The state of GMOs on social media

An analysis of state-level variables and discourse on Twitter in the United States

Christopher D. Wirz, *University of Wisconsin–Madison*

Emily L. Howell, *University of Wisconsin–Madison*

Dominique Brossard, *University of Wisconsin–Madison; Morgridge Institute for Research*

Michael A. Xenos, *University of Wisconsin–Madison*

Dietram A. Scheufele, *University of Wisconsin–Madison; Morgridge Institute for Research*

Abstract. **This study analyzes the relationship between state-level variables and Twitter discourse on genetically modified organisms (GMOs). Using geographically identified tweets related to GMOs, we examined how the sentiments expressed about GMOs related to education levels, news coverage, proportion of rural and urban counties, state-level political ideology, amount of GMO-related legislation introduced, and agricultural dependence of each U.S. state. State-level characteristics predominantly did not predict the sentiment of the discourse. Instead, the topics of tweets predicted the majority of variance in tweet sentiment at the state level. The topics that tweets within a state focused on were related to state-level characteristics in some cases.**

Key words: content analysis, science communication, genetic engineering

Genetically modified organisms (GMOs) are politically contentious in many countries, creating a complex issue for global policy. The contention generally revolves around how, or whether, genetic engineering should be used and regulated in food production. In public discourse, the term "GMO" is often used interchangeably with the terms "genetically engineered (GE) crops" and "genetically modified (GM) foods," which all generally refer to plants or animals that have had their genetic material directly manipulated in some way by humans to produce a change in the plant or animal (NASEM, 2016). Defining what constitutes a GMO has important implications for one of the controversial policy issues surrounding the technology: whether foods containing GM ingredients should be required to be labeled as such.

Although there is now a federal labeling law for GM foods (Hall, 2016), the state-level discourse on GMOs is especially interesting because debates over labeling have varied widely at the state level, with some states continuing to introduce legislation even after the federal law passed. Additionally, the policies and opinion climates at the state level are likely to affect the sale and consumption of GMOs. State-level policy often reflects public values and perspectives (Burstein, 2003; Erikson et al., 1989; Jacoby & Schneider, 2001), and public discourse on an issue can reveal these perspectives. Although political organizations and interest groups can influence state policy, the influence of public opinion on shaping state policies and explaining differences between policy priorities can be substantial and one of the largest factors affecting policy decisions (Burstein, 2003; Jacoby & Schneider, 2001). Additionally, state-level factors and the experiences of consumers can impact individuals' perceptions of controversial scientific topics (Howell et al., 2017). The political and legislative climate within each state likely influences individuals' opinions about GMOs as well.

To examine these factors, this study conducts a state-level analysis of difference in GMO-related discourse on Twitter to better understand how those social and political contexts relate to public opinion. The overarching question is, how do state-level variables relate to Twitter discourse on GMOs? Our specific research questions examine how the sentiments expressed about GMOs related to education levels, news coverage, proportion

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Corresponding author: Christopher D. Wirz, University of Wisconsin–Madison, Madison, WI. Email: *cwirz@wisc.edu*

of rural and urban counties, state-level political ideology, amount of GMO-related legislation introduced, and agricultural dependence of each U.S. state.

To assess regional dynamics involved with public perceptions of GMOs in the United States, this study analyzes how political, agricultural, media, and demographic factors relate to online discourse about GMOs at the state level on social media in particular. Platforms such as Twitter and Facebook offer a way for people around the country, and the world, to engage with individuals and organizations in a dynamic, global discussion. Regional contexts and experiences might help shape the discourse, and social media, like Twitter, can offer a constantly updated map of public expression in response to contested issues such as GMOs in general and GM foods in particular.

GMOs and social media

Social media have proved to be powerful platforms for attracting public attention and influencing public opinion about important policy issues. Many notable social movements, such as #MeToo (Mendes et al., 2018) and #BlackLivesMatter (Taylor, 2016), have leveraged platforms like Twitter to focus public opinion and demand that policymakers pay attention to specific policy issues. Previous research has also found that the complex interactions between social media, public opinion, and public policy are particularly relevant for understanding science-related policy issues, such as climate change (Anderson & Huntington, 2017) and nanotechnology (Runge et al., 2013).

Studies of scientific topics on Twitter have analyzed the discourse around the applications of technology (e.g., genetically modifed mosquitoes; Wang & Guo, 2018; Wirz et al., 2018), a specific scientific event (e.g., the release of a consensus report by the National Academies of Sciences, Engineering, and Medicine; Howell et al., 2018), or a specific controversy (e.g., the "arsenic-life" controversy; Yeo et al., 2017). Scholars have also examined how people discuss scientific topics, such as climate change, on Twitter using sarcasm and incivility (Anderson & Huntington, 2017). Research specifically focused on GMOs suggests that discussions on Twitter at the national and global levels change episodically by topic and tone in response to events like the release of the National Academies consensus report or comments made by high-profile users, such as the American politician Bernie Sanders, on Twitter (Howell et al., 2018). Topics that define GMO-related conversations in the media and on Twitter are typically the human health and safety impacts of GMOs, how products containing GMOs should be labeled and regulated, and the agronomic and environmental impacts of GE crops (Howell et al., 2018).

However, research on social media discourse around GMOs has for the most part focused on the global and national levels, with very few studies examining regional variations within discourse on an issue (for an exception, see Gupta, 2018). An analysis of Twitter discourse in the United States on nuclear energy following the Fukushima Daiichi nuclear disaster found that variations in regional experiences within a country can lead to sub-conversations on social media (Li et al., 2016). These sub-conversations can change the nature of discourse and sustain discussion of an issue after it has dropped from the mainstream news cycle. These more focused discussions can be indicative of “issue publics,” or highly interested publics who drive conversation and potentially shape opinion formation and decision-making around a particular issue (Converse, 1964; Li et al., 2016; Price et al., 2006). Given the policy relevance of state-level perceptions of GMOs, as discussed in the previous section, and the potential for discourse on social media to shape broader discourse and opinions around an issue, it is important to understand the dynamics of the discourse around GMOs on Twitter at the state level.

