Impacts of Different Spatial Resolution on Land-Use Downscaling

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1. Introduction

Land is fundamental to human survival and well-being, providing essential ecosystem services such as food, freshwater, and biodiversity. The AFOLU sector contributes about 21% of global anthropogenic greenhouse gas emissions while absorbing roughly 33% of anthropogenic CO_2, underscoring its critical role in climate change mitigation[1]. Therefore, analyzing the impacts of mitigation policies on land use is essential for achieving sustainable land management.

The estimation of spatial land-use map is conducted by Integrated Assessment Models (IAMs), while analyzing the impact of land-use change on natural environment is supported by Earth System Models (ESMs). In previous IPCC reports, the linkage between IAMs and ESMs has been weak; however, linking these two model types is essential for capturing the impacts of land-use change on natural processes and the associated feedback, since IAMs focus on representing human activities and policy scenarios, while ESMs simulate biophysical processes within the Earth system[1].

In the formulation of climate and energy policies, IAMs have been widely used as essential analytical tools. While land-use representations in most IAMs are already implemented at the grid level through downscaling or spatial allocation schemes, key supply-side information—particularly agricultural market variables such as production, trade, and demand— is typically handled at highly aggregated regional scales. This regional aggregation of agricultural market information can obscure spatial heterogeneity embedded at finer scales and weaken the transmission of upstream signals to land-use allocation processes. To address this limitation, we combine AIM-ALPHA with AIM-PLUM (both models are explained in section 2) under an alternative aggregation framework that disaggregates agricultural market outputs into approximately 400 regions prior to land-use allocation. By retaining finer spatial units in the representation of agricultural markets, this approach enables a more consistent linkage between market-driven production estimates and grid-level land-use patterns.

In this study, land-use distribution data estimated by AIM-ALPHA are aggregated into 17-region and 400-region configurations and subsequently downscaled using the same AIM-PLUM model to generate land-use change estimates for both cases. By comparing these two estimates, we aim to assess how differences in input spatial resolution influence land-use downscaling outcomes, with particular emphasis on their agreement with reference data and their ability to convey upstream model outputs.

2. Methodology

In this study, the land allocation model AIM-PLUM was used to perform downscaling under different regional resolutions, and we analyzed the resulting differences in spatial distributions. First, land-use change is estimated using AIM-ALPHA, and the resulting outputs are aggregated into 17-region and 400-region configurations. The 17-region aggregation divides the globe into 17 predefined macro-regions and aggregates agricultural and land-use projections at the regional level, whereas the 400-region aggregation groups land-use data by approximately 400 river basins (hereafter referred to as region mode and basin mode, respectively). These two aggregated datasets are then downscaled to a grid-based resolution under the same scenario, and the resulting spatial patterns are compared and analyzed. The estimation period spans from 2005 to 2100 at 10-year intervals. The baseline year is 2005, and the estimation covers the whole world.

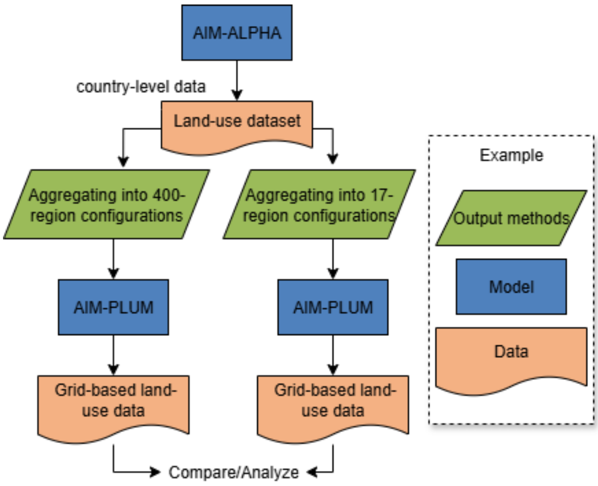

Figure 1 Overview of the study

The AIM-ALPHA model is a recursive dynamic partial equilibrium model with an annual time step, focusing on agricultural markets and land-use[2]. The model operates on an annual time step and was developed to simulate long-term agricultural and land-use dynamics. A key feature of the model is its relatively high spatial resolution at the country and basin levels, enabling simulations from the base year 2015 through 2100. On the demand side, the model represents 166 countries and regions worldwide, while the production side consists of 400 production units. These production units are defined by overlaying the 166 country and regional divisions with 230 major river basin boundaries defined by the Food and Agriculture Organization of the United Nations. Food commodities are categorized into 13 primary crops, 6 livestock products, and 3 processed products. Production is represented using a Leontief-type production function. Primary crops and livestock products require land and are produced at the production unit level, whereas processed products that do not require land are defined at the demand-side regional level across the 166 regions. Land-use is classified into five categories: cropland, pastureland, forest, other natural land, and non-arable land. Land allocation is determined by a hierarchical Logit function based on land prices. Demand is driven by population and GDP, and changes over time while accounting for income elasticity. Prices are endogenously determined at the equilibrium point of domestic supply and demand. Within domestic markets, equilibrium is maintained among production, demand, and net imports or exports, while in international markets the balance between total global imports and exports must hold. International trade is formulated using complementarity conditions. Import prices function as an upper bound for domestic prices, while export prices serve as a lower bound, thereby linking domestic market equilibrium with international prices. Commodities that have neither production nor trade in the base year are assumed not to be introduced in that country in future periods. The model is calibrated using multiple datasets, including those from the Food and Agriculture Organization of the United Nations, the Global Trade Analysis Project, and the Land-Use Harmonization 2 dataset.

