

How Cooperation and Competition Arise in Regional Climate Policies: RICE as a Dynamic Game

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Abstract—One of the most widely used models for geographical economics of climate change is the regional integrated model of climate and the economy (RICE). In this article, we investigate how cooperation and competition arise in regional climate policies under the RICE framework from the standpoints of game theory and optimal control. Our primary discovery is that the RICE model is inherently a dynamic game, where both cooperative and noncooperative solutions may emerge. In cooperative settings, we investigate the global social welfare equilibrium that maximizes the weighted and cumulative social welfare across regions, present the Pareto social welfare trade-offs between developed and developing clusters of regions, and apply receding horizon approach to approximate the global social welfare equilibrium. For noncooperative settings, we first present a recursive best-response algorithm for dynamic games (RBA-DG) to describe the sequences of best-response regional climate decisions, which indicates convergence to an open-loop Nash equilibrium (NE) when applied to the RICE game by numerical studies. We also present a receding horizon feedback algorithm for dynamic games (RHFA-DG), to describe a region’s feedback actions after observing the real-time climate and economic states and other regions’ climate mitigation decisions. All these proposed solution concepts are implemented and open-sourced using up-to-date data. The results reveal how the combination of game theory and control theory may be used to facilitate international negotiations toward consensus on regional climate-change mitigation policies, and reveal how cooperative and competitive regional relations shape climate change for our future.

Index Terms—Dynamic game, economics of climate change, model predictive control, optimal control.

NOMENCLATURE

State Variables and Control Variables Are Marked With * and *, Respectively

| Variable | Definition |
|----------|------------|
| i        | Index of a region. |
| t        | Discrete time step. |
| year(t)  | Calendar year at time step t. |

Parameter Definitions

| Parameter | Description |
|-----------|-------------|
| n         | Number of regions. |
| Δ         | Sampling rate. |
| T         | Horizon length. |

Temperature Dynamics

| Symbol     | Description                  |
|------------|------------------------------|
| *T_AT      | Atmospheric temperature deviation. |
| *T_LO      | Temperature deviation in lower ocean. |
| F          | Total radiative forcing. |
| F_EX       | Forcing from GHG other than CO₂. |

Carbon Dynamics

| Symbol     | Description                  |
|------------|------------------------------|
| *M_AT      | Carbon mass in atmosphere. |
| *M_B      | Carbon mass in upper ocean. |
| *M_LO     | Carbon mass in lower ocean. |
| σ_i        | Carbon intensity. |
| *µ_i       | Emission-reduction rate. |
| E_land     | Natural CO₂ from land use. |
| E_i        | Industrial and natural CO₂. |
| E          | Global CO₂ across all regions. |

Economic Dynamics

| Symbol     | Description                  |
|------------|------------------------------|
| L_i        | Population. |
| A_i        | Total productivity factor. |
| *K_i       | Capital. |
| g_i        | Utility. |
| C_i        | Consumption. |
| J_i        | Cumulative social welfare. |

Carbon Dynamics

| Symbol     | Description                  |
|------------|------------------------------|
| φ_11       | Diffusion coefficient. |
| φ_12       | Diffusion coefficient. |
| φ_21       | Diffusion coefficient. |
| φ_22       | Diffusion coefficient. |
| η          | Forcing of carbon doubling equilibrium. |
| ξ_2        | Multiplier for η. |
| M_AT,1750  | Atmospheric mass of carbon in year 1750. |
Economic Dynamics

\( \alpha_i \) Exponent of emission-reduction cost function.

\( \rho_i \) Rate of social time preference per year.

\( c_i \) Negishi parameter.

Carbon Dynamics

\( \xi_{11} \) Diffusion coefficient.

\( \xi_{12} \) Diffusion coefficient.

\( \xi_{21} \) Diffusion coefficient.

\( \xi_{22} \) Diffusion coefficient.

\( \xi_{23} \) Diffusion coefficient.

\( \xi_{31} \) Diffusion coefficient.

\( \xi_{32} \) Diffusion coefficient.

\( \xi_1 \) (GtC/GtCO\(_2\)) Conversion factor.

Economic Dynamics

\( \delta^k \) Depreciation rate on capital per year.

\( d_i^{[1]} \) Damage coefficient on temperature.

\( d_i^{[2]} \) Damage exponent.

\( d_i^{[3]} \) Damage coefficient on temperature squared.

\( \theta_i \) Exponent of emission-reduction cost function.

\( \gamma_i \) Capital elasticity in gross economic output.

\( pb_i \) (USD/tCO\(_2\)) Backstop technology price in year 2020.

\( \delta^b \) Decline rate of backstop cost.

\( \alpha_i \) Elasticity of marginal utility of consumption.

I. INTRODUCTION

The issue of global warming has emerged as a central environmental problem for our society and future generations over decades. As a consequence of industrialization and economic development, human-caused emissions of greenhouse gases, most notably carbon dioxide (CO\(_2\)), contribute to a significant increase in the mean atmospheric temperature in the year 2022 by 1.15 °C relative to the pre-industrial age [2]. This temperature deviation yields significant changes in the global climate and ecosystem, including increasing wildfires [3], sea level rise [4], melting of ice lands [5], and so on. To assess the damages of anthropogenic greenhouse gases, especially CO\(_2\), on society, a number of integrated assessment models (IAMs) were proposed [6], [7], [8]. IAMs simulate the dynamics of the economy-climate interactions by incorporating mathematical models from both economics and geophysical science. The dynamic integrated model of climate and economy (DICE) [8], [9], developed by William Nordhaus, who received the 2018 Nobel Memorial Prize in Economic Sciences in large part for this body of work [10], is one of the most well-known IAMs. The DICE model is globally aggregated and treats global warming as a single-player problem. Considering the crucial aspect of regional socioeconomic heterogeneity, the regional integrated model of climate and the economy (RICE) was also proposed as a regional version of the DICE model [11], [12]. By dividing the world into several regions, the RICE model takes the vantage point in determining how multiple regions may jointly design climate policies and cope with the global warming issue together.

Global society has been making efforts in developing sensible strategies to achieve international consensus on climate-change mitigation over the last several decades. In 1992, the United Nations Framework Convention on Climate Change (UNFCC) was the first formal global treaty signed by 154 (now 198) parties to address climate change, which established an annual forum for international discussions aimed at stabilizing greenhouse gas concentrations in the atmosphere [13]. These meetings produced the well-known Kyoto Protocol [14], Copenhagen Accord [15], and Paris Agreement [16]. The Kyoto Protocol was a binding agreement that was signed in 1997 and expired in 2012, which called for developed countries to reduce emissions by an average of 5% below pre-industrial levels, and established a system to monitor countries’ progress [14]. The Copenhagen meeting in 2009 was called to establish a replacement for the Kyoto Protocol. Although it failed to establish binding emission limits after 2012, countries recognized “the scientific view that the increase in global temperature should be below 2 °C” [15]. The Paris Agreement was signed in 2016 and called for all countries to set emissions-reduction pledges/targets, with the goals of preventing the mean atmospheric temperature from rising 2 °C above pre-industrial levels and pursuing efforts to keep it below 1.5 °C [16]. Despite intensified diplomacy in these meetings, most existing climate-change treaties are neither sufficient nor mandatory, some of which even stalled [17], [18]. Due to economic competition and political divide, an international enforceable agreement on specific emission-reduction control has not yet been reached.

There are two coupled but conflicting sides in regional emission reduction policies: regions are affected by the same global climate system; they also decide their climate strategies to benefit their individual economic benefits and political self-interests. Therefore, climate policies are actually a decision-making process where competition occurs. Game theory has been a fundamental tool in describing the decision-making mechanisms of independent and self-interested players in a strategic and competitive setting [19]. In a game, each player takes action to maximize its payoff function. The payoff function of each player relies on not only its own action but also other players’ actions, resulting in inherent competition. A common solution concept in game theory is Nash equilibrium (NE) under which no one will benefit by changing its action when others remain unchanged [20]. In a dynamic game, the strategic interaction among players recurs over time. The group of players is associated with a dynamic game state that depends on all players’ actions. The goal is for each player to take action to maximize each player’s cumulative payoff function over time that depends on the game state, its own action, and other players’ actions.

