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# Australia’s terrestrial industrial footprint and ecological intactness

Ruben Venegas-Li[1], Scott Atkinson[1,2], Milton A U de Andrade Junior[1], Rachel Fletcher[3], Peter Owen[4], Lucia Morales-Barquero[1], Bora Aska[1], Miguel Arias-Patino[5], Hedley S. Grantham[6,7], Hugh Possingham[1], Oscar Venter[5], Michelle Ward[1,8], James E.M. Watson[1]

[1] Centre for Biodiversity and Conservation Science, The School of the Environment, University of Queensland, St Lucia, 4072, Australia
[2] United Nations Development Program, New York, NY, United States
[3] The Wilderness Society, GIS, South Brisbane, Queensland, Australia
[4] The Wilderness Society (South Australia) Inc., 111 Franklin Street, Adelaide, SA 5000, Australia
[5] Natural Resources and Environmental Studies Institute, University of Northern British Columbia, Prince George, British Columbia V2N 4Z9, Canada
[6] Center for Ecosystem Science, School of Biological, Earth and Environmental Sciences, University of New South Wales, Sydney, New South Wales, Australia
[7] Bush Heritage Australia, Melbourne, Victoria, Australia
[8] School of Environment and Science, Griffith University, Nathan, QLD 4111, Australia

*Correspondence to*: Ruben Venegas Li (r.venegas@uq.edu.au)

**Abstract.**

Australia's unique biodiversity faces significant threats from anthropogenic activities that drive habitat destruction and degradation. This study presents the first comprehensive national-scale cumulative pressure map for terrestrial Australia since the 1980s, providing key insights into human disturbance of the landscape. We developed a Human Industrial Footprint (HIF) index incorporating 16 nationally relevant pressure layers, offering a more accurate representation of industrial influences than previous global-scale analyses. The HIF was used to derive an Ecological Intactness Index (EII), accounting for habitat quality, fragmentation, and connectivity. A technical validation comparing visually scored pressures in 1397 stratified random samples using high-resolution satellite images revealed a strong agreement with the HIF. We also conducted an uncertainty (sensitivity) analysis by adjusting individual pressure scores by up to ±50% across 100,000 simulations, which showed a moderate impact on cumulative pressure scores, confirming the robustness of our approach. We believe these high-resolution datasets can be valuable tools for guiding conservation efforts, such as informing protected area expansion, ecosystem restoration priorities, and biodiversity offset strategies. By offering a detailed assessment of cumulative pressures and ecological integrity, this study addresses a critical knowledge gap, and can support evidence-based decision-making for Australia's biodiversity conservation and sustainable development objectives. The HIF, EII, and scaled pressure layers are available at **10.5281/zenodo.15833395** (Venegas-Li et al., 2025).

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## 1 Introduction

Australia is globally recognized as one of the most biodiverse countries on Earth, hosting an array of species and ecosystems found nowhere else (Chapman, 2009). However, since European colonization, industrial activities such as agriculture, forestry, and urbanization have caused widespread habitat destruction, fragmentation, and pollution of the natural environment. As a result, during the last 200 years, one-third of native vegetation has been lost (Bradshaw 2012; Kingsford et al. 2009; Ward et al. 2019). Over 2,100 species and 100 ecological communities are now legislated as threatened with extinction in the near term, and 103 species have become extinct (Commonwealth of Australia, 2025). The threatening processes remain largely unabated (Kearney et al., 2023; Legge et al., 2023; Woinarski et al., 2015), and urgent and improved conservation efforts are needed to halt this trend (Kearney et al., 2019).

Cumulative pressure maps provide spatial insights into the extent and intensity of human disturbance of the environment, which is essential for understanding their interaction with biodiversity and designing responses to halt environmental degradation (Halpern et al., 2015; Kearney et al., 2023; Locke et al., 2019; Watson et al., 2023b). The 'Human Footprint' methodology, first developed by Sanderson and colleagues in 2002 (Sanderson et al., 2002), offers a standardized approach to quantify cumulative human pressures across landscapes. This method has been widely applied at the global and regional scales (Arias-Patino et al., 2024; Gassert et al., 2023; Hirsh-Pearson et al., 2022; Venter et al., 2016; Williams et al., 2020), and it has been used as a proxy for habitat condition, identifying connectivity between the protected area estate (Ward et al., 2020) and for highlighting the relationship between human activities and the state of biodiversity (Jones et al., 2018; Di Marco et al., 2018; Watson et al., 2023b).

More recently, Beyer and colleagues (2020) developed a metric to estimate ecological intactness, which includes a relative measure of habitat quality as well as degree of fragmentation and connectivity, using human footprint data as the input layer. Creating datasets such as an intactness metric is particularly important in the present context of the global conservation agenda (Mendez Angarita et al., 2025), where, for the first time, targets have been set for ecological intactness in the Kunming-Montreal Global Biodiversity Framework (GBF) (CBD, 2022), to which Australis is a signatory and has made commitments to. Specifically, the ecosystem component of the GBF's Goal A aims to ensure "the integrity, connectivity, and resilience of all ecosystems are maintained, enhanced, or restored, substantially increasing the area of natural ecosystems by 2050". The GBF's Target 1 aims to achieve near-zero loss of high biodiversity importance areas – "including ecosystems of high ecological integrity", and Target 2 aims to bring at least 30% of degraded terrestrial ecosystems under effective restoration by 2030 to enhance "ecological integrity" (CBD, 2022). In addition, Target 3 of the GBF aims to ensure areas of high biodiversity importance are priorities for future protected area gazettal, and areas considered containing high ecological intactness are core to this (Watson et al., 2023c).

In Australia, Lesslie and colleagues carried out pioneering work in the 1980s to create the first pressure map at a national scale (Lesslie et al., 1988; Lesslie and Taylor, 1983, 1985). However, no similar efforts have been carried out subsequently, making the available national data highly dated. While global efforts have mapped pressures in Australia, these global cumulative

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pressure maps are usually restricted to eight or fewer pressures for which data are available globally (Gassert et al., 2023; Mu et al., 2022; Sanderson et al., 2002; Williams et al., 2020) and miss nation-specific critical pressures (Hirsh-Pearson et al., 2022), such as forestry, unpaved roads, mining, and farm dams in Australia, hindering the potential use of pressure maps in the design of conservation targets and actions. Recent evidence shows that the accuracy of cumulative pressure maps to represent pressures on the ground improves as additional pressure layers are included (Arias-Patino et al., 2024).

This study aims to produce a high-resolution contemporary (circa 2020-2024) cumulative pressure map for Australia capturing 16 nationally significant pressures. We call this map the Australian Human Industrial Footprint (HIF). Using the HIF as an input, we also derive an Ecological Intactness Index (EII) using the metric from Beyer and colleagues (2020). Together, the HIF and the EII offer critical tools for guiding conservation and restoration efforts, aligning with Australia's commitments under the Global Biodiversity Framework including those targeting highly intact ecosystems (Target 1), where to undertake restoration (T2) and where are the important areas to protect (T3) and government objectives and policies such as the Threatened Species Action Plan (Commonwealth of Australia, 2022).

