Supplementary Information for *Environmental discourse exhibits consistency and variation across spatial scales on Twitter*

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1 Extended methods

1.1 Data pipeline

The procedure for extracting environmental discourse data via queries to Twitter’s application programming interface (“API”) and analyzing the data is shown in Figure 1 in the main text. The upper half of the figure displays how we scraped data from Twitter and subset our user data to those users satisfying the inclusion criteria, which were posting at least 25 English-language tweets
written after November 2017. This resulted in an initial sample of around 500,000 users. We then focused on those users with location data \((n = 221,128)\) for these analyses.

We then further subset the data to 14 countries which each had at least 1000 users \((n = 196,783)\). The lower half of Figure 1 depicts how we performed automated text analysis to process tweet data. We used the processed data to calculate discussion intensity across the 21 issues and issue prominence. Below, we provide more details on the data gathering and analytical procedure.

### 1.2 Extracting environmental data on Twitter

In this project, we defined our sample as the users who follow leading environmental non-governmental organizations (“eNGOs”). That necessitated identifying a set of eNGOs to source a universe of Twitter followers. To that end, we used industry reports from The Urban Institute and Green 2.0 to generate the eNGOs in Table S1. To obtain all of the followers of these organizations, we used the Python module Tweepy. Let the term “scrape” or “scraping” denote scripts that downloaded data via queries to Twitter’s API.

Ultimately we scraped over 7 million followers of the eNGOs from the Twitter followers/ids API endpoint. These followers constituted the initial universe of users we analyzed in this project. We then filtered out users that displayed evidence of automated, bot-like behavior using Botometer (Davis et al., 2016). Given rate limits on requesting data and performing botchecking, we checked nearly 2.2 million accounts during the data scraping period (January-May 2020).

#### 1.2.1 Scraping user timeline data

We found that 1,003,104 of those users were not bots and we scraped their timelines from the Twitter statuses/home_timeline API endpoint. Twitter defines a user’s timeline as the most recent 3,200 tweets made on their account, which can include retweets or quote tweets. Our scripts contained exception handling to catch errors, such as rate limit timeouts or service outages for Twitter’s or Botometer’s servers. When errors precluded scraping a user’s timeline, we scraped that account in a later run of the script. Our approach did not download any data from deleted or private accounts as such access is restricted by Twitter’s API.

#### 1.2.2 Inspecting the Botometer algorithm and comparing users with and without geographic data

We used a threshold of 0.43 for the comprehensive bot metric “Complete Automation Probability English” (henceforth “CAP English”) which uses user features such as as their content posting rate, social network connections, and English-language features to categorize accounts as bots (CAP English > 0.43) or human (CAP English ≤ 0.43). This value was specified by the developers...
| Organization                                | Twitter Handle          |
|--------------------------------------------|-------------------------|
| World Wildlife Fund                        | WWF                     |
| Greenpeace                                 | Greenpeace              |
| The Nature Conservancy                     | nature_org              |
| National Wildlife Federation               | NWF                     |
| 350.org                                    | 350                     |
| Sierra Club                                | SierraClub              |
| Oceana                                     | oceana                  |
| Ocean Conservancy                          | OurOcean                |
| Natural Resources Defense Council           | NRDC                    |
| Extinction Rebellion                       | ExtinctionR             |
| National Parks Conservation Association    | NPCA                    |
| Rainforest Alliance                        | RnfrstAlliance          |
| Environmental Defense Fund                 | EnvDefenseFund          |
| Earthjustice Legal Defense Fund            | Earthjustice            |
| Friends of the Earth                       | foe_us                  |
| World Resources Institute                  | WorldResources          |
| Defenders of Wildlife                      | Defenders               |
| National Audubon Society                   | audubonsociety          |
| Conservation International                 | ConservationOrg         |
| Sunrise Movement                           | sunrisemvmt             |
| Ducks Unlimited                            | DucksUnlimited          |
| The Wilderness Society                     | Wilderness              |
| Rainforest Action Network                  | RAN                     |
| Green for All                              | GreenForAll             |
| National Wild Turkey Federation            | NWTF_official          |
| Wildlife Conservation Society              | thewcs                  |
| Pheasants Forever                          | pheasants4ever          |
| Trout Unlimited                            | TroutUnlimited          |
| Quality Deer Management Association        | TheQGDMA                |
| American Rivers                            | americanrivers          |
| League of Conservation Voters              | LCVoters                |
| Quail Forever                              | quail4ever              |
| Theodore Roosevelt Conservation Partnership| TheTRCP                 |
| Trust for Public Land                      | tpl_org                 |
| The Conservation Fund                      | ConservationFnd         |
| ClimateWorks Foundation                    | ClimateWorks            |
| Energy Foundation                          | EnergyFdn               |
| Resources Legacy Fund                      | ResourcesLF             |
| Izaak Walton League                        | IWLA_org                |

