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Global evidence of human well-being and biodiversity impacts of natural climate solutions

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Natural climate solutions (NCS) play a critical role in climate change mitigation. NCS can generate win–win co-benefits for biodiversity and human well-being, but they can also involve trade-offs (co-impacts). However, the massive evidence base on NCS co-benefits and possible trade-offs is poorly understood. We employ large language models to assess over 2 million published journal articles, primarily written in English, finding 257,266 relevant studies on NCS co-impacts. Using machine learning methods to extract data (for example, study location, species and other key variables), we create a global evidence map on NCS co-impacts. We find that global evidence on NCS co-impacts has grown approximately tenfold in three decades, and some of the most abundant evidence relates to NCS that have lower mitigation potential. Studies often examine multiple NCS, indicating some natural complementarities. Finally, we identify countries with high carbon mitigation potential but a relatively weak body of evidence on NCS co-impacts. Through effective methods and systematic and representative data on NCS co-impacts, we provide timely insights to inform NCS-related research and action globally.

Natural climate solutions (NCS) are a subset of nature-based solutions consisting of 22 intentional actions ('pathways') to protect, restore and manage forests, wetlands, grasslands, coastal systems and agricultural lands to mitigate climate change[1]. Sometimes called nature-based climate solutions (we use NCS throughout for brevity), NCS are a necessary complement to rapid reductions in fossil fuel emissions[2], with nearly 96% of updated nationally determined contributions to the Paris Agreement including NCS[3]. Enthusiasm for NCS is often grounded in their potential to advance development, conservation and sustainability goals through the co-occurrence of biodiversity and human well-being benefits (that is, 'NCS co-benefits', or any combination of one or more NCS pathway and a human well-being or biodiversity co-benefit). Indeed, co-benefits are a consistent theme motivating NCS in scientific studies[1,4–6], policy reports and government documents[7–9], as well as broad appeals to accelerate NCS implementation[10–12]. Assuming NCS yield co-benefits, they also bridge the Sustainable Development Goals[13], Paris Climate Accord[14] and Global Biodiversity Framework[15] through synergies between biodiversity conservation and climate change mitigation via NCS[16,17]. These global goals increase the financial and political capital that can be leveraged to make rapid and substantial investments to implement NCS at scale[18,19]. Perhaps most importantly, NCS co-benefits have the potential to accelerate climate action by

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aligning local incentives through direct, near-term benefits to the communities who are often responsible for mobilizing NCS actions that ultimately provide a global public good[20,21].

Practical and political urgency underscore the need to understand if, how and where NCS can deliver co-benefits. Without a full accounting of the universe of evidence on NCS, there are serious threats to the credibility of the claim that all externalities are positive. In practice, decision-makers implementing NCS projects frequently grapple with trade-offs[22,23], and systematic evidence on both co-benefits and trade-offs remains poorly understood. Advancing NCS implementation without informed actions can threaten the enthusiasm and momentum seen in recent years, and may even lead to unanticipated adverse impacts on people and nature.

Despite the urgent need for a global stocktake on NCS co-benefits and trade-offs (that is, 'NCS co-impacts'), we are unaware of any effort to systematically analyse and map the broad universe of NCS co-impacts studies. Studies have provided circumstantial assessments of NCS co-benefits (for example, refs. 1,4), or have assessed one of the 22 NCS pathways, usually in isolation (for example,[24–26]). A consistent systematic evidence map on all NCS pathways, co-benefits and trade-offs would allow communities, decision-makers, investors and others with vested interests to assess potential trade-offs between multiple objectives, and to deploy resources more effectively. For example, for conservation practitioners advancing NCS projects, evidence maps can provide insight into how much evidence supports programmatic assumptions. Where evidence is weak, programmes can invest more in monitoring and adaptive management efforts. Evidence maps also provide a critical step for more focused meta-analyses and even alone have directly informed practice, policy and research investments and efforts across a diversity of topics central to sustainable development[27–30].

We identify and map evidence from peer-reviewed publications on NCS co-impacts. We overcome two challenges that have hindered systematic mapping of NCS co-impact evidence. First, research on NCS spans many fields, such as animal science, ecology, economics, public health, soil science, agronomy, traditional ecological knowledge, toxicology and environmental governance. Much of the evidence long pre-dates the organizing concept of NCS[31], making searching and identifying relevant evidence across this diversity of disciplines practically challenging due to divergent or siloed epistemologies and semantic ontologies[32,33]. Second, because cross-cutting topics often generate large volumes of potentially relevant articles, previous efforts that have examined such topics have relied on hundreds of researchers who spend thousands of hours manually searching, screening and coding papers (for example, refs. 29,30,34–37). Advances in machine learning-assisted methods have led to greater efficiencies. However, these efforts often still require substantial financial and human resources[29,34–37] that lead to evidence maps that can be several years out of date by the time they are completed and published. Even with efficiency gains from machine learning-assisted methods, researchers have still needed to constrain the universe of eligible studies to generate a subset of manuscripts manageable for human review[29,35]. Indeed, efforts to review similar literature have limited search results to ensure manageability (for example, ref. 38), but this can artificially limit the scope of the literature being surveyed. Rapid advances in machine learning for natural language processing (NLP) have yet to be well integrated into systematic reviews, particularly for domains outside the biomedical sciences[35,36]. Several studies[30,35–37] show the benefits of adopting a machine learning and expert human workflow for rapid environmental, agricultural or climate evidence synthesis. However, our study differs substantially from these prior examples, all of which used supervised machine learning classifiers or machine learning-assisted human systematic reviews in their usage of unsupervised machine learning models. As NCS is an emerging area of enquiry, we needed to induct categories of NCS pathways and co-impacts from the literature, a task most suited for unsupervised models.

