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Assessing U.S. public perceptions of global warming using social survey and climate data ☆,☆☆

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ABSTRACT

This paper presents a methodological approach for assessing the relationship between weather patterns, regional climate trends, and public perceptions of global warming in the United States with control of socioeconomic, political, and ideological variables. We combined social survey data from the Gallup Poll Social Series (GPSS) with environmental data from the National Oceanic and Atmospheric Administration (NOAA) and the PRISM Climate Group. Logistic regression models were employed, enhanced by Eigenvector Spatial Filtering (ESF) to address spatial autocorrelation. This approach allowed us to examine how both short-term weather conditions and long-term climate changes impact public concerns about global warming. Notably, the perception of warmer winters emerged as a critical factor influencing attitudes, highlighting the importance of perceived environmental changes in shaping public opinion.

- We combined survey data on public perceptions with high-resolution weather and climate data.
- We applied logistic regression models with Eigenvector Spatial Filtering to control for spatial autocorrelation.
- Our analysis emphasized both physical climate measures and perceived climate changes.

Specifications table

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Background

Public perceptions of global warming play a crucial role in influencing environmental policies and shaping public discourse. Despite scientific consensus on the human causes of global warming, significant variability persists in individual perceptions of its reality, driving forces, and severity [2–5]. Understanding the factors that contribute to these perceptions is essential for the development of effective communication strategies and policy interventions.

Research has explored how objective indicators like temperature and precipitation trends influence beliefs about climate change. Studies show that short-term weather events and long-term climate trends significantly impact public attitudes toward global warming. A meta-analysis found that even modest temperature increases can raise public anxiety about climate change [6]. Furthermore, extreme weather events, such as hurricanes and heatwaves, enhance the salience of climate change, particularly for those directly affected. However, the relationship between local weather experiences, regional climate patterns, and public perceptions is complex. Some studies suggest that personal experiences with extreme weather shape climate change beliefs [7–9], others find little to no correlation, particularly when examining longer-term trends or more subtle climatic shifts [9,10]. These mixed results underscore the need for more nuanced analyses.

There is a growing recognition that perceived changes in weather and climate, often shaped by media coverage, social discourse, and personal biases, can be equally, if not more, significant than actual physical changes in influencing public attitudes [7,11]. For instance, individuals who perceive warmer winters are more likely to view global warming as a serious threat, even if their perception does not align with objective climate data [12,13]. This disconnects between perception and reality highlights the importance of examining psychosocial factors in how people interpret and respond to environmental changes.

This study aims to disentangle the complex interplay between local weather conditions, regional climate patterns, and perceived environmental changes in shaping public perceptions of global warming. By applying a methodological framework that addresses spatial autocorrelation and multiscale environmental data, we provide a more accurate understanding of the drivers of climate change perceptions. The primary goal is to model these relationships in a statistically robust and practically relevant manner, offering insights to inform policy, public health, and communication strategies that raise awareness of global warming. This research is especially relevant in the United States, where regional climate variability—from the harsh winters of the Northeast to the heatwaves of the Southwest—provides a unique opportunity to explore how diverse environmental contexts influence public perceptions. By controlling for socio-economic, demographic, and political factors, this study seeks to isolate the specific impacts of physical weather and climate patterns, as well as perceived changes, on individuals' views of global warming. The findings have the potential to improve climate communication efforts and help bridge the gap between scientific understanding and public perception of climate change Fig. 1.

Method details

Data collection

Social data

The Gallup Poll Social Series (GPSS) is a well-established survey tool that collects public opinion data from U.S. adults across all 50 states and the District of Columbia. The GPSS aims to gather insights upon a diverse array of socio-economic, environmental, and political topics through monthly surveys, each centered on a specific theme such as the environment, economy, and health [14].

