A Risk-Informed Decision-Making Framework for Climate Change Adaptation through Robust Land Use and Irrigation Planning

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Abstract: Uncertainty and variability are key challenges for climate change adaptation planning. In the face of uncertainty, decision-making can be addressed in two interdependent stages: make only partial ex ante anticipative actions to keep options open until new information is revealed, and adapt the first-stage decisions with respect to newly acquired information. This decision-making approach corresponds to the two-stage stochastic optimization (STO) incorporating both anticipative ex ante and adaptive ex post decisions within a single model. This paper develops a two-stage STO model for climate change adaptation through robust land use and irrigation planning under conditions of uncertain water supply. The model identifies the differences between decision-making in the cases of perfect information, full uncertainty, and two-stage STO from the perspective of learning about uncertainty. Two-stage anticipative and adaptive decision-making with safety constraints provides risk-informed decisions characterized by quantile-based Value-at-Risk and Conditional Value-at-Risk risk measures. The ratio between the ex ante and ex post costs and the shape of uncertainty determine the balance between the anticipative and adaptive decisions. Selected numerical results illustrate that the alteration of the ex ante agricultural production costs can affect crop production, management technologies, and natural resource utilization.

Keywords: climate change; systemic risks; robust land use and irrigation; robust anticipative and adaptive decisions; two-stage STO; safety constraints; VaR and CVaR risk measures

1. Introduction

Climate changes affect socio-economic and environmental systems directly and indirectly through exogenous shocks from natural disasters and endogenous systemic risks due to interactions among systems and policies [1–6]. Climate changes manifest in alterations in seasonal precipitation and temperature patterns, intensification of natural disasters, sea level rise, etc. The impacts of climate changes are expected to increase and be catalyzed by the growing complexity of systemic interdependencies, introduction of new policies and technologies, growing demands, increasing frequency and severity of floods, hurricanes, storms, droughts, landslides, and prolonged heatwaves. Climate changes put stress on water availability and quality, affect agricultural production, energy usage and production, thereby threatening the water–food–energy security. Economic assessment models involved in climate change analysis and impact assessment are primarily deterministic based on common utility-maximizing principles [7–9]. They are not able to properly account for uncertainties, increasing variability and frequency of extreme events, and catastrophic risks

inherent to climate changes [7–10]. Although climate change modelers recognize that the impacts will be caused by extreme events along with changes in patterns of variability, the methods to represent these variables in climate change assessment models are very limited [9,10].

This paper discusses important improvements to the models for climate change analysis that incorporate the uncertainties, systemic risks, treatment of irreversibility, safety and security requirements, and robustness of decisions. In the presence of uncertainty [11–13] and possibility of irreversible decisions [14], decision-making can be performed in two interdependent stages: in the first stage, implement ex ante anticipative (preventive) actions keeping options open and flexible until new information is revealed; in the second stage, revise the anticipative decisions after the information about the true state of the environment (true scenario) is acquired. The two-stage stochastic optimization (STO) integrates the two types of interdependent decisions [1,15,16], i.e., anticipative ex ante and adaptive ex post, within the same modeling framework. The robustness of the two-stage decision is achieved with respect to quantile-based performance indicators and constraints, feasible decisions, and uncertainties [16–18]. The approach enables researchers to deal with imbalances, thresholds, and safety constraints, which are inherent to non-smooth, possibly discontinuous, and nonconvex interacting anthropogenic and natural systems. A robust combination of interdependent anticipative and adaptive measures reduces the chances of critical imbalances and exceedances of vital thresholds, which otherwise could lead to systemic failures [1,19,20].

This paper develops a two-stage STO model for climate change adaptation through robust land use and irrigation planning in the presence of uncertainty and risks associated with water availability. The model identifies key differences between the decision-making in the case of perfect information (full certainty), full uncertainty, and the two-stage STO approach. Coherent anticipative and adaptive actions correspond to risk-informed decision-making incorporating risk aversion in the form of quantile-based VaR (Value-at-Risk) and CVaR (Conditional Value-at-Risk) risk measures used in finance, insurance, engineering practices, extremal value theory, and catastrophic risk management [1,11,15–18,21–27].

A proper combination of ex ante anticipative and ex post adaptive decisions minimizes costs associated with irreversible and lock-in situations. The interdependencies and trade-offs between the two types of decisions in connection with irreversible investments in land conversion are discussed by Arrow and Fisher (1974) [14] and Henry (1974) [28]. Traditional integrated assessment models do not account for anticipative and adaptive measures simultaneously. The models calculate expected impacts as they cannot properly capture the effects of variability, threshold exceedances, and risks [8–10,29,30]. Instead of expected impacts, the two-stage STO under safety constraints enforces a required likelihood of vital threshold constraint satisfaction (e.g., regarding the acceptable impact) and enables the investigation of a robust combination of anticipative and adaptive measures minimizing irreversible situations and systemic failures due to critical imbalances and threshold exceedance [15–18,23–27].