## 2 Methods

### 2.1 Overview of the Human Industrial Index Mapping Method

We adapted the Human Footprint Index methodological approach (Sanderson et al., 2002) to create a cumulative pressure map for Australia, incorporating best practices from studies that have refined this method globally and regionally over the past two decades (Arias-Patino et al., 2024; Gassert et al., 2023; Hirsh-Pearson et al., 2022; Watson et al., 2023a; Woolmer et al., 2008). We identified 16 human pressures relevant to Australia with available spatial data (Table 1): 1) intensive land uses, 2) buildings, 3) mining and quarrying, 4) human population density, 5) croplands, 6) pasturelands, 7) forestry plantations, 8) reservoirs and large dams, 9) farm dams, 10) roads, 11) railways, 12) energy transmission lines, 13) oil pipelines, 14) gas pipelines, 15) hiking trails, and 16) navigable waterways. We assigned a score between 0 and 10 to each pressure, with each pressure's score relative to other pressures (Fig. 1 and Table S1 in the Supplement). For all the pressures, scores were assigned according to their "direct" disturbance on the area they overlap. For pressures 8-16, we also assigned a score to adjacent areas to reflect indirect disturbances, such as edge effects from habitat fragmentation and more cryptic forms of disturbances such as potential access for humans or invasive species to areas previously inaccessible. We defined intensive land uses, mining, cropland, and pasturelands as mutually exclusive pressures, whereas all other pressures were allowed to overlap. Where these mutually exclusive pressures coexist, only the single highest-scoring pressure value amongst the mutually exclusive land uses was assigned to the pixel.

After creating the weighted pressure layers, we summed them up to generate the terrestrial Industrial Footprint map. The analysis was conducted at a 100 m spatial resolution using the Australian Albers Equal Area projection (EPSG:3577). This resolution represented a balance between the 50 m resolution of the primary land use data and the overall accuracy of the dataset. All individual layers were processed using GRASS GIS (GRASS Development Team, 2024) or Google Earth Engine

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(Gorelick et al., 2017). The uncertainty analysis was conducted in Python 3.6 (Van Rossum and Drake Jr, 1995), and graphics were developed using the R Package ggplot (Wickham, 2016).

**Table 1 The pressures included in mapping the Australian Industrial Footprint, and the specific data layers utilised in the mapping process.**

| Data layer | Date/ last update | Scale/ Resolution/ Positional accuracy | Data Source |
|---|---|---|---|
| Intensive land uses | 2008 - 2023 | 50 m * | Catchment Scale Land Use of Australia – Update December 2023 version 2 (ABARES 2024) |
| Buildings | 2018 | Not specified | Australian Building Footprints (Microsoft 2022) |
| Mining/ Quarrying | 2008 - 2023 | 50 m * | Catchment Scale Land Use of Australia – Update December 2023 version 2 (ABARES 2024), complemented with data distributed by states and territories (Table S2) |
| Population density | 2023 | 100 m | WorldPop High-Resolution Dataset: Australia, 2024. (WorldPop 2024) |
| Croplands | 2008 - 2023 | 50 m * | Catchment Scale Land Use of Australia – Update December 2023 version 2 (ABARES 2024) |
| Forestry (plantations) | 2008 – 2023 | 50 m * | Catchment Scale Land Use of Australia – Update December 2023 version 2 (ABARES 2024), and Australia Forests 2023 (ABARES 2023). |
| Reservoirs/ dams | 2008 - 2023 | 50 m * | Catchment Scale Land Use of Australia – Update December 2023 version 2 (ABARES 2024) |
| Farm dams | 2021 | nd | Malerba et al. (2021), and references therein. |
| Pasturelands | 2008 - 2023 | 50 m * | Catchment Scale Land Use of Australia – Update December 2023 version 2 (ABARES 2024) |
| Roads | 2024 | ± 2 m urban areas. ± 10 m in rural areas | National Roads (Geoscape Australia, 2024) and Open Street Maps (OpenStreetMap contributors, 2024) |
| Railways | 2021 | Accuracy ± 20m | Foundation Rail Infrastructure (Geoscience Australia 2021) |
| Oil Pipelines | 2022 | Not specified | Oil Pipelines of Australia (Geoscience Australia 2022) |
| Gas Pipelines | 2022 | Not specified | Gas Pipelines of Australia (Geoscience Australia 2022) |
| Transmission lines | 2021 | Not specified. | Electricity Transmission Lines (Geoscience Australia 2021) Digitized using satellite images with a resolution of 0.15- 2.5 m |
| Hiking Trails | 2023 | Not specified | National Roads. (Geoscape Australia 2024), and Open Street Maps (2024) |
| Navigable waterways | 2016 | 300 m | Generated for this study following the methods in Venter et al. (2016) |

*A seamless raster was created by combining land use vector data showing a single dominant land use for each location based on the management objective of the land manager. The scale of mapping varies between 1:50,000 and 1:250,000.

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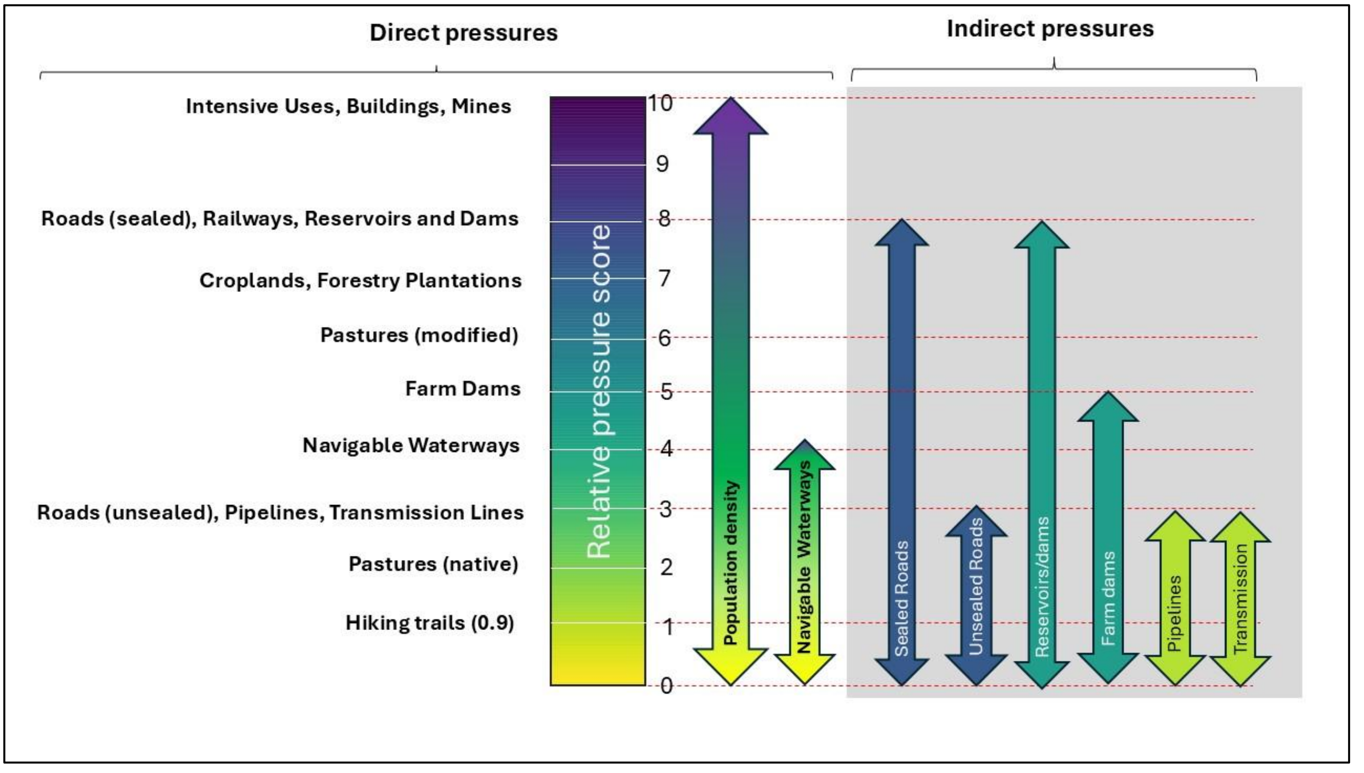