Table S1: Set of environmental non-governmental organizations (eNGOs) used to source followers sampled in this analysis.
of the tool (Davis et al., 2016) and validated by independent research by Pew (Wojcik et al., 2018). It is also a value that is well within the range of past research, which has sometimes used an even more stringent threshold of 0.25 for this metric (Zhang et al., 2019).

We performed our own analysis of the Botometer tool to ensure that this threshold for the score did not excessively filter out human (that is, non-bot) accounts. As an additional quality control check, we also inspected a random sample of 100 bot accounts. For those bot accounts, we examined their counts of friends (accounts that the user follows), followers, post rate (tweets per day), and description fields. We analyzed how the false positive rate for human accounts would change with different values of CAP English. In this context, a false positive occurs when a human account is incorrectly labelled as a bot based on the Botometer threshold. We found that at the bot threshold of 0.43 for CAP English, only around 1% of human accounts would receive false positive bot results (Figure S1).

We found that the bot accounts differed markedly from the human users included in the analysis (Table S2); bots tended to have much fewer followers and thus a much higher ratio of friends to followers. Additionally, the bot accounts tended to post descriptions at much lower rates than the human accounts and differed in terms of the distinctive terms that were mentioned in their descriptions (Table S3).
Sloan and Morgan (2015) found that users with geolocation data differed slightly but statistically significantly from non-geolocated users on Twitter. As such, we sought to evaluate whether or not the users in the dataset who had location information differed substantially from those who did not. We found that non-geolocated users exhibited different social media behavior from the users with location data—that is, different rates of making posts (Table S2). However, these two types of accounts exhibited very similar language in their user description fields (Table S3). Therefore, while the geolocated users posted tweets at lower rates than the non-geolocated users and had larger follower audiences, these two categories of users exhibited strong similarity in their user description field, indicating that there would be broad overlap in discourse patterns.

| Category | Posts | Friends | Followers | FF Ratio | Description |
|----------|-------|---------|-----------|----------|-------------|
| Bots     | 0.94 (0.48) | 557.76 (97.4) | 309.5 (142.84) | 10.9 (2.01) | 63.9% |
| Non-Geo  | 3.65 (0.03) | 1359 (19.3) | 2763 (163.12) | 5.6 (0.03) | 74.9% |
| Geo      | 2.83 (0.02) | 1659 (27.2) | 3349 (165.85) | 4.03 (0.02) | 87.8% |

1 The categories are accounts that are likely bots, human (likely non-bot) accounts that are not geolocated (Non-Geo), and human accounts that are geolocated (Geo).
2 The variable “Posts” is calculated as the rate of posting per day.
3 FF Ratio is the ratio of friends to followers, also presented in terms of its mean value with the standard deviation in parens. For all numeric columns, we display the mean values by category with the standard error of the mean in parens.
4 Description presents the percentage of users in each group that had a written description.

Table S2: Summary statistics for social media behavior for bot and non-bot accounts.

