

Regional priorities in implementing forestation and wind energy as climate solutions in facing their trade-offs

Received: 13 January 2025

Accepted: 25 March 2026

Published online: 10 April 2026

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Both forestation and wind-energy upscaling are crucial climate solutions, but they may have conflicts as forestation can increase surface roughness and reduce wind speed. Here, based on coupled land-atmosphere simulations with contrasting forest areas, we report a notable trade-off between wind energy and carbon sequestration across a range of potential forestation areas. A maximum global forestation area of 1508 Mha is estimated to enable a biomass carbon sequestration of 90.7 GtC but also contribute to a 19.5% reduction in global onshore wind energy technical potential. The strength of such carbon-energy trade-offs, however, differs among different regions. Tropics could provide large forestation-induced carbon sequestration but have a small loss in wind energy potential. Large-scale forestation in Europe and US mainland may diminish not only wind energy potential but also energy generation of their current wind installations. Our results highlight the importance of maximizing the collective benefits of potentially competing climate solutions.

The UN Climate Change Conference (COP28) urges Parties to take actions aimed at achieving the objectives of the Paris Agreement, aiming for attaining net-zero carbon dioxide emissions by 2050 and limiting global warming to 1.5 °C¹. In particular, it reaffirmed the critical role of renewable energy in meeting the objectives of the Paris Agreement and in advancing the global move towards energy systems free of fossil fuels. In addition, COP28 delivered a global agreement to accelerate efforts towards the phase-down of coal power, phasing out inefficient fossil fuel subsidies, a tripling of renewable energy capacity and doubling energy efficiency by 2030¹. This decision implies an accelerated transition in energy systems with rapid upscaling of bioenergy and renewable energy, including solar, wind, hydro and geothermal energy². Wind energy is expected to play a key role in this transition. The global installed capacity for wind energy has grown from 181 GW in 2010 to 733 GW in 2020³, covering 5.9% of global electricity demand in 2020⁴. Looking ahead, it is projected that by

2050 the global installed wind-energy capacity will increase by a factor of 3 to 5, to 2870–5806 GW, with wind energy contributing 18%–36% of the projected global electricity demand then^{5,6}.

On the other hand, realizing the 1.5 °C target also necessitates large-scale deployment of carbon-dioxide removal technologies, including carbon capture and storage (CCS) and afforestation and/or reforestation^{2,7}. In this study, based on a literature review (Supplementary Table 1), afforestation refers to the establishment of forests, whether naturally or artificially, on lands not recently forested, and reforestation refers to the re-establishment of forests, whether naturally or artificially, on lands that were historically forested. According to the Intended Nationally Determined Contributions (INDCs) to implement the Paris Agreement, 25% of planned emissions reductions globally will be realized by land use and, in particular, by forests⁸. Forestation, here including both afforestation and reforestation but excluding enhancing carbon storage of existing forests, has been

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identified as a leading nature-based climate solution^{9,10}, due to its potential for carbon sequestration¹¹ and the multiple co-benefits of biodiversity conservation, soil protection, hydrological regulation, and other ecosystem services^{12,13}. Although forest protection—such as by halting wood production in currently managed forests—can increase carbon storage, we deliberately exclude this option from our study as large-scale, global cessation of wood production appears implausible given rising global wood demand (see “Methods”).

However, the dual climate solutions of wind-energy upscaling and large-scale forestation may have internal conflicts, as boundary-layer climate processes dictate that forestation will increase surface roughness and reduce wind speed¹⁴. Although there is some controversy surrounding the exact mechanisms¹⁵, widespread surface wind speed reductions in the northern hemisphere around the turn of the 21st century have been partly ascribed to increases in surface roughness due to vegetation restoration¹⁶. Therefore, there may be potential trade-offs between wind energy and the amount of carbon that can be sequestered through forestation. To the best of our knowledge, however, such trade-offs have not been quantified, nor accounted for in the current Integrated Assessment Models (IAMs) used to lay out future deployment of forestation and wind energy for different regions across the globe.

This study used coupled land-atmosphere simulations from eight Earth System Models (ESMs) from the Land Use Model Inter-comparison Project (LUMIP, a contributory project to CMIP6¹⁷) to investigate local surface wind speed changes in response to potential forest expansion. Potential trade-offs between wind-energy technical potential and biomass carbon sequestration were then examined using different forestation scenarios. The implications of future forestation on global onshore wind installations, and the potential for technological development in the wind turbine fleet to offset the resulting reductions in wind energy, were also explored. For method details, please refer to the “Methods” section. The results show a clear trade-off between wind energy and forestation-induced carbon sequestration that must be accounted for in formulating future climate mitigation plans when both wind-energy upscaling and forestation are to be used as climate solutions.

Results

Trade-off between wind-energy technical potential and carbon sequestration

To examine the relationship between local wind-energy potential and carbon sequestration through worldwide forest expansion, four different forestation scenarios are designed (S1 to S4). Additionally, five auxiliary scenarios are derived by interpolating from the four main scenarios (Fig. 1 and Supplementary Fig. 1). Under the maximum forestation scenario (S4), all locations with potential forest distribution, except for those currently occupied by forest, cropland, or human settlement (i.e., urban land), are allowed to be forested. Moving through the scenarios from S4 to S1, the forestation area becomes progressively smaller with the gradual introduction of more constraints based on increasingly realistic considerations. In S3, pastures were excluded from forestation for safeguarding the provision of livestock products (e.g., milk and meat). Then, in S2, boreal regions are further excluded to avoid unintended climate warming by forestation-induced surface albedo reduction in these regions¹⁸. Lastly, in S1, currently protected nature reserves were further excluded to conserve biodiversity⁹.

Our analysis suggests increasing biomass carbon sequestration potential as the forestation area increases across different forestation scenarios (Fig. 1a and Supplementary Fig. 2). The biomass carbon uptake is projected to increase from 43.8 Gt C under the minimum forestation scenario S1 to 90.7 Gt C under the maximum forestation scenario S4, when the forestation area increases from 709.9 Mha (Mha = 10⁶ ha) to 1508.5 Mha. This corresponds to an increase of

17.5%–37.1% in current forest area and could store an equivalent of 5.2%–12.8% of the current atmospheric carbon pool. However, on the other hand, mean annual global surface wind speed is projected to decrease with increasing forestation area, from -0.017 m s^{-1} under the minimum forestation scenario (S1) to -0.038 m s^{-1} under the maximum forestation scenario (S4) (Supplementary Fig. 3a). The decrease in the wind energy capacity factor (CF) ranges from -0.007 (the minimum forestation scenario, S1) to -0.015 (the maximum forestation scenario, S4) (Supplementary Fig. 3b). The technical potential indicates the annual amount of electricity that could be generated over the land area suitable for wind turbine installation under the limitations of turbine technology, turbine spacing and system loss (see “Methods”). Correspondingly, a larger decline in wind-energy technical potential is also found with increasing forestation area, rising from a 50.0 PWh (PWh = 10¹⁵ Wh) (10.6%) decline under S1 to a substantial decline of 87.3 PWh (19.5%) under S4 (Fig. 1b and Supplementary Fig. 4). Hence, a notable trade-off relationship exists between wind energy technical potential and forestation-induced carbon sequestration potential (Fig. 1c).

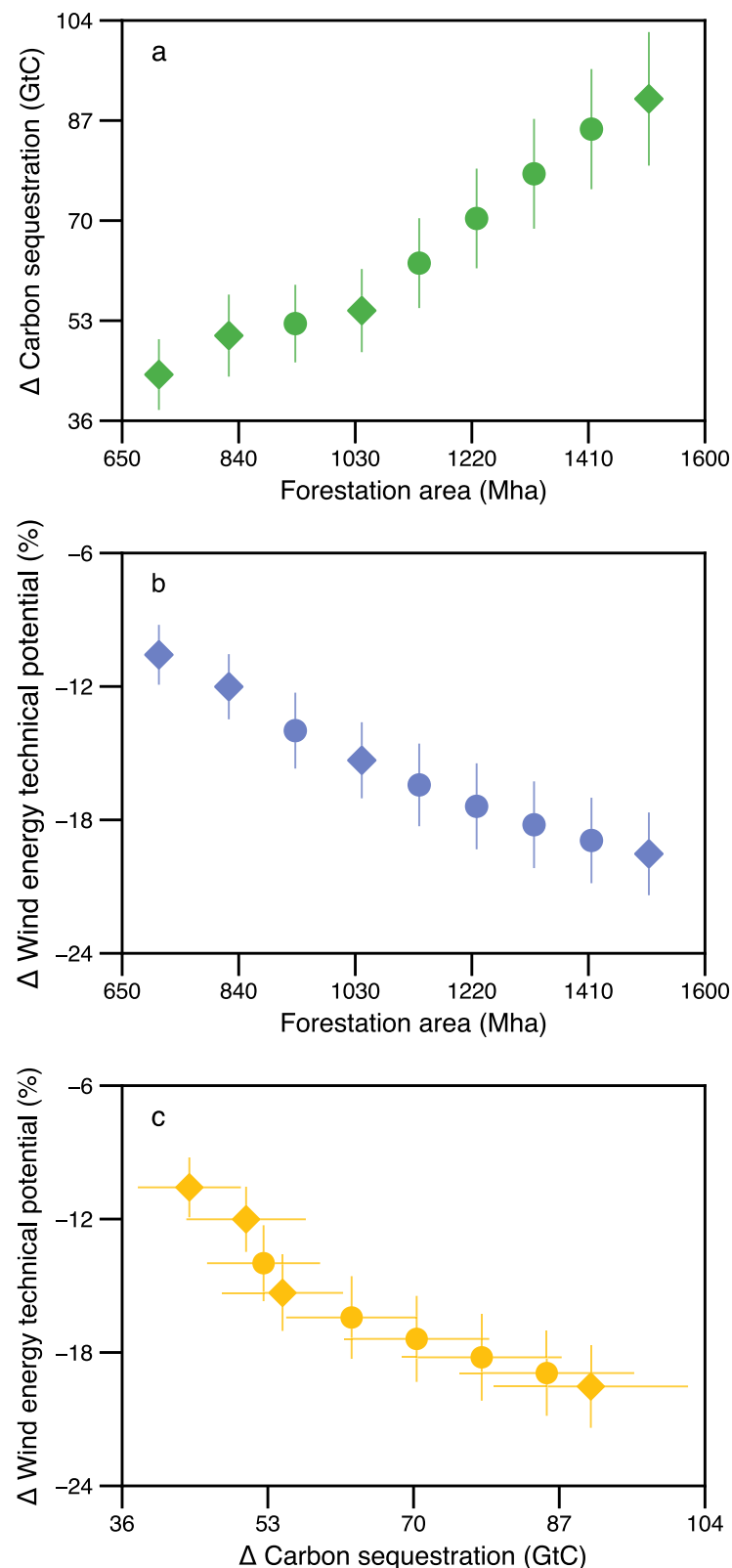
Prioritizing forestation based on the regional strength of the carbon-energy trade-off