AIM-PLUM is a global land-use allocation model which downscales land-use projections from IAMs to a grid-based resolution of 0.5° by applying profit-maximization principle, in which profit is defined as the difference between revenue and land conversion costs, with calculation methods differing between crops and afforestation[3]. In the model, cropland and afforestation areas are allocated according to the principle of profit maximization. Profit is defined as revenue minus land conversion cost, although the calculation method differs between crop production and afforestation activities. Land conversion costs include expenditures associated with road construction, irrigation infrastructure, and carbon emission costs. The model considers seven crop categories: rice, wheat, other coarse grains, oil crops, sugar crops, bioenergy crops, and other crops. For each crop type, irrigated and rainfed production systems are distinguished. Land allocated for timber production is not included in the model. In addition, constraints are imposed on the share of each land-use category. All calculations are conducted independently for each region, and therefore land transactions between regions are not assumed in the model framework. Land productivity and carbon storage density are estimated using outputs from the LPJmL (Lund–Potsdam–Jena managed Land) model and the VISIT (Vegetation Integrative SImulator for Trace gases) model. The base-year land-use map is constructed using cropland data from Monfreda et al. (2008), along with datasets from the United Nations Environment Programme and the Food and Agriculture Organization of the United Nations. Although the model was originally developed to downscale outputs from the AIM-Hub framework, it has been further extended to accommodate the 400 regional units used in the AIM-ALPHA model in order to produce estimates at higher spatial resolution.

In this study, the biodiversity assessment model PREDICTS was used to evaluate how differences in land-use distributions derived from different spatial resolution inputs influence environmental impact assessment. PREDICTS is a modeling project designed to assess the impacts of land-use change on biodiversity using a global biodiversity database[4]. It utilizes an integrated global dataset[5] that standardizes biodiversity observations collected from numerous studies worldwide together with associated regional information. Based on this database, PREDICTS constructs two types of statistical models: the Total Abundance model, which explains changes in species abundance, and the Compositional Similarity model, which explains the similarity of species composition relative to primary natural vegetation. In this study, PREDICTS is applied to estimate the Biodiversity Intactness Index (BII) using land-use change downscaling results derived from inputs with different spatial resolutions. BII represents the degree to which biodiversity remains intact relative to primary natural conditions; values closer to 1 indicate a state closer to undisturbed natural ecosystems, whereas values closer to 0 indicate a greater loss of biodiversity integrity.

To evaluate the degree of agreement between model predictions and reference data, as well as the consistency of estimation results across different years, the Kappa coefficient was employed[6]. The Kappa coefficient ranges from 0 to 1, with values closer to 1 indicating a higher level of agreement between two maps. Conversely, values close to 0 indicate that the agreement between the model estimates and the reference data is comparable to chance agreement. To assess whether the spatial dataset exhibits significant spatial autocorrelation, Global Moran's I (hereafter referred to as Moran's I) is employed[7]. Spatial autocorrelation refers to the tendency for geographically proximate locations to exhibit similar attribute values.

3. Results and discussion

3.1 The outcome and comparison of downscaling

The downscaled land-use distributions generated by AIM-PLUM, along with their difference maps, are presented in Figure 2-7 below. In each figure, the left panel represents the downscaling results based on the 17-region aggregated data, while the right panel shows the results based on the 400-basin aggregated data. Furthermore, to examine the spatial discrepancies between the two modes, the difference between the downscaling results of the region mode and the basin mode (region mode - basin mode) was calculated, and its distribution is shown below the corresponding year. For brevity, in the following sections, the results downscaled from the 17-region classification are referred to as the "region mode results," while those downscaled from the 400-basin classification are referred to as the "basin mode results."

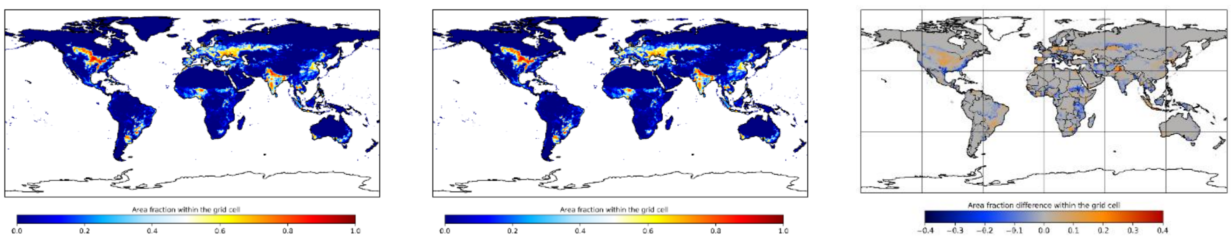

Figure 2 Estimated Cropland distribution in 2005

(Left: Region mode; Center: Basin mode; Right: Difference between the two modes)

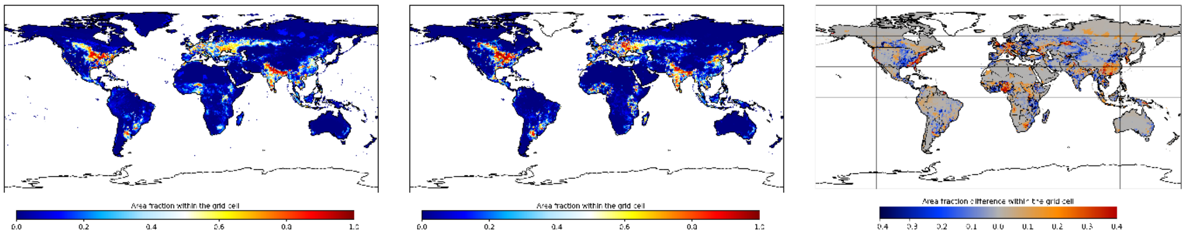

Figure 3 Estimated Cropland distribution in 2100
(Left: Region mode; Center: Basin mode; Right: Difference between the two modes)

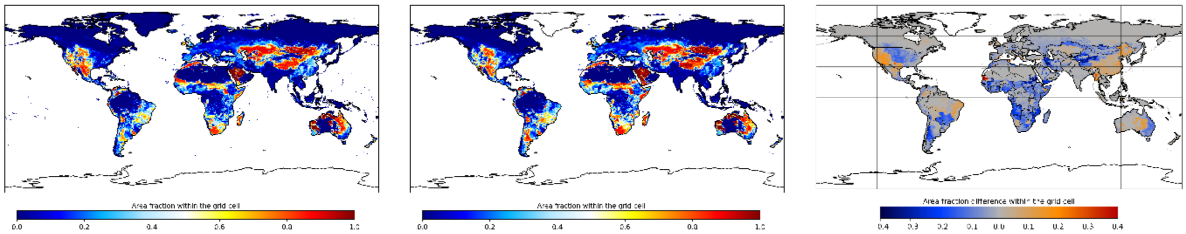

Figure 4 Estimated Pasture distribution in 2005
(Left: Region mode; Center: Basin mode; Right: Difference between the two modes)

