nature communications

Article

https://doi.org/10.1038/s41467-025-63144-4

Global decarbonization corresponding with unseasonal land cover change

Received: 25 July 2024

Accepted: 8 August 2025

Published online: 23 August 2025

Check for updates

Kehan HE [1,2], Lixing WANG [3] & Zhu LIU [2,3]

Understanding the link between unseasonal land cover changes and CO_2 emissions can indicate the decarbonization progress of a region, but limited modeling tools exist for analysis in near-real-time. Here, we developed a modeling framework to reveal a strong and robust relationship between the two quantities. By applying the Butterworth filter, unseasonal changes in land cover and fuel-consuming sectors are extracted for Autoregressive Distributed Lag regression analysis in major economies. Among all investigated economies, Russia has demonstrated the strongest co-relationship (R-squared value of 0.730) between unseasonal CO_2 emissions and land cover changes, indicative of its heavy reliance on fossil fuels. Both Brazil (1200 $km^2/MtCO_2e$ on average) and Russia (10,700 $km^2/MtCO_2e$) exhibit greatest sensitivity in land cover changes to CO_2 emission changes. This research provides an effective tool to assess the coupling between unseasonal land cover change and CO_2 emitting economic activities, presenting an alternative indicator to monitor decarbonization in real-time.

Land cover change is a critical facet of environmental research. Undeniably, land cover change relates notably to human economic activities. Studies have demonstrated the connections between changes in urban[1–3], forest[4,5], grassland[6,7], snow cover[8,9], and other land cover patterns with human economic activities. The connection between land cover change and economic activities can be observed through fossil fuel consumption, a reliable proxy for economic activities[10], and its associated CO_2 emissions[11]. Recent application of advanced tools of geospatial modeling has also been able to verify such connection[12]. Land cover change, in turn, can also drive environmental issues[13], which will further impact on economic activities and hence energy use[14]. In some studies, direct and strong correlation has already been observed between land cover change and fluctuations in specific energy consumption[15]. A comprehensive analysis of these connections can reveal the strength of the link between land cover changes and human-driven fossil fuel emissions[16]. This information can inform stakeholders about the extent of carbon decoupling in different regions[17], enabling more effective strategies for environmental and socioeconomic planning.

On the other hand, both land cover changes[18] and human economic activities[19] are profoundly influenced by the Earth's seasonal cycles. Extensive studies[20–22] have highlighted this phenomenon and stressed the need to examine how seasonal shifts create impacts on the changes of land cover vegetations and human economies. However, the substantial impact of seasonal climate fluctuations often overshadows isolated weather anomalies and economic shocks, leading to strongly synchronized changes in land cover, economic activities, and energy-related CO_2 emissions[23,24]. By effectively filtering out predictable seasonal patterns from time series data, more meaningful connections, independent of seasonal influences, can be identified, thus helping to reveal the true corelated sensitivities between land cover changes and CO_2 emissions related to fossil fuel consumption[25,26]. In the recent investigation of climate anomalies, researchers have employed the Butterworth filter, a signal processing tool designed to retain signals of certain frequency bands in time-series signals[27], to leave out the cyclical El Niño-Southern Oscillation (ENSO)[28–30]. Recent studies have successfully studied the abnormal annual sea level[31,32] and temperature changes[33] using Butterworth filter. Similar approaches have also been applied to remote sensing data from the GRACE satellite on water cycles[32,34–36]. Despite these methodological advancements, time resolutions of similar research are limited at an annual level and periods of study span over decades. Only

[1]Institute for Climate and Carbon Neutrality, The University of Hong Kong, Hong Kong SAR, China. [2]International Research Center of Big Data for Sustainable Development Goals, Beijing, China. [3]Department of Earth System Science, Tsinghua University, Beijing, China. e-mail: zhuliu@tsinghua.edu.cn

recently has it become feasible to zoom into what happens within each year with near-real-time (NRT) data available on land cover[37] and emission[38].

Here we utilized the Autoregressive Distributed Lag (ARDL) model to carry out a detailed quantitative analysis of the relationships between the Butterworth filtered unseasonal NRT land cover change (ULC) and fossil fuel-related CO_2 emissions in a high temporal resolution spanning from 2019 to 2023 for ten major economies which covers just over a half of global CO_2 emissions[39]. The ARDL model is particularly relevant in these contexts due to its ability to show how the delayed and often complex effects of policy unfold over extended periods[40,41]. It has been applied across a diverse range of fields including macroeconomics[42], finance[43,44], environmental economics[10,45], and public health[46]. The results of this framework uncover the time-lagged correlations in high temporal resolution to provide insights into how shifts in land cover can be connected with fossil fuel CO_2 emissions. Furthermore, our analysis revealed apparent disparities in the strength of link between fossil fuel CO_2 emissions and ULC across different countries. Countries such as Russia have shown a stronger co-relationship between ULC and CO_2 emissions, implying their higher reliance on fossil fuels. Both Brazil and Russia exhibit greater sensitivity in land cover changes to fossil fuel CO_2 emissions due to their extensive land resources. This research lays a solid foundation for NRT modeling of land cover change and economic activities, presenting an effective indicator to policy makers on abnormal land cover alterations and level of CO_2-economy decoupling in real time.

Result

Unseasonal land cover changes

The findings of this study demonstrate a strong ability to accurately reconstruct specific ULC patterns from fossil fuel-related CO_2 emissions. In this study, a total of 90 ARDL models were trained for the nine types of land cover across ten countries.

The processed seasonal totals for ULC across the ten countries balance out to zero as shown in Fig. 1, corroborating the logical premise that the total territorial size of the countries remains constant. The results in Fig. 1 also validate several trends observed in ULC, aligning with recent independent research findings on human-induced land cover changes. Crucially, the analysis captures anomalies in land cover change driven both by climate change and anthropogenic factors. For example, a progressive decrease in forest cover in Russia points to ongoing deforestation and re-cultivation of abandoned land[47–49]. Similarly, statistics also support our findings of continuous urban expansion in China[50], marked by consecutive increases in built-up areas. In France, the apparent cropland degradation aligns with reports[51], and Brazilian data indicate a recent slowdown in deforestation rates[52]. In addition, the sudden spike in Snow & Ice of Spain in the first season of 2021 corresponds accurately with Storm Filomena in Jan 2021, which brought record breaking snowfall to the entire Iberian Peninsula[53]. These findings underscore the effectiveness of the Butterworth filter applied in our study for isolating and analyzing ULC.

However, Fig. 1 also highlights some limitations of the Butterworth filter in recovering ULC. First, there is a dip in the Snow & Ice for Spain at the end of 2020, right before a spike at the beginning of 2021. This occurs because the filter order is set high to achieve a sharp cutoff frequency, effectively filtering out unwanted cyclical patterns. Setting a high order for Butterworth filter causes phase distortion, which degrades the quality of the output signal. As a result, the Butterworth filter introduces oscillations before the impulse caused by Storm Filomena, seen as a dip before January 2021. Additionally, a strong annual pattern is still visible in the data for Russia, particularly for Shrub & Scrub and Snow & Ice. This happens because the same filter settings are used for all land types across all countries, leading to uniform suppression strength for seasonal signals. However, the annual changes in these two land covers in Russia are much more substantial than in other land covers, meaning that the same suppression strength retains some noticeable cyclical patterns in the output signal.

To visually demonstrate the efficacy of ARDL models in this study, Fig. 2 is plotted to present the outcomes of our analysis with Russia as a case study, illustrating both filtered and reconstructed data across all nine types of land cover examined. The ARDL reconstructed ULC for all ten countries are presented in Supplementary Information. This visual representation highlights the ARDL model's robust capability in accurately reconstructing ULC from CO_2 emissions data associated with activities of the six economic sectors, which serve as independent variables in the model. Of particular note is the consistency in model performance; the comparison between the training and verification sets reveals little variation in error levels. This consistency underlines the efficacy and reliability of the ARDL model for this research.