It is also worth noting, however, that Twitter is not necessarily representative of the United States demographically or in terms of opinion. In fact, Twitter users tend to be younger and more liberal than the U.S. population (Wojcik & Hughes, 2019). Those who are motivated enough to express their ideas on social media might hold a majority opinion online, as with the pessimistic sentiments about GMOs, but actually be in the minority when compared with public opinion at the national level. Nonetheless, those who are discussing GMOs on Twitter could have outsize influence on decision-making and public opinion surround GMOs, as the literature on issue publics highlights (Converse, 1964; Li et al., 2016; Price et al., 2006). These issue publics, especially if they differ by state, are important to understand as they may impact policy and public opinion about GMOs.

Understanding perceptions of GMOs

In this study, we conduct state-level analyses in part to fill a gap in the literature on perceptions of GMOs, which

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focuses predominantly on individual-level differences. Past research on public perceptions of GMOs conducted at the individual level demonstrates several demographic and value-based characteristics that can significantly predict public opinion and regulation of GMOs in the United States (for a more detailed review of public perceptions of GMOs, see Scott et al., 2018). Individual perceptions and state-level discussions are undoubtedly different, but some of the past work at the individual level may help inform state-level analyses. For example, in this study, we focus on education and political ideology because they are demographics for which state-level data are available and because there is evidence to suggest that education and political ideology may affect the likelihood that individuals will attend to GMO-related news as well as hold particular views on regulation of GMOs. We first review the potential connections between political ideology and education before discussing other relevant variables.

Education alone is not generally a strong predictor of perceptions of GMOs (e.g., Rose et al., 2019; Rose et al., 2020); however, higher education does tend to relate to higher levels of deference to science and, in turn, support for biotechnology (a term that encompasses GMOs; see Brossard & Nisbet, 2007). Education is also associated with higher attention to biotechnology-related news and higher science knowledge levels related to biotechnology (Brossard & Nisbet, 2007). As a result, a state's education level may influence Twitter discourse indirectly because it is related to other important factors.

Debates surrounding GMOs in the United States have not clearly followed partisan lines, but views on regulation in general often depend on political ideology. Past research has demonstrated only weak or nonsignificant relationships between party identification and attitudes expressed about GMOs (Kahan, 2015; Khan, 2013; Lusk et al., 2005; Scott et al., 2016). Despite these findings, political ideology presents a complicated cue for GMOs because legislators have taken stances that may politicize the debate on social media. For example, previous analyses of GMOs on Twitter found that tweets about GMOs by the politician Bernie Sanders received a great deal of attention and were widely retweeted (Howell et al., 2018). Political ideology could also influence the extent to which a state legislature proposes regulations concerning GMOs, however, as well as the type of legislation that legislatures introduce. Therefore, it is important to control for it in our analyses.

Extending this research on perceptions of GMOs from the individual level to the state level, this study explores how a state's education level and political leaning influence how individuals in that state discuss GMOs on Twitter. More particularly, we are interested in the expressed "sentiments," generally defined as a classification of the tone or affect expressed in a post. For this study we analyzed "positive," "negative," and "neutral" sentiments, which we discuss in more detail in the methods section. To better understand these dynamics, we pose the following research questions:

> **RQ1**: How is the average education level of residents within a state related to the sentiments expressed in GMO-related Twitter discourse within each state?
>
> **RQ2**: How are estimated state-level political ideologies related to public sentiment in GMO-related Twitter discourse?

In addition to political ideology and education, there are several other important factors that may influence discussions on Twitter at the state level. For example, since the 2016 U.S. presidential election, in which the political divide between rural and urban voters was at its most stark in recent decades, scholars and media outlets have increasingly focused on distinctions between opinions in rural and urban areas and how those distinctions translate into the political sphere (Monnat & Brown, 2017; Scala & Johnson, 2017). Discussions in the media have focused on how economic conditions in particular are related to differences in voting patterns among rural and urban residents. These voting patterns build on other work that has demonstrated political divides between rural and urban residents (Cramer, 2016). Such political differences can translate into different regulatory priorities, and more rural versus more urban states could also have different agricultural experiences that impact views on GMOs. Based on this work, we pose the following research question:

> **RQ3**: How is the proportion of rural and urban counties in each state related to the expressed sentiments in GMO-related Twitter discourse at the state level?

Ruralness also relates to the role agriculture plays in each state. This is relevant for discussions of GMOs because the controversy surrounding GMOs has also been accompanied by hopes and concerns regarding the potential of this technology to reshape agricultural practices and the food we consume (NASEM, 2016). For

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states where residents are more dependent on, familiar with, and aware of agriculture, there could be a greater interest in the agroeconomic aspects relating to the impact of GMOs. Although some work has examined how farmers in particular perceive GMOs (Kondoh & Jussaume 2006), research has not widely addressed how the prominence of agriculture in a community, region, or state may impact how individuals in that area view the technology. In an analysis of Ohio residents, farmers perceived GM products more favorably than nonfarmers (Napier et al., 2004). Because GMOs are so highly tied to agriculture in the United States (NASEM, 2016), states with a higher level of agricultural activity could have a different experience and level of familiarity regarding GMOs. Because of this, we examine the following research question:

> **RQ4**: How is the proportion of farm-dependent counties in each state related to the sentiments on GMO Twitter discourse expressed at the state level?

Beyond direct experience, residents can also be exposed to GMOs and their impact at the state level through news coverage within a state. Such coverage can provide context that could shape residents' perceptions of GMOs, their relevance, and their impact on the state. This media coverage may be an especially important cue for lay audiences forming attitudes about GMOs, because the likelihood they have personal experiences with or are knowledgeable about the topic is very low (Jennings, 2018; Scheufele, 2007).

GMOs have been covered in the American media since the late 1990s, when GM foods received a great deal of media attention following an increase in their use in American agriculture and food production (Shanahan et al., 2001). Agricultural biotechnology has traditionally produced news coverage that is centered on specific issues or events or that is episodic in nature. Coverage responds quickly to these episodes, such as the release of a report about the proposed safety of GE crops, then decreases as public attention to the event fades (Howell et al., 2018; Nisbet & Huge, 2006). Under this episodic media coverage cycle, events related to agricultural biotechnology can incite a sharp increase in media coverage, which could result in increases in public attention and in GMO discourse on social media, as past research has demonstrated that changes in media coverage are related to changes in public opinion surrounding health and science issues (e.g., Chan et al., 2018; Frewer et al., 2002; Mazur, 1981). To address these dynamics, we ask the following research question:

> **RQ5**: How is the amount of news coverage at the state level related to the proportion of negative sentiments expressed at the state level?