Gallup employs a dual-frame sampling design that includes both landline and cellphone numbers, ensuring comprehensive coverage of the U.S. population [15]. Samples are drawn using random-digit-dial methods, with quotas established to ensure that at least 50 % of respondents are cellphone users and 50 % are landline users. Furthermore, Gallup implements minimum quotas based on time zone and region to enhance the representativeness of the sample. To accommodate non-English speakers, surveys are conducted in Spanish when necessary. The response rates for the Gallup Poll Social Series (GPSS) surveys in 2013 and 2014 were relatively low, at 7 % and 6 %, respectively. However, previous research indicates that such low response rates do not necessarily compromise the representativeness or quality of the survey data, provided that the final sample accurately reflects the target population [16].

Gallup applies weighting to all survey samples to correct for potential biases arising from unequal selection probability, nonresponse, and double coverage of landline and cellphone users [16]. The weights are calculated using external data sources, including the Current Population Survey (CPS), National Health Interview Survey (NHIS), and U.S. Census data. These weights are adjusted according to demographic factors such as gender, age, education, race, ethnicity, population density, region, and phone status (e.g., cellphone only, landline only, or both). This weighting process ensures that the survey results are representative of the U.S. adult population.

For this study, we acquired GPSS data from the March 2013 and March 2014 surveys, which focused on environmental topics, including public perceptions of global warming. The dataset includes responses from 1428 individuals, with a broad range of demographic and socio-economic variables. The key variables selected for analysis include:

- **Demographic Information:** Age, gender, race (with a focus on the white/non-white distinction), and education level (with a specific focus on college graduates).
- **Socio-economic Status:** Household income, categorized into 11 levels ranging from less than $10,000 to more than $500,000 annually.
- **Political and Ideological Variables:** Political affiliation (Republican, Democrat, or Independent), conservatism (on a scale from very liberal to very conservative), and religious beliefs, including the frequency of church attendance.