Implications of disparity

The R-squared values of these models vary, with the 75th percentile, 25th percentile, and mean values recorded as 0.632, 0.398, and 0.500, respectively, demonstrating the varied degree of connections between fossil fuel CO_2 emissions and land cover changes. All R-squared values of the 90 models are presented in Fig. 3.

To more effectively compare the efficacy of the ARDL models across different countries, we combined the modeled and actual data for each country and recalculated the R-squared values for the countries studied, as presented in Table 1. The aggregated R-squared values exhibit discrepancies among different nations, with countries like Russia (0.845), China (0.602), and Germany (0.667) displaying substantially higher R-squared values compared to others (visual comparison presented in Supplementary Information, Figure S1). This can be attributed to the unique economic characteristics of these countries in relation to fossil fuel consumption.

To explore this further, we compiled additional economic indicators in Table 1 and visualized their relationships in Figure S3 to provide a quantitative visualization for the observed disparities in modeling performance. In countries like Russia and China, which are heavily involved in fossil-intensive manufacturing industries, unseasonal shocks such as extreme weather events or public health emergencies tend to result in more synchronized changes in fossil fuel consumption and, consequently, CO_2 emissions. While Germany appears as an anomaly in Figure S3, other countries generally follow a pattern where a lower fossil fuel-to-GDP ratio corresponds to lower R-squared values, suggesting that the R-squared values in this research are closely related to the strength of CO_2 decoupling from economic outputs. However, since the linkages of CO_2 emissions to ULC and economic outputs are based on different rationales, anomalies like Germany do not follow this trend. Factors such as urban planning, local climate, and cultural influences can all contribute to variations in the performance of CO_2 decoupling from ULC and economic output. Further studies are recommended to include multiple variables and develop a generalized theory or relationship.

Similarly, as visually presented in Figure S2 of Supplementary Information, the aggregated R-square values are substantially higher for Snow & Ice (0.846) and Shrub & Scrub (0.898) land cover types. It is because that Shrub & Scrub and Snow & Ice ULC are more sensitive to abnormal events such as weather fluctuations when compared to other land cover types such as Crops and Built Area. Having abnormal weather condition as a commonly linked variable, fossil fuel consumption is thus highly likely associated to these two types of ULC. In addition, both types of land cover are also timely responsive to weather condition changes, meaning that a sudden change in weather conditions may quickly introduce ULC in these two types of land cover.

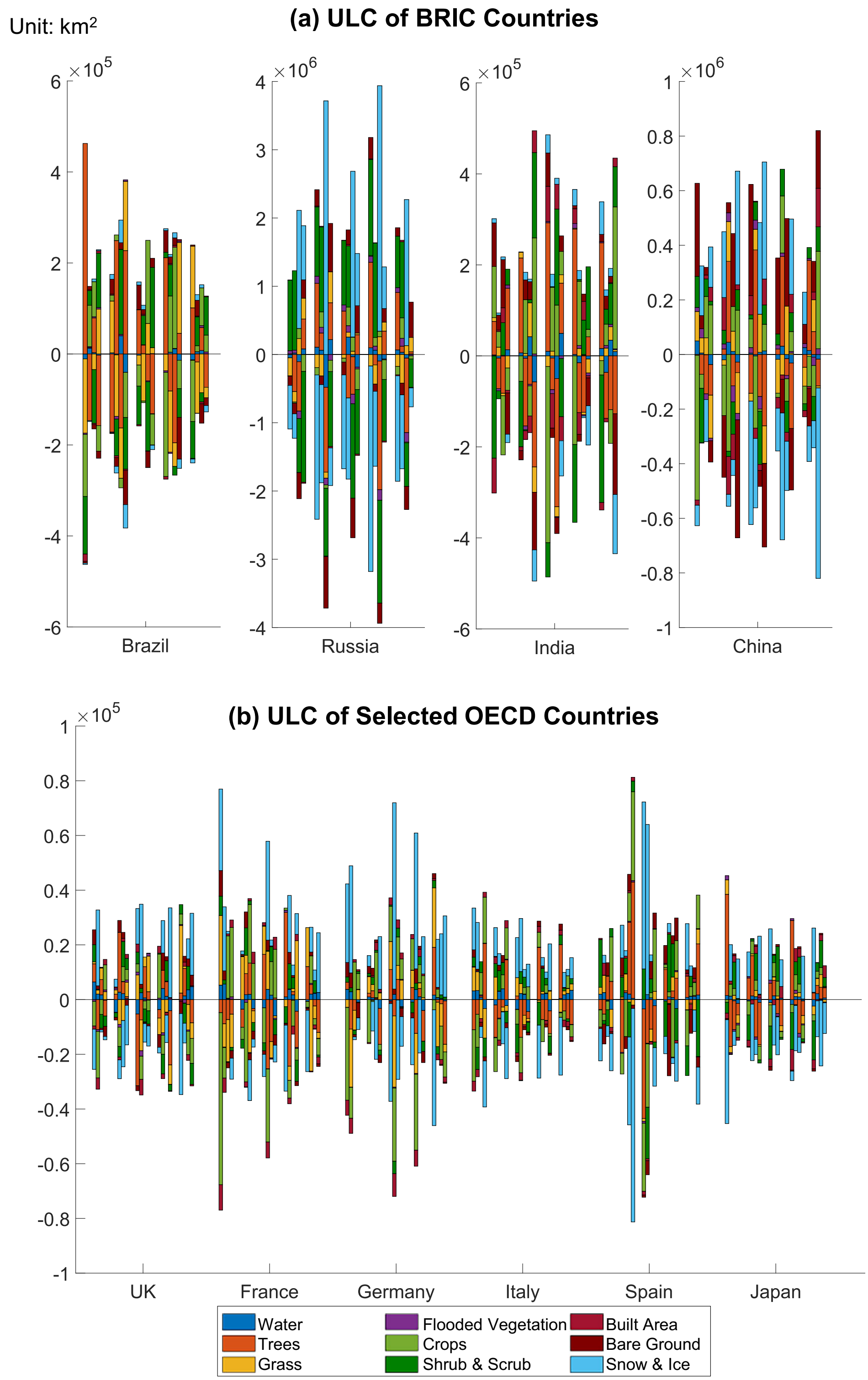

Fig. 1 | Unseasonal landcover change (ULC) for the ten investigated countries obtained from Butterworth filtering of this research. Filtered ULC are divided into (**a**) Brazil, Russia, India, and China (BRIC) countries and (**b**) selected Organization for Economic Co-operation and Development (OECD) countries. The scale of y-axis of (**a**) and (**b**) are set differently to fit the plot. Each grouped stacking bar shows seasonal (3-month) change from 2019 to 2023, with gaps added in-between years to present yearly changes in smaller clusters for each investigated country.

On the contrary, built areas are less linked to fossil fuel consumptions induced CO_2 since urbanization and construction activities are less flexible to irregular events such as sudden variation in weather conditions. Hence modeling built area ULC with fossil fuel induced CO_2 emissions is less accurate as illustrated by the low R-squared value.