**Figure 1 Direct and indirect scores assigned to each of the 16 pressures used to estimate the Australian Industrial Footprint. We set indirect effects to extend 5 km from roads, 500 m from reservoirs and dams, and 2.75 km from pipelines and transmission lines.**

### 2.2 Mapped pressures

In this subsection, we outline the rationale for including each of the 16 pressures used in this analysis and the scores assigned to them, and provide a short description of the data used to represent each pressure. We took advantage of the 2023 update of the Catchment Scale Land Use of Australia (ABARES, 2024), henceforth called CLUMP 2023, to represent several pressures. CLUMP 2023 has a high level of thematic detail (its tertiary classification has 189 classes), uses a standard national classification (State/Territory agencies compile data), and is updated regularly (e.g., previous updates include 2015, 2017, 2018, and 2020). The dataset is distributed in raster format at 50 m spatial resolution, showing a single dominant land use for each location based on the management objective of the land manager. The raster is created by combining land use vector data from State and Territory authorities, which spans various dates (2008–2023) and mapping scales (1:5,000 to 1:250,000) (Fig S2 in the Supplement). Older and coarser data correspond with arid and semi-arid regions where land use changes are less frequent. Therefore, we supplemented these data with more recent, higher-resolution datasets to improve accuracy and currency in these regions. For example, in South Australia's arid zones, which rely on older, coarser mapping, these areas are dominated by native pasturelands, and changes in pressures can be captured using current and finer data on buildings, farm

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dams, mines, roads, and other linear infrastructure. Mining data from CLUMP 2023 was further enhanced through comprehensive searches of state-managed mining resources.

A notable modification from previous applications of the HIF methodology is the exclusion of nightlight data as a proxy for infrastructure in rural areas or working landscapes like mine sites (Venter et al., 2016). Instead, we incorporated datasets on buildings and mining sites to better represent these pressures, especially in areas where CLUMP 2023 mapping was less detailed.

#### 2.2.1 Intensive land uses

This category includes pressures from land uses typically linked with infrastructure and human settlements, such as urban areas, intensive horticulture, animal production, and the infrastructure supporting services and utilities. Lands affected by these pressures are often heavily modified and constructed, making it unlikely they will revert to a natural state. These areas experience significant disruption of natural processes, leading to habitat loss and the exclusion of wildlife and ecosystem services (Venter et al. 2016). Therefore, we assigned intensive land uses a score of 10. These pressures were mapped using the CLUMP 2023 dataset, which aggregates land use data from 47 tertiary classes (Table S3) into this category. This category broadly aligns with the "Built-up" pressure identified in other human industrial footprint analyses (Sanderson et al. 2002; Venter et al. 2016; Hirsh-Pearson et al. 2022).

#### 2.2.2 Buildings

Buildings remove natural habitat under the footprint of the construction site and are often associated with habitat clearing in areas surrounding the buildings. Here, we assign a score of 10 for any pixel overlapping a building. This pressure was used as a proxy for human settlement and industrial activities outside urban areas that are potentially not captured through coarser mapping by CLUMP 2023. Building data was obtained from Microsoft (2022). To reduce commission errors in the dataset, we limited our analysis to buildings located within 200 meters of roads and mining areas, as these are typically associated with higher levels of habitat disturbance.

#### 2.2.3 Mining and quarrying

Multiple activities associated with mining, from exploration to post-closure, will negatively affect biodiversity and ecosystem services (Boldy et al., 2021; Sonter et al., 2018). Mining reshapes the landscape, alters waterways and wetlands, increases erosion, and causes pollution from noise, dust, and emissions (Haddaway et al. 2019, and references therein). Due to these multiple environmental impacts, we assigned a score of 10 to the direct pressures from mining. To create the mining pressure layer, we updated the mining land use class from the CLUMP 2023 dataset with state-level datasets (see Table S2 for data sources).

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#### 2.2.4 Human population density

Environmental degradation in a particular area is often associated with proximity to human populations due to activities such as recreation, hunting, logging, and the introduction of non-native species. Following Venter et al. (2016), we converted a human population density layer into a pressure layer with scores between 0 and 10. Locations with more than 1,000 people per $km^2$ were assigned a score of 10, assuming population density reaches saturation at this level. For areas with densities below 1,000 people/$km^2$, we scaled the pressure score logarithmically using the formula: Pressure Score = 3.333 * log (population density +1). We used the WorldPop dataset (WorldPop, 2018), which provides population density estimates at a 100 $m^2$ resolution for its most recent update (2020).

#### 2.2.5 Croplands

Croplands are often completely converted ecosystems and are subject to high levels of pesticide and fertilizer use and destructive slash-and-burn techniques, and as a consequence, have become the main driver of biodiversity decline and the degradation of the natural landscape (Green et al., 2005; Maxwell et al., 2016). Following Venter and colleagues (2016), we assigned croplands a pressure score of 7, as some native species can still utilize croplands (Grass et al., 2019), unlike in most built environments. We obtained cropland data from the CLUMP 2023 dataset using 56 tertiary classes associated with these activities (Table S4).

#### 2.2.6 Pasturelands

Grazing impacts ecosystems through the creation of fence networks, soil compaction, trampling, and intensive browsing of native vegetation, the spread of invasive species, and altered fire regimes (Kauffman and Krueger, 1984). Domestic herbivores also have multi-trophic effects on plant and animal biodiversity, contributing to biodiversity loss (Filazzola et al. 2020). In this study, we diverged from previous human-industrial footprint analyses (Venter et al., 2016), which assigned a uniform score of 4 to pasturelands. Instead, we made a distinction between modified and native pasturelands under production, a classification provided in the CLUMP 2023 dataset.

Modified pasturelands, characterized by 50% or more dominant exotic species and irrigation practices (ABARES, 2016), were assigned a score of 6 due to significant vegetation modification and frequent livestock grazing (see Table S5 for CLUMP 2023 tertiary classes). On the other hand, native pasturelands, which have undergone minimal or no deliberate modification, were assigned a score of 2. This lower score was assigned to native pasturelands to be conservative, as there might be a great similarity between pasturelands in arid zones not often grazed and areas not classified as grazing lands. Data and estimates of livestock stocking density and grazing intensity are largely unavailable, making further differentiation within this land use impossible. However, these areas are still associated with varying levels of fencing, soil compaction, and browsing by farmed animals, unpaved roads, and altered fire regimes, which have an associated impact on their native ecological communities (Tulloch et al., 2023).