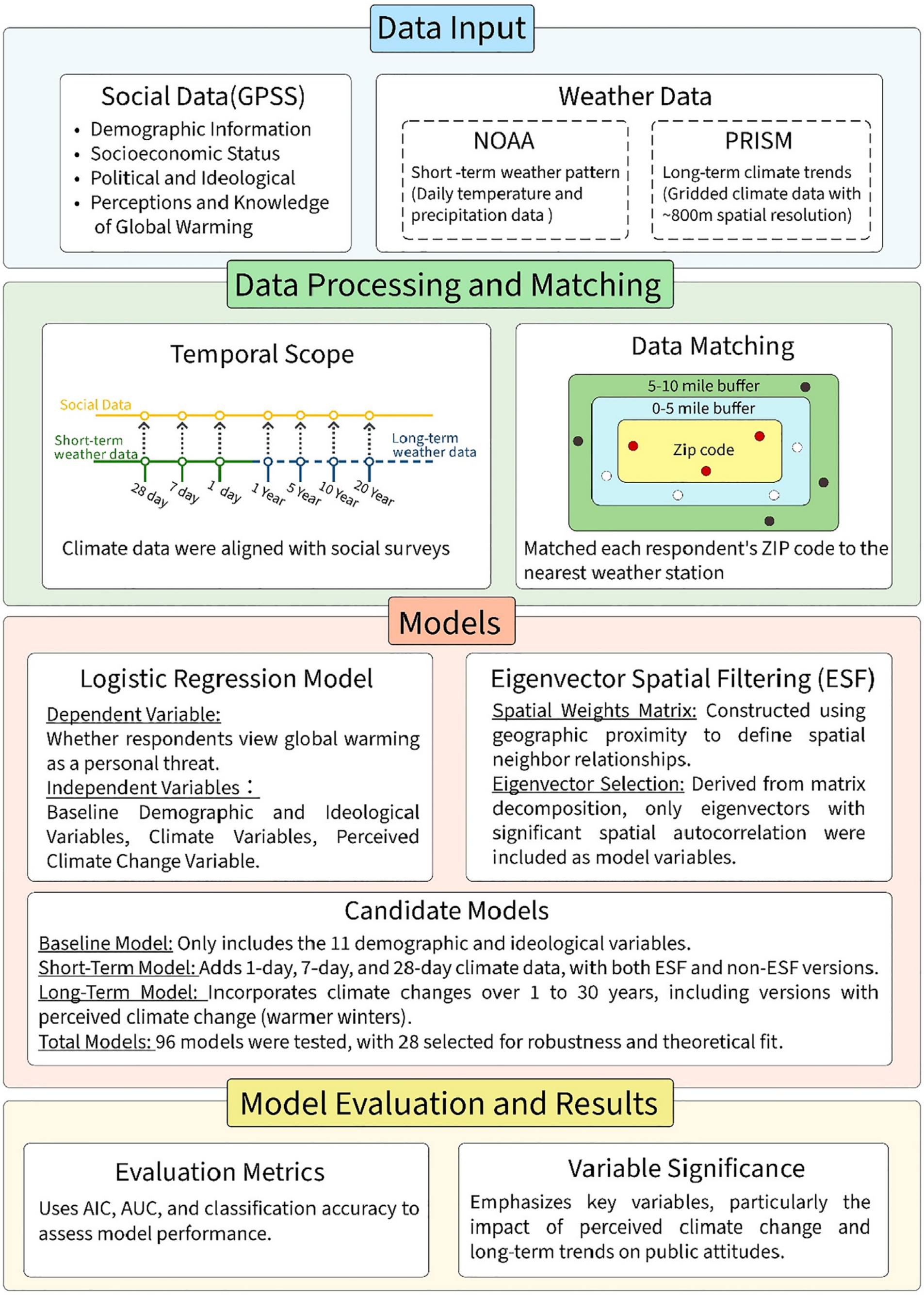

Fig. 1. Comprehensive Framework.

- **Perceptions and Knowledge of Global Warming:** Whether respondents believe that scientists agree global warming is happening, their personal knowledge of global warming, and whether they perceive global warming as a serious threat to their personal lives.

These variables were selected based on their relevance to understanding how socio-political context influences public perceptions of global warming.

The study included a sample of 1428 respondents with an average age of 54.23 years (standard deviation of 17.50), ranging from 18 to 99 years. The sample was slightly skewed toward males, who constituted 52 % of the participants, while females comprised 48 %. Approximately 55 % of the respondents held a college degree or higher. The average in 2013 and 2014 household income ranged from $40,000 to $74,999 annually. About 25 % of the respondents reported having no children under the age of 18. The racial composition was predominantly white, accounting for 83 % of the sample, and 82 % identified as Christians, including denominations such as Protestant, Catholic, Mormon, and other Christian groups. Among the respondents, 58 % agreed that scientists believe "global warming is happening", while 30 % identified as Republicans. Their knowledge about global warming averaged 3.08 on a 4-point scale. Politically, respondents tended to be moderate, with an average score of 3.08 on a 5-point scale, where 1 indicated very liberal and 5 indicated very conservative. Only 14 % of the respondents reported living in large cities.

Weather and climate data

To understand the impact of weather and climate patterns on public perceptions of global warming, we integrated GPSS data with detailed environmental data from the National Oceanic and Atmospheric Administration (NOAA) and the PRISM Climate Group (http://www.prism.oregonstate.edu/).

Data Sources and Temporal Matching:

- **NOAA Data:** We utilized daily temperature and precipitation data from NOAA's Global Historical Climatology Network (GHCN), which provides station-based measurements across the United States.
- **PRISM Data:** PRISM provides gridded climate data, including temperature and precipitation, with a spatial resolution of approximately 800 m, which allows for precise mapping of climate trends at a regional scale.

The temporal alignment of Gallup survey dates with the corresponding weather and climate data was crucial to our analysis. To examine the potential impacts of short-term weather patterns on public perceptions, we analyzed NOAA and PRISM data for the 28 days immediately preceding the start of each Gallup survey (for instance, from February 6th to March 5th for the March 2014 survey). This timeframe was selected to capture both the immediate and cumulative effects of weather conditions on public perceptions.

Data compilation and mapping

Data pooling and justification

Due to data availability, we restricted our analysis to the data collected in 2013 and 2014, during which all relevant independent variables were available. To increase the sample size, particularly for states with smaller populations (e.g., Idaho and South Dakota), we pooled the data from these two years together. This pooling approach also helps to maintain high statistical power given the large number of independent variables, many of which are binary.