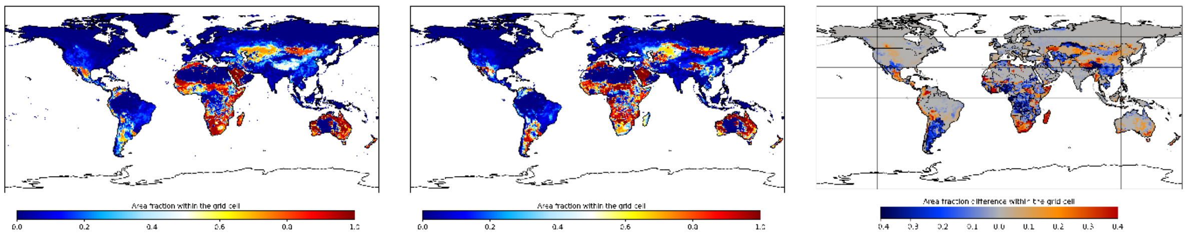

Figure 5 Estimated Pasture distribution in 2100
(Left: Region mode; Center: Basin mode; Right: Difference between the two modes)

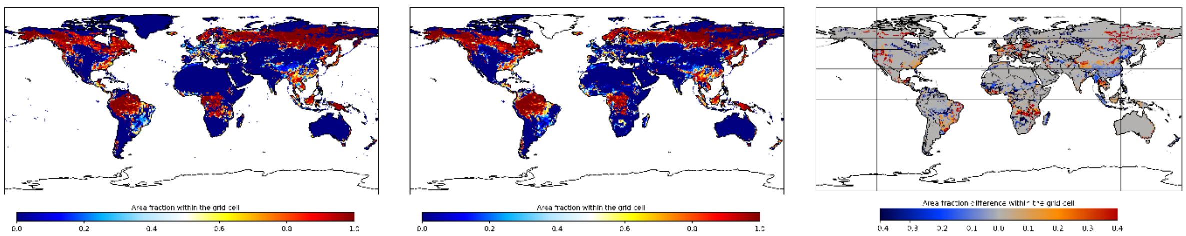

Figure 6 Estimated Forest distribution in 2005
(Left: Region mode; Center: Basin mode; Right: Difference between the two modes)

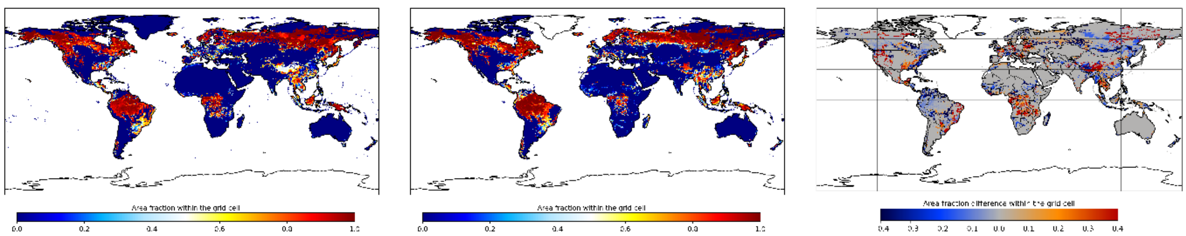

Figure 7 Estimated Forest distribution in 2100
(Left: Region mode; Center: Basin mode; Right: Difference between the two modes)

The difference between the results of the two modes (region mode − basin mode) was calculated, and for each year, the first quartile (Q1), median (Med), and third quartile (Q3) of the global grid-level differences were obtained. Q1 and Q3 represent the lower 25th percentile and upper 75th percentile of the difference distribution, respectively, and their difference corresponds to the interquartile range (IQR), which serves as an indicator of dispersion. Based on these statistical measures, the temporal evolution of the difference distributions for cropland, pasture, and forest is shown in Figure 8. For cropland and forest, both Q1 and Q3 exhibit an increasing trend over time. This indicates that the discrepancy between the two modes gradually widens, suggesting that differences in input spatial resolution led to increasingly divergent land-use estimations in the future. In contrast, for pasture, Q1 decreases over time while Q3 increases; however, no significant change is observed in the difference between Q1 and Q3. This suggests that, over time, the maximum values tend to decrease in the basin mode, whereas they increase in the region mode.

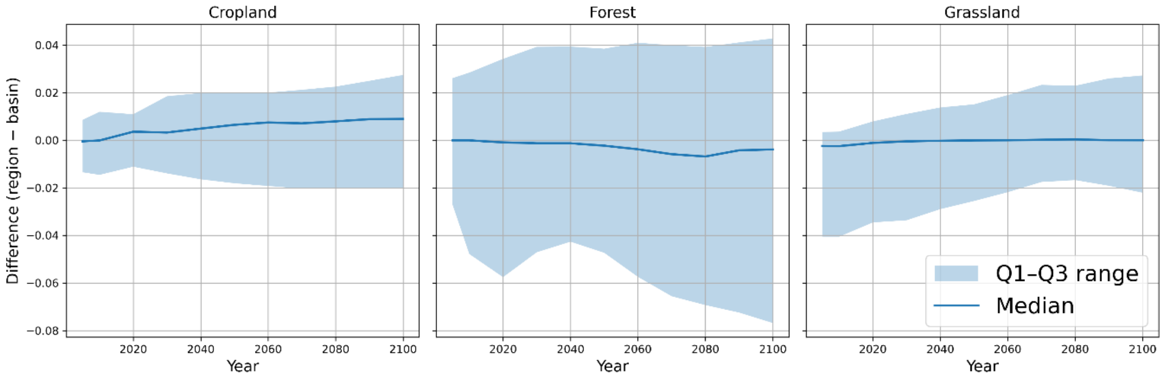

Figure 8 Temporal evolution of quartiles of forest differences

To evaluate the impact of differences in input spatial resolution on the estimation of land-use-related CO_2 emissions, the estimated CO_2 emissions for both modes are presented in Figure 9. Positive values indicate net emissions, which represent the combined effects of CO_2 emissions and removals associated with land use and land-use change, while negative values indicate net sequestration.