The maximum forestation scenario (S4) is selected to examine the spatial patterns of forestation area, forestation-induced biomass carbon sequestration, and the resulting changes in wind-energy technical potential, because it provides the largest spatial extent of forestation, which allows a complete spatial analysis. The S4 scenario illustrates spatially pervasive forestation opportunities, mainly distributed across South America, the Caribbean, the southeast of the United States mainland, Alaska and northwestern Canada, the grassland biomes in tropical Africa, the grassland belt of Eurasia, south and east Asia, tropical Asia, and part of Oceania (Fig. 2a).

The spatial patterns of forestation-induced biomass carbon sequestration potential and wind-energy technical potential loss largely follow those of forestation potential (Fig. 2b, c). However, there are some exceptions. Eastern and Southeast Asia exhibit reasonable forestation potential, but show a high carbon sequestration potential (likely because of their high biomass carbon stock density) and surprisingly low levels of wind-energy technical potential loss. Similar patterns are also present for South America, where pronounced carbon sequestration is found, corresponding to large areas of forestation potential but with a relatively low wind-energy technical potential loss. In contrast, for the US mainland, notable areas of forestation and carbon sequestration potential are accompanied by a pronounced wind-energy loss.

The clear carbon-energy trade-off reported in this study calls for prioritizing forestation activities among different regions based on the different strengths of the trade-off relationship. We propose a framework aimed at maximizing carbon sequestration potential while minimizing total wind-energy technical potential reduction. The arc-tangent of the ratio between forestation-induced total wind-energy technical potential loss and carbon sequestration potential is used to measure the forestation efficiency as a potential climate solution while accounting for the carbon-energy trade-off (Fig. 2d–f). Forestation efficiency represents the reduction in wind energy per unit of carbon sequestration achieved through forestation (a negative number). A higher efficiency indicates a greater chance for the co-success of the dual climate solutions of wind-energy upscaling and forestation, and hence assigns a higher priority to the deployment of forestation to a given region (Supplementary Fig. 5).

Of the thirteen regions of the globe, Southeast Asia exhibits exceptional efficiency, with a large amount of biomass carbon gain (15.4 Gt C) but a negligible reduction in wind energy technical potential (-1.1 PWh) (Fig. 2d). In fact, the top five regions in terms of high forestation efficiency, i.e., Southeast Asia, South Asia (-0.7 PWh vs. 2.0 Gt



C), Eastern Asia (−2.2 PWh vs. 4.8 Gt C), Central America (−1.6 PWh vs. 2.7 Gt C), and South America (−17.5 PWh vs. 29.0 Gt C), together provide 56.2% of the global total biomass carbon sink potential. These regions should be prioritized when deploying the dual climate solutions of wind energy and forestation. In contrast, Central Asia (−2.8 PWh vs. 0.8 Gt C) and Canada and Alaska (−6.1 PWh vs. 2.5 Gt C) are regions where a strong carbon-energy trade-off exists, and caution

should be taken when implementing forestation-based climate solutions, or a refined evaluation of forestation and wind farm location should be performed. The same caution should be applied for Russia, Europe and the US mainland, which have relatively large values of carbon sequestration potential (3.1 Gt C; 3.9 Gt C; 6.5 Gt C), but also the large reduction in wind-energy technical potential (−7.2 PWh; −6.1 PWh; −11.6 PWh). The reduction in wind-energy technical potential in

Fig. 1 | Trade-offs between wind energy technical potential and carbon sequestration following worldwide forestation. **a** Relationship between biomass carbon sequestration capacity and forestation area. **b** Relationship between forestation-induced change in wind-energy technical potential (%) and forestation area. **c** Relationship between forestation-induced change in wind-energy technical potential (%) and carbon sequestration capacity. Diamonds represent the four different forestation scenarios of S1–S4; the circles represent additional forestation scenarios derived by interpolating S2 and S3, and S3 and S4 (Supplementary Fig. 1), for the purpose of better visualizing the relationships (see “Methods”). The vertical lines in (a) and the horizontal lines in (c) indicate the standard deviation of changes

in carbon sequestration, derived from 10 global forest carbon density models. The vertical lines in (b) and (c) indicate the standard deviation of changes in wind-energy technical potential, derived from the eight ESMs in LUMIP. The sample size (n) for carbon sequestration changes in Panels (a) and (c) corresponds to the number of potential biomass carbon density datasets ($n = 10$), while the sample size (n) for wind-energy technical potential changes in Panels (b) and (c) corresponds to the number of Earth System Models in LUMIP ($n = 8$). The centers of the error bars (a, b, c) represent the multimodel mean values from 8 ESMs and 10 potential biomass carbon density datasets.

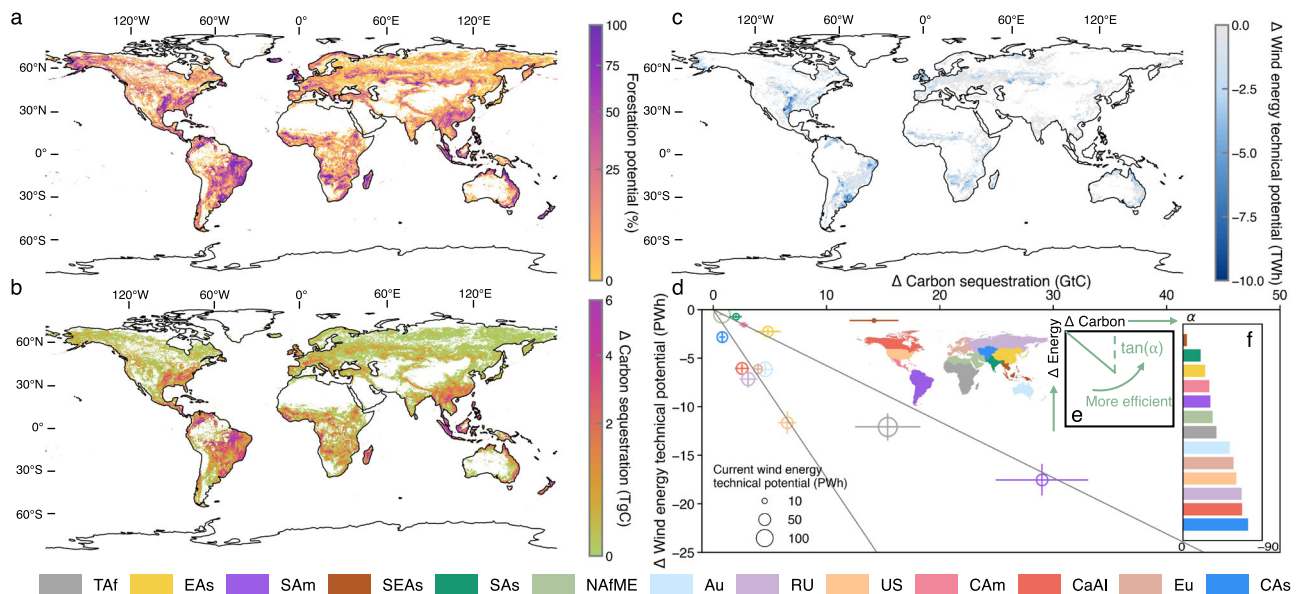


Fig. 2 | Prioritizing forestation among different regions based on their carbon-energy trade-off strengths under the maximum forestation scenario of S4. **a** Distribution of global forestation potential, shown as the percentage of forestation area within each grid cell. **b** Distribution of forestation-induced biomass carbon sequestration potential (TgC = 10^{12} gC). **c** Distribution of forestation-induced loss in wind energy technical potential (TWh = 10^{12} Wh). **d** Trade-offs between wind-energy technical potential and biomass carbon sequestration in different regions.