Topics of news coverage and discourse

In the United States, much of the recent news coverage on GMOs has focused on GMO labeling. The topics of GMOs and GMO labeling in particular have created a dynamic policy climate rife with dissenting opinions about the appropriate regulation of the technology. The majority of Americans support the labeling of GM foods when asked (Hallman et al., 2013; Runge et al., 2017). Despite some gains in political popularity in the United States, however, the issue of labeling remains contentious. In 2016, President Barack Obama signed legislation to create a national standard for labeling products containing GMOs that preempts all state-level legislation (Hall, 2016). The rule has proven controversial, and representatives have continued to introduce GMO-related legislation at the state level. Therefore, we pose the following research question:

> **RQ6**: How is the amount of legislation related to GMOs introduced in each state related to the proportion of negative sentiments expressed at the state level?

Finally, broader discussions and disagreements about GMOs often stem from varied views on the potential environmental, health, economic, and ethical impacts of GMOs (Brossard, 2012). To address these concerns, the National Academies of Sciences, Engineering, and Medicine released a consensus report on GE crops. The report reviewed research related to health, safety, regulation, and labeling, as well as agronomic and environmental aspects of GE crops (NASEM, 2016). To assess how sentiment differs within states depending on what each state is discussing related to GMOs, we also examine the following research question:

> **RQ7:** How is the topic of discussion related to the sentiment expressed in the GMO-related state-level Twitter discourse?

Methods

Twitter data

For the analysis of Twitter, we used the automated nonparametric content analysis software Crimson Hexagon ForSight to collect a census of GMO-related tweets posted between January 2016 and May 2018. For this study, we had access to all publicly available posts via the Twitter Firehose, which is an exclusive data-sharing agreement that ensures access to all tweets matching our search criteria. We collected English-language tweets posted in the United States during this time using a Boolean search string, incorporating a wide variety of topics related to GMOs (see the Appendix). The ForSight platform also collects and identifies the geographic origins of tweets for a subsample of the posts.

ForSight's algorithm uses nonparametric statistical modeling to estimate the sentiments expressed in the data (Hopkins & King, 2010). Essentially, an algorithm is "trained" to recognize patterns using a sample of posts that match human-defined and coded categories of interest. The algorithm then uses this training to classify sentiments using the human-defined categories and examples. This classification system relies on both natural language processing (Liddy, 2001) and statistical pattern recognition (Webb, 2003). First, human coders train the algorithm with posts identified as exemplars for each sentiment of interest. This trains the algorithm to recognize patterns of words representative of specific concepts being studied. The exemplars used to train the algorithm are the result of a series of human-coded reliability trials that involve coders classifying random samples of the posts manually using a codebook discussed in greater detail below.

After each trial, we calculated the percentage agreement between the coders. The codebook was updated after each trial to address any disagreements or ambiguous points. We repeated this protocol, using a new random sample each time, until the two coders reached a minimum of 80% agreement. When we reached reliability, we trained the intelligent algorithm using a subset of posts, as discussed earlier (Hopkins & King, 2010). We then reviewed the results to check the accuracy of the classifications by reviewing a random samples of 50 classifications and correcting any misclassifications by adding the post to the training set for its correct coding. We repeated this process until we did not find any misclassifications. This method is widely used in the field of science communication (e.g., Howell et al., 2018; Simis-Wilkinson et al., 2018; Wirz et al., 2018). For a more detailed review of this method, see Hopkins and King (2010) and Su et al. (2017).

To understand the sentiments of these posts and the conversation about GMOs on Twitter, we developed four categories: positive, neutral, negative, and off-topic. The positive category was for posts that mentioned GMOs in a positive, supportive, and/or optimistic way. This category also included posts that advocated for and/or clearly focused on the benefits or helpfulness of the technology. The neutral category was for posts that did not express valence about GMOs. These posts were generally updates, like a news headline. The negative category was for posts that mention GMOs in a negative, nonsupportive, and/or pessimistic way. These posts focused on the risks or harmfulness of the technology. The final category, off-topic, was for posts that were not actually referencing GMOs or agricultural biotechnology in anyway. This category was for all the irrelevant posts that our search string captured. See Table 1 for specific examples.

To assess the topics of conversation for RQ7, we conducted a second analysis using the same approach outlined for the sentiment analysis, but instead we coded for the topics of conversation. We used the major themes of the 2016 NASEM consensus report on GE crops as the foundation for our codebook, because these categories represent the most prominent aspects of the debate (NASEM, 2016) and have been used for similar analyses of social media (Howell et al., 2018). The categories we analyzed for this study were regulation and labeling, environmental, health and safety, and agronomics. The regulation and labeling category was for posts that mentioned any regulatory implications of GMOs, especially labeling. This category also included references to government action, like bans or embargos. The environmental category was for posts that mentioned GMOs in relationship to the environment or environmental problems. The health and safety category was for posts that discussed health effects relating to GMOs and whether they are dangerous or safe for consumption. The agronomics category was for posts that mentioned agriculture-specific topics, like impacts on soil, pesticide use, insecticide, or crop yield. We also included an other category to capture tweets that did not fit in these categories and an off-topic category to capture any posts not referring to GMOs or agricultural biotechnology. See Table 2 for specific examples.

Regression analyses

Using the sentiment data created through the content analysis, we then ran regression models using state-level

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Table 1. Examples of coded GMO-related tweets expressing sentiments on Twitter between January 1, 2016, and May 1, 2018.

