

Probabilistic projections of human modification of the terrestrial biosphere from 2020 to 2040

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Conservation actions are more effective when they anticipate future threats rather than respond only after loss occurs. Most spatial forecasts focus only on land-cover change and fail to capture the broader set of pressures that degrade biodiversity. To close this gap, we develop global probabilistic forecasts of cumulative human modification (HM), a continuous measure that combines 16 anthropogenic threats to biodiversity classified under the IUCN threat taxonomy. Our approach uses a convolutional long short-term memory network trained on the historical HM time series from 1990 to 2020 to generate forecasts at 1 km resolution and 5-year intervals from 2020 to 2040. The model ingests sequences of historical HM maps along with socioeconomic, biophysical, and protected-area covariates to generate forecasts of the full distribution of potential change. Model outputs outperformed a persistence baseline, which assumes that HM remains unchanged from the last observation. Conditional on the continuation of historical relationships and dynamics, the forecasts indicate that between 2020 and 2040, more than 4.5 million km² of land classified as natural (HM < 0.1) in 2020 could be lost, an area larger than India. A further 2.9 million km² of moderately modified land (HM < 0.4) could become highly modified. Upper-bound (97.5th percentile) forecasts also identify large areas of currently natural land as potential hotspots of future human modification, suggesting the potential expansion of human pressure beyond the current conversion frontiers by 2040. By providing projections of future human pressure as continuous measures with explicit estimates of uncertainty, rather than broad land-use categories, these forecasts support more informed conservation decisions. They can help identify where protection or stewardship may prevent future loss, where restoration may be more feasible, and where precautionary action is most warranted. They can also be incorporated into spatial planning, allowing future pressure and uncertainty to be considered alongside representativeness, connectivity, biodiversity, and ecosystem services in support of the Kunming-Montreal Global Biodiversity Framework.

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Background

Human activities continue to drive global biodiversity loss (1). Land-use change remains the primary threat, while climate change, overexploitation, invasive species, and pollution further contribute to ecosystem loss and degradation (2). Conservation actions, from protected areas and restoration to sustainable management and spatial planning, aim to counter these threats. A major challenge in conservation planning

is the lack of spatially explicit forecasts of how threats will change over time (3, 4). These forecasts are crucial because different threat trajectories demand different interventions. Protection and stewardship actions are often most effective where threats are expected to intensify, enabling conservation to prevent future biodiversity loss before it occurs (5–7). In contrast, restoration is typically most successful where threats have stabilised or declined, allowing ecosystems to recover without renewed degradation (8, 9). Choosing among protection, stewardship, and restoration requires spatially explicit projections of future threats, revealing where they are expected to rise, persist, or decline without intervention.

Most threat projections used in conservation planning focus on land-cover transitions, such as forest conversion to cropland or urbanisation, sometimes coupled with climate projections (10). These forecasts commonly employ demand-allocation frameworks, in which aggregate demand for land conversion is estimated using Integrated Assessment Models or historical trends and then spatially allocated based on modelled suitability (11, 12). Global examples include Demeter and FLUS, which downscale coarse-resolution socioeconomic scenarios, and the ESRI land-cover forecast, which uses deep learning to extrapolate recent trends (13–15). Focusing solely on land-use and climate change overlooks many of the threats driving biodiversity loss. The IUCN Threats Classification Scheme recognises 11 classes of direct threats and approximately 40 specific threat categories affecting ecosystems worldwide (16). Throughout, we use ‘threat’ to refer to the individual IUCN threat classes and the HM components that map to them, and ‘pressure’ to refer to the cumulative continuous quantity that results from combining them, which is what we forecast here. Some of these threats are accompanied by discrete land-cover transitions (e.g. residential and commercial development, cropland), while others, including many forms of pasture, infrastructure, pollution, and human intrusions, can impact biodiversity without changing the dominant land-cover class. Small increases in threats within largely intact ecosystems that do not trigger a change in land-cover type can still have substantial ecological consequences (17). For instance, increased human intrusion, disturbance, or hunting within forested landscapes can lead to defaunation of sensitive species without detectable changes in canopy cover (18–20). Similarly, in already modified systems, intensification processes, such as transitions from low-intensity subsistence agriculture with embedded natural veg-

etation to high-intensity industrial production systems, also negatively affect biodiversity (21, 22).

The Human Modification (HM) framework captures multiple threats related to both conversion and degradation and combines them cumulatively, therefore providing a basis for developing comprehensive threat projections. It quantifies individual and cumulative anthropogenic threats using the IUCN taxonomy (23). Following this framework, Theobald et al. (23) produced globally consistent HM maps at 300 m resolution every 5 years between 1990 and 2020, representing 16 threats grouped into eight thematic classes that map to seven of the 11 IUCN top-level direct threat categories (see Fig. 1 of Theobald et al. (23)). The individual threats that are included are combined into a cumulative HM pressure measure that weights each threat by its relative expected intensity of impact (24). The resulting measure is a continuous 0–1 value, interpreted as the degree to which a given landscape has been modified by humans. This measure is designed to support planning, implementation, and monitoring of conservation targets, such as those under the Convention on Biological Diversity's Kunming-Montreal Global Biodiversity Framework (GBF).

Here, we extend the HM dataset by producing global forecasts of cumulative human modification at 1 km spatial resolution and 5-year intervals from 2020 to 2040. Using the 300 m historical HM time series from 1990 to 2020 as training data, we generate probabilistic forecasts that estimate the full distribution of potential HM values for each forecast horizon. These forecasts represent plausible trajectories of cumulative human pressure that are consistent with past observed spatial and temporal dynamics of HM (i.e. assuming historical patterns will continue). By moving beyond categorical land-cover change and providing explicit uncertainty estimates, our forecasts enable planners and decision-makers to identify where cumulative pressures are most likely to intensify, where they may stabilise, and where future change remains highly uncertain. These forecasts are designed to complement, rather than replace, land-cover projections. Land-cover scenarios describe transitions among land-cover classes, whereas HM forecasts quantify the cumulative intensity of multiple threats on biodiversity through time. Used together, they provide a more comprehensive and decision-relevant picture of future environmental change, helping conservation planners identify where and how interventions are likely to have the greatest impact.

Methods

Overview of approach

We developed a global, gridded forecasting framework to predict future HM values at 1 km spatial resolution and five-year temporal intervals. The core objective was to estimate both expected (mean) change in HM and associated uncertainty over four forecast horizons (5, 10, 15, and 20 years ahead), conditional on past spatial and temporal threat patterns, socioeconomic trends, and static biophysical constraints. A location encoder was used to convert raw latitude

and longitude coordinates into features representing residual geographic variation not captured by covariates. Our approach couples a convolutional long short-term memory (convLSTM) network (25) with a probabilistic output layer to model the evolution of cumulative human pressure through time. The convLSTM encoder operates on short sequences of historical maps and covariates consisting of three consecutive time steps drawn from the 1990–2020 HM record and learns joint spatial and temporal patterns in human modification. We split the global land surface into 128×128 pixel tiles, approximately 128×128 km at the equator, and assigned the resulting tiles to five spatial folds, training models using five-fold cross-validation. Training optimised the full fitted distribution of future HM using the continuous ranked probability score (CRPS) as our objective. The model produces estimates of HM at 64 quantile levels from 0.00025 to 0.9999 for each forecast year. Figure 1 provides a graphic overview of the model architecture, inputs, and outputs.

We used the global cumulative HM dataset as the primary response variable. HM is a continuous, unitless measure ranging from 0 (no detectable human modification) to 1 (complete modification), derived from the cumulative influence of multiple anthropogenic threats on each grid cell. We used the harmonised HM time series described in Theobald et al. (23), which provides global terrestrial coverage (excluding Antarctica) at five-year intervals from 1990 to 2020. The original HM products were generated at 300 m resolution and were average-resampled to a common 1 km grid for this analysis. The HM framework represents eight thematic threat groups: agriculture, built environments, extraction, biological resource use, human accessibility, natural systems modification, pollution, and transportation. Each component is mapped using globally consistent remote-sensing and ancillary datasets, transformed to a standardised 0–1 impact scale, and combined into the cumulative HM score using empirically informed weights and, if applicable, distance-decay functions. The model was trained to predict cumulative HM values at unseen future time steps. Inputs to the model included cumulative HM values and the eight underlying threat layers from prior time steps.

Covariates

We selected covariates that characterise the environmental and historical context in which past development has occurred and that are commonly employed in land-use/land-cover (LULC) change forecasting (12, 14, 26). Covariates were selected based on (a) demonstrated use in existing LULC forecasting frameworks, (b) data availability over the full 1990–2020 historical period at near-global coverage, and (c) non-redundancy with inputs already incorporated in HM. Table 1 provides details on source, spatial resolution, temporal resolution, time period, units, links, and citations for all covariates. Our forecasts are conditioned on observed spatial and temporal patterns rather than on future covariate trajectories, so the model learns which combinations of conditions have historically been associated with changes in cumulative pressure and extrapolates accordingly. Where these

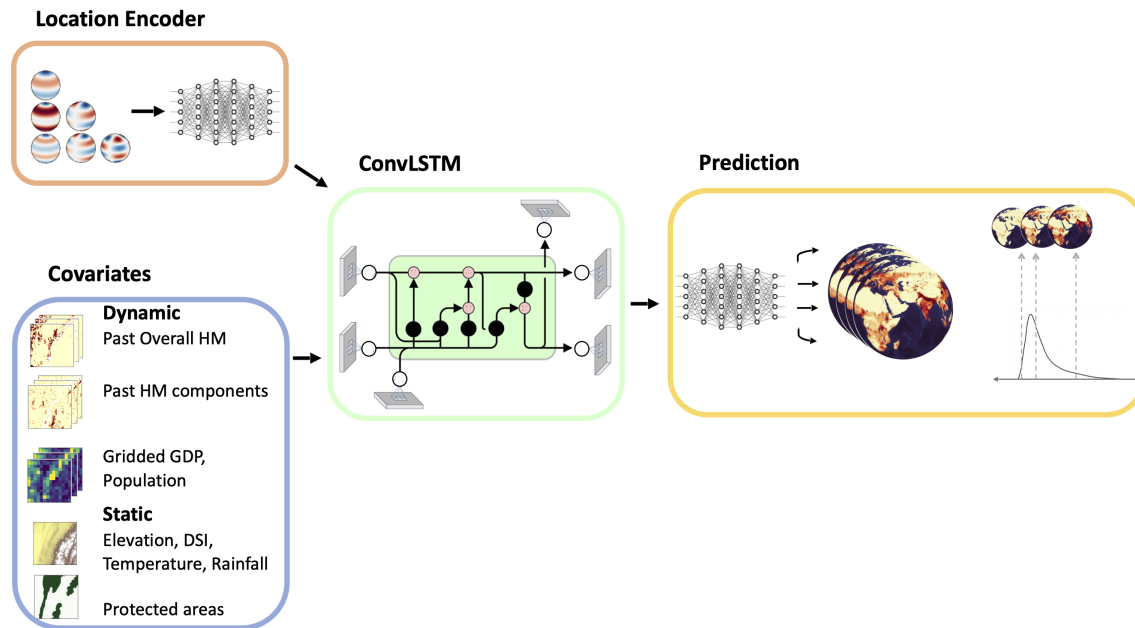


Fig. 1. Graphic overview of the human modification (HM) forecasting model architecture, inputs, and outputs. A location encoder converts coordinates into features capturing residual geographic variation. A convolutional long short-term memory (convLSTM) network operates on sequences of three consecutive historical HM maps and dynamic and static covariates to learn joint spatial and temporal patterns. ConvLSTM encodings are passed to a prediction head which outputs a full distribution of potential future HM.

measured covariates do not fully explain local dynamics, the model can draw on a learnable location encoding to capture residual spatial patterns, such as those resulting from policy regimes or cultural practices, that are not explicitly represented in the input data.

Protected areas

Protected areas are designated and managed to achieve long-term nature conservation outcomes and therefore often, though not always, constrain land use. As such, they are one of the most direct factors shaping the spatial pattern of future human modification (35). We derived two binary protected-area masks from the World Database on Protected Areas (WDPA; UNEP-WCMC and IUCN (27)): (i) strictly protected areas corresponding to IUCN management categories Ia, Ib, and II, and (ii) other protected areas comprising all remaining IUCN categories in the WDPA. We separated strictly protected areas (categories Ia, Ib, and II) from other categories because empirical studies show their effectiveness in suppressing land-cover change differs substantially (35, 36). We acknowledge that IUCN category assignment is inconsistent across reporting countries (37). WDPA polygons and points were rasterised to the 1 km analysis grid; each pixel was assigned a value of 1 if its centroid intersected at least one protected area of the relevant class and 0 otherwise. The same protected-area masks were applied to all historical time steps; we did not reconstruct protected-area extent separately for each year, so the masks represent contemporary rather than historical protection status.