The regional forestation efficiency (α) was measured by the arctangent of the ratio between wind-energy technical potential loss (Δ Energy, in the unit of PWh, PWh = 10^{15} Wh) and biomass carbon sequestration potential (Δ Carbon, in the unit of GtC, GtC = 10^{15} gC) (e), with the regional values shown in (f). The colors of the dots in (d) and bars in (f) indicate different regions (Abbreviations of the names of different regions with their corresponding colors are shown at the bottom of this figure). The sizes of the dots in (d) indicate the regional total wind-energy technical potential without accounting for forestation. The vertical lines in (d) represent the standard deviation of wind-energy technical potential change derived using the

eight ESMs in LUMIP ($n = 8$). The horizontal lines in (d) represent the standard deviation of carbon sequestration derived using 10 global forest potential biomass carbon density datasets ($n = 10$). The centers of the error bars in (d) represent the multimodel mean values from 8 ESMs and 10 potential biomass carbon density datasets. The abbreviations of region names used in the legend are as follows: TAF for Tropical Africa, EAs for East Asia, SAm for South America, SEAs for Southeast Asia, SAs for South Asia, NAFME for North Africa and the Middle East, Au for Australia, RU for Russia, US for the United States, CAM for Central America, CaAl for Canada and Alaska, Eu for Europe, and CAs for Central Asia. Panels (a–c) were produced using Cartopy (ref. 68), a Python library for geospatial data visualization, with base map data from Natural Earth (public domain dataset; <https://www.naturalearthdata.com/>). The world map used in (d) was obtained from the World Bank (<https://datacatalog.worldbank.org/search/dataset/0038272/world-bank-official-boundaries>), which is publicly available under the Creative Commons Attribution 4.0 International License (CC BY 4.0, <https://creativecommons.org/licenses/by/4.0/>). Maps have been modified.

South America (-17.5 PWh) and Tropical Africa (-12.1 PWh) is the greatest and second greatest of all the regions, but they remain comparatively high forestation efficiency because of their extremely large carbon sequestration potential.

Loss in energy generation for current onshore wind installations

Forestation-induced reduction in local surface wind speed and the consequential loss of wind-energy technical potential reported in this study also suggest unavoidable reductions in energy generation for currently installed onshore wind turbines. To assess this reduction, the capacity factor (CF) of currently installed onshore wind turbines is calculated under present-day surface wind speed (i.e., without further forestation, using the climate of 2000–2020), and under the S1 and S4 forestation scenarios, using current wind turbine technical feature

(T1 scenario, see “Methods”) (Fig. 3). Current onshore wind installations are widely distributed globally but their density is greatest in Eastern Asia, Europe, the US mainland, and South Asia. The CF of currently installed wind turbines with no forestation, averaged over all sites, is 0.278, with higher regional CF values being found in the US mainland (0.313), Canada and Alaska (0.301), Russia (0.297), and Europe (0.296) (Fig. 3a, T1 of “No forestation” scenario in Fig. 4).

However, under the minimum (S1) and maximum (S4) forestation scenarios, the global average CF of onshore wind installations falls to 0.267 and 0.251, or by 4.0% and 9.7%, respectively (Fig. 3b, c). Of the thirteen regions of the globe, Eastern Asia, Canada and Alaska, and South Asia all show less than 5% reduction in CF under both minimum (S1) and maximum (S4) forestation potential (Fig. 3b, c, and T1 under S1 and S4 scenarios in Fig. 4). In contrast, South America, Australia,

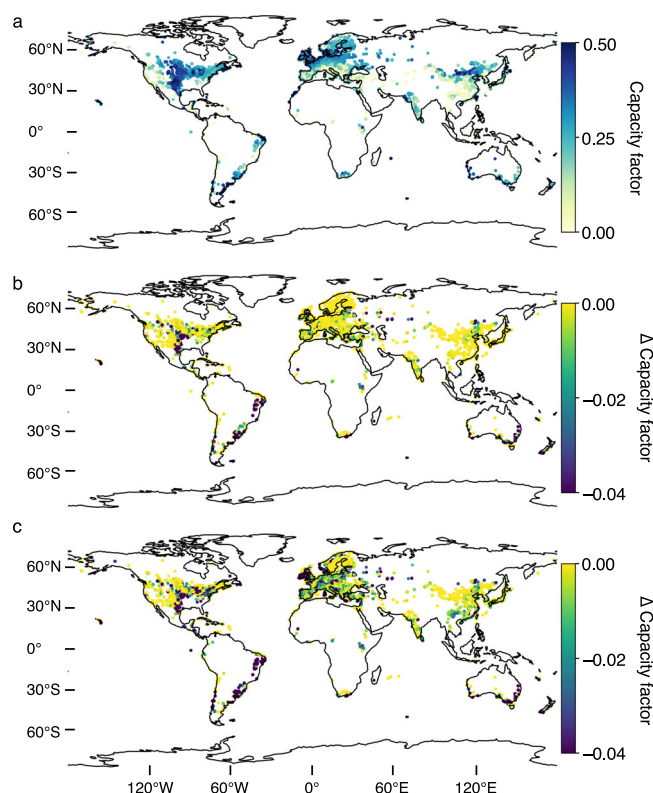


Fig. 3 | Capacity factor (CF) for currently installed onshore wind turbines with current technical features (T1 scenario) and its change in response to forestation. (a) CF of currently installed onshore wind turbines derived using the climate of 2000–2020. (b) Loss in CF of currently installed onshore wind turbines under the minimum forestation scenario (S1). (c) Loss in CF of currently installed onshore wind turbines under the maximum forestation scenario (S4). Panels a–c were produced using Cartopy (ref. 68), a Python library for geospatial data visualization, with base map data from Natural Earth (public domain dataset; <https://www.naturalearthdata.com/>).

Central Asia, Tropical Africa and the US mainland all show greater than 5% reductions in CF either under the minimum forestation scenario (S1) or the maximum forestation scenario (S4). Europe, Central America, North Africa and the Middle East, Southeast Asia, and Russia exhibit less than 5% reductions in CF under the minimum forestation scenario (S1) but greater than 5% reductions under the maximum forestation scenario (S4).

Potential changes in annual wind-energy generation for current onshore wind installations are further estimated by multiplying regional wind-energy installation capacity by the change in CF and the number of hours in a year (8760 hours) (Supplementary Tables 2 and 3). The current global wind-energy generation, without further forestation for a given total installation capacity of 838.1 GW, is estimated at 2079.3 TWh ($\text{TWh} = 10^{12} \text{ Wh}$). However, under the minimum (S1) and maximum (S4) forestation scenarios, global wind-energy generation is projected to decline by 77.7 TWh (3.7%) and 171.7 TWh (8.2%), respectively (Fig. 4 and Supplementary Table 3).

Of the thirteen regions of the globe, Eastern Asia, although it has the highest installation capacity of all regions (340.3 GW), exhibits the lowest wind-energy generation loss due to potential forestation (−8.1 TWh for S1; −13.9 TWh for S4), due to the small reduction in CF. In contrast, in Europe and the US mainland, where the installation capacity ranks second (225.2 GW) and third (144.2 GW), respectively, there is a substantial reduction in wind-energy generation. In Europe the values are −11.9 TWh for S1 and −81.1 TWh for S4 while in the US mainland they are −22.8 TWh for S1 and −28.0 TWh for S4, consistent with the strong

carbon-energy trade-off for potential forestation in these regions (Fig. 2d). In addition, there is a notable reduction in wind-energy generation in South America (−24.6 TWh for S1, −34.2 TWh for S4) which is mainly due to a large reduction in CF (−23.6% under S1 and −32.7% under S4). The discrepancy between the large reductions in wind-energy generation by currently installed wind turbines and a low carbon-energy trade-off strength in South America (Fig. 2d) is mainly because current onshore wind installations there tend to be located in coastal areas subject to large reductions in CF (Fig. 3b, c). In other regions, forestation-caused reductions in wind-energy generation for currently installed wind turbines are negligible, with reductions no greater than 10.0 TWh even under the maximum forestation scenario (S4).

Influence of potential technological improvements on the global wind turbine fleet

The energy loss in current onshore wind turbine installation sites following forestation implies that to maintain their current levels of energy generation, technological improvements in wind turbines are necessary. To assess to what extent the negative impacts of forestation could be offset by wind turbine technological improvements, the CF of current onshore installation sites under two forestation scenarios of S1 and S4 is further evaluated using two projected pessimistic (T2) and optimistic (T4) technological development scenarios developed in a recent study²⁵ (see “Methods”). When the whole globe is considered, both the pessimistic (T2) and optimistic (T4) wind turbine developments enable the post-forestation mean CF of global onshore wind installation sites to recover to or exceed the current CF level, irrespective of the forestation scenario. More specifically, under the minimum (S1) and maximum (S4) forestation scenarios, the pessimistic technological development scenario T2 is projected to increase the global mean CF of current wind installation sites to reach 0.298 and 0.281, respectively, exceeding the present CF value (0.278) with no forestation. The optimistic technological development scenario T4 is projected to increase the global CF even further, to reach 0.373 and 0.353, under the S1 and S4 forestation scenarios, respectively, approximately 1.35 and 1.27 times of the present CF value. These results indicate that, when considering the global average value, wind turbine technology improvements of current installation sites could largely compensate for the forestation-induced energy loss.

As for regional scale, all the thirteen regions, except South America, exhibit higher CF with the optimistic technological development scenario T4 than the present CF value (current wind turbine technology with no forestation), irrespective of the forestation scenario (Fig. 4). For South America (Fig. 4m) with the optimistic T4 scenario, the CF value under the minimum (S1) forestation scenario (0.295) could exceed the present CF (0.273), but the maximum (S4) forestation scenario is projected to reduce the CF to a level (0.258) below the present CF. For the same continent but with the pessimistic technological scenarios (T2), irrespective of the forestation scenario, the CF values (0.233 and 0.204 for S1 and S4, respectively) are projected to be both lower than the present CF.

