Response to referee comments

Referee comments are in black.
Responses are in blue. We indicate where in the text the changes can be found by L followed by a number that gives the line number.
Manuscript citations are in italic with changes in red.

This study presents a new framework that couples an Earth System Model with a spatially disaggregated Integrated Assessment Model to examine how climate change (i.e., temperature changes) interacts with the economy. The baseline simulation in the study shows that the economic impacts of global warming differ substantially across regions and that internal climate variability leads to significant volatility in regional GDP, emphasizing the value of high-resolution economic impact assessments. The model that this study presents fills an important gap left by previous frameworks that used coarse spatial aggregation, simplified climate representation, or weak coupling between climate and the economy. However, several aspects should be addressed before the manuscript is ready for publication.

Thank you for the careful reading and constructive comments, which we will address in our revision.

Major Comments:

1. There are several existing coupled ESM-IAM frameworks (e.g., E3SM–GCAM (Di Vittorio et al., 2025), iESM (Collins et al., 2015; Thornton et al., 2017)), and it would be helpful for the authors to explicitly acknowledge these efforts and situate NorESM2–DIAM within this broader context. Unlike E3SM–GCAM and iESM, which exchange CO_2 emissions, terrestrial productivity, and land-use information, NorESM2–DIAM currently exchanges only CO_2 emissions and temperature, with economic impacts represented through an aggregate productivity function.

   While this design allows for fine spatial resolution and transparent temperature–productivity relationships, it omits key land-mediated feedbacks, e.g., those related to land cover, albedo, soil carbon, and evapotranspiration,that are represented in NorESM2's land module. I understand that as a spatially disaggregated macroeconomic IAM, DIAM occupies a distinct niche relative to process-based IAMs like GCAM, IMAGE, and MESSAGE, which explicitly simulate land, energy, and technological dynamics. A concise discussion of these trade-offs, what NorESM2–DIAM gains in spatial detail and simplicity, and what it sacrifices in process feedbacks, would help readers clearly understand its comparative advantages and intended applications.

references:

Di Vittorio, A. V., Sinha, E., Hao, D., Singh, B., Calvin, K. V., Shippert, T., ... & Bond-Lamberty, B. (2025). E3SM-GCAM: A synchronously coupled human component in the E3SM Earth system model enables novel human-Earth feedback research. Journal of Advances in Modeling Earth Systems, 17(6), e2024MS004806.

Collins, William D., Anthony P. Craig, John E. Truesdale, A. V. Di Vittorio, Andrew D. Jones, Benjamin Bond-Lamberty, Katherine V. Calvin et al. "The integrated Earth system model version 1: formulation and functionality." Geoscientific Model Development 8, no. 7 (2015): 2203-2219.

Thornton, P. E., Calvin, K., Jones, A. D., Di Vittorio, A. V., Bond-Lamberty, B., Chini, L., ... & Hurtt, G. (2017). Biospheric feedback effects in a synchronously coupled model of human and Earth systems. Nature Climate Change, 7(7), 496-500.

Thank you for pointing out these models. We agree that this should be included and have added a couple of paragraphs that compare our model with models like iESM and E2SM-GCAM. (This also included some small adjustments to the previous paragraphs for better flow.) (L57-89)

… Finally, NorESM2--DIAM is a cost-benefit IAM ~~capable of evaluating~~: economic agents (consumers and firms) in the model solve explicitly-specified dynamic decision problems with well-defined objectives. It can therefore provide quantitative assessments of the welfare effects ~~across time and space~~ of a wide range of scenarios for climate policy---from laissez-faire to optimal carbon taxation---both across time and space.

~~However, t~~The primary goal of this paper, however, is to demonstrate, using a prototype version of NorESM2--DIAM, how to tackle two key methodological challenges in coupling an ESM with a dynamic, high-resolution economic model grounded in dynamic optimization. First, the two models operate on vastly different time scales. Second, the economic model incorporates forward-looking behavior: the decisions of agents ~~(consumers and firms)~~ depend on their expectations about the future behavior of the climate, which is itself influenced by those very decisions. Achieving consistency between agents' expectations and the climate trajectory thus requires solving for an interdependent equilibrium.

