Environmental Discourse Exhibits Consistency and Variation across Spatial Scales on Twitter

CHARLOTTE H. CHANG, PAUL R. ARMSWORTH, AND YUTA J. MASUDA

Social media platforms, such as Twitter, are an increasingly important source of information and are forums for discourse within and between interest groups. Research highlights how social media communities have amplified movements such as the Arab Spring, #MeToo, and Black Lives Matter. But environmental digital discourse remains underexplored. In the present article, we apply automated text analysis to 200,000 Twitter users in several countries following leading environmental nongovernmental organizations. Some issues such as public action to decarbonize society or species conservation were discussed more intensely than agriculture or marine conservation. Our results illustrate where environmental discourse diverges and converges on Twitter across countries, states, and characteristics, such as political ideology. Using the coterminous United States as a case study, we observed that the prominence of issues varies across states and, in some cases, covaries with political ideology across counties. Our findings show paths forward to characterizing environmental priorities across many issues at unprecedented scale and extent.

Keywords: biodiversity conservation, climate change communications, conservation social science, environmental social media, natural language processing

Conservation is fundamentally about human choices about the environment (Bennett et al. 2017, Díaz et al. 2019). Therefore, researchers have examined people's environmental values, beliefs, and attitudes (Stern et al. 1999, Bennett et al. 2017). International agreements, ranging from the Convention on Biological Diversity's Aichi targets to the sustainable development goals, highlight the urgency of catalyzing proenvironmental behavioral change among different stakeholders, including consumers, voters, and other constituencies (Reddy et al. 2017, 2020). One underexplored group that is highly promising for scalable mobilization are those engaged in environmental social media discussions (Ladle et al. 2016, Toivonen et al. 2019).

Without insight into digital constituencies, advocates lack the means to strategically engage the public online, especially those interested in conservation that may be most likely to act. Effective social media strategies hold great promise for accelerating widespread action for conservation. Democratic and social justice movements have used social media to amplify messages, organize mass action, and drive the formation of new policies (Freelon et al. 2018, Larson et al. 2019). Past environmental digital media research, also known as the field of conservation culturomics, has shown the promise of social media data (Ladle et al. 2016, Toivonen et al. 2019, Correia et al. 2021). Specifically, social media data can show differences between species in terms of public awareness or engagement (Roberge 2014, Cooper et al. 2019, Fink et al. 2020), as well as the impact of news media or documentaries on public perceptions of biodiversity (Papworth et al. 2015, Fernández-Bellon and Kane 2020).

Research focused on environmental social media has characterized public perceptions of nature recreation, citizen science, environmental nongovernmental organizations (eNGOs), differences in public interest across taxa, and disaster responses to extreme weather events (e.g., Kirilenko and Stepchenkova 2014, Cody et al. 2015, Jang and Hart 2015, Daume and Galaz 2016, Becken et al. 2017, Schwartz et al. 2019, Barrios-O'Neill 2021, Jaung and Carrasco 2021). The field of conservation culturomics has used these data to describe human–nature interactions and perceptions across a wide range of spatial and temporal scales, highlighting dynamics such as responses to seasonal biological migration or evaluating which species receive high public engagement (e.g., Roberge 2014, Fink et al. 2020). Nevertheless, previous environmental social media research has exhibited one or more of the following constraints: It has been solely focused on individual issue areas (e.g., belief in anthropogenic climate change) or has used a small, nonrepresentative

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sample (Kirilenko and Stepchenkova 2014, Cody et al. 2015, Daume and Galaz 2016, Barrios-O'Neill 2021); used nontextual features such as location data (Jaung and Carrasco 2021); or assessed public mobilization with a small number of followers for individual organizations (Coppock et al. 2016, Foos et al. 2020). To our knowledge, past research has not characterized the environmental priorities of a large sample of users on Twitter, a leading social media platform. In this study, we build on the concept of environmental Twitter introduced by Clark (2009) in sampling a population of individuals discussing a broad range of environmental issues. Characterizing the landscape of social media environmental discourse has actionable implications for mobilizing the digital public for biodiversity conservation.

We advance research on social media platforms for conservation advocacy and research in several ways. We scraped users actively following organizations with proenvironmental missions. We identified which issues stimulated particularly vociferous discussion among English-speaking Twitter users around the globe. Next, we identified significant convergence and divergence in environmental issue discourse across user characteristics and geographies. We illustrate how our approach can reveal spatial variation in the importance of issues within countries by focusing on the coterminous United States as a case study. State- and county-level analyses can provide useful insights into wider debates around environmental priorities in an era of political polarization and a growing rural–urban divide (Dunlap et al. 2016, Scala and Johnson 2017). Our study provides important insights regarding issue mobilization and discourse patterns for conservation actors and environmental social science researchers.