Climate

Long-term climatic conditions strongly influence which land uses are viable at a given location, particularly agriculture,

settlement, and the supporting infrastructure that drive most HM change, and therefore shape where pressure is most likely to emerge or intensify. Climatic constraints were represented using long-term mean annual temperature, mean annual precipitation, and minimum temperature of the coldest month, derived from CHELSA climatologies (28). These variables correspond to the climatic covariates identified as most relevant to development patterns in earlier analyses (38).

Topography

Topography constrains the suitability of land for agriculture, settlement, and transport infrastructure, with flatter and lower-elevation terrain typically more accessible to development. Topographic constraints were captured using the 1 km global elevation product from EarthEnv, derived primarily from GMTED2010 and SRTM and aggregated to a standardised global grid (29). We additionally derived slope and aspect from elevation and added these as covariates.

Development pressure

We used the Development Suitability Index (DSI; Oakleaf et al. (30)) as a static indicator of long-term development pressure. DSI is derived from a set of underlying Development Potential Indices (DPIs), which are global 1 km resolution maps depicting the suitability of land for potential expansion by five sectors: commercial agriculture, renewable energy, oil and gas, mining, and urbanisation (31, 39). Each DPI accounts for sector-specific land constraints that restrict development, such as unsuitable land cover or steep slopes; resource availability that determines land suitability for that sector; and siting feasibility factors such as the ability to transport resources, access to demand centres, proxim-

Table 1. Covariates used as inputs to the convLSTM model for forecasting cumulative human modification (HM). All covariates were resampled to a common 1 km grid in EPSG:4326 prior to model fitting (average interpolation for continuous variables, nearest-neighbour for categorical or binary layers). Dynamic covariates vary over time and were aligned to the 5-year HM observation years (1990, 1995, ..., 2020); static covariates are time-invariant within the model.

Covariate	Source dataset	Native spatial resolution	Native temporal resolution	Time period used	Units	Citation	Link / DOI
Static covariates							
Strictly protected areas mask	World Database on Protected Areas (WDPA); IUCN management categories Ia, Ib, II	Vector (rasterized to 1 km)	Static	Static	Binary (0/1)	UNEP-WCMC and IUCN (27)	https://www.protectedplanet.net
Other protected areas mask	World Database on Protected Areas (WDPA); all remaining IUCN management categories	Vector (rasterized to 1 km)	Static	Static	Binary (0/1)	UNEP-WCMC and IUCN (27)	https://www.protectedplanet.net
Mean annual temperature	CHELSA climatologies	30 arc-seconds (~1 km)	Long-term climatology (1981–2010)	Long-term mean	°C	Karger et al. (28)	https://www.chelsa-climate.org/
Mean annual precipitation	CHELSA climatologies	30 arc-seconds (~1 km)	Long-term climatology (1981–2010)	Long-term mean	mm yr ⁻¹	Karger et al. (28)	https://www.chelsa-climate.org/
Minimum temperature of coldest month	CHELSA climatologies	30 arc-seconds (~1 km)	Long-term climatology (1981–2010)	Long-term mean	°C	Karger et al. (28)	https://www.chelsa-climate.org/
Elevation	EarthEnv global elevation product (derived from GMTED2010 and SRTM)	1 km	Static	Static	m above sea level	Amanuli et al. (29)	https://doi.org/10.1038/sdata.2018.40
Slope	Derived from the EarthEnv elevation product	1 km	Static	Static	Degrees	Amanuli et al. (29)	https://doi.org/10.1038/sdata.2018.40
Aspect (sine and cosine)	Derived from the EarthEnv elevation product	1 km	Static	Static	Unitless (-1 to 1)	Amanuli et al. (29)	https://doi.org/10.1038/sdata.2018.40
Development Suitability Index (DSI)	Aggregated Development Potential Indices (DPIs) for commercial agriculture, renewable energy, oil and gas, mining, and urbanization	1 km	Static	Static	Unitless (0–1)	Oakleaf et al. (30); underlying DPIs from Oakleaf et al. (31)	https://doi.org/10.1038/s41597-024-03639-9
Dynamic covariates							
Cumulative human modification (lagged)	Global cumulative HM time series	300 m	5-year intervals	1990–2020 (1990, 1995, 2000, 2005, 2010, 2015, 2020)	Unitless (0–1)	Theobald et al. (23)	https://zenodo.org/rec/ords/14449495
HM components	HM thematic threat layers	300 m	5-year intervals	1990–2020	Unitless (0–1)	Theobald et al. (23)	https://zenodo.org/rec/ords/14449495
Population density	Global gridded historical population (statistical hindcast and observed maps)	1 km	10-year intervals (1870–2100)	1990–2020 subset (linearly interpolated to 5-year HM years)	persons per grid cell	Zhuang et al. (32)	https://doi.org/10.5281/zenodo.10968817
Gross domestic product (GDP)	Gridded GDP projections compatible with the SSPs	5 arc-minutes (~10 km)	10-year intervals (1850–2100)	1990–2020 subset (linearly interpolated to 5-year HM years)	USD (constant 2005) per grid cell	Murakami et al. (33)	https://doi.org/10.6084/m9.figshare.12016506
Distance to past HM change	Derived from the global cumulative HM time series; Euclidean distance to the nearest pixel that changed over the preceding interval	1 km	5-year intervals	1990–2020	Pixels (1 km)	Theobald et al. (23)	https://zenodo.org/rec/ords/14449495
Past HM-change density at radii 3, 30, 100 px	Derived from the global cumulative HM time series; fraction of pixels within each radius that changed over the preceding interval	1 km	5-year intervals	1990–2020	Unitless (0–1)	Theobald et al. (23)	https://zenodo.org/rec/ords/14449495
Neighbourhood mean HM at radii 3, 30, 100 px	Derived from the global cumulative HM time series; mean HM within each radius	1 km	5-year intervals	1990–2020	Unitless (0–1)	Theobald et al. (23)	https://zenodo.org/rec/ords/14449495
Neighbourhood maximum HM at radii 3, 30, 100 px	Derived from the global cumulative HM time series; maximum HM within each radius	1 km	5-year intervals	1990–2020	Unitless (0–1)	Theobald et al. (23)	https://zenodo.org/rec/ords/14449495
Static (learned) covariates							
Location encoding (spherical harmonic basis features)	Derived from pixel latitude/longitude using spherical harmonic basis functions passed through a small neural network	n/a (computed per pixel from coordinates)	Static	Static	Unitless (learned features)	Rubwum et al. (34)	https://doi.org/10.48550/arxiv.2310.06743

ity to existing development, and other economic costs. DPI values are standardised to a 0–1 scale. DSI then combines the individual DPIs into a single per-pixel summary by taking the product of their mean and maximum values at each location. This formulation gives high scores to places where multiple sectors simultaneously favour expansion, rather than to places where only one sector scores highly. The resulting raster provides a spatially explicit estimate of latent development demand not already expressed in current HM values.

Human Modification and component threats

In addition to serving as the response variable, cumulative HM was used as a predictor: lagged values of cumulative HM and its component threats were supplied as inputs. We expect past HM to be the strongest available predictor of future HM, reflecting both temporal autocorrelation and the path-dependent nature of land-use change. This is an assumption motivating covariate selection rather than a result of our analysis, and it is complicated at high HM values, where the scope for further modification declines as locations approach complete build-out (i.e. as HM approaches 1). Each of the eight component threat layers that make up HM (agriculture, built environments, extraction, biological resource use, human accessibility, natural systems modification, pollution, and transportation) is available as a separate layer for every time step. We supplied the complete time series of each of these layers individually as dynamic covariates, providing information on the changing composition of threats that is not captured by the cumulative score alone. Beyond the HM-derived covariates described above that characterise each pixel's own history, we also precomputed two covariates from the HM series that characterise the local and regional HM context for each pixel. The first describes the mean and the maximum HM value within radii of 3, 30 and 100 pixels. The second describes the distance from a pixel to the nearest pixel whose decadal change in HM exceeded 0.01. This distance is supplied both as a log-transformed value and as binary indicators of whether such change occurred within 3, 30 and 100 pixels, alongside the decadal change in HM itself.

Population

Human population density is a fundamental driver of land conversion and intensification, with demand for housing and supporting infrastructure scaling with the size and distribution of local populations. We used the 1 km global gridded population dataset of Zhuang et al. (32), which spans 1870–2100 at ten-year intervals, and subsetting it to the 1990–2020 period. This product combines observed population maps for 2000–2020 with statistical hindcasting to generate spatially coherent historical distributions.

Gross domestic product

Gridded GDP serves as a proxy for economic development and infrastructure investment in the surrounding landscape (not necessarily at the place of residence of the producing population), capturing drivers of human modification that operate independently of population density. We used gridded GDP data from Murakami et al. (33), which provides GDP

projections at approximately 10 km resolution and ten-year intervals from 1850 to 2100. We subsetting this dataset to the period 1990–2020 and aligned it to the 5-year HM observation years.

Location encoding

To represent geographic position in the convLSTM inputs, and to capture drivers that vary across space but are not directly measured, such as regional policy regimes or cultural practices, we used spherical harmonic basis functions (34) derived from geographic coordinates. Spherical harmonics are a standard mathematical tool for describing patterns on the surface of a sphere. Much as a Fourier series decomposes a signal into sine and cosine waves, spherical harmonics decompose a spatial signal across the surface of a globe. Low-order harmonics capture broad continental-scale gradients, while higher-order terms capture finer regional variation. Projecting latitude and longitude onto these basis functions, rather than feeding raw coordinates directly into the model, also avoids discontinuities at the poles and the antimeridian. These harmonic features were then passed through a small neural network that learns to combine them into location features. This network is trained jointly with the forecasting model, so the encoding it produces is optimised for predicting HM change rather than fixed in advance. The result is a flexible spatial encoding that allows the model to learn smooth, globally consistent patterns of residual variation that are not explained by the other covariates. In practice, this means the model can learn that, for example, a given level of GDP and population growth leads to different rates of HM change in Southeast Asia from those in sub-Saharan Africa without our having to specify why those regions differ.

Data preparation

Because input variables span heterogeneous units and ranges, we applied per-variable standardisation prior to training. For each variable, the mean and standard deviation were estimated from across the global grid, and values were transformed accordingly. All spatial layers were preprocessed to a common global grid at 1 km resolution in EPSG:4326 using average (mean) resampling for continuous variables and nearest-neighbour resampling for categorical or binary layers. Oceans and permanent inland water bodies encoded as no-data in the original HM data were masked across all inputs and outputs.

To define spatially disjoint regions for model development and performance evaluation, we applied a spatial blocking procedure to the global land surface. The analysis grid was tiled into 128×128 pixel tiles. We used five-fold cross-validation. Tiles were not assigned to folds individually: they were first grouped into 512×512 pixel super-blocks of 4×4 adjacent tiles, and whole blocks were then assigned to folds. In each of the five iterations, three folds were used for training, a fourth was reserved for validation, and the fifth was held out entirely and only used to evaluate models once trained. Our data-splitting strategy therefore enforced strict geographic separation between training and evaluation data.

We adopted spatial rather than temporal splitting because the historical HM record comprises only seven time steps, and a temporal holdout would substantially reduce the length of usable input sequences.

For each 128×128 pixel tile passed to the model for training, validation or testing, we constructed an input sequence consisting of three consecutive time steps and corresponding targets at multiple future horizons. For a given base year (t), the model receives as input three historical HM slices ($t - 10$, $t - 5$, t), together with all dynamic covariates evaluated at those times. Static covariates and location-encoding features do not change over time, so the same values are simply used for all three time steps. Targets are defined as cumulative HM at four future horizons relative to the final input time step: ($t + 5$), ($t + 10$), ($t + 15$), and ($t + 20$) years, where available within the historical record. When a particular horizon extends beyond the last available HM observation, the corresponding target is omitted for that sample. For example, when the input HM years are 2000, 2005, and 2010, the corresponding targets are 2015 ($t + 5$) and 2020 ($t + 10$), while $t + 15$ and $t + 20$ are omitted.

convLSTM model

We forecast the spatiotemporal evolution of HM using a tailored convLSTM architecture (25). We chose this architecture because it allowed us to track dynamic changes over time while retaining geographic context and quantifying uncertainty. Specifically, we incorporated a learnable location encoding to capture static spatial features, a convLSTM core to process spatiotemporal dynamics, and independent prediction heads for each forecast horizon (40). The network follows an encoder–decoder design. A convLSTM encoder processes the input sequence, updating a hidden state at each time step while preserving spatial structure. The final hidden state summarises recent dynamics and serves as a compact representation of spatiotemporal context.