This paper is organized as follows. Section 2 presents a basic two-stage STO model of robust land use planning for climate change adaptation through irrigation in the conditions of uncertain water supply [31–33]. Safety constraints on the water requirements for irrigation identify the vital water supply level. The aim of the model is to show that the combination of the ex ante and ex post measures depends on the representation of uncertainties and on the balance between the anticipative and adaptive costs, i.e., alteration of the ratio between the costs can lead to either more or less ex ante preventive measures.

Section 3 formulates a large-scale multi-regional two-stage STO model for robust land use planning with explicit treatment of location-specific heterogeneities regarding natural (water and land) resource availability, resource quality, costs, investment requirements, security and safety constraints, supply–demand relations, uncertainty, risks, and robust decisions. The principles of this model are included in global and regional models [17,18,23–26].

Anticipative (preventive) actions ex ante can help avoid considerable adaptation costs and impacts. Selected numerical results in Section 4 demonstrate that the alteration of farmer subsidies of the EU CAP (European Union Common Agricultural Policies) can have effects on crop production levels and irrigation land and water use. CAP subsidies are funds provided by EU to farmers within the EU to help farmers reduce the cost of production [34–36]. Flattening agricultural subsidies can result in lower agricultural production and increased import dependence in the EU. Instead, we suggest using robust subsidies calculated by accounting for uncertainty, risk exposure, security targets, profitability, and adaptive capacity of locations. Section 5 presents key conclusions.

2. Ex Ante Anticipative and Ex Post Adaptive Two-Stage Risk-Informed Decision-Making: Robust Irrigation Planning in the Presence of Uncertainty

In this section, we formulate a basic stylized land use planning model and compare three decision-making approaches: (1) in situations of the two-stage anticipative and adaptive decision-making in the presence of uncertainty, (2) in the case of perfect information, and (3) in the case of full "uncertainty". Let us consider an example of land use planning in a region where agricultural production strongly depends on efficient management of irrigation technologies, land, and water resources.

The uncertainty regarding the available water resources for irrigation adds complexity to the problem. Planning land allocation before knowing the available water level can result in the following situations: (a) the land is prepared for irrigation, but the water is not sufficient, which results in a loss of land preparation costs (irrigation development costs); (b) the land is prepared, but the water is in excess, which results in loss of profits (more land could be irrigated to bring higher production and profits). A realistic decision-making approach in the face of uncertainty about water availability scenarios can be framed as taking some anticipative precautionary decision before the uncertainty is resolved (before learning the true scenario) and then adapting this decision according to newly acquired information.

2.1. Basic Anticipative-Adaptive Model of Land Use Preparation for Irrigation

The anticipative–adaptive model of cultivated land preparation for irrigation has two time periods (two stages) $t = 1, 2$. Decisions regarding land preparation for irrigation x_t, $x_t \geq 0$, can be taken in both periods $t = 1, 2$; however, the uncertain level of the available water ω and, therefore, the irrigable land $\theta(\omega)$ resolves between periods 1 and 2. Costs C_t, $C_t > 0$ reflect land preparation costs in the two periods. In general, uncertainty $\theta = \theta(\omega)$ summarizes the uncertainty in all relevant factors ω.

The water scenario ω and, therefore, the irrigated area $\theta(\omega)$ are unknown in the first period when decision x_1 is taken; therefore, x_1 is defined as an anticipative ex ante decision. When decision x_2 is taken, the area θ is already known and x_2 depends on the known scenario of θ, $x_2 = x_2(\theta)$. In this way, the decisions complement each other, i.e., decision x_1 is adapted to (or revised by) decision x_2 after learning the exact state of θ. Formally, the anticipative–adaptive problem of land preparation for irrigation in the face of uncertainty can be formulated as the minimization of the total expected costs in the two periods for the two types of decisions:

$$C_1 x_1 + C_2 E x_2(\theta) \tag{1}$$

subject to constraints

$$x_1 + x_2(\theta) \geq \theta, \qquad \text{for all } \theta \tag{2}$$

where $E x_2(\theta)$ defines the mathematical expectation of the stochastic variable $x_2(\theta)$.

Constraints represented by Equation (2) guarantee the fulfillment of critical balances in all scenarios θ. Therefore, they help avoid situations of disequilibrium or threshold exceedances. They are often called safety or security constraints (see, e.g., [1,16–18,21,23–27]. In this simplified model, decision x_2 can be explicitly represented as

$$x_2(\theta) = max\{0, \theta - x_1\}, \tag{3}$$

where $max\{0, \theta - x_1\}$ indicates that x_2 depends nonsmoothly on decision x_1 and on uncertainty θ. Equation (3) captures strong interactions and trade-offs between the two types (anticipative and adaptive) decisions and the uncertainty.

