Leveraging a Fully Differentiable Integrated Assessment Model for RL and Inference

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Abstract

Integrated Assessment Models (IAMs) such as RICE have long provided a foundation for studying the coupled dynamics of the global economy and climate system. Traditionally, these models have been used in a forward-simulation mode, with parameters hand-calibrated and dynamics treated as fixed. In this work, we introduce RICE-N-JAX, a fully differentiable implementation of the multi-region RICE-N model in JAX. Beyond significantly accelerating the training of multi-agent reinforcement learning (MARL) agents, differentiability opens new research directions, including automated calibration to historical data, recovery of latent regional behavioral parameters (e.g., risk aversion and time preferences) and sensitivity analysis of economic and technological assumptions. Moreover, it allows us to treat policy design and international negotiation mechanisms as learnable parameters within a gradient-based optimization framework. We outline new research opportunities that arise when an IAM becomes a differentiable environment and discuss implications for climate–economics modeling, machine learning for climate policy and the fusion of data- and theory-driven approaches.

1 Introduction

The impacts of climate change are already evident: ecosystems are shifting and extreme weather events are intensifying, threatening livelihoods and economic stability and underscoring the urgent need for action [Pörtner et al., 2022].

Climate change is a shared global challenge, yet mitigation entails trade-offs. Investments in low-carbon technologies and systemic transformation can constrain short-term growth and costs are unevenly distributed: wealthier nations can invest more readily, while developing countries must balance climate goals with basic development needs. This imbalance reinforces a collective-action dilemma, where self-interest threatens global progress [Gardiner, 2001, Erickson et al., 2015].

Integrated assessment models (IAMs) quantify these climate–economic trade-offs by linking CO_2 emissions, temperatures and growth dynamics. The pioneering Dynamic Integrated model of Climate and Economy (DICE) captures global interactions among population, technology, emissions and damages within a single economy [Nordhaus, 2007]. Its regional extension, the Regional Integrated model of Climate and Economy (RICE), disaggregates these processes across multiple re-

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gions [Nordhaus and Yang, 1996] and has been extended to include tariffs and trade [Nordhaus, 2015, Lessmann et al., 2009].

Traditional IAMs such as DICE and RICE struggle to capture the strategic complexity of international climate negotiations. Their analytic formulations assume fixed policies or Nash equilibria [Nordhaus and Yang, 1996], making it difficult to represent coalition formation, commitment and adaptive strategies. They also lack mechanisms for evolving negotiation protocols, enforcement or the emergence of cooperation without central authority. As model fidelity increases, the high dimensionality of these multi-agent systems renders analytic solutions intractable [Pindyck, 2013, Farmer et al., 2015, Gazzotti, 2022].

To address these limitations, Zhang et al. introduced RICE-N, which augments RICE with multi-agent reinforcement learning (MARL) to endogenize strategic interaction [Zhang et al., 2025]. Agents learn behaviors through feedback and negotiation, forming trade and climate agreements dynamically. However, training these agents is computationally intensive, hindering large-scale sensitivity analysis and the exploration of richer negotiation protocols.

We therefore developed a **complete reimplementation of RICE-N in JAX** [Bradbury et al., 2018]. JAX provides hardware acceleration via XLA compilation and automatic vectorization, yielding substantial speedups that enable experiments previously infeasible. Training times are reduced by orders of magnitude, allowing population-based training, large-scale hyperparameter optimization and high-throughput policy evaluation.

More fundamentally, the JAX implementation introduces **full differentiability of the climate–economic simulation**. Every component—from climate dynamics and production to trade and negotiation—is differentiable with respect to parameters, initial conditions and policy choices. This enables gradient-based sensitivity analysis, differentiable policy optimization and exact computation of long-term climate derivatives with respect to early interventions. Beyond speed, differentiability unlocks entirely new research directions, outlined in Section 3 and demonstrated in Section 4.

2 Differentiable Climate-Economic Modeling with RICE-N-JAX

We present a high-performance implementation of RICE-N [Zhang et al., 2025], re-engineered entirely within the JAX ecosystem [Bradbury et al., 2018]. This re-implementation enables significant performance gains through JAX function transformations, such as `JIT` and `vmap`, for seamless vectorized execution on hardware accelerators like GPUs. This is particularly noteworthy when training RL agents fully end-to-end on the GPU [Lu et al., 2022]. Additionally, our new version allows us to easily differentiate through the entire economic simulation by simply decorating the environment step function with `@jax.grad`.