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### 2.2.7 Forestry plantations

Australia's plantation forests covered 1.96 million hectares in 2016, mainly comprising exotic pines (softwood) and *Eucalyptus* (hardwood) (ABARES, 2018). Plantation forests remove habitat for species, including tree cavities, and can alter paths of travel and fire regimes (Bradstock et al., 2002; Brockerhoff et al., 2008). Given that these plantations are (typically) monocultures, we assigned a pressure score of 7, akin to croplands. The forestry pressure layer was created by merging the CLUMP 2023 dataset, using only the plantation forest classification, with plantation forests from the Australia Forests 2023 dataset (ABARES, 2023). These layers were merged as we argue they complement each other. The CLUMP 23 dataset does not include some plantations observed in the Australia Forest 2023, while the Australia Forest 2023 dataset does not include plantations that have been recently clear-cut and are presently bare land, but that will most likely be replanted. We did not account for pressures from forestry undertaken in native forests, as spatially explicit records of activities in these areas are not consistently mapped across the continent.

### 2.2.8 Reservoirs and large dams

Dams and reservoirs inundate large areas, altering their hydrology and often converting terrestrial ecosystems into aquatic ones, causing habitat loss for many terrestrial and freshwater species, as well as altering local ecosystems (Barnett and Adams, 2020; Poff and Hart, 2002). Dams can also disrupt sediment transportation and fish migration, change water quality, and increase the risk of invasive species (Bunn and Arthington, 2002; Johnson et al., 2008; Liermann et al., 2012; Syvitski et al., 2005). Given this, we assign larger dams and reservoirs a pressure score of 8. Data for these pressures was obtained from the CLUMP 23 dataset.

### 2.2.9 Farm dams

Farm dams in the Australian agricultural landscape are ubiquitous; Malerba and colleagues (Malerba et al., 2021) found over 1.765 million dams across the country, covering an area of 4,678 km$^2$ and storing more than 20 times the amount of water in Sydney Harbour. These features catch and store water for livestock, irrigation, crop spraying, firefighting, and other domestic purposes. But, while often small in scale, farm dams can significantly affect biodiversity and biogeochemical cycles (Liddicoat et al., 2022; Woolmer et al., 2008). They directly modify the environment, accumulate pollution from run-off, and can produce greenhouse gases. In this analysis, we assign a score of 5 to farm dams, which is extended to 500 m from the dam itself to account for changes to environmental processes. We primarily obtained farm dam data from Malerba and colleagues (2021), who compiled it from different State sources and complemented it with data available in the CLUMP 23 dataset.

### 2.2.10 Roads and Trails

Roads produce numerous direct and indirect pressures on terrestrial and aquatic ecosystems, including habitat loss, fragmentation, mortality from construction, roadkill, animal behavior change, alteration of the physical and chemical

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environment, spread of invasive species, and increased use of areas by humans (Trombulak and Frissell, 2000). This linear infrastructure has direct and indirect pressures on the environment, which are accounted for in the pressure scoring. We adapted the scoring systems for roads from Venter and colleagues (2016) to assign these direct and indirect pressure scores and differentiate between sealed and unsealed roads, as we recognize that many roads in regional areas are rarely used. A score of 8 was assigned to a 0.3 km buffer from sealed roads and a decreasing pressure from 7.9 to 0.25 outward up to 5 km from the road (Arias-Patino et al., 2024). Unsealed roads were assigned a score of 3, including a 0.3 km buffer from the road and a decreasing pressure from 2.9 to 0.25 outward up to 5 km from the road (Arias-Patino et al., 2024). We also included the disturbance from footpaths/trails, as these are often the main pathways for human access-related pressures (hunting, invasive weeds, etc.) into remote and protected areas. We assigned a direct pressure score of 0.9 to trails, as an attempt to be conservative in estimating human pressures in remote areas.

To create the roads layer, we merged the National Roads dataset (Geoscape Australia, 2024) and the Open Street Map (OpenStreetMap contributors, 2024) data.

### 2.2.11 Railways

Like roads, railways are linear infrastructures that directly remove habitat, resulting also in fragmentation that can produce edge effects (Fuentes-Montemayor et al., 2009). However, railways are less conducive to providing access to natural environments than roads, given that passengers would usually only disembark at rail stations. The direct pressure of railways was assigned a pressure score of 8, with a 50 m buffer on either side of the railway. We used data from the Foundation Railway of Australia (Geoscience Australia, 2021) with a positional accuracy of ± 20 m of the line. The dataset includes open, closed, and other tracks. We removed features with a dismantled, proposed, or disused status from this dataset.

### 2.2.12 Transmission lines, and oil and gas pipelines

These types of linear infrastructure are not directly captured in global pressure mapping products, but it is possible to do so when creating national-scale maps because of data availability. This is important because this type of infrastructure has multiple pressures and environmental impacts. For example, pipeline and transmission line corridor construction leads to habitat loss and fragmentation of natural habitats and facilitates the spread of invasive species (Benítez-López et al., 2010). Moreover, pipeline leaks and spills can pollute the soil and water and contribute to greenhouse gas emissions (Brandt et al., 2014). Transmission lines can affect the mortality of flying animals (Bevanger, 1998) and increase the risk of wildfires (Keeley and Syphard, 2018). We believe these linear features represent pressures in a similar way as unsealed roads (and often have unsealed service roads alongside them). Therefore, we set a direct pressure score of 3 with a buffer of 300 m around this type of infrastructure and an indirect score decaying from 3 to 0.25 outwards to 2.5 km from the infrastructure (Arias-Patino et al., 2024).

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#### 2.2.13 Navigable waterways

Navigable waterways - in the form of navigable rivers, lakes, and marine coastlines - facilitate human accessibility to the natural environment in a way analogous to roads. We created the navigable pressure layer by applying the methods described in Venter et al. (2016), on a 100 m resolution. Areas directly alongside navigable waterways have a pressure of 4, which decreased exponentially outwards 15 km (Venter et al. 2016).

### 2.3 Technical validation and uncertainty (sensitivity) analysis of the Human Industrial Footprint

#### 2.3.1 Validation

We followed the methods outlined in Arias et al. (2024) and Venter et al. (2016) to evaluate the agreement between the HIF map and the pressures observed in situ. To this end, a single assessor visually identified industrial pressures observed through very high-resolution satellite images within 1,397 randomly stratified sample plots. The satellite images were obtained from web map services such as Google Maps (Google, 2024.), Bing Maps (Microsoft, 2024.), and Basemap ArcGIS (ESRI, 2024.), and they all corresponded to the years 2020-2023, and had a spatial resolution of 0.5 m or less.

We defined five strata based on five pressure classes (Table 2), allocating a number of samples to each of these following Olofson et al. (2013, 2014) and distributing samples according to the area and expected error for each stratum. This strategy aims to prevent oversampling large strata like low-pressure areas and minimize the standard error for small regions like high-pressure areas, which could result in an overestimation of the accuracy. The sample distribution was as follows: no pressure= 477, very low pressure = 30, low pressure = 565, moderate pressure= 205, high pressure = 120. Each sample plot consisted of a 100 m window (matching the analysis' spatial resolution) and five surrounding buffers at 300, 500, 1000, 2750, and 5000 m to aid in recording both direct and indirect pressures, following Arias and colleagues (2024). Scores were assigned as per Table S6. Indirect pressures were recorded based on the nearest observed feature and its area of influence, with scores assigned using the mean value of the two closest buffers. The sum of all observed pressure scores represented each plot's assumed actual state of in-situ pressures. Additionally, we obtained the HIF value from our pressure layers for each plot. To facilitate comparison, both HIF and validation scores were normalized to a 0-1 scale.