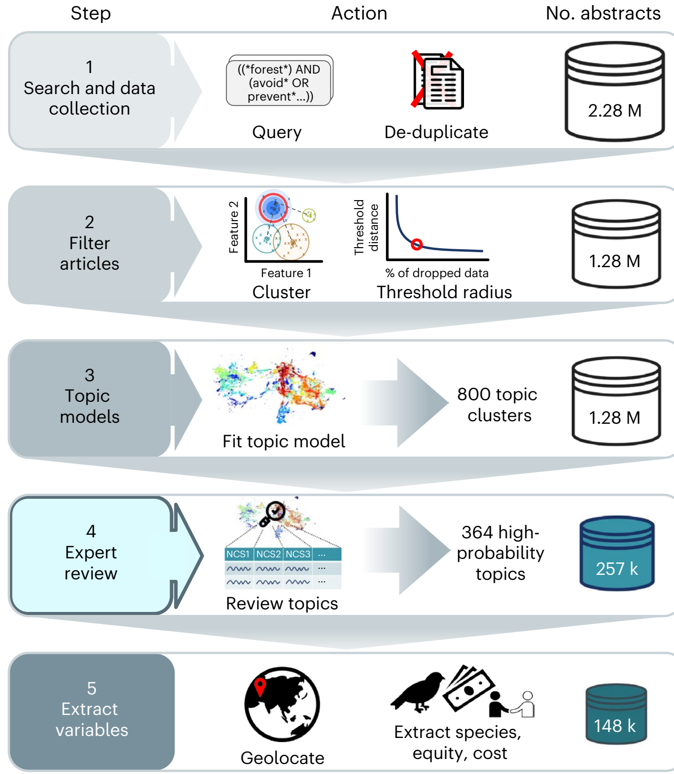

Fig. 1 | Evidence base generation process. The data generation pipeline broadly involves five steps where we search the literature, filter articles, employ LLMs to categorize abstracts to identify bodies of research on NCS co-impacts, and use state-of-the-art text parsing algorithms to extract information, alongside expert human review. Details of each step are outlined in the Methods and Supplementary Fig. 1.

Like previous studies[28,30,34,35], our evidence mapping exercise focused on English-language searches. Over 95% of manuscripts indexed in search engines such as Web of Science are written in English[39]. As a result, existing search strings for global assessments are typically written in English[40]. Moreover, existing NLP tools and datasets are biased towards the English language; both the training data and instruction-tuning data for large language models (LLMs) like those used in this study have limited validity for non-English and, especially, non-Latin or logographic writing systems such as Chinese[41–44]. We perform several robustness checks and find that our evidence map data include non-English-language articles, have a similar dominance of English-language articles reported by other scientometric studies, and have on average 95% overlap with results returned with Chinese or Spanish queries (Supplementary Section 2.2). These patterns echo previous studies comparing English with non-English-language data[45,46]. Thus we are confident that our evidence map presents robust patterns of evidence.

Our search strategy is deliberately inclusive of co-benefits and trade-offs, resulting in an evidence map that captures the full distribution of co-impact evidence measured by the volume of publications. This analytic choice derives from our recognition that implementing NCS may come with local trade-offs in human well-being, biodiversity and climate change mitigation outcomes[22,47]. We also use state-of-the-art text parsing algorithms (for example, refs. 48,49) to extract information on study geography, biodiversity and cost information, in addition to identifying abstracts with content related to Indigenous peoples and local communities and explicit equity considerations (Supplementary Information). The