RICE-N-JAX is built to closely replicate the original RICE-N codebase and therefore retains the original modular and extendable design. However, the new codebase trains agents in minutes on typical office hardware, as opposed to hours in data centers. This enables much more comprehensive experimentation across sources of variations (e.g. seeds), as well as hyperparameters and design choices. Additionally, by retaining the original modularity and improving the performance, RICE-N-JAX enables further exploration of different and more complex climate-economic scenarios.

Our open-source code [2] comes equipped with the standard scenarios previously used in RICE-N. This facilitates replicating the original results and serves as an example for future extensions. Moreover, we provide notebook examples for data visualization and for exploring the differentiability of the simulation, including the code used in Section 4.

3 Research Directions

Automated calibration IAMs traditionally rely on manual or heuristic parameter tuning (e.g., genetic algorithms, particle swarm optimization) to match historical data—an expensive, expert-driven and often non-reproducible process [Pindyck, 2017]. With a fully differentiable implementation, calibration becomes a scalable gradient-based optimization problem. Differentiable IAMs can jointly

[2] `https://github.com/mila-iqia/climate-cooperation-competition/tree/GAIA_jax/rice_jax`

calibrate hundreds of parameters, far beyond the scope of non-gradient methods [Dyer et al., 2023, Kotthoff and Hamacher, 2022]. Similar approaches in hydrology and land modeling have yielded greater physical coherence and massive computational gains [Tsai et al., 2021, Fang et al., 2024]. Using multi-region input–output (MRIO) data, we can systematically calibrate trade preferences, production levels, mitigation efficiency and emissions histories across regions and time.

Sensitivity analysis Automatic differentiation (AD) enables direct computation of gradients, Jacobians and Hessians of outcomes (e.g., welfare, emissions, temperature) with respect to model parameters, states or policies. This provides fine-grained insights into which assumptions drive results, complementing costly perturbation-based analyses that scale poorly with dimensionality [Kim et al., 2006]. It also supports systematic investigation of key uncertainties, such as the dominance of economic-growth parameters in IAM projections [Nordhaus, 2017].

Uncertainty quantification Differentiability also enables efficient probabilistic calibration and uncertainty quantification. Combining AD with methods such as Laplace approximations, variational inference or Hamiltonian Monte Carlo [Betancourt, 2018, Qu et al., 2024, Weber et al., 2025] yields full posterior distributions rather than point estimates [Gelbrecht et al., 2023]. These uncertainties can be propagated through rollouts or incorporated into RL training [Moerland et al., 2022], offering a principled approach to generate climate–economic futures and probabilities for policy analysis.

Inverse modeling Differentiability enables inverse modeling—inferring latent regional behavioral parameters (e.g., risk aversion, time preferences, mitigation bias) from observed trajectories. Similar to geoscientific inversion [Shen et al., 2023], this approach can reveal structural inequalities in trade and development. For example, MRIO data can uncover unequal exchange coefficients that capture export undercompensation in embodied resources and labor [Hickel et al., 2022]. By perturbing the inferred coefficients, we can explore counterfactual developmental trajectories and illustrate novel climate-economic scenarios.

Differentiable mechanism design Parameterizing negotiation protocols within the model allows gradient-based optimization of cooperative mechanisms [Conitzer and Sandholm, 2014, Bichler and Parkes, 2025]. Tariff levels, membership rules or enforcement penalties in climate clubs can be treated as learnable parameters, guiding designs that maximize long-term welfare or cooperation. This creates a pathway for using ML methods to the design of international governance structures.

Joint agent–environment training In MARL, differentiability enables co-adaptation: simultaneously learning agent policies and adapting environment parameters [Padakandla, 2021]. This bi-level optimization reveals how alternative economic assumptions or climate responses co-evolve with strategy learning, identifying structural conditions that promote stable cooperation and alignment between self-interest and global welfare.