Accounting for (3), optimal first-period decision x_1^* regarding the ex ante land allocation for irrigation can be derived by solving the following two-stage STO problem: minimize

$$F(x) = C_1 x + C_2 Emax\{0, \theta - x\}, \; x \geq 0, \tag{4}$$

which is a stochastic minimax problem with a non-smooth goal function $F(x)$. According to the optimality condition of stochastic minimax problems (see, e.g., [15,37], and references therein), the optimal anticipative solution x^* is identified by the quantile satisfying equation

$$P[\theta \geq x] = C_1 / C_2, \tag{5}$$

for $C_1 < C_2$ (if $C_1 > C_2$, then $x_1^* = 0$ and $x_2^*(\theta) = \theta$). Therefore, the robust x^* solution is defined by the distribution function of the uncertain parameter, the interactions between the ex ante and ex post measures, and the ex ante and the ex post costs.

The quantile defined by (5) indicates the irrigated land area that enables the meeting of the safety constraint in Equation (2) with a probability $1 - C_1/C_2$. The quantile in (5) defines the VaR risk measure indicating the maximum value fulfilling the safety constraint defined by Equation (2) with specified probability. The CVaR or the expected shortfall (or excess) characterizes the expected value of the imbalance in (12) if it occurs.

While the optimal solution of (4) is defined by the VaR risk measure, the optimal value of the goal function $F(x^*)$ can be represented by using the CVaR risk measure, the expected cost under perfect information, and the expected value of perfect information:

$$
\begin{aligned}
F(x^*) &= C_1 x^* + C_2 Emax\{0, \theta - x^*\} \\
&= C_1 x^* + C_2 E[\theta - x^*|\theta > x^*] P[\theta > x^*] \\
&= C_1 x^* + C_1 (E[\theta - x^*] - E[\theta - x^*|\theta \leq x^*]) \\
&= C_1 \overline{\theta} + C_1 (E[x^* - \theta|\theta \leq x^*]) \\
&= C_2 E\theta I(\theta \geq x^*),
\end{aligned}
\tag{6}
$$

which follows from (5) and $Emax\{0, \theta - x^*\} = E\theta I(\theta \geq x^*) - x^* P(\theta \geq x^*)$, where $E[\cdot|\cdot]$ denotes the conditional expectation; the indicator function $I(\theta > x) = 1$ if $\theta \geq x$ and $I(\theta \geq x) = 0$ otherwise.

Equation (6) shows the main indicators comprising the optimal value of the goal function $F(x^*)$:

1. The term $C_1 \overline{\theta}$ is the cost under perfect information when the decision-making regarding irrigated land preparation is made with respect to the average water availability scenario $\overline{\theta}$.
2. The term $C_1(E[x^* - \theta|\theta \leq x^*])$ represents the expected value of perfect information, i.e., the value of knowing the true scenario θ before taking an anticipative decision in stage 1. It quantifies the cost for land overpreparation if the amount of land x^* prepared in stage 1 exceeds the amount of land θ, which can be irrigated in each uncertain scenario, given that $C_1 < C_2$.
3. The term $C_2 E\theta I(\theta \geq x^*)$ defines the CVaR risk measure, i.e., the expected value of adaptation costs in stage 2 to expand for more irrigated land if the true water availability scenario permits the meeting of the safety constraints defined by Equation (2). For some distributions, it is possible to derive x^* from (5) explicitly. If θ is uniformly distributed on $[a,b]$, then it is easy to see that $x^* = \frac{C_1}{C_2}a + \left(1 - \frac{C_1}{C_2}\right)b$, i.e., x^* is between optimistic and pessimistic scenarios of emissions with weights defined by the ratio of costs C_1 and C_2.

2.2. Decisions under Perfect Information, Full Certainty, and Two-Stage STO

Using Equation (6), it is possible to compare the decision-making approaches in the cases of perfect information, full uncertainty, and the two-stage anticipative–adaptive approach. Assume that the anticipative decisions have lower costs than the adaptive, $C_1 < C_2$. In the case of perfect information, i.e., when θ is known, both x_1 and x_2 can be chosen as a function of the observed θ. The optimal solution is $x_1^* = \theta$, $x_2^* = 0$, i.e., the term $C_1 \bar{\theta}$ in (6) represents the cost under perfect information (assuming $\theta = \bar{\theta}$).

In the case of full uncertainty, the uncertain parameter θ is often substituted by its average value θ, the so-called "certainty equivalent". In this case, the solution $x_1^* = \theta$, $x_2^* = 0$ does not satisfy (2) for all θ, which may lead to imbalances and systemic failures. Another approach is to fulfill the safety constraint set by Equation (2) by choosing x_1^* relying on the worst-case scenario $\max_{\omega} \theta(\omega)$ (or $\min_{\omega} \theta(\omega)$), $\omega \in \Omega$. This approach can be very costly because of the low probability of the worst-case scenario. It is possible to introduce a safety constraint $P[x_1 \geq \theta] = 1 - \gamma$ with some confidence level γ, to provide a trade-off between the cost-effectiveness and risk. In this case, the optimal solution x_1^* under full uncertainty is defined by the quantile x_γ satisfying probabilistic equation $P[x_1 \geq \theta] = 1 - \gamma$ (since $C_1 < C_2$, $x_2 = 0$). Clearly, the risk-based solution under full uncertainty $x_1^* = x_\gamma$ may be greater or less than $\bar{\theta}$, depending on γ, the ratio C_1/C_2, and the probability distribution of θ.