The highest R-squared value of 0.907 is observed for the Shrub & Scrub land cover in Russia, indicating the highest accuracy in reconstructing and predicting ULC patterns from CO_2 emissions in Russia. We believe the differences in ARDL model efficacy are partially attributed to variations in the effectiveness of decoupling CO_2 emissions from human activities across the countries studied. Specifically, a

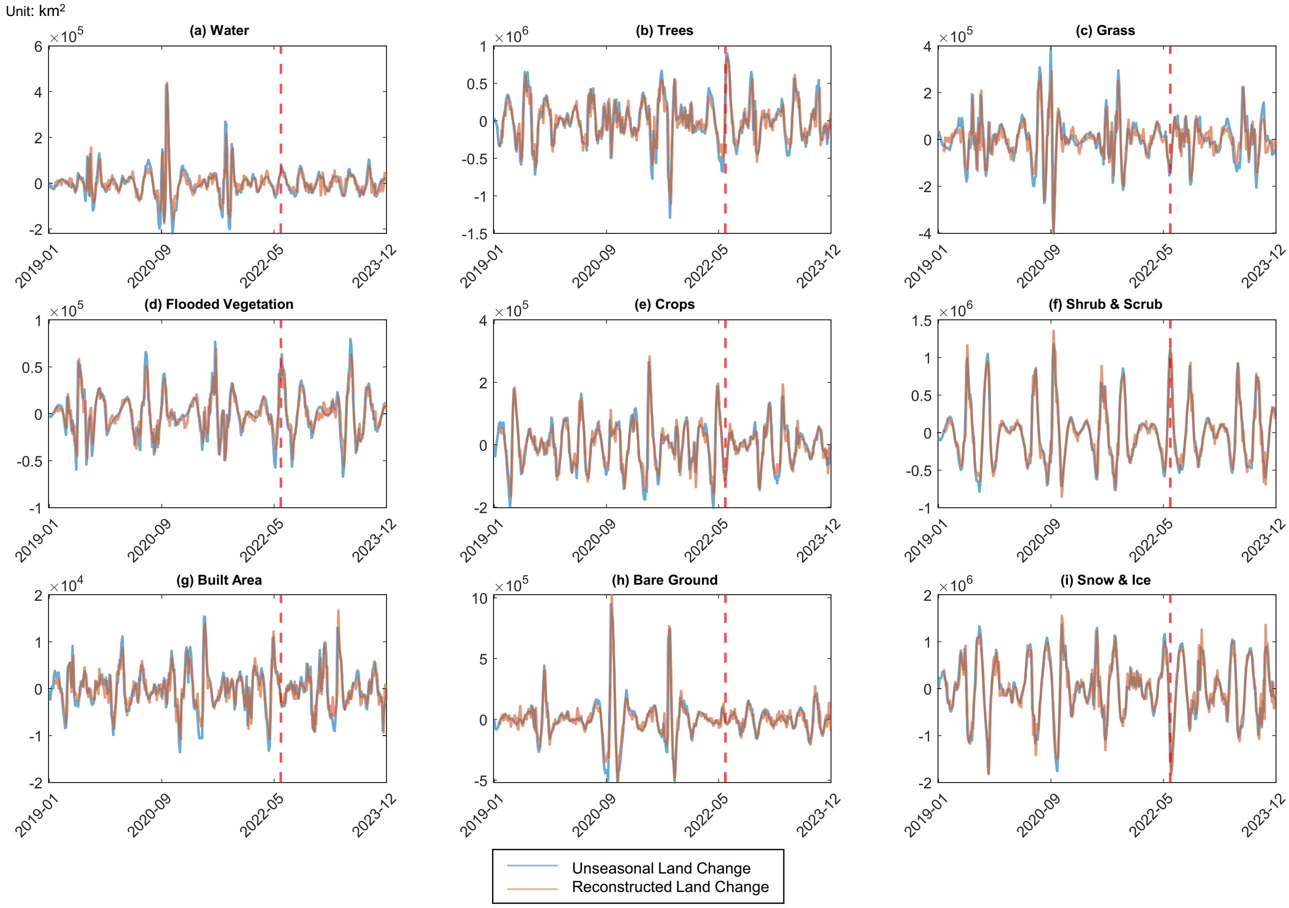

Fig. 2 | The filtered versus reconstructed Unseasonal Landcover Change (ULC) for the nine land types of Russia. The filtered versus reconstructed Unseasonal Landcover Change (ULC) for (**a**) Water, (**b**) Trees, (**c**) Grass, (**d**) Flooded Vegetations, (**e**) Crops, (**f**) Shrub & Scrub, (**g**) Built Area, (**h**) Bare Ground, (**i**) Snow & Ice land cover in Russia. To the left of the vertical red dotted lines are the training data set. To the right of the vertical red dotted lines are the verification data set.

contributing factor to the better model performance in the context of Russia could be as well attributed to the country's colder climatic conditions. Existing research has highlighted that in regions experiencing more extreme weathers, there tends to be a shift towards greater fluctuation on fossil fuels consumptions[54]. For instance, a sudden snowstorm can trigger a substantial and immediate surge in the demand for fossil fuels. Contrastingly, a sequence of warmer days during the winter might lead to brief thawing of lands, revealing cold-resistant vegetation such as shrubs and bushes. These climatic attributes are more likely scenarios in the context of Russia, thereby contributing to the enhancement of the modeling outcomes through more accurately capturing the dynamics of land cover change within this specific environmental context.

On the contrary, although both the UK and Russia experience cold winters, the UK's land cover types, including Shrub & Scrub (0.528), have substantially lower R-squared values compared to Russia. This suggests that the ULC in the UK is less associated with anthropogenic CO_2 emissions, indicating better effort in decarbonization of energy consumption. In fact, the UK uses a much higher proportion of renewable energy than Russia[55], which partly supports the explanation given in the previous paragraph.

Another interesting case is the substantially lower R-square value (0.265) for Trees land cover in Brazil. Due to Brazil's economic dependence on extracting resources from its rainforests[56], deforestation trends are likely to be more rigid, irrespective of fossil fuel activities that increase CO_2 emissions. Hence, the association between ULC for Trees and anthropogenic CO_2 emissions in Brazil weaker, resulting in less effectiveness in the model framework.

Sensitivity analysis

To further understand the linkage between CO_2-emitting sectors and ULC, our study extended its analysis through a series of sensitivity assessments by investigating how 1 $MtCO_2$ unseasonal emission alteration within each of the six sectors could be linked to marginal alterations in different types of land cover in Fig. 4. The outcomes of our sensitivity analysis revealed that countries like Russia and Brazil exhibit the strongest marginal changes across all types of land cover in connection with unit emission alterations in the six sectors. Reflected in Table 1, Russia and Brazil both possess expansive land areas and abundant per capita land resources, making land resources a comparatively cheaper factor in their economic activities. Hence, the same quantity of CO_2 emissions stemming from economic activities may be linked to larger ULC in these regions.

In fact, the vast land resources in Russia and Brazil may have resulted in less strict regulations on land type conversion. In Russia, the abandonment of farmland and its conversion to forest vegetation have sparked social controversies in recent years[57]. Meanwhile, ongoing deforestation in Brazil has been a major international concern[58]. These two opposite trends contribute to the strong yet opposite sensitivity of Tree ULC to human activities and CO_2 emissions in these countries. Specifically, the continuous expansion of ground transport infrastructure in Brazil has led to a steady increase in fossil fuel