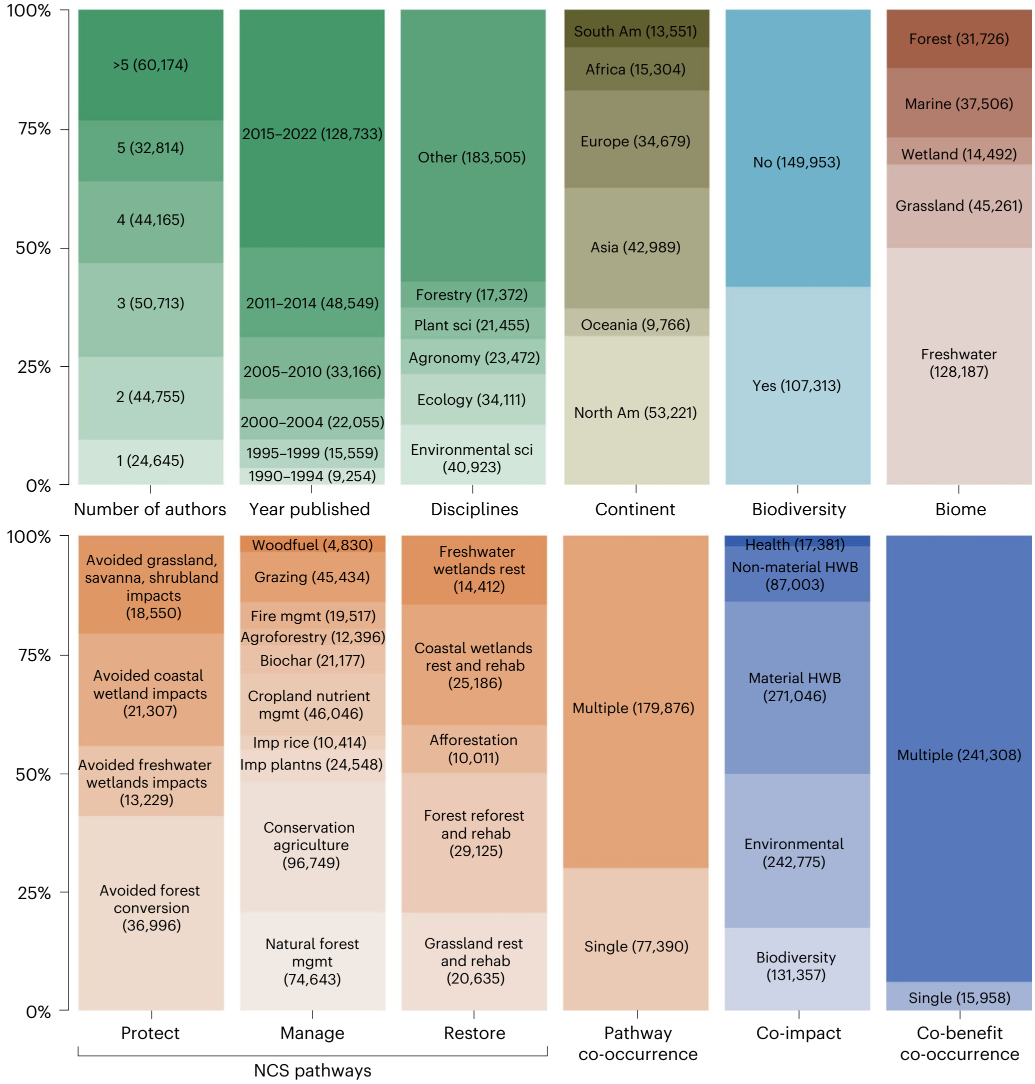

Fig. 2 | Characteristics of the evidence base. Each category is normalized to 100% of the relevant papers, where we do not display papers with missing data for disciplines, continent and biome. Further information on the other category for disciplines is available in Supplementary Table 17. Data for various grazing pathways are not shown due to space limitations. Grazing categories include optimal intensity, legumes in pastures, improved feed and animal management, and include 8,274, 4,580, 10,469 and 22,111 articles, respectively. Sci, science; Am, America; mgmt, management; imp, improved; plantns, plantations; HWB, human well-being. Descriptions for NCS pathways and co-impacts are shown in Supplementary Tables 9 and 10.

result is a replicable evidence map pipeline that can be easily and regularly reproduced.

The evidence map consists of 257,266 relevant papers on 22 NCS pathways and 11 co-impacts (see Methods for details and Supplementary Tables 9 and 10 for definitions) from an original sample of 2.28 million unique papers (Fig. 1). To categorize co-impacts, we use a framework that encompasses nine aspects of human well-being[28] in addition to biodiversity and broader environmental co-impacts. Our evidence map consists of papers found through English-language searches from 1990 to 2022 (Fig. 2). Here, relevance indicates papers that have (1) a high probability of providing information on NCS co-impacts; and (2) a close association with other papers that are likely to provide information on NCS co-impacts. The papers in our evidence map represent 181 countries, all 5 biomes, 246 disciplines and 364 unique thematic topics (details on topics in Supplementary Fig. 3 and Supplementary Table 15). We group NCS pathways into protection, management and restoration groups[5]. The vast majority of papers (87%) included manage pathways (for example, conservation agriculture, trees in croplands, natural forest management), while 30% of the papers covered protection (for example, avoided forest, wetland, grassland conversion), and 29% covered restoration pathways (for example, wetland, grassland and forest restoration). Many of the papers contained information on biodiversity (41%) or biome (39%), but some attributes were relatively rare: we detected that fewer than 2% of the papers contained an explicit reference to cost, equity or information related to Indigenous peoples and local communities (see Supplementary Tables 11–14 for search queries). As an important caveat, our review is only able to detect when these categories are an explicit research focus mentioned in the abstract. We are unable to identify when research considers these topics implicitly or does not refer to such topics in the abstract. Nonetheless, our search results comprehensively encompass external NCS meta-analyses that have had a constrained and expert-reviewed sample[50] (Supplementary Table 3).

The evidence map provides insights on evidence gaps (where more research is needed) and high-priority areas for further investigation and investment (where abundant evidence exists). Such foundational evidence is needed to accelerate strategic NCS research and implementation for climate change mitigation and adaptation, biodiversity conservation and sustainable development.

