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Research Report

A value-based topography of climate change beliefs and behaviors

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Abstract

While research has documented clear regional differences in environmental attitudes and behaviors, less is understood about the role of shared moral values in shaping these variations. This gap poses a critical challenge to designing effective climate action strategies. Many environmental initiatives rely on "moral framing" to promote proenvironmental behavior, often targeting specific geographical areas like cities or counties. However, these strategies may falter if they fail to account for the unique moral landscapes that shape climate beliefs and actions in different regions. To maximize the success of these interventions, it is crucial to understand how collective moral values influence environmental engagement across diverse communities. Across two studies, we offer insights at the collective level into the moral psychology of climate change by investigating how county-level moral values can predict (i) green attitudes and (ii) household carbon emissions within those counties after accounting for political behavior and region-specific factors. Using Bayesian geospatial modeling, we find that counties that endorse purity and fairness show higher environmental concerns and lower emissions across 3,102 US counties in 48 states. While political orientation strongly predicts environmental attitudes, moral values appear to be a more important factor in predicting carbon footprints. We discuss how county-level dynamics deviate from individual-level dynamics. Our community-level evidence can be leveraged to enhance green interventions on a regional scale by aligning them with the local populace's prevailing values and lived experiences, thus bolstering public support and increasing the likelihood of successful climate action initiatives.

Keywords: morality, climate change, spatial modeling, county-level analysis

Significance Statement

Our research enhances understanding of climate action by examining the influence of moral norms on green attitudes and household carbon footprints (HCFs) at the county level across the United States. Using Bayesian geospatial modeling, we demonstrate that moral norms uniquely predict green attitudes and HCFs, controlling for diverse factors from political behavior to temperature anomalies and population density. Counties where purity and fairness norms are prevalent show higher environmental concern and lower emissions, while those where authority norms dominate tend to have higher emissions and less green engagement. These findings highlight the complex, spatially varying relationship between moral values and climate action, emphasizing the need for tailored, evidence-based interventions at the community level.

Introduction

Climate change poses a significant global challenge, but its effects vary significantly from region to region. Past research suggests that climate change attitudes, such as recognizing climate change as a real, human-induced, and negative phenomenon, are not uniformly distributed across different regions. For instance, in the United States, coastal and urban areas express greater concerns about climate change, while more rural and inland states show less. Specifically, belief in the reality of global warming is widespread in Hawaii and the District of Columbia (75–81%), but considerably lower in West Virginia and Wyoming (54–55%). Similarly, the conviction that human activity is the primary driver of climate change is more prevalent in states like California and New York, while lagging in Wyoming and West Virginia. Counties in California, particularly urban centers like San Francisco, also demonstrate strong support for regulating carbon dioxide (CO_2) as a pollutant and embracing renewable energy policies (79%). On the other hand, rural areas, especially in states like Kentucky and Arkansas, where industrial and fossil fuel-based economies dominate, show lower levels of belief in global warming (as low as 43% in Trimble County,

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Kentucky) and are less supportive of policies that regulate emissions or encourage renewable energy use (1).

Regional variation in green behaviors has also been documented. Urban areas with high population density, such as New York City and San Francisco, generally have lower household carbon footprints (HCFs) (around 40 tCO_2e per household) due to factors such as smaller home sizes, reduced commuting distances, and access to public transportation (2, 3). In contrast, suburban areas like those surrounding Houston and Atlanta show higher HCFs (often exceeding 50 tCO_2e) due to larger homes, longer commutes, and car dependency. Consequently, states with sprawling suburban developments, such as Texas and Georgia, exhibit higher CO_2 emissions per household, whereas denser states with well-planned urban centers, like New York and California, demonstrate lower emissions (2). Furthermore, regions with economies heavily reliant on fossil fuels might resist climate change policies, perceiving them as threats to local economic stability (4). However, state-level incentives, such as subsidies for renewable energy, play a crucial role in shifting attitudes and encouraging greener practices (5).

These variations are often aligned with the demographic, cultural, and ideological compositions of these areas, as individuals with similar profiles tend to live in closer proximity (6–9). For instance, rural areas with predominantly conservative populations may be less likely to perceive climate change as a significant threat, as their ideological affiliations often prioritize economic growth over environmental regulation (9). Conversely, urban regions with higher concentrations of liberal and highly educated individuals tend to exhibit stronger support for climate action, often linking extreme weather events to broader patterns of global climate change (6). Furthermore, people from different regions interpret their personal experiences with climate events differently, shaping their perceptions and beliefs. For example, individuals in coastal areas frequently exposed to hurricanes or rising sea levels may develop a heightened concern about climate change, while those in arid regions experiencing drought might frame these events in terms of water management rather than global warming (10–12).