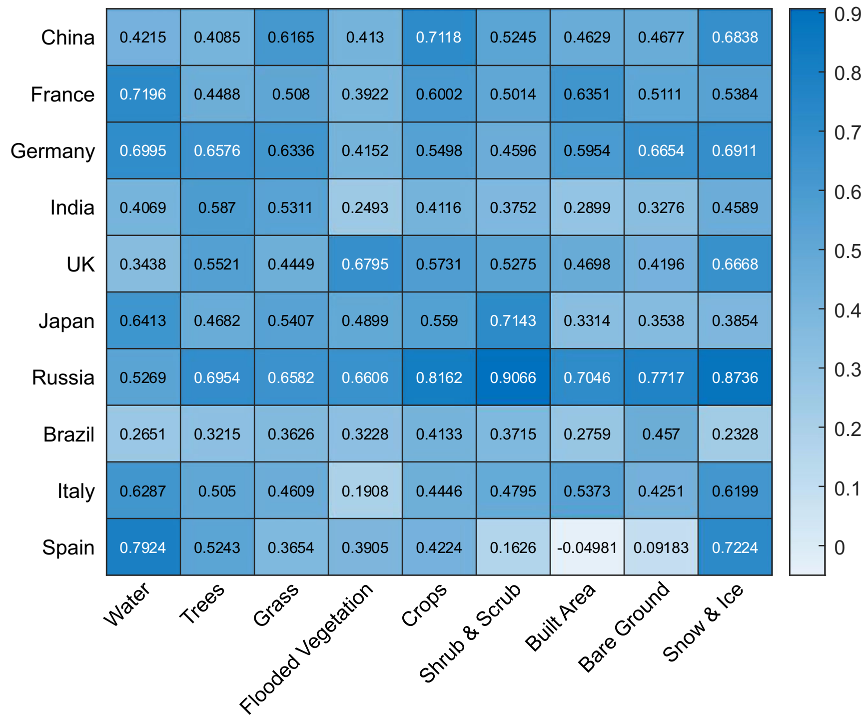

Fig. 3 | R-squared values for the models. A complete heatmap display of R-squared value for models trained for the respective country and land cover.

Table 1 | Comparison between energy consumption intensity[75] and the effectiveness of ARDL models measured in country-aggregated R-squared values for the investigated countries in 2020

Entity	Fossil fuels per capita (kWh)	GDP per capita, PPP ($)	Fossil fuels / GDP (kWh/$)	Land per capita (km^2)	R^2
Russia	47.80	26583.80	0.001798	0.1174	0.845
China	24.39	16296.78	0.001497	0.0068	0.602
India	5.61	6114.03	0.000918	0.0021	0.480
Japan	32.88	39935.47	0.000823	0.0030	0.465
Germany	30.70	51840.33	0.000592	0.0043	0.667
Spain	20.57	35967.89	0.000572	0.0107	0.545
Brazil	8.00	14021.96	0.000571	0.0399	0.431
Italy	22.20	39065.28	0.000568	0.0051	0.541
United Kingdom	21.66	41984.11	0.000516	0.0036	0.495
France	18.65	42233.14	0.000442	0.0085	0.560

consumption in this sector[59]. Conversely, the aviation industry in Russia has experienced a rebound since the start of the Russo-Ukraine war[60]. These distinctive changes in both emissions and ULC of Russia and Brazil are captured in (b) and (a)&(d) of Fig. 4 respectively, highlighting the potential of this research to offer an additional quantitative indicator to identify the intriguing and varied patterns in ULC and human activities, depending on each country's specific circumstances.

Furthermore, among the various land covers analyzed, Grasslands and Forests stood out for higher marginal changes in connection with unit emission alterations. This may be attributed to the inherent economic value ascribed to forests and grasslands within national economies. Studies have emphasized the significance of Forests[61] and Grasslands[62] in providing readily accessible resources, such as raw materials and recreational services. The economic value they offer is directly linked to their size, meaning that economic shock events can induce changes in the size of these land types over a short period. In contrast, other land types, such as cropland and built areas, also provide economic benefits but do not typically change in size over short periods, as their dimensions are planned in advance and are less flexible. Consequently, they exhibit smaller marginal changes in response to unit CO_2 emissions.

In order to assess the reliability and robustness of the model approach, we conducted an uncertainty analysis by manipulating the parameter t, which denotes the number of days of lags incorporated into the ARDL model. The findings of this uncertainty analysis are aggregated and presented in Table 2 to provide a comprehensive overview of the uncertainties associated with different lag settings. Our analysis unveiled that setting the ARDL model with no lags effectively reduces it to a basic multivariate regression model, devoid of temporal dynamics. It resulted in an unacceptably low R-squared value, rendering the model invalid for our analytical purposes. Conversely, as the lag settings were progressively increased, the ARDL model essentially expanded in the number of independent variables incorporated, thereby capturing more complex chronological interactions.

By systematically adjusting the lag parameter t and observing its impact on the model's performance, the uncertainty analysis underscored the critical role of temporal dynamics in capturing the linkages between fossil fuel induced CO_2 emissions and ULC. In Table 2, it reveals a diminishing gain in model performance as the value of t increases. Hence, considering a compromise between model performance and cost, the lag of the ARDL model is set as 25 days ($t = 5$) in this study. This empirical exploration again confirmed and highlighted the importance of temporal considerations in the study of NRT emission-land change nexus.

Limitations in data sources may introduce uncertainty into this study. The accuracy of Dynamic World for individual LULC classification is mostly above 70%, with an overall accuracy of 73.8% (Table S2)[37]. Missing pixels in the Dynamic World dataset could be a consequence of satellite sensing restrictions, possibly due to weather conditions, occupying a certain proportion of the dataset. The extrapolation