To quantify the level of agreement between the HIF and validation scores, we utilized the root mean square error (Chai and Draxler, 2014). The root mean squared error (RMSE) expresses the average error in the units of the variable of interest, tending to penalize large errors; a lower RMSE indicates higher agreement between the HIF and the validation scores. We also calculated the percentage of validation samples with agreement between the HFI and validation scores, considering the HIF to match the validation score if they were within 20% of each other on the 0-1 scale (Venter et al., 2016).

#### 2.3.2 Uncertainty analysis.

To understand the degree of uncertainty in our results, associated with the scores assigned to the different pressures, we followed Arias et al. (2024) and randomly adjusted intensity scores in the validation samples, by up to ±50% using the bootstrap

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technique. We chose to adjust pressure scores by up to ±50%, a wider range than the ±30% used by Arias-Patiño et al. (2024), in order to test the robustness of our cumulative pressure scores under a wider range of values. This approach allowed us to evaluate whether the model remains stable even when pressure intensity values are varied well beyond the expected range of expert-derived variability. Each simulation involved selecting a random factor between 0.1% and 50%, which was then applied to each pressure layer. Specifically, we multiplied this factor by the original pressure intensity (PI) value for each layer and randomly added or subtracted the result from the validation sample. We adjusted the pressure intensity ($PI$) by layer ($s$) as follows.

$$Modified\ PI_s = PI_s \pm (PI_s \times n);\ \ n\ = random\ number\ between\ 0.01 - 0.5 \qquad (1)$$

Using the modified scores, we calculated the simulated cumulative pressure value for each validation plot containing mapped values and then assessed the error by comparing it to the original mapped values. This simulation was repeated 100,000 times to ensure statistical robustness. Finally, we generated an uncertainty map by interpolating the standard deviation of the error using the inverse distance weighting (IDW) technique.

### 2.3.3 Comparison with Global Human Footprint datasets

To assess the added value of the fine-scale national Human Industrial Footprint (HIF), we compared its agreement with visual validation scores to that of the Global Human Footprint datasets at 1 km for 2013 (Williams et al., 2020) and at 100 m resolution for 2020 (Gassert et al., 2023).

## 2.4 Classified Human Industrial Footprint – Accuracy Assessment

Various research studies have applied thresholds to cumulative pressure maps to describe the level of pressures at different scales, aiming to inform conservation interventions. For example, it has been used to identify the last of the wild (Sanderson et al., 2002), the most globally intact areas (Watson et al., 2016; Williams et al., 2020), wilderness areas and vegetation condition assessments in Australia (Lesslie et al., 1988; Lesslie and Taylor, 1985; Thackway and Lesslie, 2008), and for assessing the extinction risk to species (Di Marco et al., 2018). Here, we carried out an accuracy assessment of a thematic map of five pressure levels (Table 2), following good practices from Oloffson et al (2014), that would allow potential users to assess whether the classified map is fit for purpose. Using the stratified random samples described above, we estimated the user's, producer's, and overall accuracy metrics using the proportion of area, as implemented in the 'mapaccuracy' R package (Costa 2024). The agreement for the accuracy assessment was done by evaluating whether the sample plots fall within the same pressure classes when the visual and the HIF are used, once they are classified based on their score and Table 2. The accuracy assessment also allows to produce an error-adjusted estimator of the area for each class (Olofsson et al., 2013)

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Table 2. The HIF was classified into five descriptive categories representing diverse levels of pressure.

| Category | Corresponding HIF score | Description |
|---|---|---|
| **No pressure** | < 1 | Areas free or almost free of measurable or indirect pressures from linear infrastructures and human population. |
| **Very low pressure** | ≥ 1 and < 2 | Areas where the score arises primarily from indirect pressures from linear infrastructure or areas with a human population density of at least 1 person/km$^2$. |
| **Low pressure** | ≥2 and < 6 | Areas with scores primarily due to grazing in native pastures, isolated linear infrastructure with lower pressure scores (pipelines, electricity transmission lines, unpaved roads). |
| **Moderate pressure** | ≥ 6 and < 10 | Areas representing modified agricultural landscapes and a relatively lower level of cumulative pressures (e.g., grazing in native pastures, unpaved roads, and some level of human density). |
| **High pressure** | ≥ 10 | Areas highly modified by humans, such as mines, urban areas, and other settlements, and a higher level of cumulative pressures (e.g., overlap of intensive farming and roads). |

### 2.5 The ecological intactness index

The results from the HIF can be used as a proxy for habitat quality and to categorize the land in terms of intactness (Watson et al., 2016; Williams et al., 2020). However, while the HIF incorporates some indirect pressures that spread out to a buffer from the direct pressure, it does not explicitly account for the spatial configuration of the pressures or how a pressure occurring in one area could affect the surrounding areas due to the loss and degradation of habitat, and loss of landscape-level connectivity. For example, a narrow strip of native vegetation between agricultural fields could appear to have no pressure because there is no indirect pressure for cropland in the HIF; however, a narrow patch of remaining native vegetation surrounded by agriculture is impacted by significant edge effects and unmapped human presence, indicating that the strip is somewhat degraded and not intact as the HIF would indicate. Here, we overcome this by calculating an intactness metric (Beyer et al., 2020) for Australia sensitive to changes in habitat area, quality, and fragmentation. The metric is calculated using the HIF, with the intactness calculated for each cell parameterized to: a) be proportional to habitat area when there is no habitat fragmentation; b) decline mono-tonically as fragmentation increases, and be sensitive to both the number of nearby patches and the separation between patches, and (c) to be proportional to habitat quality for a given total area of habitat and degree of fragmentation. The result is an ecological integrity (EII) metric that, as mentioned above, accounts not only for estimated

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habitat quality from direct and inferred pressures in a cell but also for the fragmentation that occurs due to the pressures acting in surrounding cells.

## 3. Results

### 3.1 Human Industrial Footprint map and validation analysis

The Australian Human Industrial Footprint Index (Fig 2a) map covers an area of 7,692,047 km$^2$ and has a spatial resolution of 100 m, mapped in Albers Equal Area projection. The scores range between 0 (areas with no mapped pressures) and 56.5 (densely populated built-up urban regions), with a mean score of 3.05 ± 4.18.

The technical validation results indicate a strong agreement between the Human Industrial Footprint scores and those obtained through visual interpretation. A strong relationship ($R^2$= 0.86) exists between the human industrial footprint scores and the validation scores (Fig 2b). The RMSE for the 1397 validation plots was 0.059 on the normalized 0-1 scale, which indicates an average error of approximately 6%. Furthermore, for 98% of plots, the HIF and the visual scores were within 20% agreement; only 27 plots did not reach this level of agreement (Fig 2a). Of these 27 plots, only five scored 20% higher than the visual score, and 22 of them 20% lower, i.e. where there is disagreement, the HIF tends to underestimate pressure. Even when we consider a stricter threshold of 15% for agreement, we still obtained a 96.2% match between the HIF and the visual scores.