Employing dynamic game theory as a structured mathematical framework empowers decision-makers to understand, analyze, and solve problems that are characterized by temporal dynamics and strategic interactions. This framework facilitates the exploration of optimal strategies within both cooperative
and noncooperative settings [21], [22]. In this article, we are motivated to reformulate the RICE model into a dynamic game. We will show that this game-theoretic perspective will enhance our comprehension of how cooperative and competitive regional relations mold the future of climate change, and shed light on how dynamic game theory may facilitate international negotiations toward a consensus on regional climate-change mitigation policies.

A. Related Work

In the control community, there are a few efforts on studying global climate-change mitigation measures under the DICE framework. The work of [23] provided a tutorial introduction to the DICE model and proposed a receding horizon approach to DICE. A bi-objective optimal control problem (OCP) on DICE was studied, the objectives of which are maximizing social welfare and minimizing atmospheric temperature deviation [24]. The work of [25] studied a multi-objective stochastic OCP on DICE, which accounts for stochastic disturbances and aligns with physical targets posed by international agreements on climate change mitigation. However, there are few studies devoted to regional climate-change mitigation measures under the RICE framework. The work of [26] introduced RICE50+, a benefit-cost optimizing IAM with more than 50 independently deciding regions or countries and provided new data calibrations. However, it did not study behavioral interaction among regions. The work of [27] created a DIRESCU model, which classified the globe into only two regions of the North and the Tropic-South, and studied two solution concepts of social planner’s maximization and two-player feedback NE. However, such solution concepts are unlikely to emerge spontaneously in the real world. In this sense, studies on how regional behaviors of cooperation and competition arise in regional climate policies are limited in the literature. On the implementation side, there has been little contribution to the RICE literature. An excel implementation (without an optimization module) and a GAMS implementation were provided at [28], which is currently inaccessible. Although the work of [29] created an implementation in Julia programming language, it just re-coded the Excel version of RICE without an optimization module [29]. The work of [27] presented an algorithm for computing two-player feedback NE under their DIRESCU model.

B. Main Results

Our central discovery is that the RICE model inherently represents a dynamic game, giving rise to both cooperative and noncooperative solutions.

1) In cooperative settings, regions work together to seek optimal decisions that maximize collectively agreed-upon payoffs.

a) We first delve into the concept of a global social welfare equilibrium that maximizes cumulative and weighted social welfare across regions.

b) We next explore the Pareto social welfare trade-offs that emerge between developed and developing clusters of regions.

c) We finally present the receding horizon approach to approximate the global social welfare equilibrium for robustness and computational efficiency.

2) In noncooperative settings, regions strategically maximize their own payoffs given the information they have.

a) We first provide a recursive best-response algorithm for dynamic games (RBA-DG) to characterize the sequences of best-response regional climate decisions, demonstrating convergence to an open-loop NE when applied to the RICE game through numerical experiments.

b) We also provide a receding horizon feedback algorithm for dynamic games (RHFA-DG) to describe a region’s feedback actions after observing real-time economic and climate states, as well as other regions’ climate mitigation decisions.

We have developed implementations of these various solution concepts for RICE from the proposed dynamic-game perspective, building upon the previous efforts of [30] and [31]. Our implementation is open-sourced as the RICE-GAME framework, featuring a MATLAB and Casadi-based implementation of the RICE game available for download at [32], along with a complementary manual [33].

C. Contributions

The results in this article reveal how the combination of game theory and control theory may be used to facilitate international negotiations toward consensus on regional climate-change mitigation policies, as well as how cooperative and competitive regional relations shape climate change for our future. The Pareto results indicate that the social welfare of developed and developing regions is not significantly dependent on the distribution of climate responsibility between the two clusters over a wide range. The open-loop NE produced from RBA-DG holds higher promise for wide acceptance among regions since no region gains benefits from deviation. The feedback NE produced from RHFA-DG captures the essence of regions’ real-world decision dynamics, portraying how regions strategically respond to real-time economic and climate situations and other regions’ decisions.

Some preliminary results of this article were presented at the 22nd International Federation of Automatic Control World Congress in July 2023 [1]. Compared with the work in [1], we extend the prior work in the following ways: 1) under cooperative settings, we extend the idea of MPC-DICE to MPC-RICE and 2) under noncooperative settings, we study online receding horizon feedback decisions of the RICE game and propose a RHFA-DG.

D. Organization

The article is organized as follows. Section II provides preliminaries of the DICE/RICE model and dynamic games. Section III represents the RICE model as a dynamic game. Section IV considers cooperative solutions for the RICE game under three cooperative settings: global social welfare maximization, RICE Pareto frontier, and receding-horizon global
social welfare maximization. Two noncooperative settings are then considered. Best-response dynamics and open-loop NE for the RICE game are studied in Section V. A receding horizon feedback planning approach for the RICE game is proposed in Section VI. The article ends with concluding remarks in Section VII.

II. PRELIMINARIES

In this section, we introduce some preliminary knowledge of the DICE/RICE model and dynamic games.

A. DICE Model

The DICE model [8] is an IAM that simulates the interplay between the economy and climate and quantifies the social cost of CO₂ emissions. The DICE model operates in periods of five years and its latest version of DICE-2016 starts from the year 2015 as the initial year [9]. The DICE model is composed of two sectors (see Fig. 1): a geophysical sector (blue dotted block) that accounts for the global interaction between carbon and temperature, and an economic sector that is globally aggregated (red dotted block).

1) Geophysical and Economic Sectors: In the geophysical sector, the DICE model considers CO₂ emissions as the major contributor to climate change. The geophysical sector is constructed as follows.

1) There are two main sources of CO₂ emissions: industrial CO₂ emissions related to the carbon intensity (denoted by σ) of global economic activities and natural CO₂ emissions due to land use changes, \( E^{\text{land}} \). The global CO₂ emissions as the sum of industrial and natural emissions drive the carbon cycle of the Earth.

2) The carbon dynamics are described by a three-reservoir model [34] on the carbon flows among the three reservoirs: the atmosphere, the upper oceans and biosphere, and the deep oceans. The average carbon masses in those reservoirs are represented by \( M^{\text{AT}} \), \( M^{\text{UP}} \), and \( M^{\text{LO}} \), respectively.

3) Accumulations of CO₂ emissions and other greenhouse gases warm the Earth’s surface through enhanced radiative forcing. Radiative forcing resulting from CO₂ emissions has a logarithmic dependence on the atmospheric carbon mass; greenhouse gases other than CO₂ emissions contribute to exogenous radiative forcing \( F^{\text{EX}} \).

4) The rise in temperature at the Earth’s surface is driven by radiative forcing. Temperature dynamics are captured by a two-layer model [35]. Given the temperature in the year 1750 as zero reference, \( T^{\text{AT}} \) and \( T^{\text{LO}} \) represent the temperature deviation in the atmosphere and in the lower ocean from those of the reference year, respectively.

The economic sector of DICE is based on the Cobb–Douglas production function [36], where gross economic output is determined by total factor productivity \( A \), labor \( L \), and capital \( K \). The total factor productivity and labor evolve exogenously; the capital dynamics follow the Solow-Swan model [37], where capital depreciates over time and is replenished by investment.

2) Climate-Economy Feedback: The DICE model establishes two feedback loops between the geophysical sector and the economic sector: 1) the industrial CO₂ emissions are a by-product of economic activities and 2) the atmospheric temperature rise has a negative impact on economic production.

3) Control Inputs: The DICE model assumes two control decisions: the saving rate \( s \) and the emission-reduction rate \( \mu \). The saving rate \( s \) represents the ratio of investment to the economic output; the emission-reduction rate \( \mu \) represents the rate at which industrial CO₂ emissions are reduced. By adjusting the saving rate, it is possible to balance consumption today and consumption in the future. By increasing the emission-reduction rate to slow down CO₂ emissions as a “climate investment,” the currently available amount of consumption and investment will be reduced [8]. This climate investment will lower climate damage and therefore potentially increase consumption in the future.

4) System Outputs: The economic output is counted as output net of emission abatement cost and climate damage. Social welfare is calculated as the discounted sum of the population-weighted utility of per capita consumption.