Given that future wind installations may not follow the spatial distribution of existing sites and that future regional wind installation capacity remains uncertain, we further assess the influence of wind turbine technological improvements on wind-energy technical potential for the globe and for different regions (Supplementary Fig. 6). Similar to the influence of technological improvements on the CF of current onshore installation sites, both the pessimistic (T2) and optimistic (T4) technological development enable the post-forestation global total wind-energy technical potential to recover to or exceed the pre-forestation level. Under the minimum (S1) and maximum (S4) forestation scenarios, global total wind-energy technical potential with pessimistic technological development (T2) is projected to reach 735.3 PWh and 684.3 PWh, respectively, both exceeding the pre-forestation level (596.9 PWh). The global total wind-energy technical potential

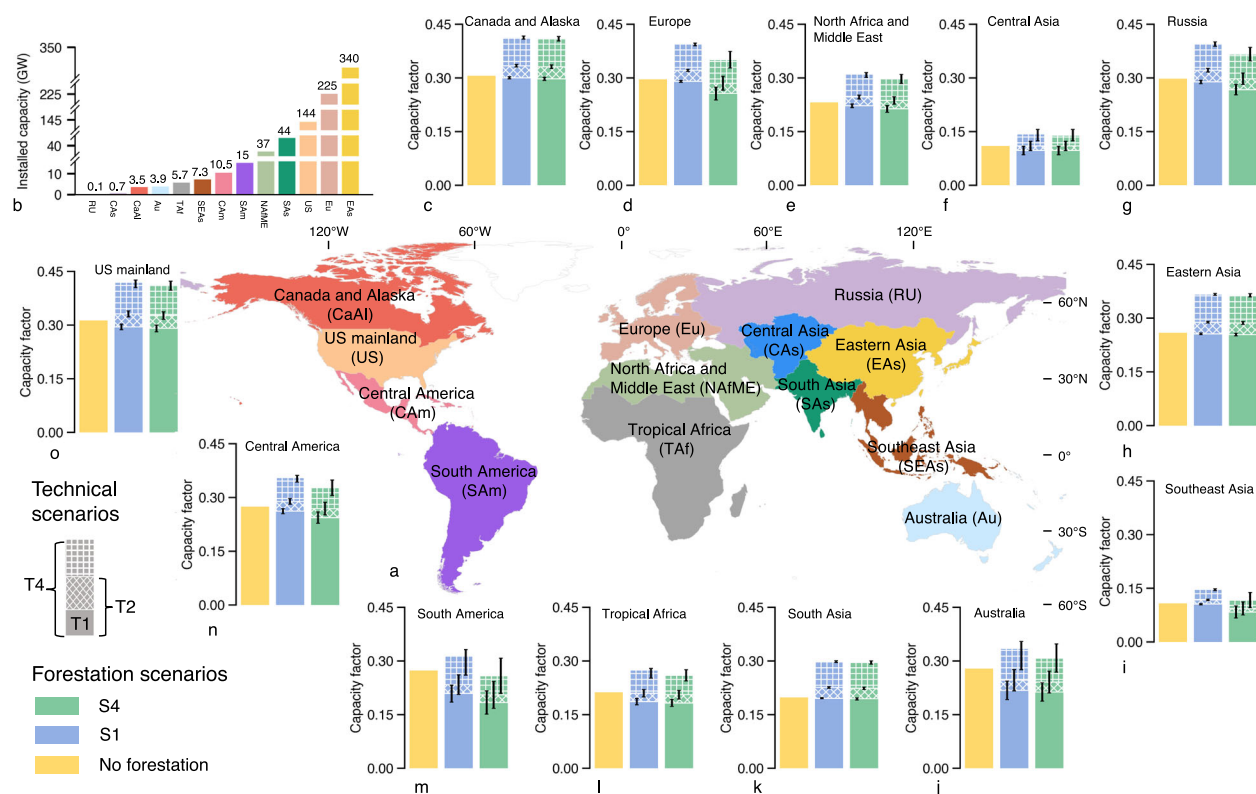


Fig. 4 | Forestation-induced changes in the average capacity factor (CF) for current onshore wind installations with different technological development scenarios for different regions. a The division of the globe into thirteen regions. **b** Total installed capacity of onshore wind installations in different regions. Panels (c) to (o) show the average CF of currently installed onshore wind turbines for different regions, for the case of no forestation (i.e., present day using the climate of 2000–2020) (yellow) and under the minimum (S1) (blue) and maximum (S4) (green) forestation scenarios. For the no-forestation scenario, the bar plots are calculated using the ERA5 dataset, and consequently, each bar corresponds to a single value. In addition, Panels (c) to (o) show the average CF of currently installed onshore wind turbines in different regions, for the case of T1 technical scenario (i.e.,

current technical scenario) (no texture), and under the T2 technical scenario (cross-hatched pattern) and T4 technical scenario (plus-hatched pattern). The results, based on the multi-model mean output, are shown as bar plots; the uncertainties (error bars) were derived by using the standard deviation of the eight ESMs in LUMIP outputs ($n = 8$). The average CF of currently installed onshore wind turbines under the T1 technical scenario for different regions was derived from Fig. 3. The world map used in (a) was obtained from the World Bank (<https://datacatalog.worldbank.org/search/dataset/0038272/world-bank-official-boundaries>), which is publicly available under the Creative Commons Attribution 4.0 International License (CC BY 4.0, <https://creativecommons.org/licenses/by/4.0/>). Maps have been modified.

with optimistic technological development (T4) under the minimum (S1) and maximum (S4) forestation scenarios could even reach 2003.3 PWh and 1863.7 PWh, respectively.

At the regional scale, the forestation-induced loss in wind-energy technical potential could be compensated for by the pessimistic technological development scenario T2 for almost all regions, irrespective of the forestation scenario. Exceptions are Europe, the US mainland, Southeast Asia, South America, and Central America, where the wind energy technical potential loss under the maximum forestation (S4) could only be compensated by the optimistic T4 scenario but not the pessimistic T2 one. In addition, for South America, the wind-energy technical potential under the minimum forestation (S1) and pessimistic technological development (T2) scenario is also projected to be below its pre-forestation level.

Discussion

Our forestation area for the S1 scenario (709.9 Mha), which accounts for food security, local biophysical warming, and biodiversity conservation, is consistent with the estimate (678.0 Mha) made in previous work⁹ with similar considerations. Our estimated living biomass carbon sequestration potential of 90.7 Gt C with a maximum forestation area of 1508.5 Mha (S4), is consistent with previous estimates. Mo et al.¹⁹ reported a carbon sequestration potential in living tree biomass

of 91.4 Gt C when existing forest, urban and cropland areas were excluded from forestation, similar to our scenario of S4. Our study and the previous studies all indicate substantial biomass carbon sequestration potential dependent on forestation area. But our results go a step further to suggest clear trade-offs between wind-energy potential and forestation-induced carbon sequestration.

Our reported forestation-induced reductions in surface wind speed and the associated reductions in wind energy are both of meaningful magnitudes. Previous studies have reported pronounced surface wind stilling since the 1980s, possibly in response to vegetation thickening or decadal ocean-atmosphere oscillations^{15,16}, with the reduction in global surface wind speed reaching -0.26 m s^{-1} over 1978–2010¹⁵. Our results indicate a surface wind speed reduction in forestation areas of $0.21\text{--}0.27 \text{ m s}^{-1}$ (Supplementary Fig. 7) in response to future forestation: a value of comparable magnitude to previously reported surface wind stilling. This result highlights the important impact of future forestation on surface wind speed through increasing land surface roughness²⁰ and by altering regional-scale circulation driven by orography, land-sea contrasts, and thermally-driven circulation contrasts between the open land and forested area^{21,22}. Although global surface wind speed recovered after 2010, increasing at a rate of 0.24 m s^{-1} per decade, such a recovery may not be sustained in forestation areas because it's driven by ocean-atmosphere circulations²³.

Furthermore, our results show that the positive effect of recent wind speed recovery on wind energy could be canceled out by future forestation.

On the other hand, surface wind speed is projected to decrease over the northern hemisphere, being partly offset by slight increases in the southern hemisphere under mid-to-high anthropogenic warming in the future^{23,24}. Nonetheless, the global average CF of current onshore wind installations is projected to decrease by 0.005–0.010 between 2020 and 2060 in response to different extents of anthropogenic climate warming²⁵. We find a reduction of 0.007–0.015 in the CF of current onshore wind installations caused by future forestation, a reduction comparable with, or even exceeding, the CF reduction caused by the worst climate warming. At the same time, the reductions in global onshore wind-energy technical potential range between –10.6% under our minimum forestation scenario and –19.5% under our maximum forestation scenario, both of which exceed the reduction in global onshore wind energy (–4.1%) under future climate change corresponding to mid-to-high level warming (RCP6.0) projected by a recent study²⁶. However, technological improvements in the wind turbine fleet could offset the reductions in wind energy caused by either climate change²⁵ or forestation.

The trade-off between forestation-induced carbon sequestration and reduced wind energy potential implies that mitigating forestation's negative impact on wind power requires either deploying more turbines or advancing turbine technology, as shown by our analysis. Since wind energy avoids CO₂ emissions that could otherwise occur from fossil fuel generation of the same electricity⁵, forestation-induced wind slowdown indirectly diminishes this emissions-avoidance benefit, thereby partly offsetting the carbon removal gained from forestation. A rough calculation (Supplementary Methods, Supplementary Table 4) indicates that the resulting loss of avoided CO₂ emissions could offset only 3–6% of forestation's carbon uptake under today's global wind capacity (6.2% of electricity generation²⁷). However, if installed wind capacity grows elevenfold by 2050—as projected in the IEA Net Zero roadmap, when wind could supply ~30% of global electricity²⁸ the offset rises to approximately 20%.