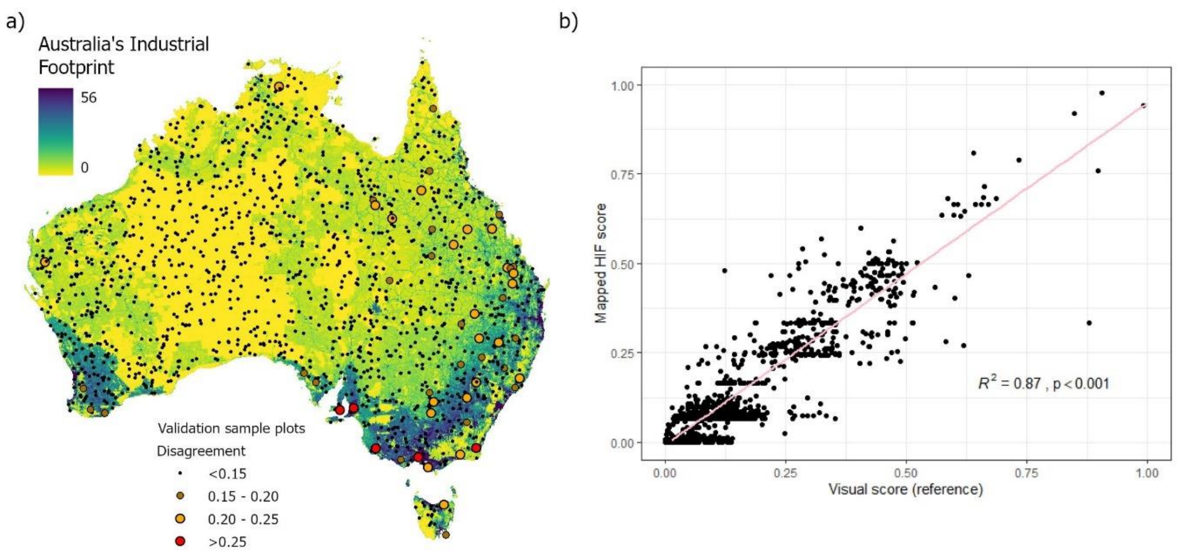


**Figure 2. a) Australia's human industrial footprint map on land, showing the location of the validation sample plots. The larger points are those plots where the HIF and the visual score differed by more than 20% on a normalized (0-1) scale. b) Relationship between the reference score (visual score) and the score obtained through the HIF for Australia.**

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### 3.2 Uncertainty in pressure values

Changes in the pressure scores had only a limited impact on the cumulative pressure values. Adjusting the scores, either increasing or decreasing them by up to 50%, resulted in a moderate difference (error) between simulated and mapped values (mean = 0.002 ± 1.129). The maximum and minimum errors observed were 2.745 and -2.57, respectively, representing slightly above one-quarter of the full pressure scale.

Across the 100,000 simulations, nearly 90% of validation plots with mapped features (Figure ) exhibited errors within a narrow range, between -0.15 and 0.16 (corresponding to the 5th and 95th percentiles). As expected, larger adjustment factors led to increased variability; however, even at the maximum adjustment level of 50%, 73% of plots still displayed relatively small errors (ranging from -2.5 to 2.5). The uncertainty map (Fig. 4) shows that areas where multiple pressures converge, particularly densely populated regions near major cities, are more vulnerable to uncertainties in pressure values.

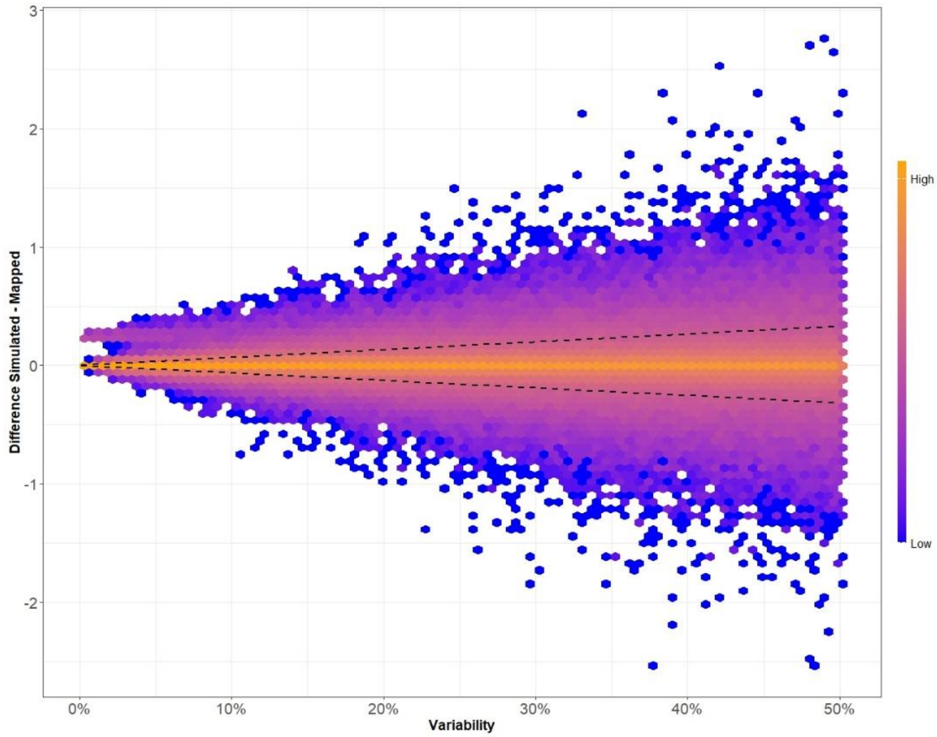


**Figure 3. Density plot depicting the difference between simulated value and mapped value (y-axis) relative to the percentage of variability of pressure scores (x-axis). The color scale represents the number of plots that include this transition, with orange indicating a high number of plots and blue indicating a few plots (legend is log-scaled). Black dashed lines represent the 5th and 95th percentiles of the distribution of the difference. Plots with no mapped features were excluded from the analysis.**

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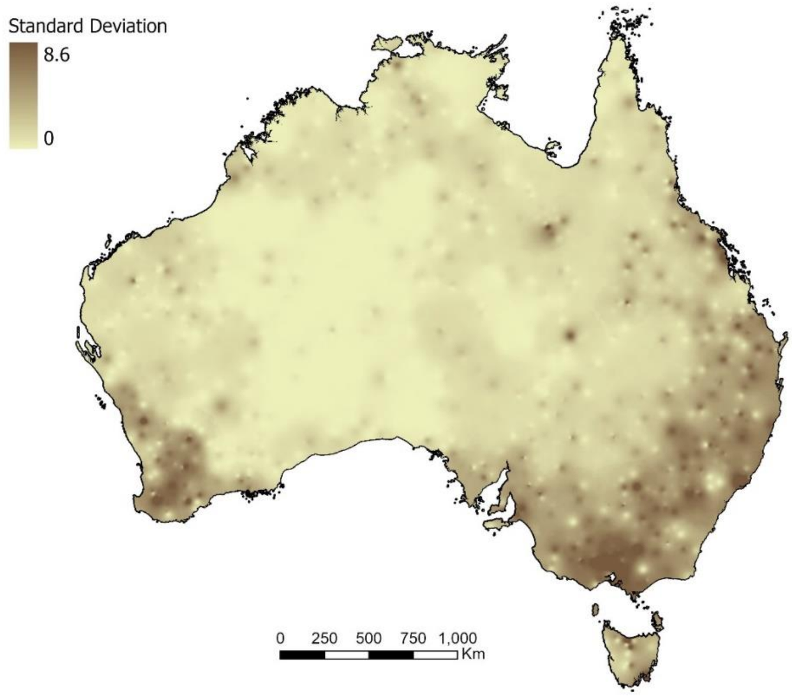


**Figure 4. Spatial distribution of the uncertainty of pressure scores across Australia when these are increased or decreased by 50%. Darker tones represent areas with high standard deviation of the mean cumulative pressure value.**

### 3.3 Comparison with global footprint datasets

The comparison with global human footprint datasets highlights the value of using high-resolution, nationally relevant data for mapping cumulative pressures. The Australian HIF demonstrated the highest agreement with validation scores, with an RMSE of 0.0595 and an $R^2$ of 0.85. In contrast, the global 1 km and 100 m products had higher RMSEs (0.1118 and 0.1074, respectively) and substantially lower $R^2$ values (0.47 and 0.51, respectively). These results highlight the importance of using high-resolution, nationally relevant data sources to map cumulative human pressures at the country scale. These results were expected, as the cumulative pressure maps' accuracy improves with each additional pressure layer (Arias et al. 2024).