While geography and demographics directly shape climate change attitudes and actions, moral values also play an indirect yet pivotal role, as they vary significantly across regions. Past research used the moral foundations theory (MFT; 13) to document these spatial variations (14–16). MFT, which posits moral judgments, is rooted in "gut level" intuitions regarding care, fairness, loyalty, authority, and purity. Each foundation has developed in response to culturally chronic problems in the social world. Care is rooted in people's empathy and compassion in an interpersonal context, while Fairness involves belief in reciprocity and justice. Loyalty stresses the importance of unity and community protection. Authority centers around the tendency to maintain social order and traditions, while Purity is about physical and spiritual cleanliness in terms of valuing sacredness (13).

Geographical variations in moral foundations emerge from interactions of ecological, social, and historical influences. For example, in the United States, fairness and care are more prevalent in coastal areas such as the Northeast and West Coast, while loyalty, authority, and sanctity dominate in rural areas of the Midwest and Southern states. These patterns reflect how resource scarcity and environmental threats heighten loyalty and authority concerns as survival necessitates group cohesion (17). High relational mobility fosters care and fairness to support trust-based relationships, while urbanized, diverse regions emphasize inclusivity, contrasting with rural areas' focus on loyalty and respect for authority (18). Pathogen prevalence in certain areas strengthens purity, hierarchy, and ingroup loyalty to reduce infection risks from outsiders (19), highlighting how diverse conditions shape moral concerns across regions. These geographical variations in moral values have been shown to predict important real-world outcomes, such as county-level hate-group activities (15) and COVID-19 vaccination rates (16).

Moral norms can shape regional climate change attitudes by influencing how communities collectively interpret and respond to environmental challenges. For example, in a region experiencing extreme heat waves, residents might be more inclined to acknowledge climate change and adopt eco-friendly behaviors. However, if the dominant moral norms prioritize loyalty to traditional industries like coal or oil, people may downplay or dismiss the evidence, viewing climate action as a threat to their way of life. This can lead to a collective stance that contradicts the environmental realities they face. Indeed, moral norms act as a filter through which scientific information is interpreted and prioritized, sometimes leading to the selective acceptance or rejection of evidence based on moral alignment (8). Consider the example of purity norms. Past research has shown that in regions with a high prevalence of infectious diseases, people often develop strong moral values centered around purity and cleanliness (20, 21). These purity norms serve as psychological strategies to cope with the visible threat of pathogens, encouraging behaviors that help prevent disease spread.

Similarly, climate change represents a significant environmental threat that could possibly provoke comparable responses. Communities may become more attuned to purity values as a means to cope with the climate crisis, viewing the environment as something pure and sacred that must be shielded from contamination—whether in the form of germs or pollution. This moral perspective could lead people to adopt protective behaviors and support policies that aim to preserve the integrity of the natural world, responding to climate change not only as a practical issue but as a matter of safeguarding environmental purity.

A large body of work has shown that personal moral values predict personal climate attitudes and actions (22–25). However, the relationship between regional moral norms and collective environmental attitudes and actions involves unique dynamics. Unlike individual-level values, which vary widely within a population, regional averages in moral concerns reflect shared norms that shape collective moral values. Individual values are influenced by psychological factors such as environmental knowledge, education, political views, direct exposure to environmental impacts (e.g. natural disasters, pollution), and income (26, 27). However, region-level green norms and collective environmental actions are shaped by region-level factors such as local industries, economic dependencies, political climate, population density, and urban planning.

One key application of the moral psychology of climate change is the use of "moral framing" techniques, which tailor green interventions to align with specific moral values (28). Since green interventions are sometimes implemented at geographic levels such as cities, counties, and states, understanding regional variations in climate beliefs and moral values is essential to ensure their effectiveness and success (29–31).

The present work

In the current work, we offer a new perspective on the moral psychology of climate change by investigating how collective moral values can shape collective green attitudes and behaviors. Our first study uses county-level estimates of moral concerns to predict green concerns (e.g. beliefs regarding the reality, human causation, and negative impacts of climate change) after controlling for climate-relevant variables such as anomalous temperature and precipitation measures and other important demographic factors such as education and income and political leaning of the county, population density, and urban–rural ratio. The aggregate-level estimates of moral concerns conceptually serve as proxies for moral norms, as they represent the average scores for each moral foundation within a given county.

Another contribution of the current work is the inclusion of an ecologically valid metric of region-level proenvironmental behavior. Given that a large body of work shows that environmental attitudes do not always map onto behavior (32), it is important to investigate whether collective moral concerns were predictive of climate behavior as well as attitudes. Therefore, in our second study, we examine the role of county-level moral values in predicting HCF, which represents a real-world climate action. HCF encompasses most aspects of everyday green decision-making across various sectors, including goods, food, services, and transportation.

Study 1

In this study, we predict environmental attitudes based on estimates of moral concerns at the county level. Our spatial modeling will account for several variables, including the political leanings of counties, population density, urban–rural ratio, temperature and precipitation anomalies, and household income and education levels within each county.

