

RESEARCH ARTICLE

Anthropogenic Disturbance Dampens Climate-Driven Greening in the Arctic

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Arctic vegetation is a critical component of the Earth system, regulating high-latitude carbon balance, surface energy exchange, and ecosystem resilience. Despite the widespread greening observed under recent warming, Arctic vegetation responses to the combined pressures of accelerating climate change and expanding human activity remain poorly understood, limiting our ability to anticipate future ecosystem trajectories and climate feedbacks. Here, by integrating 2 decades of 30-m Landsat observations with a novel attribution framework, we disentangled the respective contributions of climatic forcing and anthropogenic disturbance to vegetation dynamics within human footprint areas (HFAs) across the circumarctic. Based on 2,221 distinct HFA clusters, we found that while climatic warming has broadly enhanced vegetation greenness, anthropogenic disturbance has imposed strong, spatially concentrated browning, explaining 16.1% of the observed total greenness variability within HFAs. These disturbance effects are most pronounced in industrial and mining regions and intensify toward lower latitudes. Our findings reveal that human activity is emerging as an important modifier of Arctic vegetation dynamics, highlighting the need for disturbance-aware monitoring and adaptive management to sustain ecological integrity across the vulnerable Arctic.

Introduction

Although constituting a small portion of Earth's surface, the Arctic is crucial for regulating the global climate system [1,2], storing vast reservoirs of organic carbon in permafrost soils [3], and supporting unique wildlife found nowhere else on the planet [4–6]. However, this northernmost region is undergoing the fastest rate of warming on Earth [7,8], leading to severe disruptions in its ecological networks. These changes pose a critical threat to the survival of native species [9] and the livelihoods of Indigenous communities who have depended on these ecosystems for millennia [10,11]. Terrestrial vegetation, a fundamental component of the Arctic's biosphere, plays a key role in biogeochemical cycles through photosynthesis [12]. As primary producers, Arctic plants underpin food webs [13], support biodiversity [4], and provide various ecological services [8,14,15]. Additionally, the structure of vegetation communities in the Arctic affects surface albedo and energy balance, triggering a feedback loop that may accelerate climate change by absorbing more solar heat [16,17]. Given their pivotal role in ecological functioning and climate feedback mechanisms, systematic monitoring and assessment of Arctic vegetation

dynamics are essential for understanding broader Earth system change and its global consequences [18–20].

Satellite-based Earth observations have revealed augmented vegetation growth across the terrestrial Arctic since the early 1980s [21–24]. These changes, typically quantified using spectral vegetation indices, represent a conspicuous biospheric response to rapid climate warming in high northern latitudes [25–27]. However, the magnitude and persistence of pan-Arctic greening are far from uniform [28,29]. Pronounced differences have emerged among spatial-temporal scales, vegetation types, permafrost status, and regional climate regimes. Earlier studies documented strong warming-associated increases in plant greenness during the late 20th century [23], yet more recent analyses have identified localized stagnation or declines in vegetation activity (commonly termed “browning”) [29]. Declining vegetation activity has been attributed to stressors, including diminished soil moisture [29], thermokarst and permafrost thaw [30], and shifts in nutrient constraints [31]. The coexistence of both greening and browning reflects complex interactions among temperature, moisture, and nutrient availability, as well as feedbacks involving snow cover and soil thermal regimes [25,29]. Consequently, Arctic vegetation change cannot

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be understood as a simple linear response to warming. Instead, its dynamics reflect a balance among multiple, sometimes opposing, climatic and ecological processes [32]. This intrinsic heterogeneity further contributes to substantial uncertainty in projections of northern ecosystem functioning [12], complicating efforts to forecast future carbon uptake, nutrient cycling, and hydrological feedbacks under continued climate warming [19].

Alongside climatic forcing, anthropogenic disturbance has emerged as an influential factor shaping Arctic vegetation trajectories, directly altering species assemblages and spatial patterns of productivity. In northern Fennoscandia, for example, mining operations have transformed tundra landscapes, leading to shifts toward functionally distinct plant communities [33]. Across the Yamal Peninsula, extensive hydrocarbon development has altered shrub composition, reduced lichen cover, and disrupted surface hydrology [34–36]. On Alaska's North Slope, infrastructure and thermokarst interactions have been shown to degrade tundra vegetation adjacent to roads and pipelines, amplifying ground subsidence and wetland expansion [37–39]. Collectively, these regional examples demonstrate that human-induced disturbance can weaken or locally override warming-driven greening trends. However, previous assessments remain geographically fragmented, temporally limited, or methodologically inconsistent, constraining our ability to generalize disturbance impacts across the circumpolar domain. As the Arctic becomes increasingly accessible through sea-ice retreat and expanding resource exploitation, the magnitude and extent of human influence are expected to intensify, underscoring the urgent need for a unified, pan-Arctic framework to assess how anthropogenic pressures and climatic forcing jointly regulate vegetation change.

Here, we focused on pan-Arctic human footprint areas (HFAs) as key interfaces where climatic and anthropogenic drivers converge. These areas, encompassing settlements, industrial developments, and mining operations, represent critical frontiers for examining how vegetation responds to simultaneous climatic and disturbance pressures. Because HFAs are spatially heterogeneous and often composed of fine-scale disturbance mosaics, their vegetation dynamics cannot be fully resolved by coarse-resolution satellite products such as the Advanced Very High Resolution Radiometer [40] or Moderate Resolution Imaging Spectroradiometer (MODIS) [41]. The Landsat archive, with its multidecadal continuity and 30-m spatial detail, provides a unique opportunity to quantify vegetation trajectories within human-dominated landscapes at ecologically meaningful scales [11,42]. Leveraging this capability, we investigated long-term trends and variability in vegetation greenness across and within Arctic HFAs from 2000 to 2020. Specifically, we examined spatial patterns and drivers of contemporary vegetation dynamics, emphasizing the potential synergies and trade-offs between anthropogenic disturbance and climate influences. By addressing these questions, our study advances understanding of how climatic and human factors interact to shape vegetation change in the rapidly transforming Arctic, informing future ecological monitoring and sustainable land management.

Materials and Methods

Study area

This study was conducted within the entire Arctic landmass, delineated according to the 2015 *Arctic Human Development Report* (AHDR) [43]. The AHDR Arctic spans an area of over

40 million km² (or approximately 8% of Earth's total land area), encompassing Alaska, northern Canada (60°N northward), Greenland, Iceland, Norway, Sweden, Finland, and the northernmost regions of Russia (Fig. 1A). While broadly consistent with previous pan-Arctic research studies [44–46], our boundary places a stronger emphasis on regions shaped by sustained socioeconomic activity, thereby enabling a more targeted investigation of Arctic vegetation change in relation to both climate variability and human influence. The majority of the study area is underlain by continuous permafrost (Fig. 1B), while discontinuous permafrost is primarily found in the lower Arctic, including southern Alaska, interior Canada, and parts of Siberia. Toward northern Fennoscandia and the southern margins of the region, permafrost coverage diminishes further, transitioning to sporadic or isolated patches. Vegetation biomes follow pronounced biogeographic gradients (Fig. 1C), ranging from extensive boreal forests across the sub-Arctic to the treeless tundra in the high Arctic and alpine zones. Small patches of temperate forest and grassland/shrub are found along the southern fringes. In this study, biomes other than tundra and taiga/boreal forest (due to their limited coverage) were incorporated.

Datasets

Landsat images

Satellite observations from the Landsat program were used to evaluate vegetation greenness dynamics within Arctic HFAs. As one of the most widely used sources of terrestrial remote sensing data, Landsat offers a globally consistent, fine-spatial-resolution, and freely accessible record that enables rigorous analysis of vegetation dynamics over multidecadal time scales [47–49]. Among numerous Landsat products, we utilized Collection 2 Tier 1 imagery for its enhanced radiometric and geometric consistency, ensuring the reliability of long-term series analysis. Due to inconsistent data availability in the early record, we restricted the study period to 2000 to 2020, within which all usable Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) images acquired between 1 June and 1 October were retrieved from the US Geological Survey via the Google Earth Engine platform [50]. We removed images with more than 80% cloud obscuration. Invalid observations including snow, cloud, and cloud shadow were further screened out by applying the CFmask algorithm [51]. The spatial distribution of Landsat data availability (including the number of clear observations, the clear observation percentage, and the temporal length of Landsat time series) is shown in Fig. S1.

Nighttime lights

Satellite-derived nighttime light (NTL) data offer a distinctive proxy for identifying human presence and activity, with strong potential for quantifying anthropogenic pressures on natural ecosystems [52]. In this study, we employed the harmonized global NTL dataset [53] as the primary source to delimit the extent of Arctic HFAs. This product integrates NTL observations from the Defense Meteorological Satellite Program's Operational Linescan System (1992 to 2013) and the Visible Infrared Imaging Radiometer Suite onboard the Suomi National Polar-orbiting Partnership satellite (since the year 2012). Systematic corrections were applied to address issues such as observation noise, temporal discontinuity, and intersensor radiation difference [53,54]. As a result, the dataset offers the longest globally consistent record of annual nighttime