The pooled data are treated as if they were collected randomly at a single time point, with a covariate added to control for the year of data collection. This method is justified for the following reasons:

1. **Sample Size Increase:** Pooling allows for a larger and more robust sample, particularly beneficial for less populous states.
2. **Consistency:** The data from both years were collected from the same population, using the same survey procedures and questions, with only a short time gap (one year) between them.
3. **Literature Support:** Previous research on repeated cross-sectional data supports pooling as a valid approach when analyzing samples that measure the same population over time. This method increases the precision of estimates and provides insight into the stability of the findings [17].

To ensure the validity of this approach, we performed additional tests to address potential concerns, such as incorrect standard errors and the assumption of static parameters when pooling data across multiple time points.

Interaction terms and regression models

We included interaction terms between the year-based dummy variable (yr_2013) and each of the 11 Gallup-based independent variables in our baseline logistic regression model. This model is formulated as:

$$logit(E(y_j)) = a_0 + \sum_{i=1}^{11}(a_i \times x_{ij}) + \sum_{i=1}^{11}\left(b_i \times year_j \times x_{ij}\right) + c_1 \times year_j \quad (1)$$

where:

- y_j is the dependent variable indicating whether the respondent perceives global warming as a personal threat (psnal_threat).
- x_{ij} are the Gallup-based independent variables.
- a_i and b_i are the coefficients for the independent variables and their interaction terms with the year dummy variable, respectively.
- c_1 is the coefficient for the year dummy variable.
- The logit function is used because the dependent variable is binary.

We also regressed each of the 11 Gallup-based variables against the year dummy variable using both Ordinary Least Squares (OLS) for continuous variables (e.g., age) and logistic regression for binary variables (e.g., living in a big city). The regression form is:

$$g\left(E\left(x_j\right)\right) = b_0 + b_1 \times year_j \quad (2)$$

where g(·) is the link function, linear for OLS and logit for logistic regression.

The results showed that, except for one marginally significant interaction term (between the year dummy variable and income), all other interaction terms were insignificant. Only knowledge about global warming (gw_knowledge) showed significance across different models. To address potential confounding, we performed regression analyses separately for 2013 data, 2014 data, and the pooled data using the following model:

$$logit(E(y_j)) = a_0 + a_1 \times gw\_knowledge_j + a_2 \times income_j \tag{3}$$

The coefficients were consistent across different datasets, confirming the robustness of the relationships between knowledge, income, and perceptions of global warming.

Geographical data matching and weather station assignment

We mapped the ZIP codes of respondents to the nearest weather stations to ensure accurate assignment of local weather data. Our analysis showed that 72 % of ZIP codes contained at least one weather station within their boundaries, while 12 % had the nearest station within a 0–5 mile buffer, and 15 % within a 5–10 mile buffer. This distribution supports the reliability of the weather data used in the analysis.

Creation of change measures

To analyze the impact of long-term climate changes on public perceptions, we calculated changes in temperature and precipitation for different time spans (1, 5, 10, 20, and 30 years) leading up to the survey dates. For instance, we computed the change in the 7-day average maximum temperature (N_tmax_7day and P_tmax_7day) by comparing the values from 1, 5, 10, 20, and 30 years prior. These variables were centered and scaled before being used in the regression models to enhance interpretability and mitigate multicollinearity.

Model details

Model specification

We employed logistic regression models to assess the likelihood that an individual perceives global warming as a personal threat. The dependent variable in our models is binary, coded as 1 if the respondent perceives global warming as a threat and 0 otherwise. The independent variables encompass a wide array of factors, including demographic characteristics (age, gender, education level, income), political and religion orientation (e.g., party affiliation and conservatism), as well as environmental factors such as local weather conditions (temperature and precipitation) and broader regional climate trends.