What environmental issues are discussed on Twitter and how?

We defined our starting point as the 7 million accounts following one or more leading eNGOs. To our knowledge, there is no data set that has identified a full and systematic set of eNGOs and their associated social media accounts. As such, we used technical reports from the Urban Institute and Green 2.0 that focused on organizations with public visibility to identify 39 eNGOs that had a social media presence on Twitter (please see the supplement for more details). Our workflow for systematically querying and processing data from Twitter's application programming interface is shown in figure 1. Below, we describe each step shown in the research schema.

Of the 7 million follower accounts, we analyzed the timeline—each user's most recent 3200 tweets—of 2 million users that we bot checked using the Botometer algorithm (Davis et al. 2016). Botometer has been independently validated by the Pew Research Center (Wojcik et al. 2018) and social media research (Varol et al. 2017). We randomized the order of the 7 million follower accounts on the basis of the relative counts of followers for each of the 39 eNGOs that initiated the sample. Therefore, when we queried accounts to be bot checked, we ensured that the 2 million bot-checked accounts would preserve the same general pattern as the 7 million followers.

We evaluated the sensitivity and specificity of the Botometer algorithm. Our first analysis focused on the comprehensive bot metric of complete automation probability English, which we used to determine which accounts were likely bots or humans. We found that our threshold value was appropriate for the data (supplemental figure S1). This threshold value was also supported by past research (Varol et al. 2017, Wojcik et al. 2018, Zhang et al. 2019). Please see the supplement's section 1.2.2 for more details.

Of the 1 million nonbot users in the data set, we ultimately limited our data to approximately 500,000 users who satisfied our inclusion criteria: posting at least 25 tweets in English since 7 November 2017, when Twitter instituted its 280-character rule for tweet length. Of those 500,000 users, we then focused on approximately 220,000 users who had location data. We then limited the sample to countries that each had at least 1000 users to facilitate comparison across countries. This produced a final sample of around 200,000 users in 14 countries, including the United States. For the roughly 126,000 American users in our data set, we estimated their political ideology using Tweetscores, which has been validated against millions of voter file records (Barberá 2015, Barberá et al. 2015).

We compared a sample of 100 bot accounts, the 220,000 geolocated users, and the approximately 280,000 users who did not have location information. We found that the bot accounts differed substantially from the human accounts, which included the geolocated and nongeolocated users (supplemental tables S2 and S3). However, although the nongeolocated users posted at slightly higher rates than the geolocated users and had fewer followers on average, their user description fields indicated broad overlap in the types of accounts that did and did not have location information (tables S2 and S3).

Subsequently, we characterized environmental discourse by applying two text models to the user timelines: a sentiment model developed for Twitter text data (Hutto and Gilbert 2014) and an unsupervised machine learning text model that we developed and trained. We opted to identify distinct issues emerging in environmental discourse from an inductive approach, using an unsupervised text model; to our knowledge, there has not been a comprehensive inductive or deductive identification of the environmental issues discussed on social media. Therefore, we felt it was most appropriate to determine what issues emerged from the environmental social media data. To identify distinct environmental issues, we trained a probabilistic latent Dirichlet allocation topic model on Twitter data from over 11,000 environmental pundits.

We identified these environmental pundits by snowball sampling Twitter lists using the 39 eNGOs as an initial sample of environmental voices. Researchers have used Twitter lists to crowdsource leaders of political parties, consumer product influencers, or central individuals for certain group identities or issue affinities (Culotta and Cutler 2016). When using topic