1.2.3 Obtaining data to identify environmental topics on Twitter

With the data in hand, we needed a way to categorize the distinct issues that emerged in this public discourse. To that end, we used an unsupervised machine learning model called probabilistic latent Dirichlet allocation (“LDA”) so that environmental topics could emerge from a corpus of Twitter data. We felt that an unsupervised machine learning model was superior in this context because we did not have a pre-defined taxonomy of environmental social media issues. As such, we did not

| Category | Distinctive terms |
|----------|-------------------|
| Bot      | animals, Instagram, love, human, service, free, best, work, social, data |
| Non-Geo  | love, life, world, writer, music, fan, people, views, student, nature |
| Geo      | love, life, views, writer, world, fan, director, social, nature, enthusiast |

Table S3: An analysis of the description fields for the three categories of users. The column “Distinctive terms” presents up to 10 words from the description fields that are strongly associated with users in each category (bot, non-geolocated users, and geolocated users).
want to artificially constrain or pre-define topic areas \textit{a priori}. To train the LDA topic model, we focused on Twitter data where environmental issues would be discussed at a high frequency. We leveraged Twitter “lists” which group accounts thematically. Lists have been used to crowdsource political leaders, product influencers, or pundits with shared group identities or issue affinities (Culotta & Cutler, 2016). Thus, we scraped lists from the \texttt{lists/memberships} API endpoint by initially querying for any and all lists that contained at least one of the eNGOs in Table S1.

\section{Identifying environmental issues discussed on Twitter}

\textbf{Text processing} Following recommendations from natural language processing (NLP) researchers (Bird et al., 2009; Mimno, 2012; Schofield et al., 2017), we used the steps below to process raw tweet text:

- convert all whitespace characters to a single space character;
- concatenate any quote tweet message with the original retweeted status;
- remove ampersands, URL links, and the @ symbol before user names mentioned in tweets;
- keep hashtag terms but remove the “#” symbol;
- tokenize each tweet into individual words.

For training the LDA topic model, we used several additional pre-processing rules. LDA topic model training tends to perform worse when individual documents are too short or too long (Boyd-Graber et al., 2017). Individual tweets tend to be too short for training topic models, thus we pooled pundit tweets into sets of 10 consecutive tweets within each pundit’s timeline, generating documents for training the topic model. To further improve topic model training, we removed any documents that were less than 50 tokens (i.e. words) in length, producing a final set of 1,124,909 pooled documents. The average pooled document contained 174.3 tokens (individual words) with a median of 174 tokens.

We then removed extremely common words from the documents. We filtered out stopwords defined by their frequency in the English language and our corpus. Reducing the set of input features via removing stopwords tends to improve topic model fit (Schofield et al., 2017). Our stopwords included a minimal set of English stopwords (e.g. “the”, “of”, “and”; Bird et al., 2009) and extremely rare or highly common words in our pundit corpus by excluding any terms that occurred in less than 100 (0.0089\%) or more than 90\% of the documents. These thresholds were highly conservative for filtering terms (Mimno, 2012). Our final corpus was 61,749 words across 1,124,909 pundit documents.

We trained our LDA topic model using MALLET (MAchine Learning for Language Toolkit). We used the default settings for MALLET with the following modifications: increasing 1) the number of intervals for Dirichlet hyperparameter estimation from 0 (the default) to 10, and 2) the output
Figure S2: Topic model quantitative evaluation metrics. In panel (a), coherent topics exhibit smaller absolute values for each metric. In panel (b), larger values correspond to more coherent topics. The number of topics is on the x-axis and the score for each metric is on the y-axis.

for the number of most probable words associated with each topic to 30 from 20.

**Topic model selection** Our model training procedure was silent on the number of topics that we would find in our data. Therefore, we performed a grid search over LDA topic models ranging from 25, 50, 75, 100, 150, to 200 topics. Evaluating the validity of topic models is a difficult task. To compare topic models, NLP researchers have devised different “topic coherence metrics.” These coherence metrics seek to capture the human readability of a topic along with its ability to depict major themes in documents. We used three leading topic model coherence metrics: held-out likelihood (“Wallach”), reflecting the degree to which a document held-out from model training is perplexing (Wallach et al., 2009), the “UMass” metric which defines coherent topics as those where the leading terms tend to co-occur across documents, with a weighting factor adjusting for the commonness of any given term (Mimno et al., 2011), and a normalized pointwise mutual information metric (“NPMI”) which extends the PMI metric to account for the union of co-occurring terms over their individual occurrences and increases the importance of term co-occurrence (Lau et al., 2014). We observed differing degrees of support across the LDA models in comparing these metrics (Figure S2).