Hybrid IAMs Differentiable IAMs can be combined with data-driven components to form hybrid models that bridge process-based theory and machine learning [Reichstein et al., 2019]. Similar approaches are transforming Earth System Models, where neural components complement physical representations of unresolved processes [Beucler, 2025]. In climate–economic modeling, analytical modules such as production, damages or abatement can be augmented with neural surrogates trained on empirical or high-resolution simulation data, capturing socio-economic dynamics difficult to formalize analytically. Embedded within frameworks like RICE-N, these modules retain end-to-end differentiability while enhancing realism and flexibility. Universal Differential Equation (UDE) formulations [Rackauckas et al., 2021] provide a natural foundation, enabling joint optimization of physical and neural components. The result is a new class of IAMs that remain empirically grounded, theoretically coherent and interpretable for policy.

4 Proof of Concept

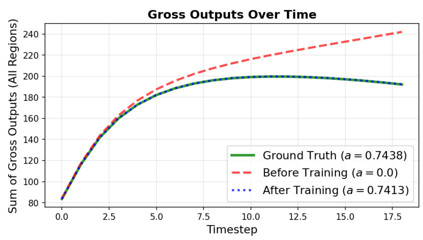
As a proof of concept, we perform an end-to-end calibration of the damage function, a key IAM component linking temperature increases to economic losses. It has long been criticized as arbitrary or poorly justified [Pindyck, 2017, Drupp and Hänsel, 2021]. We adopt a functional form from recent meta-analyses [Howard and Sterner, 2017, Hänsel et al., 2020]:

$$f_{\text{dmg}}(T) = 1 - \frac{aT^2}{100},$$

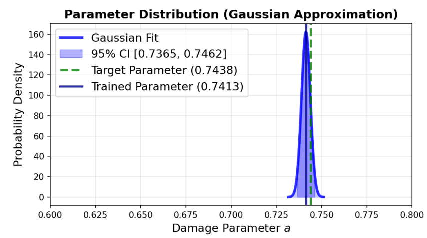
where the true parameter $a = 0.7438$ serves as the calibration target.

Training Data To generate training data, we fixed a to its target value and rolled out the environment under static agent policies (no mitigation, savings rate $= 0.25$). The aggregate gross output across all regions—directly affected by climate damages—served as the calibration target, though other observables such as temperature or regional output could also be used.

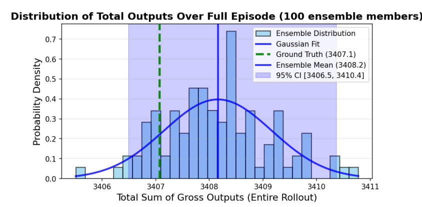
Calibration of the Damage Function Starting from $a = 0$ (no damages), we optimized a using Adam for 400 iterations in the differentiable environment. As shown in Figure 1a, simulated gross output initially deviated from the ground truth but converged rapidly. The estimated $a = 0.7413$ closely matches the target, showing that differentiable calibration efficiently recovers structural parameters.



(a) Gross output trajectories over time before and after calibration.



(b) Laplace-approximated posterior for the damage parameter a.



(c) Histogram of outputs over stochastic rollouts based on the uncertainty of the damage parameter.

Figure 1: Combined visualization of calibration results: (a) Gross output trajectories over time before and after calibration. (b) Laplace-approximated posterior for the damage parameter a. (c) Histogram of outputs over stochastic rollouts based on the uncertainty around the damage parameter.

Uncertainty Estimation Rather than scenario-based sensitivity tests, we leverage differentiability to compute the Hessian of the loss with respect to a, yielding a Laplace-approximated posterior variance. Figure 1b shows the Gaussian approximation centered near the estimate, with the true value within the 95% confidence interval.

Stochastic Rollout Using this inferred uncertainty, we ran Monte Carlo rollouts to quantify how uncertainty in a propagates to economic outcomes. The JAX implementation enables efficient stochastic inference even in high-dimensional settings, as illustrated by the output distribution in Figure 1c.

5 Conclusion

Next Steps Future work will extend this demonstration beyond a single parameter by using empirical or scenario-based datasets (e.g., GDP or emissions from SSP or NGFS) as ground truth for multi-parameter calibration. The differentiable framework also enables non-parametric damage functions, where neural or spline-based surrogates $f_{\text{dmg}}(T; \theta)$ are fitted directly to data, relaxing quadratic assumptions while preserving interpretability through smoothness and monotonicity constraints. This evolution moves from estimating scalar coefficients to learning functional relationships, supporting data-informed and flexible damage formulations in next-generation IAMs.