Positive	• RT @MoreScienceNews Genetically modified technology a safe tool to help meet food supply demands, plant scientists say • We're All Eating GMOs! And That's a Good Thing (will need to do even more to feed 10B people by 2050)
Neutral	• The #GMO Story #FYW is out! https://t.co/OMySsKU99l Stories via @KittyAntonik @LinReimersdahl @DSIJ • Top genetically modified organisms articles from last 48 hrs https://t.co/NI9Ths4xXh
Negative	• RT @OrganicLiveFood #Biotech is taking us 2ward a more #pesticide-dependent agriculture/Chemical in #AgentOrange is gonna b in #GMO co . . . • RT @TheTimberGroup The Public Health Ramifications of GMOs and Herbicides https://t.co/LyzOpL6UcZ #Health #GMO #SaynotoGMO
Off-topic	• GM, Ford, Honda winners in 'Car Wars' study as industry growth continues http://dlvr.it/LHjY5b #car #news

Table 2. Examples of topics of conversation for coded GMO-related tweets on Twitter between January 1, 2016, and May 1, 2018.

Health and safety	• @Kauairockchick @kauairockchick While they discuss more than GE soy, the refs I give are a great overview of the safety of GMOs. Yes, even the EU agrees! • RT @WyoWeeds Here are 12 different long-term studies that show the safety of #GMOs. https://t.co/gJhlft9U6m
Regulation and labeling	• RT @SenSanders When labeling genetically modified food is required in 64 countries around the world, why is it not required in the United States? • Ban on local GMO ordinances challenged in Legislature
Environmental	• The influence of a #GMO organism on the food chain can damage the local ecology. Causing unforeseen changes in the environment. • The environmentally friendly side of genetically modified crops http://bit.ly/1qmgCmm G.M.Os are not all bad #envir490
Agronomics	• RT @welovegv .@GMOInside is lying to people now. Roundup is still used by farmers for "Non-GMO" crops. • RT @USRealityCheck Farmers report better animal health with non-#GMO feed https://t.co/jFeVaugXWy #GMOs
Other	• RT @saclboy .@Uber my driver won't stop harassing me about the fact that we can't escape genetically modified foods in this da-
Off-topic	• GM, Ford, Honda winners in 'Car Wars' study as industry growth continues http://dlvr.it/LHjY5b #car #news

factors and the topics of conversation to predict the sentiment of tweets about GMOs in each state. The results of the content analysis were integrated into regression models by using the proportions for each sentiment category for each state. These values are listed and described in more detail in the results section (Table 3). We used hierarchical ordinary least-square (OLS) regression to test models predicting the proportion of negative, positive, and neutral tweets about GMOs in each state during the time period, captured using the methods described earlier. Based on the results of those analyses, we then ran OLS regression models predicting how each of the state-level variables predicted what topic of focus dominated GMO-related Twitter discourse within a state.

The predictor variables were entered in the regression model in blocks according to their assumed causal order. The block-by-block approach allows us to evaluate the variance explained by each set of variables as they are entered as predictors (Cohen et al., 2013). The independent variables, in the order they entered the models, are described next.

Education at the state level was measured by the percentage of residents with a bachelor's degree or higher in the state (M = 29.8, SD = 5.0) (U.S. Census Bureau, 2015). We captured state-level *political ideology* with Berry et al.'s (2010) measurement of citizen ideology at the state level. This analysis used the most recent estimates, from 2013, developed using the revised 1960–2013 citizen ideology series (M = 49.9, SD = 15.5).

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Table 3. Volume of relevant posts, proportion of sentiments, and proportion of topics in each state.

State	Total posts	Negative	Neutral	Positive	Health & safety	Enviro.	Ag.	Reg. & labeling
California	311,570	42%	30%	27%	14%	12%	13%	26%
Texas	220,415	51%	27%	21%	12%	11%	14%	24%
New York	124,292	43%	29%	27%	12%	13%	15%	23%
Florida	88,056	44%	29%	26%	13%	12%	14%	22%
Illinois	53,508	40%	31%	28%	12%	12%	15%	25%
Washington	43,383	41%	29%	29%	12%	12%	15%	25%
Ohio	39,963	46%	29%	25%	15%	13%	12%	19%
Colorado	39,843	43%	28%	28%	14%	12%	13%	22%
Pennsylvania	39,773	41%	29%	29%	13%	13%	15%	21%
Arizona	39,472	47%	29%	23%	16%	11%	12%	21%
Oregon	32,761	39%	32%	27%	12%	12%	14%	25%
Michigan	32,005	38%	30%	30%	12%	13%	15%	21%
North Carolina	31,579	47%	28%	23%	15%	12%	14%	18%
Massachusetts	30,522	39%	32%	28%	11%	13%	14%	24%
Virginia	29,802	46%	27%	26%	14%	13%	15%	16%
Georgia	28,721	41%	29%	28%	13%	14%	14%	19%
Missouri	26,594	41%	27%	29%	14%	14%	15%	18%
Minnesota	23,439	40%	31%	27%	13%	12%	14%	21%
New Jersey	22,993	42%	31%	26%	12%	11%	14%	23%
Nevada	22,277	49%	28%	21%	16%	10%	12%	20%
Wisconsin	20,661	45%	29%	24%	15%	12%	14%	22%
Indiana	17,801	38%	30%	30%	11%	13%	15%	23%
Tennessee	17,291	40%	31%	26%	12%	12%	14%	22%
Maryland	16,902	42%	29%	27%	14%	13%	14%	18%
Hawaii	15,169	59%	19%	21%	14%	13%	14%	18%
Alabama	14,258	46%	30%	22%	15%	12%	13%	19%
Louisiana	12,968	47%	32%	20%	17%	12%	11%	16%
Kansas	11,293	37%	36%	24%	14%	13%	14%	24%
Oklahoma	11,116	42%	31%	24%	15%	12%	13%	21%
Iowa	10,678	34%	27%	37%	11%	14%	18%	21%
Kentucky	10,470	45%	27%	25%	13%	11%	17%	19%
Nebraska	10,309	48%	24%	25%	17%	11%	12%	17%
Connecticut	9,789	36%	34%	27%	9%	12%	14%	28%
Idaho	6,519	41%	30%	25%	17%	13%	13%	17%
New Mexico	6,258	47%	28%	22%	16%	9%	11%	20%
South Carolina	6,050	37%	31%	28%	11%	13%	16%	19%
Arkansas	5,925	46%	25%	26%	12%	11%	15%	20%
Vermont	5,705	29%	49%	19%	8%	11%	9%	46%
Maine	5,168	39%	35%	23%	10%	11%	12%	33%
Utah	5,149	34%	29%	34%	11%	12%	15%	20%
Alaska	4,976	49%	35%	14%	21%	13%	9%	18%
Montana	4,392	36%	32%	28%	11%	16%	15%	25%
New Hampshire	3,487	38%	34%	23%	8%	11%	14%	31%
Mississippi	3,322	37%	27%	32%	11%	13%	19%	17%
Rhode Island	3,197	35%	37%	25%	11%	12%	16%	24%
South Dakota	2,767	43%	18%	36%	12%	14%	22%	15%
West Virginia	2,632	36%	32%	29%	11%	9%	12%	28%
Wyoming	1,751	38%	35%	24%	13%	18%	17%	21%
North Dakota	1,738	28%	37%	31%	9%	18%	19%	20%
Delaware	1,492	37%	30%	29%	11%	11%	14%	24%
Overall	**1,530,201**	**41%**	**30%**	**26%**	**13%**	**12%**	**14%**	**22%**