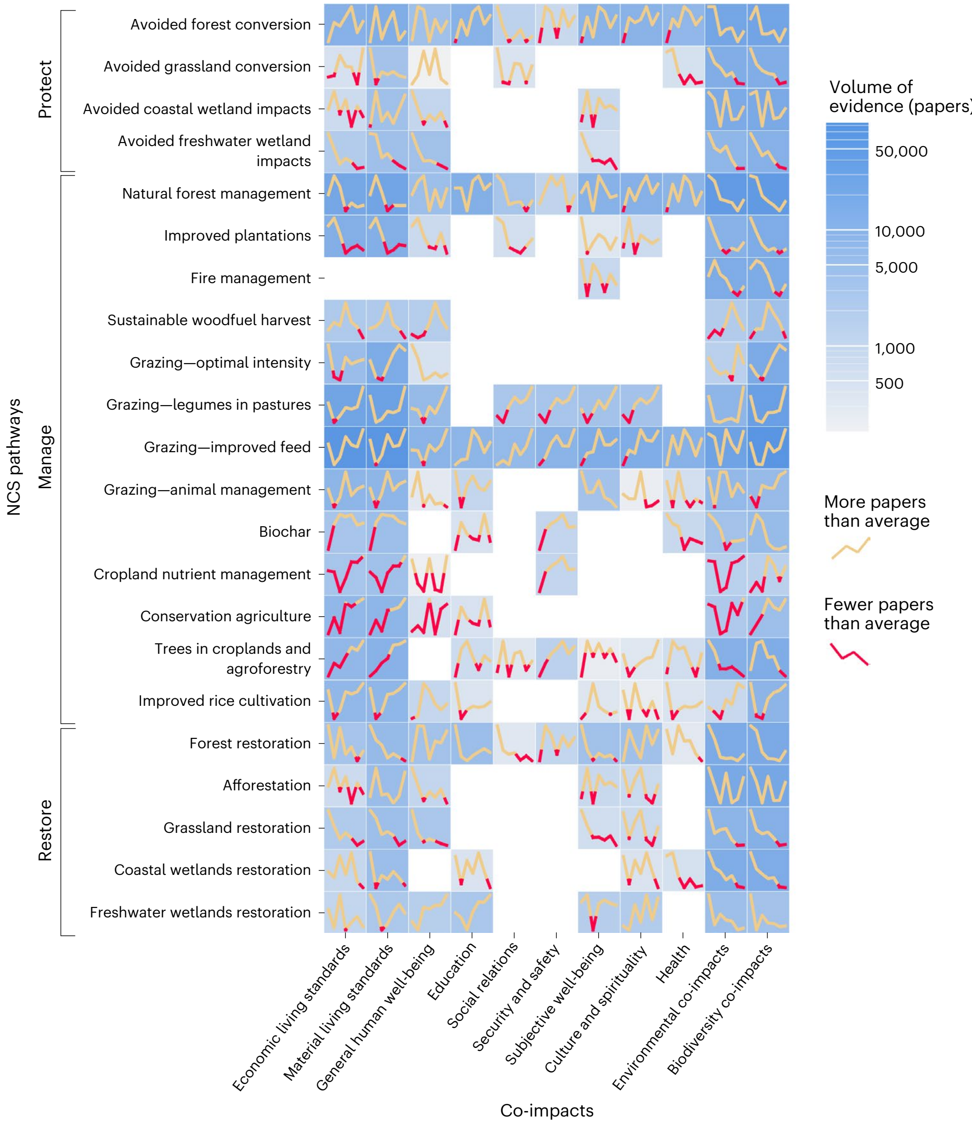

Fig. 3 | NCS and co-impacts evidence base. Darker shaded cells denote greater-than-average volume of papers relative to the total evidence base. Line graphs within each cell represent how evidence for the NCS co-impact combination changed over time. Yellow lines indicate year-over-year growth that exceeds the average growth of the overall body of evidence; red lines indicate lower-than-average growth of NCS papers discussing this pathway–co-impact combination. Definitions for NCS pathways and co-impacts are provided in Supplementary Tables 9 and 10.

Results

Gaps versus coverage in NCS evidence

Our evidence map highlights two areas of evidence needs based on (1) the overall distribution (Fig. 3); and (2) the spatial breakdown of NCS co-impacts evidence (Fig. 4). Figure 3 shows that many of the NCS pathways with the highest carbon mitigation potential have the highest level of evidence and vice versa. Exceptions to this pattern include wetland protection and restoration, a pathway that includes important habitats such as peatlands, which can contribute approximately 6% of total global NCS mitigation potential by 2030[1]. Cumulatively, there is a greater concentration of evidence in management-related NCS compared with protection (1.8 times more evidence per NCS pathway) and restoration (3.3 times more) pathways. Although the global body of evidence on NCS co-impacts has grown in total volume over time, it is far from uniform (Fig. 3). We plotted normalized deviates for literature growth for each NCS–co-impact combination (the NCS–co-impact pair minus the overall trend in the data), and observed that combinations such as avoided forest conversion and economic living standards, or grazing (legumes in pastures) and education, exhibited sustained growth. Others, such as cropland nutrient management and human health, or biochar and biodiversity, represent a decreasing share of NCS co-impact studies.

The evidence map, however, is not necessarily correlated with mitigation potential. For instance, conservation agriculture has the most evidence of any pathway, but its maximum mitigation potential of 516 Tg CO_2 yr^{-1} by 2030 is less than that of biochar, trees in croplands or optimizing grazing intensity. Conversely, a lack of evidence in Fig. 3 does not necessarily mean there are no meaningful NCS–impact links. For example, we find limited evidence connecting grassland restoration and education or social relations, but such connections may exist beyond the scope of published literature.

We compare regions based on their co-impact evidence base and their climate change mitigation potential to determine which areas may be prioritized for NCS action and where there may be an evidence base to inform whether NCS can help address human or environmental challenges. We merge articles that contain location information in the abstract with countries' climate mitigation potential from NCS[1,4,51–57], threatened biodiversity[58] and human well-being[59]. We stratify the articles by NCS pathways using protect, manage and restore categories[5]. By combining these datasets, we identify regional 'action areas' with

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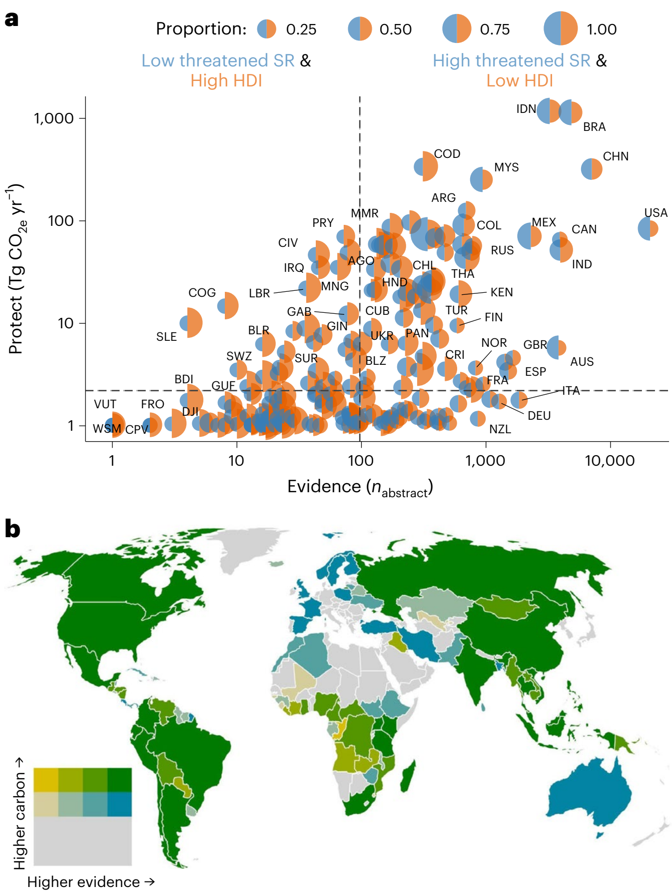

Fig. 4 | The volume of evidence for NCS 'protect' strategies across countries versus their maximum climate mitigation potential through NCS and threatened biodiversity. **a**, Semi-circles on the left (blue) show threatened biodiversity and on the right (orange) show the national HDI. Larger semi-circles correspond to a country having higher threatened biodiversity or lower HDI. The dashed vertical line corresponds to the country-median quantity of evidence, while the dashed horizontal line marks the country-median climate mitigation value for 'protect' pathways. SR denotes species richness and CO_{2e} denotes carbon dioxide equivalents. **b**, The degree of climate mitigation potential for each country as well as the paucity of evidence is displayed. Countries that are more intensely coloured in gold are those that have high climate mitigation potential but limited evidence. See Supplementary Table 8 for a full list of country abbreviations. Details for the 'manage' and 'restore' pathways as well as country-level data are provided in Supplementary Fig. 6 and Supplementary Table 8.

high NCS potential and large bodies of evidence versus 'need areas' that have high NCS potential but relatively little evidence (Fig. 4).