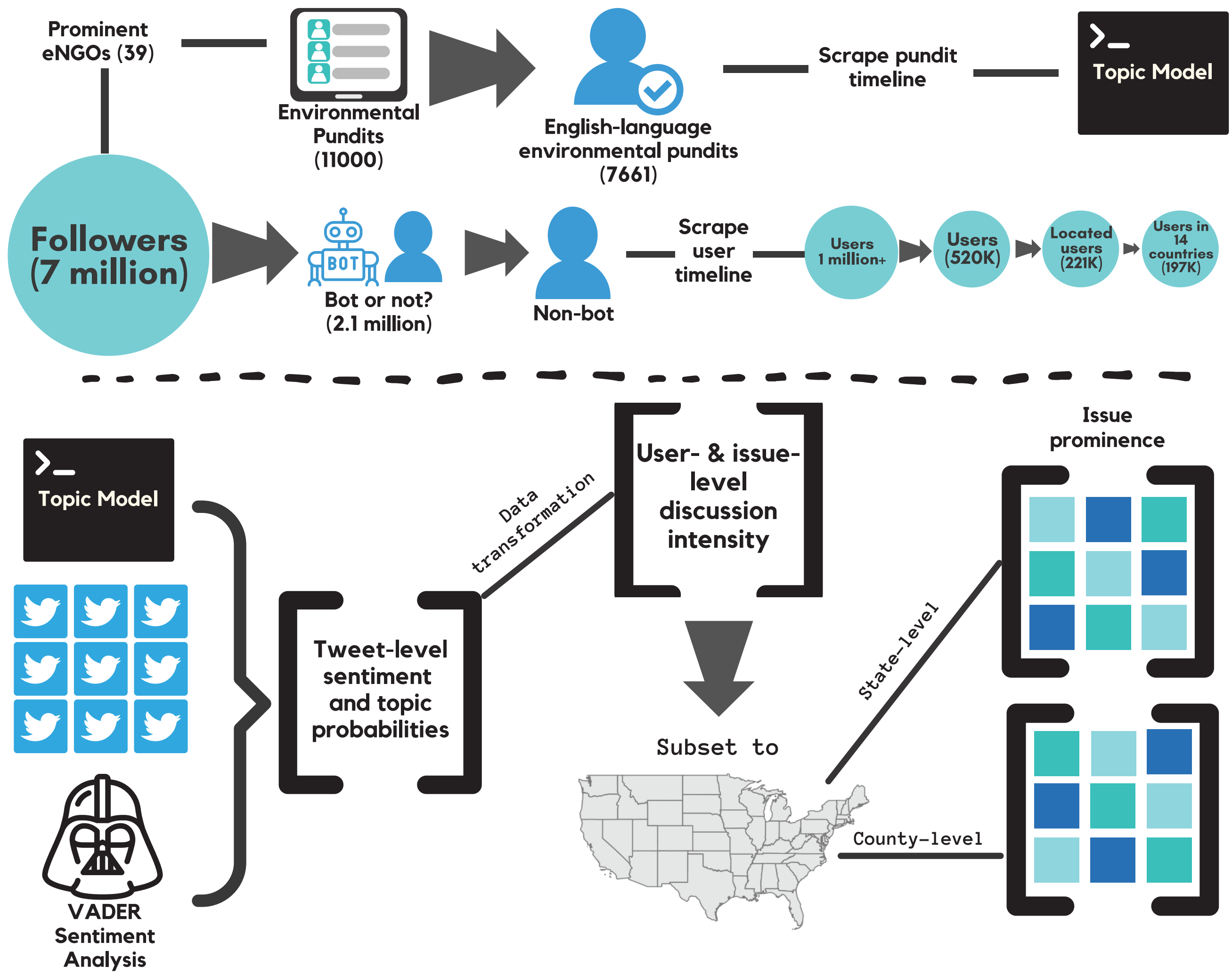

Figure 1. Research schema for obtaining environmental discourse data from Twitter and processing the data to identify discourse intensity across countries as well as issue prominence within the coterminous United States. The arrows represent procedures for whith the data were filtered. The lines represent input–output (left to right) processes. The right brace denotes variables that were combined together.

models, researchers must determine the number of topics that are appropriate. Typically, these topics are then aggregated into distinct issue areas using expert interpretation (DiMaggio 2015). We used coherence metrics and expert assessment among the three coauthors to determine the number of topics that most appropriately partitioned the data. Ultimately, we found that there were 21 distinct environmental issues, which ranged from mass mobilization for climate change mitigation (climate action) to public lands to marine conservation.

In the analyses below, we compared discourse patterns involving the 21 environmental issues that emerged from our text analysis. We focus on two metrics. The first is intensity, which depicts both the rate at which each issue was discussed (topic probability, which ranges from 0 to 1) and the degree to which discourse pertaining to that issue is opinionated relative to objective speech (sentiment scores, which range from –1 to 1). Our intensity metric arose from taking the absolute value of a normalizing data transformation applied to user discourse data; as such, intensity is dimensionless. The second metric is prominence, which represents how much users in a given locality discuss an issue relative to all other environmental issues. We calculated issue prominence by first normalizing all intensity scores across all issues and users in the data set, finding the mean value of normalized scores at a particular geographic scale (e.g., state or county), and then finally calculating the ranks of these scores. Similar to intensity, issue prominence does not have dimensions. Please see the supplement's section 3.1 for the mathematical specification of these metrics.