Four independent convolutional decoder branches, one per forecast horizon, map this representation to outputs. Within each branch, we emit the shape of a full conditional distribution of HM by estimating the HM value at each of 15 fixed quantile levels. The 15 values are parameterised as a median plus 14 positive increments, so the quantiles cannot cross, and the quantile function is interpolated linearly between them, giving a monotone linear spline whose CRPS can be computed in closed form (41, 42). The spline allows the resulting model to look up the estimated HM at any quantile level, not only the 15 that were fitted. We evaluated alternative architectures, including Swin Transformers and 3D U-Nets, but did not observe meaningful improvements in performance or spatial realism. The model was implemented in PyTorch (43) and trained using PyTorch Lightning.

Our primary objective is to generate forecasts that faithfully predict the distribution of potential future HM values rather than a point prediction with uncertainty attached after the fact. We therefore train by minimising the CRPS (44), which compares the full predicted quantile function to the single observed HM value at each pixel and horizon. It rewards

predictions that are both confident and correct, and penalises a confidently incorrect prediction more heavily than an uncertain one. The loss is averaged over valid land pixels and uniformly over the four forecast horizons. Validation CRPS was monitored throughout training, and the weights used for prediction were the average of the model weights over the final 20 training epochs.

Models were trained using the Adam optimiser with a learning rate of 0.001 and a batch size of 8. Each fold model was trained for 150 epochs, with 100 randomly sampled 128×128 training tiles per epoch. Validation used deterministic grid sampling over the designated validation fold at a stride of 1,024 pixels, rather than a fixed number of validation tiles. Hyperparameter optimisation was conducted using random search. The convLSTM backbone used a hidden dimension of 64, 3×3 convLSTM kernels, four convLSTM layers, and a location encoder with 10 Legendre polynomial terms and eight output channels.

Prior to generating our final seamless global forecasts, we retrained a single model using all available data. This approach ensured that the forecasts were informed by all available observations across the globe to generate the most robust predictions possible. Forecasts for 2025–2040 were generated at 1 km resolution using inputs from 2010–2020. Data were passed to the model as 128×128 pixel tiles with a 64-pixel overlap between adjacent tiles to reduce edge effects. As a result, each pixel was predicted multiple times, and overlapping predictions were blended using a weighted average, with each prediction weighted by the pixel’s distance to the edge of its tile. Final mosaics were masked to exclude non-terrestrial areas.

Data Records

Per-pixel distributions are stored as unsigned 16-bit integer (uint16) data cubes in Icechunk format, encoding HM on the 0–1 scale with a scale factor of 1/65535 and 65535 reserved as the fill value. These data cubes have dimensions latitude, longitude, year and percentile. We export data in EPSG:4326 with approximately 1 km pixel resolution at the equator covering a maximum and minimum latitude of 84.00° N and 70.00° S, respectively. Statistics and descriptions of regional patterns in the data reported here are calculated after transforming to an equal-area projection (Lambert Cylindrical Equal Area, EPSG:6933). For ease of use, we also export selected layers as single-band float32 rasters in GeoTIFF format. We generate one raster per forecast year for the mean value of HM, the upper (97.5%) percentile, the lower (2.5%) percentile, the expected probability that HM will exceed 0.1 and the expected probability that HM will exceed 0.4. These are published under the naming convention “hm_year_variable.tif” where *year* is 2025, 2030, 2035, or 2040 and *variable* is one of *lower*, *mean*, *upper*, *gt01*, or *gt04*. We also make available the historical HM data resampled and masked to align with forecasts so that users can work with a seamless HM time series from 1990 to 2040. These rasters are named using a similar convention: “hm_year_obs.tif”. GeoTIFFs are available on Zen-

odo at <https://zenodo.org/records/19700998>. Data cubes are available from Arraylake at <https://app.earthmover.io/marketplace/6abb60fba504351ef2a29c6f>. The human modification datasets, including the forecast datasets, are licensed under CC BY 4.0.

Data Overview

Using an absolute change threshold of 0.05 HM units, our mean forecasts project substantial increases of human modification by 2040 across 7.1% (9.2 million km²) of global terrestrial land, with no pixels showing mean decreases of at least 0.05 (Fig. 2). By comparison, observed human modification increased across 7.9% (10.3 million km²) and decreased across 0.6% (0.8 million km²) between 2000 and 2020 (Fig. S1). These estimates reflect mean change at each pixel, integrated across the full fitted distribution. As discussed later, the uncertainty associated with our forecasts does not exclude the possibility of decreases or large increases for most pixels. Figures S2–S4 show mean HM change for 2025, 2030 and 2035.

We define ‘natural lands’ as pixels with HM equal to or below 0.1, following Kennedy et al. (21) and Theobald et al. (23). For each pixel and forecast horizon, we estimate the expected area of loss of natural lands using the predicted probability that HM will exceed 0.1. Of all 91.9 million km² classified as natural in 2020, our forecasts project that cumulatively 1.2% (1.1 million km²) will lose this status (i.e. HM > 0.1) by 2025, increasing to 2.5% (2.3 million km²) by 2030, 3.7% (3.4 million km²) by 2035, and 4.9% (4.5 million km²) by 2040 (Fig. 3a).

The largest increases in HM are projected to occur in areas that are already in the moderately modified class (0.1 < HM ≤ 0.4), including agricultural landscapes in the Indian sub-continent, West and East Africa, and Indonesia and Malaysia. In these regions, increases primarily reflect intensification of existing land uses, such as transitions from low-intensity agriculture to industrial production systems or expansion of settlements into mosaic agricultural landscapes, rather than direct conversion of natural lands. Globally, of all 28.7 million km² classified as moderately modified in 2020, our forecasts project that cumulatively 2.3% (0.7 million km²) will become highly modified (i.e. exceed the HM = 0.4 threshold) by 2025, increasing to 4.9% (1.4 million km²) by 2030, 7.4% (2.1 million km²) by 2035, and 10.2% (2.9 million km²) by 2040 (Fig. 3b).

While regions containing extensive natural lands do not generally emerge as hotspots of HM increase in the mean forecasts, relatively small increases in HM may have disproportionate ecological consequences in these largely natural systems. For example, an increase in HM from 0.05 to 0.1 represents a doubling of cumulative impact and may expose sensitive species to conditions under which populations can no longer persist. The upper (97.5th percentile) forecast shows that 23.7% of natural land pixels may exceed the 0.1 HM threshold, with vast areas far from current development frontiers projected to be at risk (Fig. S5). Here, extensive areas of natural land in southern and central Africa, the Brazilian

Table 2. Pixel-level performance of forecasts of human modification over all forecast horizons. RMSE measures the accuracy of the mean forecasts and CRPS the performance of the full fitted distribution. The persistence baseline assumes human modification remains at the last observed value over all forecast horizons.

Forecast Horizon	5 Years	10 Years	15 Years	20 Years
RMSE				
ConvLSTM	0.0133	0.0203	0.0264	0.0312
<i>Skill vs. persistence</i>	<i>0.041</i>	<i>0.188</i>	<i>0.229</i>	<i>0.241</i>
CRPS				
ConvLSTM	0.0030	0.0053	0.0073	0.0089
<i>Skill vs. persistence</i>	<i>0.155</i>	<i>0.261</i>	<i>0.299</i>	<i>0.299</i>

Cerrado, the Colombian Llanos, and eastern Mongolia are identified as being at risk of crossing the natural-land threshold. These projected increases are concentrated primarily in grasslands and savannas, where vast areas currently exhibit low HM, with the potential to increase substantially. In contrast, in the lower (2.5th percentile) forecast, fewer than 0.01% of pixels are projected to transition from natural to non-natural (Fig. S6). This reflects the fact that very little land is certain to increase in HM between 2020 and 2040.

Technical Validation

We assessed the predictive capability of the distributional convLSTM model using a combination of quantitative metrics and visual diagnostics, focusing on calibration of uncertainty and accuracy of estimated distributions across all four forecast horizons (5, 10, 15, and 20 years). To contextualise the performance of point forecasts of expected HM from the convLSTM architecture, we benchmarked the convLSTM against an assumption that present conditions will persist, referred to here and in Table 2 as the persistence baseline. The persistence baseline assumes that human modification remains static through time and projects the last observed HM value forward for all future horizons. The assumption of persistence is not a trivial baseline, as no change is often the most likely outcome, and it outperforms assumptions of linear continuation of past trends.

Accuracy assessment

To quantify predictive performance, we used mean squared error (MSE) and forecast skill (% improvement in MSE relative to the persistence baseline) to measure deviations between observed and predicted mean HM values on the held-out test data when attempting to predict unseen HM at 5-, 10-, 15-, and 20-year forecast horizons (Table 2). We similarly calculated CRPS and CRPS skill for the full forecast distribution. The convLSTM achieved the lowest MSE and CRPS at all horizons. Differences among models became increasingly pronounced with forecast lead time. Low absolute MSE across all horizons does not necessarily imply accurate prediction of HM change magnitudes. Instead, it partly reflects the rarity of change, as illustrated by the relatively low MSE of the persistence baseline.

The mean HM change surface systematically underpredicts both large increases and large decreases (Fig. 4). This shrink-

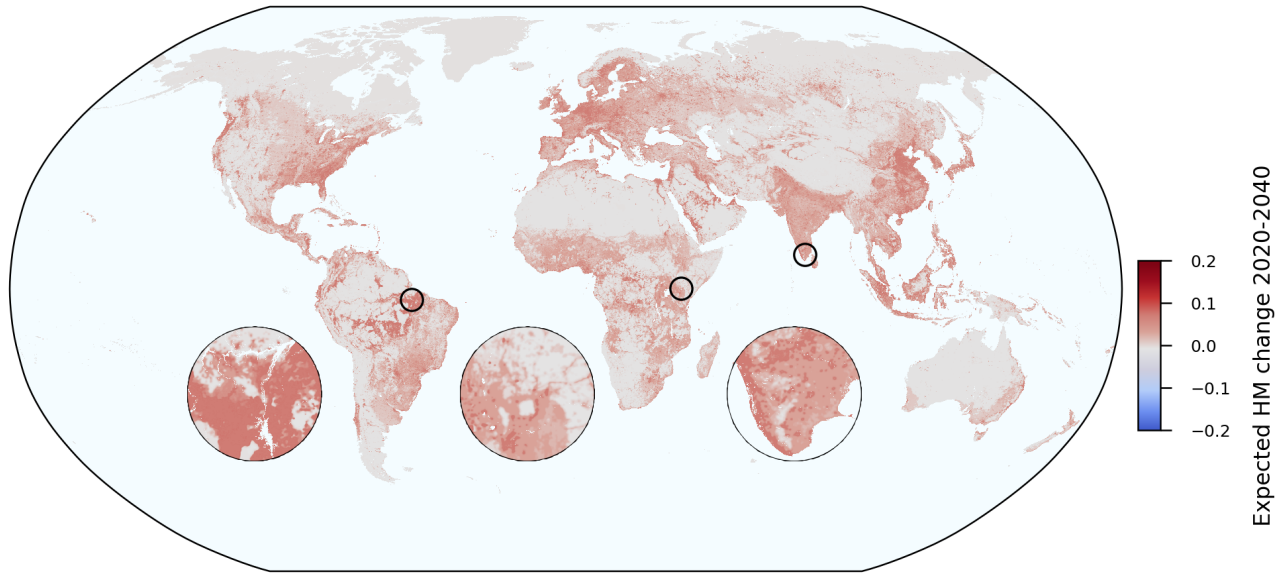


Fig. 2. Predicted mean estimates of change in human modification between 2020 and 2040. The locations of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India.

age is a property of the point estimate rather than of the forecast. An expected value cannot represent rare events because averaging a rare large change against a common near-zero one returns a moderate change that occurs nowhere. Comparing observed counts against the expected counts implied by the full predictive distribution recovers the tails that the mean surface removes: bins between 0.02 and 0.5 agree to within roughly 20%, against discrepancies of up to two orders of magnitude for the same bins when compared with the mean forecast, and decreases beyond -0.05 are underpredicted by a factor of about 3 rather than 40.