In the case of anticipative–adaptive two-stage decision-making, the optimal anticipative decision x_1^* may exceed the "certainty equivalent" $\bar{\theta}$ or it may be below this level depending on the relation between the costs C_1, C_2, and the shape of uncertainty. For example, if θ is normally distributed and if $C_1/C_2 = 1/2$, then the anticipative decision x_1^* is equal to the certainty equivalent $x_1^* = \bar{\theta}$. If probability distribution is non-normal, the optimal land allocation can be below or above $\bar{\theta}$.

Thus, the balance between the anticipative and the adaptive decisions strongly depends on the ratio of respective costs and the shape of the probability distribution. Under full uncertainty, the solutions in the two periods also depend on the costs and the shape of the uncertainty, but there is no interaction between the two period decisions. All land preparations are made either in period 1 or 2, depending on when the costs are lower. The amount of land preparations to be made depends on the probability γ with which the safety constraint defined by Equation (2) is desired to be met.

2.3. Example: Anticipative-Adaptive Two-Stage Irrigation Planning

Let us illustrate the application of the two-stage two period STO model for land use and irrigation planning with the following simple but detailed example. Assume there are stochastic scenarios of water availability $\omega = (\omega_1, \omega_2, \ldots, \omega_S)$ and respective frequencies $(p_1, p_2, \ldots, p_S)$. Denote the total area to be prepared for irrigation ex ante before knowing the water scenario by x, $x \leq L$, L is total irrigable acreage.

If the available water level is known in advance (e.g., is equal to the average water availability level), the decision is taken with full certainty. It depends, for instance, on whether the net revenue per hectare of irrigated area c_1 is greater than the net revenue c_2 from a hectare without the use of irrigation. The parameter c_1 includes the costs of measures that are necessary for the use of irrigation such as leveling, construction of water distribution network, pumping stations, etc.

The stochasticity of the water supply creates essential difficulties. If q is the total water required for irrigation of a hectare, then there may be two situations: a) if $xq > \omega_s$, there is a risk of losing profit $c_2 - c_3$ per hectare of irrigated land that is prepared for irrigated production but without sufficient water. The amount of land irrigated is $x - \omega_s/q$, where ω_s/q is the adaptive decision. When more water is available for irrigation and $xq < \omega_s$, there is a risk of losing profit $c_1 - c_2$ per hectare of land not prepared in advance for irrigation, and the adaptive decision is $\omega_s/q - x$. Thus, there are three adaptive decisions $y = (y_1, y_2, y_3)$, where y_1 is the use of irrigated land, $y_2 = x - \omega_s/q$ is the use of land that was prepared for irrigated cultivation but cannot be irrigated, and $y_3 = \frac{\omega_s}{q} - x$ is the use of

land that was not prepared for irrigation. Thus, if $xq < \omega_s$ and $c_1 \geq c_2$, then $y_1(x, \omega_s) = x$, $y_2(x, \omega_s) = 0$, $y_3(x, \omega_s) = L - x$.

But if $xq < \omega_s$ and $c_1 < c_2$, then $y_1(x, \omega_s) = 0$, $y_2(x, \omega_s) = x$, $y_3(x, \omega_s) = L - x$. In the case of $\omega_s \leq xq$, $c_1 \geq c_2$, the value $y_1(x, \omega_s) = \omega_s / q$, $y_2(x, \omega_s) = x - \omega_s / q$, $y_3(x, \omega) = L - x / q$.

The cost function (welfare) of irrigated area production planning is formulated as

$$W(s, x, y(x, \omega_s)) = \begin{cases} \frac{c_1 \omega_s}{q} + c_2(L - x) + c_3\left(x - \frac{\omega_s}{q}\right), & \omega_s < xq, \\ c_1 x + c_2(L - x) + c_3\left(x - \frac{\omega_s}{q}\right), & \omega_s \geq xq, \end{cases}$$

and the expected welfare is

$$W(x) = \sum_{(I_s: \, \omega_s < xq)} p_s \left[\frac{c_1 \omega_s}{q} + c_2(L - x) + c_3\left(x - \frac{\omega_s}{q}\right) \right] +$$

$$\sum_{(I_s: \, \omega_s \geq xq)} p_s \left[c_1 x + c_2(L - x) + c_3\left(x - \frac{\omega_s}{q}\right) \right].$$

In each scenario s, the welfare function $W(s, x, y(x, \omega_s))$ is a convex but non-differentiable function, with discontinuities of derivatives. Such a structure of welfare functions is typical for management under risk and uncertainty, since the presence of risk results in different profits depending on whether the agent in the ex ante decision 'hits' or 'misses' the uncertainties, such as $\omega_s < xq$ or $\omega_s \leq xq$. In this simple model, the evaluation of the land potential is formulated with introduction of anticipative ex ante decisions x and adaptive ex post decisions $y(x, \omega_s)$. The formulated model incorporates both types of decisions and allows researchers to find a robust anticipative decision x^* which is optimal against all possible scenarios. The robust solution is quite different from a scenario-dependent solution of a model without uncertainty, i.e., depending on the ratio of costs, all land in the compartment is either irrigated or not.