Dataset and procedure

Green attitudes estimates

The dataset is derived from 12 climate change opinion surveys conducted between 2008 and 2013 under the aegis of the Yale Project on Climate Change Communication and the George Mason Center for Climate Change Communication, comprising 12,061 respondents. Eleven of these surveys were conducted online using probability-based methods, while one was a nationally representative telephone survey. Respondents were geolocated with ZIP + 9 codes or geocoded addresses, allowing for subsequent inferring of their residence at the state, county, and congressional district. Custom population crosstabs were formed using the 2012 American Community Survey (ACS) 5-year estimates, categorizing by race, education, and gender, although specific categorizations presented minimal double-counting errors (1).

The survey questions explored beliefs in climate change, conviction that climate change is human-caused, perception of a scientific consensus on climate change, support for carbon regulation, advocacy for a utility renewable energy standard, and the perceived threat of climate change to people in the United States. The multilevel regression and poststratification (MrP) was employed to project localized climate opinions throughout the United States (33). The poststratification phase of MrP employed the regression results to project the average opinion for specific demographic–geographic–year groups. The model permitted 32 unique categorizations based on sex, race, and education, which interacted with various geographic categories, leading to unique population types at state, congressional district, and county levels. These were then weighted based on demographic and geographic distributions, aiming for a representative projection of climate change opinions across different subnational segments. The model's precision was augmented by incorporating variables such as driving behavior, percentages of same-sex households, and the Democratic vote share from the 2008 presidential election.

Moral values estimates

Our moral estimates are grounded in MFT (13), providing a theoretical framework for examining how moral norms shape societal behaviors. The data for these moral values were sourced from Hoover et al. (15), who used responses to the Moral Foundations Questionnaire (MFQ; 34). The MFQ assesses five key moral domains—care, fairness, loyalty, authority, and purity—and the dataset was drawn from the website YourMorals.org, an online platform for collecting diverse psychological data from the public. This dataset spans 2012 to 2018 and includes 106,465 participants, offering a rich source of moral data.

To ensure that the data represented moral values at the county level across the United States, Hoover *et al.* (15) used the multilevel regression and synthetic poststratification (MrsP) technique. This advanced method extends traditional MrP by introducing hierarchical autoregressive priors, a feature that enables spatial smoothing. Spatial smoothing improves estimates for counties with sparse data by borrowing information from neighboring counties with similar demographic and cultural characteristics. This ensures that the estimates are not only representative but also accurate across all counties, regardless of population size. The reliability of the MrsP technique has been rigorously validated by Hoover and Dehghani (14) through Monte Carlo simulations. These simulations tested the performance of MrsP under challenging conditions, such as biased and sparse data. Results showed that MrsP consistently outperformed simpler estimation methods, demonstrating superior accuracy and robustness. The method was further validated by comparing county-level estimates of Catholic adherence, generated using MrsP, against data from the US Religious Census. The high agreement between these estimates and the census data confirmed the method's accuracy, even in sparsely populated regions.

The moral estimates derived using MrsP have been independently validated in multiple ways to demonstrate their alignment with real-world outcomes. First, Hoover et al. (15) compared county-level estimates of conservative proportions (based on binding moral foundations such as loyalty, authority, and purity) to the 2016 Republican Presidential vote share. The strong correlation ($r = 0.63$) confirmed that these estimates aligned closely with known ideological patterns, underscoring their reliability. Second, Hoover et al. (15) also examined the relationship between county-level moral values and the prevalence of hate groups, using data from the Southern Poverty Law Center. They found that counties with higher scores in binding moral foundations were significantly more likely to host hate groups, even after controlling for demographic and political factors. This demonstrated the predictive utility of the moral estimates for understanding real-world social phenomena. Third, in a separate study, Reimer et al. (16) linked these moral estimates to county-level differences in COVID-19 vaccination rates across the United States. Their findings revealed that counties with higher Purity concerns had lower vaccination rates, while those with stronger Fairness and Loyalty concerns had higher rates. Importantly, these associations persisted after accounting for demographic, structural, and political factors, showcasing the power of moral estimates to predict meaningful health behaviors. This multifaceted validation process demonstrates the robustness of moral estimates and their utility for analyzing regional-level dynamics.