Large, stochastic events leading to changes in pressure are inherently difficult to predict, which makes it important to validate whether the prediction intervals are wide enough to contain the outcomes that actually occurred, including these rare large changes. Coverage measures how often the observed values fall inside the model's prediction intervals. A well-calibrated forecast will contain 95% of observations inside its 95% interval. Our model's outer intervals were well calibrated at every horizon: the 99% interval covered 99.0–99.1% of observations, and the 95% interval covered 95.0–95.5% at 5, 15 and 20 years, dipping to 91.7% at 10 years (Table 3). Its inner intervals were slightly too narrow. The 50% interval covered only 42–48% of observations and the 80% interval 76–77%, so the forecasts were somewhat overconfident close to the median. Coverage of the 50% interval improved as the horizon lengthened. We also assessed the calibration of forecasts across all quantiles using the probability integral transform (PIT; Fig. 5). The PIT value for each observation is the cumulative probability the predictive distribution assigns to that observed value. If the model is well calibrated, the true value is equally likely to fall in any quantile interval of the predicted distribution, so PIT values should be uniformly distributed across bins. Our forecasts demon-

Table 3. Coverage of the forecast prediction intervals over all forecasted horizons: the fraction of observed human modification values that fall within each central prediction interval. A well-calibrated forecast has coverage equal to the nominal level of the interval.

Forecast Horizon	5 Years	10 Years	15 Years	20 Years
50% interval	0.421	0.427	0.449	0.482
80% interval	0.773	0.762	0.760	0.772
95% interval	0.950	0.917	0.953	0.955
99% interval	0.991	0.991	0.991	0.990

strated reasonably calibrated uncertainty across all quantiles, with no systematic deviation indicative of over- or underconfidence. The PIT distribution does show some fluctuation around the expected uniform density, with several bins - particularly around 0.2, 0.5, and 0.9 - exceeding the reference line, and others - notably around 0.1 and 0.4 - falling below it.

Quantitative metrics were complemented by ad hoc visual inspection of tile-level maps comparing predicted and observed HM change across regions. These diagnostics were used to assess physical plausibility and correspondence between observed and predicted patterns of HM change. We present results for randomly selected tiles within specifically chosen regions that illustrate forecasts in two very different ecosystem types on different continents: a savanna woodland ecosystem in northern Zambia experiencing progressive intensification of cumulative pressure and a forested region in Chaco Province, Argentina, where sudden large increases in HM are driven by large-scale deforestation. Figure 6 shows spatial patterns of observed and predicted change in HM for these regions. In both examples, mean predicted change is substantial only close to hotspots of past change; however, the probability of loss of natural status is still elevated many kilometres from the hotspots of change.

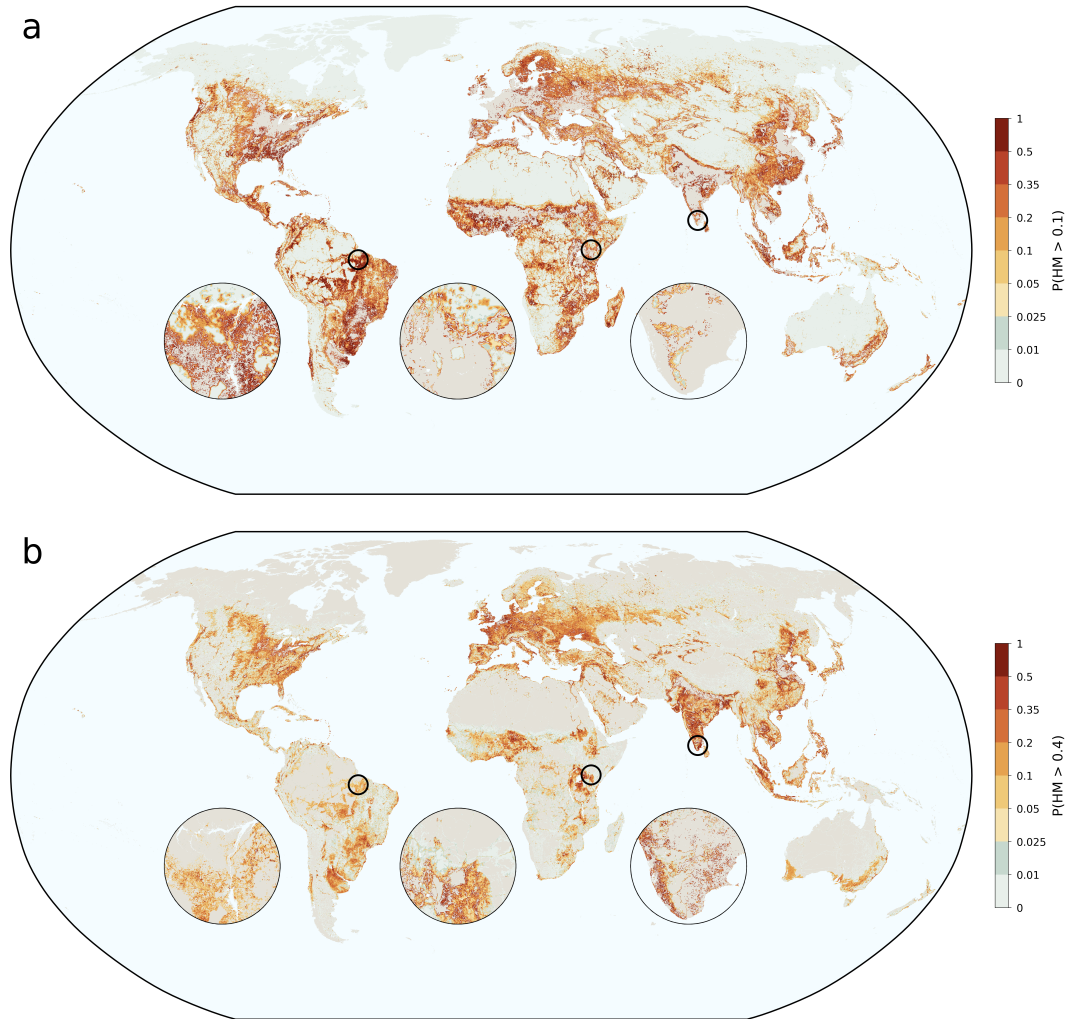


Fig. 3. Probability of loss of natural lands (a - defined as lands with human modification ≤ 0.1) and probability of loss of moderately-modified lands (b - as defined as human modification ≤ 0.4 and > 0.1) between 2020 and 2040 based on the full forecast distribution of HM. Grey areas in each map represent areas mapped with HM > 0.1 (a) and HM > 0.4 (b) in 2020. The locations of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India.

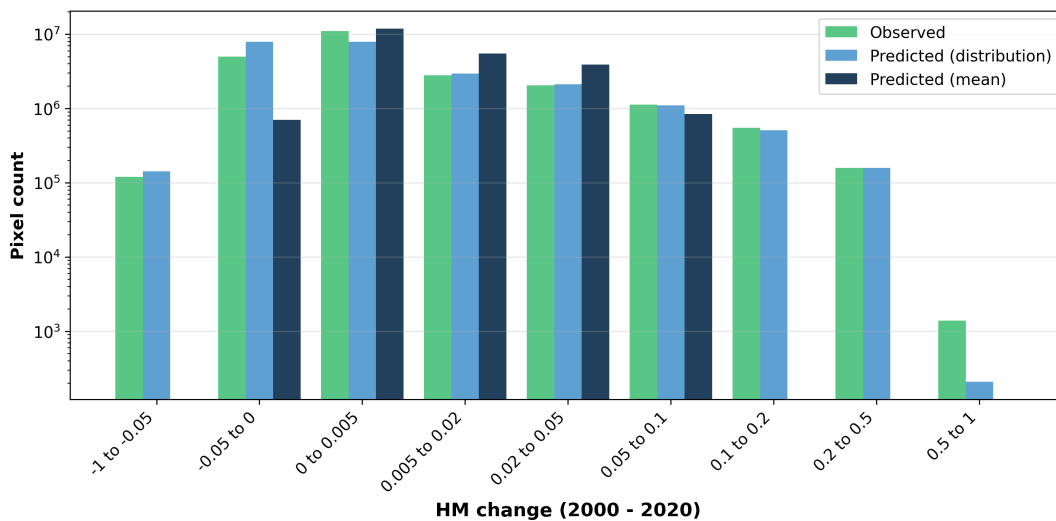


Fig. 4. Aggregated observed (green bars) human modification change magnitudes and predicted human modification change from the forecast mean (dark blue bars) and the full forecast distribution (light blue bars) between 2000 to 2020. Bar height gives the count of pixels whose observed or predicted change falls within a given bin, shown on a logarithmic scale. The pixel counts for the full distribution are calculated by assigning weight to each bin based on the full distribution within each pixel and summing within bins across all pixels.

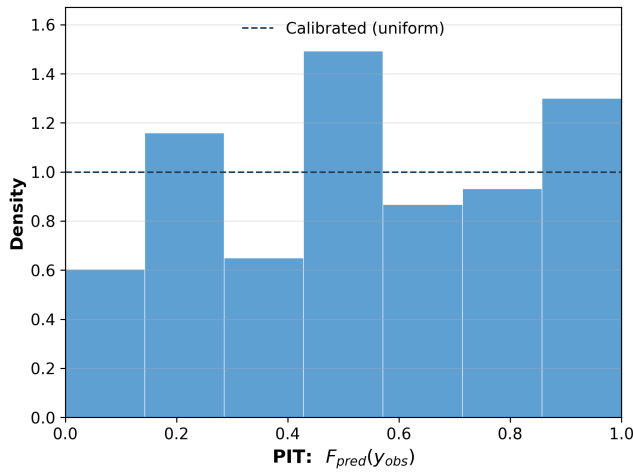


Fig. 5. Probability integral transform (PIT) calibration across quantiles. The PIT value for each observation is the cumulative probability the predictive distribution assigns to that observed value. If the model is well-calibrated, the true value is equally likely to fall in any quantile interval of the predicted distribution (i.e. 10% of observations should have a cumulative probability over 0.9, 10% between 0.5 and 0.6, etc), hence PIT values should be uniformly distributed across bins. Density is calculated as the observed count of PIT values in each bin vs the expected number under perfect calibration.

Visualisation of observed and predicted HM time series in the savanna and forest biomes further illustrates the value of interpreting the full distribution of forecast HM. In some cases, there is a narrow uncertainty range around the median estimate of continued low HM, with only the very highest percentiles showing the potential for increases (Fig. 7a). Critically, there are also regions where the median forecasts do not predict the recently observed changes in cumulative pressure, such as the deforestation example (Fig. 7b). However, the wide prediction interval indicates that such an outcome is not ruled out by the model. Across the global forecast, large areas show this pattern of mean change estimates near zero but upper-percentile estimates exceeding 0.1, concentrated in low-HM mosaic landscapes adjacent to development frontiers, most extensively in the deforestation frontiers of the Amazon Basin, Borneo and the African Great Lakes region (Fig. S6).

Comparison with alternative conversion forecasts

To highlight how the forecasts presented here differ from existing conversion-pressure products, we compared projected HM change to other datasets that similarly represent gradients of potential change: the Conversion Pressure Index (CPI) and the ESRI Land Cover Vulnerability Change 2050 map (Fig. 8). We compared our forecasts of mean HM change to these products and note that a more faithful comparison would compare the full forecast distribution of HM to similar probabilistic forecasts of future threats. We are not aware of the existence of such forecasts and thus restrict our comparison to point forecasts. The CPI is a 1 km resolution global product that identifies conversion pressure from multiple drivers, including energy, mining, and agriculture, by combining historical rates of HM change with future development potential indices (30). It represents cumulative anthropogenic pressure on a 0–1 scale projected to the

year 2030, rather than explicit land-cover transitions. The ESRI Vulnerability Change 2050 map, developed by Clark Labs, models the relative vulnerability of land cover to anthropogenic change by 2050 (15). At 300 m resolution, it assigns a vulnerability score based on a statistical model relating observed expansion of agricultural and urban land cover between 2010 and 2018 to a set of quantitative and qualitative covariates. Both datasets were resampled to match the resolution, extent, and projection of the HM forecasts from this study prior to comparison.