Summary This proof of concept shows how differentiability transforms IAM calibration from manual tuning into systematic, data-driven optimization. RICE-N-JAX can efficiently reproduce established results while serving as a foundation for hybrid, empirically grounded climate–economic modeling.

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References

Hans O Pörtner, Debra C Roberts, Helen Adams, Carolina Adler, Paulina Aldunce, Elham Ali, Rawshan Ara Begum, Richard Betts, Rachel Bezner Kerr, Robbert Biesbroek, et al. Climate change 2022: impacts, adaptation and vulnerability, 2022.

Stephen M Gardiner. The real tragedy of the commons. *Philosophy & public affairs*, 30(4):387–416, 2001.

Peter Erickson, Sivan Kartha, Michael Lazarus, and Kevin Tempest. Assessing carbon lock-in. *Environmental Research Letters*, 10(8):084023, 2015.

William D. Nordhaus. A review of the Stern review on the economics of climate change. *Journal of economic literature*, 45(3):686–702, 2007.

William D. Nordhaus and Zili Yang. A regional dynamic general-equilibrium model of alternative climate-change strategies. *The American Economic Review*, pages 741–765, 1996.

William D. Nordhaus. Climate clubs: Overcoming free-riding in international climate policy. *American Economic Review*, 105(4):1339–70, 2015.

Kai Lessmann, Robert Marschinski, and Ottmar Edenhofer. The effects of tariffs on coalition formation in a dynamic global warming game. *Economic Modelling*, 26(3):641–649, 2009.

Robert S. Pindyck. Climate change policy: What do the models tell us? *Journal of Economic Literature*, 51(3):860–72, September 2013. doi: 10.1257/jel.51.3.860. URL `https://www.aeaweb.org/articles?id=10.1257/jel.51.3.860`.

J Doyne Farmer, Cameron Hepburn, Penny Mealy, and Alexander Teytelboym. A third wave in the economics of climate change. *Environmental and Resource Economics*, 62(2):329–357, 2015.

Paolo Gazzotti. Rice50+: Dice model at country and regional level. *Socio-Environmental Systems Modelling*, 4:18038–18038, 2022.

Tianyu Zhang, Andrew Robert Williams, Phillip Wozny, Kai-Hendrik Cohrs, Koen Ponse, Marco Jiralerspong, Soham Rajesh Phade, Sunil Srinivasa, Lu Li, Yang Zhang, Prateek Gupta, Erman Acar, Irina Rish, Yoshua Bengio, and Stephan Zheng. AI for global climate cooperation: Modeling global climate negotiations, agreements, and long-term cooperation in RICE-n. In *Forty-second International Conference on Machine Learning*, 2025. URL `https://openreview.net/forum?id=PX29zF9wRb`.

James Bradbury, Roy Frostig, Peter Hawkins, Matthew James Johnson, Chris Leary, Dougal Maclaurin, George Necula, Adam Paszke, Jake VanderPlas, Skye Wanderman-Milne, and Qiao Zhang. JAX: composable transformations of Python+NumPy programs, 2018. URL `http://github.com/jax-ml/jax`.

Chris Lu, Jakub Kuba, Alistair Letcher, Luke Metz, Christian Schroeder de Witt, and Jakob Foerster. Discovered policy optimisation. *Advances in Neural Information Processing Systems*, 35:16455–16468, 2022.

Robert S. Pindyck. The use and misuse of models for climate policy. *Review of Environmental Economics and Policy*, 11(1):100–114, 2017. doi: 10.1093/reep/rew012. URL `https://doi.org/10.1093/reep/rew012`.

Joel Dyer, Arnau Quera-Bofarull, Ayush Chopra, J. Doyne Farmer, Anisoara Calinescu, and Michael Wooldridge. Gradient-assisted calibration for financial agent-based models. In *Proceedings of the Fourth ACM International Conference on AI in Finance*, ICAIF '23, page 288–296, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400702402. doi: 10.1145/3604237.3626857. URL `https://doi.org/10.1145/3604237.3626857`.

Florian Kotthoff and Thomas Hamacher. Calibrating agent-based models of innovation diffusion with gradients. *Journal of Artificial Societies and Social Simulation*, 25(3):4, 2022. ISSN 1460-7425. doi: 10.18564/jasss.4861. URL `http://jasss.soc.surrey.ac.uk/25/3/4.html`.