We performed a qualitative “human-in-the-loop” inspection of the topics in addition to the coherence metrics above. For any particular context, DiMaggio (2015) note that combining expert assessment with quantitative coherence metrics better identifies which model best parses meaningful structure from text data. Based on the relative ranks of the topic models from the coherence metrics, we chose to focus on the 50, 75, and 100 topic models for expert review, performed by the co-authors.

In our qualitative analyses, we 1) examined the clarity of each topic (represented by its leading
3 terms), 2) reviewed the topic labels assigned to a set of validation tweets. We found that the 75- and 100-topic models had greater comprehensibility. For instance, we found that the 50-topic model tended to confusingly merge discrete issue areas such as climate change and marine species conservation. As an author team, we iteratively identified a taxonomy of issues that mapped across multiple topics, arriving at a set of 21 environmental issues and one catch-all “non-environmental” issue (Table S4).

In comparing the 75- and 100-topic model, the lead author and a skilled NLP researcher (N.R. Deshmukh) then inspected a validation dataset of tweets with their dominant topic labels. The validation dataset contained 440 tweets (20 tweets per issue area) as well as the leading topic labels assigned by the 75- and 100-topic models. The leading topic labels were determined based on the topic probability associated with that tweet-topic combination. For example, one validation tweet, “Amazing bird—a closer look at the Northern Shoveler”, was given a 0.5 document-topic probability for a 75-model topic containing terms such as “bird birding park one photo red nest”. We evaluated our degree of agreement on a three-point Likert scale (agree, neutral, disagree). Less than 8% of the validation tweets scored a “neutral” rating, and the “neutral” rating captured tweets that were difficult for even a human to interpret. As such, for each issue area and topic model, we then calculated the degree of agreement as $\frac{n_{agree}}{n_{agree} + n_{disagree}}$. Based on the agreement scores, we selected the 75-topic model.

3 Characterizing environmental discourse across issues and geographies

3.1 Processing user timelines and obtaining user covariate data

As shown in Figure 1, we initially had 1,004,913 user timelines. To be included in this analysis, accounts had to have location information and at least 25 English-language tweets written after November 2017; this filtered our sample to roughly 500,000 accounts. We used data from each user’s description field and their 10 most recent tweets to identify their location (Dredze et al., 2013). Based on the location requirement, we initially subset our data to 221,128 users. These users were located in 184 countries, but 14 countries contained the vast majority of our sample. To facilitate comparisons among countries, we therefore subset the data again to the 196,783 users who were located in those 14 countries.