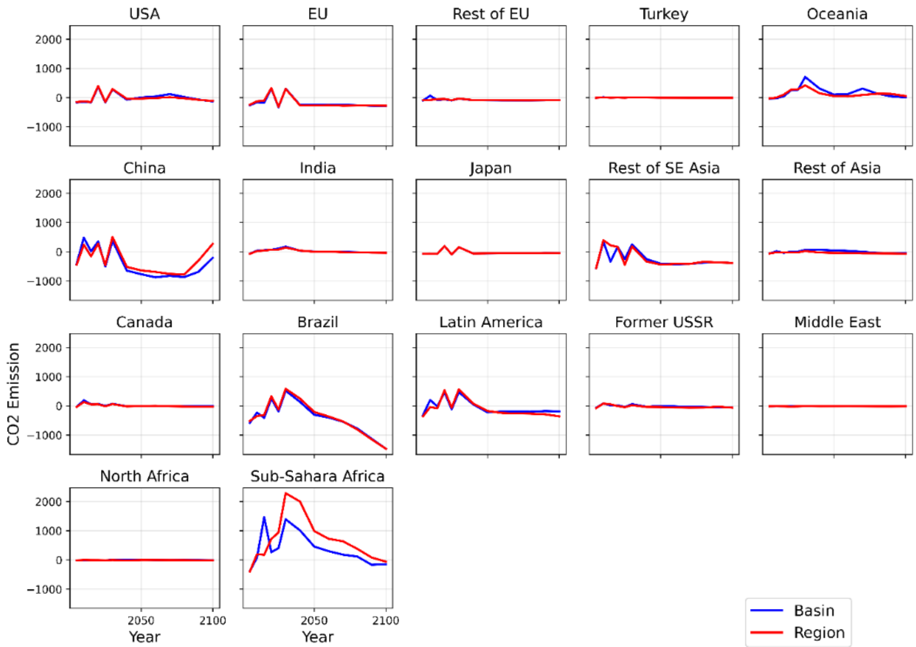

Figure 9 Estimated land-use-related CO_2 emissions under the two modes

At the regional level, China and Brazil exhibit CO_2 emissions during the first half of the century, which shift to net absorption in the latter half. In contrast, Sub-Saharan Africa shows continuous CO_2 emissions throughout the century.

Comparing the two modes, the differences in estimated emissions are generally small; however, in Sub-Saharan Africa, the estimates from the region mode tend to exceed those from the basin mode. One possible explanation is that, in the region mode, cropland is more intensively allocated, leading to conversions from forest to cropland in certain grid cells and a consequent reduction in forest area. This results in decreased CO_2 sequestration by forests and, consequently, higher net CO_2 emissions. In contrast, the basin mode, with its higher input spatial resolution, allows AIM-PLUM to directly incorporate basin-level information derived from the upstream AIM-ALPHA model into the estimation. As a result, cropland is preferentially allocated to grid cells with lower land conversion costs, thereby mitigating impacts on forest areas. Consequently, the total CO_2 emissions estimated under the basin mode are comparatively lower.

3.2 The agreement with reference datasets

To evaluate the estimation results under the two modes, we applied the kappa coefficient to quantify their agreement with reference land-use patterns from the LUH3 dataset for the baseline year 2005, as shown in Figure 10. At the global scale, the basin mode achieved a Kappa value of 0.736, whereas the region mode yielded a value of 0.683, indicating a higher level of agreement between the basin-mode estimates and the reference data. At the regional level, no substantial differences between the two modes were observed in North Africa or Japan. In contrast, in the Middle East, the Kappa coefficient for the region mode exceeded that of the basin mode. For all other regions, the basin mode exhibited relatively higher Kappa values than the region mode.

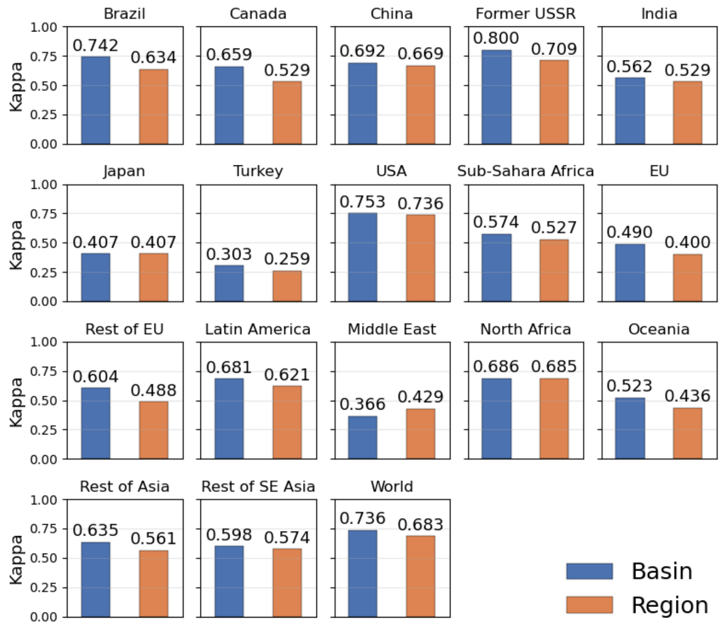

Figure 10 Kappa coefficient relative to the base year

Next, to evaluate the magnitude of temporal changes in land-use estimates under the two modes, the Kappa coefficient for each year relative to the base year was calculated, and the results are presented in Figure 11. At the global level, the Kappa coefficient relative to the base year shows a decreasing trend over time; however, the magnitude of variation remains relatively small. At the regional level, notable declines in the Kappa coefficient are observed in Oceania, Brazil, North Africa, the Middle East, and China. In the comparison between modes, the difference is not substantial at the global scale, although the Kappa coefficient under the basin mode is slightly lower than that under the region mode. Regionally, in China and Oceania, the Kappa coefficient under the region mode tends to decline more significantly than that under the basin mode. In contrast, in North Africa and South America (excluding Brazil), the Kappa coefficient under the basin mode shows relatively lower values.