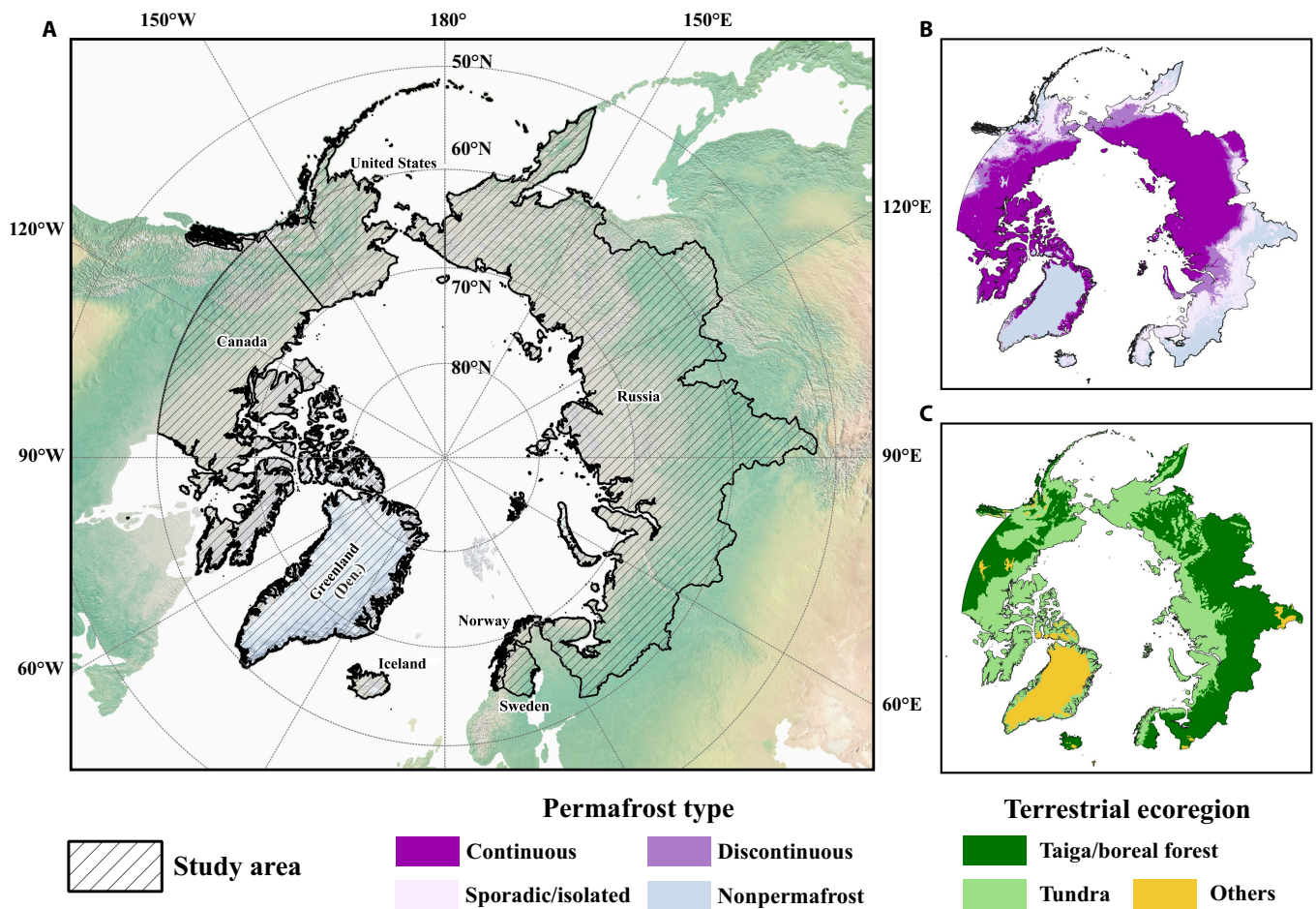


Fig. 1. Overview of the study area. (A) Spatial extent of Arctic Human Development Report (AHDR) Arctic landmass (shaded polygons with stripes) [43], overlaid on the Natural Earth basemap (<https://www.naturalearthdata.com/>). (B) and (C) display permafrost composition [108] and biogeographic zonation [109] within the study area, respectively.

illumination, with digital number (DN) values ranging from 0 to 63. In this study, we used the 30-arc-second harmonized NTL dataset available from the Figshare repository [55].

Global mining areas

To address the limitations of NTL data in capturing small-scale human presence [56,57], we further incorporated 2 global mining datasets [58,59] to enhance the delineation of Arctic HFA boundaries. Both datasets were derived from the visual interpretation of high-resolution, multisource satellite imagery and were optimized for global assessments of surface mining operations, capturing features such as excavation pits, overburden dumps, leaching areas, and related processing infrastructure. We merged the 2 datasets by retaining all mining polygons identified by either source. The combined dataset initially contained duplicates, erroneous entries, and records that did not meet the criteria of this study. To ensure data quality, we conducted a manual double check of each polygon, resulting in a validated set of mining features that collectively covered a substantial area across the Arctic.

Land disturbance maps

In this study, disturbance refers to a broad spectrum of events that result in stand-replacing conversions from one land cover type to another [60]. Such transitions may arise from anthropogenic

activities (e.g., infrastructure development, deforestation, and surface mining) or from natural processes (e.g., wildfire and flooding). However, our statistical, observation-based assessment indicates that 93.7% of observed land disturbances within Arctic HFAs are attributable to direct human activities (construction, agriculture, and urban management), with natural disturbances (fire, stress, and permafrost thaw) contributing only marginally (Fig. S2). Accordingly, we treated mapped disturbances within Arctic HFAs predominantly human induced in our analyses. To quantify these land transitions, we utilized the Global Land Cover and Land Use Change (GLCLU) dataset, developed by the Global Land Analysis and Discovery (GLAD) laboratory at the University of Maryland [61]. Derived from an ensemble of thematic bitemporal maps generated using regionally calibrated machine learning models, GLCLU provides global land surface change information at a 30-m spatial resolution from 2000 to 2020. It captures pixel-level transitions within and between major land cover classes such as tree cover, croplands, built-up areas, open water, and perennial snow and ice. Note that the GLCLU dataset is unavailable in parts of the study domain, including Greenland, the Svalbard Archipelago, and the Canadian high Arctic (north of 75°N). To fill these gaps, we incorporated the Global Land Cover Estimation (GLanCE) dataset [62], which offers comparable land change detection results for a closely aligned timeframe (from 2001 to

2019). Pixels exhibiting no recorded land cover change during the study period were classified as stable, whereas those with one or more transitions were identified as disturbed areas.

Ancillary data

Several ancillary datasets were incorporated into this study. The Global Human Settlement Layer population grid (GHS-POP R2023A) provides global residential population estimates at a 100-m resolution in 5-year intervals from 1975 to 2020 [63]. We used the 2020 layer to estimate the population sizes of detected HFAs, categorizing them as settlements (≥ 200 persons) or nonsettlements (< 200 persons). Topographic information was obtained from the Copernicus GLO-30 Digital Elevation Model, which offers 30-m resolution global elevation estimates based on radar imagery from the TanDEM-X mission. To exclude permanent and seasonal water bodies, we applied the Global Surface Water Occurrence dataset developed by the Joint Research Centre of the European Commission (JRC-GSWO) [56]. Administrative boundaries were defined using the Database of Global Administrative Areas (GADM 4.1) [57]. For comparison with our Landsat-based analysis of HFA greenness dynamics, we additionally collected 3 contemporary global HFA/urban extent products [52,54,64] and MODIS normalized difference vegetation index (NDVI) data from the Terra satellite (MOD13Q1 V6.1), which provides a 250-m spatial resolution and a 16-d revisit.

Delineating circumarctic HFAs

HFAs represent the geographic extent where human activities have substantially altered natural ecosystems [65–67]. While existing global human footprint index maps [52,54,64,66,68,69] and related datasets such as wildland–urban interface [70,71] and urban boundary [72,73] provide valuable insights at broad scales, they inadequately capture the Arctic context due to incomplete spatial coverage and limited ability to represent the combined impacts of multiple anthropogenic pressures. To address these limitations, we reproduced a new mapping layer of circumarctic HFA extents based on harmonized NTL illumination intensity, which serves as a robust proxy for distinguishing human-influenced areas from pristine landscapes [74,75]. Potential HFA clusters were extracted using Otsu's thresholding segmentation algorithm. To mask out water bodies, the 30-m JRC-GSWO dataset was aggregated to the NTL resolution, with pixels classified as water if over 50% of the underlying finer-resolution cells indicated permanent or seasonal water (labeled as 2 or 3). We retained areas associated with gas flaring, as they represent direct evidence of industrial activity and contribute substantially to environmental pressures such as air pollution, greenhouse gas emissions, and habitat disturbance. The segmentation was then applied to cumulative NTL DN values from 2016 to 2020, reducing the influence of transient or nonanthropogenic light sources and yielding initial HFA clusters composed of spatially contiguous pixels with similar illumination characteristics.

Due to the blooming effect inherent in NTL data [76], the initially extracted HFA clusters may encompass not only human-influenced areas but also adjacent undeveloped land. We therefore adopted a quantile-based approach [68,77] to refine the geographic extent of each potential HFA cluster. This approach leverages the probability distribution of NTL DN values (ranging from 0 to 63) within potential HFA clusters and identifies the turning point on the quantile curve where

the maximum deviation occurs from a linear reference line. Such a point represents the boundary at which NTL illumination intensity shifts markedly from core HFA regions to their peripheries. Depending on the degree of human presence and the spatial scale of the detected cluster, thresholding is applied once or iteratively to progressively exclude wildlands and transitional fringe areas. Unlike previous methods constrained by external calibration data, this approach enables consistent, data-driven delineation of HFAs across large and heterogeneous Arctic landscapes. To further address the limitations of NTL in detecting small-scale, low-luminance human presence, the identified HFA clusters were augmented using the derived mining polygon dataset (see the “Global mining areas” section). This integration is essential, as mining operations in the Arctic are spatially extensive yet emit minimal or no nighttime illumination, leading to their underrepresentation in NTL-based assessments. The mining polygons provide critical complementary information, capturing nonluminous but ecologically consequential disturbances, such as open-pit mines, tailings ponds, and associated infrastructure, thereby improving the completeness and accuracy of Arctic HFA delineation.

Estimating vegetation greenness dynamics

We adopted the NDVI to quantify the greenness trend of vegetation within Arctic HFAs. As one of the most widely used vegetation indices, NDVI offers a consistent, well-validated measure of photosynthetic activity, even in low-biomass environments such as alpine and polar ecosystems [78–80]. In addition, NDVI is computationally efficient and requires only red and near-infrared bands, enabling scalable analysis across large and heterogeneous Arctic landscapes. We focused on the annual maximum growing-season NDVI (NDVI_{max}) because it serves as a robust proxy for Arctic vegetation activity and mortality [24,81]. To minimize artifacts caused by the view angle effect, Landsat surface reflectance measurements were corrected using the c-factor method, which applies fixed parameters from the RossThick-LiSparse bidirectional reflectance distribution function model [82]. Furthermore, reflectance values from Landsat 5 TM and Landsat 8 OLI were harmonized to the Landsat 7 ETM+ baseline using polynomial regression with coefficients optimized for tundra and boreal ecosystems [24].