For each user, we pre-processed the tweets in their timeline following the steps enumerated in Section 2. Our initial data structure was essentially a large matrix with $[N \times T]$ tweets. We then used the Valence Aware Dictionary and sEntiment Reasoner lexicon-based model (“VADER” for short, see Figure 1) to calculate a sentiment score for each tweet (Hutto & Gilbert, 2014). We
| Issue area                                           | Leading terms                                                                 | Topic areas |
|-----------------------------------------------------|-------------------------------------------------------------------------------|-------------|
| Agriculture                                         | nebraska, farmer, farm, corn, usda, soil, food, agriculture, organic, land     | 7, 71       |
| Animal welfare                                      | animal, help, wild, dog, rescue                                               | 27          |
| Climate action                                       | climate, vote, people, change, need, gretathunberg, climatestrike, action, future, strike | 10, 13, 46  |
| Belief in anthropogenic climate change (Climate belief) | climate, change, world, global, warm, emission, ice, arctic, datum, record    | 14, 15, 34  |
| Decarbonization policy (Climate policy)              | climate, COP, global, carbon, parisagreement, resilience, adaptation, disaster, security, development | 39, 42, 47  |
| Renewable energy (Climate renewables)                | energy, solar, power, clean, renewable, nuclear, wind, electricity, grid, cleanenergy | 2, 61       |
| Consumer dietary choices                            | food, meat, vegan, eat, diet                                                  | 38          |
| Corporate social responsibility (CSR)                | sustainability, business, company, green, CSR                                 | 50          |
| Fossil fuels                                         | oil, china, gas, market, energy, pipeline, fossil, carbon, fuel, coal          | 17, 48, 68  |
| Habitats and species                                 | nature, biodiversity, land, forest, bird, wildlife, conservation, tree, plant, whale | 3, 23, 29, 57, 66 |
| Marine                                               | ocean, marine, sea, fish, coral                                               | 26          |
| Birdwatching                                         | bird, birding, park, photo, nest, morning, warbler, audubon, reserve, owl     | 5, 35, 73   |
| Gardening                                            | species, bee, garden, nature, plant                                           | 11          |
| Hiking                                               | beautiful, nature, great, hike, lovely                                         | 55          |
| Hunting & angling                                    | hunt, fish, deer, day, season, wildlife, conservation, river, quail, trout    | 18, 56      |
| Environmental policy                                 | EPA, climate, administration, federal, sustainable, green, urban, rural, farmer, infrastructure | 9, 30, 74   |
| Pollution                                            | clean, air, water, health, EPA, plastic, waste, use, pollution, recycle       | 22, 52      |
| Public lands                                         | wildlife, public, national, land, interior, park, national, trail, day, findyourpark | 36, 58      |
| Transportation infrastructure                        | electric, transportation, mobility, transit, tesla, city, bike, public, lane, cycle | 12, 28      |
| Freshwater                                           | water, river, clean, drink, quality                                           | 20          |
| Extreme weather                                      | fire, california, forest, wildfire, smoke, hurricane, storm, weather, rain, flood | 21, 53      |

Table S4: Terms associated with each of the 21 environmental issue areas. The “Leading terms” field presents up to 10 distinctive terms associated with each issue area. “Topic areas” denotes which topics in the 75-topic model corresponded to each issue area.
also applied the trained 75-topic model to generate tweet-topic probability vectors. We then aggregated these numeric tweet-level data to the level of users. We calculated a sentiment vector, \( s = [T \text{ tweets} \times 1] \), and a topic-probability matrix, \( P = [T \text{ tweets} \times 75 \text{ topic probabilities}] \). Let \( i \) denote the \( i^{th} \) environmental issue, \( j \) the \( j^{th} \) tweet, \( k \) the \( k^{th} \) topic area, and \( \{i\} \) the set of \( k \) topic areas associated with each \( i^{th} \) issue (Table S4).

We converted \( P \) to a \([T \text{ tweets} \times 21 \text{ issue probabilities}]\) matrix by applying the following function to each row: \( p_j = \sum_{75}^{k=1} m_{j,k} \forall k \in \{i\} \) where \( p_j \) denotes the row-vector of issue probabilities, and \( m \) the tweet-topic probability for each of the 75 topic areas. We then calculated a user sentiment-issue matrix \( U = [T \text{ tweets} \times 21 \text{ issues}] \) by performing a matrix-vector multiplication given by \( U = Ps \) where each entry is given by \( p_{i,j} s_j \); note that \( p_{i,j} = \sum_{75}^{k=1} m_{j,k} \forall k \in \{i\} \) from above. Each user was then collapsed into a single environmental issue row vector with 21 entries, \( u \), by taking the column-wise mean of \( U \). Finally, we concatenated each \( i^{th} \) user’s \( u_i \) row vector, creating \( D \), a 196,783 user (row) by 21 issue (column) matrix. Initially, the values of \( D \) exhibited a tendency to be concentrated about 0. This corresponded to relatively infrequent discourse for multiple environmental issues. As an example, the vast majority of users may not frequently discuss corporate social responsibility in their Twitter timelines, thereby driving those values toward 0. We applied the Bickel and Doksum (1981) normalizing data transformation and took the absolute value of the entries, creating \( D^* \).