The distributions of projected mean HM change, CPI, and ESRI vulnerability are shown in Fig. 9. CPI spans a broader range by construction, whereas convLSTM HM change and ESRI vulnerability are strongly right-skewed and concentrated near zero. CPI and HM change are moderately correlated (Spearman's $\rho = 0.61$). This correlation is partly expected by construction, because CPI partially incorporates historical HM trajectories and because the development potential indices underlying CPI also underlie the DSI used as a covariate in our model. In contrast, ESRI vulnerability exhibits little correspondence with projected HM change (Spearman's $\rho = 0.21$). To facilitate spatial comparison, all three datasets were transformed to a common scale by converting values to percentile ranks and mapping these ranks to a shared beta distribution ($\alpha = 0.8$, $\beta = 5$). This transformation preserves relative ordering while enforcing comparable marginal distributions. There is substantial spatial overlap between high-risk areas identified by CPI and HM change, such as the Brazilian Cerrado, Sumatra, and Borneo. All three products highlight regions with high past rates of land-cover change, such as the deforestation frontier in Pará, Brazil, and the southeastern USA. As already noted, areas of the highest projected HM increase occur primarily in regions that are already moderately modified ($0.1 < \text{HM} \leq 0.4$) but have potential for further intensification, including the Indian subcontinent, East and West Africa, Java, and eastern China (Fig. 8). The ESRI product, however, assigns notably higher relative scores to frontier-distant areas, such as the boreal regions of Russia and Canada, which contributes to its weaker correlation with the other two products.

Usage Notes

Forecasting human pressure is fundamental to proactive conservation planning because it enables decisions to be made in anticipation of change rather than in response to observed loss (3, 4). Unlike conventional LULC models, HM forecasts capture the intensification of human pressure within human-dominated land-cover classes as well as within natural and semi-natural lands. This cumulative degradation is a major driver of biodiversity loss but is often missed by categorical land-cover change products. Our forecasts therefore have several important applications. They can support risk-informed siting of protected and conserved areas under GBF Target 3, evaluate conservation additionality by comparing observed outcomes against expected cumulative pressure trajectories, and provide forward-looking inputs for biodiversity impact models and ecosystem condition assessments. They

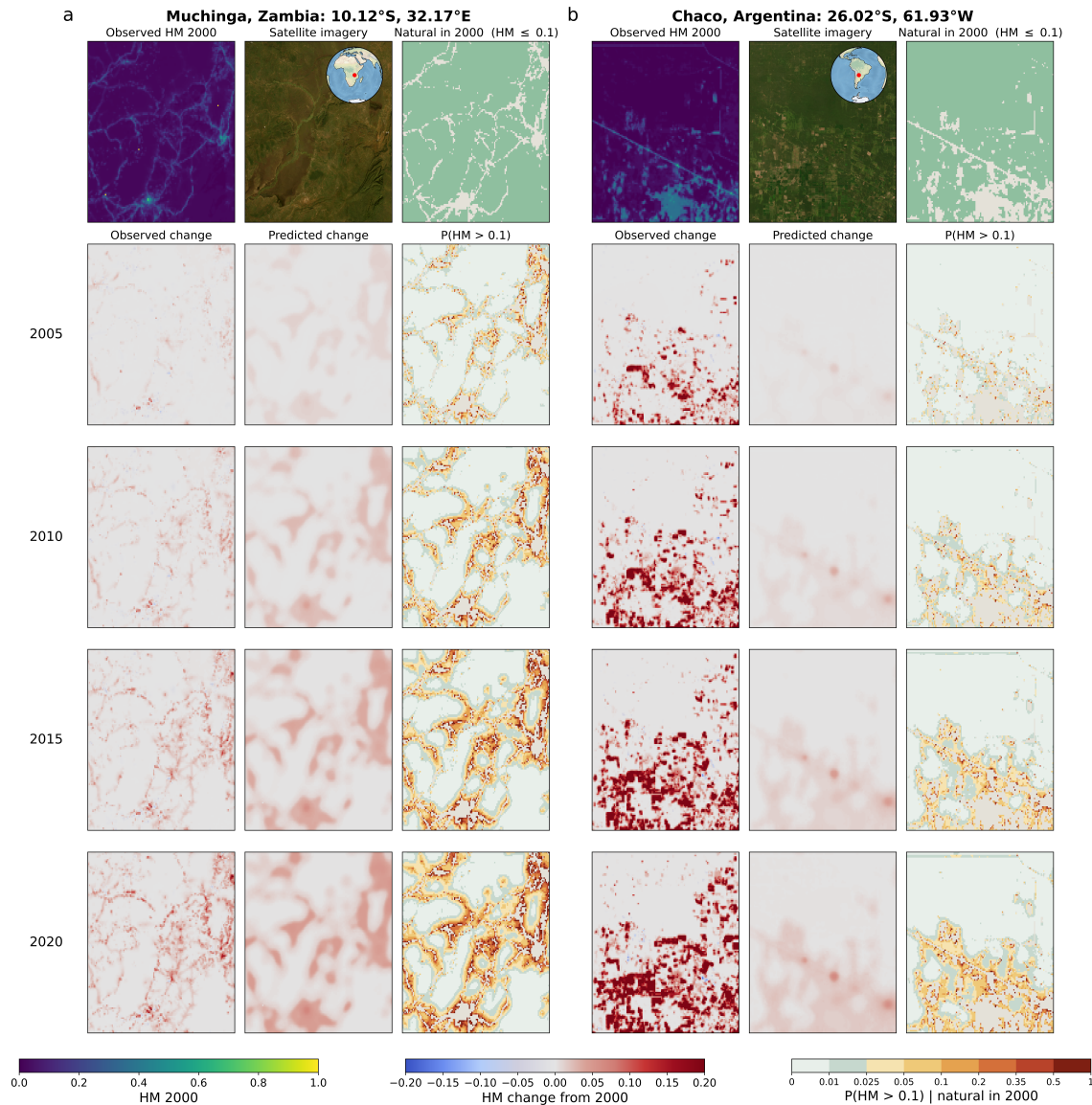


Fig. 6. Observed and predicted spatial patterns of human modification change over approx. 128 x 128 km tiles at a randomly chosen location in two priority conservation landscapes (a: Muchinga province, Zambia; b: Chaco Province, Argentina). The top row establishes the baseline conditions: the leftmost panel of each region shows the cumulative state of human modification at 2000, the center panel shows a recent satellite basemap for context and the rightmost panel shows the distribution of natural land ($HM \leq 0.1$) in 2020. Subsequent rows illustrate the change in human modification from 2000 over four time steps: 2005, 2010, 2015, and 2020. For each region, the observed change columns display the observed human modification, the predicted change columns display the predicted mean estimates from the model and $P(HM > 0.1)$ shows the estimated probability of loss of natural lands expected based on the full forecast distribution.

can also help identify restoration priorities under Target 2 of the GBF by highlighting areas where cumulative pressures are projected to stabilise, and can inform strategic spatial planning under Target 1 by complementing conventional land-use scenarios with forecasts of cumulative human pressure (45, 46).

As an example of how these forecasts can support implementation of the GBF, we evaluated how projected losses of natural land may affect opportunities to achieve Target 3, assuming at least 30% of natural areas are protected within each terrestrial ecoregion. Because Target 3 does not distinguish among IUCN protected-area management categories, this analysis counts all protected areas recorded in the WDPA regardless of category, together with other effective area-based conservation measures (OECMs) not included in our

covariates used for modelling. Our analysis identifies five groups of ecoregions (Fig. 10): (1) those that have already reached 30% protection (13.6% of ecoregions); (2) those that can still achieve the target through new conservation measures on natural land with a low ($<0.025\%$) forecast risk of loss (57.0%); (3) those that can still achieve the target through new conservation measures on natural land with a moderate (0.025%–0.5%) forecast risk of loss (12.7%); (4) those that can only achieve the target through new conservation measures on natural land with a high ($>0.5\%$) forecast risk of loss (1.2%); and (5) those where historical habitat loss has already made the target unattainable based on natural areas alone (13.9%). The first group, which already meets or exceeds the 30% target through existing protected areas or OECMs, includes the Namib Desert, Serengeti volcanic

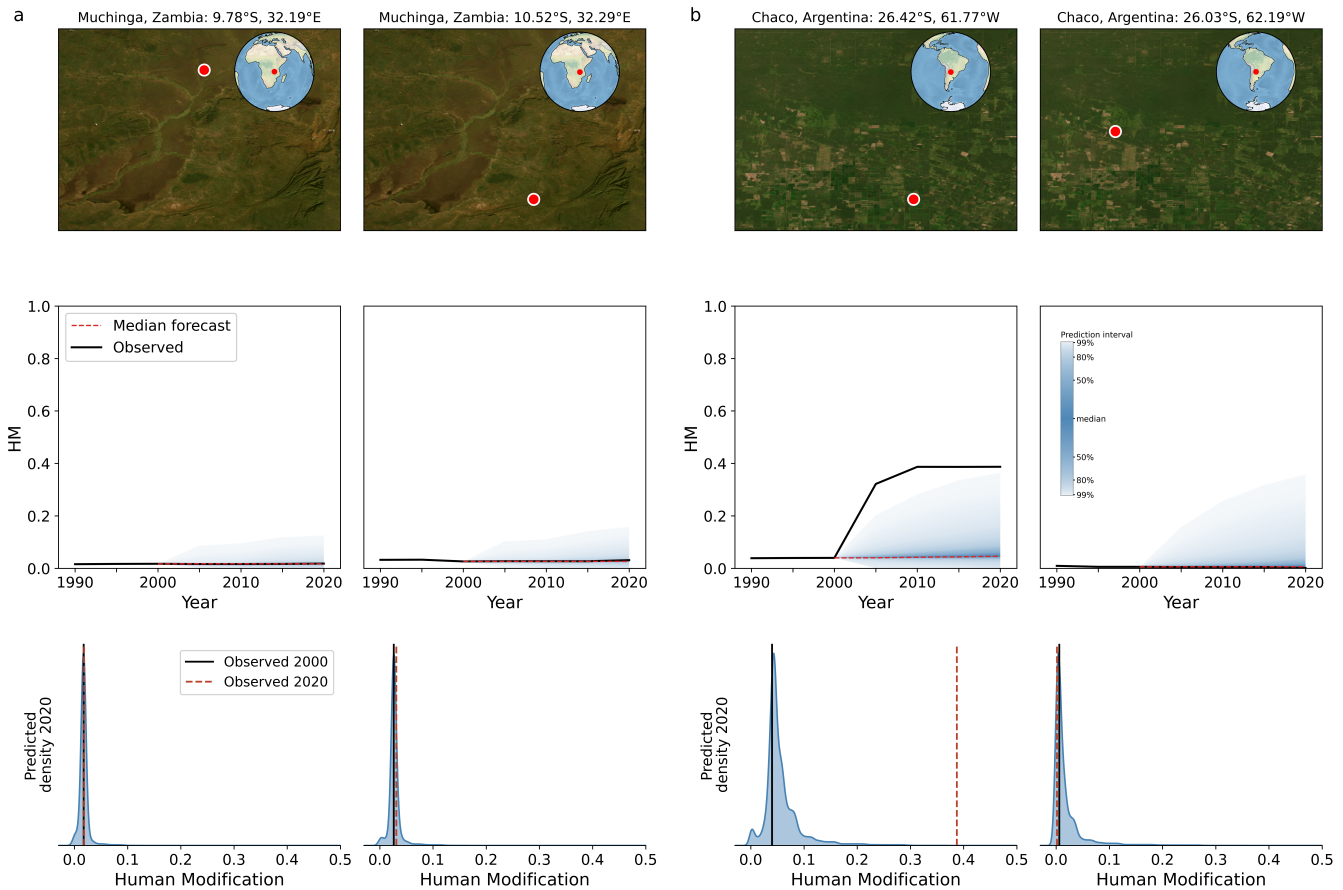


Fig. 7. Observed and predicted trends in human modification between 1990 and 2020 at two randomly chosen locations within two priority conservation landscape (a: Muchinga province, Zambia; b: Chaco Province, Argentina). Models are fitted on data between 1990 and 2000 and predictions from 2005 to 2020 compared to unseen observations. The top row shows a satellite overview of the focal area. The second row shows the observed HM time series against the full forecast distribution and median forecasts through time on held-out data. The bottom row shows the fitted distribution of HM in 2020 for each site against the observed HM in 2000 and 2020.

grasslands, Pantepui forests and shrublands, and Fiordland temperate forests. The second and third groups, where protection currently falls short but sufficient natural land exists at low to moderate risk, include ecoregions such as the Central Congolian lowland forests, East Siberian taiga, Patagonian steppe, and Borneo montane rain forests. The fifth group - where the target cannot be reached because too little natural land remains - may nonetheless contain important areas to target for restoration and improved management; examples include the Cross-Niger transition forests, Pernambuco interior forests, and Eastern Java-Bali rain forests. From a proactive conservation perspective, the most important group is the fourth: ecoregions that remain capable of achieving the 30% target but only on natural land with a high ($>0.5\%$) forecast risk of loss by 2040. This group includes the Uruguayan savanna, Puget lowland forests, Ordos Plateau steppe and Sumatran peat swamp forests. Projections are best read as a precautionary screen identifying ecoregions that could plausibly lose the option of meeting a 30% protection target on natural areas alone, rather than as a prediction of area loss. These ecoregions nonetheless represent high-priority opportunities for immediate conservation action, because delays could foreclose the possibility of meeting the target without restoration. The proportions of land that are protected, non-

natural, and natural within the three risk categories are shown in Fig. S7. The same assessment can be applied across countries, biomes, or other planning units, providing a flexible framework for national biodiversity planning, biome-scale prioritisation, and coordination across transboundary ecoregions.