Conservatism

To account for the role of political ideology in our predictive model, we collected data from presidential elections in the

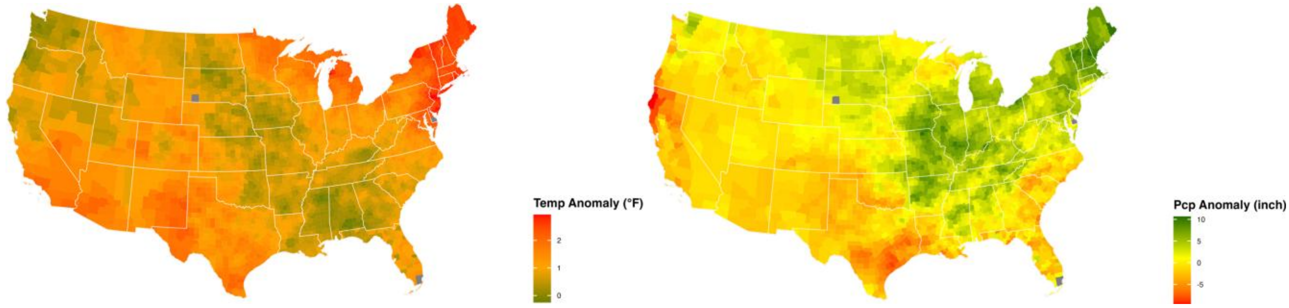

Fig. 1. Temperature (left map) and precipitation (right map) anomaly across US counties.

United States. To quantify political leanings at the county level, we devised a conservatism index. This index was calculated by taking the difference in votes between the Republican and Democratic parties and dividing this value by the total number of votes in that county (total included votes for the Green party) spanning the 2000–2020 presidential elections.

Temperature and precipitation anomaly

Public perceptions of climate change often hinge on observed variations in temperature and precipitation relative to historical benchmarks. To control for this perspective, we turned to the National Center for Environmental Information as a valid source of comprehensive climate-related data. This institution provides detailed records of historical temperature and precipitation patterns, which is essential for understanding and quantifying the anomalies and variations over time. To compute the temperature anomaly, we subtracted the average temperature of the 20th century from that of the 21st century. A similar approach was employed for precipitation to deduce its anomaly (see Fig. 1).

Median household income and education

Prior works have highlighted the significant role of socioeconomic factors such as income (26) and education (35) in shaping environmental attitudes. Consequently, we included median household income and the proportion of residents with a bachelor's degree or higher as control variables in our prediction model. These data were obtained using the get_acs() function in R, which grants access to detailed datasets from the ACS. To ensure consistency with the period during which our green attitudes data were collected, we focused on an average of 2009 to 2013.

Population density and rural–urban ratio

Past research has emphasized the influence of population density (36) and suburbanization (37). Therefore, we controlled for these factors and acquired the necessary data from the U.S. Department of Agriculture Economic Research Service, specifically through their county-level datasets available at https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data/.

Analytic plan

We employed a Bayesian modeling approach to predict green attitudes, incorporating moral norms and the control variables previously mentioned. The choice of the beta distribution for the regression was motivated by the proportional nature of our dependent variable, green attitude, which is continuously scaled between 0 and 1. Our predictors were standardized, meaning that the coefficients in our geospatial model represent the expected change in green attitudes for a 1-SD increase in the predictor, assuming that all other variables are held constant. This standardization facilitates the interpretation of the model's coefficients by providing a common scale for comparison across different variables. To account for the inherent spatial structure in our data, we integrated an adjacency matrix. This matrix captures the geographical proximity of counties by encoding whether pairs of counties are neighbors (denoted as 1) or not (denoted as 0). The presence of spatial autocorrelation, where observations from neighboring counties might exhibit similar patterns due to shared geographic or environmental characteristics, was addressed using the Besag–York–Mollié model for conditional autoregressive (CAR) structures (38). This approach allows us to adjust for spatial dependencies, ensuring that the residuals of our model do not exhibit spatial patterns. Furthermore, including random intercepts for states in our model helps account for unobserved heterogeneity across states. This adjustment is crucial for acknowledging potential variations in green attitudes that could arise from state-specific policies, practices, or other unmeasured factors, thereby enhancing the robustness and interpretability of our findings.

Our reporting process includes point estimates of the model parameters, based on the posterior samples' median. This offers a central value around which our parameter estimates are likely to revolve. To provide a measure of uncertainty surrounding these estimates, we also detail the 95% uncertainty intervals derived from the quantiles of posterior samples. These intervals give a range within which our true parameter values lie with a 95% probability, thus offering insights into the precision and reliability of our model's predictions.