3. General Model

The model in Section 2 is a fragment of a large-scale multi-regional multi-sectoral two-stage land use planning model capable of evaluating interdependent ex ante anticipative and ex post adaptive land use planning decisions, including investments in irrigation technologies, grain and water storage, and trade flows between locations [38–42]. The availability of the two-type decisions (anticipative strategic and adaptive operational) substantially increases the adaptive capacity of a region by reducing the likelihood of critical supply–demand imbalances and threshold exceedances in relations between different economic systems and regions [17,18,38–42]. The optimal and robust balance between the anticipative and adaptive actions helps producers to sustain and adapt to changing conditions in "bad" years by using grain and water storage, potential imports, or financial help. The main idea of anticipative strategic decisions is to keep pace with gradually changing requirements while adaptive decisions help anticipative decisions to operate under various stochastic conditions.

Generalizing the model of Section 2, we discuss the representation of the anticipative and adaptive decisions in large-scale multi-regional models [17,18,38–42]. In addition to irrigated land management, the anticipative ex ante decisions comprise storage facilities (grain and water), land transformations, and management systems. Adaptive ex post decisions adjust anticipative ex ante decisions in each uncertainty scenario as discussed in Section 2. The adaptive decisions are decisions regarding the actual use of irrigation water and land, energy consumption, fertilizer application, allocation of labor and machinery, change of planting dates, and replanting of crops in each uncertainty scenario. Adaptive decisions also include export and import flows to cope with production excess or shortages to avoid supply–demand imbalances.

Modeling crop production in large-scale multi-regional models is represented at the level of fine resolutions (e.g., grids) with the aim of reflecting the diversity of location-specific bio-physical and economic factors and parameters [17,18,38–45]. For this, regions or countries are divided into sublocations, for example, homogeneous response units characterized by soil types $j = 1, \ldots, J$. For the sake of simplicity, we do not include other location-specific characteristics such as altitude, slope, available water capacity, etc. Variable x_{jk}^i denotes acreage of land allocated to crop $k = 1, \ldots, K$, and

$$\sum_k^K x_{jk}^i \leq L_j^i \tag{7}$$

is a constraint on total land use of soil type j, $j = 1, \ldots, J$, in location i, $i = 1, \ldots, I$, allocated to all crops $k = 1, \ldots, K$. Denote with $a_{jk}^i(s)$ a yield attainable by crop k in uncertain scenario s on soil type j in location i. Based on location-specific characteristics, stochastic yield scenarios $a_{jk}^i(s)$ can be derived with a bio-physical crop model EPIC [45] involving stochastic weather (precipitation and temperature) and economic (costs, investments) parameters. Then, production of crop k in location i and stochastic scenario s equals

$$A_{jk}^i(s) = \sum_j^J a_{jk}^i(\omega_s, s)\, x_{jk}^i, \; i = 1, \ldots, I. \tag{8}$$

Similar to the model in Section 2, a part of the initially allocated land x_{jk}^i can be adaptively treated through ex post decisions, for example, a portion of $y_{jk}^i(t, \omega_s, s)$ of land x_{jk}^i can be reallocated to non-irrigated crops or replanted with another crop. In general, the decisions x_{jk}^i can be represented as a sum of adaptive decisions, i.e., $x_{jk}^i = \sum_t^{T(s)} y_{jk}^i(t, \omega_s, s)$, where $t = 1, \ldots, T(s)$ defines the adaptive decisions in each scenario s.

Therefore, land constraint (7) can be rewritten accounting for potential adaptive decisions as

$$\sum_k^K [x_{jk}^i + \sum_t^{T(s)} y_{jk}^i(t, \omega_s, s)] \leq L_j^i \tag{9}$$

where some of decisions x_{jk}^i cannot be adjustable in scenario s. Both types of decisions $(x, y(x, \omega_s, s))$ define the set of feasible decisions for all scenarios of uncertainties ω_s, $s = 1, \ldots, S$.

Food security constraints, e.g., minimum production targets by sublocations $\overline{A}_{jk}^i(\omega_s, s)$ (or at aggregate level), require the introduction of the additional food security constraints

$$\sum_j^J a_{jk}^i(s)\, x_{jk}^i \geq \overline{A}_{jk}^i(\omega_s, s). \tag{10}$$

In addition to land resource constraints (7) or (9), a more general set of scenario-specific resource constraint can be defined as

$$\sum_k^K [\alpha_{jk}^i x_{jk}^i + \sum_t^{T(s)} \beta_{jk}^i y_{jk}^i(t, s)] \leq R_j^i(\omega_s, s), \tag{11}$$

for example, to reflect alternative scenarios of water availability or targeted emissions reductions, where α_{jk}^i and β_{jk}^i are various technical coefficients defining potential productivity or area increase as in the case of crop rotation or multi-cropping systems.