These spatially explicit forecasts can be integrated into systematic conservation planning software, such as Marxan (47) or prioritizr (48), to evaluate how priorities change when future pressure and uncertainty are considered. By incorporating projected HM values as dynamic cost layers or spatial penalty metrics, practitioners can design protected-area networks that explicitly target vulnerable ecosystems and account for future pressures, rather than relying solely on current conditions (49). This enables conservation priorities to be evaluated alongside other planning objectives, such as representativeness, connectivity, and areas of particular importance for biodiversity, ecosystem functions, or ecosystem services. Our forecasts also support time-bound planning by providing multiple prediction horizons. Rather than producing a single, static estimate of future risk, our HM projections quantify the location, magnitude, and rate of projected changes in cumulative human pressure. This temporal dimension enables practitioners to distinguish between ar-

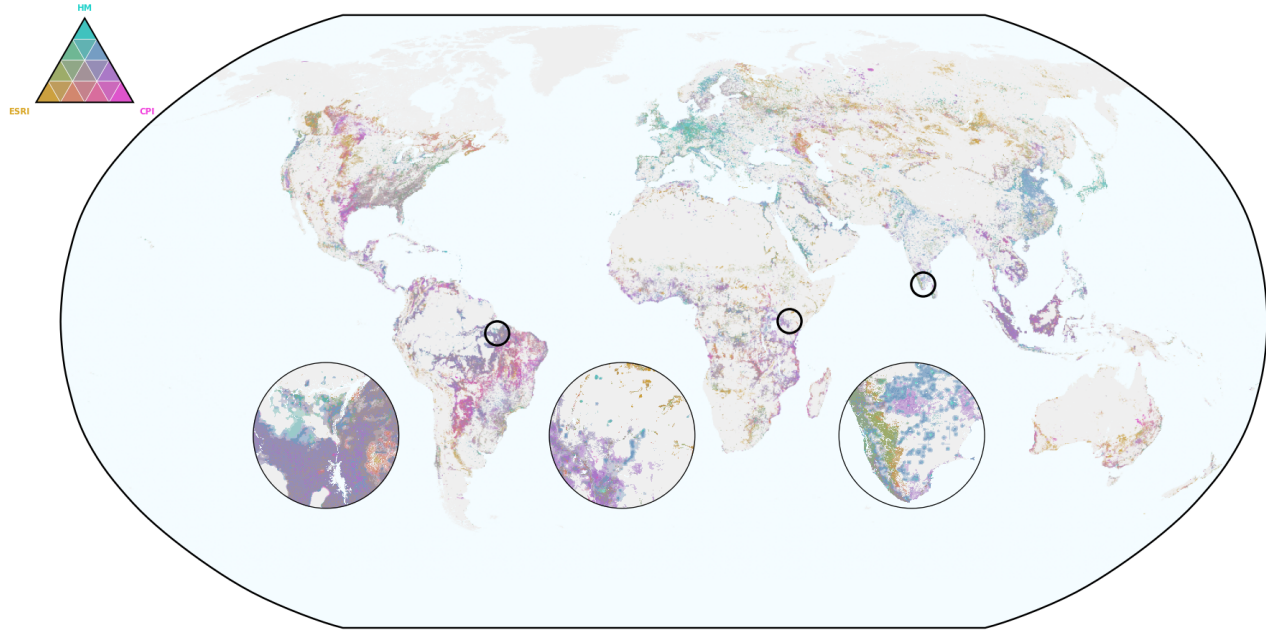


Fig. 8. Spatial agreement between the Conversion Pressure Index (CPI), the ESRI Land Cover Vulnerability to Change (ESRI) and the mean convLSTM human modification forecast (HM). The distributions of all three products are transformed to fit a common distribution by converting them to percentile ranks and mapping ranks onto a Beta distribution with $\alpha = 0.8$ and $\beta = 5$, forcing every variable to adopt the exact same gentle decay profile while strictly preserving the relative ordering of the data. The locations of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India. Green or teal pixels describe areas where only the HM forecast predicts increasing pressure, yellow or orange pixels where the only ESRI product predicts increasing pressure, and pink or purple pixels where only CPI predicts increasing pressure. A mix of colors, towards greyish pixels describe where models overlap.

areas are likely to experience gradual degradation and those facing rapid increases in pressure, informing tailored policy responses and intervention timelines.

Crucially, the HM forecasts provide the full distribution of potential future pressure. Conservation planning is inherently risk-adjusted, requiring decision makers to weigh the likelihood of adverse outcomes against the costs of action, the probability of success, and the consequences of inaction (50). Reliance on a single estimate, such as a mean projection, can obscure low-probability events that may carry high ecological consequences (49). This limitation is particularly important for anthropogenic threats, which are often driven by episodic or stochastic processes rather than smooth, linear trends. Because most pixels exhibit little projected change, while a small fraction experiences large increases (yielding a strongly right-skewed distribution), mean estimates are dominated by the large number of low-change pixels and systematically underrepresent the potential for extreme increases. Interpreting upper percentiles or risk-of-loss maps is therefore essential for risk screening: identifying locations where large increases in cumulative pressure, while uncertain, cannot be ruled out and may warrant precautionary conservation action.

To capture the full scope of uncertainty, we recommend interpreting the mean HM projection alongside its associated prediction intervals (percentiles). For applications where the cost of underestimating risk is high (e.g. siting protected areas, identifying restoration priorities), we recommend also interpreting the HM projection using the upper bound, or us-

ing the provided estimates of probability of loss of natural or moderately modified land. The upper-bound forecast should be viewed as a precautionary risk screen, highlighting areas where substantial increases in human modification, while not the most likely outcome, remain plausible and may warrant additional conservation attention.

We also caution against inappropriate aggregations of pixel-level quantile information into regional scenarios. Estimated distributions of HM change are generated independently for each pixel and do not account for joint spatial covariance. Summing or averaging HM at a given percentile across a region therefore does not yield a valid area-based aggregate: averaging the 97.5th percentile across a region gives the correct regional 97.5th percentile only if every pixel realises this unlikely outcome simultaneously. Reporting the proportion of pixels crossing a given threshold at a particular percentile remains valid. Statistics of expected HM change, or of expected area beyond a given HM threshold, can be aggregated freely. These statistics are calculated, respectively, from the mean HM surface and from the per-pixel exceedance probability. This is because they represent expectations, and the expectation of a sum is the sum of the expectations, regardless of the covariance between pixels. For example, two 1 km² pixels each with a 0.2 probability of crossing an HM threshold of 0.1 contribute 0.4 km² to the expected area of loss, regardless of whether they cross the threshold together or independently. We use these estimates of expected area change in our examples in the Usage Notes.

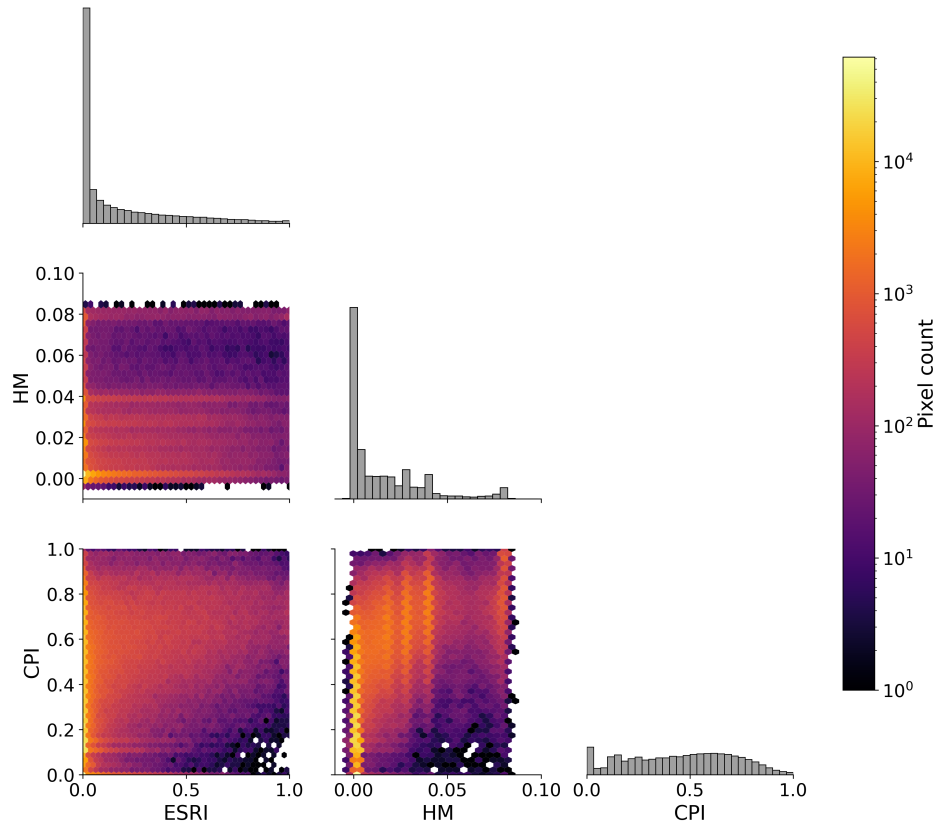


Fig. 9. Distributions and pairwise relationships among the Conversion Pressure Index (CPI), the ESRI Land Cover Vulnerability to Change product (ESRI), and the mean convLSTM human modification change forecast (HM), based on 1 000 000 randomly sampled terrestrial pixels. Off-diagonal panels are two-dimensional density plots of each pair of products, with color indicating the number of sampled pixels per bin on a logarithmic scale. Diagonal panels are histograms of each product, with counts on a logarithmic y-axis. Note that the three products are measured on different scales and are not directly comparable in absolute terms: CPI and ESRI vulnerability are relative 0–1 indices, whereas HM change is expressed in units of change in cumulative human modification. Spearman rank correlations are $\rho = 0.61$ between CPI and HM change and $\rho = 0.21$ between ESRI vulnerability and HM change. Data represent untransformed raw values.

Data Caveats

The forecasts presented here inherit several important limitations from the underlying data and modelling assumptions that should be considered when interpreting and applying the results.

First, the HM time series is treated as the best available representation of cumulative human pressure and is used as the reference truth for model training and validation. As a result, any errors, omissions, or biases present in the input datasets used to construct HM are propagated into the forecasts. In addition, the HM framework incorporates numerous expert-derived decisions regarding how individual threats are represented, weighted, and combined, including judgements about the relative intensity of different threats (as described in Theobald et al. (23)). While these decisions are grounded in the best available science, they nonetheless introduce subjectivity that is necessarily carried forward into the forecast products. HM does not currently represent several important threat types, including invasive species, climate change and extreme weather, and geological events. Furthermore, the HM time series only represents change in a subset of the overall threats, notably excluding change in the extent of roads due to the absence of reliable data on historical road development.

Second, the forecasts focus on cumulative HM rather than on

individual threat components. This limits the direct applicability of the forecasts for fine-scale conservation action planning that requires detailed information on specific threats and their future dynamics (4, 51). Developing robust forecasts for individual threat types will likely require more process-based representations of underlying drivers, or hybrid approaches that combine process-based models with statistical or machine-learning methods. Producing separate forecasts for individual HM-component threats remains an important area for future research.

Third, many conservation decisions operate on time horizons longer than the 20-year window considered here. The forecast horizon from 2020 to 2040 is constrained by the temporal length of the historical HM record, which limits the ability to validate predictions and their associated uncertainty at longer lead times. As the HM dataset is extended temporally, we anticipate updating the forecasts and exploring longer horizons. However, uncertainty increases rapidly with forecast lead time, and at longer horizons additional sources of uncertainty not explicitly represented here, such as climate change impacts and socioeconomic scenario uncertainty, may dominate (52, 53). These factors should be considered when interpreting the forecasts for long-term strategic planning.