### 3.4 Accuracy assessment of a classified HIF

The classified HIF map shows that more than one-third of the Australian landscape (32%) is free or almost free (score <1) of the 16 pressures included in this analysis, and another 2.9% experiences very low pressures (i.e., scores of <2) (Fig 5). Another 47.5% of the Australian landscape has a low industrial pressure footprint (HIF value of 2 or more and less than 6). These low-pressure areas are primarily pastoral leases that operate without extensive introduction of non-native pastures. However, this analysis does not account for stocking intensity, and we acknowledge that the pressure in some of these areas might be underestimated. Finally, 14.2% of the Australian landscape presents more considerable industrial pressures (scores $\geq 6$), with

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5.6% of the land being under moderate pressure (scores between 6 and 10) and a further 8.5% experiencing high industrial pressure (scores ≥ 10). The overall accuracy of the classified map is 85.0%, where most errors arise from the HIF underestimating the in-situ pressure observed during the visual inspection of high-resolution satellite images (Table 3). These suggest that the HIF can be considered a conservative estimate of human pressures on the environment. Moreover, the confusion matrix shows that the very low-pressure class has both low producer's and user's accuracy, indicating the difficulty of detecting low-impact activities that can occur in highly intact landscapes.

| Legend | Pressure class | Mapped area $Km^2$ | CI 95% ($Km^2$) |
|---|---|---|---|
| | No pressure | 2,429,491 | 93,862 |
| | Very Low | 223,451 | 66,900 |
| | Low | 3,903,901 | 102,525 |
| | Moderate | 255,383 | 48,853 |
| | High | 879,820 | 57,266 |

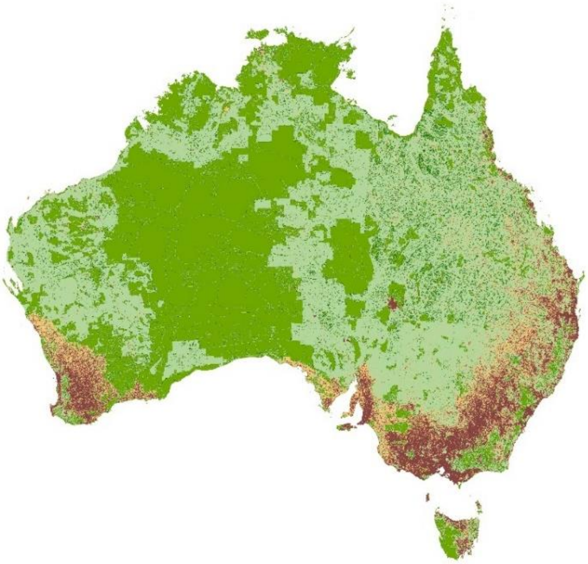

**Figure 5. Australian Human Industrial Footprint map categorized into five industrial pressure classes, from no pressure to very high pressure (see Table 2). The table shows the error-adjusted area, and 95% confidence intervals estimated for each class.**

**Table 3 Error matrix showing the performance of a thematic map of five pressure classes obtained from the classification of the HIF against the pressure class obtained from the reference data (visual scores), using sample counts (for an error matrix estimated by proportions of area see Table S7). Accuracy measures are presented with a 95% confidence interval, and the overall accuracy was 85%.**

| | Reference data | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Pressure classess from HIF** | **No pressure** | **Very Low** | **Low** | **Moderate** | **High** | **Total** | **Producer's accuracy** | **Weights** |
| **No pressure** | 408 | 21 | 49 | 1 | | 479 | 97.66 ± 1.23 | 0.362 |
| **Very Low** | 9 | 11 | 8 | 1 | | 29 | 27.4 ± 11.98 | 0.021 |
| **Low** | 1 | 6 | 526 | 4 | 10 | 547 | 90.04 ± 1.94 | 0.475 |
| **Moderate** | | | 18 | 71 | 71 | 160 | 75.18 ± 10.98 | 0.056 |
| **High** | | | 3 | 7 | 172 | 182 | 70.58 ± 4.31 | 0.085 |
| **Total** | 418 | 38 | 604 | 84 | 253 | **1397** | | |
| **Users accuracy** | 85.18 ± 3.19 | 37.93 ± 17.97 | 96.16 ± 1.61 | 44.38 ± 7.72 | 94.51 ± 3.31 | | | |

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### 3.5 Ecological Intactness Index

395 The Ecological Intactness Index map for Australia (Fig. 6) covers the same area as the HIF and was calculated using the same spatial resolution of 100 m. The mean intactness value obtained through this map for Australia is 0.52 ± 0.32 (on a scale of 0 to 1, with 1 representing high intactness). Approximately 60.5% of the country has an EII value of < 0.5, with 9.4% of the landscape experiencing the most severe levels of degradation (EII < 0.1). Due to the EII considering fragmentation, connectivity, and degradation of natural areas, it provides a different perspective on the degree of industrial influence on these areas when compared to the HIF. For example, smaller patches of areas mapped with low scores through the HIF and therefore considered as potentially intact lands (Williams et al., 2020), are mapped by the EII as areas with low or moderate intactness due to the spatial configuration of the landscape.