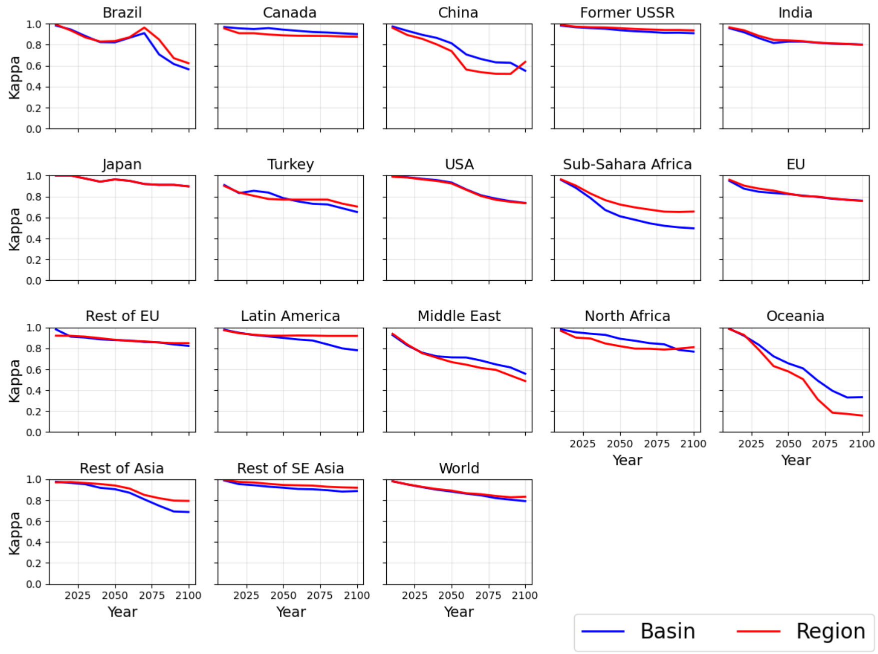

Figure 11. Changes in the Kappa coefficient relative to the base year

3.3 The ability to reflect upstream model information

Figure 12 and 13 compares agricultural production estimated directly by the upstream model AIM-ALPHA with production obtained after downscaling by AIM-PLUM under the 17-region and 400-region aggregation schemes. The results show that downscaled outputs based on the 400-region aggregation exhibit substantially closer agreement with the original AIM-ALPHA production estimates than those based on the 17-region aggregation, indicating that finer input resolution enables downstream models to better reflect upstream production patterns.

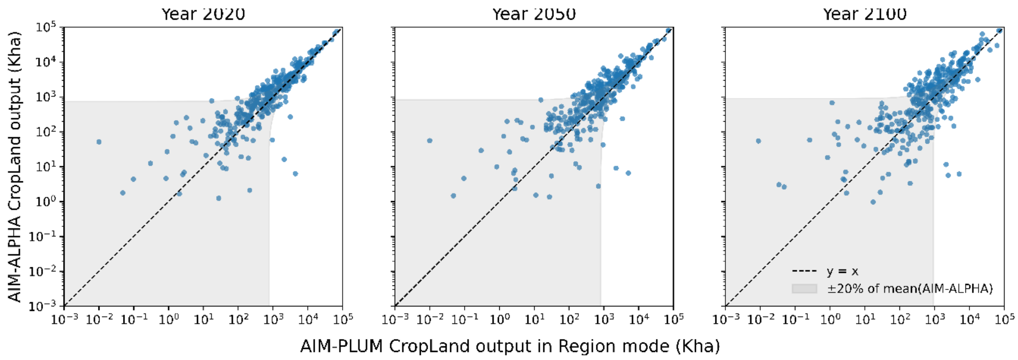

Figure 12 Comparison of basin-level cropland areas between AIM-ALPHA estimates and those allocated by AIM-PLUM (region mode)

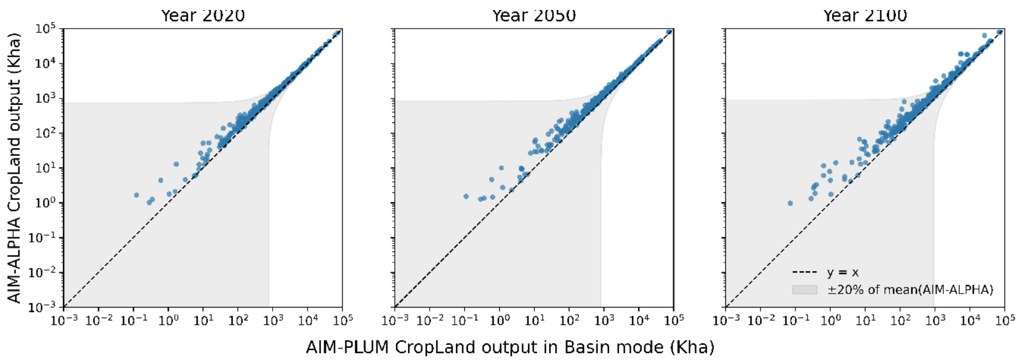

Figure 13 Comparison of basin-level cropland areas between AIM-ALPHA estimates and those allocated by AIM-PLUM (basin mode)

To quantitatively evaluate the estimation performance of the two modes, the proportion of basins for which the cropland area allocated by AIM-PLUM falls within ±20% of the AIM-ALPHA estimates was calculated, and the results are presented in Table 4.1. The results show that this proportion is substantially higher in the basin mode than in the region mode, indicating that land-use allocation under the basin mode more accurately reflects the AIM-ALPHA estimates.

Table 1 Proportion of basins within ±20% error range

	2020	2050	2100
region mode	67.3%	65.7%	57.7%
basin mode	92.2%	83.8%	78.4%

This difference arises from the way upstream information is aggregated prior to downscaling. AIM-ALPHA explicitly represents country-level heterogeneity by accounting for national imports and exports, productivity, and domestic demand when estimating crop production. When these outputs are aggregated into 17 macro-regions, a portion of the country-specific information is averaged out, weakening the transmission of upstream signals to the land-use allocation model AIM-PLUM. As a result, AIM-PLUM outputs under the 17-region aggregation scheme may inadequately capture both the spatial distribution and the magnitude of agricultural production implied by AIM-ALPHA. In contrast, the 400-region aggregation retains finer spatial units and preserves a greater degree of upstream heterogeneity, allowing AIM-PLUM to more effectively convey the production structure embedded in the original AIM-ALPHA outputs.