Fourth, the convLSTM learns to forecast HM by detecting patterns in the historical record from 1990 to 2020. This

Risk of missing a 30% protection target on land natural in 2020

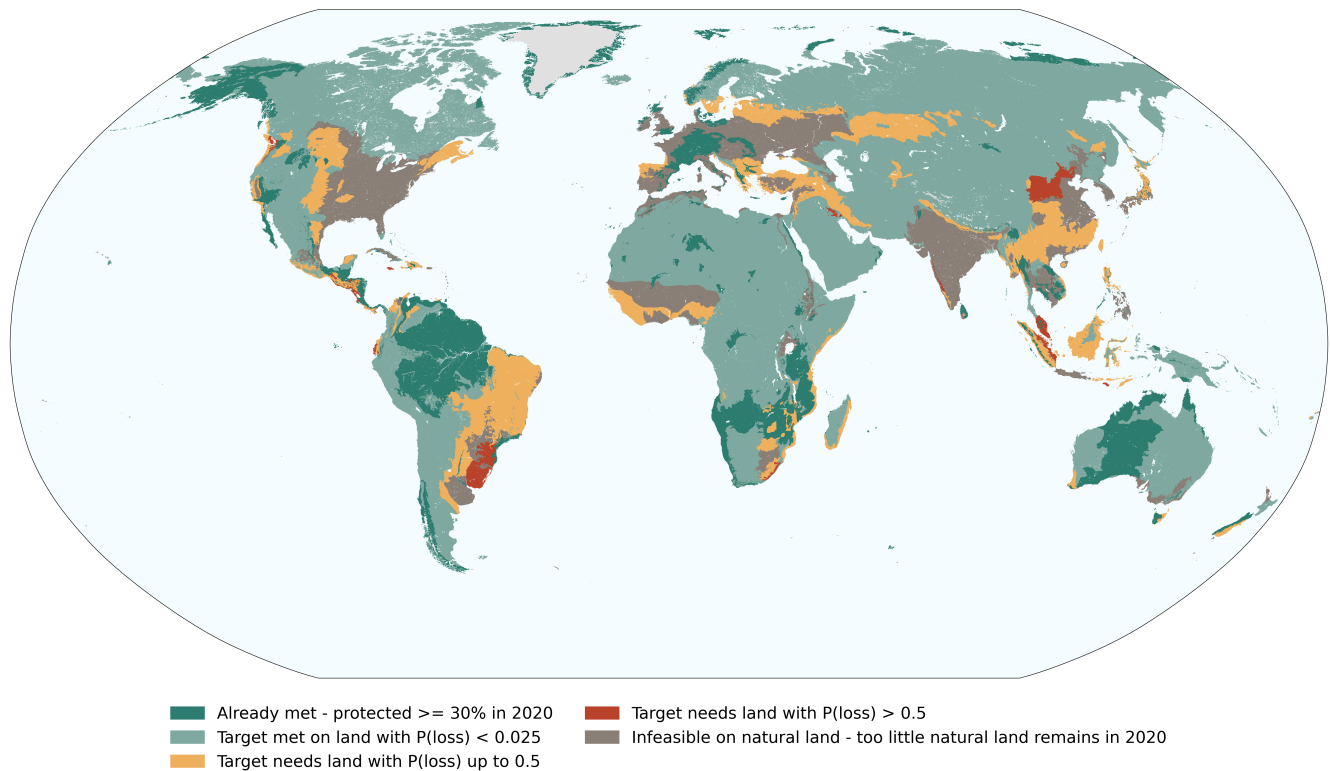


Fig. 10. Risk of missing a 30% protection target on natural land based on forecasts of the risk of loss of natural land ($HM \leq 0.1$) between 2020 and 2040. We assign each terrestrial ecoregion to one of five categories based on its extent of natural land in 2020, current proportion protected, and forecasted risk of loss by 2040. Ecoregions are defined as those that: (1) have already reached 30% protection (dark green); (2) can still achieve the target through new conservation measures on natural land with a low ($<0.025\%$) forecasted risk of loss (light green); (3) can still achieve the target through new conservation measures on natural land with a moderate ($0.025\%–0.5\%$) forecasted risk of loss (yellow); (4) can only achieve the target through new conservation measures on natural land with a high ($>0.5\%$) forecasted risk of loss (red); and (5) are areas where historical habitat loss has already made the target unattainable based on natural land areas alone (grey). Protected area is calculated from all protected areas recorded in the WDPA, regardless of IUCN management category, and OECMs. The proportions of land that are protected, non-natural, and natural within the three risk categories are shown in Figure S7.

means the model assumes that the spatial and temporal patterns that drove HM change over this period will continue to operate in the future. This assumption is unlikely to hold in regions where demographic, technological, or economic shifts are producing novel threat patterns that are unrepresented in the training data. The renewable energy transition and the growing energy and land demands of data centres supporting artificial intelligence are clear examples: both are reshaping where new infrastructure is sited, with little precedent in the historical record. Methods that learn from historical spatiotemporal patterns, including the one used here, are unlikely to identify where these emerging threats will be most concentrated, and our forecasts should be paired with sector-specific or scenario-based analyses where decisions depend on these drivers.

Fifth, the protected-area inputs inherit the limitations of the World Database on Protected Areas. Coverage is incomplete, boundaries and designation dates contain errors, and the IUCN management-category scheme is applied unevenly, with many countries assigning categories inconsistently or not at all (37). Our Target 3 analysis presented above is robust to this unevenness because it counts all protected areas

regardless of category. The distinction between strictly protected and other protected areas used as a model covariate is affected by it, however, and the model's learned response to protection status should be interpreted with this in mind.

The published prediction intervals should be treated as a lower bound on true forecast uncertainty. They represent the spread of HM outcomes observed historically among locations with similar recent HM trajectories, threat composition, and covariates. This captures the stochastic component of HM change, including the possibility of abrupt large increases at locations where the mean forecast is near zero, but excludes further sources of uncertainty mentioned above such as model structural uncertainty, error in the inputs, and scenario uncertainty.

Data Availability

Historical HM time-series data for 1990–2020 are available at <https://zenodo.org/records/14449495>. Forecasts of HM per forecast year for the mean value of HM, the upper 97.5% percentile, the lower 2.5% percentile, the expected probability that HM will exceed 0.1, and the probability that HM will exceed 0.4 are available on Zenodo at

<https://zenodo.org/records/19700998> under a CC-BY-4.0 licence. Data cubes containing full percentile information with dimensions latitude, longitude, year and percentiles can be accessed on Arraylake at <https://app.earthmover.io/marketplace/6abb60fba504351ef2a29c6f>. An interactive browser-based viewer is hosted at gmoncrieff.github.io/hm_forecasts_app/.

Code Availability

All code for fitting and evaluation of the convLSTM is available on GitHub at <https://github.com/GMoncrieff/spatio-temporal>. The GitHub repository contains further technical details on model architecture and fitting. Code to produce figures and tables can be found at https://github.com/GMoncrieff/hm_forecasting_paper.

AUTHOR CONTRIBUTIONS

G.R.M. led the analysis and writing. C.M.K., M.V., J.R.O. and G.R.M. conceptualised the study and designed the analysis. G.R.M., M.V., C.M.K., J.R.O., J.K., K.S.W., J.A.F. and D.M.T. contributed to manuscript writing.

COMPETING FINANCIAL INTERESTS

The authors declare no competing interests.

ACKNOWLEDGEMENTS

Funding to support this work was provided by The Nature Conservancy and One Earth. We are grateful for input on previous versions of this analysis from Kim Hall.

AI STATEMENT

Claude Opus 4.8, 5.0, and 5.5 were used to check spelling and grammar, improve the style and clarity of the manuscript, and review earlier drafts. Claude Code was also used to assist with model development and code generation. All AI-assisted outputs were reviewed and verified by the authors, who take full responsibility for the content of the manuscript.

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Supplementary Information

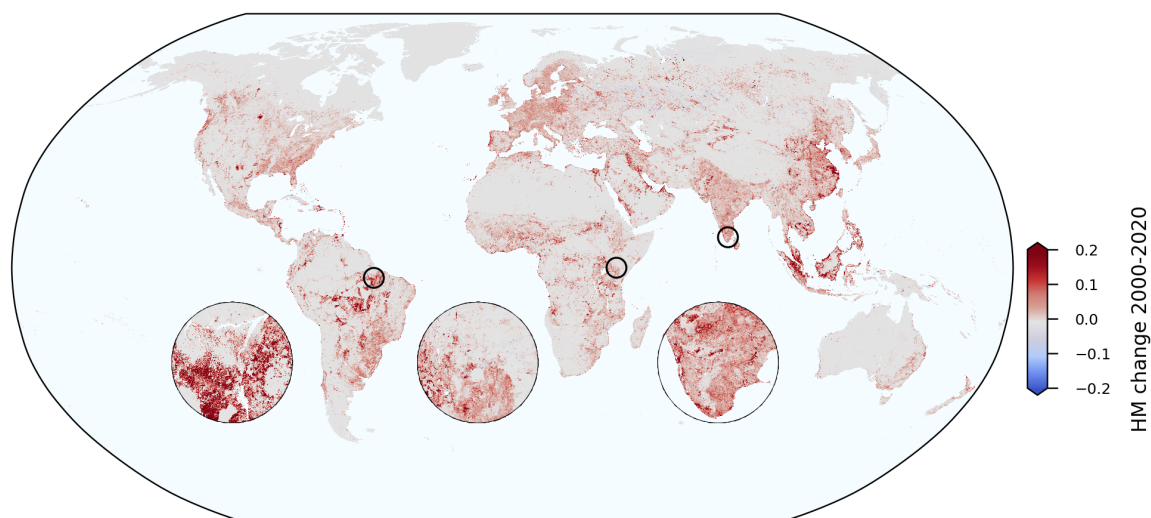


Fig. S1. Observed change in human modification between 2000 and 2020. The location of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India.

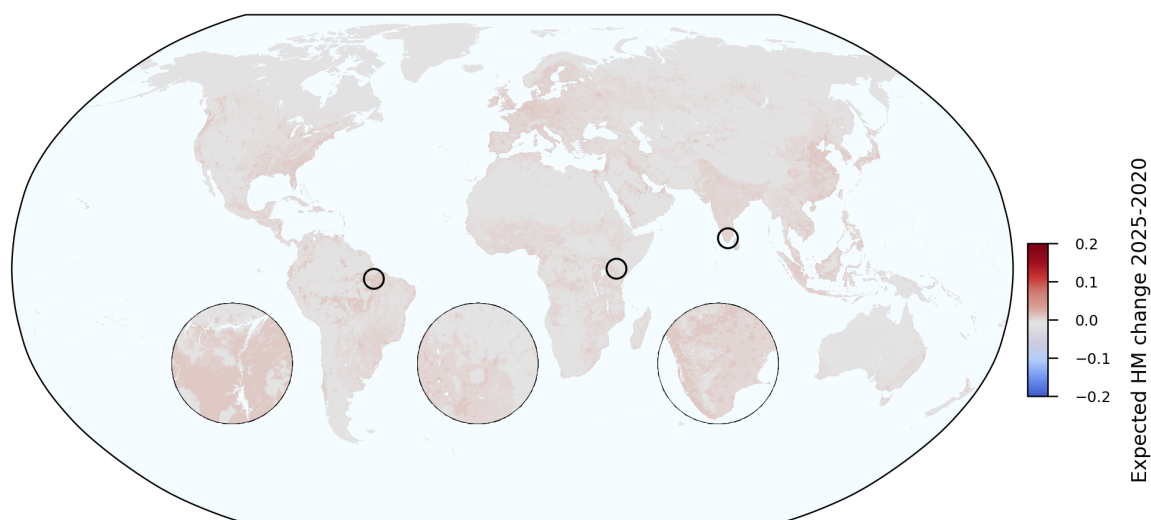


Fig. S2. Predicted mean estimates of change in human modification between 2020 and 2025. The location of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India.