Previous studies have indicated that greenness trends derived from NDVI_{max} may be substantially overestimated due to the temporal increase in available Landsat observations [83,84]. To overcome this issue, we adopted the method of Choler et al. [79] to adjust the estimates of NDVI_{max} at the pixel level using land surface phenology information. Specifically, we fitted a harmonic function to the seasonal cycle of multiannual NDVI over a 17-year window (8 years before and after the target year). This phenological curve allowed us to estimate the difference in Landsat NDVI between the peak of the growing season and the actual day that each satellite observation was acquired ($\Delta\text{NDVI}_{\text{DOY}}$). In essence, $\Delta\text{NDVI}_{\text{DOY}}$ represents the expected adjustment in NDVI if the observation had occurred at peak greenness, rather than earlier or later in the season. We then estimated NDVI_{max} by applying this phenology-based adjustment to each individual NDVI observation:

$$\text{NDVI}_{\text{max}} = \text{NDVI}_{\text{DOY}} + \Delta\text{NDVI}_{\text{DOY}} \quad (1)$$

where NDVI_{DOY} is the observed NDVI value on a specific day within the growing season. Note that this method depends on

well-defined vegetation phenology and was therefore not applied to pixels with a mean growing-season NDVI below 0.15. For years with multiple observations, the final NDVI_{max} was estimated as the median of the adjusted NDVI_{max} values derived from each individual observation. To evaluate the performance of the correction, we conducted sensitivity tests by systematically removing valid NDVI observations when estimating NDVI_{max}. This analysis was performed using all pixels with at least 13 valid observations in 2016, the year with the highest number of clear-sky Landsat acquisitions. Notably, the corrected NDVI_{max} estimates exhibit reduced bias compared to the uncorrected values, particularly when fewer observations were available within the growing season (Fig. S3).

We assessed vegetation greenness trends across pan-Arctic HFAs using annual NDVI_{max} estimates at both pixel and cluster scales. To ensure reliability, pixels that were persistently unvegetated (minimum NDVI_{max} < 0.10) or had insufficient data records (<15 years) were excluded. Long-term trends in NDVI_{max} ($\Delta\text{NDVI}_{\text{max}}$ hereafter) were quantified using ordinary least squares (OLS) linear regression, which provides continuous, comparable estimates of trend magnitude. Unlike nonparametric methods such as the Mann–Kendall test, which assumes monotonic trends and is less responsive to directional shifts, ordinary least squares more effectively captures both gradual and abrupt changes in vegetation associated with land transitions and has been widely applied in previous studies to evaluate anthropogenic influences on vegetation dynamics [85–87]. The $\Delta\text{NDVI}_{\text{max}}$ significance was assessed using a 2-tailed Student *t* test ($P < 0.05$). Trends were classified as greening, browning, or unchanged (insignificant). Only pixels with significant trends were included in subsequent analyses unless noted otherwise, and the proportion of significant pixels within each HFA cluster is shown in Fig. S4.

Decomposing greenness trend signal

Vegetation greenness changes within Arctic HFAs are governed by 2 principal categories of drivers: climatic forcing and land disturbance. Climate-related influences encompass biophysical and biogeochemical processes such as rising air temperatures, permafrost thaw, altered nitrogen deposition, and earlier snowmelt, all associated with long-term climatic variation. Land disturbance, by contrast, involves direct human modification of surface conditions through activities such as infrastructure expansion, mining, deforestation, and urban management, which can change vegetation cover and alter soil thermal and hydrological regimes. In practice, vegetation responses in HFAs reflect the combined influence of climate forcing and anthropogenic disturbances, which cannot be independently resolved using satellite observations alone [88,89]. To address this challenge, we implemented a conceptual framework (Fig. 2) derived from the widely applied “proximity-pixel-reference” approach [85,90–92]. In this framework, each focal pixel identified as disturbed was paired with a set of nearby reference pixels characterized by stable land cover. Benchmarking greenness trajectories of focal pixels against these references enables the attribution of observed trends to either disturbance-related or climate-related processes. This approach provides a standardized means of isolating the respective contributions of human-induced land surface transformation and background climatic variation to vegetation greenness dynamics across Arctic HFAs.

As a first step, we normalized the annual NDVI_{max} time series at the pixel level using *z*-scores:

$$z = (x - \mu) / \sigma \quad (2)$$

where *z* is the *z*-score, *x* is the annual NDVI_{max} estimate, and μ and σ represent the multi-year mean and standard deviation of *x*, respectively, calculated over the study period from 2000 to 2020. Based on these normalized values, the observed greenness trend of the target pixel ($\Delta z_{\text{OBS}}^{\text{Pix}_{\text{target}}}$) was decomposed into 2 additive components:

$$\Delta z_{\text{OBS}}^{\text{Pix}_{\text{target}}} = \Delta z_{\text{DD}}^{\text{Pix}_{\text{target}}} + \Delta z_{\text{CD}}^{\text{Pix}_{\text{target}}} \rightarrow \Delta z_{\text{DD}}^{\text{Pix}_{\text{target}}} = \Delta z_{\text{OBS}}^{\text{Pix}_{\text{target}}} - \Delta z_{\text{CD}}^{\text{Pix}_{\text{target}}} \quad (3)$$

where $\Delta z_{\text{DD}}^{\text{Pix}_{\text{target}}}$ and $\Delta z_{\text{CD}}^{\text{Pix}_{\text{target}}}$ represent the contributions from disturbance and climate change drivers, respectively. For each target pixel, $\Delta z_{\text{DD}}^{\text{Pix}_{\text{target}}}$ was estimated from surrounding reference pixels with stable land cover, where disturbance effects were negligible ($\Delta z_{\text{DD}}^{\text{Pix}_{\text{reference}}} \cong 0$), such that $\Delta z_{\text{OBS}}^{\text{Pix}_{\text{reference}}} \cong \Delta z_{\text{CD}}^{\text{Pix}_{\text{reference}}}$.

To ensure climatic comparability, reference pixels were selected from within a 6-km radius of the target pixel. This threshold was selected to balance local climatic representativeness with a sufficient sample size of stable reference pixels. Importantly, sensitivity analyses with varying radii (2, 4, 6, 8, and 10 km) confirmed that the estimated contributions were robust and insensitive to this specific choice (Fig. S5). To further control for orographic effects, we excluded pixels with elevation differences greater than ± 500 m, a threshold established in previous studies to minimize phenological divergence caused by temperature lapse rates [93]. The average *z*-score trend of these reference pixels was then used to approximate $\Delta z_{\text{CD}}^{\text{Pix}_{\text{target}}}$. Finally, $\Delta z_{\text{DD}}^{\text{Pix}_{\text{target}}}$ was derived as the residual between observed and climate-driven trends.

We further aggregated the pixel-level contributions of disturbance and climate drivers to the observed greenness trend at the scale of each HFA cluster, using pixel area as a weighting factor to ensure representativeness. The overall *z*-score trend for a given HFA cluster ($\Delta z_{\text{OBS}}^{\text{HFA}_{\text{target}}}$) was decomposed as

$$\Delta z_{\text{OBS}}^{\text{HFA}_{\text{target}}} = \Delta z_{\text{DD}}^{\text{HFA}_{\text{target}}} + \Delta z_{\text{CD}}^{\text{HFA}_{\text{target}}} + \Delta z_{\text{RES}}^{\text{HFA}_{\text{target}}} \quad (4)$$

$$\Delta z_{\text{OBS}}^{\text{HFA}_{\text{target}}} = \sum_{i=1}^n \Delta z_{\text{OBS}}^{\text{Pix}_{\text{target}}} / n \quad (5)$$

$$\Delta z_{\text{CD}}^{\text{HFA}_{\text{target}}} = \sum_{i=1}^n \Delta z_{\text{CD}}^{\text{Pix}_{\text{target}}} / n \quad (6)$$

$$\Delta z_{\text{DD}}^{\text{HFA}_{\text{target}}} = \left(\sum_{i=1}^m \Delta z_{\text{DD}}^{\text{Pix}_{\text{target}}} / m \right) \times (m/n) = \sum_{i=1}^m \Delta z_{\text{DD}}^{\text{Pix}_{\text{target}}} / n \quad (7)$$

where $\Delta z_{\text{OBS}}^{\text{HFA}_{\text{target}}}$ denotes the observed mean *z*-score trend for the target HFA cluster, computed as the average of all pixel-level trends (*n* total pixels). $\Delta z_{\text{CD}}^{\text{HFA}_{\text{target}}}$ and $\Delta z_{\text{DD}}^{\text{HFA}_{\text{target}}}$ represent the respective contributions from climate and disturbance drivers.