To show how Twitter and social media data can reveal patterns in environmental attitudes and issues at subnational scales, we focused on the United States, where there is also a body of research describing patterns in environmental priorities that can be used to assess how informative these data are. We used a mixed effects regression model to examine covariation between political ideology, rurality (US Department of Agriculture Economic Research Service 2020), and county-level issue prominence (R_{issue}) for agriculture, climate action, hunting and angling, and public lands (Bates et al. 2015). We selected these four issues because of their importance to environmental conservation in the United States. Our users were located in 1100 counties. We included random intercepts for states to account for cultural and spatial variation. We accounted for regional impacts using the census region as a covariate and county-level access to social media using internet penetration (Tolbert and Mossberger 2020). Our variables of interest were the median political ideology score of users in each county and county rurality. For each issue, we specified the following regression model (equation 1).

$$R_{issue} \sim \alpha + \zeta_{state} + \beta_{political\ ideology} + \beta_{urban} + \beta_{broadband\ internet} + \beta_{census\ region} \tag{1}$$

We did not observe violations of model assumptions and also performed a robustness check. We used variance inflation factors to ensure that the chosen independent variables did not exhibit multicollinearity. All analyses were performed in R (version 4.0.2) and Python (version 3.7).

How are environmental issues discussed on Twitter?

Discourse intensity represents the frequency with which each environmental issue is discussed and its emotionality relative to neutral speech. Across countries, discourse intensity tended to be consistent across issues (figure 2a).

Climate and terrestrial conservation issues are discussed more intensely on Twitter. Public mobilization for decarbonization (climate action), belief in anthropogenic climate change (climate belief), and habitat and species conservation exhibited particularly high levels of intensity (see also supplemental table S5). Marine and freshwater issues were discussed at roughly half of the intensity of the leading climate and conservation issues. Within the broader umbrella of climate, some issues were discussed much more intensely; action and belief were discussed 1.3 to 1.4 times as much as climate policy, which focused on adaptation strategies or international treaties such as the Paris Agreement, or renewable energy, which focused on power generation via solar panels, wind turbines, or other technologies. However, despite the broad consistency across countries in discourse intensity, there were also several issues which showed diverging patterns.

Discussions of some issues vary in intensity among countries. There were greater cross-country differences in discussion intensity among the most intensely discussed topics. Users in the United States and Australia exhibited significantly higher levels of discussion intensity for climate action compared with other countries. Kenyan and Australian users intensely discussed habitat and species issues. Two issues that US users discussed with marked intensity were public lands (figure 2b) and hunting and angling (figure 2c); figures 2b and 2c display normalized discussion intensities showing that public lands or hunting are discussed at a much higher level of intensity in the United States than in other countries.

Prominent issues vary across regions and states. We used the coterminous United States as a case study to demonstrate how subnational analyses can reveal how the importance of environmental issues varies significantly across regions such as provinces, states, or counties. In the present article, we examine issue prominence, which is a measure capturing how much users discuss particular issues relative to other issues. Issue prominence ranks the average intensity of discussion across all issues in each locale (e.g., state or county). Across states in the coterminous United States, hunting and angling, public lands, and agriculture were among the most prominent issues; on average across states, these issues were twice as prominent as the lowest-ranked issues of renewable energy, corporate social responsibility, and climate policy.

We used the spatial autocorrelation statistic, Moran's I, to examine which issues exhibited clear spatial variation within the coterminous United States. We found that 11 issues clearly evinced systematic spatial variation on the basis of the Moran's I statistic (supplemental table S6). Of those issues, we focused on analyzing state-level differences in the importance of agriculture, climate action, public lands, hunting and angling, habitat, and freshwater conservation (Moran's I scores for these issues ranged from .18 to .33 and were all statistically significant; see supplemental table S6).

Our data indicate that certain issues are more prominent in some regions and states than in others. For example, if we look at discourse prominence across states for hunting and angling (figure 3), we see that this issue is more prominently discussed by residents in the Midwest, the Southeast, and some parts of the Northeast. Taking the Northeast as an example, hunting and angling were prominently discussed in Maine and New Hampshire but declined sharply in prominence for residents of Vermont, New York, Massachusetts, and New Jersey, before rising in prominence again in Pennsylvania. Agriculture showed a pattern of greater discussion prominence in the Midwest and the South. Overall, public lands exhibited a pattern of greater prominence in the American West alongside other states across the United States. Climate action was primarily prominent along the West Coast and in several states such as Illinois. On the other hand, the prominence of habitat and freshwater discourse did not exhibit clear patterns across the coterminous United States. Looking across the remaining 15 environmental issues, we also observed varying patterns of issue prominence (supplemental figure S2). For instance, birdwatching was a more prominent issue in the interior of the United