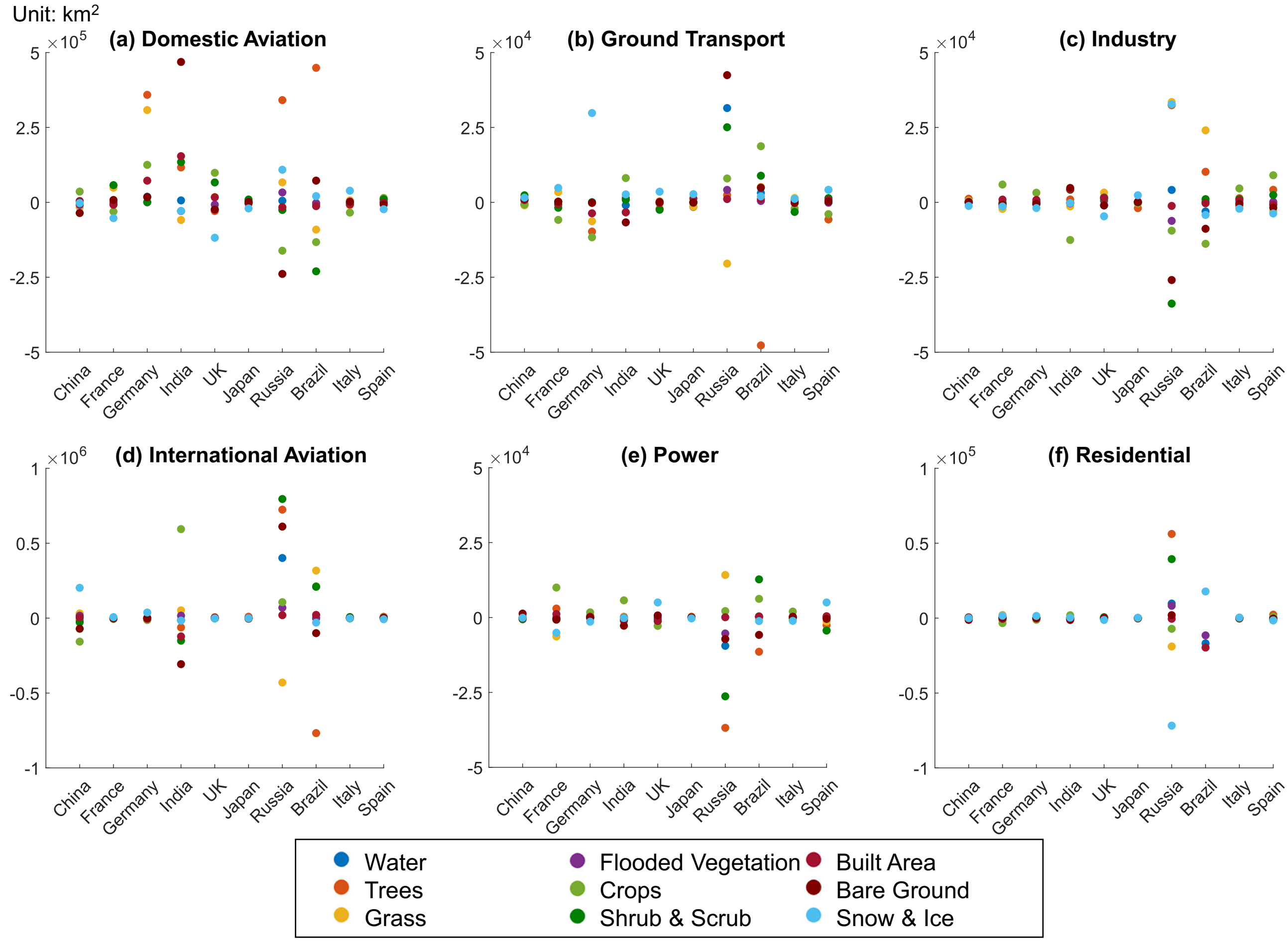

Fig. 4 | The sensitivities for land cover change to CO_2 emissions. The connection between land cover change and 1 MtCO2e emissions in (**a**) Domestic Aviation, (**b**) Ground Transport, (**c**) Industry, (**d**) International Aviation, (**e**) Power, and (**f**) Residential sectors in the countries studied. Y-scales are adjusted so that they are best fitted to data points and anomalies are omitted. Source data can be found in Table S1.

method described in the methodology reduces the overall missing data proportion to 6.5%, but this procedure also introduces additional uncertainties into the analysis. The Carbon Monitor reports CO_2 emission data with varying levels of uncertainty across different sectors, resulting in an overall uncertainty level of ±6.8%[63].

Discussion

Understanding the complex nexus among carbon, economics, and ecology is challenging for process-based modeling due to complex interaction mechanisms. Additionally, setting parameters requires quantitative evidence, adding another layer of uncertainty. The ARDL analysis conducted on NRT data in this research offers a complementary approach to process-based modeling for exploring the carbon-economic-ecology nexus. By comparing the sensitivities and R-squared values of different ARDL models, it provides an empirical, data-driven method to understand this nexus, with real-world implications, thereby enriching scientific databases essential for robust policy formulation and future research. As a result of this research, a framework to quantitatively assess how susceptible anthropogenic CO2 emissions are to environmental anomalies in different countries using readily accessible NRT datasets has been established.

Specifically, this methodological framework allows for a rapid assessment of carbon decoupling strength across different countries and sectors through comparative analysis of model performance. As previously explained, smaller R-squared values indicate a weaker link between CO_2 emissions from various regional sectors and types of ULC. This research suggests that both ULC and CO_2 emissions respond to irregular events, such as weather anomalies. In economies heavily reliant on fossil fuels, these anomalies cause ULC and CO_2 emissions to change in a synchronized manner. Thus, R-squared values can serve as dynamic indicators, updating in real-time to reflect the degree of CO_2 decoupling within regions and economies. This provides valuable insights for policymakers to develop more targeted carbon mitigation strategies. For instance, a higher correlation between residential carbon emissions and snow and ice conditions might suggest great potential for decarbonization in the heating sector, as fossil fuel-related CO_2 emissions in this region are more affected by snowfall and thus temperature drops. Additionally, the sensitivity of ULC to changes in CO_2 emissions has important implications, too. In regions with abundant land resources and less stringent land management policies, land conversion occurs more rapidly and substantially in response to fossil fuel-driven economic activities. This can serve as an indicator of the strictness of land management policies across different regions.

In this study, strong R-squared values and larger sensitivities are observed across almost all types of ULC in Russia, indicating a stronger coupling of fossil fuel-induced CO_2 emissions with ULC and less stringent land management under external shocks. This finding suggests that Russia should devise more targeted strategies to decouple fossil fuel consumption with land use policies. For instance, as a resource reliant economy[64], Russia's resource extraction activities such as open mining should consider transition to renewable energy

Table 2 | Aggregated R-square for all ARDL models when varying lag from 0 days ($t = 0$) to 25 days ($t = 5$)

Lags	0 days	5 days	10 days	15 days	20 days	25 days
R^2	0.0453	0.7490	0.8014	0.8063	0.8168	0.8226
Adjuested R^2	−0.0559	0.7223	0.7802	0.7856	0.7971	0.8035
No. observations	366	365	364	363	362	361

source. Land restoration should also follow to prevent extensive land degradation.

From an academic perspective, this research contributes to the methods and data in geography and climate mitigation interdisciplinary studies. When combined with consumption-based land cover change inventories and related research[65,66], this study serves as a validating framework that reinforces existing knowledge in the field. Moreover, the filtering methodology used for satellite sensing is a promising monitoring tool for policy enforcement, enabling the timely detection of abnormal land cover changes and supporting regulatory actions when needed. Additionally, the concept of directly interpreting a set of regression models and evaluating their effectiveness through R-squared values offers a promising direction in econometric studies to provide empirical insights.

Nevertheless, it is important to acknowledge the limitations in this study. One notable limitation lies in the assumption of linear relationships between emission sectors and land cover changes, which may oversimplify the interactions between human activities and land dynamics. The actual interplay between these variables is much more complex. It is also crucial to recognize that the associations observed are correlative rather than causal, emphasizing the need for caution in interpreting the results and development of a more coherent process-based model framework that integrates the domain of physical meteorology. Econometric research of this kind often lacks explanatory power for observations; therefore, process-based modeling can complement this study to verify or refute the hypotheses proposed. Furthermore, since Carbon Monitor database only provides CO_2 emission by sectors at national level, the geographic information in Dynamic World dataset cannot be retained for the analysis. It limits this research to only examine the relationship between emission sectors and land cover changes at an aggregated national level and forgoes the geospatial interactions that exist. In addition, as explained in the "Method section", Dynamic World data utilized in this study contains anomalies, which may persist when applied with filtering and propagate errors into the processed dataset. It will have an advert impact on the accuracy of the modeling outcomes. Care should thus be given when interpreting the results. Lastly, the temporal dynamic nature of economic structures implies that the relationships between emission sectors and land cover changes are subject to change over time. As economic structures evolve, the model coefficients may no longer hold true, necessitating continual updates and revisions to ensure the model reflects the current environmental and economic landscape accurately.

In response to the limitations of this study, subsequent research should aim to enhance the modeling framework by preserving geospatial information related to emission activities and land cover changes. For instance, utilizing gridded results can offer a more diverse array of data for scientific analysis and policy formulation, particularly at a higher territorial resolution. This approach can retain the enriched geospatial information contained in the Dynamic World database and thus provide a high geospatial resolution gridded database to complement similar database[67]. If geospatial resolution can be improved, this framework could be applied at a subnational level to provide more insights into regional carbon decoupling strategies. In addition, there is a critical need to incorporate meteorological and economic mechanisms into the modeling process to establish causal and precise linkages between various factors. A crucial avenue for further exploration involves developing methodologies that can isolate natural land cover changes from those induced by economic activities. By disentangling human-induced alterations from naturally occurring phenomena, researchers can gain a more comprehensive understanding of the complex nexus between human actions and environmental outcomes in real time. Together with improved resolution on sectorial economic activities[68], this could facilitate the dissection of annual land use change databases such as EXIOBASE[69] into NRT series. Furthermore, future investigations should revisit the coefficients attributed to fossil fuel sectors obtained in this study. Reassessment on these coefficients can reflect changes in efficiencies over time and gauge countries' progress in decoupling emissions from fossil fuel consumption. By updating and refining these coefficients, researchers can capture and assess the evolving trends and advancements in emission decoupling efforts.