### 3.2 Multi-scale environmental discourse: intensity and prominence

We defined the matrix \( D^* \) as the input data for discourse intensity. For the comparisons of discourse intensity across countries, we calculated the mean value of \( D^* \) for each issue for all users located in each country. When we moved to a finer spatial scale–state or county in the coterminous US–we calculated a metric of prominence for each issue. We defined issue prominence by 1) calculating normalized intensity scores for each issue across all users in our dataset, 2) finding the mean value of the normalized scores at a state- or county-level, and 3) comparing the mean scores for the 21 issues within each state or county. We assigned a score of 1 for the issue that had the highest level of discourse among residents in each state or county and 21 for the issue with the least discourse.

### 4 Extended results

Table S5 displays discourse intensity for each of the 21 issues. Each row corresponds to an issue while the columns represent the 14 countries in our dataset. Mean values are displayed; values are aggregated across all individuals in each country.
| Issue                      | Australia | Canada | France | Germany | India | Indonesia | Ireland |
|----------------------------|-----------|--------|--------|---------|-------|-----------|---------|
| Climate action             | 0.394     | 0.379  | 0.377  | 0.383   | 0.376 | 0.37      | 0.385   |
| Habitats & species         | 0.361     | 0.346  | 0.343  | 0.337   | 0.348 | 0.348     | 0.349   |
| Climate belief             | 0.349     | 0.347  | 0.348  | 0.341   | 0.349 | 0.345     | 0.349   |
| Environmental policy       | 0.331     | 0.334  | 0.336  | 0.337   | 0.331 | 0.327     | 0.337   |
| Fossil fuels               | 0.318     | 0.337  | 0.319  | 0.32    | 0.318 | 0.316     | 0.321   |
| Transit infrastructure     | 0.303     | 0.308  | 0.3     | 0.302   | 0.305 | 0.296     | 0.312   |
| Pollution                  | 0.292     | 0.296  | 0.29   | 0.287   | 0.292 | 0.287     | 0.299   |
| Birdwatching               | 0.287     | 0.29   | 0.283  | 0.28    | 0.287 | 0.284     | 0.297   |
| Renewable energy           | 0.285     | 0.281  | 0.279  | 0.281   | 0.282 | 0.275     | 0.282   |
| Diets & consumer goods     | 0.276     | 0.278  | 0.27   | 0.272   | 0.274 | 0.27      | 0.276   |
| Climate policy             | 0.274     | 0.271  | 0.276  | 0.277   | 0.275 | 0.275     | 0.276   |
| Extreme weather            | 0.274     | 0.276  | 0.271  | 0.272   | 0.275 | 0.271     | 0.28    |
| Public lands               | 0.269     | 0.277  | 0.264  | 0.263   | 0.269 | 0.263     | 0.274   |
| Animal Welfare             | 0.268     | 0.268  | 0.265  | 0.26    | 0.268 | 0.266     | 0.266   |
| CSR                        | 0.262     | 0.259  | 0.259  | 0.253   | 0.261 | 0.257     | 0.262   |
| Hunting & angling          | 0.248     | 0.262  | 0.243  | 0.241   | 0.249 | 0.243     | 0.253   |
| Gardening                  | 0.246     | 0.246  | 0.242  | 0.241   | 0.246 | 0.239     | 0.256   |
| Hiking                     | 0.237     | 0.238  | 0.237  | 0.237   | 0.235 | 0.235     | 0.253   |
| Marine                     | 0.225     | 0.223  | 0.222  | 0.221   | 0.221 | 0.229     | 0.225   |
| Agriculture                | 0.223     | 0.227  | 0.223  | 0.217   | 0.222 | 0.218     | 0.226   |
| Freshwater                 | 0.21      | 0.214  | 0.206  | 0.204   | 0.211 | 0.205     | 0.21    |
Table S5: Mean discourse intensity for each issue across 14 countries with at least 1000 users (table continued).