For tropical regions with high forestation efficiency and substantial biomass carbon density potential, the substantial biomass carbon created by forestation in these regions could partly offset the associated wind-energy reduction. These regions should therefore be prioritized for integrated climate strategies that combine wind energy development with forestation. For regions with substantial installed wind-energy capacity and relatively low forestation efficiency, particularly Europe and the United States, widespread forestation may already be reducing wind power generation by increasing surface roughness. Forestation projects in these regions should explicitly consider potential spatial overlap between wind installations and forest expansion, ensuring that new forests do not compromise the wind energy resource of existing or planned turbines. Likewise, strategic placement of wind turbines in locations of low forest cover could effectively mitigate the wind energy reduction arising from increased surface roughness.

The intricate but critical interaction whereby forestation reduces wind energy potential and, in turn, diminishes wind generation partly offsets forestation's carbon-sequestration benefit arises from complex Earth-system feedback processes that must be incorporated into climate mitigation policy. Integrated Assessment Models (IAMs), which simulate energy–economy–land–climate interactions to design pathways that limit warming well below 2 °C, consistently project both massive forestation (500–1000 Mha) and a roughly tenfold increase in wind capacity—scales comparable to those examined here—as essential measures. Yet, to our knowledge, current IAMs do not account for the negative forestation–wind interaction identified in this study. Our findings, therefore, underscore the urgent need to enhance IAMs by including such trade-offs and synergies²⁹, potentially through better

representation of Earth-system feedbacks, to improve the reliability of future mitigation pathways. Concurrently, future Earth-system model research should explore not only the impacts of land-based mitigation on wind resources but also the reciprocal effects of large-scale wind deployment on forest dynamics and surface–atmosphere exchanges^{30,31}.

Several potential caveats in our analysis should be kept in mind when using our results for the optimization of forestation activities and wind-energy upscaling across the globe. First, the forestation-induced changes in surface wind speed were calculated by using coupled climate model simulations, which assume climate conditions in equilibrium with contrasting forest areas. Consequently, the forestation-caused wind-energy changes assessed here represent the biophysical effects of a fully developed forest, which may take years to decades after stand establishment. In addition, the biophysical effects of forest protection (allowing existing forests to restore to a mature or old-growth state) are not included in our study. Basic forest ecophysiology indicates that forest protection or releasing currently managed forests by halting rotational wood harvest could enable recovery of tree height, leaf area index and biomass³², thereby increasing surface roughness³³ and further reducing near-surface wind speed. However, these biogeophysical effects are likely incremental compared to those from establishing new forests. Indeed, rare modeling studies investigating the biogeophysical effects of current global wood harvest reveal only minor, nearly negligible impacts on surface roughness³⁴ or land surface temperature³⁵, relative to deforestation effects. Moreover, although several studies explored the potential of carbon removal through halting wood harvest^{36,37}, this approach conflicts with rising global wood demand^{38,39}, making widespread harvest cessation an unlikely large-scale strategy for enhancing terrestrial carbon storage. We acknowledge that this study focuses on carbon storage as the primary metric for evaluating forest ecosystem benefits, without explicitly assessing other important services such as biodiversity conservation, habitat provision, or soil protection—benefits that forest protection can also deliver. These aspects fall outside the scope of our study and warrant investigation in future research.

Second, widespread forestation might alter atmospheric circulation patterns at mesoscales or larger, thereby affecting the wind speed of non-forestation areas²². However, our results show that wind speed change in grid cells without forest change, i.e., the nonlocal effect, has been largely insignificant (Supplementary Fig. 8). Hence, in this study, our methodology focused on the local surface wind effect of forestation and ignored the nonlocal effect. It should be noted, however, that the local surface wind effect of forestation simulated by ESMs reflects the well-mixed conditions of the lower atmosphere, and hence applies over the whole grid cell rather than being differentiated among vegetation types within it. It is thus reasonable to apply the simulated wind speed to wind installations in forestation grid cells that still contain some non-forest areas suitable for wind turbine installation. Third, wind energy was estimated on a monthly time scale, being limited by the temporal resolution of the LUMIP model output, whereas in reality, wind speed fluctuates at much higher temporal frequencies. Although using monthly wind speed leads to an underestimation of wind energy compared to using hourly wind speed (Supplementary Fig. 9), which is in line with previous reports^{24,40}, the reported reductions in wind-energy potential as well as the relative strengths of carbon-energy trade-offs are highly robust and independent of the temporal resolution of the wind speed (Supplementary Fig. 10).

Fourth, although previous studies²⁴ showed that using coarse-grid wind speed data yields wind-power estimates comparable with those obtained by using site-level wind speed data, our results are sub-optimal for direct application to carbon-energy optimization on a local scale. Instead, we argue that deploying both forestation and wind energy on a local to regional scale needs careful planning. Fifth,

although climate model simulations using preindustrial atmospheric CO₂ were used, we show that the derived sensitivity of wind speed to forest cover change and the associated changes in wind energy following different forestation scenarios, are very close under pre-industrial climate (including CO₂ concentration) and the SSP1-2.6 future climate (see “Methods,” Supplementary Figs. 11 and 12). This increases the relevance of our results for future climate scenario where large-scale employment of forestation and wind energy are mostly likely, because the SSP1-2.6 scenario was designed for future warming below 2 °C which is consistent with the goal of Paris Agreement⁴¹.

Despite these limitations, our results provide a benchmark and an overarching framework for managing potential carbon-energy conflicts when deploying forestation for global climate mitigation. Although on a global scale, the reported carbon-energy trade-off seems an unavoidable constraint, regional opportunities remain when such trade-offs are less strong. Primarily, tropical regions, including Southeast Asia, South Asia, Eastern Asia, Central America, and South America (56.2% of the global total), experience relatively small decreases in wind-energy technical potential. In contrast, for Europe, the US mainland and Australia, large-scale forestation could not only reduce wind-energy technical potential but also reduce the amount of energy generated by currently installed wind turbines. Forestation in these regions is thus suboptimal, and science-based planning is essential. The wind energy infrastructure, such as road construction, turbine installation, and operational noise, can have negative effects on wildlife, including birds, even in unprotected regions⁴². The rollout of renewable energy infrastructure required to meet climate objectives should proceed in a way that does not present a major threat to local conservation efforts, either within or outside protected regions. We also stress that a holistic approach, incorporating careful planning at both regional and local scales, is essential in international climate mitigation efforts to maximize the collective benefits of diverse climate solutions.

Methods

An overview of the procedure and how the various datasets and analysis steps are connected is shown in Supplementary Fig. 13.

Potential forestation area under different forestation scenarios

We conducted an extensive literature review to define key relevant terms related to forestation—afforestation, reforestation and forest restoration (Supplementary Table 1). The review examined about 40 usages of these three terms in academic journals and reports from international organizations (e.g., FAO, UNFCCC). Based on the review, in this study, “afforestation” refers to the establishment of forest (naturally or artificially) on land that has not recently been forested but where local climate and soil conditions can support forest growth, and “reforestation” refers to the re-establishment of forest (naturally or artificially) on land that was historically forested and where local climate and soil conditions still support forest growth. Thus, both afforestation and reforestation involve converting land from an unforested to a forested state and do not necessarily entail establishing monoculture plantations.

Following the mainstream of the literature (Supplementary Table 1), we define “forestation” as encompassing both afforestation and reforestation. Given that “forest restoration” carries multiple meanings—including (a) recovering lost forest (i.e., reforestation)⁴³, (b) increasing tree cover regardless of land-use history (thus including afforestation⁴⁴, (c) restoring degraded forests to their original undisturbed state⁴⁵, and (d) enhancing ecological integrity and diversity of an existing forest by recovering native species composition⁴⁶, we excluded it from “forestation.” We emphasize that forestation here does not imply unmanaged, single-species, or unguided planting; rather, we strongly advocate careful, science-based planning and management to ensure positive ecological outcomes and prevent

unintended long-term harm. This could be realized through, for example, forest establishment guided by ecological suitability and effective management practices, including planting native species, promoting mixed-species forests and maintaining proper spacing.

Although several studies explore the potential of carbon removal by increasing carbon stock in existing forests—primarily through halting wood harvest^{36,37}—this approach conflicts with rising global wood demand^{38,39}, making widespread harvest cessation an unlikely large-scale solution for enhancing terrestrial carbon storage. Moreover, site-level quantitative studies on how enhancing carbon stocks of existing forests (i.e., post-harvest recovery) affects local surface wind speed are scarce, and idealized simulations of large-scale wood harvest impacts on wind speed remain absent (see the introduction about LUMIP below), due in part to inadequate representation of harvest processes in current models^{34,35}. Accordingly, this study excludes carbon-stock enhancement in existing forests and focuses solely on forestation, defined as the expansion of forest area.

To obtain the spatial distribution of potential forestation areas, we used global potential tree cover distribution under current climate and environmental conditions as predicted by a recent study⁴⁷ (Supplementary Fig. 14). In that study, tree-cover measurements were made using direct photo interpretation in globally distributed, protected nature reserves, where vegetation is considered little affected by human activity, and hence “potential” tree cover as determined by environmental conditions is assumed to be reached. With tree cover measurements spanning the entire range of environmental and climatic gradients, potential tree cover was predicted using random forest modeling for each 30-arcsec (~1 km) pixel across the world. In our study, pixels that could be potentially forested are defined as those with a potential tree cover >25%, consistent with the definition used in previous studies⁴⁸. We assume that this approach maps areas suitable for forest growth by including both places where forests have historically been distributed, and where recent changes in climate and other environmental conditions make it possible for forests to grow. Fire disturbance, which is reported as critical for maintaining low tree cover in savanna biomes where forests are climatically suitable⁴⁹, was not included in Bastin et al.³⁵ for predicting tree cover, thus likely resulting in an overestimation of potential forest area. But on the other hand, widespread woody encroachment in African dryland over the past decades was reported in response to changes in precipitation, population and burned area⁵⁰, reflecting the possibility of forest distribution. Nonetheless, we urge that active afforestation should be avoided at places that are naturally unsuitable for forest growth, for example, the savanna biomes that are critical to maintain biodiversity, including many animals.