5) DICE Variables: All variables described above are time-dependent, although not explicitly written. The variables \( T^{\text{AT}}, T^{\text{LO}}, M^{\text{AT}}, M^{\text{UP}}, M^{\text{LO}}, \) and \( F^{\text{EX}} \) belong to the geophysical sector, whereas the variables \( K, A, L, \sigma, \) and \( E^{\text{land}} \) belong to the economic sector. Some variables evolve independently, whereas others evolve in an interdependent manner. The variables that evolve independently as exogenous signals are \( F^{\text{EX}}, A, L, \sigma, \) and \( E^{\text{land}} \); the variables evolving in an interdependent manner are \( T^{\text{AT}}, T^{\text{LO}}, M^{\text{AT}}, M^{\text{UP}}, M^{\text{LO}}, \) and \( K \).

B. RICE Model

The RICE model is a variant of the DICE model that accounts for regional climate damages and control decisions [12], [38]. Since being proposed in the 1990s, the calibration of the RICE model has been updated several times, and the latest version of the RICE model is the RICE-2011 model on which our study is based. The RICE-2011 model uses a time-step of ten years, starting from the year 2005 as the initial year.
The RICE-2011 model integrates a global geophysical sector with regional economic sectors (see Fig. 2).

1) The global geophysical sector of the RICE-2011 model contains the same carbon dynamics and temperature dynamics as the DICE model.

2) The regional economic sectors of the RICE-2011 model disaggregate the world into 12 regions (USA, EU, Japan, Russia, Non-Russian Eurasia, China, India, Middle East, Africa, Latin America, other high-income countries, and other Asian countries), each of which is equipped with region-specific climate damage level, economic factors, and saving rate and emission-reduction rate as local control inputs.

**RICE Variables:** The variables $\mathcal{T}^{AT}, \mathcal{T}^{LO}, M^{AT}, M^{UP}, M^{LO},$ and $F^{EX}$ in the global geophysical sector of the RICE-2011 model are inherited from the DICE model, while the variables $K_i, A_i, L_i, \sigma_i,$ and $E_i^{\text{land}}, i \in \{1, 2, \ldots, 12\},$ in the regional economic sectors of the RICE-2011 model correspondingly depend on specific regions.

### C. Dynamic Games

The theory of dynamic games lies in the interface between game theory and optimal control, which involves a dynamic decision process for multiple players [21]. An $n$-player discrete-time dynamic game over a finite horizon is defined as follows.

**Dynamic Game:** The $n$ players are indexed in $\mathcal{V} := \{1, 2, \ldots, n\};$ time is discrete with the steps indexed in $\mathcal{T} := \{0, 1, \ldots, T\}.$ Each player can manipulate the game through its control decisions, and the control decision space of player $i \in \mathcal{V}$ is denoted by $\mathcal{U}_i \subseteq \mathbb{R}^d.$ At each step time $t = 0, 1, \ldots, T,$ the decision executed by player $i$ is denoted by $u_i(t) \in \mathcal{U}_i.$ We also use $u(t) = [u_1(t); \ldots; u_n(t)], U_i = [u_i(0); \ldots; u_i(T)]$ and $U = [U_1; \ldots; U_n]$ to represent the all-player decision profile at time $t,$ the $i$th player’s decision throughout the time horizon, and the decision profile for all players and for all time steps. The control decisions of all players excluding player $i$ at time step $t$ are denoted by $u_{-i}(t),$ and the control decisions of all players excluding player $i$ over the entire horizon are represented by $U_{-i}.$

For each $t = 0, 1, \ldots, T,$ the group of players are associated with a dynamical state $x(t) \subseteq \mathbb{R}^m$ that evolves according to

$$x(t + 1) = f(t, x(t), u(t)), \quad x(0) = x_0, \quad t = 0, 1, \ldots, T$$

with $x_0$ being the initial state. At each time $t = 0, 1, \ldots, T,$ upon playing $u_i(t),$ the player $i$ receives a payoff $g_i(x(t), u_i(t), u_{-i}(t)) \in \mathbb{R}$ given other players’ actions $u_{-i}(t)$ and the current state $x(t),$ where $g_i(x(t), u_i(t), u_{-i}(t))$ is a continuous function with respect to $x(t), u_i(t),$ and $u_{-i}(t).$ The cumulative payoff of player $i$ throughout the time horizon is therefore,

$$J_i(X, U_i, U_{-i}) = \sum_{t=0}^{T} g_i(x(t), u_i(t), u_{-i}(t))$$

where $X = [x(0); \ldots; x(T)].$ Each player’s goal is to make decisions for maximizing its cumulative payoff function; the system dynamics produces a terminal state $x(T + 1)$ toward the end of the time horizon as a result of those decisions.

In what follows, we present cooperative and noncooperative settings as well as three solution concepts for discrete-time dynamic games: Pareto solution, open-loop NE, and feedback NE.

1) **Cooperative Setting:** In the cooperative setting, players are able to communicate and cooperate with each other to achieve their objectives, and all players know the system dynamics and payoff functions of other players. Pareto optimality is an efficiency concept [39] under which any attempt to benefit one player by deviating to some other outcome will necessarily result in a loss in satisfaction of another player.

**Definition 1 (Pareto Efficiency):** A decision profile $U^p$ is Pareto efficient for the dynamic game if there does not exist another decision profile $U$ such that as follows.

1) There holds for all $i \in \mathcal{V}$

$$J_i(X^p, U^p_i, U_{-i}) \leq J_i(X, U_i, U_{-i}).$$

2) There exists at least one $k \in \mathcal{V}$ such that

$$J_k(X^p, U^p_k, U^p_{-k}) < J_k(X, U_k, U_{-k}).$$

Here $X$ and $X^p$ are the states evolved under $U$ and $U^p,$ respectively. The set of all Pareto solutions is called the Pareto frontier.

The following Lemma provides a convenient way of computing Pareto solutions [40, Lemma 6.1].

**Lemma 1:** Consider a set of parameters $\mathcal{B} := \{b = (b_1, \ldots, b_n) : b_i \geq 0, \text{ and } \sum_{i=1}^{n} b_i = 1\}.$ If a decision profile $U^p$ is such that

$$U^p \in \arg \max_U \left\{ \sum_{i=1}^{n} b_i J_i \right\}$$

for some $b \in \mathcal{B},$ then $U^p$ is Pareto efficient.

2) **Noncooperative Setting:** In the noncooperative setting, NE marks one of the most important solution concepts. For a dynamic game, the information structure in terms of what players know before a decision is made at a particular time becomes critical in properly defining NE. There are two
basic types of information structure: the open-loop information structure and the feedback information structure.

In the open-loop information structure, each player knows the initial state $x_0$ and then plans at $t = 0$ all the control decisions $u_i(t)$ for $t \in \mathcal{T}$. Consequently, the open-loop control decision of $u_i(t)$ can be written as

$$u_i(t) = \pi_i(t, x_0).$$

Denote an open-loop decision profile by $U^*$ where $U^* = [u^*_i(0, x_0); \ldots; u^*_i(T, x_0)], i \in V$. We introduce the following definition. With slight abuse of notation, we also write $J_i(X, U_i, U_{-i})$ as $J_i(x_0, U_i, U_{-i})$ noting the fact that $X$ is uniquely determined by $x_0$ and $(U_i, U_{-i})$.

Definition 2 (Open Loop NE): Given the initial state $x_0$, a control decision profile $U^*$ is said to be an open loop NE control decision profile if there holds for all $i \in V$ and all $U_i$ that

$$J_i(x_0, U^*, U_{-i}^*) \geq J_i(x_0, U_i, U_{-i}^*).$$

In the feedback information structure, at time step $t \in \mathcal{T}$, each player knows the current state $x(t)$ to determine its decisions by

$$u_i(t) = \pi_i(t, x(t)).$$

In this case, we denote the overall feedback law as $\pi = [\pi_1; \ldots; \pi_n]$ and then write $J_i(X, U_i, U_{-i})$ as $J_i(x_0, \pi_i, \pi_{-i})$ noting $(X, U_i, U_{-i})$ is uniquely determined by $x_0$ and $\pi$. We introduce the following definition.