Methods

Near-real-time data

As noted in the introduction section of this article, energy consumption and the associated CO_2 emissions serve as effective proxies for assessing economic activities. Thus, having access to NRT emissions data is crucial for the objectives of our research. To fulfill this need, we utilized data from the Carbon Monitor database[63], which is a recently developed database with daily CO_2 emission resolutions in six key sectors: Domestic Aviation, Ground Transport, Industry, International Aviation, Power, and Residential. Many important studies have been conducted using the data from Carbon Monitor. For instance, the study conducted by Liu, et al.[38] reveals a distinct annual pattern in the NRT emissions data particularly related to fossil fuels. The clarity of these patterns underscores the effect seasonal changes have on human economic activities. This observation also affirms that seasonal patterns have a strong influence on energy consumption patterns in real-time.

Regarding NRT land cover (LULC) data, we adopted the Google's Dynamic World dataset[37] to extract temporal changes in land cover area. This dataset leverages Sentinel-2 satellite imagery and deep learning classification algorithms to generate 9 categories of LULC maps globally, at a resolution of 10 m, with an update frequency ranging from 2 to 5 days (varies according to latitude). Other available LULC datasets lack the capacity for NRT updates, exhibiting coarse resolutions and high classification errors[70,71]. In contrast, the Dynamic World dataset allows for NRT updates, presenting considerable advantages in capturing fine temporal changes in land cover and demonstrating superior classification accuracy compared to similar products[37]. The dataset computed the producer and user's accuracies for 9 LULC classes using an expert consensus confusion matrix, organized as Table S2. Most accuracies are above 70%, with an overall accuracy of 73.8% across all classifications[37]. We extracted the time series of area changes for the 9 LULC categories within national borders, at a 5-day time resolution, using the Google Earth Engine platform. Due to concerns regarding data quality, certain pixels within the classified images may be missing. To mitigate area statistical errors, we adopted a methodology where the non-null value of the pixel is traced back to the most recent date for the current value. Even though, Dynamic World is still currently one of the most reliable database on LULC as older satellites image based database had higher error rates in classification[72]. Typically, the pixel value can be traced within a time window of 1-2 weeks, with the longest time span not exceeding 1 month. Post-analysis unveiled that each LULC sequence displayed varying degrees of interannual variability, suggestive of the intertwined effects of natural phenomena and human activities.

The next essential step is to ensure the compatibility of data specifications. The 5-day interval time resolution of the Dynamic World database contrasted with the Carbon Monitor, which tracks CO_2 emissions on a daily basis. To harmonize these datasets for a cohesive analysis, we adapted the Carbon Monitor emissions data to a 5-day resolution by aggregating the daily emissions data over each consecutive 5-day period. Consequently, this alignment resulted in a total of 366 data points covering the five-year span from 2019 to 2023. Further alignment was necessary regarding the geographical coverage of the data. Both databases encompass a broad range of countries, but for the purpose of this study, we limited our analysis to the 10 countries represented in both databases. These countries are China, France, Germany, India, the United Kingdom, Japan, Russia, Brazil, Italy, and Spain. In addition, since the Carbon Monitor database does not contain pixelized geographical information on CO_2 emissions, we aggregate the land cover change data in Dynamic World dataset to national level to match the two database for the analysis.

Butterworth filter

In an effort to refine our analysis by isolating specific influences from broad, cyclical impacts, our research has adopted advances in signal processing, drawing inspiration from recent studies on meteorological cycles using Butterworth filter[31–33]. In the referenced studies, Butterworth filter is recognized for its effectiveness as a high-pass filter in studying the ENSO cycle where it is used to isolate higher frequency cycles from annual ones.

However, the specific demands of our study required a different approach. Given our research focus on non-seasonal fluctuations which occur at lower frequencies than seasonal ones, we chose to use a low-pass Butterworth filter. This methodological adaptation allows us to effectively filter out high-frequency seasonal patterns, thereby preserving the lower-frequency and non-cyclical fluctuations that are independent of the usual seasonal impacts. In the application of Butterworth filter, we selected the filter's cutoff frequency to be three times the annual occurrence frequency. This specific choice ensures that any occurrences less frequent than annually are filtered out, thereby focusing our analysis on the more irregular natural and economic events. Since we are interested in the unseasonal changes in the dependent and independent variables, namely NRT ULC and fossil fuel CO_2 emissions, the Butterworth filter has been applied to both Dynamic World and Carbon Monitor datasets for further correlation analysis.

Autoregressive distributed lag model

In recent years, the field of data modeling has seen tremendous advances with the advent of machine learning technologies. These methods have been particularly effective in quickly developing models that can forecast changes in various quantities, such as land cover, using high-frequency time series data. This capability has been extensively applied in the analysis of remote sensing data, where the high temporal resolution of observations benefits from machine learning algorithms[73,74]. While the ability of machine learning models to forecast changes based on historical patterns is remarkably accurate, a notable limitation exists. These models, primarily due to their design and operational mechanics, often fall short in revealing why those changes occur. Unlike traditional statistical models that can provide insights into the relationships, machine learning models typically act as black boxes. This fundamental drawback highlights a critical trade-off between the depth of insight and predictive accuracy.

Hence, in this research, we selected the ARDL model as our principal analytical tool, a decision informed by the specific requirements of our study. The ARDL model is a robust econometric technique that is adept at capturing both the short- and long-term influences of independent variables on a dependent variable within a dynamic context. Its modeling capabilities are particularly suited for scenarios where the effects of the independent variables on the dependent variable do not manifest immediately, but rather unfold over time through interactions with past values of the dependent variable. Furthermore, the ARDL model incorporates autoregressive terms, which involve the past values of the dependent variable itself. Thus, ARDL allows for a deeper exploration of how historical trends and immediate factors combine to shape current outcomes, providing a layered and detailed understanding of the underlying economic processes. This modeling approach aligns perfectly with the goal of our research to dissect and comprehend the temporal dimensions of the relationships between variables.

Mathematically, the current state of a specific land cover change can be presented by the following equation using ARDL model.

$$y_{i,j(t)} = \sum_{l=1}^{n} a_{i,j,l} y_{i,j(t-l)} + \sum_{k=1}^{m} \sum_{l=0}^{n} b_{i,k,l} x_{i,k(t-l)} + e_t$$

In this research, $m = 6$ number of energy consumption sectors and $n = 4$ number of lags are considered. $y_{i,j(t)}$ and $y_{i,j(t-l)}$ is the value of the jth type of land cover change of ith country at time t and $t-l$ respectively. $x_{i,k(t-l)}$ is the past values of the CO_2 emissions induced by fossil fuel energy consumption of the kth sector in ith country up l lags. $a_{i,j,l}$ and $b_{i,k,l}$ are the linear coefficients representing the immediate and lagged effects of the variables. e_t is the error term. t is set to be 5, meaning that 25 days of lags are considered in the ARDL modeling.

In this research, a data segmentation strategy was implemented with the ARDL model. The initial segment comprising the first 250 data points, spanning from January 2019 to June 2022, was utilized to training the ARDL model. Subsequently, the remaining data points encompassing the period from July 2022 to December 2023 were reserved for verification purposes.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The source data generated for the figures in this study have been deposited in the Zenodo database under accession code (https://doi.org/10.5281/zenodo.14407070).

Code availability

The Matlab code used to generate the analysis of this research has been deposited on Zenodo (https://doi.org/10.5281/zenodo.14407070).

References

1. Xu, Y. et al. Linking ecosystem services and economic development for optimizing land use change in the poverty areas. *Ecosyst. Health Sustainability* **7**, 1877571 (2021).
2. He, C., Huang, Z. & Wang, R. Land use change and economic growth in urban China: a structural equation analysis. *Urban Stud.* **51**, 2880–2898 (2014).
3. Sealey, K. S., Binder, P. M. & Burch, R. K. Financial credit drives urban land-use change in the United States. *Anthropocene* **21**, 42–51 (2018).