Lower values for this item indicate more conservative states and higher values indicate more liberal states. For reference, Utah scored the lowest with 20.98 and Connecticut scored the highest with 91.85. See Berry et al. (2010) and Berry et al. (1998) for more information about the measure. This ideology estimate integrates multiple data sources to provide a more stable and accurate measure.

For capturing *rural versus urban*, we used the average rural-urban continuum codes from the U.S. Department of Agriculture's Economic Research Service (2016) for all counties in each state ($M = 4.7$, $SD = 1.6$). These codes range from 1, “counties in metro areas of 1 million population or more,” to 9, “completely rural or less than 2,500 urban population, not adjacent to a metro area” (USDA Economic Research Service, 2016).

We evaluated the importance of *agriculture* in each state by including the percentage of counties that are defined as “farm dependent” in each state (M = 12.7%, SD = 18.4%). The classification is for counties with 25% or more of their earnings coming from farming or 16% of their employment involved with farming (USDA Economic Research Service, 2015).

We captured *newspaper coverage* through a count of newspaper articles that mentioned GMOs in the top circulated newspaper in each state (Agility PR Solutions, 2016) (M = 8.3, SD = 8.4). We searched each newspaper’s website manually and counted each of the relevant articles published during the time of our study (January 1, 2016–May 1, 2018).

Finally, to consider the differences in the state-level policy climates, we looked at proposed state *legislation*. The legislative data were collected using the LegiScan database (https://legiscan.com). We searched for state bills using the following search string: ((Genetic OR genetically) AND (modified OR modifying OR engineering OR engineered)) OR (GMO) OR ((GM OR GE) AND (crop OR food)). We collected the amount of legislation that was introduced from January 2014 to March 2017 in each state (M = 5, SD = 8.8). This measure provides a quantification of the prominence of genetic editing and engineering on each state’s legislative agenda. For example, several states had no bills introduced using these terms, while others had over 40 bills during the same time. We selected this range to account for legislation that may have been debated and active during the time of our study but was introduced before we began collecting tweets. We selected our end date several months after the federal labeling bill was finalized to collect any state-level legislation that may have been introduced as a response to the new federal standard.

Results

Twitter data

We collected 4,813,197 relevant tweets about GMOs posted from January 1, 2016, to May 1, 2018. Of these posts, 42% had a negative sentiment, 29% were neutral, and 29% were positive. Of the total posts about GMOs, 1,530,201 had an identifiable U.S. state associated with them. The state-specific Twitter results are listed by volume of posts in Table 3. There was a wide range in the number of tweets about GMOs in each state, partly reflecting population differences, ranging from 311,570 tweets in California to 1,492 in Delaware.

Consistent with the aggregate results, most states had more negative sentiments than positive (Table 3). The states ranged from 59% negative in Hawaii to 28% in North Dakota. By contrast, the proportion of positive sentiments were much lower, with Iowa having the highest proportion of positive tweets about GMOs (37%) and Alaska having the lowest (14%). Vermont had the highest proportion of neutral content (49%) and only 29% of sentiments were negative (Table 3). Vermont’s comparatively low percentage of negative sentiments is interesting, considering the state has been a key proponent of GMO labeling. This may be the result of a large volume of updates and news content surrounding the state’s legislation and role in the federal labeling laws, which would increase the proportion of neutral tweets.

Regression results

Models predicting sentiment We used 0.1 as our alpha level for this study, as we had a small number of observations (n = 50) and interpreted results with p-values less than or equal to .1 as statistically significant. As seen in Table 4 (Models 1–3), state-level characteristics overwhelmingly did not predict the sentiment of GMO-related Twitter discourse within a state, providing some answers to RQ1–6. As the incremental adjusted R^2 results indicate, a few of the state-level characteristics were significant predictors until the topic of Twitter discussion within a state (Block 7) entered the model, and they appear to be more strongly related to positive and neutral sentiments in Twitter discourse than to negative sentiments. Education level was significantly positively related to more neutral sentiments, until the model included the particular topics of GMO conversation (RQ1). Agricultural dependence had a stronger and more consistent relationship to sentiment. Before the topics entered the model, the agricultural dependence of a state significantly related to higher levels of positive sentiment and lower levels neutral sentiment (RQ4), with the variable accounting for 11.4% and 7.7% of the variance in the proportion of positive and neutral sentiment tweets within a state, respectively.