Definition 3 (Feedback NE): For any initial state $x_0$, a feedback profile $\pi^*$ is said to be a feedback NE for the dynamic game if there holds for all $i \in V$ and all $\pi_i$ that

$$J_i(x_0, \pi^*_i, \pi^*_{-i}) \geq J_i(x_0, \pi_i, \pi^*_{-i}).$$

III. RICE AS A DYNAMIC GAME

In this section, we show that the RICE Model is inherently a dynamic game where regional saving rates and emission-reduction rates regulate the rise of global temperature, and then the global temperature rise has a negative impact on regional social welfare through climate damage. Our presentation is based on the RICE-2011 model with slight modifications, but the nature of being a dynamic game is embedded in all RICE models.

A. Settings

There are 12 regions in the RICE-2011 model. Each region is considered a player and the regions are indexed in $V = \{1, 2, \ldots, n\}$ with $n = 12$. The updated RICE-2011 model starts from the year 2005 and operates every 10 years, while the latest DICE-2016 model [9] starts from the year 2015 and operates every five years. In this article, the framework of the RICE game starts from year 2020 and inherits the time step of five years from the DICE-2016 model, compared with the RICE-2011 model starting from year 2005 and operating every ten years. Taking the discrete time step index $\mathcal{T} = \{0, 1, \ldots, T\}$, the relation between an actual calendar year and the corresponding discrete time step is determined by

$$\text{year}(t) = \text{year}(0) + 5t, \quad \text{year}(0) = 2020.$$ (8)

In the following presentation of the RICE game, many variables and parameters are involved. For the sake of readability and comprehensibility, the definitions of variables and parameters have been collected in Nomenclature section. We refer to [38, Supplementary Material] for a more detailed explanation of variables and parameters. The values for parameters can be found in [28], [29], [32], and [33]. Note that although most variables in the RICE-2011 model are defined as flows per year and only some variables are in flows per decade, all variables in the RICE game are defined as flows per year. Also note that the framework of the RICE game is very flexible. The sampling period, horizon length, and geophysical and economic parameters can be adjusted to produce updated climate predictions. The MATLAB implementation of the RICE game can be found in [32].

B. System Dynamics

We define the dynamical state of the RICE-2011 model at time step $t \in \mathcal{T}$ as

$$x(t) = [T^{\text{AT}}(t); T^{\text{LO}}(t); M^{\text{AT}}(t); M^{\text{UP}}(t); M^{\text{LO}}(t)];$$

$$K_1(t); \ldots; K_n(t)] \in \mathbb{R}^{n+5}.\quad (9)$$

Let the control decision of region $i \in V$ at time step $t \in \mathcal{T}$ be

$$u_i(t) = [s_i(t); \mu_i(t)] \in \mathbb{R}^{24}_i.\quad (10)$$

Consequently, the control decisions of the RICE game at time step $t \in \mathcal{T}$ of all players are

$$u(t) = [s_1(t); \mu_1(t); \ldots; s_n(t); \mu_n(t)] \in \mathbb{R}^{24}_n.\quad (11)$$

According to the RICE-2011 model, the dynamics of $x(t)$ can be written as

$$x(t + 1) = f(t, x(t), u(t)), \quad x(0) = x_0, \quad t \in \mathcal{T}$$

where $f := [f_1; f_2; \ldots; f_{n+5}]^\top$ follows from the interdependency among the geophysical signals and the economic signals, and the feedback between the geophysical and economic sectors. In what follows, we briefly describe the dynamics $f$. For a more detailed description, please refer to [38].

1) Carbon Dynamics: There are three carbon reservoirs: the atmosphere, the upper oceans and the biosphere, and the deep oceans. The atmospheric carbon reservoir has an additional input, the global CO$_2$ emissions $E(t)$ that is related to economic activities and land use at time $t$. The carbon dynamics for carbon transition among the three reservoirs are described by

$$\begin{bmatrix}
M^{\text{AT}}(t + 1) \\
M^{\text{UP}}(t + 1) \\
M^{\text{LO}}(t + 1)
\end{bmatrix} =
\begin{bmatrix}
\xi_{11} & \xi_{12} & 0 \\
\xi_{21} & \xi_{22} & \xi_{23} \\
0 & \xi_{32} & \xi_{33}
\end{bmatrix}
\begin{bmatrix}
M^{\text{AT}}(t) \\
M^{\text{UP}}(t) \\
M^{\text{LO}}(t)
\end{bmatrix}
+ \begin{bmatrix}
\delta_{1} \\
\delta_{2} \\
\delta_{3}
\end{bmatrix} E(t)$$

where the parameters $\xi_{11}, \xi_{12}, \xi_{21}, \xi_{22}, \xi_{23}, \xi_{32}$, and $\xi_{33}$ are diffusion coefficients between carbon reservoirs, and the parameter $\delta_{1}$ is a conversion factor from emissions to carbon masses.
2) Temperature Dynamics: The evolution of the atmospheric and ocean temperature is governed by the following equations:

\[
\begin{bmatrix}
T_{AT}(t+1) \\
T_{LO}(t+1)
\end{bmatrix} = \begin{bmatrix}
\phi_{11} & \phi_{12} \\
\phi_{21} & \phi_{22}
\end{bmatrix} \begin{bmatrix}
T_{AT}(t) \\
T_{LO}(t)
\end{bmatrix} + \begin{bmatrix}
\xi \\
0
\end{bmatrix} F(t). \tag{15}
\]

The parameters \(\phi_{11}, \phi_{12}, \phi_{21}, \) and \(\phi_{22}\) are diffusion coefficients between temperature layers, and the parameter \(\xi\) is a multiplier for the radiative forcing. The radiative forcing at time step \(t\), \(F(t)\), is computed as

\[F(t) = \eta \log_2 \left( \frac{M_{AT}(t)}{M_{AT,1750}} \right) + F_{EX}(t). \tag{16}\]

The parameters \(\eta, M_{AT,1750}, \) and \(F_{EX}\) represent the forcing associated with equilibrium carbon doubling, atmospheric carbon masses in the year 1750, and the radiative forcing due to other greenhouse gases at time step \(t\), respectively [23].

3) Economic Dynamics: The economy of each region \(i \in \mathcal{V}\) at time step \(t \in \mathcal{T}\) follows the Cobb–Douglas production function [36]:

\[Y_i(t) = A_i(t) K_i(t)^{\gamma_i} L_i(t)^{1-\gamma_i} \tag{17}\]

where \(Y_i(t), A_i(t), K_i(t),\) and \(L_i(t)\) represent region \(i\)'s gross economic output, total factor productivity, capital stock, and labor at time step \(t\), respectively. Each region \(i\)'s total factor productivity \(A_i\) and labor \(L_i\) are exogenously estimated variables. The parameter \(\gamma_i, i \in \mathcal{V}\) represents region \(i\)'s capital elasticity.

4) Economy–Climate Feedback: Global CO\(_2\) emissions at time step \(t\) are the sum of natural emissions because of each region’s land use at time step \(t\), \(E_{i}^{\text{land}}(t)\), and industrial emissions resulted from each region’s economic activities at time step \(t\). Each region \(i\)'s industrial emissions depend on each region \(i\)'s carbon intensity at time step \(t\), \(\sigma_i(t)\), which is an exogenously estimated variable. Consequently, global CO\(_2\) emissions at time step \(t\) is described by

\[E(t) = \sum_{i=1}^{n} (\sigma_i(t)(1 - \mu_i(t))) Y_i(t) + E_{i}^{\text{land}}(t) \tag{18}\]

where \(\mu_i(t), i \in \mathcal{V}, t \in \mathcal{T}\), are control decisions representing the emission-reduction rate.