Control variables were carefully selected to account for potential confounding factors. For instance, political ideology and educational attainment, which are known to significantly influence environmental perceptions, were included to ensure that the observed relationships between environmental variables and global warming perceptions were not confounded by these socio-political influences.

Spatial autocorrelation and eigenvector spatial filtering (ESF)

A major methodological challenge in our analysis was spatial autocorrelation, which occurs when data points geographically close to each other exhibit similar values due to their proximity, leading to potential biases in the regression estimates. To address this issue, we applied Eigenvector Spatial Filtering (ESF), a technique that mitigates the effects of spatial autocorrelation by decomposing spatial variables into spatial and non-spatial components.

The ESF approach begins by defining a spatial weights matrix (C), where each entry represents whether a pair of observations are considered spatial neighbors, based on geographic proximity. This matrix is then transformed to produce the MCM matrix:

$$MCM = \left(I - 11^T/n\right)C\left(I - 11^T/n\right) \tag{4}$$

where *I* is the identity matrix, *1* is a column vector of ones, and n is the number of observations [1,18,19]. The eigenvectors of the MCM matrix, denoted as E_1, E_2, ...E_n, correspond to the spatial structure of the data, with each eigenvector capturing a distinct spatial pattern. The eigenvectors associated with the largest eigenvalues typically account for the most salient spatial autocorrelation in the data.

Rather than using all eigenvectors, which could decrease degrees of freedom and introduce noise to the model, we selected a subset of the most influential eigenvectors. These were included as additional regressors in our logistic regression models, effectively filtering out the spatial autocorrelation and allowing us to obtain more accurate and unbiased estimates of the relationships between environmental variables and perceptions of global warming [18,20].

The selection of the eigenvectors was guided by stepwise regression procedures and other criteria such as the magnitude of the eigenvalues, ensuring that only the most relevant spatial patterns were included in the models [20].

Model equation

In addition to the logistic regression models, we also calculated the probability that a respondent would perceive global warming as a personal threat. This probability was modeled using the following equation:

$$prob\left(psnal\_threat_j = 1\right) = \frac{\exp\left(\sum_{i=1}^{k} b_j X_{ij} + \sum_{i=1}^{q} c_j Z_{ij} + u_j\right)}{1 + \exp\left(\sum_{i=1}^{k} b_j X_{ij} + \sum_{i=1}^{q} c_j Z_{ij} + u_j\right)} \tag{5}$$

Table 1
Models with combinations of the four classes of data.
(Adopted from main text supplementary material).

Variable class	Type **1**	Type **2**	Type 3	Type **4**	Type **5**	Type **6**	Type **7**	Type **8**
11 human variables	Control	Control	Control	Control	Control	Control	Control	Control
Physical weather/ climate measures (3-L*)		√			√	√		√
Physical change in climate (5-L)			√			√	√	√
Perceived change in weather/ climate (1-L)				√	√		√	√
Selected ESFs	√	√	√	√	√	√	√	√
Sum # of possible models	2	3 × 2 = 6	5 × 2 = 10	2 × 1 = 2	3 × 1 × 2 = 6	3 × 5 × 2 = 30	5 × 1 × 2 = 10	3 × 5 × 1 × 2 = 30
Total	96							

Note:
* Physical weather/climate measures have three levels (1, 7, and 28 days). Like the rest variable classes: physical weather/climate change is measured at 5time spans (1, 5, 10, 20, 30 years), perceived change in climate has one option (including or excluding the perception of warmer winters). Each model specification may be tested with two options (i.e., with or without ESFs).

Here, $X_j = (x_{1j}, x_{1j}, , x_{kj})$, $Z_j = (z_{1j}, z_{1j}, , z_{qj})$ represent the vectors of the human and environmental variables respectively, while j indexes the respondents. The coefficients b_j and c_j are estimated via maximum likelihood estimation. The model's goodness-of-fit was evaluated using the Akaike Information Criterion (AIC), which is particularly useful for comparing nested models. The stepwise regression was conducted using the glmnet and MASS packages in R, which allowed for efficient model selection and regularization.