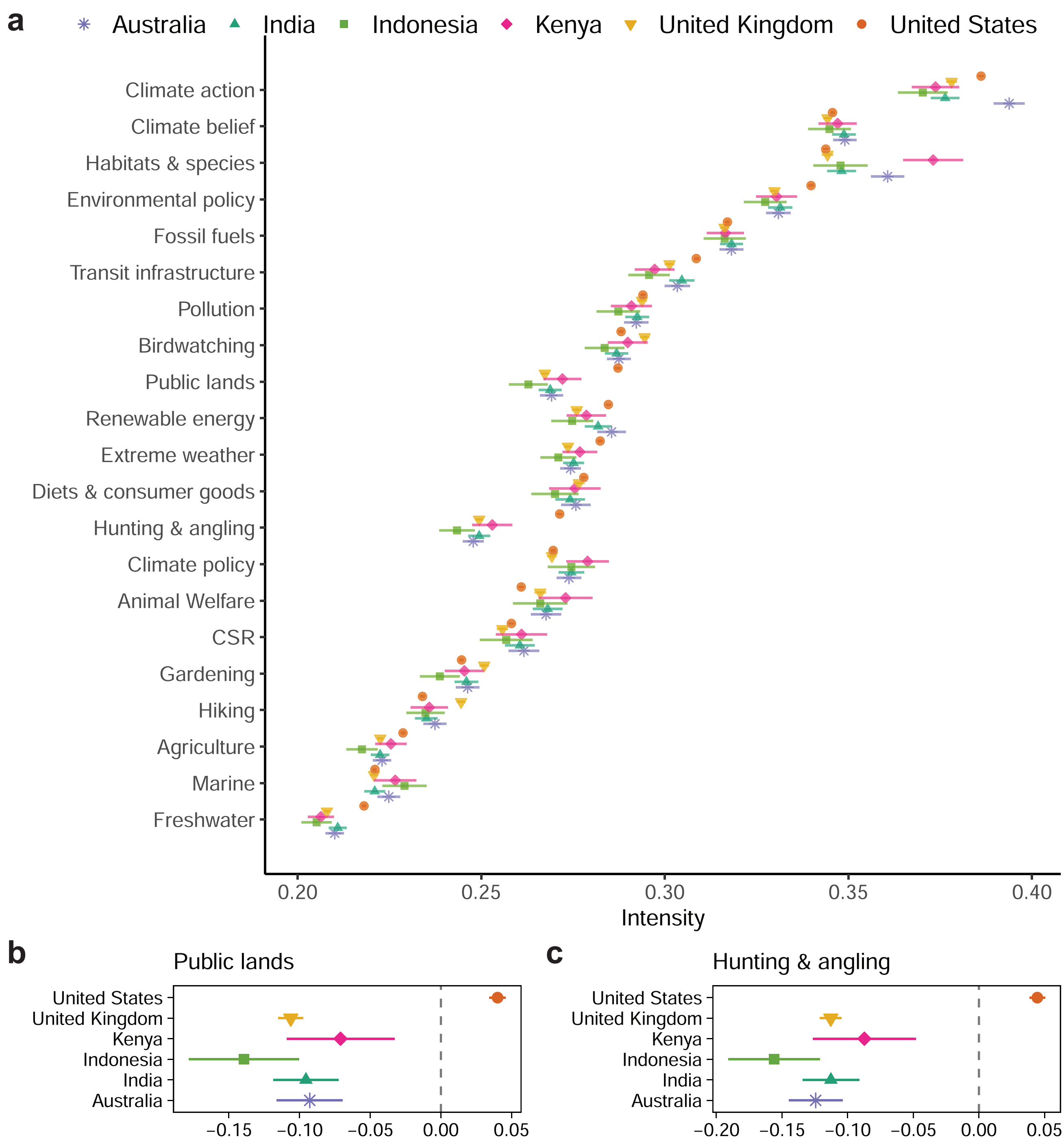

Figure 2. The intensity of discussion for 21 environmental issues. Our metric of discourse intensity is unitless. Discourse intensity as a function of issue across all users in six countries (a); the issues are ordered in terms of descending discussion intensity on the basis of the values observed among United States–based users. The subplots depict normalized discussion intensity for public lands (b) or hunting and angling (c) across the six countries. For all figures, the mean and 95% confidence interval are depicted. Abbreviation: CSR, corporate social responsibility.