Successfully addressing these challenges lays the groundwork for using NorESM2–DIAM as a platform to explore the spatial and temporal dimensions of *climate–economy interactions, and to assess climate policy with a degree of geophysical and economic realism that is rare in existing IAMs. This platform contributes to a small but growing literature using dynamic, forward-looking, structural economic models to study the spatial effects of climate change (see, for example, Brock et al., 2014; Desmet and Rossi-Hansberg, 2015; Fried, 2022; Krusell and Smith, 2022; Rudik et al., 2021; Bilal and Rossi-Hansberg, 2023; Cruz and Rossi-Hansberg, 2024; Kubler, 2023; Kotlikoff et al., 2024).*

Our approach to coupling an ESM and an IAM, embodied in NorESM2–DIAM, contrasts with the approach taken in iESM (Collins et al., 2015; Thornton et al., 2017; Calvin and Bond-Lamberty, 2018) and E3SM–GCAM (Di Vittorio et al., 2025), two other frameworks that couple an ESM and an IAM. The main difference is that both iESM and E3SM–GCAM couple an ESM with the Global Change Assessment Model (GCAM), a process-based rather than a cost-benefit IAM. Although both DIAM and GCAM are dynamic, recursive models, in DIAM agents make decisions taking into account the entire future time horizon, whereas GCAM solves for outcomes one step at a time, considering only the current state.

The two approaches also differ in spatial resolution and sectoral detail. GCAM represents multiple sectors—including energy, industry, transport, agriculture, and land use—but divides the world into only 14 (iESM) or 32 (E3SM-GCAM) socioeconomic regions. In contrast, NorESM2–DIAM contains only a single sector, focusing directly on gross domestic product (GDP), but at a very high degree of spatial resolution (1°×1° cells), enabling high-resolution analysis of the impacts of climate and weather on GDP and emissions.

Finally, the three models differ in how they represent climate–economy interactions. iESM and E3SM-GCAM exchange biogeochemical variables from the ESM to GCAM, whereas in our framework, temperature directly affects the economy through the productivity of labor. GCAM also explicitly represents agriculture and land use, allowing iESM and E3SM–GCAM to generate land-mediated feedbacks that are absent in NorESM–DIAM. Thus, although all three frameworks couple an IAM with an ESM, our approach employs a fundamentally different IAM, providing a complementary perspective to the two existing frameworks.

2. Explanation of aggregate GDP deviations (Lines 600–602)

   The current explanation, that aggregate GDP deviations persist mainly due to spatially correlated temperatures and concentrated economic activity, is not entirely convincing to me. Spatial correlation in temperature does not necessarily translate to homogeneous economic responses. For example, the northern and southern United States likely respond differently to warming: although northern regions show greater temperature increases than southern ones (Figure 11), they still experience gains in GDP per capita, whereas parts of the South show declines (Figure 12). This pattern may reflect differences in each region's position relative to the optimal temperature shown in Figure 3. I encourage the authors to revise this explanation.

We agree that the explanation needed to be fleshed out more. We now include a comparison with a simulation without spatial correlation (as simulated by the standalone model), which gives aggregated GDP deviations that are an order of magnitude smaller than in the coupled model with spatial correlation. Additionally, we have added a stylised example in the appendix to further demonstrate the role of spatial correlation in generating aggregate GDP fluctuations. (L623-633)

Finally, as shown in Fig. 11 (b), global GDP itself experiences large fluctuations relative to its trend, about 1% in magnitude. The patterns of spatial correlation in regional temperatures generated by NorESM2 play a key role in driving this variability in global GDP. To examine the role of these patterns, we simulated the behavior of the standalone model with regional temperature shocks drawn according to Eq. (2), with the parameters of the regional AR(1) processes calibrated to simulated data from NorESM2 as described in Sect. 4. In the standalone model, these shocks are assumed to be statistically independent across regions and therefore exhibit no spatial correlation by construction. In this case, fluctuations in global GDP are about 0.1%, an order of magnitude smaller than in the fully-coupled model. Failing to account for patterns of spatial correlation would therefore lead to a large understatement of volatility in global GDP.