The emission abatement cost fraction as the percentage of gross economic output spent on emission-reduction effort at time step \(t\) is given by

\[\Lambda_i(t) = \theta_i^{[1]}(t) \mu_i(t) Y_i^{[3]} \tag{19}\]

where the parameter \(\theta_i^{[1]}(t), i \in \mathcal{V}, t \in \mathcal{T}\) represents region \(i\)'s cost estimate of mitigation efforts at time step \(t\), and the parameter \(\theta_i^{[2]}\) is region \(i\)'s exponent of emission-reduction cost fraction function. The parameter \(\theta_i^{[1]}(t), i \in \mathcal{V}, t \in \mathcal{T}\) is calculated by

\[\theta_i^{[1]}(t) = \frac{pb_i}{10000\theta_i^{[2]}} \left( 1 - \delta_i^{pb} \right)^{t-1} \sigma_i(t) \tag{20}\]

where the parameter \(pb_i, i \in \mathcal{V}\) represents region \(i\)'s price of a backstop technology that can remove carbon dioxide from the atmosphere, and the parameter \(\delta_i^{pb}, i \in \mathcal{V}\) is region \(i\)'s decline rate of the backstop technology price. The damage function \(\Omega_i(t)\) is the percentage of gross economic output damaged by temperature rising. As a result, the net economic output \(Q_i(t)\) after the emission-reduction spending and climate damage is given by

\[Q_i(t) = (1 - \Omega_i(t))(1 - \Lambda_i(t)) Y_i(t). \tag{21}\]

The Solow–Swan model [37] gives a description of capital accumulation of each region \(i \in \mathcal{V}\)

\[K_i(t+1) = (1 - \delta^K_i) K_i(t) + s_i(t) Q_i(t) \tag{22}\]

where the parameter \(\delta^K_i, i \in \mathcal{V}\), is region \(i\)'s depreciation rate on capital per year, and \(s_i(t), i \in \mathcal{V}, t \in \mathcal{T}\), is region \(i\)'s control decision of saving rate at time step \(t\), i.e., the percentage of net economic output invested in capital.

C. Damage Functions

The rising atmospheric temperature has a negative impact on economic production. Although there are various specifications offering various estimates of the damage function, there are no substantial discrepancies among them [41]. In the RICE-2011 model, damages to economic gross output caused by rising temperatures are considered to be region-specific and dependent on factors such as atmospheric temperature deviation, sea level rises, and atmospheric carbon masses. However, the form of the damage function of the RICE-2011 model is not given explicitly. In the current study, a simplified form of the damage function is employed, which only depends on the rising atmospheric temperature deviation

\[\Omega_i(t) = a_i^{[1]} T_{AT}(t) + a_i^{[2]} T_{AT}(t) a_i^{[3]} \tag{23}\]

The parameters \(a_i^{[1]}, a_i^{[2]},\) and \(a_i^{[3]}, i \in \mathcal{V}\) are region \(i\)'s damage coefficient on temperature, damage exponent, and damage coefficient on temperature squared, respectively. They are calibrated to yield a certain amount of damage loss to regional economic gross output. Each region’s damage loss to its regional economic gross output at 2 °C is presented in Table I. For example, India would suffer a damage loss of 1.55% to its economic gross output when the atmospheric temperature deviation reaches 2 °C.

D. Payoff Functions

Note that from the net economic output \(Q_i(t)\), a total amount of \(s_i(t) Q_i(t)\) has been made as an investment. The remaining part \(C_i(t) = (1 - s_i(t)) Q_i(t)\) can then be used for consumption. In RICE models, for region \(i\), the social welfare of the population \(L_i(t)\) consuming \(C_i(t)\) of economic output

| Region            | US   | EU   | Japan | Russia | Eurasia | China |
|-------------------|------|------|-------|--------|---------|-------|
| Loss              | 0.56%| 0.64%| 0.45% | 0.46%  | 0.52%   | 0.66% |
| India, Middle East, Africa, Latin America, Other, OIH, Other Asia | 1.53% | 1.19% | 1.47% | 0.66% | 0.62% | 1.04% |

TABLE I

Each region’s damage loss with respect to its gross economic output when the atmospheric deviation is at 2 °C, as sourced from [28] and [29].
at time \( t \) is defined by the population-weighted utility of per capita consumption

\[
g_i(C_i(t), L_i(t)) = L_i(t) \cdot \left( \frac{C_i(t)}{L_i(t)} \right)^{1-\alpha_i} - 1
\]

where the parameter \( \alpha_i, i \in V \) represents region \( i \)’s elasticity of marginal utility of consumption. The cumulative social welfare of region \( i \) across the time horizon is then given by

\[
J_i = \sum_{t=0}^{T} \frac{g_i(C_i(t), L_i(t))}{(1+\rho_i)^{st}}
\]

\[
= \sum_{t=0}^{T} \left( \left( A_i(t)L_i(t)^{1+\alpha_i-\gamma_i} \right) \left( 1 - u_{i(2)}(t) \right) \left( 1 - a_i^{[1]} x_i(t) - a_i^{[2]} x_i(t)^{\gamma_i} \right) \left( 1 - \theta_i^{[1]}(t) u_{i(1)}(t)^{\gamma_i} \right) - \frac{L_i(t)}{(1-\alpha_i)(1+\rho_i)^{st}} \right)
\]

\[
:= J_i(X, U_i, U_{i+1})
\]

where \( \rho_i, i \in V \) represents region \( i \)’s discounting factor of social time preference per year. For each region \( i \in V \), it naturally attempts to maximize its cumulative social welfare.

We have now formally represented the RICE-2011 model as a dynamic game, termed the RICE game, where regions as players seek to plan their control decisions in emission-reduction rates and saving rates for the entire time horizon \( U_i = [s_i(0); \mu_i(0); \ldots; s_i(T); \mu_i(T)] \) so as to maximize their payoff functions (25) subject to the underlying dynamical system (13), represented in (14)–(22).

When we implement the proposed RICE game, the values of the initial state \( x(0) \) and the parameters are updated in the following way: the initial state is calibrated to match the data in the year 2020; the parameters in the geophysical sector use the latest updated values in the DICE-2016 model [9], while the parameters in the regional economic sector remain the same as in the RICE-2011 model [12]. In the following simulations of Sections IV–VI, we inherit the time horizon setup (600 years) from the RICE-2011 model. Readers can specify their preferred time horizon before running the codes provided in our MATLAB implementation [32].

E. Social Cost of CO2

The social cost of CO2 (SCC) is a central concept for understanding and implementing climate change policies. In a market setting like a cap-and-trade regime, the SCC would serve as the trading price of carbon emission permits. In a carbon-tax regime, the SCC would be the carbon tax for the regions that want to emit carbon emissions. The SCC in a particular year is defined as the decrease in aggregate consumption in that year that would change the current expected value of social welfare by the same amount as a one-unit increase in carbon emissions [42]. The regional SCC is then given by

\[
SCC_i(t) = -1000 \cdot \frac{\partial J_i}{\partial E_i(t)} / \frac{\partial J_i}{\partial C_i(t)}
\]

IV. RICE GAME: COOPERATIVE SOLUTIONS

In this section, we study the solutions to the RICE game under cooperative settings. First of all, we revisit the classical RICE solution concept defined by a system-level social welfare maximization and present numerical solutions under the latest calibration of climate damage function and the updated geophysical and economic parameters. Next, we look at Pareto solutions to the proposed RICE game and present the Pareto social welfare frontier between developing and developed regions. Finally, we introduce a receding horizon solution to the classical RICE solution as the counterpart for MPC-DICE developed in [31] and [43].

A. RICE Social Welfare Maximization

The RICE-2011 model focused on the sum of the weighted regional social welfare across all regions

\[
W_c = \sum_{i=1}^{n} c_i J_i
\]

where \( c_i \) is known as the Negishi weight for region \( i \in V \). The values of \( c_i, i \in V \) were calibrated in the work of [38] to be the inverse of the marginal utilities of consumption when maximizing (27) subject to RICE dynamics (14)–(22) under the assumption that there is no abatement of CO2 emissions [8], [11], [44].

1) Solution Concept: One benchmark cooperative solution to the RICE game is for a centralized climate policy planner to optimize \( W_c \), for a given initial condition \( x_0 \).