Wen-Ping Tsai, Dapeng Feng, Ming Pan, Hylke Beck, Kathryn Lawson, Yuan Yang, Jiangtao Liu, and Chaopeng Shen. From calibration to parameter learning: Harnessing the scaling effects of big data in geoscientific modeling. *Nat. Commun.*, 12(1):5988, October 2021.

Jianing Fang, Kevin Bowman, Wenli Zhao, Xu Lian, and Pierre Gentine. Differentiable land model reveals global environmental controls on ecological parameters, 2024. URL https://arxiv.org/abs/2411.09654.

Jong G. Kim, Elizabeth C. Hunke, and William H. Lipscomb. Sensitivity analysis and parameter tuning scheme for global sea-ice modeling. *Ocean Modelling*, 14(1):61–80, 2006. ISSN 1463-5003. doi: https://doi.org/10.1016/j.ocemod.2006.03.003. URL https://www.sciencedirect.com/science/article/pii/S146350030600028X.

William Nordhaus. Integrated assessment models of climate change. *NBER Reporter*, pages 16–20, 2017. URL https://hdl.handle.net/10419/178753.

Michael Betancourt. A conceptual introduction to hamiltonian monte carlo, 2018. URL https://arxiv.org/abs/1701.02434.

Yongquan Qu, Mohamed Aziz Bhouri, and Pierre Gentine. Joint parameter and parameterization inference with uncertainty quantification through differentiable programming, 2024. URL https://arxiv.org/abs/2403.02215.

Tobias Weber, Bálint Mucsányi, Lenard Rommel, Thomas Christie, Lars Kasüschke, Marvin Pförtner, and Philipp Hennig. laplax – laplace approximations with jax, 2025. URL https://arxiv.org/abs/2507.17013.

M. Gelbrecht, A. White, S. Bathiany, and N. Boers. Differentiable programming for earth system modeling. *Geoscientific Model Development*, 16(11):3123–3135, 2023. doi: 10.5194/gmd-16-3123-2023. URL https://gmd.copernicus.org/articles/16/3123/2023/.

Thomas M. Moerland, Joost Broekens, Aske Plaat, and Catholijn M. Jonker. Model-based reinforcement learning: A survey, 2022. URL https://arxiv.org/abs/2006.16712.

Chaopeng Shen, Alison P. Appling, Pierre Gentine, Toshiyuki Bandai, Hoshin Gupta, Alexandre Tartakovsky, Marco Baity-Jesi, Fabrizio Fenicia, Daniel Kifer, Li Li, Xiaofeng Liu, Wei Ren, Yi Zheng, Ciaran J. Harman, Martyn Clark, Matthew Farthing, Dapeng Feng, Praveen Kumar, Doaa Aboelyazeed, Farshid Rahmani, Yalan Song, Hylke E. Beck, Tadd Bindas, Dipankar Dwivedi, Kuai Fang, Marvin Höge, Chris Rackauckas, Binayak Mohanty, Tirthankar Roy, Chonggang Xu, and Kathryn Lawson. Differentiable modelling to unify machine learning and physical models for geosciences. *Nature Reviews Earth & Environment*, 4(8):552–567, Aug 2023. ISSN 2662-138X. doi: 10.1038/s43017-023-00450-9. URL https://doi.org/10.1038/s43017-023-00450-9.

Jason Hickel, Christian Dorninger, Hanspeter Wieland, and Intan Suwandi. Imperialist appropriation in the world economy: Drain from the global south through unequal exchange, 1990–2015. *Global environmental change*, 73, 2022.

Vincent Conitzer and Tuomas Sandholm. Complexity of mechanism design, 2014. URL https://arxiv.org/abs/1408.1486.

Martin Bichler and David C. Parkes. Differentiable economics: Strategic behavior, mechanisms, and machine learning. *Commun. ACM*, 68(9):80–88, August 2025. ISSN 0001-0782. doi: 10.1145/3725809. URL https://doi.org/10.1145/3725809.

Sindhu Padakandla. A survey of reinforcement learning algorithms for dynamically varying environments. *ACM Comput. Surv.*, 54(6), July 2021. ISSN 0360-0300. doi: 10.1145/3459991. URL https://doi.org/10.1145/3459991.

Markus Reichstein, Gustau Camps-Valls, Bjorn Stevens, Martin Jung, Joachim Denzler, Nuno Carvalhais, and Prabhat. Deep learning and process understanding for data-driven earth system science. *Nature*, 566(7743):195–204, February 2019.