To gain further insight into the role of spatial correlation in generating aggregate fluctuations, Sect. A8 in Appendix A shows analytically, in a stylized model, that spatial correlation can amplify the size of these fluctuations under certain conditions that our calibrated model satisfies.

~~percentage term. Evidently, even though the number of regions is large, deviations of regional GDP do not wash out in the aggregate, for two reasons. First, regional temperatures are correlated in space. Second, economic activity is highly concentrated in space. As a result, the effective number of regions is much smaller than 19,000, slowing down the action of the law of large numbers.~~

Added in Appendix A1 (L708-709):

Section A8 uses a stylized model to examine the role of spatial correlation in generating fluctuations in global aggregates.

From Appendix A8 (L926-944)

A8 Spatial correlation and aggregate fluctuations: a stylized model

This section uses a stylized model that captures some of the key features of NorESM2–DIAM to show that spatial correlation in regional temperatures can amplify aggregate fluctuations under certain conditions that our calibrated model satisfies.

Consider a model in which regional temperatures are drawn from a jointly normal distribution at any point in time. Specifically, assume that

$$T = (T_1, \ldots, T_M)^\top \sim N(\overline{T}_i, \Sigma),$$

with $\Sigma_{ii} = \sigma^2$ and $\Sigma_{ij} = \rho\sigma^2$ for $i \neq j$, where $\rho \in [0,1]$. Define $\hat{T}_i \equiv T_i - T^*$ and $\mu_i \equiv \overline{T}_i - T^*$, where T^* maximizes the damage function. Then $\hat{T}_i \sim N(\mu_i, \sigma^2)$ and $\text{corr}(T_i, T_j) = \rho$ for $i \neq j$, i.e., the deviation of regional temperature from the optimal temperature, T^*, is normally distributed with a region-specific mean, μ_i, and a common variance, σ^2, across regions; and the correlation between temperature deviations in any pair of regions is equal to ρ.

Assume that the damage function $D(T_i) = \exp(-\kappa(T_i - T^*)^2)$, so that D is symmetric around the optimal temperature (in NorESM2–DIAM, by contrast, the damage function is not quite symmetric).

Let each region be assigned a weight w_i, with

$$\sum_{i=1}^{M} w_i = 1.$$

and let S be the weighted average of the logarithm of regional productivity:

$$S \equiv \sum_{i=1}^{M} w_i \log D(T_i) = -\lambda \sum_{i=1}^{M} w_i \hat{T}_i^2.$$

The variance of S is then a measure of the volatility of aggregate productivity, one of the key drivers of volatility in global GDP. The question is how this variance varies as the correlation between regional temperatures increases. The variance is given by:

$$\text{Var}(S) = 2\sigma^2\lambda^2 \left[\sigma^2 W_2 + 2M_2 + \sigma^2\rho^2(1 - W_2) + 2\rho(M_1^2 - M_2)\right],$$

where

$$M_1 \equiv \sum_{i=1}^{M} w_i\mu_i,\ M_2 \equiv \sum_{i=1}^{M} w_i^2\mu_i^2,\ W_2 \equiv \sum_{i=1}^{M} w_i^2.$$

This expression is an increasing function of ρ over the entire range $[0,1]$ if and only if $M_1^2 - M_2 > 0$, or equivalently, if and only if $R \equiv M_1^2/M_2 > 1$.

This condition can be checked using different weighting schemes for the 16,826 distinct cells in NorESM2–DIAM, with the μ_is corresponding to the deviation of regional pre-industrial temperatures from the optimal temperature. Most relevant for global GDP is weights corresponding to regional GDP in 1990, in which case $R = 184.4$. Alternatively, for weights corresponding to regional population in 1990, $R = 722.5$. In both cases, therefore, the required condition is easily satisfied.

Although this simple model is quite stylized in that it does not correspond exactly to the behavior of NorESM2–DIAM, nonetheless these calculations do suggest that positive spatial correlation between regional temperatures amplifies aggregate fluctuations in NorESM2–DIAM. They are also consistent with the finding reported in Sect. 5.4 that the standalone model (in which spatial correlation is absent) produces much smaller aggregate fluctuations than the fully-coupled model.