To discern the relative contribution of moral norms in predicting green attitudes, we constructed and compared two models. Model 1 provided a baseline, focusing exclusively on control variables. In model 2, we add moral norms to control variables to measure the unique role of morality in explaining the green attitudes variation. To compare model performance, we utilized the Bayesian analog of R^2 with its 95% uncertainty interval, as described by (39). It is important to highlight that our calculation of R^2 values was based on nonspatial fixed effects. This approach ensures we achieve a fairer comparison, devoid of the inflated influences from spatial dependencies. For each model, we conducted the analysis using the "brms" package (40) in R programming language version 4.3.1 (41), interfacing with Stan. For the fixed effects, noninformative priors were utilized. Specifically, for the intercept, a Student's t-distribution with 3 degrees of freedom, a location parameter of 0.23, and a scale parameter of 2.5 has been used as the prior. The SD of random effects adopts a Student's t-prior with 3 degrees of freedom and a scale of 0.03. The spatial correlation in a CAR structure is modeled with a beta prior with parameters 1 and 1, indicating

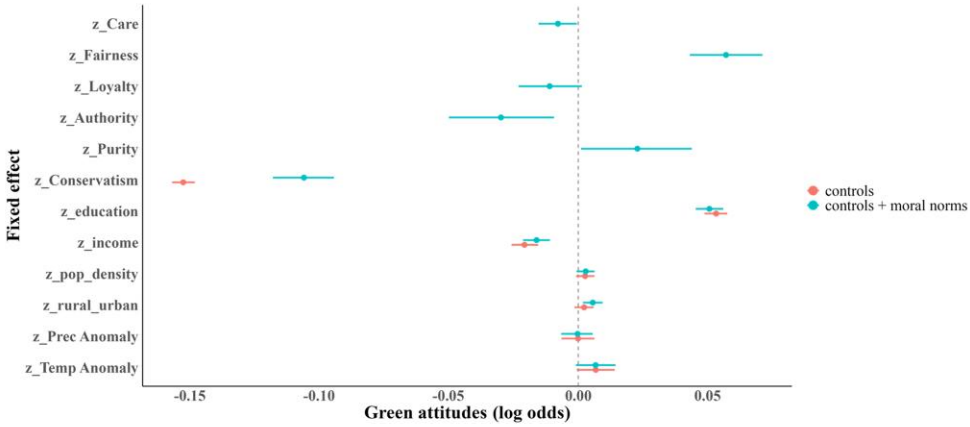

Fig. 2. Results from the two geospatial regression models estimating green attitudes. Model 1 accounted for control variables, and model 2 encompassed all the control variables from model 1 along with moral norms.

that it is uniformly distributed between 0 and 1. The residual variance (sigma) of the model is governed by a Student's t-prior with 3 degrees of freedom and a scale of 2.5.

Results and discussion

Figure 2 illustrates the spatial regression coefficients of both models in log odds. To better interpret the results, we convert the log odds (beta coefficients) into odds ratios (ORs) by taking their exponential. This transformation allows us to understand how a one-unit increase in the predictor variables affects the odds, making the results more intuitive. Model 2 indicates that counties emphasizing fairness norms are associated with 1.06 times higher odds of favoring green practices (OR = 1.06, 95% CI [1.04, 1.07]). Similarly, a stronger presence of purity norms corresponds to 1.02 times higher odds (OR = 1.02, 95% CI [1.00, 1.04]), and higher education levels are linked to 1.05 times higher odds (OR = 1.05, 95% CI [1.05, 1.06]). In contrast, greater adherence to authority norms is associated with slightly lower odds (OR = 0.97, 95% CI [0.95, 0.99]), higher levels of conservatism with significantly lower odds (OR = 0.90, 95% CI [0.89, 0.91]), and increased income with marginally lower odds (OR = 0.98, 95% CI [0.98, 0.99]) of supporting green initiatives. Among our region-specific variables, the rural–urban ratio is positively correlated with green attitudes. A 1-SD increase in the rural–urban ratio is associated with odds of having green attitudes that are 1.01 times higher (OR = 1.01, 95% CI [1.00, 1.01]) compared with urban areas. Model 1, which includes control variables, accounted for 78% of the variation in green attitudes. Model 2, which adds moral norms to the predictors, accounted for 81% of the variance. Thus, the inclusion of moral norms alone explains an additional 3% of the variance in green attitudes.

Among all predictors, a county's political leaning has the strongest influence on the prevalence of green norms, with fairness norms ranking as the second. We found a negative but marginal effect on the care foundation, distinguishing the community-level dynamics from the individual-level results, which often show a positive relationship between care and green behavior. However, it is crucial to highlight that in the MFQ, care concerns are framed rather impersonally, which might influence their impact on proenvironmental norms at the county level. The role of income is also interesting because, while individual-level studies often find that wealthier people tend to express more proenvironmental attitudes (26), our results show that richer counties have fewer proenvironmental norms. However, the effect of education aligns with individual-level research, with greater education leading to stronger proenvironmental attitudes and behaviors, as higher education levels are often associated with greater awareness of environmental issues (26). These results demonstrate how accounting for regional factors can paint a more nuanced picture of the topography of climate change attitudes. Additionally, including moral norms in the predictive model renders the effect of the rural–urban ratio significant, indicating that rural areas exhibit more green norms, suggesting that the direct connection to nature and cohesive community values in rural settings amplifies the influence of moral norms on environmental attitudes.