As the coefficients in Table 4 indicate, however, these relationships between state-level characteristics and the sentiment of Twitter discourse related to GMOs lost significance once the topics of Twitter discourse entered the models. As seen in the large coefficients and incremental

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Table 4. Predicting the proportion of negative, positive, and neutral sentiments about GMOs at the state-level

	Negative	Positive	Neutral
	Model 1: Std. β (*SE*)	Model 2: Std. β (*SE*)	Model 3: Std. β (*SE*)
Block 1: Education	0.013	0.102	–0.064
Bachelor's degree or higher (%)	(*0.002*)	(*0.001*)	(*0.001*)
Incremental adjusted R^2 (%)	*0.4*	*–2.1*	*4.2**
Block 2: State-level political ideology	0.164	–0.084	–0.127
2013 estimates (low = conservative)	(*0.001*)	(*0.000*)	(*0.000*)
Incremental adjusted R^2 (%)	*–2.1*	*2.1*	*2.1*
Block 3: Rural versus urban	0.040	0.003	–0.111
Average of counties (high = rural)	(*0.006*)	(*0.004*)	(*0.005*)
Incremental adjusted R^2 (%)	*–0.1*	*–1.7*	*0.7*
Block 4: Agricultural dependence	–0.033	–0.005	0.013
Percentage of farm-dependent counties	(*0.000*)	(*0.000*)	(*0.000*)
Incremental adjusted R^2 (%)	*–2.0*	*11.4***	*7.7***
Block 5: GM legislation	0.114	–0.140	0.024
Amount of legislation introduced	(*0.005*)	(*0.003*)	(*0.003*)
Incremental adjusted R^2 (%)	*–2.4*	*–1.7*	*–1.4*
Block 6: News coverage	–0.025	0.134	–0.056
Number of articles in top circulating state newspaper	(*0.001*)	(*0.001*)	(*0.001*)
Incremental adjusted R^2 (%)	*1.2*	*–0.6*	*–0.1*
Block 7: Topics of GMO Twitter conversation†			
Percentage about environmental aspects	–0.293*	0.286**	0.081
	(*0.437*)	(*0.304*)	(*0.319*)
Percentage about health and safety	0.746***	–0.555***	–0.287**
	(*0.586*)	(*0.407*)	(*0.427*)
Percentage about agronomics	–0.343**	0.701***	–0.271*
	(*0.536*)	(*0.372*)	(*0.391*)
Percentage about regulations and labeling	–0.616***	–0.064	0.715***
	(*0.303*)	(*0.210*)	(*0.221*)
Incremental adjusted R^2 (%)	*56.8****	*50.4****	*48.8****
Adjusted R^2 (%)	**51.8**	**57.8**	**62.0**

N = 50. * $p \leq .1$; ** $p \leq .05$; *** $p \leq .01$ (two-tailed).
† Before-entry coefficients.

adjusted R^2 across Block 7 in Models 1–3 (Table 4), the particular topic of conversation overwhelmingly related to the sentiment of conversation. Greater levels of conversation around the environmental aspects of GMOs were significantly related to more positive and less negative sentiments, as were greater levels of conversation about agronomics, which were also related to less neutral sentiments. In the case of conversation on agronomics, the proportion of agronomics-focused tweets that were positive in sentiment could have resulted in a significantly lower likelihood of negative or neutral tweets in comparison.

In contrast, conversation about health and human safety aspects of GMOs significantly related to higher levels of negative sentiment in the state-level Twitter discourse and lower levels of positive and neutral sentiments. This could indicate that the high proportion of negative sentiment in discourse on these topics led to significant decreases in positive and neutral discourse in comparison. Higher levels of discourse around regulations and labeling concerning GMOs interestingly related to significantly more neutral sentiments within the GMO conversation in a state and fewer significantly negative sentiments (RQ7). This is somewhat surprising considering the political nature of the topic and the possibly contentious nature of the topic. It could also reflect, however, that because the topic was especially relevant on the news agenda at the time of data collection, many of the captured tweets reflect posts from media outlets, which could have had a more neutral tone in their journalistic coverage of the topic.

The topics alone explain close to or greater than half of the variance in sentiments in GMO Twitter discourse within a state. The topic variables were highly related to each other, as each represents a proportion out of the total of tweets, so we report upon-entry coefficients for each of these in Block 7 of Models 1–3 to avoid multicollinearity affecting the coefficients due to the high correlations between these topic variables (Hair et al., 1998).

Table 5. Predicting the proportion of the Twitter conversation about GMOs at the state-level about regulation and labeling and agronomics.

	Regulation & labeling		Agronomics	
	Model 4: Std. β (*SE*)		Model 5: Std. β (SE)	
Block 1: Education	0.112		–0.140	
Bachelor's degree or higher (%)	(*0.002*)		(*0.001*)	
Incremental adjusted R^2 (%)		*11.1***		*–0.7*
Block 2: State-level political ideology	0.492***		–0.123	
2013 estimates (low = conservative)	(*0.001*)		(*0.000*)	
Incremental adjusted R^2 (%)		*13.7****		*1.0*
Block 3: Rural versus urban	0.394**		–0.290	
Average of counties (high = rural)	(*0.006*)		(*0.003*)	
Incremental adjusted R^2 (%)		*1.8*		*–2.0*
Block 4: Agricultural dependence	–0.347**		0.548***	
Percentage of farm-dependent counties	(*0.000*)		(*0.000*)	
Incremental adjusted R^2 (%)		*3.4**		*15.0****
Block 5: GM legislation	–0.001		0.119	
Amount of legislation introduced	(*0.005*)		(*0.003*)	
Incremental adjusted R^2 (%)		*–1.4*		*–0.7*
Block 6: News coverage	0.219		0.047	
Number of articles in top circulating state newspaper	(*0.001*)		(*0.000*)	
Incremental adjusted R^2 (%)		*1.6*		*–1.8*
Adjusted R^2 (%)		**31.2**		**10.5**

N = 50. * $p \leq .1$; ** $p \leq .05$; *** $p \leq .01$ (two-tailed).

Models predicting topic of GMO conversation

Because some of the state demographic and contextual variables, such as dependence on agriculture, lost significance when the topics of GMO Twitter discourse entered the model, it is possible that they are mediated by the topic of discourse in shaping overall state-level sentiment of the Twitter conversation. Therefore, we ran models to analyze whether different states have differently focused conversations depending on their state-level demographics, ruralness, agricultural dependence, and GMO news and legislation-related experiences. This was to further explore how state experience could predict different types of discourse, which, as the previously described results indicate, then predicts different sentiments in discourse.

As seen in Table 5, only two of the topics had significant relationships to the state-level variables captured in these models. The other two models predicting tweets focused on environmental aspects and on human health and safety aspects of GMOs did not have significant model fit, indicating that the state-level characteristics we focus on were not good predictors of level of Twitter conversation focused on those topics.