States. On the other hand, some issues such as corporate social responsibility or climate policy were not prominent in the majority of states but were highly prominent in states such as California and New York.

US environmental discourse on Twitter shows patterns of political polarization. Finer spatial resolution of social media data allows us to examine how social or demographic factors relate to discourse on environmental issues. We examined

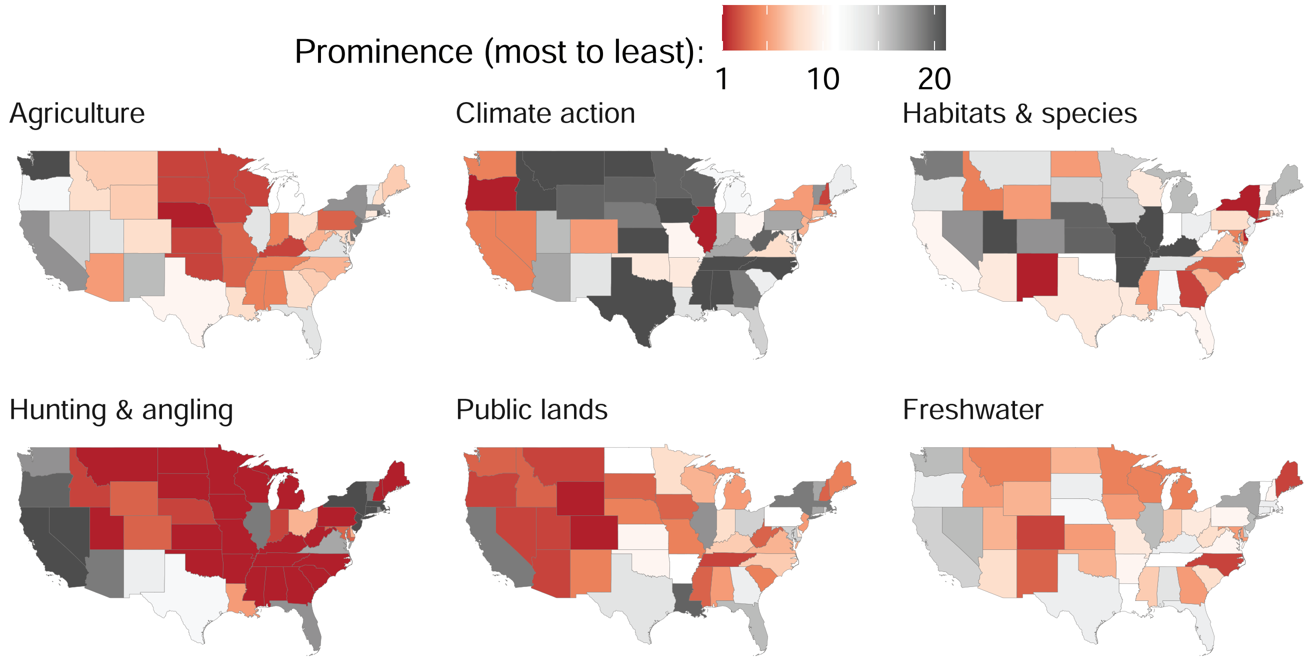

Figure 3. Issue prominence for residents in each state (n = 119,416). The issue prominence metric does not have units and presents the ranking of issues within a state. A value of 1 indicates that a given issue was the most prominently discussed issue among the residents in that state.

how environmental discourse covaries with political ideology and rural–urban gradients by resolving our data to county scale within the coterminous United States. We focused on the prominence of agriculture, climate action, hunting, and public lands discourse across counties; these issues are important to applied conservation and may exhibit political polarization. It was unclear whether these environmental social media data would exhibit comparable patterns given the fact that they include users actively following eNGOs.

Figure 4 illustrates relationships between the prominence of the four issues and political ideology and rurality. Agriculture, hunting and angling, and climate action varied significantly in prominence as a function of political ideology (figure 4a), with users in right-leaning counties exhibiting more prominent agriculture and hunting and angling discourse after controlling for the effect of state, rurality, and broadband penetration. Climate action was more prominent in left-leaning counties. Only agriculture exhibited different levels of prominence across the rural–urban gradient. Agriculture was significantly more prominent for users in rural counties, after controlling for state, political ideology, and broadband penetration (figure 4b).

Environmental discourse on Twitter differs across issues and spatial scales

We systematically characterized environmental discourse on Twitter, finding a diverse set of perspectives across and within countries. Globally, issues such as climate or habitat and species conservation were much more intensely discussed, and we observed general consistency in the intensity of environmental issue discussion across countries. However, issues such as public lands or hunting clearly varied in intensity between the United States and other countries. Using the coterminous United States as a case study, we observed that issues varied in their prominence across states. The county-level analysis indicated political polarization for agriculture, climate action, and hunting, and a rural–urban difference for agricultural discourse.