Study 2

In this study, we predict HCFs based on estimates of moral concerns at the county level. Our spatial modeling will account for green attitudes, political leanings of counties, and temperature and precipitation anomalies. Given our reliance on predicted HCF data, which incorporates estimates from 41 distinct predictors (such as income, race, education, home size, ownership status, vehicle ownership, population density, energy prices, etc.), we will not readjust for these variables in our model. Reintroducing these factors would result in a redundant analysis since their impacts have been previously considered in the prediction of the HCF data (for more details, see (2)).

Dataset and procedure

Household carbon footprints

To operationalize climate change action, we relied on household tons of CO_2 equivalent per year (tCO_2e/yr). The "tCO_2e" is "metric tons of CO_2 equivalent." This is a standard unit for measuring carbon footprints, which allows for the inclusion of various greenhouse gases (e.g. methane or nitrous oxide) by converting their warming potential into an equivalent amount of CO_2. The spatial distribution of US-predicted HCF is provided by UC Berkeley CoolClimate Network (2). Using national household surveys, they developed econometric models to predict the demand for energy, transportation, food, goods, and services. These models were subsequently applied to determine the average HCFs across 3,125 US counties within the 48 contiguous states and the District of Columbia. Key predictors in their model encompassed demographics (e.g. income, household size, race, and education), home attributes (including size, ownership status, structure

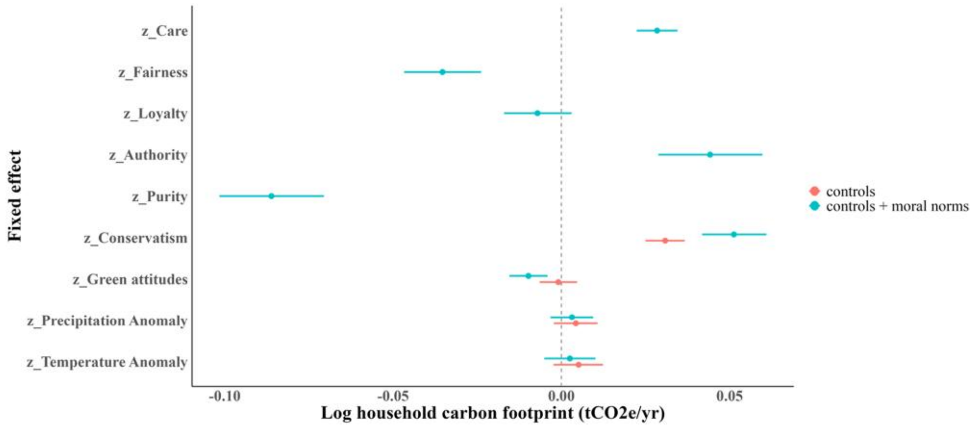

Fig. 3. Results from the two geospatial regression models estimating HCF. Model 1 accounted for control variables, including political differences, climate-related factors, and green attitudes. Model 2 encompassed all the control variables from model 1 along with moral norms.

type, and heating fuel), travel behaviors (e.g. vehicle ownership, commute mode, and commute duration), geographic specifics (such as population density and weather conditions), and economic factors (e.g. energy prices). Data for their study were collected from the ACS, National Household Travel Survey, Residential Energy Consumption Survey, and Consumer Expenditures Survey, focusing on the period from 2000 to 2008.

Analytic plan

We chose the Gaussian distribution for the Bayesian spatial modeling since our dependent variable, HCF, is continuous and normally distributed. Since our predictors were standardized, the coefficients in our geospatial model show the expected change in HCF for a 1-SD increase in the predictor, with all other variables held constant. We also accounted for within-state autocorrelation, like the approach taken in the first study. To discern the relative contribution of moral norms, attitudes toward climate change, and location-specific control variables in predicting carbon footprints, we constructed and compared two models. Model 1 provided a baseline, focusing exclusively on climate-related controls, green attitudes, and conservatism. As we advanced to model 2, we added moral values to control variables, enabling us to measure the unique role of morality in explaining the HCF variation.

For the fixed effects, noninformative priors were utilized. Specifically, for the intercept, a Student's t-distribution with 3 degrees of freedom, a location parameter of 5.6, and a scale parameter of 2.5 has been used as the prior. The SD of random effects has a Student's t-prior with 3 degrees of freedom and a scale of 2.5. The spatial correlation in a CAR structure has a beta prior with parameters 1 and 1, which means that it is uniformly distributed between 0 and 1. The residual variance (sigma) of the model has a Student's t-prior with 3 degrees of freedom and a scale of 2.5.

Results and discussion

In model 1, the spatial autocorrelation was estimated to be 0.99 (95% CI [0.98, 1.00]). This strong correlation suggests that counties geographically closer to each other tend to have similar carbon footprints, highlighting the presence of spatial dependencies in the data. State variation was captured with the intercept having a SD of 0.03 (95% CI [0.02, 0.04]). This suggests that while counties within the same state might exhibit similar carbon footprint behaviors due to shared state-level policies or factors, variability exists between states.