Spatially explicit information about existing land cover types was used to preclude certain land cover types (e.g., cropland and urban land) from potential forestation opportunities and to design different forestation scenarios (detailed below). The current distribution of forest, agricultural, grazing, and urban land (Supplementary Fig. 15 and Supplementary Table 5) was retrieved from the ESA CCI land cover dataset. The ESA CCI product was re-gridded from 300-m resolution to 1-km according to the dominant land cover type (i.e., the most frequent land cover type) of all 300-m pixels within a 1-km grid cell. For grassland, a distinction was made between more intensively managed “pasture” and extensively managed “rangeland” (Supplementary Fig. 16), following a similar method to that used in the widely adopted HYDE product⁵¹. Specifically, grassland is defined as rangeland if one of two criteria is met: (1) the aridity index (calculated as annual precipitation divided by annual potential evapotranspiration) is below 0.5; (2) the aridity index exceeds 0.5, but the population density is less than 5 inhabitants per km². Otherwise, grassland is considered pasture.

Forestation scenarios are subject to constraints regarding the source land cover type, with various considerations of food security, net biophysical warming, and biodiversity conservation^{9,12}. Four different

forestation scenarios were designed, ranging from potential forestation with the maximum constraint (the S1 scenario, corresponding to the smallest forestation area) to that with the minimum constraint (the S4 scenario, corresponding to the largest forestation area). More specifically, the maximum forestation scenario (S4) assumes forestation of all areas of potential forest distribution, excluding those currently occupied by existing forests, cropland, or human settlements. In this scenario, it is assumed that all grassland (pasture and rangeland) can be reforested. In the S3 scenario, forestation over pasture was excluded, to ensure the provision of livestock products such as meat and milk. In Scenario S2, boreal regions obtained from a climate-zone dataset⁹ (Supplementary Fig. 17) were additionally excluded from forestation, to avoid the less advantageous or even detrimental biophysical warming effect of forestation at high latitudes, which is caused by the associated surface albedo reduction⁵². Under the minimum forestation scenario of S1, currently protected nature reserve areas, as retrieved from the World Database on Protected Areas (WDPA) (Supplementary Fig. 18), were additionally excluded from forestation for the purpose of biodiversity conservation.

To ensure consistency in spatial resolution with the surface wind speed data (detailed below), all forestation scenarios were aggregated to 0.25° resolution, with the value for each grid cell indicating the fraction of ground area suitable for forestation. To better visualize the relationship between forestation-induced wind-energy change and carbon sequestration potential, five additional auxiliary forestation scenarios (V1 to V5) were interpolated using S2 and S3, and S3 and S4, respectively. This procedure resulted in equal intervals of global forestation area of approximately 100 Mha (10⁶ ha) between each consecutive forestation scenario (Fig. 1a and Supplementary Fig. 1).

Forestation-induced changes in local surface wind speed derived using multiple coupled climate models

Multiple coupled climate model simulations were used to derive forestation-induced changes in local surface wind speed at a height of 10 m. To diagnose the sensitivity of surface wind speed to forest coverage (i.e., the percentage of ground area covered by forest), paired simulations with different global forest areas are needed. For this purpose, the piControl simulation of CMIP6 was used as a forestation scenario⁵³, and the idealized global deforestation simulation (“deforest-glob”) of the LUMIP was used as a reference scenario. In part due to inadequate model representation, idealized simulations of forest wood harvest were not included in LUMIP, preventing us from using it for investigating harvest impacts on wind speed. The piControl simulation is a long-term (≥500 years) fully coupled simulation⁵³. It was forced with a background volcanic aerosol close to the mean value for 1850–2014 and a solar constant fixed at its mean value for 1850–1873. Orbital parameters, atmospheric composition (including CO₂ concentration), and land use were fixed at their 1850 levels to represent the period prior to the onset of large-scale industrialization. The deforestation simulation branches off from the piControl simulation, with a total area of 20 × 10⁶ km² of forest being removed in a temporally linear fashion over a period of 50 years and replaced by grassland. Nine ESMs carried out the “deforest-glob” experiment: MPI-ESM-1.2.0, IPSL-CM6A, CESM2, CNRM-ESM2-1, CanESM5, BCC-CSM2-MR, MIROC-ES2L, UKESM1-0LL, and EC-Earth3-Veg (for details of the models, refer to Supplementary Table 6; for the spatial pattern of deforestation area for each model, refer to Supplementary Fig. 19). We used output from all of these models except MIROC-ES2L, which was excluded from our analysis because its land cover type was fixed as woody vegetation following deforestation, and forest recovery started soon after the completion of deforestation⁵⁴. All external forcings in the idealized “deforest-glob” and piControl simulations are identical except for forest cover⁵⁴. The difference in simulated surface wind speed between these two simulations can then be ascribed to forest coverage change.

To quantify the sensitivity of local surface wind speed to forest coverage, two regional-scale regression models relating surface wind speed change to forest coverage change were constructed, and the one with the better performance was adopted. The relative change in monthly surface wind speed (ΔW_{mon}) was quantified by comparing the simulated surface wind speed between the piControl and deforest-glob simulations as ((piControl minus deforest-glob)/deforest-glob × 100%). For this purpose, the multi-year average wind speed for the years 51–80 since the branching year of both deforest-glob and piControl simulations was used (for the branching year for each model, please refer to Supplementary Table 6). Forest coverage change (FCC, percentage of ground area) was defined as the difference in forest coverage between the piControl and deforest-glob simulations (i.e., piControl minus deforest-glob). For the first model (M1), the relative change in monthly wind speed (ΔW_{mon}) was regressed against forest coverage change (FCC) across different grid cells within each region (with the globe being separated into 13 regions):

$$\text{M1: } \Delta W_{\text{mon}} = \beta_0 + \beta_1 \text{FCC} + \varepsilon \quad (1)$$

For the second model (M2), the monthly wind speed simulated by the deforest-glob simulation, termed the reference monthly wind speed (refWind), was additionally included as an independent variable in the regression:

$$\text{M2: } \Delta W_{\text{mon}} = \beta_0 + \beta_1 \text{FCC} + \beta_2 \text{refWind} + \varepsilon \quad (2)$$

For each region, the above two regression models were constructed individually using outputs from eight ESMs. The mean value of the multiple model outputs, together with the individual values from each ESM, was then utilized for subsequent analysis.

The adjusted R^2 and root mean square error (RMSE) of M1 and M2 were calculated for all 12 months and 8 ESMs for all 13 regions of the globe. For each region, the M2 model yields a higher adjusted R^2 and lower RMSE than M1 when averaged over the 12 months with 8 ESMs (Supplementary Figs. 20 and 21; Supplementary Table 7). Hence, the M2 model, fitted using multi-model mean output, was finally used to estimate forestation-induced relative wind speed change for different future forestation scenarios. In addition, the M2 model was also constructed based on the individual model output and the derived changes in relative wind speed and wind energy were used to derive the uncertainty (Figs. 1, 2, 4). The uncertainty was defined as the standard deviation of the eight individual model outputs.

Both piControl and deforest-glob simulations used an atmospheric CO₂ concentration of 1850, and hence the derived sensitivity of surface wind speed to forest coverage change (β_1 value) is best suited for preindustrial CO₂ and climate, which are different from future climate scenarios under which both forestation and wind power upscaling are likely to be employed as climate solutions. Of the future climate scenarios used by the most recent IPCC assessment reports of AR6, SSP1-2.6 represents one with strong climate mitigation and a warming magnitude of below 2 °C, consistent with the goal of the Paris Agreement and most likely feasible for large-scale employment of forestation and wind power. Hence, to maximize the relevance of our results for future climate scenarios, we additionally examined the β_1 values derived using the available ScenarioMIP ssp126 experiment and LUMIP ssp126-ssp370Lu, which both used the SSP1-2.6 climate scenario.

More specifically, the ScenarioMIP ssp126 simulations used the climate scenario of SSP1-2.6 with the associated land use scenarios, which show forest area increase compared with the current time⁵⁵. The LUMIP ssp126-ssp370Lu simulation also used the SSP1-2.6 climate scenario but with the land use change of the SSP3-7.0 scenario (the “370Lu” stands for Land Use scenario of SSP3-7.0), a medium warming

scenario with appreciable forest loss compared with current time⁵⁵. Hence, the ScenarioMIP ssp126 simulation was used as the forestation scenario, whereas the LUMIP ssp126-ssp370Lu simulation was used as the reference scenario, to examine the change in surface wind speed following forestation. The regression model of M2, as described above, was again used to derive the values of β_1 . The relative change in monthly surface wind speed (ΔW_{mon}) was quantified as $((\text{ssp126 minus ssp126-ssp370Lu}) / \text{ssp126-ssp370Lu} \times 100\%)$. The multi-year average wind speed for the last 10 years (2090–2100) of both ssp126 and ssp126-ssp370Lu was used. Forest coverage change (FCC, percentage of ground area) was defined as the difference in forest coverage between the ssp126 and ssp126-ssp370Lu simulations (i.e., ssp126 minus ssp126-ssp370Lu).

Five ESMs (MPI-ESM1-2-LR, IPSL-CM6A-LR, CESM2, CNRM-ESM2-1, UKESM1-0-LL) carried out all simulations (piControl, LUMIP deforest-glob, ScenarioMIP ssp126 and LUMIP ssp126-ssp370Lu), both for pre-industrial and SSP1-2.6 climate, and therefore they enabled comparisons of β_1 values derived for both preindustrial and future climate. As shown in Supplementary Fig. 11, the β_1 values for different regions derived under preindustrial CO₂ and climate are very close to those derived under SSP1-2.6 CO₂ and climate, which indicates low dependence of β_1 on atmospheric CO₂ level. In the meantime, the derived changes in global wind speed and wind energy under different forestation scenarios are also close between the two climate scenarios (Supplementary Fig. 12).

Current global wind turbine technical features and scenarios for future development

The calculation of forestation-induced wind energy change requires information on the current technical features of global wind turbines. We adopt the technical feature that is representative of the average rated power of the global current wind turbine fleet according to a recent study by Jung and Schindler²⁵ (the T1 scenario, see below). In that study, a detailed onshore wind turbine fleet dataset mainly including those in the United States, Germany, and Canada was compiled, which together accounted for 26.6% of global onshore installed capacity in 2020. They found an average rated power of 1.69 MW in these countries, which closely matches that of turbines in China (1.7 MW) but also worldwide (1.71 MW).

Jung and Schindler²⁵ further classified the current wind turbines into eight power classes (PC) according to their rated power (Pr): PC1000 (600 kW <Pr ≤1400 kW); PC1800 (1400 kW <Pr ≤2200 kW); PC2350 (2200 kW <Pr ≤2600 kW); PC2700 (2600 kW <Pr ≤2900 kW); PC3000 (2900 kW <Pr ≤3500 kW); PC3600 (3500 kW <Pr ≤3900 kW); PC4350 (3900 kW <Pr ≤5200 kW) and PC6200 (Pr >5200 kW). The power classes represent different levels of wind turbine technical advancement, as more recent, advanced technology enables turbines with greater Pr values. In addition, the wind turbines are also categorized into six hub height classes (HC): HC60 (hub height ≤60 m), HC80 (60 m <hub height ≤90 m), HC100 (90 m <hub height ≤110 m), HC120 (110 m <hub height ≤130 m), HC140 (130 m <hub height ≤150 m) and HC160 (hub height >150 m). In general, wind turbines with higher Pr are associated with greater HC. To describe a wind turbine by both its rated power and hub height, 29 power-height combinations (PHC) are defined.

Based on the classification of wind turbines, the technical features of currently installed global onshore wind turbines, as well as their potential evolution in the future, can then be described by different shares of 29 power-height combinations (PHC)²⁵. Jung and Schindler²⁵ defined the share of the 29 power-height combinations (PHC) classes of wind turbine (denoted as T1, Supplementary Table 8), which is representative of the mean Pr value (about 1.7 WM) of the global wind turbine fleet, and three additional scenarios (denoted as T2, T3 and T4), which represents the pessimistic, middle and optimistic developments of the global wind turbine fleet up to 2060, respectively.

We also examined how potential technological developments in the global wind turbine fleet counteract the forestation-induced negative impacts on wind energy by adopting the T2 and T4 technical scenarios of Jung and Schindler²⁵. Specifically, the technical development scenarios are based on the trends of the past and the expected increase in the deployment of modern wind turbine types with high Pr values and rotor heights. The T2 scenario assumes a linear development of wind turbine type shares in line with the development during 2014–2020. The T4 scenario assumes a more ambitious modernization of the global wind turbine fleet with higher rated power. The shares of high PC increase more strongly compared to T2, which is mapped with a two-degree polynomial for PC3600 and a three-degree polynomial for PC4350 based on the wind turbine share for 2014–2020. In addition, it considers a massive integration of the most powerful onshore turbine (PC6200). Starting at 10% in 2021, the share of PC6200 in the combined share of PC4350 and PC6200 increases by 2.0% every year until 2060. For details, please refer to Jung and Schindler²⁵. For both T2 and T4, the wind turbine type shares in 2060 were used (Supplementary Table 8).

Wind-energy technical potential change under different forestation scenarios and technical scenarios

To quantify wind energy change, we used the concept of “technical potential,” which was widely adopted by international agencies and extensively used in previous research^{56–60}. Technical potential refers to the amount of electricity that can be generated over the land area suitable for wind turbine installation for a given region, known as geographical suitability, combined with the limitations of turbine technology, turbine spacing and system loss^{26,56,57}. The use of “technical potential” enabled us to account for land areas suitable for wind turbine installation when comparing different regions.

To estimate the wind energy technical potential, we first identified the global land area suitable for onshore wind turbine installation at a 1-km resolution, consistent with the resolution at which our forestation potential maps were derived (see above). Consistent with previous studies^{56–60}, the global land area suitable for onshore wind turbine installation was obtained after accounting for geographic and environmental constraints. The following lands are considered as unsuitable for wind turbine installation: existing forests, water bodies (ESA CCI land cover dataset), high elevation areas (more than 3000 m, 1-km SRTM digital elevation database version 4.1), steeply sloped areas (>20%) (derived from 1-km SRTM digital elevation database) and urban areas (ESA CCI land cover dataset). When potential forestation (scenarios of S1–S4) areas are considered in our study, the respective forestation areas were further excluded from the suitable land for wind turbine installation. Subsequently, the global land area suitable for onshore wind turbine installation in different forestation scenarios was aggregated from the 1-km resolution to 0.25° resolution (Supplementary Fig. 22). Finally, we calculated the global and regional onshore annual wind energy technical potential (PE, in the unit of kWh) in different forestation scenarios according to Eq. 3, following a similar approach employed in previous studies⁵⁷.

$$PE = P_{\text{rated}} \times CF \times \frac{A}{0.58} \times 8760 \quad (3)$$

where P_{rated} represents the wind turbine rated-power (kW), CF denotes the capacity factor, and A denotes the land area suitable for onshore wind turbine installation (in km²). A factor of 0.58 (in the unit of km² per wind turbine), which represents the land area required per turbine, was used to derive the number of turbines that could be installed in a given land area. The value 8760 corresponds to the total number of hours in a year.

The calculation of CF requires the wind speed, the share of the 29 PHC classes of wind turbine and the specific power curve

corresponding to each PHC class, which describes the actual wind-energy output as a fraction of the rated energy output. The wind power curve is a piecewise function of wind speed (W) at the rotor hub height (H_C) consisting of four parts (Eq. 4, see Supplementary Table 9 for parameter values of different PHC wind turbine types): (a) below a cut-in speed, CF is zero, (b) between the cut-in speed and the rated speed, CF is a sigmoid function, (c) between the rated speed and the cut-out speed, CF is 1, i.e., the rated-power is fully reached, and (d) above the cut-out speed, CF is zero:

$$CF = \begin{cases} 0 & (0 < W_{HC} < \text{Cut in speed}) \\ \frac{Pr_{fit}}{1 + \exp(-k_{fit}(W_{HC} - v_{0,fit}))} / P_{rated} & (\text{Cut in speed} < W_{HC} < \text{Rated speed}) \\ 1 & (\text{Rated speed} < W_{HC} < \text{Cut out speed}) \\ 0 & (W_{HC} > \text{Cut out speed}) \end{cases} \quad (4)$$

To estimate forestation-induced changes in wind-energy technical potential under T1, T2 and T4 technical scenarios, the following seven steps were carried out. (1) The relative change in surface wind speed (%) was obtained by multiplying the regression coefficient of β_1 derived in the M2 models by the forestation fraction (converted to percentage) under different forestation scenarios. A similar approach has also been used in previous studies to derive biogeophysical changes induced by forest cover change, e.g., local surface air temperature change in response to forest cover change⁶¹ and local carbon storage change in response to deforestation-induced climate change⁶². (2) The relative change in monthly surface wind speed was multiplied by the current monthly wind speed to derive the forestation-induced monthly surface wind speed change across the globe for all forestation scenarios (Supplementary Figs. 23–26). For the current monthly wind speed, we used the monthly average surface wind speed for the current period (2000–2020) derived from ERA5 reanalysis climate data produced by the European Centre for Medium-Range Weather Forecasts. (3) Surface wind speed following potential forestation was obtained by adding the ERA5 surface wind speed and the wind speed change derived in the previous step. (4) Both the original surface wind speed (mean value of 2000–2020) and that following forestation were extrapolated to the rotor hub height using a neutral stability exponent (α) (Eq. 5). To account for the spatial variations in the stability component (α) as influenced by topography and vegetation composition, a gridded map of α was calculated through the Eq. 6 (see below) by using the gridded wind speed at 10 m and 100 m heights, averaged over the period 2000–2020 for each month, of the ERA5 climate reanalysis dataset with a spatial resolution of 0.25° (Supplementary Fig. 27).

$$W_{100} = W_{10} \left(\frac{100\text{m}}{10\text{m}} \right)^\alpha \quad (5)$$

$$\alpha = \frac{\ln(W_{100})}{\ln(W_{10})} \quad (6)$$

where W_{100} and W_{10} represent the wind speeds (in the unit of m s^{-1}) at 100 m and 10 m height in ERA5 reanalysis dataset, respectively. The values of 10 and 100 in $\ln(\frac{100}{10})$ represent the height (in the unit of m).

(5) The wind-energy CF for each PHC under the current conditions (i.e., before any forestation) and under all forestation scenarios and the scenarios of wind technical development, were calculated by employing Eq. 4. (6) The capacity factors under all forestation scenarios and technical scenarios were calculated by weighting the share and capacity factor of each PHC under the corresponding technical scenario. The rated power under all technical scenarios was also calculated based on the share and rated power of each PHC to represent the technical features of global wind turbine fleet under corresponding technical scenario. (7) Forestation-induced changes in wind-energy

technical potential under corresponding technical scenario were calculated by employing Eq. 3 with weighted capacity factor, rated power and corresponding land area suitable for onshore wind turbine installation.

Using global climate model simulations imposed a coarse spatial (0.25°) and temporal (monthly) resolution on the surface wind speed data used to estimate wind energy in this study. This practice, however, is the state of the art for evaluating large-scale wind energy changes in response to future climate change^{24,40}. Karnauskas et al.²⁴ reported that using coarse-grid wind speed data yields wind-power estimates comparable with those obtained by using site-level wind speed data, which include the temporal variability of wind power. However, using monthly average wind speed results in an underestimation of monthly total energy compared to using hourly data, but the global spatial pattern of wind energy is little influenced²⁴. Their results demonstrate the feasibility of using climate model outputs of coarse-grid monthly surface wind speed to investigate spatial-temporal changes in global wind energy, lending credibility to the approach taken here.

We also explored the effect of using monthly average wind speed on derived wind-energy change in response to forestation. The time series of global monthly mean wind energy derived by using hourly wind speed were compared with those derived by using the same hourly wind speed but aggregated to a monthly scale before computing wind energy, using ERA reanalysis climate data for 1980–2020 (Supplementary Fig. 9a). Our results confirm previous reports⁴⁰ that using a monthly average wind speed results in an underestimation of wind energy. However, the spatial pattern of global mean wind energy is quite similar between those derived using monthly average wind speed and those calculated using hourly wind speeds (Supplementary Fig. 9b, c). Thus, a persistent low bias due to using monthly average wind energy should be kept in mind when interpreting the absolute wind power values in this study. In addition, we compared wind-energy reductions following different forestation scenarios between those derived from monthly wind speed and hourly wind speed but applying the monthly-scale wind-speed model (M2). Comparable reductions in wind-energy potential for different forestation scenarios were found between those derived by using monthly and hourly wind speed data (Supplementary Fig. 10a). The strengths of the carbon-energy trade-off across the 13 regions, derived by using monthly wind speed, show almost no changes in comparison to those derived by applying the monthly wind speed model (M2) on hourly wind speed (Supplementary Fig. 10b). These results demonstrate the robustness of our conclusions to different temporal resolutions of wind speed data.

Changes in wind-energy generation by current onshore wind installations due to potential forestation

To estimate changes in wind-energy generation by currently installed onshore wind turbines due to future forestation, we used a dataset of global wind installation distribution⁶³. The dataset contains the geographical coordinates of 266,672 onshore wind installations, but contains no information on installation capacity or wind turbine type. Hence, capacity factor (CF) changes under different forestation and technical scenarios for each wind installation were derived by extracting the CF changes obtained in the previous section for the corresponding 0.25° grid cell where the wind installation is located. To explore changes in energy generation by current wind installations under future forestation and technical development scenarios for different regions, information on wind-energy installation capacity for different countries in 2022 was obtained from previous reports^{64,65} and used to calculate regional wind-energy installation capacities (Supplementary table 2). The annual wind-energy generation for the 13 regions of the globe was calculated by multiplying

the regional average capacity factor (CF) of current wind installations by the total regional installation capacity and the number of hours in a year (8760 hours).

Biomass carbon sequestration potential for different forestation scenarios

Biomass carbon sequestration potential following forestation was estimated as the carbon accumulation in forest biomass when restored forests reach an old-growth stage, i.e., when their biomass stock reaches equilibrium. The equilibrium biomass carbon density for different grid cells was obtained using global potential living tree biomass under the natural potential as predicted by a recent study¹⁹.

In that study, the global forest carbon density potential under hypothetical natural conditions was predicted by two sets of models. The first set of models (GS1 and SD1) combined aboveground forest carbon measurements and satellite-derived biomass products with spatially explicit data reflecting climate, soil conditions, topography, forest canopy cover and human disturbance, using random-forest machine-learning models to interpolate biomass carbon density across the globe. The global potential living tree biomass density under the natural potential in the first set of models was estimated by statistically accounting for the impact of human disturbance, setting all variables directly reflecting human disturbance to zero. The second set of models (GS2 and SD2) differs from the first set of models (GS1 and SD1) in a reduced number of observations (only pixels with minimal human disturbance) and a reduced number of predictors (no human-disturbance variables). The global potential living tree biomass density under the natural potential in the second set of models was estimated using aboveground forest carbon measurements and satellite-derived biomass products from protected areas with minimal human disturbance.

To account for uncertainties in canopy-cover estimates from ground-sourced data, this study incorporated upper and lower boundaries of canopy cover in each pixel, resulting in a total of four GS models: GS1_MAX, GS1_MEAN, GS2_MAX and GS2_MEAN. To assess the uncertainty in biomass density potential across various satellite-derived biomass products, this study included three satellite-derived biomass products (ESA-CCI⁶⁶, Walker et al.¹⁰ and harmonized⁶⁷), resulting in a total of six SD models: SD1_ESA-CCI, SD1_Walker, SD1_Harmonized, SD2_ESA-CCI, SD2_Walker and SD2_Harmonized. In this study, forestation-induced biomass carbon sequestration was subsequently calculated using global potential living tree biomass density derived from a full combination of models under the natural potential (Supplementary Fig. 28) and the forestation area under the different forestation scenarios.

Trade-off between wind-energy change and carbon sequestration induced by forestation

The potential trade-off between wind-energy changes and biomass carbon sequestration following forestation was assessed using different forestation scenarios. The maximum forestation scenario (S4) was selected for the examination of the spatial distributions of forestation area, forestation-induced biomass carbon sequestration and wind-energy change because it provides the largest spatial extent of forestation, thus allowing a complete spatial analysis. Specifically, the change in biomass carbon sequestration potential following forestation was calculated by multiplying forestation area (m²; Supplementary Fig. 1) and potential forest carbon density (gC/m²; Supplementary Fig. 28). The wind energy loss in forestation areas was calculated by multiplying the forestation fraction and the response of wind speed change to forestation (β_1 in Eq. 2). Regional forestation efficiency (α) was quantified as the arctangent of the ratio of the total wind-energy technical potential loss (in the unit of PWh) to total biomass carbon sequestration potential (in the unit of GtC) for each region (Eq. 7). To avoid the regional forestation efficiency obscure subnational

differences, we additionally present its spatial difference at pixel scale by calculating the arctangent of the ratio of the wind-energy technical potential loss (in the unit of TWh) to biomass carbon sequestration potential (in the unit of TgC) in each pixel (Supplementary Fig. 5). To minimize wind-energy reduction while maximizing carbon sequestration, forestation should be prioritized in those regions with a small reduction in wind-energy technical potential in comparison to their biomass carbon sequestration.

$$\text{Forestation efficiency}(\alpha) = \text{ArcTan}\left(\frac{\Delta \text{wind energy technical potential}}{\Delta \text{carbon sequestration}}\right) \quad (7)$$

To examine the robustness of our conclusion to variations in the specific details of the wind turbine power curve and rotor hub height used, the forestation-induced wind-energy technical potential reduction obtained by using 29 individual power-height combinations (PHC) described above was compared. Our results showed that the wind turbine types with different hub heights do not affect the conclusion regarding forestation-induced wind energy reduction or the ranking of forestation efficiency among different regions. (Supplementary Figs. 29 and 30).

Reporting summary

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

Data availability

The dataset of global tree-restoration potential can be retrieved from <https://www.science.org/doi/10.1126/science.aax0848>. The ESA-CCI land cover dataset is available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-land-cover?tab=form>. The aridity index database can be downloaded from https://figshare.com/articles/dataset/Global_Aridity_Index_and_Potential_Evapotranspiration_ETO_Climate_Database_v2/7504448/5. The world database on protected areas can be downloaded from <https://www.protectedplanet.net/en/thematic-areas/wdpa?tab=WDPA>. The global population dataset is available at <https://landscan.ornl.gov/>. The climate zones dataset can be obtained from <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DSDDQK>. The multi-model outputs (experiment names: piControl, deforest-glob) are available at <https://esgf-node.llnl.gov/projects/cmip6/>. The ERA5 reanalysis can be obtained at <https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5>. The current global wind installation locations are available at https://figshare.com/articles/dataset/Harmonised_global_datasets_of_wind_and_solar_farm_locations_and_power/11310269/2. This work makes use of Cartopy, a Python library for cartographic projections and geospatial data visualization⁶⁸, with base map data from Natural Earth (public domain dataset; <https://www.naturalearthdata.com/>)⁶⁹. The world maps used in Figs. 2d, 4a and Supplementary Fig. 6a were obtained from the World Bank (<https://datacatalog.worldbank.org/search/dataset/0038272/world-bank-official-boundaries>), which is publicly available under the Creative Commons Attribution 4.0 International License (CC BY 4.0, <https://creativecommons.org/licenses/by/4.0/>). Maps have been modified.

Code availability

The code in this study is archived on Zenodo at <https://doi.org/10.5281/zenodo.10669514>.

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Acknowledgements

We thank the Coupled Models Intercomparison Project Phase 6 (CMIP6) and Land Use Model Intercomparison Project (LUMIP) for providing simulation outputs that make this study possible. This study was supported by the National Natural Science Foundation of China (42525103) (C.Y.), the National Key Research and Development Program of China (2023YFB3907403) (C.Y.), the National Natural Science Foundation of China (42542708) (Z.L.), the National Natural Science Foundation of China (42571148) (W.L.), and Major Project of the National Social Science Fund (24&ZD108) (H.Z.).

Author contributions

C.Y. designed the study. P.Z., F.G., and Z.Z. performed the analysis. C.Y., P.Z., F.G., W.L., H.Z., and Z.L. drafted the paper and contributed to the interpretation of the results and to the writing.

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/s41467-026-71674-8>.

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Peer review information *Nature Communications* thanks Edgar Virguez and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. A peer review file is available.

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