In the short term for each anticipative strategic decision x^i_{jk} and scenario ω_s, s, sublocation i maximizes its welfare (net profits)

$$F^i(x, y(x, s)) = max \left[\sum c^i_{jk}(s) x^i_{jk} + \sum_l d^i_{jk}(s) y^i_{jk}(x, s) \right] \qquad (12)$$

with respect to the vector of adaptive decisions $y^i_{jk}(x, s) \geq 0$ satisfying a set of linear equations (11) for a given scenario ω_s, s and strategic decisions x^i_{jk}. Coefficients c^i_{jk} and d^i_{jk} can reflect costs or benefits and, therefore, they are positive or negative, respectively.

We assume that for each feasible strategic decision x^i_{jk} there exist feasible adaptive decisions. The strategic optimization problem then requires a decision vector x^i_{jk} that maximizes the location-specific expected welfare:

$$F^{*i}(x) = max \left[\sum c^i_{jk} x^i_{jk} + \sum_{s=1}^{S} p_s \left(\sum_l d^i_{jk}(s) y^i_{jk}(x, s) \right) \right] \qquad (13)$$

subject to constraints $\sum \delta^i_{jk} x^i_{jk} \leq Q^i_{jk}$, where $y^i_{jk}(s) = y^i_{jk}(x, s)$ are adaptive decisions maximizing (12) subject to constraints (11). Goal functions (13) maximize the welfare of individual geographical locations represented by anticipative and adaptive decisions and costs.

In large-scale two-stage STO models [17,18,38–42,45], crop production is modelled at the level of locations (grids) while demand, consumption, trades, storage, and prices can be calculated at regional or subregional levels. This simplification allows for considerable computational time reduction. The decisions fulfil various economic and bio-physical balance equations, i.e., supply–demand equilibrium, water requirements, food security, environmental norms, GHG emission targets, and biofuel mandates, at various levels of aggregation. The location-specific goal functions (13) are aggregated into regional (and global) goal functions with explicit representation of region-specific storage capacities and trade flows. In the general form, the goal of a large-scale multiregional multisectoral two-stage STO aims to maximize the total expected producer and consumer surpluses (14) with respect to a portfolio of interconnected anticipative x and adaptive $y(\omega)$ decisions $((x, y(\omega))$ subject to food, energy, water, and environmental safety security constraints (15):

$$F(x) = E_\omega f(x, y(\omega), \omega) = \int f(x, y(\omega), \omega) P(d\omega), \qquad (14)$$

$$g_i(x, y(\omega), \omega) \leq 0, \ i = \overline{1, m}. \qquad (15)$$

The security constraints (15) are similar to constraints (2), (10), and (11). They set vital requirements for the necessary level of food and feed production, water provision, energy supply, and environmental security standards. Thus, the food security constraint ensures the necessary nutrients and energy intake per capita, and the feeds security constraint requires that livestock feeds from crops, grass, and byproducts correspond to the livestock dietary requirements in nutrients and energy. Water security identifies the required level of water use. Biofuel production mandates are fulfilled from crops, woody biomass and agricultural residues, i.e., they fulfil a joint constraint on biofuel production from the first and the second generation biofuels. Because of various uncertain parameters, the joint food–feed–biofuel security constraints introduce competition for the natural resources (land and water) and the trade-offs between the allocation of the resources to resource-based sectors, producers, and consumers.

Using targeted levels g^*_i of food, nutrition, energy, water norms and indicators, constraints (15) can be reformulated in the form of probabilistic constraints:

$$P[g_i(x, y(\omega), \omega) - g^*_i \geq 0] \geq \gamma_i \qquad (16)$$

Replacing constraints (16) with expected shortfalls $Emax\{0, g_i(x, y(\omega), \omega) - g_i^*\}$, the models (14) and (15) can be reformulated as maximizing:

$$\sum_{s=1}^{S} p_s f(x, y^s, \omega^s) - \sum_{i=1}^{m} \sum_{s=1}^{S} p_s \pi_{is} max\{0, g_i(x, y^s, \omega^s) - g_i^*\}. \tag{17}$$

From the general formulation of the goal function (18)

$$F(x) = E\left[f(x, y(\omega), \omega) - \sum_{i=1}^{m} \pi_i(\omega) max\{0, g_i(x, y(\omega)) - g_i^*\}\right] \tag{18}$$

the optimal condition of systemic risk equilibrium is derived as follows: if $x_j^* > 0$, then

$$F_{x_j}(x^*) = c_j - \sum_{i=1}^{m} \pi_i P[g_i(x, y(\omega), \omega) \geq g_i^*] = 0 \tag{19}$$

where c_j are costs relevant to first-stage anticipative (preventive) decisions x and parameters π_i characterize the costs of adaptive adjustments/actions $y(\omega)$. The sum $\sum z_{is}$, $z_{is} = max\{0, g_i(x, y^s, \omega^s) - g_i^*\}$, defines global production shortage or, in other words, the demand for global storage, an "insurance" fund, or new technologies necessary to relax tight supply–demand relations and avoid systemic imbalances and systemic risks in complex multi-regional multi-sectoral systems. Thus, the two-stage anticipative and adaptive decision-making framework enables the analysis and management of systemic risks emerging in multi-regional and multi-sectoral systems [17,42].