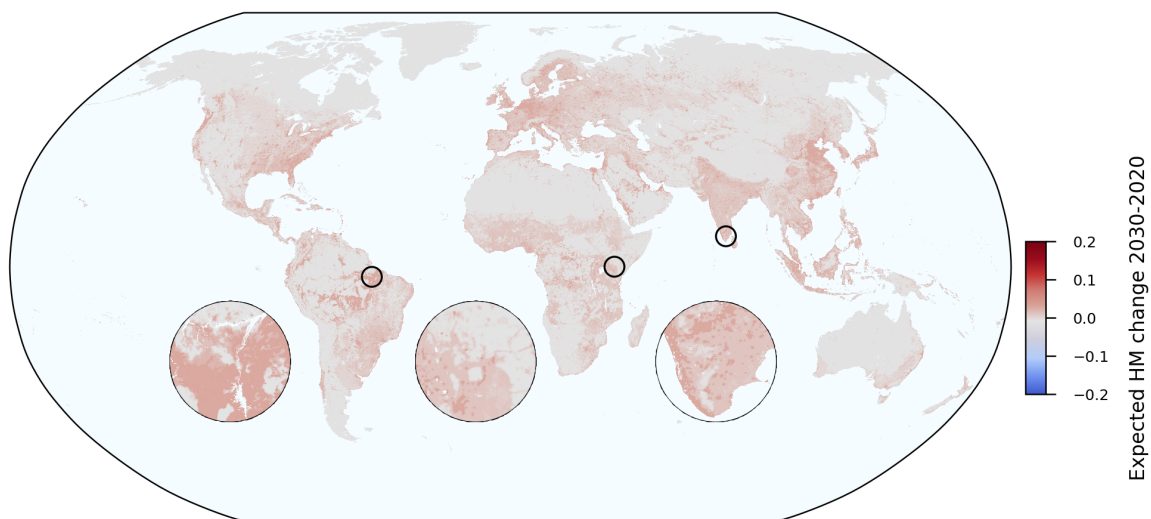


Fig. S3. Predicted mean estimates of change in human modification between 2020 and 2030. The location of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India.

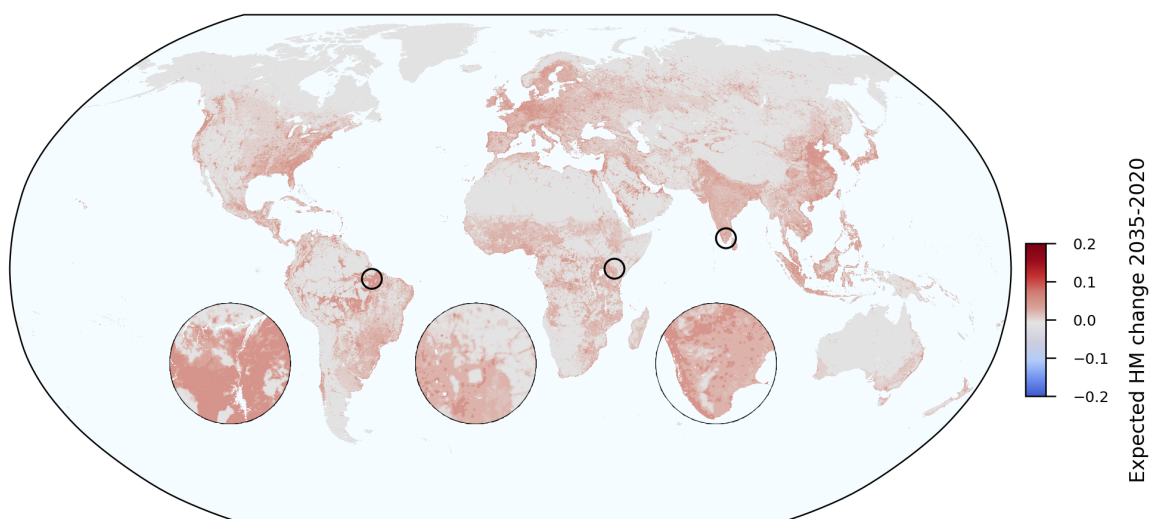


Fig. S4. Predicted mean estimates of change in human modification between 2020 and 2035. The location of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India.

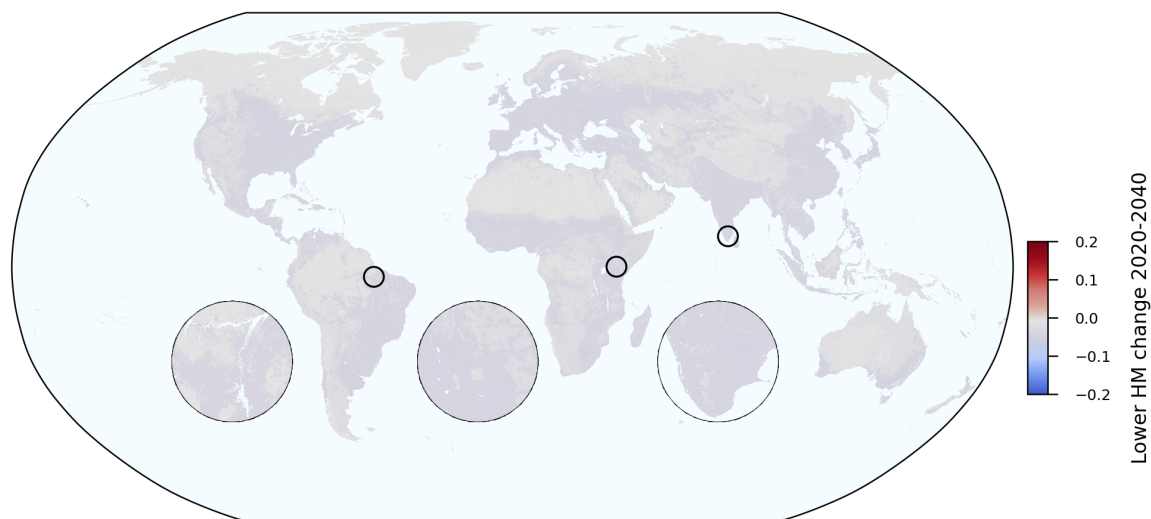


Fig. S5. Predicted lower (2.5% percentile) estimates of change in human modification between 2020 and 2040. The location of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India.

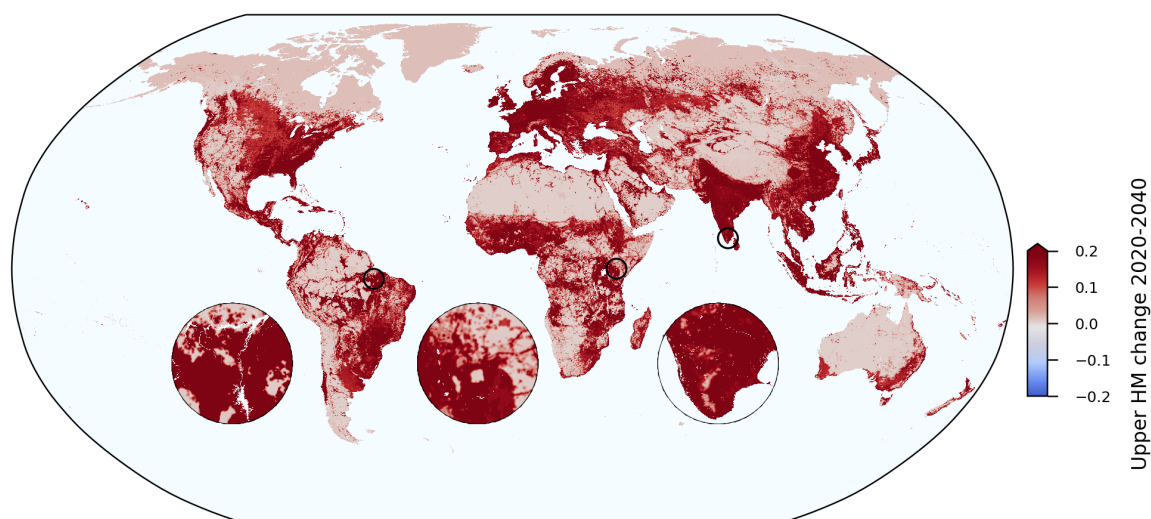


Fig. S6. Predicted upper (97.5%) percentile estimates of change in human modification between 2020 and 2040. The location of inset maps are indicated by black circles and display selected areas of conservation importance undergoing rapid change (from left to right): Para, Brazil; Central Kenya; Southern India.

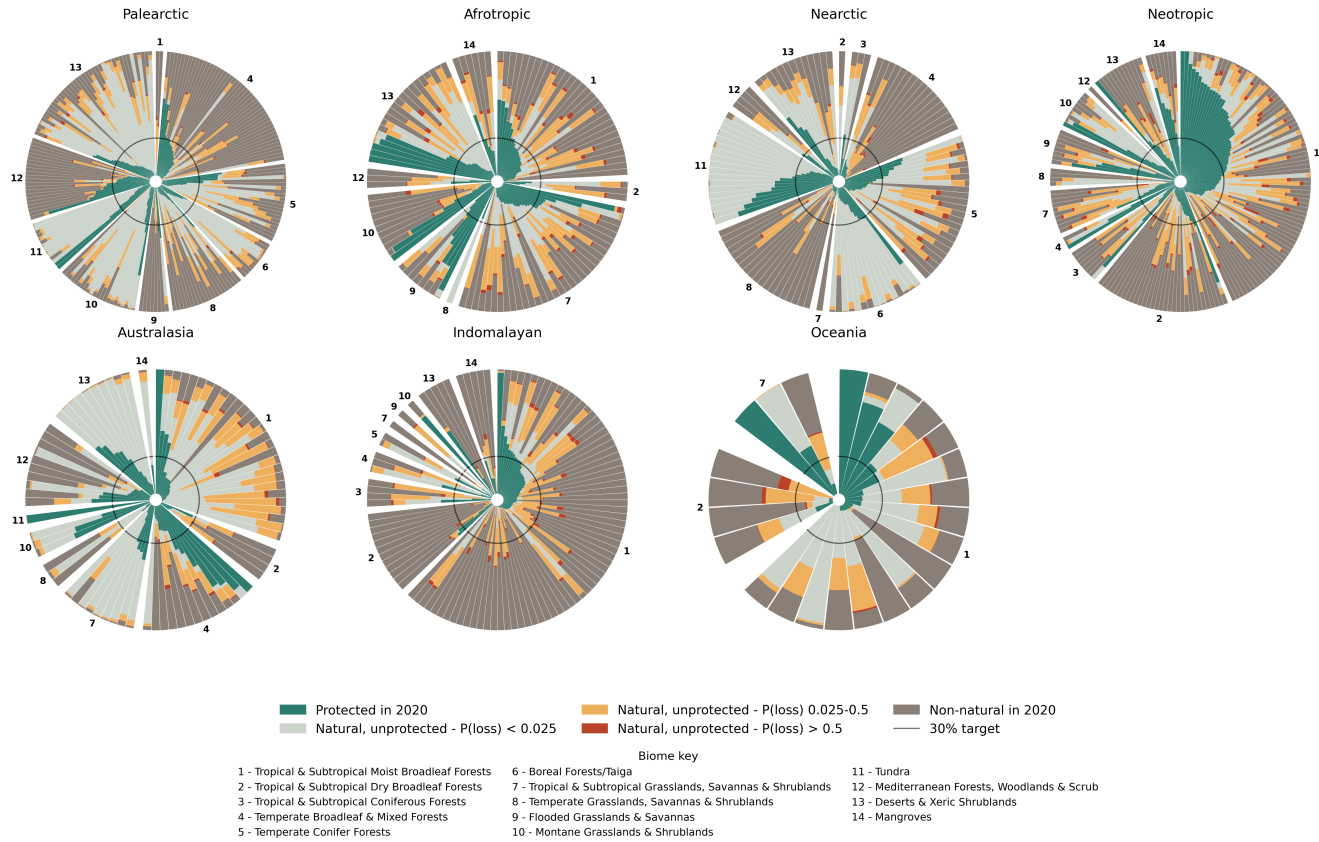


Fig. S7. Risk of missing a 30% protection target on natural land based on forecasts of the risk of loss of natural land ($HM \leq 0.1$) between 2020 and 2040. We divide the land within each terrestrial ecoregion into five categories based on the extent of natural land in 2020, the current proportion protected, and the forecasted risk of loss by 2040. Separate circles are drawn for each biogeographic realm. Each radial bar represents one terrestrial ecoregion, grouped by biome. Bar segments show the proportion of each ecoregion's land area that is, from the centre outwards: (1) currently protected (dark green); (2) natural in 2020 with a low ($<0.025\%$) forecasted risk of loss (light green); (3) natural in 2020 with a moderate ($0.025\%–0.5\%$) forecasted risk of loss (yellow); (4) natural in 2020 with a high ($>0.5\%$) forecasted risk of loss (red); and (5) non-natural in 2020 (light brown, $HM > 0.1$). Protected area is calculated from all protected areas recorded in the WDPA, regardless of IUCN management category. The black arc at 30% provides a visual reference for the GBF Target 3 30% area-based protection target. Ecoregions where the dark green segment alone reaches the 30% arc have already met the target through formal protection, whereas ecoregions where the combined green, yellow, and red segments fall below the 30% arc cannot meet the target on natural land in 2040, even if every remaining unprotected natural pixel were brought into formal protection.