Candidate models

Our candidate models were constructed by varying the inclusion of different sets of variables. Initially, we tested models that included only the 11 human variables (e.g., demographics, political affiliation) as predictors. Then, we added the ESFs selected from the eigenvector filtering process to form a second set of models. These two basic model types are detailed in Table 1.

When physical weather and climate variables were introduced, we considered these at three temporal levels: 1 day, 7 days, and 28 days before the survey. For instance, at the 1-day level, variables such as N_tmax_1day (maximum temperature on the day before the survey) and P_ppt_1day (precipitation on the day before the survey) were included. Similar variables were defined for the 7-day and 28-day levels. For each temporal level, we created models both with and without ESFs, resulting in six distinct model types within this category. Furthermore, we examined models that accounted for changes in climate variables over various time spans, including 1, 5, and 10 years. This approach generated a total of 96 potential model specifications. However, to ensure the robustness and theoretical coherence of our models, certain configurations were excluded if they lacked empirical or theoretical support. For example, single-day temperature measures over extended time scales were considered too volatile and thus omitted. To prevent multicollinearity, highly correlated weather and climate variables (with correlation coefficients > 0.70) were not included in the same model.

Our final set of candidate models included 28 robust models, each assessed using coefficients, p-values, standardized coefficients, and three overall goodness-of-fit indices (AIC, area under the ROC curve, and classification accuracy).

Model testing

After specifying the models, we performed cross-validation by randomly splitting the dataset into a training set (70 % of the data) and a testing set (30 % of the data). We then evaluated the models by examining the classification accuracy and calculating the area under the ROC curve (AUC). The accuracy and AUC metrics were averaged across the testing datasets to ensure the reliability and generalizability of the model findings.

Method validation

This section focuses on the systematic evaluation of the model's performance, ensuring that the predictive accuracy and the robustness of the estimates are maintained across various configurations.

Stepwise model selection

We utilized stepwise regression techniques to iteratively add or remove variables based on their statistical significance and impact on the model's overall fit. While we considered both the original independent variables and the spatial eigenvectors generated during the ESF procedure, certain variables—such as minimum and maximum temperatures—were excluded from the final model due to their lack of statistical significance or multicollinearity. This approach enabled us to derive models that are parsimonious, retaining only the most statistically significant predictors while minimizing issues of multicollinearity and overfitting.

Goodness-of-Fit measures

To assess the effectiveness of each model configuration, we employed multiple goodness-of-fit metrics, including the Akaike Information Criterion (AIC) to evaluate model simplicity versus complexity, the area under the ROC curve (AUC) to measure classification performance, and classification accuracy to gauge the proportion of correctly predicted outcomes. These metrics provided a comprehensive view of model quality, allowing us to identify the optimal model configuration for understanding the relationships between the independent variables and global warming perceptions (Fig. 2).

Cross-Validation

As described in Section Model Testing, cross-validation was employed to assess the generalizability of the models. This procedure involved splitting the dataset into training and testing subsets, with the models trained on 70 % of the data and tested on the remaining 30 %, ensuring robust validation of model performance.

Model results

Our analysis began with examining the descriptive statistics and the impact of control variables on the perception of global warming as a personal threat. In the years 2013 and 2014, approximately 30 % of respondents in the Gallup Poll perceived global warming as a personal threat. This finding aligns with similar studies and highlights the steady concern among a significant portion of the population. The control variables, including socio-economic factors such as age, gender, income, and political affiliation, were analyzed using a logistic regression model (Model 1, see Table 3 in main text for coefficients). Specifically, younger individuals, females, respondents with children, urban dwellers, those not leaning towards conservative political ideologies, and individuals with lower incomes were more likely to consider global warming a personal threat. Additionally, control variables were consistent across various models, underscoring their robust influence in shaping environmental perceptions (refer to Table 3 in main text for a detailed breakdown of the control variable coefficients across different model specifications). These results underscore the importance of demographic factors in shaping environmental perceptions, reflecting the broader social dynamics at play.