4. Selected Numerical Results

The alteration of ex ante and ex post costs, as illustrated in Sections 2 and 3, may distort the balance between the anticipative and the adaptive decisions and thereby increase the risk of imbalances (shortfalls or excesses in supply–demand relations) in safety constraints similar to (2) and (15). This section presents selected numerical results derived from a multi-regional multi-sectoral two-stage GLOBIOM model [17,42] illustrating the possible implications of changing costs on agricultural activities and natural resource utilization at the level of EU regions and countries. We argue that the implementation of flat subsidies according to new the EU CAP can affect agricultural production and management characteristics, in particular, irrigation land expansion and water consumption.

CAP subsidies are funds provided by the EU to farmers within the EU to help farmers reduce the cost of production. The flattening of subsidies [34–36] aims at decreased production intensification, reduced pollution, and reduced fertilizer application. At the same time, flat subsidies can lead to decreasing production and technological investments and increased import dependence in the EU countries. In what follows, we compare the effects of "Historic" and "Flat" payments on the production of main grains (wheat, corn, rice, soya), irrigation land expansion, and water consumption. Additionally, we introduce the so-called "robust" subsidies and discuss their benefits. A short description of the three subsidies schemes is as follows:

1. The "Historic" direct payments reflect countries' past production and profitability. The European Commission [34] considered the decoupling of direct payments linked to historical support values as the most neutral design of support in terms of impact on farms' asset values. The "Historic" payments reflect the conditions for agricultural production in a specific region, in particular, the differences in economic and natural conditions across EU countries.

2. The "Flat" (or "EU average") payments scheme is based on providing the same level of aid per hectare to all farmers in the EU. The implementation of this scheme can lead to losses in countries where "Historic" payments are above the average and to gains where "Historic" payments are below the average.

3. The "Robust" payments are calculated with the two-stage strategic-adaptive stochastic GLOBIOM model [17,42] accounting for profitability, risk exposure, adaptive capacity, self-sufficiency policies, and environmental commitments of the EU countries. The "Robust" payments can also include other agricultural, economic, and fairness criteria.

The level of farmers' support for the three alternative schemes is presented in Figure 1.
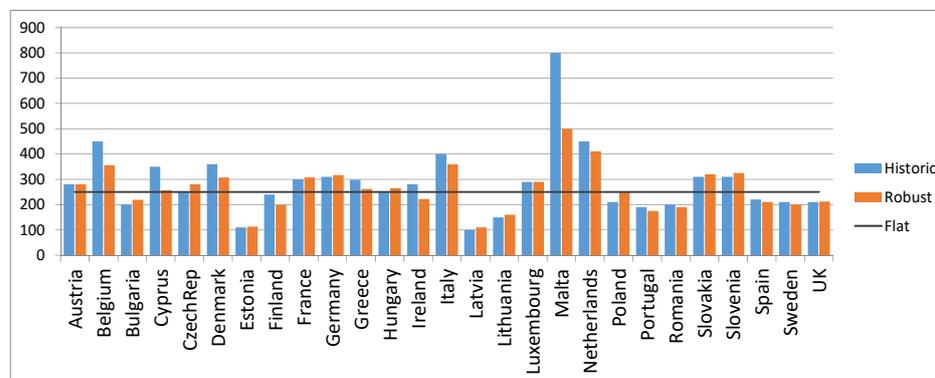

Figure 1. Alternative schemes for distribution of CAP pillar I payments across EU countries, in EUR/ha: "Historic", "Robust"; and "Flat".

The "Flat" ("EU average") level of direct payments is around 250 EUR/ha, and "Historic" payments are derived from [34–36]. Other approaches to "exogenous" allocation of payments can be tested ("MAX" or "MIN" rate); however, these schemes do not account for risk considerations. The three schemes are implemented in the stochastic two-stage strategic-adaptive GLOBIOM model per hectare of cultivated land and are compared in terms of demand and supply of major crops, acreage of irrigated land, and water consumption.

