) \\ \Leftrightarrow x^* &= (y_t - rI) \left[\frac{\delta}{r} \left(\frac{\beta^*}{\beta^* - 1} \right) \right]^{\frac{1}{1-\varepsilon}}, \end{aligned}$$

where β^* is a unique negative (positive) root when $0 < \varepsilon < 1$ ($\varepsilon > 1$) of equation (A4).

Our dual solutions of the fundamental equation β^* differ from those obtained by standard ROA models because we consider the risk preference parameters, i.e., the CRRA utility takes both positive values when $0 < \varepsilon < 1$ and negative values when $\varepsilon > 1$. As we show in Appendix A1.3, for the adaptation investment to be profitable, it is necessary for a root of the fundamental polynomial equation (4) to be negative (positive) when $0 < \varepsilon < 1$ ($\varepsilon > 1$). A unique negative (positive) root exists for equation (4) when $0 < \varepsilon < 1$ ($\varepsilon > 1$), where the positive root is larger than 1.

The convenience yield δ represents an incentive to hustle the investment to reduce the negative effects of climate change on the decision-maker's utility. On the other hand, the hurdle rate, $h = [\beta^*/(\beta^* - 1)]^{1/(1-\varepsilon)}$, represents an incentive to delay investment to collect more information on the uncertain payoff. Because of the above-mentioned characteristics of β^* , this term is smaller than 1 irrespective of ε . Therefore, ROA threshold is always lower than the EPV threshold where hurdle rate equals to 1.

Since there is no analytical solution for the equation (4), for a given set of parameters s , we obtain the numerical solution for $\hat{\beta}^*(s)$. We then substitute $\hat{\beta}^*(s)$ into the equation (3) to obtain the threshold $\hat{x}^*(s)$.