Definition 4: A decision profile \( U^w \) is a global social welfare equilibrium if it is a solution to the following optimization problem:

\[
\max_{u_1, \ldots, u_n} W_c(X, U)
\]

s.t. \( x(t+1) = f(t, x(t), u(t)), \quad x(0) = x_0, \quad t \in T \)

\[
u(t) \in [0, 1]^2, \quad t \in T.
\]

2) Results: We run a total of 120 five-year periods, and therefore we set \( T = 120 \). We obtain the global social welfare equilibrium \( U^w \) for the RICE game under Definition 4 by solving (28). Each region’s optimal control decisions in emission-reduction rate and saving rate under \( U^w \) are plotted in Fig. 3. It is noticeable that the emission-reduction rates and saving rates stay at a specific steady state for the major part of the time horizon until they finally drop, which is known as the turnpike property [45]. This is because regions do not care about social welfare beyond the prescribed time horizon \( T \). When regions reduce the emission-rate during the end of the time horizon, they can improve the cumulative social welfare over the prescribed time horizon.
at the sacrifice of future atmospheric temperature deviation that does not harm the social welfare over the prescribed time horizon. It is also notable that regions including China, Africa, India, Eurasia, OthAsia, and Russia have relatively high emission-reduction rates that should reach carbon neutral status (i.e., the emission-reduction rate \( \mu_i(t) \) becoming exactly 1) relatively sooner. The reason for that could be twofold. First, regions such as Africa and India bear the greatest damage loss caused by rising atmospheric temperature as presented in Table I. Second, it takes regions such as China, Eurasia, and Russia comparatively lower cost to reduce carbon emissions (see the estimated price for a backstop technology that can remove carbon dioxide from the atmosphere in the year 2020 in Table II).

Table II: Estimated Price (USD/tCO2) for a Backstop Technology in Each Region That Can Remove Carbon Dioxide From the Atmosphere in Year 2020, as Sourced From [28] and [29]

| Region   | USD  | EU   | Japan | Russia | Eurasia | China |
|----------|------|------|-------|--------|---------|-------|
| Price    | 1051 | 1635 | 1635  | 701    | 701     | 817   |
| India    | 1284 | 1167 | 1284  | 1518   | 1284    | 1401  |

Then, in Fig. 4, we examine the trajectory of the atmospheric temperature deviation when the emission-reduction rates and saving rates under \( U^w \) are taken. The work of [38] also solved the OCP (28) with the same horizon length (600 years) starting from the year 2005. Although we are inaccessible to the exact and complete data of results in [38, Fig. 3], the atmospheric temperature deviation trajectory in Fig. 4 appears to be similar to that in [38]. Furthermore, the atmospheric temperature deviation by the end of this century is about 2.3 °C. This shows that even with full cooperation, we will not be able to meet the 2 °C temperature target set by the Paris Agreement.

Finally, the social cost of CO2 in each region under the global social welfare equilibrium is presented in Fig. 5. It shows that the social cost of CO2 under \( U^w \) in India, Africa, and OthAsia is significantly higher than those in other regions. The reason for that could be that both prices for backstop technology and optimal emission-reduction rates for these regions are higher than those for other regions.

B. RICE Pareto Frontier

Noting the global social welfare equilibrium is a solution concept where the Negishi weights \( c_i, i \in V \) are calibrated in a centralized manner. Since the weight \( c_i \) may greatly impact the optimal emission rates and saving rates for region \( i \) and then its own social cost of carbon, the regions have intrinsic incentives in negotiating the distribution of the \( c_i \). In recent
years, the divide between developed and developing regions in international climate policy forums has been one of the main barriers to a global consensus on carbon emission rates [15], [46], [47]. In this section, we focus on the social welfare Pareto frontier between developed and developing regions involved in the RICE game.

1) Solution Concept: We classify the regions in the RICE-2011 model into two clusters: developed regions (USA, EU, Japan, and other high-income countries) and developing regions (Russia, Non-Russian Eurasia, China, India, Middle East, Africa, Latin America, and other Asian countries). We denote $V_{\text{developed}} = \{1, 2, 3, 11\}$ and $V_{\text{developing}} = \{4, 5, 6, 7, 8, 9, 10, 12\}$. Correspondingly, the social welfare of the two clusters is defined as, respectively

$$W_{\text{developed}} = \sum_{i \in V_{\text{developed}}} J_i, \quad W_{\text{developing}} = \sum_{i \in V_{\text{developing}}} J_i.$$ 

For the considered RICE game over these two clusters, we consider the Pareto optimality.

Definition 5: For the RICE game with developed and developing clusters, a decision profile $U^p$ is a Pareto social welfare equilibrium between the developed and developing clusters if there does not exist another decision profile $U$ such that as follows.

1) There holds

$$W_{\text{developed}}(X^p, U^p, U_{-i}) \leq W_{\text{developed}}(X, U, U_{-i})$$
$$W_{\text{developing}}(X^p, U^p, U_{-i}) \leq W_{\text{developing}}(X, U, U_{-i}).$$

2) Either one of the above two inequalities holds strictly.

Here $X$ and $X^p$ are the states evolved under $U$ and $U^p$, respectively.

Based on Lemma 1, we utilize weighted sum method to approximate the Pareto social welfare frontier between the developed and developing clusters by solving the family of optimization problems for a given initial condition $x_0$

$$\max_{U_1, \ldots, U_n} p \cdot W_{\text{developed}} + (1 - p) \cdot W_{\text{developing}}$$
$$\text{s.t. } x(t + 1) = f(t, x(t), u(t)), \quad x(0) = x_0, \quad t \in \mathcal{T}$$
$$u(t) \in [0, 1]^{24}, \quad t \in \mathcal{T} \quad (29)$$

where $p$ is selected in the interval $[0, 1]$. For any fixed $p \in [0, 1]$, we obtain a Pareto social welfare equilibrium, and their collection forms the Pareto frontier between the developed and developing clusters. The Pareto formulation might have the potential to serve as a benchmark for the interchanges of positions between developed regions and developing regions on climate policies. The parameter $p$ serves as a quantitative characterization to the allocation of climate responsibility between developed regions and developing regions: If $p$ is close to 0, developed regions will take higher responsibility, as the developing regions will if $p$ is close to 1.

Weighted sum method inherently generates Pareto optimal solutions. However, the absence of convexity introduces a constraint on its capacity to encompass the entire set of Pareto optimal solutions. As a result, the curve produced by weighted sum method serves as an approximation of the Pareto front, indicating the need for comprehensive computation to achieve the strict Pareto front. Importantly, weighted sum method holds tangible significance. The parameter $p$ embodies the distribution of climate responsibility between the two clusters. While our curve does not precisely cover the strict Pareto front, it effectively captures the dependence and variation in social welfare for the two clusters regarding climate responsibility distribution. Obtaining the complete set of Pareto optimal solutions is a computationally challenging problem. The works of [48], [49], [50], and [51] may potentially offer a more comprehensive coverage of Pareto optimal solutions.

2) Results: We set a total of 120 five-year periods. We take 999 linearly spaced values between 0.001 and 0.999 as the values of $p$. For each $p$, we obtain the Pareto solution $U^p$ by solving the respective OCP (29). We plot the social welfare Pareto frontier between developed and developing regions in Fig. 6. We also plot the atmospheric temperature deviation at the final time step, $T^{AT}(120)$, versus the parameter $p$ in Fig. 7. Each circle in Fig. 7 represents the atmospheric temperature deviation at the last time step under a specific parameter $p$.

These results reveal a few notable effects.

1) From Fig. 6, it can be seen that the values of $p$ cannot drastically change the social welfare received for both the developing and developed clusters. The maximal ($p = 0.999$) and minimal ($p = 0.001$) values for $W_{\text{developed}}$ differs only by 0.35%; the maximal ($p = 0.001$) and minimal ($p = 0.999$) values for $W_{\text{developing}}$
differ only by 0.56%. We believe the observed flatness in the Pareto social welfare frontier is a plausible outcome. In one scenario where developing regions take on a greater burden of climate responsibility compared to developed regions, the high cost of emission mitigation efforts significantly affects the economic output of the developing regions. Despite their mitigation attempts, their limited capacity to cut emissions leads to substantial global temperature increases. As a result, although developed regions do not bear much of the climate responsibility, their economic output is being damaged by the rising global temperature. Conversely, in the other scenario where developed regions shoulder more of the climate responsibility, the cost of emission reduction becomes substantial for developed regions. Although developing regions have a lesser role in emission reduction, their constrained economic development limits their output. Combining two scenarios, the difference in social welfare is minimal. This suggests a dilemma for both sides: either accepting emission reduction costs or bearing economic damage caused by climate change.