We observe direct relationships between NCS mitigation potential and NCS evidence for the protect, manage and restore pathways (Fig. 4, Supplementary Fig. 6 and Supplementary Table 7 (refs. 1,4,51–57)). The correlation is strongest for management-related pathways ($\rho = 0.77$, $P < 0.001$), and weakest for protection ($\rho = 0.31$, $P < 0.001$) and restoration pathways ($\rho = 0.41$, $P < 0.001$). Thus, many countries with the greatest potential to contribute to climate mitigation through the protection or restoration of natural habitats contain comparatively fewer studies on the biodiversity, human well-being or environmental benefits or trade-offs that NCS can provide.

High-income countries and countries with the greatest NCS mitigation potential constitute the preponderance of evidence on NCS co-impacts. For example, Australia, Brazil, Canada, China, India, Indonesia, Mexico and the United States are action areas across all pathway types. This reinforces the importance of leveraging current findings to rapidly inform where and how to implement NCS (Fig. 4).

Regions with multiple countries categorized as 'need areas' in at least two of the three pathway categories ($n = 17$) include central South America (Paraguay and Uruguay), West and Central Africa (Ivory Coast, Gabon, Guinea, Mali, the Republic of the Congo and Sierra Leone), and Central Asia (Kazakhstan and Uzbekistan). Ranking 'need areas' according to their human development index (HDI) and threatened species richness indicates that West and Central African nations comprise six of the top ten countries with the highest number of threatened species and lowest HDI. Together, need areas contain over 124 million people who are multi-dimensionally poor[60] and 2,162 endemic species of animals and plants[58].

Equally weighting HDI, threatened species richness and climate mitigation from NCS shows that Sierra Leone, New Caledonia, the Republic of the Congo, Burundi, Mauritius, Somalia, the Solomon Islands, Haiti, Puerto Rico and Yemen are among those with the lowest rates of evidence across all pathway categories (Supplementary Table 8).

Co-occurrence of NCS and co-impacts

NCS pathways are rarely studied in isolation. Approximately 70% of papers ($n = 179{,}876$) are predicted to contain information on more than one NCS pathway (Fig. 5). Pathways that most commonly co-occur within the data include nutrient management and conservation agriculture ($n = 33{,}167$), and natural forest management and avoided forest conversion ($n = 31{,}745$). Examining the most notable trends for individual pathways, over 96% of papers on fire management also consider natural forest management ($n = 17{,}232$), and 61% of papers on avoided coastal wetland impacts and conversion co-occur with research on coastal wetland restoration ($n = 20{,}814$). Though the most common co-occurrence exists within habitat types, some pathways also show considerable co-occurrence across habitats. For example, 14% of papers that examine conservation agriculture also consider natural forest management ($n = 13{,}955$), and 12% include avoided forest conversion ($n = 10{,}899$). Although we do not evaluate whether there is complementarity or trade-offs among these pathways, our findings indicate that NCS research typically evaluates multiple land uses or land cover changes together when assessing co-impacts.

We find specific NCS co-impacts were often studied together. Most (94%) studies are predicted to analyse more than one co-impact ($n = 241{,}308$). Economic, material and environmental/ecosystem service outcomes demonstrate the greatest amount of co-occurrence. For example, studies that examine economic co-impacts also often include information on potential material co-impacts ($n = 114{,}270$; 34%) and environmental/ecosystem services ($n = 95{,}622$; 28%). The common co-occurrence involving human health and biodiversity ($n = 8{,}904$) or environmental/ecosystem services ($n = 18{,}919$) may reflect a growing awareness of the interplay between these sectors, evident also within the literature on planetary health[61]. Similarly, 15% of papers that include information on culture and spirituality also contain analyses of economic impacts ($n = 14{,}210$), which may reflect a concern that economic development will negatively impact local traditions. Further research will be necessary to determine the direction of this and other relationships among potential co-impacts.

Discussion

The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services–Intergovernmental Panel on Climate Change report[16] articulates the critical importance of simultaneously advancing climate change mitigation, biodiversity conservation and sustainable development objectives. NCS are climate-focused, nature-based solutions that have gained widespread interest and investment in multilateral frameworks and national policies to address multiple societal challenges[62]. Yet, there are uncertainties surrounding whether and where NCS can deliver on these multiple objectives, as well as potential trade-offs that must be considered[16]. Using established frameworks on

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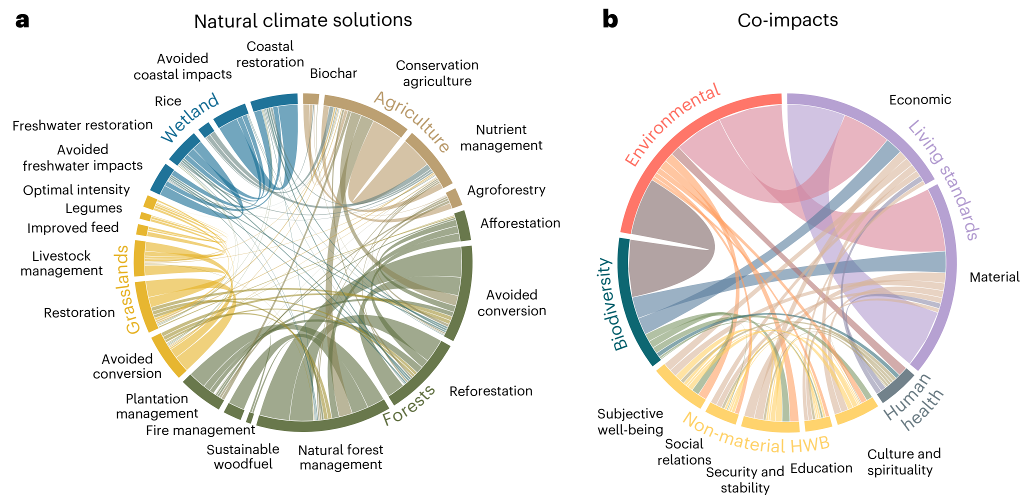

Fig. 5 | Co-occurrence of NCS and co-impact categories. Proportion of pathway (**a**) and specific co-impact (**b**) co-occurrence. Articles that have more than one NCS pathway (n = 179,846) or co-impact (n = 241,308) are displayed. Articles that contain more than two pathways or co-impacts are represented by multiple dyadic chords. Detailed information on co-occurrence is provided in Supplementary Table 15.