Starting with the model focused on regulation and labeling discourse, state-level education was significantly related to the amount of Twitter discourse within a state that focused on this topic, until state-level political ideology entered the model (Model 4). States with higher education levels were significantly more likely to have discussion focused on regulation and labeling, although at a *p*-value of .1, this did not appear to be an especially strong relationship but did account for 11% of the variance. Once state-level political ideology entered the model, education was no longer significant. State-level political ideology, however, did significantly predict tweets on the topic, with more politically liberal states more likely to discuss regulation and labeling, relative to other topics related to GMOs. This remained significant after controlling for the other state-level variables and could reflect how the issue was highlighted by public figures, particularly Bernie Sanders, who are politically liberal and could have driven conversation among populations similarly politically inclined within states, as we describe in the discussion.

As seen in Table 5 (Model 4), the rural-urban distinction and agricultural dependence also appeared to be significant positive predictors of amount of Twitter conversation focused on regulation and labeling once all the variables entered the model. However, because these two variables were highly related to each other, the effect captured in the model could be capturing multicollinearity between those items. As possible evidence in support of this, on their own, neither rural-urban nor agricultural dependence was highly correlated with tweets about

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regulation and labeling (Pearson's $r = -0.108$, $p = .454$ and $r = -0.251$, $p = .078$, respectively).

The multicollinearity statistics do not indicate problematic collinearity between rural-urban and agricultural dependence based on the generally recommended cutoffs of 0.1 tolerance and 10 VIF (Hair et al., 1998). Tolerance values for rural-urban and agricultural dependence were 0.478 and 0.544, respectively (VIF = 2.09; 1.84), but these were lower than the tolerance values of each when the other was not included in the model, 0.745 (VIF = 0.1.34) and 0.847 (VIF = 1.18). Further, because the two independent variables were more related to each other than each was to the dependent variable of discussion about regulation and labeling, and with the small sample size, it is possible that multicollinearity was skewing the results in Model 4 and hindering interpretability of those results (Hair et al., 1998).

Moving to the model predicting discourse focused on agronomics, however, agricultural dependence appeared to be a significant predictor of state-level Twitter discourse on the topic. This is perhaps not surprising, as that topic could be more relevant within states more reliant on agriculture for economic well-being. It is interesting to see how much the two relate, however, with agricultural dependence accounting for 15% of the variance in the model predicting tweets focused on agronomics.

Discussion

The purpose of this study was to understand the relationship between different state-level characteristics in the United States and conversations about GMOs on Twitter. We found that state-level variables seemed to have limited influence on the Twitter conversations happening in each state. The sentiment of discourse about GMOs on Twitter was not explained by the state-level variables we included in our analyses (education, state-level political ideology, rural/urban differences, agricultural dependence, GM legislation, and news coverage). Instead, public sentiments about GMOs were significantly related to the topics of conversation. These results suggest that discussions about GMOs on Twitter are not necessarily geographically bound, but rather are influenced by the aspect of the technology that is being discussed. State-level variables, however, were related to some extent to the topic of conversation.

Overall, consistent with understanding social media as hosting national and global discourse, we did not find state-level factors significantly related to differences in the sentiment of tweets on GMOs coming from within a state. Agricultural dependence was the exception: it was significantly related to more positive and more neutral sentiments of Twitter discourse on GMOs until the models controlled for topic of conversation. Topic of conversation, then, is the dominant factor that can be associated with a specific public sentiment about GMOs at the state level. States with more discussion of the health and safety of GMOs also tended to express more negativity, which could suggest that this conversation was largely shaped by the belief among some publics that GMOs pose a health risk, despite scientific consensus on the relative safety for human consumption (NASEM, 2016).

States with higher levels of discourse on environmental and agroeconomic aspects of GMOs, in contrast, were more likely to be positive, and states that discussed regulation and labeling more tended to be more neutral. These results could suggest that discussions that focus more on agroeconomic aspects are more likely center on the perceived agricultural and economic benefits of GMOs or GE crops. Surprisingly, states with more environmentally focused discourse tended to be more positive. Many opponents of GMOs express reservations over environmental impacts, such as GM seeds spreading and affecting nearby habitats or increasing the use of pesticide. At the same time, however, recent news coverage has also focused on using GMOs as a way to reduce overall pesticide and fertilizer use in agriculture—two large sources of environmental degradation from agriculture—which could be part of the overall more positive discourse on GMOs and the environment.

The positive relationship between neutrality of discourse on regulation and labeling may be somewhat surprising, as well, given the contentiousness of such proposals for state-level regulation and responses to federal-level legislation preempting state-level policy. It could also reflect a larger amount of news coverage being shared by mainstream news organizations through Twitter and retweeted by other Twitter users. Such tweets often end up neutral in sentiment, as they typically report a bill being proposed or other legislative action, free of expressed opinion or sentiment.

There were, however, variations in which state-level experiences appeared to be important for shaping what discourse emerged from a state. Discourse on health and safety and on the environmental aspects of GMOs was not significantly related to the state-level characteristics included in this study. This could suggest that those are part of less geographically bound conversations, or at least interests that are shared by people across the United

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States and more dependent on individual-level characteristics than on state-level environment.

Discourse on agroeconomics and on regulation and labeling, however, was partly explained by state-level context. For discourse on agroeconomics, more agriculturally dependent states were more likely to tweet about the agricultural economic aspects of GMOs. This makes sense and is important evidence of how state context can affect concerns that, in turn, shape discourse. As these agriculturally dependent states were more likely to discuss agroeconomic impacts and more discourse on agroeconomic impacts was more likely to be positive, these results together could provide a picture of how an issue public—in this case, agroeconomic-focused stakeholders with shared state-level experiences—can shape the nature of discourse on an issue more broadly. As Twitter discourse transcends geopolitical boundaries, these geographically bound publics could then shape Twitter discourse overall.