Model 2 indicates that counties with a higher prevalence of fairness ($\beta = -0.04$, 95% CI [−0.05, −0.02]) and purity ($\beta = -0.09$, 95% CI [−0.10, −0.07]) norms, as well as green attitudes ($\beta = -0.01$, 95% CI [−0.02, 0.00]), have lower levels of HCF. In contrast, higher levels of authority ($\beta = 0.04$, 95% CI [0.03, 0.06]) and care ($\beta = 0.03$, 95% CI [0.02, 0.03]) norms, as well as conservatism ($\beta = 0.05$, 95% CI [0.04, 0.06]), are associated with higher emissions in counties (see Fig. 3). Compared with model 1, the second model showed a marked improvement, accounting for ∼17% of the variation with the addition of moral norms as predictor variables. Notably, moral norms alone explain 8% of the variance. Figure 4 illustrates the prediction accuracy of the full model with moral norms (model 2) for predicting attitudes in study 1 and HCF in study 2.

A key finding from our analysis is that while purity norms emerge as the strongest predictor of actual climate action, conservatism is most indicative of green attitudes. Additionally, including moral norms in our model clarifies and enhances the significance of green attitudes. Echoing the patterns observed in the initial study, we found that purity, typically considered a conservative value positively correlates with green actions, while care, typically considered a liberal value, negatively correlates with green actions—a robust effect consistently observed across both studies focused on green actions and attitudes. The effects of fairness and authority also align with the findings of the first study. Specifically, authority, which was negatively associated with green attitudes, has a positive effect when predicting HCF, indicating that higher authority norms lead to more emissions. Conversely, fairness, which was positively associated with green attitudes, is negatively associated with HCF in this context. These results highlight the complex relationship between morality and environmental behavior, in terms of both actual practices and community-level attitudes, which may differ from individual-level behaviors. It is important to note that the variance explained in our study should not be construed as directly elucidating the variance in the raw, observed carbon footprint data. Instead, it should be viewed as offering supplementary insights into the variation that the original model's predictions remain unaccounted for.

General discussion

Past research has established the role of morality in predicting green attitudes and actions. Current research offers a novel approach to examining this role at the collective level using advanced spatial modeling. Our results from two studies indicate

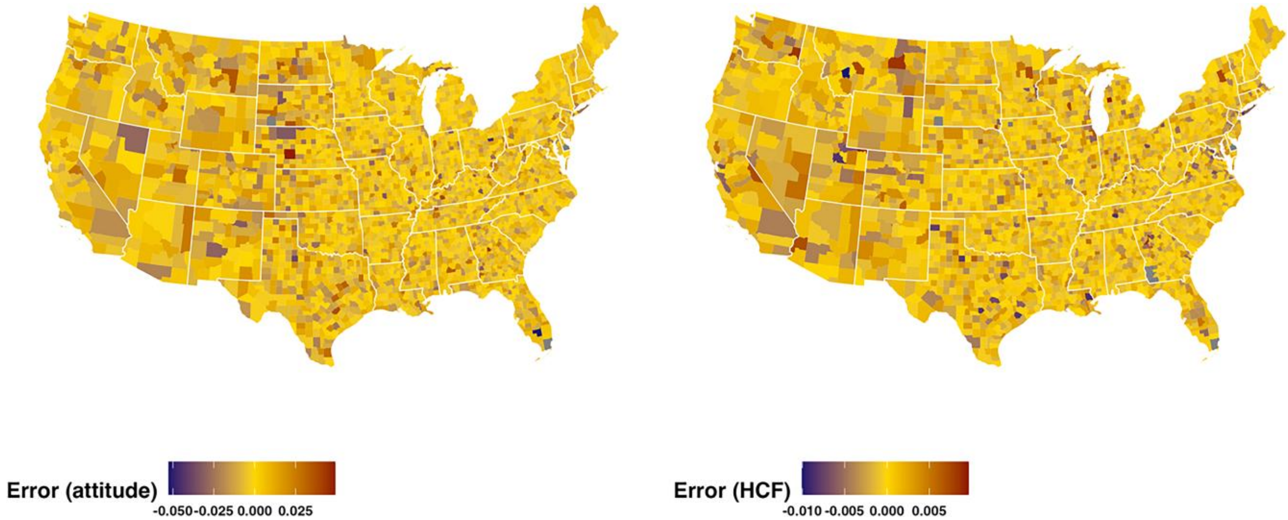

Fig. 4. The error of prediction in model 2 (difference between observed and predicted values) for attitudes (left panel) and HCF (right panel).

that moral norms predict both green attitudes and HCF in the same direction but with varying magnitudes. At the county level, fairness and purity norms correlate with more positive green attitudes and a lower HCF, whereas authority and care norms are linked to less favorable green attitudes and a higher HCF. Notably, fairness norms have a more pronounced effect on attitudes, while purity norms exert a greater influence on HCF, surpassing even conservatism and green norms.