4. Rudel, T. K. et al. Forest transitions: towards a global understanding of land use change. *Glob. Environ. Change* **15**, 23–31 (2005).
5. Barbier, E. B., Delacote, P. & Wolfersberger, J. The economic analysis of the forest transition: a review. *J. For. Econ.* **27**, 10–17 (2017).
6. Han, Z., Song, W., Deng, X. & Xu, X. Grassland ecosystem responses to climate change and human activities within the three-river headwaters region of China. *Sci. Rep.* **8**, 9079 (2018).
7. Zhang, Y., Wang, Q., Wang, Z., Yang, Y. & Li, J. Impact of human activities and climate change on the grassland dynamics under different regime policies in the Mongolian Plateau. *Sci. Total Environ.* **698**, 134304 (2020).
8. Challa, D. R., Eagon, M. J. & Northrop, W. F. Influence of snowfall on the fuel consumption of winter maintenance vehicles. *Transportation Res. Part D: Transp. Environ.* **139**, 104543 (2025).
9. Kukavskaya, E. A. et al. Fire emissions estimates in Siberia: evaluation of uncertainties in area burned, land cover, and fuel consumption. *Can. J. For. Res.* **43**, 493–506 (2013).
10. Mensah, I. A. et al. Analysis on the nexus of economic growth, fossil fuel energy consumption, CO_2 emissions and oil price in Africa based on a PMG panel ARDL approach. *J. Clean. Prod.* **228**, 161–174 (2019).
11. Liao, C. H., Chang, C. L., Su, C. Y. & Chiueh, P. T. Correlation between land-use change and greenhouse gas emissions in urban areas. *Int. J. Environ. Sci. Technol.* **10**, 1275–1286 (2013).
12. Wu, R., Li, Z. & Wang, S. The varying driving forces of urban land expansion in China: insights from a spatial-temporal analysis. *Sci. Total Environ.* **766**, 142591 (2021).
13. Zhang, M. et al. The spatial spillover effect and nonlinear relationship analysis between land resource misallocation and environmental pollution: Evidence from China. *J. Environ. Manag.* **321**, 115873 (2022).
14. Datta, S. K. & De, T. in *Environmental Sustainability and Economy* (eds Pardeep Singh, Pramit Verma, Daniela Perrotti, & K. K. Srivastava) 85–110 (Elsevier, 2021).
15. Wang, P., Yu, P., Lu, J. & Zhang, Y. The mediation effect of land surface temperature in the relationship between land use-cover change and energy consumption under seasonal variations. *J. Clean. Prod.* **340**, 130804 (2022).
16. Schwalm, C. R. et al. Modeling suggests fossil fuel emissions have been driving increased land carbon uptake since the turn of the 20th Century. *Sci. Rep.* **10**, 9059 (2020).
17. Zhao, Y. et al. Have those countries declaring “zero carbon” or “carbon neutral” climate goals achieved carbon emissions-economic growth decoupling? *J. Clean. Prod.* **363**, 132450 (2022).
18. Hu, J. & Zhang, Y. Seasonal change of land-use/land-cover (LULC) detection using MODIS data in rapid urbanization regions: a case study of the Pearl River delta region (China). *IEEE J. Sel. Top. Appl. Earth Observations Remote Sens.* **6**, 1913–1920 (2013).
19. Lam, N. L. et al. Seasonal fuel consumption, stoves, and end-uses in rural households of the far-western development region of Nepal. *Environ. Res. Lett.* **12**, 125011 (2017).
20. Hamilton, T. W., Ritten, J. P., Bastian, C. T., Derner, J. D. & Tanaka, J. A. Economic impacts of increasing seasonal precipitation variation on southeast Wyoming cow-calf enterprises. *Rangel. Ecol. Manag.* **69**, 465–473 (2016).
21. Susilo, E., Purwanti, P., Fattah, M., Qurrata, V. A. & Narmaditya, B. S. Adaptive coping strategies towards seasonal change impacts: Indonesian small-scale fisherman household. *Heliyon* **7,** e06919(2021).
22. Ayejoto, D. A. et al. in *Climate Change Impacts on Nigeria: Environment and Sustainable Development* (eds Johnbosco C. Egbueri, J O. Ighalo, & Chaitanya B. Pande) 423-447 (Springer International Publishing, 2023).
23. Liu, Z. et al. Global patterns of daily CO_2 emissions reductions in the first year of COVID-19. *Nat. Geosci.* **15**, 615–620 (2022).
24. Ke, P. et al. Carbon monitor Europe near-real-time daily CO_2 emissions for 27 EU countries and the United Kingdom. *Sci. Data* **10**, 374 (2023).
25. Felbermayr, G., Gröschl, J., Sanders, M., Schippers, V. & Steinwachs, T. The economic impact of weather anomalies. *World Dev.* **151**, 105745 (2022).
26. Auer, A. H. Correlation of land use and cover with meteorological anomalies. *J. Appl. Meteorol.* **17**, 636–643 (1978).
27. Butterworth, S. On the theory of filter amplifiers. *Wirel. Eng.* **7**, 536–541 (1930).
28. Wu, Z. et al. The modulated annual cycle: an alternative reference frame for climate anomalies. *Clim. Dyn.* **31**, 823–841 (2008).
29. Craig, J. W. & Timothy, J. O. Recent and future modulation of the annual cycle. *Clim. Res.* **22**, 1–11 (2002).
30. Qian, C., Wu, Z., Fu, C. & Zhou, T. On multi-timescale variability of temperature in China in modulated annual cycle reference frame. *Adv. Atmos. Sci.* **27**, 1169–1182 (2010).
31. Calafat, F. M., Wahl, T., Lindsten, F., Williams, J. & Frajka-Williams, E. Coherent modulation of the sea-level annual cycle in the United States by Atlantic Rossby waves. *Nat. Commun.* **9**, 2571 (2018).
32. Hamlington, B. D., Reager, J. T., Chandanpurkar, H. & Kim, K.-Y. Amplitude modulation of seasonal variability in terrestrial water storage. *Geophys. Res. Lett.* **46**, 4404–4412 (2019).
33. Li, J. et al. El Niño modulations over the past seven centuries. *Nat. Clim. Change* **3**, 822–826 (2013).
34. Chandanpurkar, H. A. et al. The seasonality of global land and ocean mass and the changing water cycle. *Geophys. Res. Lett.* **48**, e2020GL091248 (2021).
35. Nie, Y. et al. Amplitude modulations of seasonal variability in the Karimata Strait throughflow. *Front. Mar. Sci.* **10** https://doi.org/10.3389/fmars.2023.1085032 (2023).
36. Scanlon, B. R. et al. Linkages between GRACE water storage, hydrologic extremes, and climate teleconnections in major African aquifers. *Environ. Res. Lett.* **17**, 014046 (2022).
37. Brown, C. F. et al. Dynamic World, Near real-time global 10 m land use land cover mapping. *Sci. Data* **9**, 251 (2022).
38. Liu, Z. et al. Near-real-time monitoring of global CO2 emissions reveals the effects of the COVID-19 pandemic. *Nat. Commun.* **11**, 5172 (2020).
39. Friedlingstein, P. et al. Global carbon budget 2023. *Earth Syst. Sci. Data* **15**, 5301–5369 (2023).
40. Khosravi, A. & Karimi, M. S. To investigation the relationship between monetary, fiscal policy and economic growth in Iran: autoregressive distributed lag approach to cointegration. *Am. J. Appl. Sci.* **7**, 415 (2010).
41. Khan, M. A. & Sajjid, M. Z. The exchange rates and monetary dynamics in Pakistan: an Autoregressive Distributed Lag (ARDL) approach. *Lahore J. Econ.* **10**, 87–99 (2005).
42. Shahbaz, M., Loganathan, N., Zeshan, M. & Zaman, K. Does renewable energy consumption add in economic growth? an application of auto-regressive distributed lag model in Pakistan. *Renew. Sustain. Energy Rev.* **44**, 576–585 (2015).
43. Allen, D. E. & McAleer, M. A nonlinear autoregressive distributed lag (NARDL) Analysis of the FTSE and S&P500 Indexes. *Risks* **9**, 195 (2021).
44. Majid, M. S. A. & Yusof, R. M. Long-run relationship between Islamic stock returns and macroeconomic variables: an application of the autoregressive distributed lag model. *Humanomics* **25**, 127–141 (2009).
45. Bentzen, J. & Engsted, T. A revival of the autoregressive distributed lag model in estimating energy demand relationships. *Energy* **26**, 45–55 (2001).
46. Ullah, I. et al. Public health expenditures and health outcomes in Pakistan: evidence from quantile autoregressive distributed lag model. *Risk Manag Healthc Policy*, **14**, 3893–3909 (2021).