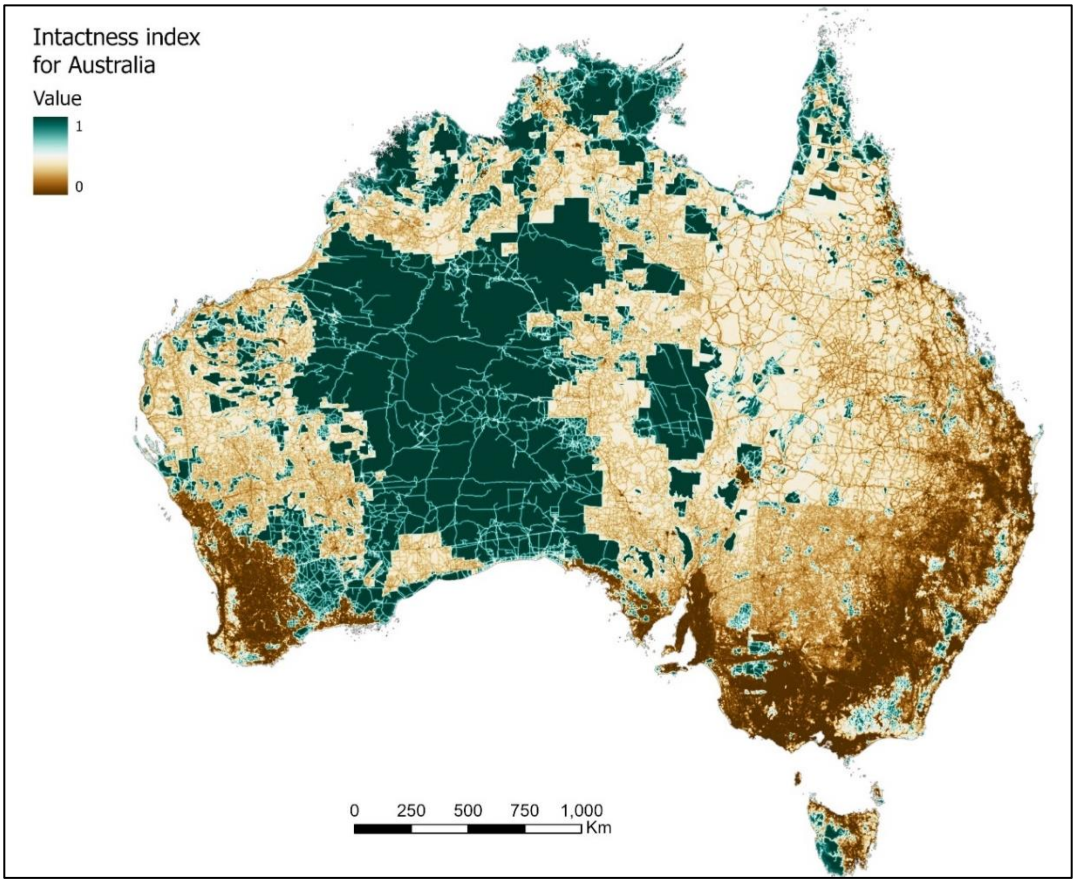


**Figure 6. Ecological intactness index map for Australia calculated based on Beyer et al. (2020) using the Australian Industrial Footprint as an input habitat condition layer.**

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## 4 Discussion

This terrestrial, human industrial footprint analysis is Australia's first national cumulative pressure map since the National Wilderness Inventory was undertaken in the 1980s and 1990s (Lesslie and Taylor, 1985). We followed well-established and scientifically robust methods to create both the human industrial footprint and the ecological intactness index maps. This allowed us to provide a comprehensive, contemporary, and much-needed spatial view of Australia's industrial-level pressures and ecological integrity. Both layers should be of interest to all those involved in biodiversity management when considering Australia’s Strategy for Nature 2024-2030 (Commonwealth of Australia, 2024) and Nature Positive Plan (DCCEEW, 2022), as well as its global commitments to the Kunming-Montreal Global Biodiversity Framework with respect to targets 1-4 especially (CBD, 2022). These analyses provide potentially important input data for achieving the ‘30 by 30’ protected area (Target 3) and restoration agendas (Target 2), and in particular, to the commitment to no net loss of highly intact ecosystems (Target 1).

## 5 Limitations and Uncertainty

While comprehensive, the product we present here is subject to several limitations. Some limitations are inherent in cumulative pressure mapping (Watson et al., 2023b), while others are specific to the data and assumptions made for this Australian analysis. Here, we present these limitations to help interpret the HIF and EII products and guide future efforts.

As with other cumulative pressure maps, some general limitations include omitting pressures such as invasive species, disease, pollution, climate change, changes in groundwater regimes, and changes in natural fire regimes. This omission is because we restricted our analysis to observable (or mapped) industrial pressures, and we note that the maps we produce do not include all disturbance regimes (and some places mapped as highly intact could be severely affected by an unmapped degrading process). Moreover, we assumed a uniform pressure score across the landscape for the pressures we mapped, but the actual response to pressures will likely vary between ecosystems. It is, therefore, essential to highlight that the HIF measures only the industrial pressures humans place on nature, not the realized impacts on natural systems. This being said, the HIF has been shown to be an excellent proxy for assessing species extinction and ecological degradation (see discussion in Watson et al. 2023b).

In the methods section, we outlined the specific limitations of each data set and the assumptions we made, but we discuss some in more detail here. Roads and grazing in native pasturelands are the two most prevalent pressures in the Australian landscape. We attempted to compile Australia's best possible road dataset by merging the Geoscape National Roads dataset and the Open Street Maps dataset. However, upon close inspection using high-resolution satellite images, we observed that many kilometers of roads, particularly unpaved roads in rural areas and private properties, are unmapped in the data sources we utilized, and the completeness of the data varies between states and territories. For example, rural roads in New South Wales appear to be better mapped than in the adjoining areas in Queensland and South Australia. We believe the pressure from roads in these two states is underestimated through our maps, as well as the pressure in remote areas. We also recognize that “grazing” of native pastures occupies vast areas of the country, and no data on the stocking density, or intensity of the different areas is available.

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Therefore, to minimize overestimating the pressures from these types of land use, we used a conservative pressure score of 2. We note that this might underestimate the degree of pressure in some areas.

One key concern with additive methods for mapping cumulative pressure maps is the use of expert judgment to assign pressure intensity scores to each spatial layer. While this introduces a degree of subjectivity, we attempted to minimize its impact by using scoring approaches from established, peer-reviewed global and national studies (Arias-Patino et al., 2024; Hirsh-Pearson et al., 2022; Venter et al., 2016; Woolmer et al., 2008). Scores were applied uniformly across the landscape using reproducible scripts, and all datasets and code are provided openly to enable full transparency and reproducibility. To further address concerns about subjectivity and its influence on the final cumulative pressure scores, we conducted a comprehensive uncertainty analysis. Following the methodology of Arias-Patiño et al. (2024), we adjusted pressure scores by up to ±50% in 100,000 simulations. The resulting differences in cumulative pressure scores were generally small, with nearly 90% of validation plots showing errors within a narrow range. These findings confirm the robustness of the HIF to reasonable variations in pressure score inputs.

## 6 Data and code availability

The datasets generated from this work are available at Zenodo https://zenodo.org/records/15833395 (Venegas-Li et al., 2025). It is provided in a standard raster format (tif). The code to create the individual pressure layers and the human footprint are available through the same repository.

## 7 Conclusions

The Human Industrial Footprint (HIF) and Ecological Intactness Index (EII) developed in this study provide a high-resolution assessment of cumulative pressures on Australia's landscapes and a proxy for ecological degradation. These datasets offer valuable insights for understanding human impacts on biodiversity and ecosystem intactness and degree of degradation, addressing a long-standing gap in national-scale pressure mapping. By incorporating 16 nationally relevant pressure layers, the HIF provides a more accurate and context-specific representation of industrial influences than global-scale analyses, improving our ability to guide conservation and land-use planning. These maps can potentially have far-reaching implications for informing environmental policy and reporting. By identifying areas of high intactness and those under significant industrial pressure, these datasets can inform protected area expansion, ecosystem restoration priorities, and biodiversity offset strategies. Beyond conservation policy, the HIF and EII have applications in environmental impact assessments, regional land-use planning, and climate adaptation and mitigation strategies. Their integration into national and subnational decision-making processes can help halt further biodiversity loss, improve connectivity between protected areas, and support sustainable development objectives.

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## Author Contributions

RVL, SA, RF, PO, and JW conceptualized the study, with contributions to the development of the methods from all other co-authors. RVL, BA, and SA prepared the data. SA implemented the HIF and EII mapping. MAUAJ, RVL, LM, and MAP contributed to the technical validation and uncertainty analysis. Funding was secured by PO and RF. The original draft was prepared by RVL, JW, and SA, with review and editing contributions from all other co-authors. JW was the leader of the project.

## Competing Interests

The authors declare that they have no conflict of interest.

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