These findings suggest that the dynamics at the community level vary, to a certain degree, from those observed at the individual level. Consequently, green messaging targeting counties and cities should exercise caution in applying individual-level evidence. Notably, purity, often regarded as a conservative value, is shown by our findings to predict both green attitudes and action. More intriguingly, our interaction analysis between purity and conservatism reveals that in counties with higher levels of conservatism, the positive influence of purity norms on climate action promotion is diminished. Therefore, in the context of climate change, purity may resonate more with liberal residences. Theoretically, certain aspects of purity, which underscore a preference for natural and organic foods over genetically modified ones and careful attention to what is consumed, align well with liberals (42). However, certain elements also appeal to conservative residents, such as religious or traditional teachings that stress spiritual and physical purity. This variability in purity content may partly explain its strong predictive power regarding HCF. Overall, framing environmental action in terms of purity or sanctity (e.g. keeping the Earth pure and untainted) might be an effective strategy in certain areas, especially those where these norms are strong (23, 43, 44).

Fairness norms have a bigger effect on attitudes than actions. The association between the prevalence of fairness norms, higher green attitudes, and lower HCF can be attributed to viewing climate change as an issue of justice (45). This perspective emerges from the fact that most vulnerable populations, who contribute the least to climate change, suffer its most severe consequences, whereas wealthier households, which have larger carbon footprints (2), have lower levels of green attitudes, as our results suggest.

We also observed that higher authority norms correlate with increased emissions at the country level. Prior studies indicate that both the maintenance of social order and the value placed on liberty can predict skepticism toward climate change (46). At the county level, adherence to traditions and a tendency to maintain the status quo and economic/social order often translate to a persistent dependence on fossil fuels.

Overall, our county-level findings provide a framework for policymakers interested in employing moral framing techniques (47). By aligning regional green messages with the predominant moral norms of local populations, interventions can be more culturally and contextually relevant, potentially increasing their effectiveness. Although our results offer a broad overview of trends across the United States, targeted interventions require more granular analysis.

To achieve this, we recommend reducing the sample size to a state-specific context and running the spatial models within individual states. This approach can reveal significant variations that are crucial for tailoring policy measures. For instance, while fitness values might be the most significant predictor of carbon footprint in California's counties, purity norms could play a more decisive role in Alabama. Such distinctions are critical for state-level policymakers, who should consider conducting bespoke spatial analyses to develop interventions that resonate strongly with their specific constituencies.

Our work presents the first value-based topography of green attitudes and action, moving beyond controlled settings of individual-level research, accounting for regional variables, and offering community-level evidence. However, some caveats deserve mention. First, while our study factored in a variety of explanations for these county-level associations, caution should be exercised when interpreting our geospatial results. The observed link, where counties with higher purity values tend to exhibit lower emissions, should not be hastily applied to other spatial aggregations, whether more detailed (e.g. individuals, towns, or neighborhoods) or broader (e.g. states). While past geospatial studies have successfully found consistent associations across different spatial layers (e.g. 48), others have not (49). Second, our findings are rooted in the context of the United States, mainly because detailed county-level carbon footprint data are accessible here. As such, researchers should exercise caution when extrapolating these insights to different countries, though we do hope our study will inspire similar investigations elsewhere. Thirdly, data related to green attitudes, HCFs, and moral norms were collected over distinct time frames, specifically

2008–2013 for green attitudes, 2000–2008 for HCF, and 2012–2018 for moral norms. Despite the differing periods, existing studies suggest that both individual adherence to moral principles (50) and regional variances in psychological attributes (51) tend to remain consistent over time. Lastly, it is important to note that our results are correlational. While this might raise concerns about causality, it is essential to understand that in county-level analyses, correlational research is often the primary available method. Hence, interpretations should be made with this limitation in mind.

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Author Contributions

Conceptualization: F.K., S.S., and M.D.; data preparation and analysis: F.K.; interpretation: F.K., S.S., and M.D.; initial draft: F.K.; review and editing: F.K., S.S., and M.D.; supervision: M.D.

Preprints

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Data Availability

County-level estimates of moral concerns have the potential of being misused for targeting in influence campaigns. To mitigate this risk, we do not share the exact estimates of moral concerns. Instead, we used the "synthpop" R package (version 1.6-0) to create synthetic data that mimic the original estimates of moral concerns and preserve the relationships with the other variables in the dataset but sever the link between each county and its residents' moral concerns. All other variables sufficient to reproduce models 1 and 2 are provided unaltered. All materials used in this project, including datasets and code, are openly available in Open Science Framework at https://osf.io/t57b3/.

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