NCS pathways[1] and co-impacts[28], our evidence map provides a global stocktake on co-impacts provided by 22 NCS pathways, providing a foundation to guide actions and research priorities for NCS implementation.

The evidence map presents the latest evidence across the 22 NCS pathways, including where there has been relatively abundant attention and research (for example, forest protection; North America) and a more recent focus (for example, coastal restoration; parts of West Africa). Importantly, our evidence map indicates we have large volumes of evidence for many NCS pathways with high climate change mitigation potential, but there are exceptions such as wetland protection and restoration pathways, despite their estimated 6% contribution to climate change mitigation potential globally[1]. The growth in NCS co-impact evidence is not uniform. Evidence map users can conduct deeper dive investigations along the various facets, such as by pathway, geography, co-impact type and biome. To date, the global distribution of evidence on NCS co-impacts has been unknown, and a clear next step is a careful assessment of the direction (positive, negative or neutral) and size of impacts for a given geography and sub-population of interest for any given NCS co-impact. Although our synthesis could not assess trade-offs and synergies that different NCS produce through co-impacts given methodological and space limitations (similar to refs. 30,34,36,37), the evidence map's underlying literature can be used to further investigate NCS and related co-impacts.

Analysing the overlap between areas of high or low evidence with indicators for NCS climate mitigation potential, threatened biodiversity and human development provides deeper insights into where more research is needed versus where abundant evidence exists to inform action. Brazil, India, China, Mexico, the United States, Australia and Canada are high mitigation potential countries with abundant co-impact evidence. On the other hand, there are countries, predominantly in West and Central Africa, that lack extensive published evidence despite high mitigation potential, threatened biodiversity and opportunities for improving human well-being. For stakeholders who equally value carbon alongside biodiversity and potential social benefits, a different set of priority countries emerge such as New Caledonia, Burundi, Mauritius, Somalia, Haiti and Yemen. It is possible that we find little evidence in these countries because we focused on articles published in English or due to historical biases in science funding and capacity; however, the spatial distribution of our evidence map closely aligns with other global climate impacts, food security or biodiversity conservation and poverty alleviation reviews[28,34,36,37].

We also found that the majority of management NCS pathways co-occur, indicating that implementation around just one pathway in a particular location may overlook the complementarities with other NCS pathways. Conservation agriculture, nutrient management and trees in croplands are likely to be compatible activities, and programmes focused on a singular NCS pathway may miss key opportunities for climate change mitigation. Given that the funding gap to reverse biodiversity decline alone by 2030 is US$722–967 billion per year[63], and that nearly US$400 billion per year is needed to implement forest-based NCS alone[64], identifying synergistic opportunities where multiple NCS can cost-effectively advance multiple goals will be important in a resource-constrained world. The evidence map presented here aims to help guide groups additionally invested in understanding the co-impacts that climate actions produce[21].

Research about the impacts of protection, improved management and restoration of ecosystems has existed for decades, but the vast majority was conducted before 'NCS' proliferated as a climate change mitigation strategy and term. A comprehensive analysis thus necessitates analysing a scale of published studies that defies manual review. We are unaware of any data-driven taxonomy that could identify which articles and topics map to NCS pathways prior to our study. Our unsupervised large language topic model permitted us to discover a categorization of literature to NCS pathways and co-impacts using established frameworks[1,28]. Before recent watershed advances in language modelling, processing the relatively nuanced differences between scientific abstracts would have been difficult, if not impossible. An important advance is that our evidence map pipeline is replicable and easily updated given our use of modern machine learning approaches. Such built-in automation decreases effort and costs while preserving scientific robustness.

Nevertheless, there are ample opportunities for future advances. The most notable is how we predict relevant articles—not every study in our sample may fulfil more stringent inclusion criteria, such as an estimation of an effect size or direction of impact. However, our dataset allows a drastic reduction in search and screening effort by providing a funnel to direct more targeted meta-analyses. Given that the evidence map represents 246 disciplines and a diversity of research methods and designs, conducting a meta-analysis across the entire evidence map is unfeasible, as the objectives for variable extraction may vary across different NCS co-impacts. However, researchers may leverage the NCS co-impacts evidence map for specific NCS and a co-impact to accelerate meta-analysis efforts. At a minimum, our approach systematically and rigorously identifies current research efforts and gaps for future research. While computer vision approaches that extract tables could offer additional machine-aided steps, we are unaware of any way that more intensive analyses such as a meta-analysis could be reliably performed end-to-end by a machine learning pipeline, especially across such a diverse body of research. A particularly fruitful area of exploration that can utilize the evidence map data is in uncovering mechanisms and barriers to successful implementation of NCS. Our analysis was also limited to papers with English-language abstracts. Expanding the machine-aided pipeline to capture non-English papers will ensure equitable evaluation of all scientific evidence that is generated across diverse geographies. However, overall, our data and multi-lingual robustness checks (Supplementary Section 2.2) indicate that geographic bias in places where studies are conducted, broadly, is a much larger issue than bias introduced by just using English-language searches. Finally, if there were relatively small and isolated bodies of literature that could be pertinent to NCS co-impacts, our large language topic model may have failed to identify these clusters of papers.