2) **Fig. 7** shows that the atmospheric temperature deviation at the final time step varies in a wide range from 2.8 °C to 3.3 °C with respect to \( p \) under the Pareto equilibrium. It is also clear that a higher or a lower \( p \) will both result in a lower atmospheric temperature deviation in the final year, while \( p = 0.862 \) leads to the highest terminal atmospheric temperature deviation, i.e., global warming in the worst case.

### C. Receding Horizon RICE

Equation (28) is an OCP for a nonlinear dynamical system with a nonconvex cost function. When the horizon length gets larger, it becomes more difficult to solve the problem numerically. The work of [23] established a novel receding horizon solution to DICE, which provides robustness and computational efficiency compared to solving DICE in a long time horizon directly. In what follows, we extend the idea of [23] to RICE.

1) **Solution Concept:** For the receding horizon approach, we denote the prediction horizon by \( T_{rh} \) and the simulation horizon by \( T_{sim} \). We introduce

\[
I(t, x(t), u(t)) := \sum_{i=1}^{n} c_i \frac{g_i(C_i(t), L_i(t))}{(1 + \rho_i)^{S_t}}
\]

and assume a full measurement or estimate of the state \( x(t) \) is available at each time step \( t \in T_{sim} := \{0, 1, \ldots, T_{sim}\} \). The receding horizon process to approximate the global social welfare equilibrium \( U^w \) is proposed in Algorithm 1. A decision profile \( U^{rhw} = \{u_1^{rhw}(0); \ldots; u_{T_{sim}}^{rhw}(T_{sim})\} \) as output of Algorithm 1 is said to be a receding horizon global social welfare equilibrium.

2) **Results:** We set the simulation horizon to be \( T_{sim} = 120 \) (600 years) and implement MPC-RICE under prediction horizons \( T_{rh} \in [10, 20, 60] \). We also reproduce MPC-DICE with a simulation horizon of 600 years under prediction horizons \( T_{rh} \in [10, 20, 60] \).

#### Algorithm 1 MPC-RICE

**Input:** simulation horizon \( T_{sim} \); prediction horizon \( T_{rh} \).

1: \( t \leftarrow 0 \)
2: while \( t \leq T_{sim} \) do
3: \( \text{observe } x(t) \)
4: \( \text{compute the optimal solution } u^*(s), s \in S := \{t, t+1, \ldots, t+T_{rh}\}, \) to the following optimization problem over the receding horizon \( S \)
5: \( \text{apply } u^{rhw}(t) := u^*(t) \) to RICE game
6: \( \text{return } U^{rhw} \)

In Fig. 8, we plot trajectories of the optimal emission-reduction rates under global social welfare equilibrium \( U^w \) and the optimal control decision \( U^{rhw} \) obtained by MPC-RICE with \( T_{rh} \in [10, 20, 60] \). When the prediction horizon gets larger, the optimal emission-reduction rates under \( U^{rhw} \) converge toward those under \( U^w \) for most time steps. Moreover, the optimal emission-reduction rates under \( U^{rhw} \) are more steady in the sense that they do not drop back to lower levels toward the end of the simulation horizon, which is the case under \( U^w \). It is because when approaching the end of the simulation horizon in Algorithm 1, regions also care about the social welfare beyond the simulation horizon due to the sliding window of the receding horizon approach. The economic damage caused by the rising temperature outweighs the cost of reducing emissions produced by economic production. It is optimal for regions not to drop emission-reduction rates and keep them high for slowing the temperature rise beyond the simulation horizon. Furthermore, compared with [43], MPC-RICE and MPC-DICE present similar approximation features under large prediction horizons.

In Fig. 9, we plot trajectories of atmospheric temperature deviation for the entire simulation horizon under the optimal solutions from DICE OCP, MPC-DICE with \( T_{rh} = 60 \), \( U^w \), and \( U^{rhw} \) with \( T_{rh} = 60 \). The trajectories of atmospheric temperature deviation under DICE OCP and MPC-DICE with \( T_{rh} = 60 \) are higher than under \( U^w \) and \( U^{rhw} \) with \( T_{rh} = 60 \) in most time steps except at the beginning. To this extent, the RICE model and MPC-RICE raise more concerns about global warming.

### V. RICE GAME: Best-Response Dynamics and Open-Loop NE

In this section, we study the best-response dynamics and open-loop NE of the RICE game.

#### A. Best-Response Recursions for Dynamic Games

In game theory, best-response dynamics is a classical model that describes how players strategically behave in repeated plays [52]. In standard best-response episodes, each player...
Fig. 8. Comparison of each region’s optimal emission-reduction rates under \( U^w \) and \( U^{rbw} \) with different prediction horizons \( T_{rh} \in \{10, 20, 60\} \).

Fig. 9. Comparison of atmospheric temperature deviation for the entire simulation horizon under the optimal solutions from DICE OCP, MPC-DICE with \( T_{rh} = 60 \), \( U^w \), and \( U^{rbw} \) with \( T_{rh} = 60 \).

Algorithm 2 Recursive Best-Response Algorithm for Dynamic Games

1: compute an optimal cooperative solution \( U^c \) by the following problem
2: \[
\begin{align*}
\max_{U_1, \ldots, U_n} \sum_{i \in \mathcal{V}} c_i \cdot J_i(X, U_i, U_{-i}) \\
\text{subject to } x(t+1) = f(t, x(t), u(t)), x(0) = x_0, \\
u(t) \in [0, 1]^{24}, t \in T.
\end{align*}
\]

3: \( k \leftarrow 0 \)
4: while \( k < N \) do
5: for each player \( i \in \mathcal{V} \) do
6: observe \( U^{(k)}_{-i} \)
7: compute \( U^{(k+1)}_{i} \) by solving the problem
8: \[
\begin{align*}
\max_{U_i} J_i(X, U_i, U_{-i}), \\
s.t. \quad x(t+1) = f(t, x(t), u(t)), \\
U_{-i} = U^{(k)}_{-i}, \\
x(0) = x_0.
\end{align*}
\]
9: \( k \leftarrow k + 1 \)
10: return \( U^{NE} = U^{(N)} \)

The implementation of RBA-DG requires two conditions. First, the initial value of the system \( x(0) = x_0 \) needs to be known by all players at the beginning of the process. Second, at the end of each episode \( k = 1, \ldots, N \), every player should be able to observe or know all other players’ decision sequences over the episode \( U^{(k)}_{-i} \). Then the update of the player decisions for the next episode follows directly from the best-response dynamics. We present the following result, which holds true immediately from the definition of open-loop NE.

**Proposition 1:** Consider the repeatedly played \( n \)-player dynamic game. Let \( N = \infty \) in the RBA-DG. Suppose there exists \( U^* \) such that there holds \( \lim_{k \to \infty} U^{(k)} = U^* \). Then \( U^* \) is an open-loop NE for the dynamic game.

**B. Recursive Best-Response for RICE**

The RICE model describes the interplay of the various regions in the world in terms of their climate-change mitigation policy over a few centuries (for example, RICE-2011 assumes a total time horizon of 600 years [38, Supplementary Material]). As a result, despite the fact that the RBA-DG may be conceptually applied to RICE since RICE has been identified as a dynamic game, it is important to clarify the real-world implication of the recursive best response for RICE.
1) Regional Climate Policy Negotiations: We propose to adopt RBA-DG over RICE as a mechanism for regional climate policy negotiations. The overall negotiations take prescribed $N$ episodes. In each round of the negotiations, regions accept RICE as the standing model for climate-economy integration and decide their emission reduction rates and saving rates for a fixed time horizon. At the end of each round, all regions reveal their current planning of the emission reduction rates and saving rates for the entire time horizon to other regions. Then, during the next round of negotiations, regions get to revise their planned decisions and adopt RBA-DG as their principle of updating such planned decisions. After the $N$ episodes of negotiations, if all regions realize none of them can unilaterally change their climate actions and gain a significant increase in social welfare, such a mechanism will produce an approximate open-loop NE for the RICE game in view of Proposition 1. Such a NE holds a higher promise of being accepted by all regions since no region is able to benefit from a revised decision when all other regions take action from the NE.

2) Results: Now we implement the RBA-DG over the RICE game. We set the number of episodes to be $N = 21$.

   a) Convergence: In Fig. 10, we plot the trajectory of $\|U^{(k+1)} - U^{(k)}\|$ versus episode $k$. The result shows that when applying RBA-DG over the RICE game, the obtained sequence of $U^{(k)}$ converges to a steady point, and after five episodes, the $\|U^{(k+1)} - U^{(k)}\|$ has become very close to zero. From Proposition 1, this implies that the RBA-DG may also serve as an efficient algorithm for computing the open-loop NE of the RICE game.

   b) Cooperation versus competition: In Fig. 11, we plot the comparison of each region’s optimal emission-reduction rates under global social welfare equilibrium $U^w$ (cooperative solution) in blue solid line and under open-loop NE $U^*_{NE}$ (competitive solution) in solid red line. From the results, with competition, substantially higher atmospheric temperature deviation occurs under $U^*_{NE}$, as a consequence of lower emission-reduction rates. For example, in 2620, the atmospheric temperature deviation under the open-loop NE $U^*_{NE}$ is around 6°C while the atmospheric temperature deviation under global social welfare equilibrium $U^w$ is about 3°C.

VI. RICE GAME: RECEIVING HORIZON FEEDBACK DECISIONS

In this section, we present a framework for dynamic games where in a single play over the time horizon, players observe regions leaving signed climate treaties, e.g., Canada opt-out from Kyoto Protocol in 2012 [17], and the United States formally quit Paris Agreement in 2020 [18] because a less aggressive regional policy leads to higher economic benefit even facing climate change damages.

In Fig. 12, we plot the comparison of the atmospheric temperature deviation trajectories under $U^w$, $U^*_{NE}$, and $U^*_{RHF}$ with $T_{rh} = \{5, 10, 20\}$. 

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the underlying dynamic process and other players’ actions and then apply receding-horizon feedback decision-making for a prediction horizon. Then we apply this receding horizon feedback process to the RICE game to capture the competitive nature of regional climate policies and to show how such competitions have an impact on the global climate dynamics.

A. Receding Horizon Feedback Decisions for Dynamic Games

Consider the dynamic game introduced in Section II-C with \( n \) players over a finite horizon \( T \). The game is played only once, and the players take the following feedback decision process in the receding horizon sense.

The players apply a receding horizon approach and compute their feedback decisions \( u_i(t) \). At each time \( t = 0, \ldots, T - 1 \), each player \( i \) observes other players’ played action \( u_{-i}(t) \) and the system state \( x(t) \). Then, every player \( i \) assumes that \( u_{-i}(t) \) will continue to be played over \( [t + 1, t + T_{rh}] \), and decides its best feedback decision plan \( u_{RHF}^i(t; t + t + T_{rh}) \), where \( u_{RHF}^i(t; t + t + T_{rh}) \) maximizes the cumulative payoff of player \( i \) over the time horizon \( [t + 1, t + T_{rh}] \) conditioned on that \( u_{-i}(t) \) is be played over \( [t + 1, t + T_{rh}] \). Finally, each player \( i \) plays the first planned decision \( u_{RHF}^i(t; t + t + T_{rh}) \) for the step \( t + 1 \), and the process moves forward recursively. Denoting \( u_{RHF}(t) \) as the actions generated by the receding horizon feedback decision process, clearly, there is an underlying feedback law \( \pi_i \) such that

\[
u_{RHF}^i(t) = \pi_i(t, x(t), u_{RHF}(t)).
\]

Note that the decisions \( u_{RHF}^i(t) \) are actually played by the players at each time \( t \). The resulting collective decisions over the entire time horizon are written as \( U_{RHF} \). The computational process of this receding horizon feedback decision framework is presented in the following RHFA-DG as in Algorithm 3. As known in sequentially played games, future decisions of other players are difficult to anticipate. Whether and how previous moves imply future trends depend on intentions of other players. Our adoption of best-response myopic assumption is grounded in two key considerations. First, the principle of best-response is commonly adopted in classical game theory. Second, climate policies change relatively over time, and therefore current observation is a good estimate for other players’ future decisions.

B. Receding Horizon Feedback for RICE

In the current climate-change mitigation measures, there has been no international consensus on the emission reduction rates and the saving rates for different regions or for the globe collectively, despite the successful adoption of global or regional climate-change agreements such as the Paris Agreement. In fact, most climate treaties are neither substantial nor mandatory [55]. The objective of such treaties has not been the actual emission-reduction rate, but rather to establish environmental norms at the international level. The hope is that such international environmental norms may then be translated into domestic climate policies according to each region’s political processes [56].

In the real world, regions revise their climate-change policies from time to time and attempt to compete with each other while acknowledging the importance of climate-change mitigation. Indeed, such revisions of regional climate-change policies may depend on many factors such as public opinion shifts, government changes, and new international environmental norms. In the end, the nature of regional competitions persists as aggressive climate-change mitigation policy for a region may benefit other regions economically in the short run, although collectively aggressive climate-change mitigation policy benefits every region as shown from the comparison between cooperative social welfare equilibrium and the approximate open-loop NE. Here, we propose to apply RHFA-DG on RICE as an attempt to model the real-world regional climate-policy evolution given the economically competitive nature of such policies.

C. Results

We implement RHFA-DG over the RICE game. We set the simulation horizon and prediction horizon to be \( T_{sim} = 120 \) and \( T_{rh} = \{5, 10, 20\} \). In Fig. 11, we plot the comparison of each region’s optimal emission-reduction rates under global social welfare
equilibrium \( U^w \), the approximated open-loop NE \( U^{NE} \) solved from RBA-DG (Algorithm 2), and the receding horizon feedback decisions \( U^{RHF} \) solved from RHFA-DG (Algorithm 3) with \( T_{rh} = \{5, 10, 20\} \). First, with competition, the receding horizon feedback decisions of emission-reduction rates solved from RHFA-DG are significantly lower than those under global social welfare equilibrium. Second, due to the receding horizon and myopic assumption of other regions’ future decisions, the emission-reduction rates from RHFA-DG are lower than those obtained from RBA-DG in the early time steps. However, interestingly, the former continues to climb in the final time steps, while the latter drops back to lower levels at the end of the simulation horizons.

In Fig. 12, we plot the comparison of the atmospheric temperature deviation trajectories under \( U^w, U^{NE}, \) and \( U^{RHF} \) with \( T_{rh} = \{5, 10, 20\} \). There are several observations on the results. First, the atmospheric temperature deviation under \( U^{RHF} \) is substantially higher than that under \( U^w \), and slightly higher than that under \( U^{NE} \). Second, for \( U^{RHF} \) with \( T_{rh} = \{5, 10, 20\} \), the smaller the prediction horizon, the higher the atmospheric temperature deviation. This implies that a longer prediction horizon forces the regions to take the long-term climate damages more into their receding horizon decisions, and therefore leads to better climate-change mitigation.

VII. CONCLUSION

In this article, we investigated how cooperation and competition arose in regional climate policies under the RICE framework from the standpoints of game theory and optimal control. Our primary discovery was that the RICE model was inherently a dynamic game, where both cooperative and noncooperative solutions emerged. In cooperative settings, we investigated the global social welfare equilibrium that maximizes the weighted and cumulative social welfare across regions, then presented the Pareto social welfare trade-offs between developed and developing clusters of regions, and finally applied receding horizon approach to approximate the global social welfare equilibrium. For noncooperative settings, we first presented a RBA-DG to describe the sequences of best-response regional climate decisions, which indicated convergence to an open-loop NE when applied to the RICE game through numerical studies. We also presented a RHFA-DG to describe a region’s feedback actions after observing the real-time climate and economic states and other regions’ climate mitigation decisions. All these proposed solution concepts were implemented and open-sourced using the latest updated data. The results revealed how the combination of game theory and control theory could be used to facilitate international negotiations toward consensus on regional climate-change mitigation policies, as well as how cooperative and competitive regional relations shape climate change for our future.

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