In addition, to support the evaluation of the two modes, spatial autocorrelation analysis was conducted as a supplementary indicator rather than a primary evaluation metric. Specifically, Global Moran's I was calculated for land-use estimates under the region and basin modes at the global scale, in order to provide additional evidence of their ability to represent spatial patterns. Figure 14 shows the temporal changes in Global Moran's I for cropland, pasture, and forest under both modes. For Cropland, the values under the region mode are consistently lower than those under the basin mode throughout the entire period, and Global Moran's I exhibits a decreasing trend over time in both modes. This indicates that, compared with the region mode, the basin mode produces a more spatially dispersed land-use distribution, and that spatial dispersion increases over time in both modes. For pasture, the values of the two modes are nearly identical, and no significant change in spatial dispersion is observed throughout the analysis period. For forest, the results indicate that the land-use distribution under the region mode is more spatially dispersed than that under the basin mode over the entire period. However, little temporal variation is observed in either mode.

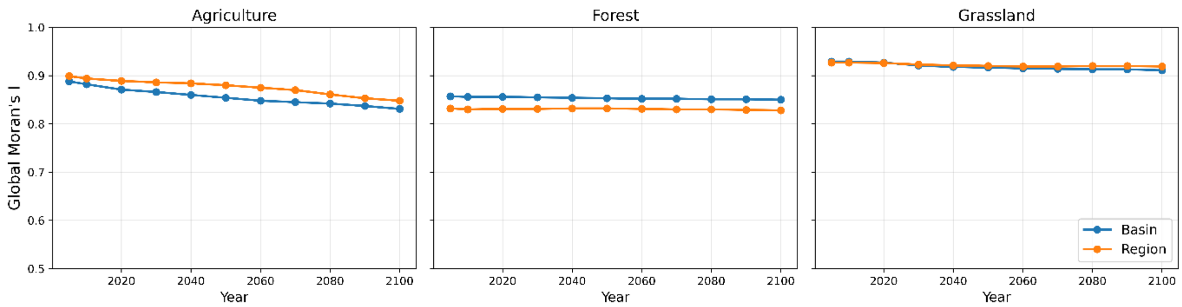

Figure 14 Changes in Global Moran's I for cropland, pasture, and forest

The temporal changes in regional Global Moran's I for cropland, pasture, and forest are shown in Figures 15 -17, respectively. For Japan, since the estimates from both modes are identical, their trajectories are presented as a single line. For cropland, in Brazil, Canada, Sub-Saharan Africa, Oceania, and the former Soviet Union, the values for both modes coincide in the base year; however, in subsequent periods, the values under the basin mode tend to be lower than those under the region mode. In contrast, in China, India, Japan, Turkey, and Southeast Asia, spatial autocorrelation under both modes remains broadly consistent throughout the analysis period. In the United States, the Middle East, North Africa, and South America (excluding Brazil), the region mode exhibits higher values than the basin mode in the early 21st century, whereas after the mid-century, the basin mode tends to exceed the region mode. For pasture, no significant differences between the two modes are observed in most regions, except for Canada and India. In these two regions, the total pasture area remains extremely small throughout the entire period, which likely leads to increased variability in Global Moran's I. For forest, while no significant temporal changes are observed at the global scale, substantial variability is found in the Middle East, Oceania, Turkey, and Africa. This is likely because the estimated forest area in these regions is relatively small, making Global Moran's I highly sensitive during the calculation process. As a result, the values become statistically unstable, potentially limiting the ability to adequately evaluate spatial autocorrelation.