Contrary to what might be expected, physical weather and climate variables, particularly short-term measures, demonstrated limited predictive power in influencing perceptions of global warming. For instance, precipitation levels measured at the 7-day and 28-day intervals before the Gallup survey did not emerge as significant predictors. This suggests that immediate weather conditions, such as a recent rainy period, do not substantially alter the likelihood of individuals perceiving global warming as a threat. Similarly, temperature variables (both minimum and maximum) within the 28-day window were excluded during the model selection process due to their lack of statistical significance (Table 1 in main text). These findings suggest that while weather fluctuations may affect daily life, they do not necessarily translate into heightened concern about long-term climate issues.

In contrast to short-term measures, long-term changes in weather and climate, particularly over spans of 5 to 30 years, showed a more nuanced impact on public perceptions. For example, changes in maximum temperature and precipitation over a 5-year period were consistently found to be positive predictors of the perceived threat of global warming. Interestingly, the impact of these variables was dependent on the data source. Localized weather data from NOAA and regional climate data from PRISM played different roles in shaping these perceptions. NOAA data, collected from individual weather stations, provided precise measurements for specific locations, making it more effective in capturing temperature variations. In contrast, PRISM data, which covers larger spatial scales through interpolation, was more sensitive to long-term precipitation changes. When eigenvector spatial filters were included, additional significant effects were uncovered, particularly with long-term precipitation changes, which showed varied impacts depending on the data source and time span. This highlights the complexity of climate perception, where long-term environmental changes, rather than immediate weather conditions, influence public concern about global warming.

The inclusion of perceived climate change variables, such as the perception of warmer winters, significantly enhanced the model's predictive power. When added to the best-practice model, which consisted of weather change variables (e.g., changes in maximum temperature and precipitation over 5 years), eigenvector spatial filters to account for spatial autocorrelation, and key control variables (such as age, gender, and political affiliation), the perceived warming variable emerged as a strong predictor, even outperforming some physical climate change indicators (Table 3 in main text). This finding reinforces the idea that perceptions of climate change, which may be influenced by media, personal experiences, and social discourse, are crucial in shaping public attitudes towards global warming. The perceived change in winter temperatures, in particular, appears to resonate strongly with individuals, potentially because of its direct and observable impact on daily life.

Scenario analysis and mapping outcomes

To further explore the influence of physical and perceived climate changes on public perceptions, we conducted scenario analyses. These analyses were based on varying the parameters of temperature, precipitation, and the proportion of respondents perceiving local warming. Our mapping outcomes, which visualized these scenarios at different cutoff values (e.g., 0.30, 0.40, 0.50), revealed interesting geographical patterns. For instance, only a few states, such as Wisconsin, North Carolina, and New Jersey, showed a significant portion of their population (over 30 %) perceiving global warming as a personal threat. However, as the parameters for temperature and precipitation were adjusted, additional states began to exhibit increased concern, indicating that both physical and perceived climate changes could potentially shift public opinion in significant ways.