4.1. Demand and Supply of Crops

At the aggregated EU level, production of wheat towards 2050 could be at least 20% higher under the "Robust" scheme compared to "Flat" scheme. If the "Robust" scheme is compared with the "Historic" scheme, wheat production could be about 5% higher. Corn production under the "Robust" scheme is estimated to be about 9% and 3.5% higher toward 2050 under the "Flat" and "Historic" schemes, respectively. Rice production could be about 4 % higher under the "Robust" scheme compared to the "Flat" scheme, and output of soya is expected to be higher by about 10% and 6% under the "Flat" and "Historic" schemes, respectively. At the level of EU countries and economic regions, the effects from different payment schemes may be even more visible and diverse. For example, robust subsidies could stimulate the activities of farmers in central eastern countries (e.g., Slovakia, Slovenia, Bulgaria, Hungary, Poland) and middle western countries (e.g., Austria, Germany, France, The Netherlands), where production of grains (e.g., wheat, corn, rice, soya) could increase by about 30 %. In the south (e.g., Spain, Portugal, Italy, Cyprus), the effects may be negative: the production of main cereals could decrease by about 14%. Somewhat negative effects can be expected in the Baltic and norther countries such as Estonia, Latvia, Lithuania, and Finland as well as in midwestern and in central eastern countries.

4.2. Irrigated Area Expansion and Water Demand

"Robust" subsidies are expected to stimulate more efficient water management in more profitable and less risk-exposed regions with lower costs for advanced irrigation technologies. For example, in Baltic and northern countries (e.g., Latvia, Estonia, Norway, Sweden, Denmark), "Robust" subsidies lead to more irrigated area expansion than under the "Flat" scheme but less than under the "Historic" scheme. In central eastern countries such as Hungary and Slovakia, "Robust" subsidies, if compared with the "Historic" scheme, are likely to decrease the irrigated area, while, if compared with the "Flat" scheme, they

are expected to increase the irrigated area. In the middle west (e.g., Germany, France, Austria) and in the north (Sweden), "Robust" subsidies could increase irrigated area but decrease water consumption as these regions are able to invest in more efficient water saving and irrigation technologies. In the southern countries (e.g., Spain, Italy), "Flat" subsidies could lead to larger expansion of irrigated areas than the "Historic" and "Robust" subsidies, which can be explained by the shortage of water and inefficiency of investments in advanced irrigation (i.e., high water price).

Baltic and northern countries will likely have higher water demand under the "Robust" than under "Flat" and "Historic" schemes. Furthermore, in central EU countries (e.g., Hungary, Czech Republic, etc.), "Robust" subsidies could increase the demand compared with the "Historic" and "Flat" schemes. In Germany, "Robust" subsidies lead to a decrease and in France to a slight increase in demand compared with the "Historic" scheme. In southern countries (e.g., Spain, Italy), "Robust" water demand is lower than under other schemes, which also corresponds to lower irrigated area expansion.

By altering costs c^i_{jk}, d^i_{jk} and π_s in (13), (17), and (19), the trade-offs can be investigated between the ex ante anticipative and ex post adaptive decisions, demands and feasibility of domestic production, land and water use, and irrigation land expansion. That is, the model enables the analysis of what ex ante anticipative (precautionary) decisions, such as irrigation technologies, grain and water storage, allow the minimization of climate change and weather impacts by preventing various systemic imbalances and threshold exceedances at lower costs than myopic ex post actions, e.g., imports at spot prices or instantaneous land use conversion.

5. Discussion and Conclusions

Climate change is expected to have significant and highly uncertain impacts on socio-economic and environmental systems. Improvements to traditional economic assessment models are needed to incorporate central issues in climate change mitigation and adaptation such as uncertainty, variability, treatment of irreversibility, safety and security requirements, and robustness of decisions. In the face of uncertainty, decision-making can be addressed in two interdependent stages (or time periods), namely, the period of decision-making in the face of uncertainty and decision-making after receiving additional information about the real state of the environment. Therefore, in the first period (first-stage decisions), ex ante anticipative actions are made only partially to keep options open. The decisions are adapted in the second stage after more information about the true state of the environment (uncertainty scenario) is acquired. This approach corresponds to the two-stage STO modeling. In this study, with an example of a two-stage STO model of robust land use adaptation through irrigation planning, we investigate the differences between decision-making in the cases of perfect information, full uncertainty, and dealing with uncertainty with the two-stage anticipative–adaptive STO approach.

The two-stage STO decision-making in the face of uncertainty enables the preparation of socio-economic and environmental systems in advance and facilitates their proper adaptive responses to changing conditions. These anticipative and adaptive measures reduce the chances of critical imbalances and exceedances of vital thresholds, which could otherwise lead to systemic failures. With a simple model in Section 2, we show that there are complex non-smooth interactions among the anticipative ex ante and adaptive ex post decisions, costs, and probability distributions of uncertainty. Thus, the trade-offs between the anticipative and the adaptive actions depend on the ratio of costs and the shape of the uncertainty probability distribution, determined by Equations (13), (18) and (19). In other words, the lower ex ante costs can lead to more active anticipative actions and reduce the adaptation costs. Selected numerical results illustrate that the alteration of the ratio between the costs can affect production and resource utilization and increase risks of imbalances. The proposed two-stage STO model can be further extended to a dynamic version with rolling time horizons and "stopping time" events, which have strong connections with dynamic versions of CVaR risk measures and endogenous discounting [1,46].

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