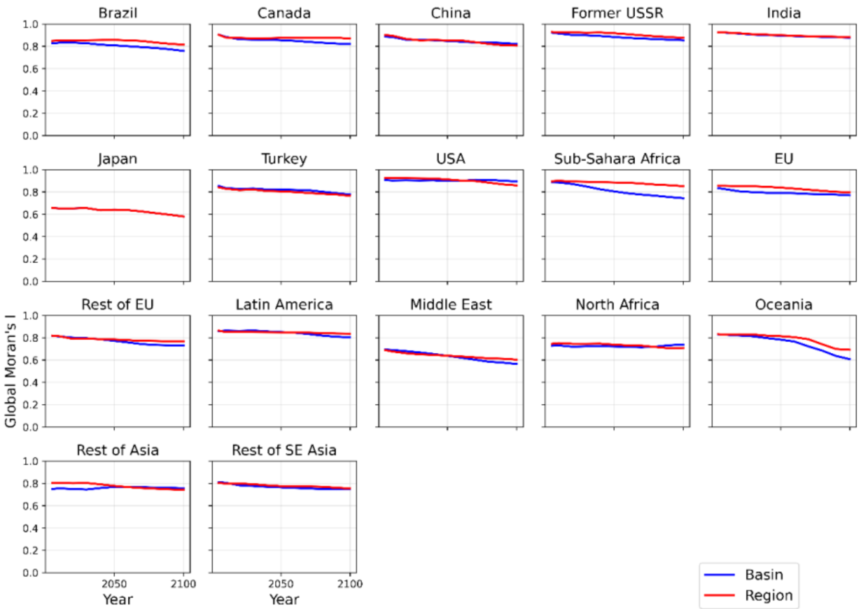

Figure 15 Regional changes in cropland

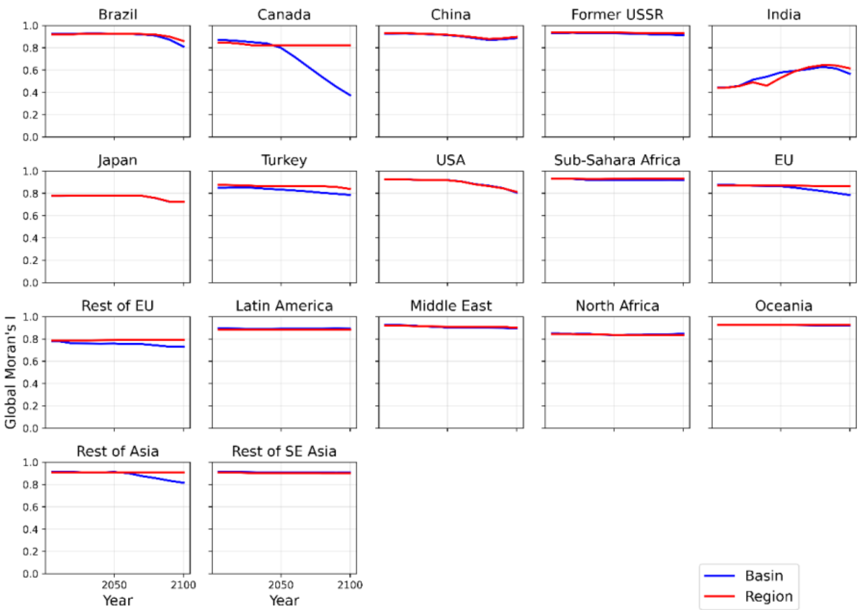

Figure 16 Regional changes in cropland

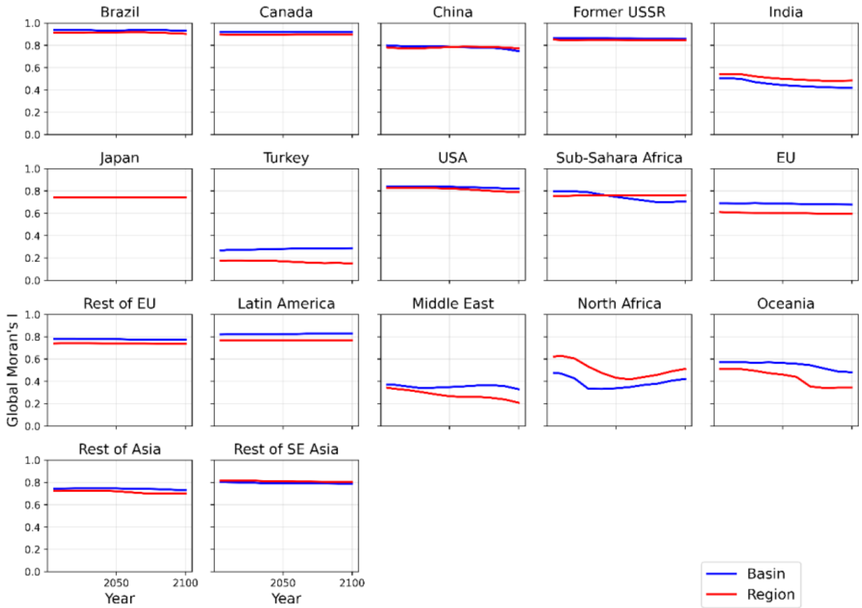

Figure 17 Regional changes in cropland

The weaker spatial clustering observed under the basin mode can be attributed to differences in input spatial resolution. The outputs of AIM-ALPHA are originally estimated at the basin level, and in regions such as North Africa and the EU, a large number of basins (e.g., 104 and 62, respectively) are aggregated within a single region. In the region mode used in this study, land-use estimates from these numerous basins are aggregated into a single regional unit, resulting in the averaging of spatially heterogeneous information across basins. Consequently, land-use distributions become more homogeneous within each region, leading to more spatially clustered patterns. In contrast, under the basin mode, land-use estimates are allocated within the spatial extent of each individual basin, preserving basin-level heterogeneity. This reduces the spatial smoothing introduced by coarse aggregation and results in a more disaggregated and geographically dispersed distribution. As reflected in the Global Moran's I results at both global and regional scales, the basin mode consistently exhibits weaker spatial clustering than the region mode, with particularly large differences observed in North Africa, the EU, and Oceania. This result is consistent with the upstream–downstream comparison, where the basin mode better reproduces agricultural production patterns implied by AIM-ALPHA by preserving finer-scale spatial heterogeneity. The more spatially heterogeneous patterns under the basin mode indicate a stronger transmission of upstream information from AIM-ALPHA to AIM-PLUM. Taken together, these findings confirm that finer aggregation in the basin mode allows downstream land-use allocation to more faithfully reflect upstream model outputs.

3.4 Impact of differences in land-use estimation on environmental impact assessment

To analyze the impact of differences in land-use estimates arising from different input spatial resolutions on environmental impact assessment, the global biodiversity index (BII) was calculated using PREDICTS based on the results of both modes, and the results are shown in Figures 18 and 19. In each figure, the left panel represents the region mode, while the right panel represents basin mode.

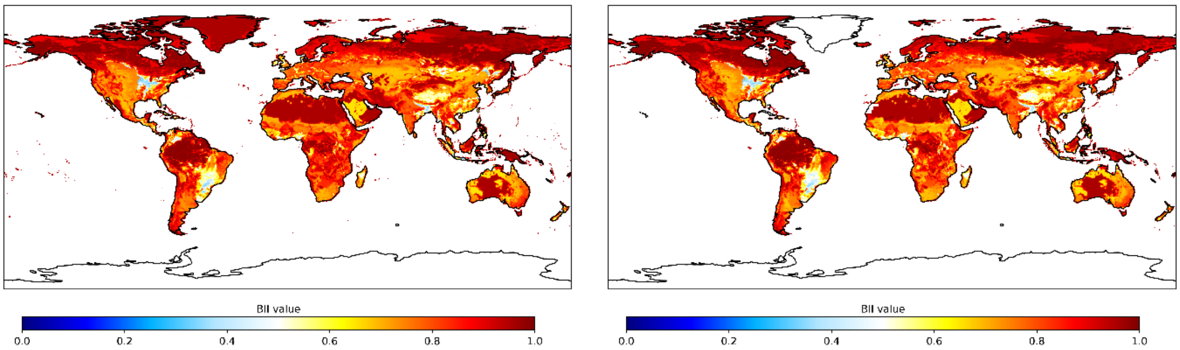

Figure 18 Estimated BII under both modes in 2005
(Left: Region mode; Right: Basin mode)