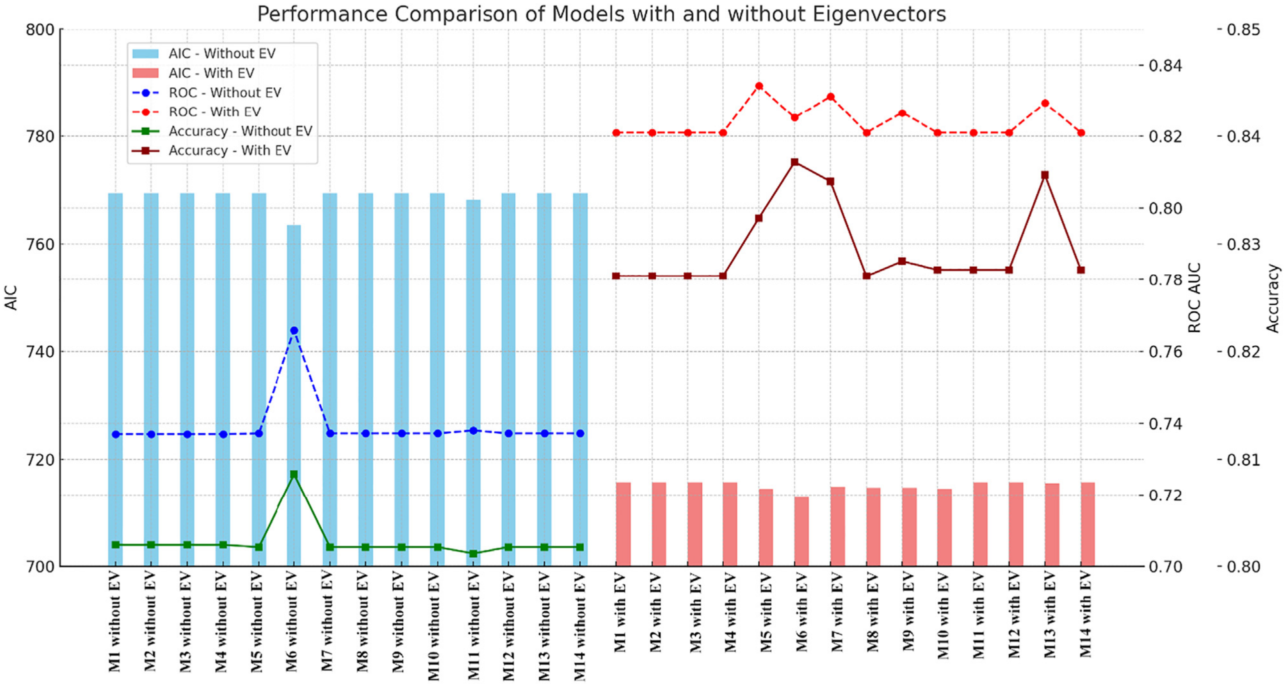

Fig. 2. Performance Comparison of Selected Models with and without Eigenvectors.
Note: *This figure compares the performance of models without eigenvectors (EV) and with EV in predicting perceived global warming threat. Models without EV include variables such as demographic factors, socioeconomic status, political views, and knowledge of global warming, resulting in higher AIC values and lower ROC and accuracy scores. Models with EV incorporate spatial eigenvectors, significantly improving performance, as indicated by lower AIC and higher ROC and accuracy scores. Model M6 performs best, with an AIC of 712.9937, ROC of 0.8252, and accuracy of 0.8376. These results suggest that adding eigenvectors enhances predictive power (*model detail see main text supplementary material table S6 – S19*).

Limitations

This study has several limitations. First, we used zip codes to map the locations of survey respondents, but zip codes can cover large areas. This means the weather data we linked to respondents may not always reflect their exact location. For example, people living in large zip codes may not have experienced the same weather conditions as those measured at the nearest station.

Second, although we used weather and climate data from reliable sources like NOAA and PRISM, there are still some challenges. Weather stations might be far from some respondents, which could reduce the accuracy of the temperature and precipitation data linked to them. PRISM data, while useful for capturing regional climate, may smooth out extremes and reduce the accuracy of some climate measurements.

Third, our study focused only on the years 2013 and 2014. While we pooled the data to increase sample size, this approach limits our ability to capture trends over a longer time period. Additionally, our analysis does not account for changes in people's political or religious views, which could affect their perceptions of global warming over time.

Finally, we did not explore how people's perceptions of global warming may have been influenced by media coverage or disinformation campaigns during the study period. Future research could include these factors to provide a more comprehensive understanding of public attitudes towards climate change.

CRediT author statement

Xiaoxiao Wei: Writing - Original Draft, Writing - Review & Editing, Validation, **Eve Bohnett:** Software, Validation, Formal analysis, **Li An:** Conceptualization, Writing - Review & Editing, Project administration and Funding acquisition.

Ethics statements

This study involved human subjects, and the data were collected through the Gallup Poll Social Series (GPSS) surveys. The data used in this research were fully anonymized and obtained with the informed consent of participants, as per Gallup's survey protocols. No additional personal identifiers were included in the dataset, and the research complies with the ethical guidelines for handling human subject data.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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