Strategic and targeted implementation of NCS is an important component for realizing environmental, biodiversity and human well-being goals, as well as for assessing trade-offs in the event that achieving multiple aims is challenging[16]. Enthusiasm for NCS has, in part, been rooted in the assumption that they will deliver on multiple objectives[1,4,5,7–12], yet substantial barriers have hindered systematic evidence maps that could evaluate such assertions. Evidence maps on such a rich and multidisciplinary topic such as NCS co-impacts provide a first step in moving from evidence to policy and practice by providing a systematically generated explorable visual tool that characterizes areas with abundant and scarce evidence[27]. An important next step will be to assess the direction, size, distribution, sustainability and timing of co-benefits offered by NCS pathways in isolation or combination, and potential trade-offs that implementation of NCS may present, especially for vulnerable or already marginalized populations and endangered species. Given the increased political will and financial commitments towards climate change mitigation[18,19], and the relative immediacy and readiness of NCS implementation compared with other forms of carbon mitigation, mapping where and what co-benefits and trade-offs NCS realize can provide valuable and actionable insights to inform global climate change mitigation that can also address biodiversity conservation and human development.

Methods

Our analysis involved five major steps (Fig. 1 and Supplementary Fig. 1): (1) developing search strings corresponding to the NCS pathways and co-impacts framework to query academic research databases; (2) filtering articles based on distance to each NCS pathway's centroid; (3) training an unsupervised machine learning topic model ('BERTopic') to identify categories that were then mapped to NCS pathways and co-impact categories; (4) extracting geolocation information from abstracts and identifying the biome associated with specific locations using machine learning methods (for example, named entity recognition used in packages such as Mordecai[65]); and (5) determining which species were mentioned in the abstracts. For more detailed information regarding any of these steps, please refer to Supplementary Sections 2–4. We conducted several robustness checks with human review and by comparing against other evidence mapping efforts (details in Supplementary Section 3.2).

Compiling NCS evidence

We performed 242 queries to Web of Science and Scopus in August 2022 resulting in 2.28 million unique citations, or abstracts with metadata. The search strings were informed by International Union for Conservation of Nature definitions of biomes[66] and definitions of NCS pathways from Griscom et al.[1]. We adopt the concept of NCS because we use the Griscom et al.[1] definition and framework for NCS pathways, as well as the NCS hierarchy from Cook-Patton et al.[5] when presenting results. We recognize that NCS and nature-based climate solutions are often conflated and conceptually similar, and we refer readers to ref. 67 for clarification of these concepts and what constitutes NCS. Note that we do not use 'natural climate solutions' in any of the search strings, given that this would artificially narrow our sample to studies after 2017, when Griscom et al.[1] catalysed its broader use. Rather, for each NCS pathway we articulate specific terms that capture biome-specific terms for the intentional protection, restoration or management actions adhering to NCS principles and definitions[1,67] (Supplementary Information and Supplementary Tables 9 and 10). Furthermore, note that Griscom et al.[1] identified 20 NCS pathways, but we added two additional pathways given greater certainty and evidence supporting the mitigation potential for afforestation and grassland restoration. This mirrors the emphasis of refs. 67 and 68 on allowing additional NCS pathways to emerge as certainty and evidence for an NCS pathway's mitigation potential increases. We used the framework from McKinnon et al.[28] for human well-being categories.

Our search strings comprehensively captured the presently known universe of NCS co-impacts; our search results contained over 99% papers captured in external NCS meta-analysis projects[50] (Supplementary Section 3.4). For each search string query, we defined a more restrictive set of terms ('focused queries') designed to yield a higher proportion of pertinent abstracts and a less restrictive set of terms ('broad queries') that would sample the broader universe associated with each search target; that is, an NCS pathway and a type of co-impact. The team iterated and calibrated search strings until the results were deemed by team members to be inclusive of relevant papers on a random selection of articles. The focused queries yielded 800,000 abstracts while the broad queries produced 1.4 million additional abstracts. Each abstract was converted to a numerical representation (an 'embedding') using a large language transformer model, specifically, SentenceBERT[69].

Categorizing and identifying relevant abstracts

We refined the initial sample of 2.2 million abstracts using distance-based thresholding, as initial human validation of hundreds of randomly selected abstracts showed that only 65% clearly agreed with the NCS pathway and co-impact that generated the search string producing that abstract. This was thus preliminary evidence that not all co-impact and pathway combinations may have coverage in the literature, indicating that we needed to induct pathway and impact combinations from the data. We grouped abstracts based on NCS pathway as these group sizes were more even than groups based on pathway and co-impact. We then calculated abstract distances to the centroid for each pathway, and bucketed these distances into five groups, where a distance of 0% indicates an abstract was next to the centroid while 100% would be farthest from the centroid, and we examined the proportion of abstracts dropped beyond each set of distances. The distance thresholds were those locations at which there would be less than a 5% reduction in abstracts (Supplementary Section 3 and Fig. 1). Because BERTopic uses density-based clustering to discover topics among documents, highly outlying abstracts could degrade the model's performance by creating poorly agglomerated or spurious topic clusters. After this distance-based filtering to refine the input, we applied BERTopic to cluster the remaining 1.28 million abstracts. At this step, our sample contained 92.6% of the papers analysed in manually reviewed external NCS evidence mapping exercises focused on different objectives than our evidence mapping project, which was primarily focused on inducting categories of NCS co-impacts from a vast literature[50] (Supplementary Table 3). We then applied BERTopic, an unsupervised learning approach that builds upon traditional topic modelling using simpler bag-of-words features with cutting-edge LLM, transformer-based embeddings that capture the semantic structure of language[70].

BERTopic has been used to describe viewpoints towards climate change belief[71] and to perform a systematic review of machine learning in urban studies[72]. The major advantage of using BERTopic is that it can scale to large text datasets such as ours, and does not require a pre-existing labelled dataset, which itself necessitates a known taxonomy of NCS pathways and co-impacts[72]. At the outset of our research, we were uncertain which, if any, of the NCS pathway and co-impact combinations would have any coverage in academic research, and thus sought an approach that would allow categories to emerge from the data.