T. Beucler. Towards Hybrid Earth System Modeling: A Living Review (v1.0). https://doi.org/10.5281/zenodo.16967529, 2025. GitHub repository with a living review.

Christopher Rackauckas, Yingbo Ma, Julius Martensen, Collin Warner, Kirill Zubov, Rohit Supekar, Dominic Skinner, Ali Ramadhan, and Alan Edelman. Universal differential equations for scientific machine learning, 2021. URL https://arxiv.org/abs/2001.04385.

Moritz A. Drupp and Martin C. Hänsel. Relative prices and climate policy: How the scarcity of nonmarket goods drives policy evaluation. *American Economic Journal: Economic Policy*, 13 (1):168–201, February 2021. doi: 10.1257/pol.20180760. URL https://www.aeaweb.org/articles?id=10.1257/pol.20180760.

Peter H. Howard and Thomas Sterner. Few and not so far between: A meta-analysis of climate damage estimates. *Environmental and Resource Economics*, 68(1):197–225, Sep 2017. ISSN 1573-1502. doi: 10.1007/s10640-017-0166-z. URL https://doi.org/10.1007/s10640-017-0166-z.

Martin C. Hänsel, Moritz A. Drupp, Daniel J. A. Johansson, Frikk Nesje, Christian Azar, Mark C. Freeman, Ben Groom, and Thomas Sterner. Climate economics support for the un climate targets. *Nature Climate Change*, 10(8):781–789, Aug 2020. ISSN 1758-6798. doi: 10.1038/s41558-020-0833-x. URL https://doi.org/10.1038/s41558-020-0833-x.

6 Appendix

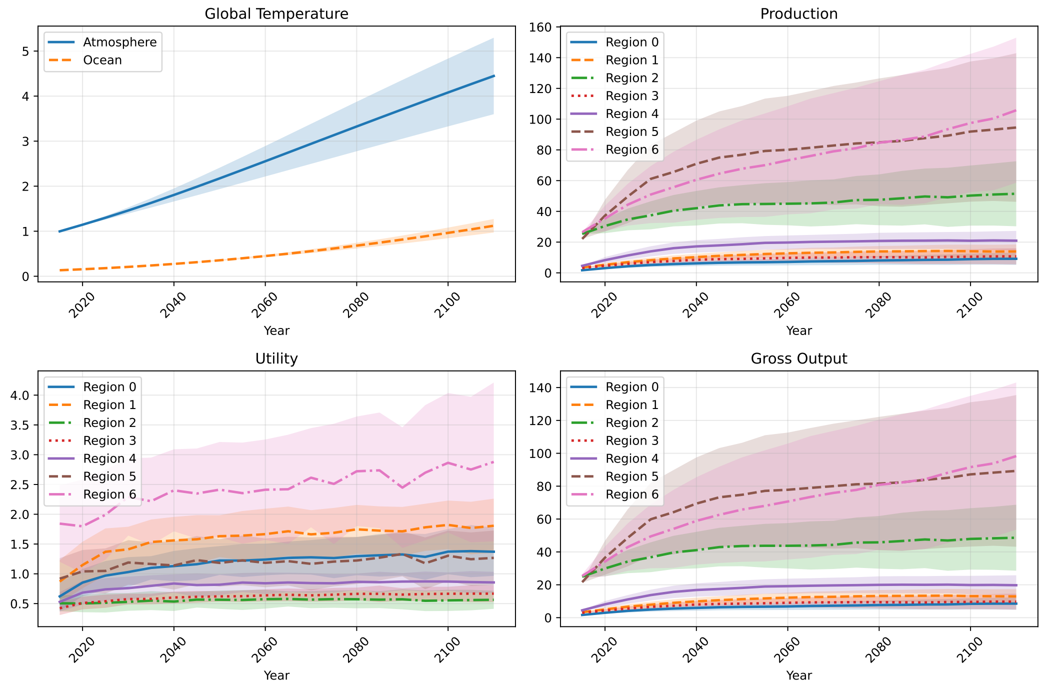

Figure 2: State attributes throughout an episode averaged over a 1000 rollouts with the shaded area representing standard deviation. To obtain these results, we trained all agents 100 times in a negotiation disabled setting for 1 million timesteps. After each training run we performed 10 rollouts.