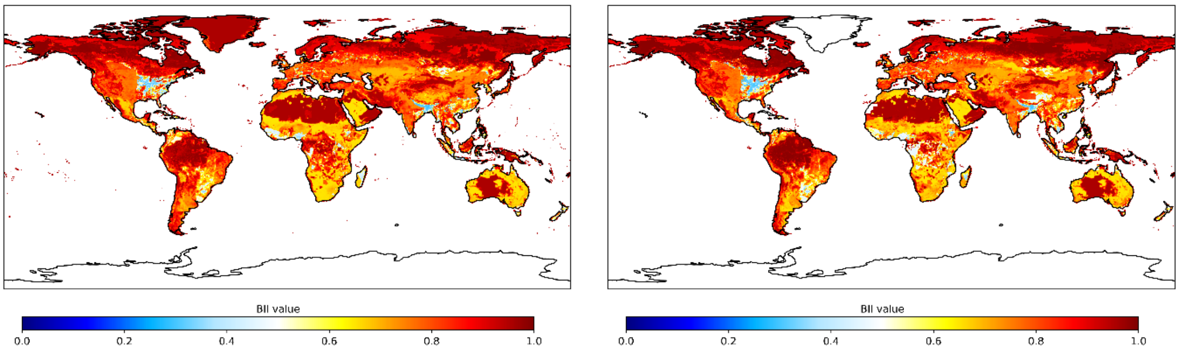

Figure 19 Estimated BII under both modes in 2100
(Left: Region mode; Right: Basin mode)

To evaluate spatial differences between the two modes, the difference in BII estimates between the region mode and the basin mode (region mode − basin mode) was calculated, and the results are shown in Figure 20. In 2005, the overall differences between the two modes were relatively small. Within this, the basin mode shows relatively higher BII estimates in western America, eastern Brazil, eastern China, and central Australia. In contrast, higher BII values under the region mode are observed in eastern America, Sub-Saharan Africa, and western China. By 2100, the differences between the two modes become more pronounced compared to 2005, with particularly large variability in BII estimates observed in Sub-Saharan Africa, China, and Southeast Asia. In these regions, the Kappa coefficients between the two modes are relatively low, indicating substantial differences in the estimated land-use distributions of pasture and forest between the region and basin modes. Since pasture and forest serve as primary habitats for many species, differences in their spatial distribution can have a significant impact on biodiversity estimation outcomes.

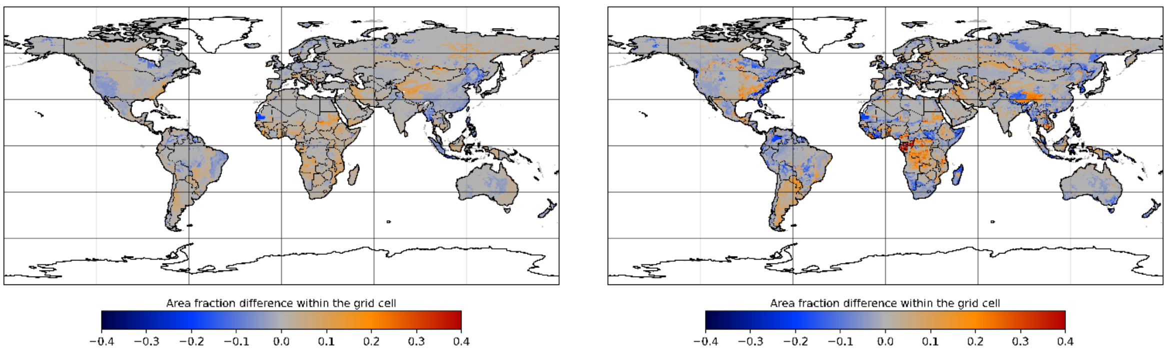

Figure 20 Difference in BII estimates(Left: 2005; Right: 2100)

The primary objective of downscaling IAM outputs is to enable their integration with ESMs in order to evaluate the environmental impacts of land-use change. Therefore, improving the accuracy of environmental impact assessments requires enhancing the accuracy of the input land-use estimates generated by IAMs. The results of this study demonstrate that increasing the spatial resolution of IAM output improves their agreement with reference data and allows for a more accurate representation of information from upstream models. In other words, using higher-resolution IAM outputs as inputs can enhance the reliability of environmental impact assessments related to land-use change. Overall, these findings suggest that improving the spatial resolution of inputs plays a crucial role in enhancing the accuracy of environmental impact assessments through the integration of IAMs and ESMs.

4. Conclusion

This study aimed to clarify the impact of differences in the spatial resolution of inputs to a land-use allocation model on land-use downscaling results. First, land use was estimated using AIM-ALPHA, which explicitly represents agricultural markets and land use, and the results were aggregated into 17 global regions and 400 regions, respectively. These aggregated datasets were then downscaled using the land-use allocation model AIM-PLUM, and the resulting grid-level land-use distributions were compared and analyzed.

Evaluation of reproducibility in the base year shows that, at the global scale, the basin mode with higher input spatial resolution achieves better agreement with reference data than the region mode. This can be attributed to the fact that more finely resolved input data constrain land allocation at the grid level under more localized conditions, thereby improving the reproducibility of land-use distributions.

Analysis of future projections indicates that, when higher-resolution inputs are used, the spatial heterogeneity embedded in the upstream model is better preserved and reflected in the downscaled land-use distributions. Specifically, under the basin mode, land-use allocation is performed while maintaining the high spatial resolution of the upstream estimates, resulting in strong consistency with the upstream model and a high capacity to reproduce its outputs. In contrast, under the region mode, the lower input resolution leads to a loss of spatial heterogeneity during the aggregation process, resulting in reduced reproducibility in the downscaled land-use distributions. Furthermore, due to the sequential estimation structure of AIM-PLUM, differences in estimation accuracy in the base year accumulate over time, making the discrepancies between the two modes, driven by differences in input spatial resolution, increasingly pronounced in future projections.

From a spatial perspective, increasing input spatial resolution leads to a more dispersed land-use distribution under the basin mode and a corresponding reduction in spatial autocorrelation. In addition, differences in the spatial resolution of input land-use estimates are shown to affect the results of subsequent environmental impact assessments.

Overall, this study suggests that increasing the spatial resolution of input data enables land-use downscaling results to better reflect fine-scale spatial information, thereby improving estimation accuracy and enhancing the ability to incorporate upstream model information into land-use estimates.

5. References

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