| Issue                      | Kenya | Nigeria | Pakistan | South Africa | Spain | UK   | US   |
|----------------------------|-------|---------|----------|--------------|-------|------|------|
| Climate action             | 0.374 | 0.375   | 0.378    | 0.378        | 0.375 | 0.378| 0.386|
| Habitats & species         | 0.373 | 0.342   | 0.34     | 0.36         | 0.341 | 0.344| 0.344|
| Climate belief             | 0.347 | 0.339   | 0.341    | 0.346        | 0.346 | 0.344| 0.346|
| Environmental policy       | 0.33  | 0.33    | 0.326    | 0.335        | 0.341 | 0.33 | 0.34 |
| Fossil fuels               | 0.316 | 0.315   | 0.314    | 0.32         | 0.315 | 0.316| 0.317|
| Transit infrastructure     | 0.297 | 0.301   | 0.299    | 0.305        | 0.302 | 0.301| 0.309|
| Pollution                  | 0.291 | 0.289   | 0.287    | 0.294        | 0.293 | 0.294| 0.294|
| Birdwatching               | 0.29  | 0.286   | 0.287    | 0.291        | 0.29  | 0.294| 0.288|
| Renewable energy           | 0.279 | 0.281   | 0.274    | 0.286        | 0.279 | 0.276| 0.285|
| Diets & consumer goods     | 0.275 | 0.27    | 0.279    | 0.276        | 0.269 | 0.277| 0.278|
| Climate policy             | 0.279 | 0.281   | 0.268    | 0.275        | 0.275 | 0.269| 0.27 |
| Extreme weather            | 0.277 | 0.271   | 0.267    | 0.273        | 0.273 | 0.274| 0.282|
| Public lands               | 0.272 | 0.264   | 0.266    | 0.273        | 0.265 | 0.267| 0.287|
| Animal Welfare             | 0.273 | 0.253   | 0.267    | 0.274        | 0.268 | 0.266| 0.261|
| CSR                        | 0.261 | 0.253   | 0.253    | 0.26         | 0.251 | 0.256| 0.258|
| Hunting & angling          | 0.253 | 0.251   | 0.248    | 0.256        | 0.248 | 0.249| 0.271|
| Gardening                  | 0.245 | 0.24    | 0.243    | 0.248        | 0.244 | 0.251| 0.245|
| Hiking                     | 0.236 | 0.236   | 0.236    | 0.24         | 0.233 | 0.244| 0.234|
| Marine                     | 0.227 | 0.224   | 0.214    | 0.229        | 0.224 | 0.221| 0.221|
| Agriculture                | 0.225 | 0.222   | 0.218    | 0.222        | 0.22  | 0.222| 0.229|
| Freshwater                 | 0.206 | 0.212   | 0.207    | 0.216        | 0.209 | 0.208| 0.218|
Table S6 shows the spatial auto-correlation statistic for issue prominence analyzed across states in the coterminous US. Note that we include the District of Columbia as a distinct entity.

Table S6: Spatial auto-correlation statistic (Moran’s I) for each of the issues based on their ranking across U.S. states.

| Issue                             | Moran’s I | p-value |
|-----------------------------------|-----------|---------|
| Agriculture                       | 0.330     | 0.001   |
| Hunting & angling                 | 0.430     | 0.001   |
| Corporate Social Responsibility   | 0.280     | 0.003   |
| Public lands                      | 0.290     | 0.003   |
| Extreme weather                   | 0.290     | 0.003   |
| Diets & consumer goods            | 0.250     | 0.004   |
| Climate policy                    | 0.250     | 0.008   |
| Habitats & species                | 0.210     | 0.013   |
| Freshwater                        | 0.220     | 0.015   |
| Climate action                    | 0.180     | 0.027   |
| Birdwatching                      | 0.170     | 0.034   |
| Pollution                         | 0.140     | 0.064   |
| Renewable energy                  | 0.120     | 0.077   |
| Environmental policy              | 0.069     | 0.190   |
| Hiking                            | 0.055     | 0.240   |
| Animal Welfare                    | 0.041     | 0.250   |
| Gardening                         | 0.024     | 0.320   |
| Climate belief                    | -0.0004   | 0.360   |
| Transit infrastructure            | -0.034    | 0.550   |
| Marine                            | -0.070    | 0.680   |
| Fossil fuels                      | -0.110    | 0.820   |

Neighbor connectivity was assigned using Queen adjacency.
Table S7 provides the coefficient estimates for the mixed effect regression model visualized in the main text in Figure 4. The sample totalled 76,803 users located to 1,100 counties within the coterminous US. 9 counties had incomplete data and were removed, resulting in a total of 1,091 county-level observations. We also performed likelihood ratio tests for the four models against a null model with just an intercept and random intercepts for states (Bates et al., 2015); we applied the Bonferroni family-wise error correction to the results of these tests. We found support for our models ($p_{adj} < 0.05$ for each of the models below).