47. Global Forest Watch. Russia Deforestation Rates & Statistics. https://www.globalforestwatch.org/dashboards/country/RUS/ (2024).
48. Meyfroidt, P., Schierhorn, F., Prishchepov, A. V., Müller, D. & Kuemmerle, T. Drivers, constraints and trade-offs associated with recultivating abandoned cropland in Russia, Ukraine and Kazakhstan. *Glob. Environ. Change* **37**, 1–15 (2016).
49. Estel, S. et al. Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sens. Environ.* **163**, 312–325 (2015).
50. Statista. Degree of urbanization in China in selected years from 1980 to 2023. https://www.statista.com/statistics/270162/urbanization-in-china/ (2024).
51. France24. *Fewer, older, poorer: France's farming crisis in numbers*, https://www.france24.com/en/business/20240124-france-farming-crisis-in-numbers (2024).
52. BBC. *Amazon rainforest: Deforestation rate halved in 2023*, https://www.bbc.com/news/world-latin-america-67962297 (2024).
53. Insua-Costa, D. et al. Extraordinary 2021 snowstorm in Spain reveals critical threshold response to anthropogenic climate change. *Commun. Earth Environ.* **5**, 339 (2024).
54. Zhao, W. et al. Reliance on fossil fuels increases during extreme temperature events in the continental United States. *Commun. Earth Environ.* **4**, 473 (2023).
55. IEA, World Energy Statistics and Balances, IEA, Paris https://www.iea.org/data-and-statistics/data-product/world-energy-statistics-and-balances (2024).
56. Feltran-Barbieri, R., Bruno, F. & Simpkins, A. *Ending Deforestation in the Amazon Can Grow Brazil's GDP—but That's Not the Only Reason to Do It*, https://www.wri.org/insights/zero-amazon-deforestation-can-grow-brazil-gdp (2023).
57. Vorbrugg, A., Fatulaeva, M. & Dobrynin, D. Envisioning "new forests" on abandoned farmland in Russia: a discourse analysis of a controversy. *Environ. Sci. Policy* **161**, 103871 (2024).
58. Haddad, E. A. et al. Economic drivers of deforestation in the Brazilian Legal Amazon. *Nat. Sustain.* **7**, 1141–1148 (2024).
59. Holler Branco, J. E., Bartholomeu, D. B., Alves Junior, P. N. & Caixeta Filho, J. V. Evaluation of the economic and environmental impacts from the addition of new railways to the brazilian's transportation network: An application of a network equilibrium model. *Transp. Policy* **124**, 61–69 (2022).
60. Tikhonov, A. I., Prosvirina, N. V. & Siluyanova, M. V. Import Substitution in the Aviation Industry. *Russian Eng. Res.* **44**, 280–283 (2024).
61. Taye, F. A. et al. The economic values of global forest ecosystem services: a meta-analysis. *Ecol. Econ.* **189**, 107145 (2021).
62. Liu, H., Hou, L., Kang, N., Nan, Z. & Huang, J. The economic value of grassland ecosystem services: a global meta-analysis. *Grassl. Res.* **1**, 63–74 (2022).
63. Liu, Z. et al. Carbon Monitor, a near-real-time daily dataset of global CO_2 emission from fossil fuel and cement production. *Sci. Data* **7**, 392 (2020).
64. Kalyuzhnova, Y. & Nygaard, C. State governance evolution in resource-rich transition economies: an application to Russia and Kazakhstan. *Energy Policy* **36**, 1829–1842 (2008).
65. Zeng, L. & Ramaswami, A. Impact of locational choices and consumer behaviors on personal land footprints: an exploration across the urban–rural continuum in the United States. *Environ. Sci. Technol.* **54**, 3091–3102 (2020).
66. Shaikh, M. A., Hadjikakou, M. & Bryan, B. A. National-level consumption-based and production-based utilisation of the land-system change planetary boundary: patterns and trends. *Ecol. Indic.* **121**, 106981 (2021).
67. Dou, X. et al. Near-real-time global gridded daily CO_2 emissions. *The Innovation* https://doi.org/10.1016/j.xinn.2021.100182 (2022).
68. He, K., Coffman, D. M., Hou, X., Li, J. & Mi, Z. An electricity big data application to reveal the chronological linkages between industries. *Economic Systems Research*, https://doi.org/10.1080/09535314.2024.2357167 (2024).
69. Stadler, K. et al. EXIOBASE 3: developing a time series of detailed environmentally extended multi-regional input-output tables. *J. Ind. Ecol.* **22**, 502–515 (2018).
70. Venter, Z. S., Barton, D. N., Chakraborty, T., Simensen, T. & Singh, G. Global 10 m land use land cover datasets: a comparison of dynamic world, world cover and esri land cover. *Remote Sens.* **14**, 4101 (2022).
71. Yu, L. et al. FROM-GLC Plus: toward near real-time and multi-resolution land cover mapping. *GIScience Remote Sens.* **59**, 1026–1047 (2022).
72. Sandler, A. M. & Rashford, B. S. Misclassification error in satellite imagery data: implications for empirical land-use models. *Land Use Policy* **75**, 530–537 (2018).
73. Karpatne, A., Jiang, Z., Vatsavai, R. R., Shekhar, S. & Kumar, V. Monitoring land-cover changes: a machine-learning perspective. *IEEE Geosci. Remote Sens. Mag.* **4**, 8–21 (2016).
74. Wang, J., Bretz, M., Dewan, M. A. A. & Delavar, M. A. Machine learning in modelling land-use and land cover-change (LULCC): current status, challenges and prospects. *Sci. Total Environ.* **822**, 153559 (2022).
75. Our World in Data, Fossil fuel consumption per capita, 2024. https://ourworldindata.org/grapher/fossil-fuels-per-capita (2025).

Acknowledgements

This research has been supported by: The Open Research Program of the International Research Center of Big Data for Sustainable Development Goals, Grant No. CBAS2023ORP06 The Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. STG2/P-705/24-R) The Institute for Climate and Carbon Neutrality Postdoctoral Fellowship Fund, the University of Hong Kong.

Author contributions

K.H. designed the methodology. K.H. and L.W. developed the code and processed the data. K.H. took the lead in writing the manuscript. Z.L. supervised the project. All authors provided critical feedback, discussed the results and contributed to the final manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41467-025-63144-4.

Correspondence and requests for materials should be addressed to Zhu LIU.

Peer review information *Nature Communications* thanks Jan Sandstad Næss and Brinda Yarlagadda for their contribution to the peer review of this work. A peer review file is available.

https://doi.org/10.1038/s41467-025-63144-4