Our results provide new foundational insights for environmental social media analyses while reinforcing related environmental discourse findings. We found that climate change-related issues, such as mobilizing the public to combat global warming (climate action), and belief in anthropogenic climate change had consistently high intensity, in line with climate communications research (Kirilenko and Stepchenkova 2014, Cody et al. 2015, Jang and Hart 2015, Moore et al. 2019). At the same time, our data yielded insights about habitat and species discourse, public lands, and freshwater conservation that we would not have expected given the dearth of prior knowledge.

Within our data set, we observed differences in discussion intensity across countries despite a generally consistent pattern. Deviations away from background levels of discussion intensity may reveal which issues are especially compelling in specific countries, such as public lands and hunting in the United States or climate action in Australia. The unprecedented scale and extent of social media data also permit subnational analyses that can parse finer grain variation. Within the coterminous United States, our findings for hunting

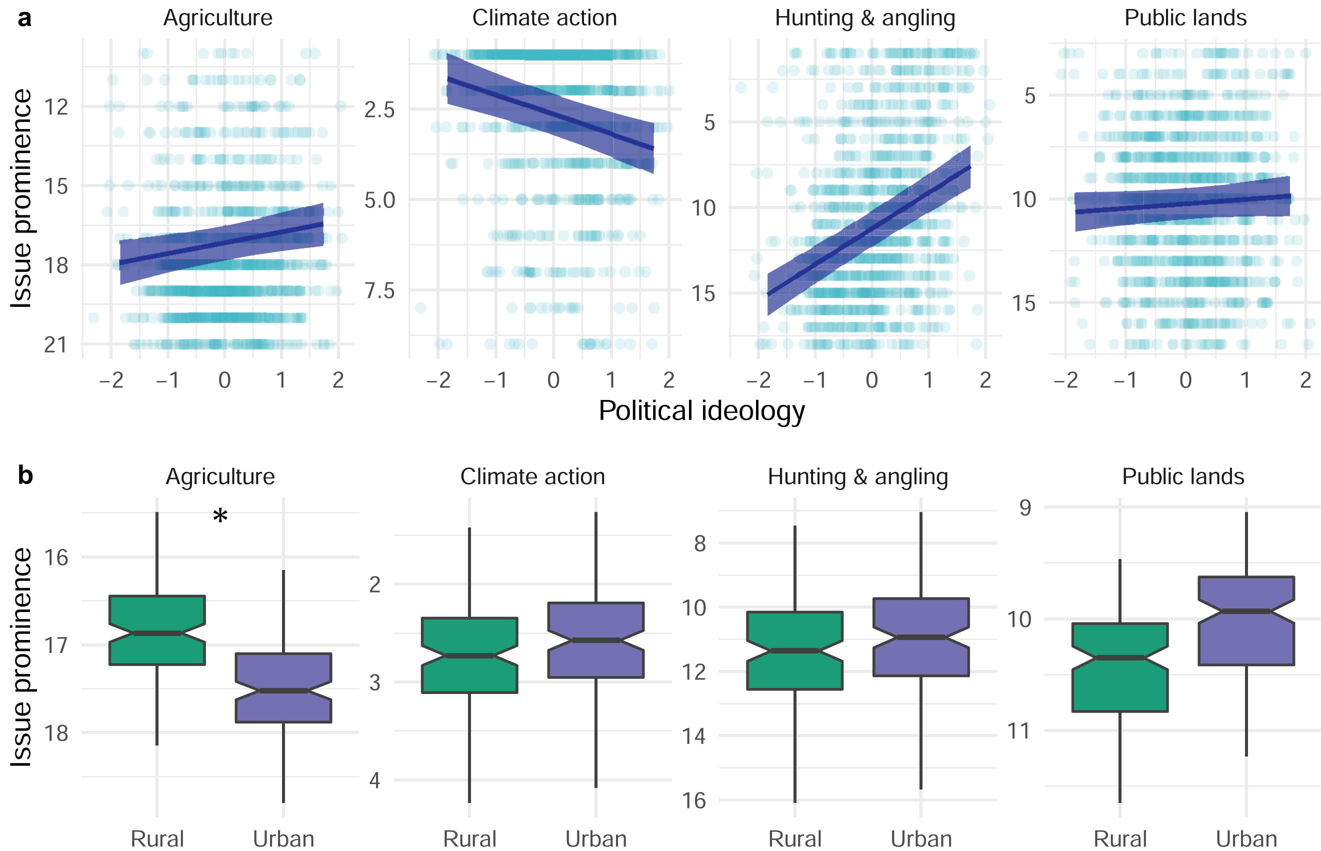

Figure 4. Modeled predictions for issue prominence from a regression model including political ideology and rurality after controlling for state and broadband penetration (n = 1091 counties). Panel (a) displays observed county-level issue importance using slightly transparent dots; the line and band displays the mean and 95% confidence interval for model prediction. In panel (b), the asterisk (*) denotes a significant difference in issue prominence between rural and urban counties based on supplemental table S7.

and agricultural prominence broadly aligned with survey or economic data for these issues (Duda et al. 2019, US Department of Agriculture National Agricultural Statistics Service 2021). The prominence of climate action across states echoes high-resolution opinion data from the Yale Program on Climate Change Communications (Maibach et al. 2011, Howe et al. 2015). Recovering known state-level patterns, as well as demonstrating novel variation, emphasizes the promise of analyzing social media to cast light onto environmental perceptions in understudied regions.

Survey and voting data suggest troubling divisions regarding important environmental issues, such as belief in anthropogenic climate change, decarbonization, or public lands regulation along lines of partisan identity (Dunlap, McCright, and Yarosh 2016, Johnson and Schwadel 2019) or rurality (Howe et al. 2015, Scala and Johnson 2017). It was unclear whether those same patterns would emerge for digital environmental constituencies. Political ideology correlated with the prominence of climate action, agriculture, and hunting discourse. Our climate action results align with findings that US conservatives exhibit less belief in anthropogenic climate change and are more opposed to decarbonization (Dunlap, McCright, and Yarosh 2016). Among users in our data, rurality may not be a strong factor shaping public environmental perceptions. However, our sample may be more digitally engaged than the average resident, and there are known issues of representativeness in rural areas for social media data (Barberá and Steinert-Threlkeld 2020). Our results underscore how social media data support new inquiries into the impacts of fine-scale socioeconomic factors on environmental attitudes.