Tweets on regulation and labeling, conversely, were more likely to emerge from states with less reliance on agriculture and with higher education levels and a more liberal political ideology, suggesting that this discourse is shaped by a different public with a different local experience than that of those talking about agroeconomic impacts. That the liberal political leaning within a state significantly related to greater Twitter discourse focused on regulation and labeling, however, could also be indicative of national-level discussion and coverage of the topic. Previous work analyzing Twitter discourse during part of the same time frame found that Bernie Sanders, a politically liberal prominent figure in national discourse, contributed to discussion of regulation and labeling of GMOs at the time and that tweets focused on this topic spiked after he did so (Howell et al., 2018). Overall, however, for most of the topics and sentiment of Twitter discourse on GMOs, political leaning of a state does not appear to significantly relate to state-level discourse. This aligns with previous work on individual-level perceptions that typically finds that conservative-liberal measures of political ideology do not significantly or consistently relate to views of GMOS.

Interestingly, despite the possibility of rural-urban divides in the United States on controversial societal issues such as GMOs, we did not find that the proportion of rural-urban counties in each state likely predicted topic or sentiment of conversation. Because rural-urban proportion was highly correlated (Pearson's r = 0.642, p = .000) with agricultural dependence, this collinearity could be why both variables became significant when they were together in the model predicting conversation focused on regulation and labeling. In the case of conversation focused on agroeconomics, however, we see that agricultural dependence did relate to higher proportions of conversation on that topic, while rural-urban distinctions alone did not.

Given the overlap between rural-urban with political ideology and with agricultural dependence—two variables that did significantly relate to aspects of the state-level Twitter discourse on GMOs—rural-urban distinctions could be a useful proxy for understanding patterns of political preferences and economic experiences in general, as the literature on rural-urban divides highlights. Based on the results of these analyses, however, it appears that it is these more specific experiences—in this case state political ideology and agricultural dependence in particular—of which rural-urban is a more general indicator or covariant, that matter for understanding aspects of concerns and discourse relevant to views of GM crops. Focusing only on "rural versus urban" would miss these important potential drivers of the distinction in experiences and resulting state- and individual-level concerns.

There are also several limitations to consider. First, not all tweets are geotagged. By not being able to incorporate untagged posts, we might be missing some valuable pieces of the conversation online. This could be more of an issue if there is reason to believe that geotagged tweets are likely to systematically vary from non-geotagged tweets in a way that would bias the results captured here. However, there is a not a clear theoretical reason to suspect that that is the case. Second, as mentioned earlier, Twitter is not necessarily representative of the United States demographically or in terms of opinion, however, those who are discussing GMOs on Twitter could have outsized influence on decision-making and public opinion surround GMOs.

Third, the state-level characteristics represent averages and might not represent the characteristics of the individuals engaged in communicating on Twitter in each state. Additionally, the categorization of introduced legislation related to GMOs does not reflect the nuances of proposed legislation. We could not effectively sort each piece of legislation in a way that would identify each as being either for or against GMOs. Future research should attempt to go beyond the number of bills introduced and explore whether the specific types of bills introduced impact the discussion of GMOs on social media. We also did not analyze the authors of each tweet, so we do not know how this conversation is shaped by different actors. As a result, our analyses cannot answer questions about who the dominant voices are in the conversation or the types of accounts generating the tweets we analyzed (e.g., organizations, individuals, bots). Finally, Twitter and the software we used to collect the census of tweets only records geo-locations by state, so the maximum number of cases is 50 (the number of states studied). The small number of cases may limit our ability to reject the null hypothesis.

Despite these limitations, our study provides relevant information for policymakers at the state and national levels. We provide an in-depth analysis of the national- and state-level conversations on Twitter surrounding GMOs, a contentious and evolving issue for science policy. Our study provides a more granular view by focusing on the state level, which is relatively unique for analyses of social media. This level of detail gives stakeholders a more direct look at the conversation in their states to understand factors that might shape the policy climate as well as to achieve more effective communication about GMOs by understanding this climate and discourse.

Conclusion

This study adds to the very small body of research focusing on how state-level context shapes public discourse of an issue on social media and adds important contributions to our understanding of policy-relevant public concerns and the extent to which discourse on such concerns is more local, national, or global in nature. Based on the results, it appears that Twitter discourse on GMOs is largely the latter—a conversation among interested publics that span geographically bounded experiences. These individuals might be motivated to share and discuss information on GMOs because of more globally shared concerns or individual experiences that are not captured through state-level contexts. This appears to especially be the case for conversation focused on health and safety and on environmental aspects of GMOs.

There are caveats to this conclusion, however, which can have important implications for understanding the state-level communication- and policy-relevant context. Public focus on issues of regulation and labeling and of agroeconomic aspects of GMOs do vary with relevant state-level factors, especially a state's agricultural dependence. That people in more educated, liberal, and less farm-dependent states are more likely to tweet about regulation and labeling of GMOs while more people in more farm-dependent states are more likely to tweet about agricultural economic impacts of GMOs suggests that these conversations are partly driven by issue publics with different priorities depending on their shared state-level experiences. That the amount of discourse on these different topics concerning GMOs have different sentiments attached to them—health and safety more negative, environment and agroeconomics more positive, and regulation and labeling more neutral—could suggest that these issue publics can also shape the broader sentiment of discourse on these areas.

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Appendix. Boolean search string used to collect Twitter data

(GMO* OR GEcrop* OR GEplant* OR GEfood* OR GMcrop* OR GMplant* OR GMfood* OR (Ag* AND (biotech* OR (bio AND tech*))) OR agbiotech* OR Frankenfood* OR (franken* AND food*) OR (genetic* AND (engin* OR modifi* OR alter*) AND (food* OR crop* OR organism* OR plant* OR ingredient*)) OR ((GE OR GM) AND (food* OR crop* OR organism* OR plant* OR ingredient*)) OR ((crop* OR ingredient* OR food* OR plant* OR corn* OR soy* OR cotton* OR salmon*) AND (engin* OR modifi* OR alter* OR Transgenic*))) AND -(motor OR GMA OR youtube OR Forbes OR Chevrolet OR Chevy OR ChevyVolt OR Buick OR Cadillac OR GMC OR car OR cars OR vehicle OR vehicles OR gmorn* OR gmoney* OR gmom* OR gmod OR "General Electric")

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