Minor Comments:

1. Line 586: Please double-check "(see Fig. 4.5)". I cannot find Figure 4.5. Perhaps this refers to Section 4.5 instead?

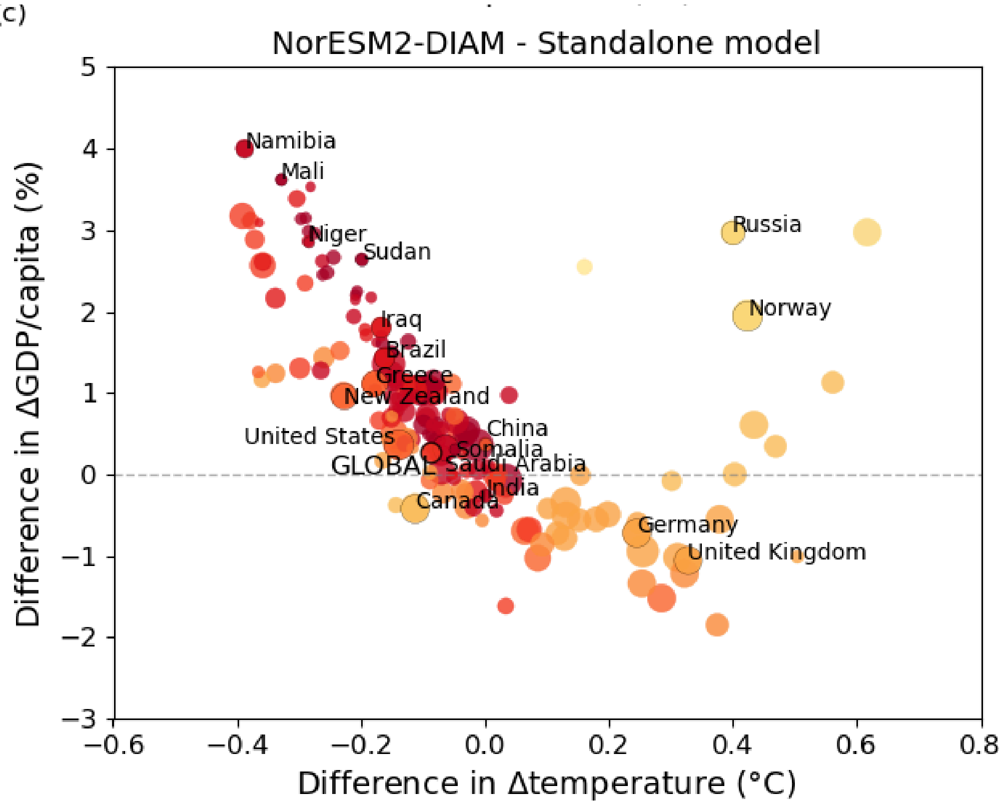
Indeed, this should be “section” rather than “figure”. This is now fixed. (L610)

Second, average regional temperatures vary greatly across space, so that regions are located at very different points along the inverse U-shaped damage function (see Sect. ~~Fig.~~ 4.5) determining regional productivity.

2. Figure 13(c): Some regional labels overlap and are difficult to read. I suggest adjusting the layout or font size to improve readability.

The labels are now adjusted so that they do not overlap. (Page 28)

(c)



3. Figure 5: There appears to be a sharp change between 2100 and 2120. Could the authors clarify the potential reason for this sharp change?

We have made the text clearer and added a clarification for this sharp change in the text (L451-465):

… We assume that $\phi_t = 0$ for $t \geq t_g$, after which point energy use is fully green. ~~We assume that $\phi_t = 0$ for $t \geq t_g = 111$, implying that energy use is fully green by the year 2100.~~

…

This function is close to 1 when t=0 and declines slowly at first before accelerating, with H(10) = 0.99, ~~and~~ H(75) = 0.5, and H(140) = 0.01. …

…

To conserve on computation time, we run the fully-coupled model only until 2100, at which point we assume that energy use becomes fully green (i.e., we set t_g = 111). We make this assumption so that, when computing decision rules using the standalone model, regional temperatures reach a steady state in 2100. The resulting small kink in the greening function has negligible effects on the quantitative results because annual emissions are already quite low by 2100 and, consequently, their impact on cumulative emissions is close to zero by that point.