Nevertheless, our data and findings inevitably have several important limitations. Our study was confined to primarily anglophone users on Twitter; future research can and should extend the automated text analysis approaches used in the present article to other global communities. The composition of social media users can be skewed relative to a regional or national population at large. Namely, social media users tend to be younger, more left leaning, and can also differ in educational attainment and gender composition (Barberá and Steinert-Threlkeld 2020). In addition, for bridging the value–action gap, analyses must move beyond individual issues to the totality of a person's worldview. Segmenting users into groups on the basis of shared environmental expressions could permit for identifying in-group messengers to more effectively advocate for conservation (Maibach et al. 2011, Jones et al. 2019, Chang et al. 2022). Moreover, given that eNGO industry reports have focused historically on organizations headquartered in the United States (Straughan and Pollak 2008, Green 2.0 2018), future work could seek to broaden the set of organizations and users for environmental discourse analyses. However, at present, the United States is the largest source of Twitter's users, likely composing 35%–40% of Twitter's user base (Statista 2022).

Conclusions

We observed that climate change and habitat or species conservation topics were among the most intensely discussed environmental issues on Twitter. There was broad consistency among countries in terms of their average environmental discourse intensity. However, there were also differences, such as the increased intensity of public lands or hunting discourse in the United States compared with other countries. Within the coterminous United States, there was spatial variation in the prominence of environmental issues, and results suggesting political polarization but a more limited rural–urban impact on environmental issue prominence. It is imperative that environmental advocates identify effective public communication strategies on social media platforms. We provide an advance for applied conservation in an era of mass digital communication by spatially characterizing discourse intensity for a wide range of environmental issues discussed on social media. Evaluating how environmental issue discourse changes in intensity or prominence across spatial scales—from countries to states or provinces to localities—permits for multiscale public engagement planning at the scale and pace of social media discourse.

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Supplemental material

Supplemental data are available at *BIOSCI* online.

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Charlotte Chang (chchang@pomona.edu) is an assistant professor in the Department of Biology and Environmental Analysis Program at Pomona College, in Claremont, California, in the United States. Paul Armsworth (p.armsworth@utk.edu) is a professor in the Department of Ecology and Evolutionary Biology at the University of Tennessee, in Knoxville, Tennessee, in the United States. Yuta Masuda (ymasuda@tnc.org) is a senior sustainable development and behavioral scientist in global science with the Global Science Program at The Nature Conservancy, in Arlington, Virginia.