Table S7: Coefficients for mixed-effect model of county-level issue salience ($n = 1,091$).

| Variable          | Agriculture | Climate action | Hunting & Angling | Public lands   |
|-------------------|-------------|----------------|-------------------|----------------|
| Political Ideology| -0.41 (-0.69,-0.13) | 0.54 (0.31,0.77) | -2.1 (-2.5,-1.7) | -0.22 (-0.55,0.11) |
| Urban             | 0.66 (0.07,1.3) | -0.15 (-0.65,0.33) | -0.42 (-1.2,0.44) | -0.42 (-1.1,0.29) |
| Broadband         | 6.3 (3.2,9.3) | -7.9 (-10,-5.3) | 0.99 (-3.3,5.4) | -3.4 (-7,0.19) |
| Northeast         | 1.2 (0.36,2) | -0.89 (-1.6,-0.17) | 1.1 (-0.2,2.4) | 0.95 (0.02,1.9) |
| South             | 0.57 (-0.035,1.2) | -0.69 (-1.2,-0.14) | 0.11 (-0.9,1.1) | 0.11 (-0.57,0.8) |
| West              | 0.82 (0.041,1.6) | -0.71 (-1.4,-0.024) | 0.14 (-1.1,1.4) | -0.47 (-1.3,0.42) |
| $\chi^2_{df=6}$   | 65.8        | 90.2           | 121              | 17.7           |
| $p_{adj}$         | $1.2 \times 10^{-11}$ | $1.1 \times 10^{-16}$ | $4.7 \times 10^{-23}$ | 0.028 |

95% confidence interval calculated for covariates using profile likelihood.

As the prominence scores are bounded between 1-21, we performed a robustness check using a logistic mixed effects regression. We specified that the response was prominence as the number of successes and 21-prominence as the number of failures. Table S8 shows coefficient estimates for this logistic regression model. We observed that the coefficients have the same sign when comparing Tables S7 and S8. We also found that all of the significant variables in Table S7 are also significant in Table S8.

Table S8: Robustness check for modelled relationship between county-level issue salience using a logistic GLMM.

| Variable          | Agriculture | Climate.action | Hunting & Angling | Public lands |
|-------------------|-------------|----------------|-------------------|--------------|
| Political Ideology| -0.11 (-0.15,-0.065) | 0.22 (0.16,0.27) | -0.39 (-0.43,-0.36) | -0.031 (-0.066,0.0042) |
| Urban             | 0.14 (0.05,0.22) | -0.04 (-0.15,0.065) | -0.1 (-0.18,-0.028) | -0.081 (-0.16,-0.006) |
| Broadband         | 1.8 (1.3,2.3) | -3.3 (-3.8,-2.7) | 0.083 (-0.33,0.5) | -0.66 (-1.1,-0.26) |
| Northeast         | 0.44 (0.22,0.66) | -0.47 (-0.76,-0.19) | 0.24 (0.017,0.47) | 0.21 (0.054,0.37) |
| South             | 0.18 (0.012,0.36) | -0.32 (-0.55,-0.099) | 0.031 (-0.16,0.22) | 0.026 (-0.1,0.15) |
| West              | 0.29 (0.095,0.5) | -0.36 (-0.62,-0.096) | 0.03 (-0.18,0.24) | -0.1 (-0.25,0.047) |

95% profile likelihood confidence intervals presented.
Figure S3 shows the prominence for all of the remaining environmental issues that were not included in the main text across states in the coterminous US.

Figure S3: Issue prominence for all issues not displayed in the main text across states in CONUS.
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