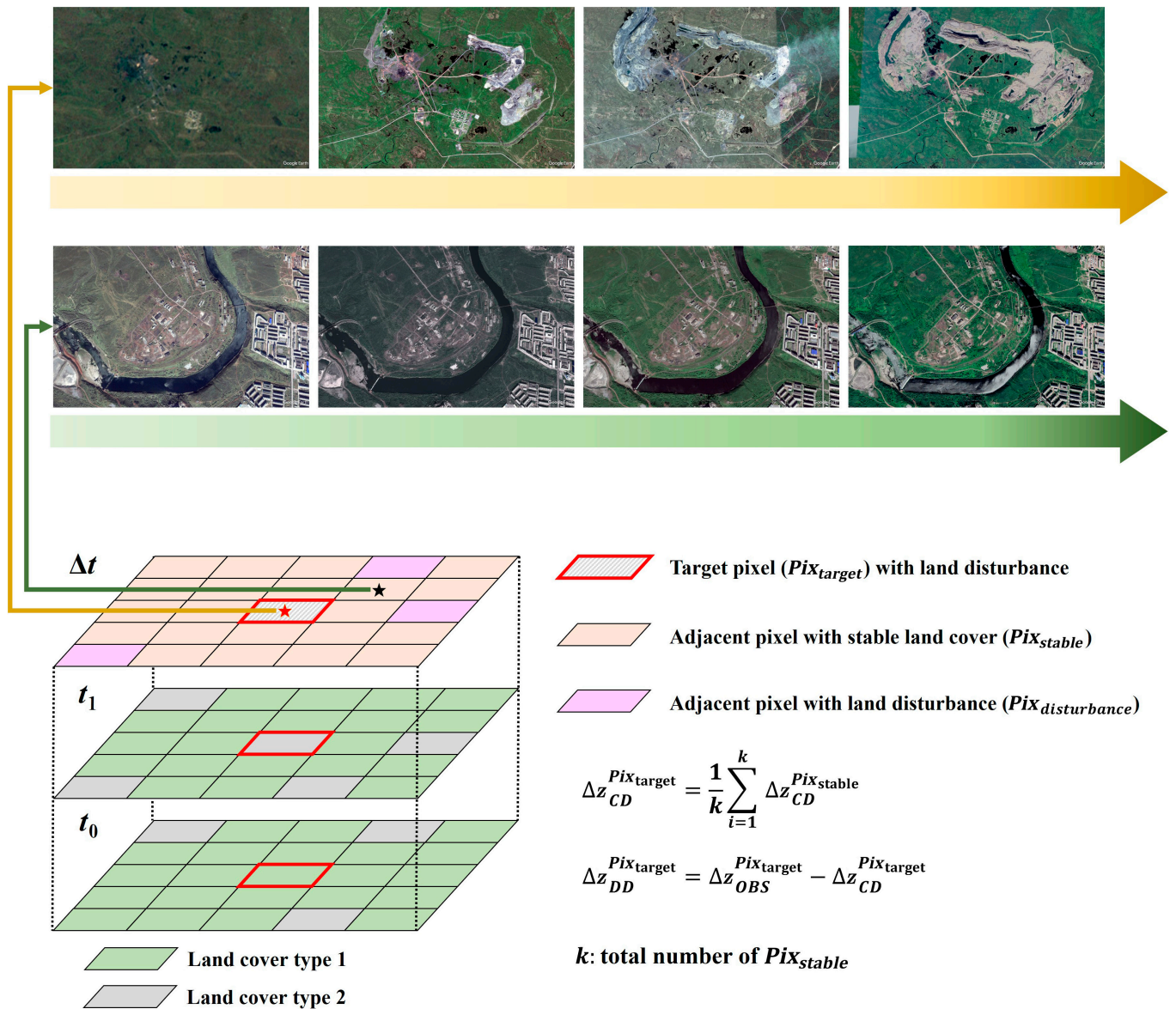


Fig. 2. Conceptual framework for attributing vegetation greenness changes within Arctic human footprint areas (HFAs). Satellite image sequences illustrate disturbance (top) and stable land cover (middle). The focal pixel (outlined in red) is benchmarked against surrounding reference pixels with stable land cover to separate the land disturbance-related and climate-driven components of vegetation greenness trends.

m is the number of pixels that experienced land disturbance within the HFA cluster. Since land disturbance affects only a subset of pixels ($m \leq n$), its contribution was proportionally scaled by the fraction of affected pixels relative to the total cluster area. $\Delta z_{RES}^{HFA_{target}}$ represents the residual term, capturing potential errors and additional influencing factors not explicitly accounted for in our analysis. To determine the dominant driver of vegetation greenness change, we quantified the relative contributions of each component as follows:

$$C_{DD} = |\Delta z_{DD}| / |\Delta z_{DD} + \Delta z_{CD} + \Delta z_{RES}| \times 100\% \quad (8)$$

$$C_{CD} = |\Delta z_{CD}| / |\Delta z_{DD} + \Delta z_{CD} + \Delta z_{RES}| \times 100\% \quad (9)$$

$$C_{RES} = |\Delta z_{RES}| / |\Delta z_{DD} + \Delta z_{CD} + \Delta z_{RES}| \times 100\% \quad (10)$$

where C_{DD} , C_{CD} , and C_{RES} represent the percentage contributions of land disturbance, climatic forcing, and residual effects, respectively. The driver category with the highest contribution was identified as the major control of greenness trend for each unit. These contribution metrics was computed at cluster levels, enabling spatially explicit attribution and offering mechanistic insight into the drivers of greening or browning within Arctic HFAs.

Results

HFA distribution across the Arctic

Across the Arctic, we mapped 2,221 distinct HFA clusters with a combined area of 21,402 km² (Fig. 3A and B). Although settlements were far fewer than nonsettlements (435 vs. 1,786), they covered a larger share of the total HFA (12,902 km² vs. 8,500 km²). Disturbance intensity varied markedly among clusters, ranging

from nearly undisturbed (0%) to almost entirely disturbed (99.6%). On average, nonsettlement HFAs exhibited greater disturbance (mean = 17.2%) than settlement HFAs (mean = 11.8%). Settlement HFAs spanned a wide range of scales: small (<10 km²), medium (10 to 100 km²), and large (>100 km²) clusters represented 41.6%, 53.1%, and 5.3% of all settlements, respectively, but collectively contributed 5.5%, 61.0%, and 33.5% of the total settlement area. In contrast, nonsettlement HFAs were overwhelmingly composed of small and medium clusters, together comprising 99.3% of all clusters and 72.8% of the total area. To elucidate geographic patterns, we aggregated HFA cluster area and disturbance intensity by country, permafrost type, and biome (Fig. 3C). At the country level, Russia contained by far the largest HFA (18,018.8 km²), followed by the North American Arctic (1,961.2 km²) and the Nordic countries (1,422.0 km²). When grouped by permafrost type, HFAs were extensive in isolated/sporadic permafrost zones. Biome-level patterns showed that HFAs occurred predominantly within boreal forest, where forestry, mining, and energy development are concentrated. Collectively, these patterns highlight the coupling between human activity, permafrost characteristics, and biome-specific resource availability across the Arctic, shaped in part by national policies and regional development priorities. To illustrate this diversity, we selected 8 representative Arctic HFAs (Fig. 3D to K) for detailed analysis. These sites encompass a wide spectrum of geographic settings and development intensities, ranging from established urban agglomerations to intensive resource extraction zones. Comparisons with existing global datasets confirmed that our results more accurately delineate these HFA extents (Fig. S6), enabling a precise characterization of their variation in size and spatial configuration. For instance, cities including Krasnoyarsk, Murmansk, and Fairbanks exhibit complex urban forms shaped by settlement and transportation infrastructure. In contrast, resource-dependent sites display distinct morphological signatures. The Mirny diamond mine and Fort Knox gold mine feature concentric, excavation-driven footprints, whereas Vorkuta (coal) displays elongated, corridor-like structures constrained by transportation networks and local terrain.

Diverging vegetation trends across disturbed and stable Arctic HFAs

We identified contrasting vegetation trajectories between disturbance-affected and stable areas within Arctic HFAs over the past 2 decades (Fig. 4A). Specifically, disturbed areas exhibited a pronounced browning trend ($\Delta\text{NDVI}_{\text{max}} = -109.7 \times 10^{-4} \text{ year}^{-1}$, $P < 0.05$), whereas stable areas showed a moderate greening trend ($\Delta\text{NDVI}_{\text{max}} = 37.8 \times 10^{-4} \text{ year}^{-1}$, $P < 0.05$). A distinct greenness shift occurred around 2011, after which the NDVI_{max} of stable areas remained higher than that of disturbed regions, suggesting an increasing divergence in vegetation response. Across pan-Arctic HFAs, $\Delta\text{NDVI}_{\text{max}}$ displayed a clear negative relationship with disturbance intensity (Fig. 4B). Low-intensity disturbances were frequently associated with vegetation greening, yet as the disturbance percentage increased, $\Delta\text{NDVI}_{\text{max}}$ declined progressively, indicating a transition toward browning in heavily disturbed clusters (each 1% increase in disturbance corresponded to an estimated 2.3-unit decrease in $\Delta\text{NDVI}_{\text{max}}$). Spatially, disturbed areas exhibited negative $\Delta\text{NDVI}_{\text{max}}$ values in 58.7% of all HFA clusters, although the browning magnitude varied considerably across demographic, geographic, and ecological contexts (Fig. 4C and Fig. S7). Notably, browning

hotspots were particularly concentrated in the lower Arctic, including southern Siberia, Sweden, and parts of the Canadian Arctic. In contrast, stable areas displayed a predominance of greening HFA clusters (67.7%), more than double the proportion of browning clusters (32.3%). Greening signals in stable areas were widespread across Eurasia and Alaska, with the strongest positive $\Delta\text{NDVI}_{\text{max}}$ observed in taiga-dominated and high-latitude permafrost regions (Fig. 4D and Fig. S7).

We further selected 3 representative subset regions (Mirny, Yellowknife, and Fort Knox) to illustrate contrasting greenness dynamics between disturbed and stable areas within Arctic HFAs (Fig. 5). These sites capture the diversity of Arctic climate zones, geographic settings, and socioecological conditions. Quantitative analysis confirmed that anthropogenic disturbance markedly suppresses vegetation greening trends across all 3 diverse settings. Two-sided Wilcoxon rank-sum tests revealed highly significant differences ($P < 0.0001$) in the distribution of $\Delta\text{NDVI}_{\text{max}}$ between disturbed and stable areas (Fig. 5A to C), with disturbed zones consistently exhibiting lower NDVI_{max} trends than stable areas, although the magnitude of difference varied among regions. Spatially, greening was concentrated within urban cores, whereas browning occurred predominantly in peripheral vegetated zones, along transport corridors, and around industrial facilities. Despite the mosaic of greening and browning patterns, high-resolution Google Earth imagery from ~2000 and ~2020 reveals a clear spatial correspondence between mapped disturbance zones and observed land transformations, including infrastructure development, vegetation loss surrounding settlement areas, and the expansion of mining footprints (Fig. 5D to F). In contrast, stable landscapes within these HFAs generally retained or enhanced greenness during the same period, underscoring a consistent spatial separation between disturbance-related browning and background greening signals across the pan-Arctic domain. Notably, $\Delta\text{NDVI}_{\text{max}}$ values derived from Landsat closely matched those from MODIS but provided substantially finer spatial detail, capturing localized greening and browning patterns that are largely obscured in coarser-resolution satellite products (Fig. S8).

Attribution of vegetation greenness responses to disturbance and climate

The observed greenness trend was further partitioned into climate-related and disturbance-related components (Fig. 6). Among analyzed vegetated pixels within HFAs, climate contributions were predominantly positive: 76.3% of pixels exhibited greening and 23.7% browning, yielding a mean Δz of +0.05 (year⁻¹). By contrast, disturbance contributions were overall negative: 68.9% of pixels showed browning and 31.1% greening, with a mean Δz of -0.05 (year⁻¹). Spatial patterns further underscored the contrasting signatures of the 2 drivers (Fig. 6A and B). Climate-related greening extended over broad, contiguous areas of western Siberia and central Alaska, with additional coverage across northern Eurasia and Arctic North America. Climate-related browning was less extensive, mainly distributed in southern and eastern Siberia, the Canadian Arctic, and parts of Fennoscandia. In sharp contrast, disturbance-related browning was prominent across the entire Arctic. The strongest signals occurred in settlement-dense regions of western Russia and northern Fennoscandia, in major mining zones of Arctic Canada and Siberia, and along transportation corridors including roads and pipelines. Disturbance-related greening was limited and appeared only in small, spatially scattered patches. The joint influence of these forces created a mosaic of

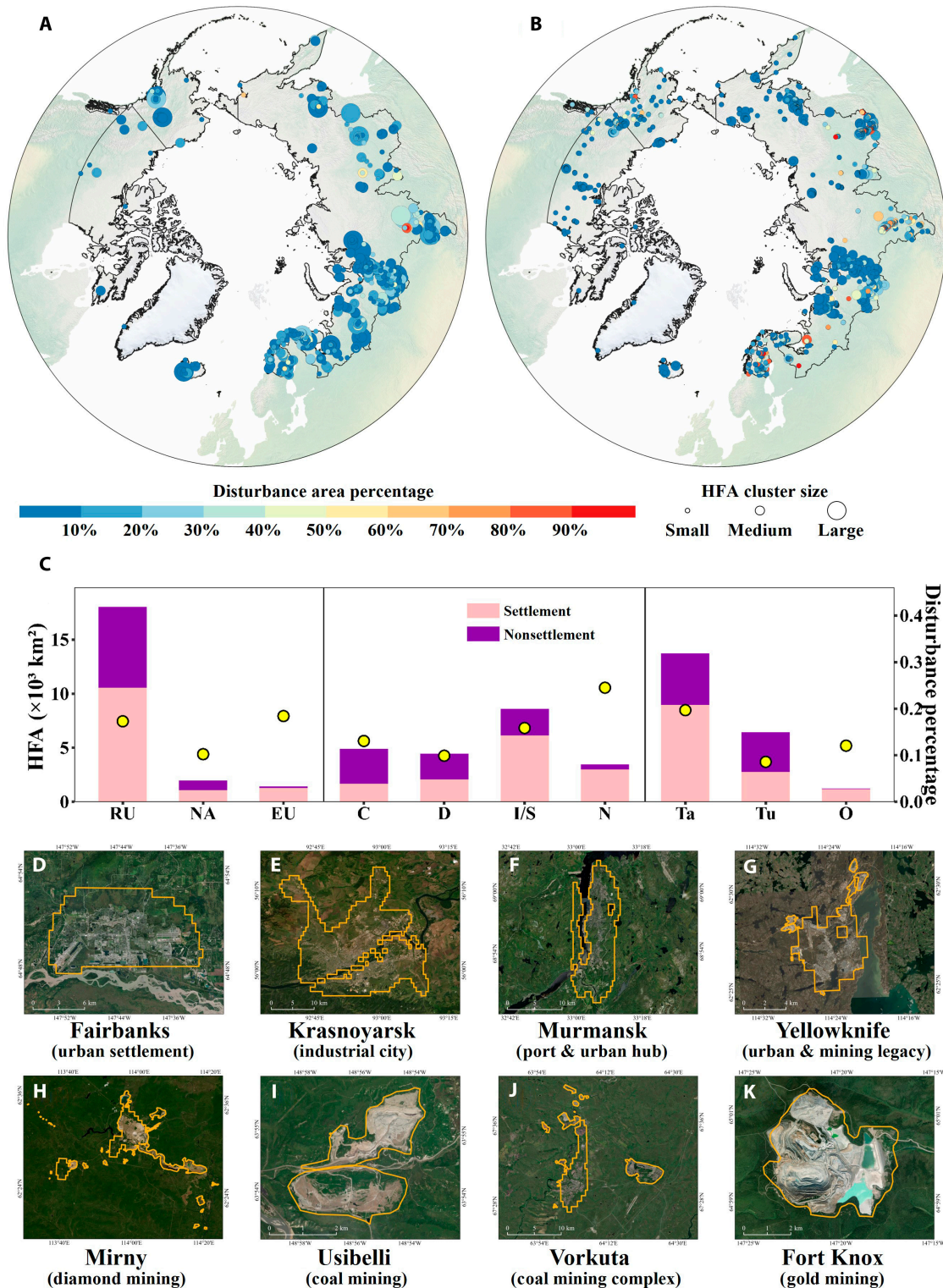


Fig. 3. Circumpolar distribution of human footprint areas (HFAs). (A) and (B) are maps of Arctic HFA clusters categorized as settlement ($n = 435$) and nonsettlement ($n = 1,786$), respectively. Points are colored by land disturbance area percentage and sized by cluster area, with 3 size classes: small ($<10 \text{ km}^2$), medium (10 to 100 km^2), and large ($>100 \text{ km}^2$). (C) Total area (bars) and mean disturbance percentage (yellow dots) of Arctic HFAs grouped by country (RU, NA and EU represent Russian, North American and European Arctic, respectively), permafrost type (C, continuous; D, discontinuous; I/S, isolated/sporadic; N, nonpermafrost), and biome (Ta, taiga/boreal forest; Tu, tundra; O, other biome types). (D) to (K) are 8 representative HFAs, explicitly labeled by their dominant disturbance driver: Fairbanks (64.8°N , 147.7°W), Krasnoyarsk (56.0°N , 92.9°E), Murmansk (69.0°N , 33.1°E), Yellowknife (62.5°N , 114.4°W), Mirny (62.5°N , 114.0°E), Usibelli coal mine (63.9°N , 148.8°W), Vorkuta (67.5°N , 64.1°E), and Fort Knox gold mine (65.0°N , 147.4°W).

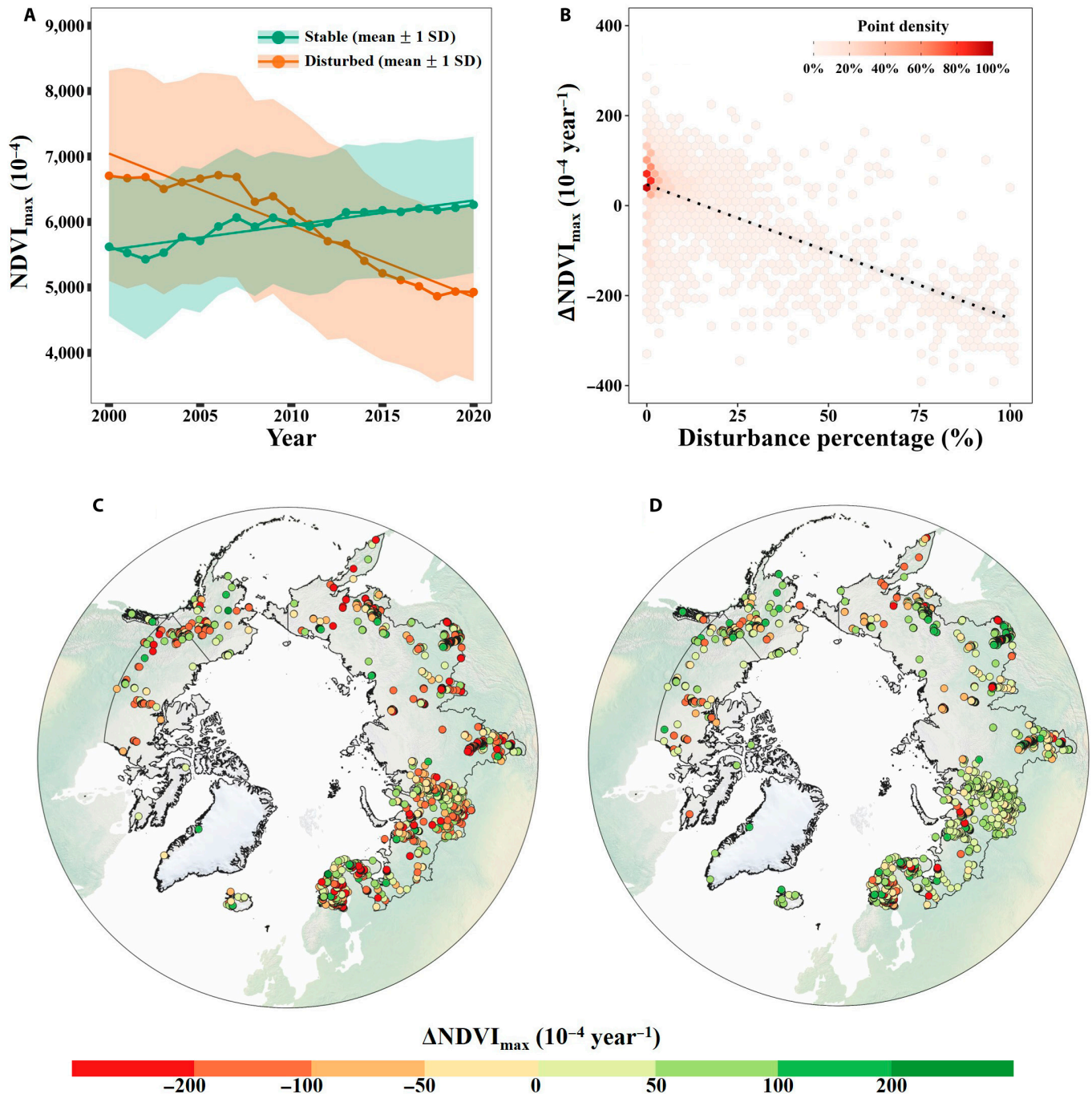


Fig. 4. Inter-annual NDVI_{max} change within pan-Arctic human footprint areas (HFAs) from 2000 to 2020. (A) Annual NDVI_{max} time series for stable (green) and disturbed (orange) areas, with shaded area representing ± 1 standard deviation. (B) Gradient in $\Delta\text{NDVI}_{\text{max}}$ along the disturbance percentage at the HFA cluster level. Each hexagon summarizes the local density of points falling within that portion of the 2-dimensional space, with warmer colors indicating areas of higher point density. The dotted line represents the trend derived from linear regression. (C and D) Spatial distribution of $\Delta\text{NDVI}_{\text{max}}$ for disturbed (C) and stable (D) areas, aggregated at the HFA cluster level. NDVI, normalized difference vegetation index.

reinforcing and offsetting signals, characterized by 4 co-change types: climate-greening with disturbance-browning, climate-browning with disturbance-greening, concordant greening, and concordant browning (Fig. 6C). Spatially, climate-greening with disturbance-browning was dominant, accounting for 50.3% of the total Arctic HFAs, with notable concentrations in western Russia and parts of southern Siberia. Concordant greening and concordant browning followed, covering 26.5% and 21.5% of the area, respectively, while climate-browning

with disturbance-greening was rare (1.7%). To further synthesize these interactions, we aggregated the co-change types into broad categories of reinforcing and offsetting effects (Fig. S9). This simplified view confirms that antagonistic interactions, where human disturbance opposes climate impact, are the defining vegetation greenness trend characteristic of Arctic HFAs.

The box-scatter plots (Fig. 6D and E) provide a complementary perspective by summarizing driver contributions across demographic, regional, and ecological contexts. In all groups,

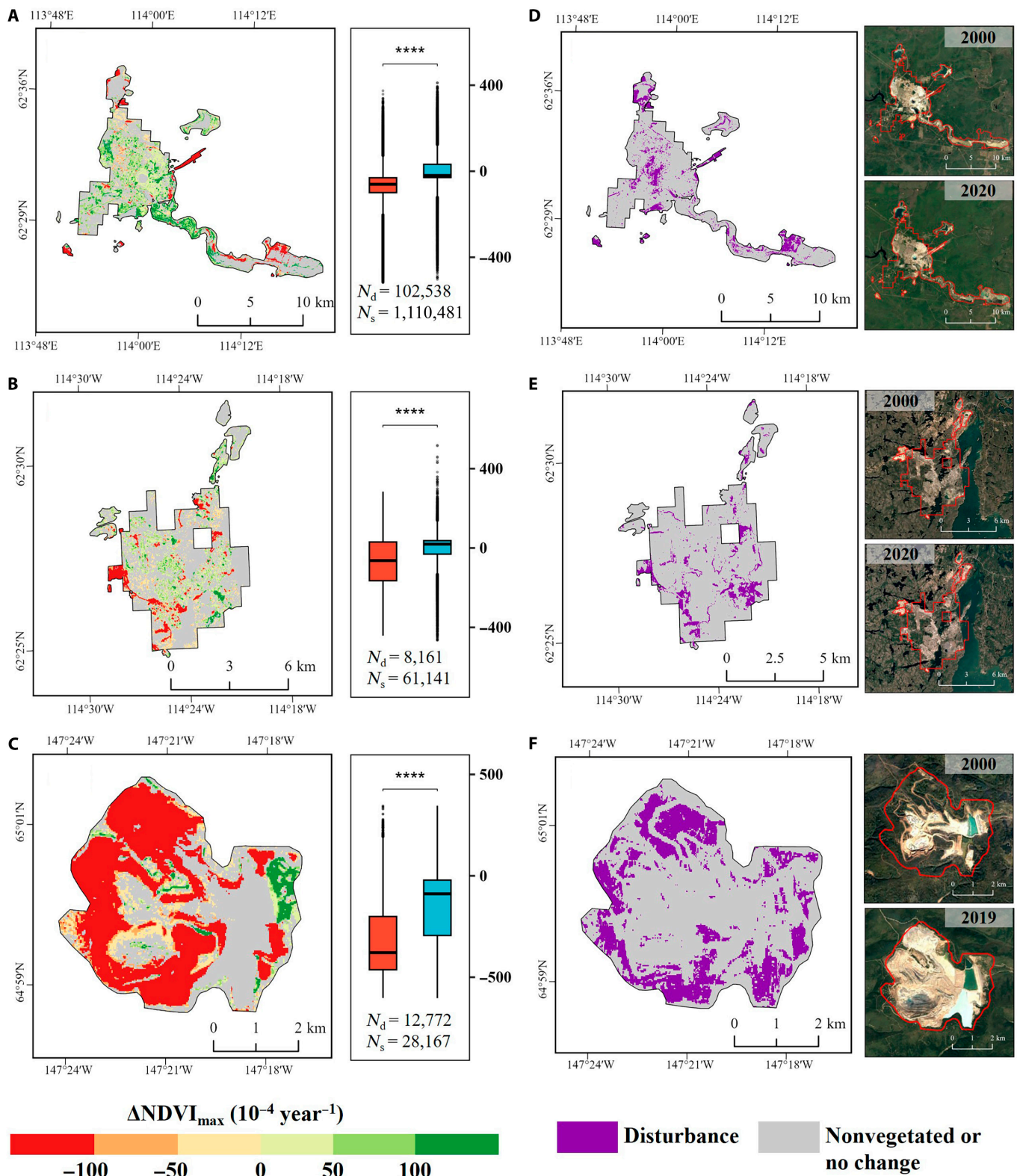


Fig. 5. Regional subsets of $\Delta\text{NDVI}_{\text{max}}$ and land disturbance for 3 representative human footprint areas (HFAs), namely, Mirny, Yellowknife, and Fort Knox. (A to C) $\Delta\text{NDVI}_{\text{max}}$ maps with accompanying box plots for disturbed (red) and stable (light blue) areas. In the box plots, the centerline represents the median, box limits indicate the interquartile range (IQR; 25th to 75th percentiles), and whiskers extend to $1.5 \times \text{IQR}$. Statistical differences between groups were assessed using 2-sided Wilcoxon rank-sum tests. Significance brackets denote the test results, where **** indicates $P < 0.0001$. The exact sample size (number of analyzed pixels) for disturbance and stable area groups (N_d and N_s) is displayed below the corresponding box plot; (D to F) Land disturbance maps with corresponding high-resolution Google Earth imagery (~2000 and ~2020) shown alongside each subset. Disturbed lands are highlighted in purple, while nonvegetated and pixels with insignificant greenness change are shown in gray. NDVI, normalized difference vegetation index.

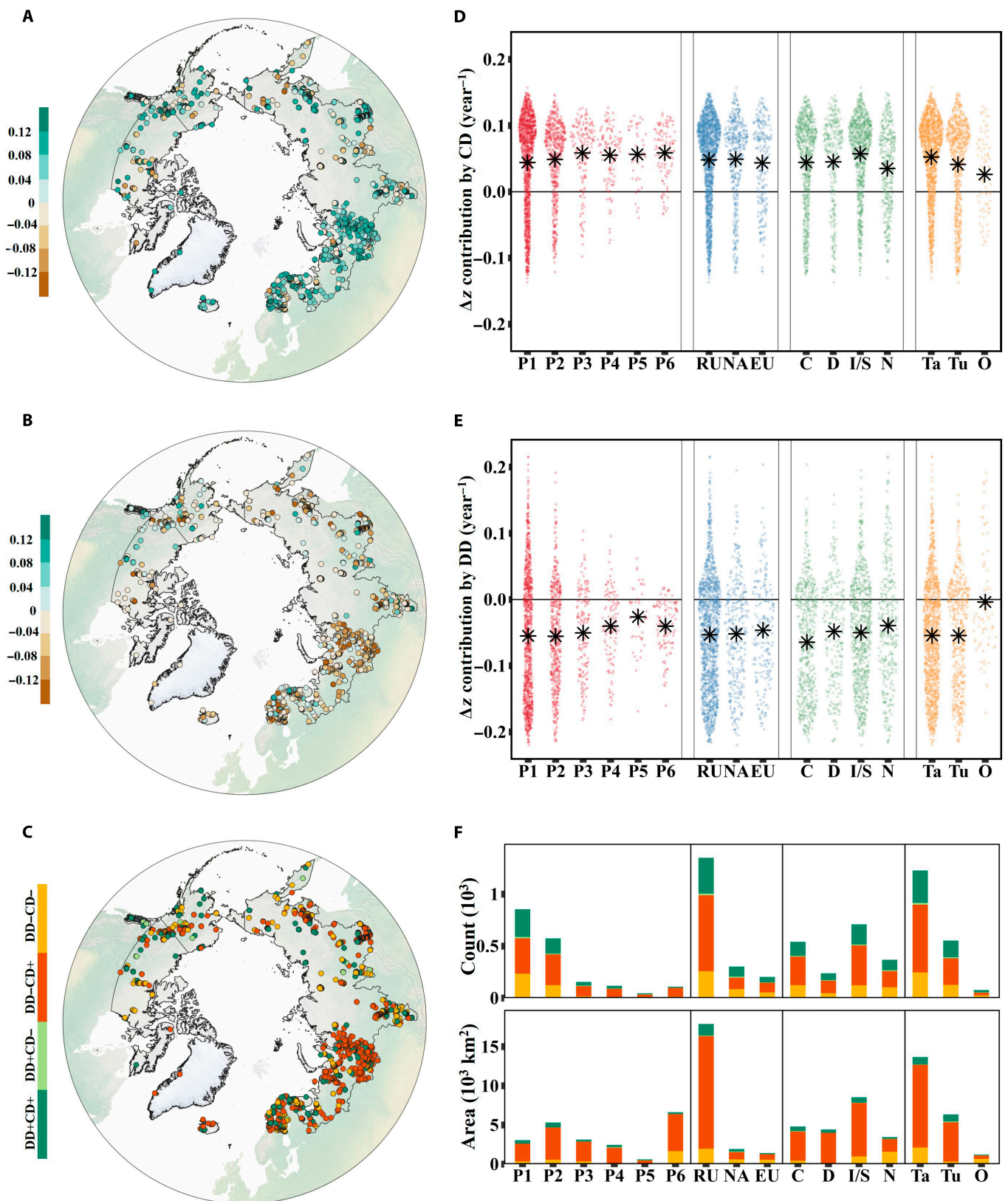


Fig. 6. Patterns of vegetation greenness dynamics within Arctic human footprint areas (HFAs) attributed to climate-driven (CD) and disturbance-driven (DD) components. (A and B) Spatial distributions of Δz (year^{-1}) from CD and DD, respectively. (C) Spatial distribution of co-change categories combining CD and DD, with “+” and “-” denoting greening and browning, respectively. (D and E) Statistical distributions of Δz contributions from CD and DD grouped by population size (P1 to P6), country, permafrost type, and biome. Small points represent individual HFA clusters, and black asterisks denote group means. (F) Stacked bar charts summarizing the count (top) and total area (bottom) of HFAs for each co-change type across different categories. Population classes are defined by inhabitant count: P1 (0), P2 (1 to 200), P3 (201 to 1,000), P4 (1,001 to 5,000), P5 (5,001 to 10,000), and P6 (>10,000). Abbreviations for countries, permafrost types, and biomes follow Fig. 3.

climate-related greening and disturbance-related browning prevailed, although climate contributions exhibited broader variability. Notably, the magnitude of climate-associated greening tended to increase with population size, while the strength of disturbance-related browning showed partial attenuation along the same gradient. By contrast, no systematic trends emerged among Arctic countries or permafrost types. At the biome scale, taiga and tundra exhibited stronger climate-associated greening and disturbance associated browning than other ecosystems, underscoring that both drivers consistently act in opposing directions but with differing intensity depending on ecological setting. Stacked bar summaries (Fig. 6F) further confirmed that disturbance-induced browning frequently counteracts climate-driven greening across groups: a pattern that is noticeably more pronounced when assessed by total HFA rather than frequency count. Together, these results indicate that although climate forcing generally enhances vegetation greenness, anthropogenic disturbance exerts concentrated browning pressures, and their interaction amplifies the spatial heterogeneity of vegetation change.

By quantifying the relative contributions of disturbance and climate drivers, we identified spatially divergent controls of vegetation greenness dynamics within Arctic HFAs (Fig. 7). Although disturbance contributed modestly on average (16.1%), it imposed disproportionately strong browning pressures in several regions, including western Russia, southern Scandinavia, and major industrial and mining corridors in Siberia and Alaska (Fig. 7A). Grouped comparisons further showed that climate forcing consistently dominated across population classes, countries, permafrost zones, and biomes, yet disturbance remained a substantial contributor in boreal forest biomes, isolated/sporadic permafrost regions, and Russian HFAs (Fig. 7B). Notably, HFAs with larger populations generally exhibited stronger climate-driven contributions, whereas disturbance exerted greater constraints in sparsely populated clusters. Latitudinal profiles revealed a transition from disturbance influence at lower latitudes to climate dominance toward the high Arctic, with climate-associated greening strengthening above $\sim 65^{\circ}\text{N}$ and disturbance impacts weakening across all regions (Fig. 7C). Such a pan-Arctic gradient was overwhelmingly shaped by Russian HFAs, which exhibited the steepest decline in disturbance influence toward higher latitudes and the strongest amplification of climate-driven greening. In contrast, North American HFAs showed weaker disturbance signals and more muted latitudinal variation, reflecting their concentration within midlatitude permafrost zones and smaller industrial footprints. European HFAs displayed comparatively narrow latitudinal ranges, with disturbance impacts peaking near settlement corridors and diminishing rapidly northward.

Discussion

The rapid expansion of human activities into previously undisturbed Arctic landscapes has intensified ecological pressures across the northern high latitudes. Our pan-Arctic assessment reveals contrasting vegetation greenness trajectories between disturbed and stable portions of HFAs. While stable areas exhibited overall greening, disturbed land surfaces experienced pronounced browning, revealing a pronounced human-induced ecological divergence (Figs. 4A and 5). Browning signals were geographically extensive, with notable concentrations across southern Siberia, northern Fennoscandia, and portions of

interior Canada, where industrial development, urban infrastructure, and mining operations are most concentrated (Figs. 3 and 4C). Moreover, variations within HFA groups suggest that nonsettlement clusters experienced more severe browning than settlements, likely due to the more intensive land surface modification and persistent vegetation removal in extractive zones (Fig. 4B and Fig. S7). In contrast, stable portions of HFAs showed persistent greening across most of the Arctic, despite considerable regional heterogeneity (Figs. 4D and 5). Collectively, our analysis echoes broadscale reports of pan-Arctic greening associated with recent warming [24,26,94] but indicates strong local reversals of this trend under direct human impact.

To elucidate the drivers behind these contrasting trajectories, we developed a novel attribution framework that integrates fine-scale HFA delineation with adjacent-pixel reference analysis. Our results reveal that while climate forcing governs the long-term background greening, anthropogenic disturbance predominantly regulates the browning pattern within HFAs, affecting 68.9% of analyzed HFA clusters (Fig. 6B) and accounting for 16.1% of overall vegetation greenness dynamics (Fig. 7A). This contribution is substantially greater than previous global-scale estimates [25,40], highlighting that traditional coarse-resolution analyses may obscure fine-scale disturbance signatures by blending them into the broader greening trend [32,89,95]. Unlike the gradual and pervasive influence of climate forcing, disturbance acts abruptly and heterogeneously, triggering immediate cascading ecological consequences. Concurrent secondary stressors, such as industrial dust and soil compaction, further inhibit regrowth and exacerbate local browning [96]. These impacts are magnified by Arctic ecological constraints including short growing seasons (typically 60 to 90 d), shallow rooting depths, and nutrient-poor soils, together restricting recovery and rendering vegetation highly sensitive to disturbance [32,97,98]. Critically, vegetation recovery following mechanical disruption operates on decadal to centennial time scales, often failing to return to predisturbance biomass levels due to irreversible hydrological changes [33,37]. Consequently, the strong browning signals observed in our study likely represent persistent ecological scars rather than transient fluctuations.

Despite the severity of these local impacts, the spatial reach of disturbance-induced browning appears confined. We examined $\Delta\text{NDVI}_{\text{max}}$ in the 10- to 30-km buffer zones surrounding each HFA and observed no significant correlation between HFA disturbance intensity and buffer zone greenness trajectories (Fig. S10). Unlike extensive urban agglomerations found at lower latitudes that often exert regional ecological footprints, Arctic HFAs appear to function as patches of disturbance, and their browning effects are largely contained within the footprint boundaries, while the surrounding landscapes largely remain dominated by the background climate signals at this scale. This contrast reinforces the discrete nature of Arctic development, wherein anthropogenic impacts are spatially confined yet locally dominant, potentially decoupling local vegetation trajectories from the regional climatic trends. However, the cumulative magnitude of this decoupling varies across the Arctic. Climatic effects dominate in the high Arctic but weaken southward as human disturbance increases (Fig. 7C). Such a poleward decline in anthropogenic footprint largely reflects the logistical and economic constraints on infrastructure expansion in the high Arctic, where extreme environmental conditions and remoteness limit the feasibility of large-scale industrial

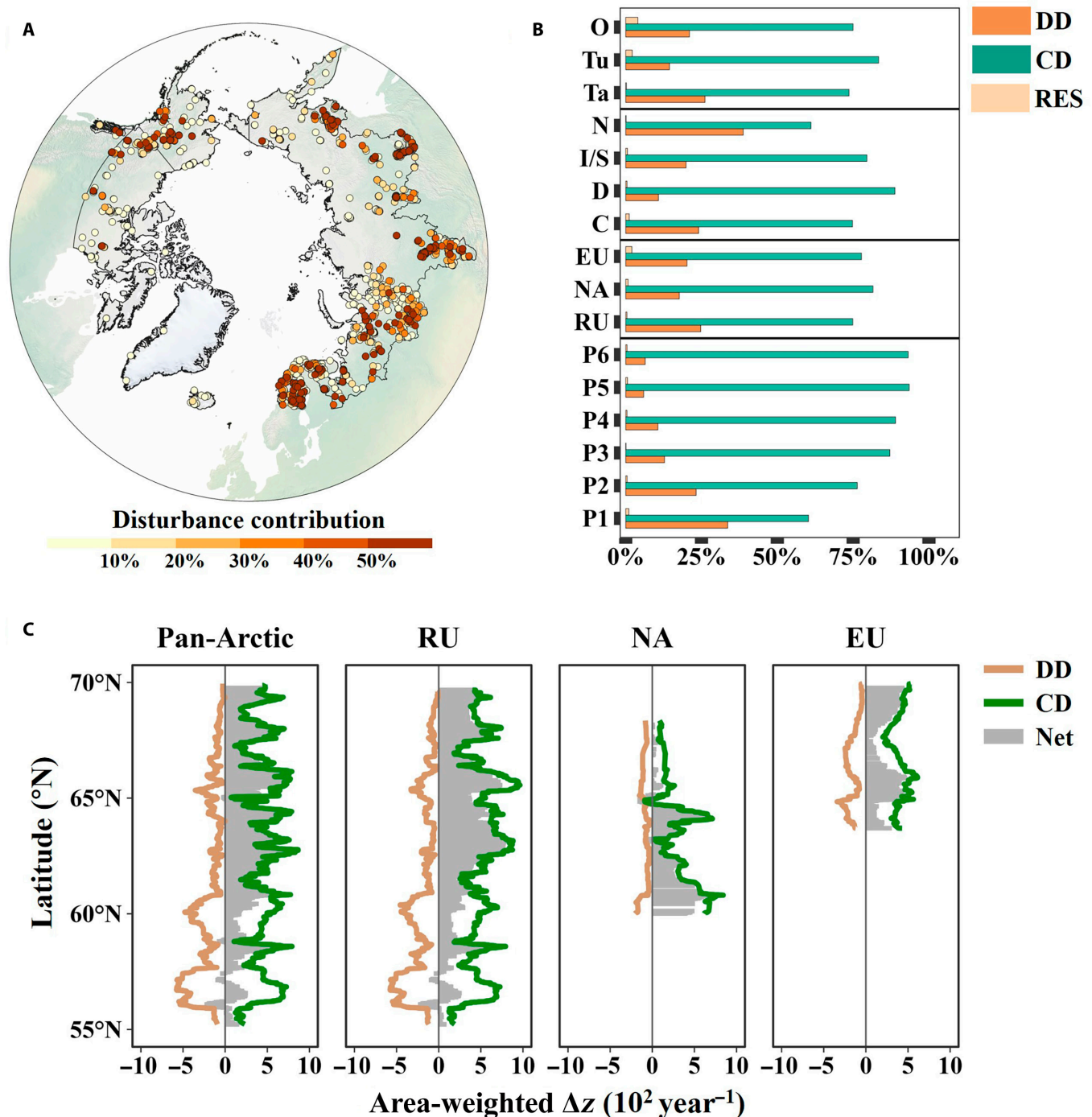


Fig. 7. Contributions of disturbance and climate drivers to vegetation greenness dynamics within Arctic human footprint areas (HFAs). (A) Spatial distribution of disturbance contribution percentages. (B) Comparative contributions from disturbance drivers (DD), climate drivers (CD), and residual factors (RES), grouped by population size, country, permafrost type, and biome (abbreviations as in Fig. 3). (C) Latitudinal variation in area-weighted Δz contributions from DD and CD, along with their net joint effects.

development and land-use pressure. This asymmetry also marks a critical biogeographic transition in the terrestrial Arctic that governs productivity, surface energy fluxes, and carbon exchange along northern latitudinal gradients [20,27,99,100]. As warming persists, the interplay among these processes may increasingly weaken the resilience of Arctic ecosystems [18,101].

Our study demonstrates that Arctic vegetation change cannot be characterized by a uniform “greening” phenomenon. Instead, it underscores a complex interplay between broad

climatic forcing and expanding human activity across the circumpolar domain [34,97]. This duality exposes a major blind spot in current Arctic greening research, carrying both methodological and practical implications. Methodologically, existing ecosystem models often fail to capture the complexity of Arctic vegetation dynamics. This limitation arises largely because they underrepresent the abrupt biophysical changes associated with human activity [88,89,95,102]. Leveraging 2 decades of 30-m Landsat observations and explicit HFA delineation, our proposed

framework provides a direct, observation-based benchmark for robustly quantifying and separating climate- and disturbance-driven vegetation responses at ecologically meaningful scales. This capacity not only improves attribution accuracy across the Arctic but also provides a transferable tool for other climate-sensitive regions such as alpine zones and the Antarctic Peninsula, where snow and ice retreat are accompanied by vegetation change yet the role of localized disturbance remains poorly constrained [78,79]. Practically, our circumarctic assessment highlights the urgency of integrating human land-use activities into Earth system analyses and climate adaptation strategies. As industrial infrastructure and resource extraction continue to advance northward, cumulative disturbance may progressively offset climate-driven productivity gains and diminish the Arctic's role as a terrestrial carbon sink. Mitigating these risks requires low-impact infrastructure design [103], strengthened land management in permafrost regions [3], and targeted restoration efforts in areas where vegetation loss is concentrated [88,104]. More broadly, the insights presented here align with the United Nations Sustainable Development Goals and provide actionable knowledge for Arctic Council initiatives seeking to reconcile ecological resilience with sustainable economic opportunities [2,10]. By improving the capacity to monitor and attribute vegetation change, our study supports local communities, Indigenous knowledge systems, and regional stakeholders in balancing environmental stewardship with livelihood opportunities in a rapidly transforming Arctic.

Although our study advances fine-scale attribution of Arctic greenness dynamics within HFAs, several limitations remain that frame avenues for future work. We combined NTL observations with mining inventory data to represent human footprints across the Arctic. However, isolated or small-scale HFAs may still be missed due to the incomplete detection of subsurface activities. Such omission could lead to underestimation of the true extent and ecological influence of anthropogenic disturbance, particularly in regions where industrial infrastructure leaves subtle but persistent landscape imprints [105]. Addressing this detection challenge requires multisource fusion strategies, such as integrating synthetic-aperture radar to identify structural signatures invisible to optical sensors and employing very high-resolution imagery for targeted validation. In this study, we relied primarily on NDVI as the sole proxy for vegetation dynamics, which cannot fully capture the complexity of ecosystem responses [93,106]. Incorporating complementary indicators such as leaf area index [89,107] and solar-induced chlorophyll fluorescence [93] would provide a more nuanced view of canopy structure and photosynthetic activity when their higher-resolution products become available in the near future. Additionally, while our phenology-based NDVI_{max} correction effectively minimizes temporal sampling bias, the underlying harmonic model assumes a consistent seasonal trajectory. Consequently, this method may be less reliable in pixels with high spatial heterogeneity or those undergoing abrupt, short-term surface changes.

The proximity-based decomposition framework offers a valuable potential for attributing vegetation trajectories to climate versus disturbance. However, the residual term (Δz_{RES}) underscores the influence of unmodeled local complexities. This component likely reflects variability driven by factors distinct from the broad climate-disturbance dichotomy, potentially including microtopographic constraints, soil moisture heterogeneity, or cryptic natural disturbances (e.g., pest outbreaks). Analyzing the spatial patterns of these residuals could help identify regions where local biophysical conditions decouple

from the regional background signal. Furthermore, the framework does not yet resolve the individual roles of specific climatic drivers (such as temperature, precipitation, or radiation) or capture the full types of human-relevant disturbances. Specifically, due to the resolution mismatch between fine-scale Landsat observations and coarse-scale gridded climate products, our approach groups all background climatic forces into a single aggregate driver. Similarly, the lack of a consistent, attribute-rich pan-Arctic disturbance inventory prevented us from using statistical modeling to quantify the individual contributions of specific activities, such as mining excavation versus road construction, or to evaluate postdisturbance recovery trajectories. Bridging this gap will require integrating emerging high-resolution climate datasets and detailed disturbance taxonomies to resolve these specific drivers. Moreover, the current analysis focuses exclusively on vegetation dynamics, representing only one dimension of Arctic ecosystem change. Future work should expand to carbon fluxes, ecosystem resilience, and biodiversity functions, thereby linking vegetation dynamics more directly to the long-term sustainability of human and natural systems in a rapidly warming Arctic.

Conclusion

Our study provides a comprehensive, fine-scale assessment of Arctic vegetation change within HFAs over the past 2 decades. By integrating 2 decades of 30-m Landsat observations with a novel attribution framework, we demonstrated that Arctic vegetation dynamics are jointly governed by climate and anthropogenic disturbance. Climate forcing has broadly promoted greening across stable landscapes, yet human activities have induced pronounced, spatially concentrated browning, accounting for 16.1% of total greenness variability within Arctic HFAs. This quantitative separation reveals that the expansion and intensification of human presence are already counteracting climate-driven vegetation gains, particularly in industrial and mining regions. Our findings highlight the growing vulnerability of Arctic ecosystems to cumulative disturbance and provide an observation-based benchmark for improving model representation of human impacts in high-latitude environments. Continued integration of fine-scale monitoring, process-based modeling, and policy-oriented management will be essential to safeguard the ecological resilience and climate-regulating capacity of the Arctic under accelerating environmental change.

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Author contributions: Chong Liu and X.C. conceived the idea. Chong Liu and Y.Z. designed the research and developed the methodology. J.W. and Chong Liu performed the analysis. All authors, including Chong Liu, J.W., Y.Z., Q.Z., N.D., Caixia Liu, T.L., and X.C., contributed to the writing and editing of this paper.

Competing interests: The authors declare that they have no competing interests.

Data Availability

All datasets used in this study are publicly available. Landsat 5, 7, and 8 Collection 2 Tier 1 surface reflectance imagery; the

MOD13Q1.061 Terra NDVI time series; the Copernicus GLO-30 Digital Elevation Model; and the Global Surface Water Occurrence dataset were accessed through the Google Earth Engine data catalog via <https://developers.google.com/earth-engine/datasets>. The harmonized NTL dataset was obtained from Figshare at <https://doi.org/10.6084/m9.figshare.9828827.v5>. Two global mining inventories are available at <https://doi.org/10.1594/PANGAEA.942325> and <https://doi.org/10.5281/zenodo.6806817>. Population data were derived from the Global Human Settlement Layer (GHSL) Population Grid, 2020 via <https://doi.org/10.2905/2FF68A52-5B5B-4A22-8F40-C41DA8332CFE>. The GLAD GLCLU dataset and the GLanCE dataset were used for land cover mapping via <https://glad.umd.edu/dataset/GLCLUC2020> and <https://doi.org/10.5067/MEASURES/GLanCE/GLanCE30.001>. Three global HFA or urban extent products used for comparison were accessed from <https://doi.org/10.6084/m9.figshare.16571064>, <https://doi.org/10.5061/dryad.ttdz08m1f>, and <https://doi.org/10.6084/m9.figshare.16602224.v1>. The derived data products supporting this paper are available from the corresponding authors upon reasonable request.

Supplementary Materials

Figs. S1 to S10

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Anthropogenic Disturbance Dampens Climate-Driven Greening in the Arctic

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Arctic vegetation is a critical component of the Earth system, regulating high-latitude carbon balance, surface energy exchange, and ecosystem resilience. Despite the widespread greening observed under recent warming, Arctic vegetation responses to the combined pressures of accelerating climate change and expanding human activity remain poorly understood, limiting our ability to anticipate future ecosystem trajectories and climate feedbacks. Here, by integrating 2 decades of 30-m Landsat observations with a novel attribution framework, we disentangled the respective contributions of climatic forcing and anthropogenic disturbance to vegetation dynamics within human footprint areas (HFAs) across the circumarctic. Based on 2,221 distinct HFA clusters, we found that while climatic warming has broadly enhanced vegetation greenness, anthropogenic disturbance has imposed strong, spatially concentrated browning, explaining 16.1% of the observed total greenness variability within HFAs. These disturbance effects are most pronounced in industrial and mining regions and intensify toward lower latitudes. Our findings reveal that human activity is emerging as an important modifier of Arctic vegetation dynamics, highlighting the need for disturbance-aware monitoring and adaptive management to sustain ecological integrity across the vulnerable Arctic.

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