We performed hyperparameter optimization on the BERTopic model. The final model generated 800 topics that the author team inspected for relevance, defined as having a clear connection to NCS pathways and at least one type of human well-being or environmental co-impact. We also coded topics for NCS pathways and co-impacts. At all steps, at least two coders examined a topic for its relevance, NCS pathway and co-impact. At this juncture, our dataset contained 76.4% of the NCS biodiversity co-impact papers manually analysed by external expert teams[50] (Supplementary Table 3). Our author team discussed any disagreements in topic coding and resolved any differences between coders. We dropped topics that did not capture an NCS pathway and co-impact (436 topics dropped), resulting in a total of 364 topics covering ~257,000 articles. Ultimately, we focused on the highest density region for all of the 364 topics, reducing the sample to 257,266 abstracts by requiring each abstract to have a topic assignment probability >0.5. At this stage, while our dataset exhibited reduced overlap with articles included by the external manually curated dataset, we also observed much lower levels of overlap with articles excluded by the external manual review process[50] (Supplementary Table 3). We also compared the overlapping and non-overlapping external articles in terms of their NCS pathway and Web of Science category distributions, and did not observe any consistent differences that would indicate topical or pathway bias (Supplementary Tables 4 and 5). While we observed similar linguistic patterns between the overlapping and non-overlapping abstracts, the overlapping abstracts had distinctive *n*-grams consistent with reporting quantitative findings (Supplementary Table 6).

Extracting variables from abstracts

We used Python modules to extract cost information, geolocate abstracts and identify taxa mentioned in abstracts. The cost information and geolocation approaches used named entity recognition approaches (for example, Supplementary Table 16), while the biodiversity extraction used regular expressions for the scientific and common names of species drawn from the Open Tree of Life[73]. For more information, please refer to Supplementary Section 4.

Analysis

We performed descriptive analyses of trends in evidence, evidence gaps and NCS co-impact co-occurrence. For NCS evidence gaps focused on identifying high-priority areas for action and need, we combined information on country-level mitigation potential for protect, manage and restore pathways[5], threatened biodiversity[58] and human development[59]. All analyses were conducted using Python (v. 3.11) or R (v. 4.1).

Ethics and inclusion statement

All collaborators of this study have fulfilled the criteria for authorship required by Nature Portfolio journals and have been included as authors. Local research relevant to our study was taken into account in citations. The research presented here is a desktop analysis and was not restricted or prohibitive to participating researchers.

Reporting summary

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

Data availability

All data and materials used in the analysis are available at our GitHub repository at https://github.com/lexunit-ai/ncs-evidence-map.

Code availability

Code used for this study is available at our GitHub repository at https://github.com/lexunit-ai/ncs-evidence-map.

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Author contributions

C.H.C., B.E.R., J.T.E., L.L., Y.J.M., I.M., D.P. and P.F. conceived the idea for the manuscript, generated new methods and performed the research. C.H.C., B.E.R., J.T.E., Y.J.M., I.M., D.P. and S.C.-P. performed data analysis and modelling, generated figures and tables, and drafted sections of the manuscript. A.R.T., S.C.-P., R.I.M., T.G., J.P.H., P.W.E., E.E.P., T.K., S.H.C., P.W., S.A.W., M.C., L.S.S., K.G.A. and P.F. performed critical reviews. Y.J.M., E.E.P., J.T.E. and R.I.M. obtained funding.

Competing interests

The authors declare no competing interests.

Additional information

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Data were conducted using Python (v. 3.11) or R (v 4.1) to extract data from Web of Science and Scopus using relevant APIs (Mordecai, LexNLP, price-parser). Data available here: https://github.com/lexunit-ai/ncs-evidence-map
Data analysis	All analyses were conducted using Python (v. 3.11) or R (v 4.1). Code available here: https://github.com/lexunit-ai/ncs-evidence-map

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Recruitment	N/A
Ethics oversight	N/A

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	We created a systematic evidence map on the human well-being and biodiversity co-benefits and trade-offs (i.e., co-impacts))of natural climate solutions using novel large language models, machine learning methods, and human checks. Briefly, our study involved the following steps: 1) developing search strings corresponding to the NCS pathways and co-impacts framework to query academic research databases; 2) filtering articles based on distance to each NCS pathway's centroid; 3) training an unsupervised machine learning topic model ("BERTopic") to identify categories that were then mapped to NCS pathways and co-impact categories; 4) extracting geolocation information from abstracts and identifying the biome associated with specific locations using machine learning methods (e.g., named entity recognition used in packages such as Mordecai); 5) determining which species were mentioned in the abstracts. Details are provided in the SI.
Research sample	The sample universe is from English language searches of papers from 1990-2022 that were captured by search strings on 22 NCS pathways and 11 co-impacts in Web of Science and Scopus. Note that there is no known sampling universe for these NCS studies, as it is a relatively recent concept that groups areas of work that long predates NCS. However, search strings were tested/developed to be as representative as possible, and our data pipeline approach was broad by design to capture as much of the sample universe as possible before filtering and analytical steps.
Sampling strategy	Our aim is to capture the entire universe of studies that would fit within 22 NCS pathways and 11 co-impacts, then using a cluster analysis/topic modeling to identify relevant papers that meet specific statistical thresholds for relevance. The sampling procedure was to first develop search strings that captured as much of the relevant universe of NCS studies as possible, and then conduct a number of steps to refine this sample to only include probabilistically relevant studies on NCS and co-impacts. In short, the aim was to conduct a census of the entire relevant evidence base of NCS and their co-impacts. See above for more information on these steps.
Data collection	Our data collection pipeline consists of extracting all paper information and abstracts that meet search criteria from Web of Science and Scopus into an Elasticsearch database, where we use state-of-the-art text parsing algorithms to extract information on study geography, biodiversity, cost, and other relevant variables. Our final sample was roughly 257,000 abstracts that met our analytical criteria.
Timing	We use data extracted in August 2022.
Data exclusions	Papers that were not identified as relevant in the cluster analysis and human review are excluded; this set of excluded papers totaled 1.7 million abstracts.
Non-participation	No participants were involved in the study.
Randomization	No randomization was used beacuse the aim was to collecting a systematic and probabilistically relevant set of studies capturing NCS and their co-impacts. As a result, there was no "treatment" or other reason for randomization of units. The only relevant analog is that there were random checks at some steps as part of the human-in-the-loop process for our semi-automated data pipeline.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology and archaeology
☒	☐	Animals and other organisms
☒	☐	Clinical data
☒	☐	Dual use research of concern
☒	☐	Plants

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging