Evolving Drivers of Brazilian SARS-CoV-2 Transmission: A Spatiotemporally Disaggregated Time Series Analysis of Meteorology, Policy, and Human Mobility

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Abstract

Brazil has been severely affected by the COVID-19 pandemic. Temperature and humidity have been purported as drivers of SARS-CoV-2 transmission, but no consensus has been reached in the literature regarding the relative roles of meteorology, governmental policy, and mobility on transmission in Brazil. We compiled data on meteorology, governmental policy, and mobility in Brazil's 26 states and one federal district from June 2020 to August 2021. Associations between these variables and the time-varying reproductive number ($\mathrm{R_t}$) of SARS-CoV-2 were examined using generalized additive models fit to data from the entire fifteen-month period and several shorter, three-month periods. Accumulated local effects and variable importance metrics were calculated to analyze the relationship between input variables and $\mathrm{R_t}$. We found that transmission is strongly influenced by unmeasured sources of between-state heterogeneity and the near-recent trajectory of the pandemic. Increased temperature generally was associated with decreased transmission and specific humidity with increased transmission. However, the impact of meteorology, policy, and mobility on $\mathrm{R_t}$ varied in direction, magnitude, and significance across our study period. This time variance could explain inconsistencies in the published literature to date. While meteorology weakly modulates SARS-CoV-2 transmission, daily or seasonal weather variations alone will not stave off future surges in COVID-19 cases in Brazil. Investigating how the roles of environmental factors and disease control interventions may vary with time should be a deliberate consideration of future research on the drivers of SARS-CoV-2 transmission.

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Key Points:

- Unmeasured sources of between-state heteorogneity and recent waves of cases are the dominant drivers of SARS-CoV-2 transmission in Brazil.
- The impacts of policy, meteorology, and mobility on transmission vary in direction and magnitude within subperiods of our study.
- Relying on proven mitigation measures such as mass vaccinations should be the key priority in the continued fight against COVID-19.

Abstract

Brazil has been severely affected by the COVID-19 pandemic. Temperature and humidity have been purported as drivers of SARS-CoV-2 transmission, but no consensus has been reached in the literature regarding the relative roles of meteorology, governmental policy, and mobility on transmission in Brazil. We compiled data on meteorology, governmental policy, and mobility in Brazil's 26 states and one federal district from June 2020 to August 2021. Associations between these variables and the time-varying reproductive number (R_t) of SARS-CoV-2 were examined using generalized additive models fit to data from the entire fifteen-month period and several shorter, three-month periods. Accumulated local effects and variable importance metrics were calculated to analyze the relationship between input variables and R_t. We found that transmission is strongly influenced by unmeasured sources of between-state heterogeneity and the near-recent trajectory of the pandemic. Increased temperature generally was associated with decreased transmission and specific humidity with increased transmission. However, the impact of meteorology, policy, and mobility on R_t varied in direction, magnitude, and significance across our study period. This time variance could explain inconsistencies in the published literature to date. While meteorology weakly modulates SARS-CoV-2 transmission, daily or seasonal weather variations alone will not stave off future surges in COVID-19 cases in Brazil. Investigating how the roles of environmental factors and disease control interventions may vary with time should be a deliberate consideration of future research on the drivers of SARS-CoV-2 transmission.

Plain Language Summary

Environmental factors such as outdoor temperature and humidity can affect the spread of the flu and other respiratory viruses. For this reason, early studies on the COVID-19 pandemic hypothesized that temperature, humidity, and other environmental factors might create favorable or less favorable conditions to facilitate the spread of COVID-19. At times, politicans and the media have disseminated these hypotheses without proper vetting. COVID-19 has caused major impacts in Brazil, and in this study we use a statistical model that allows us to investigate how environmental factors, governmental policies, and human mobility are related to COVID-19 transmission in Brazil from June 2020—August 2021. We found that temperature and humidity were not very important in explaining COVID-19 transmission. Governmental policies and human mobility played a larger role in explaining transmission, but whether changes in policies or human mobility led to increased versus decreased transmission varied throughout our study period. These changes with time may explain why the conclusions of other studies on what drives the spread of COVID-19 may appear at odds with each other. Continuing to rely on proven mitigation measures such as mass vaccinations should be the key priority in the fight against COVID-19 in Brazil.

1 Introduction

The COVID-19 pandemic, caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has ravaged Brazil. As of July 2022, the country had recorded the second-highest number of cases and second-highest number of deaths globally (CSSE, 2022). Disinformation sowed by Brazilian politicians; the defense of ineffective treatment based on chloroquine; less restrictive social isolation measures in some states and municipalities, especially those aligned with the federal government; difficulty in controlling the virus in

Brazil's favelas (informal settlements); and a strained healthcare system have been suggested as key reasons for Brazil's unfortunate ranking with respect to the pandemic (Ponce, 2020).

Seasonality and meteorology, particularly temperature and humidity, have been purported drivers of SARS-CoV-2 transmission based on their impact on aerosolization of virus droplets, virus survival on fomites, host susceptibility, and human behavior (Lowen & Steel, 2014; Tamerius et al., 2013; Yang et al., 2015). Yet, a myriad of early studies investigating the associations between meteorology and COVID-19 have not always reached consistent findings regarding the role of meteorological factors (Colston et al., 2022; Ma et al., 2021; Sera et al., 2021), although these and other studies generally emphasize that while the associations between COVID-19 and meteorological variables may be significant, they are small compared with disease control interventions and could not entirely explain excess disease burdens. Several factors have been suggested as reasons for these inconsistent findings: a short temporal data record; simplistic statistical frameworks such as correlation analyses that overlook confounding factors; and error-prone variables such as case counts, which could be biased towards the null due to underreporting, testing delays, and the proliferation of at-home testing (Kerr et al., 2021; Mecenas et al., 2020).

Brazil's diverse climate, spanning equatorial and tropical zones in the north to temperate zones in the south, provides a unique range of meteorological conditions over which to examine these roles. Equally diverse is the political spectrum in Brazil's federative system, which gives relative autonomy to states and municipalities. This autonomy resulted in an ensemble of uncoordinated approaches towards COVID-19 including, for example, facilitating the propagation of the virus given both strict and relaxed measures at different times (Castro et al., 2021; Kortessis et al., 2020).

Here, we conduct a spatiotemporally disaggregated time series study examining the roles of mobility, policy, and meteorology on SARS-CoV-2 transmission in Brazil's 26 states and federal capital district (hereafter generically referred to as "states"). Our innovative space-time disaggregation additionally allows us to document how the drivers of transmission varied throughout the pandemic in 2020-2021. By incorporating 15 months of data into a flexible and interpretable statistical framework, we advance our understanding of what drives SARS-CoV-2 transmission gleaned from earlier studies that only considered data from earlier periods of the pandemic.

2 Materials and Methods

2.1 Data Sources

Our data-driven study synthesizes time series of meteorological variables, policy, and mobility for each of Brazil's states over the period 1 July 2020 to 31 August 2021. The start date of this study is a few months after the first COVID-19 case was detected in Brazil (25 February) but represents a period in which surveillance capabilities in Brazil were likely more well-developed. Our fifteen-month study period allows us to understand the impacts of meteorology, policy, and behavior on COVID-19 transmission dynamics over an entire annual seasonal cycle.

The Johns Hopkins unified environmental-epidemiological dataset synthesizes data on meteorology, demography, and COVID-19 control policies (Badr et al., 2021). From this database we extracted state-level time series of population-weighted daily average temperature and specific humidity at 2 meters, originally derived from the fifth generation ECMWF atmospheric reanalysis. We also incorporated a state-level policy index from the Oxford COVID-19 Government Response Tracker (OxCGRT), which estimates the strictness of lockdown policies using information on containment and closure policies and public information campaigns (Hale et al., 2021).

We included two mobility indicators from Google's COVID-19 Community Mobility Reports (Google, LLC, 2022) in our study. Specifically, we consider time series of Google's workplaces and residential indicators. These changes represent departures from a pre-pandemic baseline period (3 January to 6 February 2020) and account for day-of-week variations. While these two mobility measures are inversely correlated (Spearman's rank correlation coefficient = -0.72), they represent different population-level behaviors with respect to trip purpose and are measured differently. The residential indicator measures daily changes in the time spent in places of residence, and the workplaces indicator measures daily changes in total visitors to places of work.

The time-varying reproductive number of COVID-19 (R_t) for each Brazilian state, generated with EpiNow2 (Abbott et al., 2020), was used as the response variable in our study. For a given day in each state, EpiNow2 estimates R_t using available case data from the previous 12 weeks and accounts for delays between infection onset and case reporting (Abbott et al., 2020; Gostic et al., 2020). This approach accounts for quantifiable sources of uncertainty and propagates these uncertainties from the inputs to the final R_t estimates. Recent work suggests R_t is likely centered around 1 in most of the world in contrast to previous studies that reported a substantially higher value (Abbott et al., 2020). We found a mean R_t of 0.996 (95% CI 0.994–0.998) in Brazilian states during our study period. R_t for the entire nation was also generated to contrast with state-level estimates.

2.2 Statistical Analysis

The impact of the meteorological, mobility, and policy on R_t is quantified using generalized additive models (GAMs), semiparametric models that estimate the response variable, in our case R_t, as the sum of nonlinear variable combinations or "smooth functions" (Hastie & Tibshirani, 1990). Examining individual smooth functions allows us to see the impact of a single variable or interactions between variables on R_t. GAMs have been extensively used to assess the environmental health outcomes and drivers of COVID-19 variability (Colston et al., 2022; Dominici, 2002; Sera et al., 2021).

We specified six different GAMs. The first used data from the entire study period, and the others used data from five different three-month periods: June - August 2020 (JJA 2020), September - November 2020 (SON 2020), December 2020 - February 2021 (DJF 2020-2021), March-May 2021 (MAM 2021), and JJA 2021. These different GAMs allow us to understand the role of the environment, mobility, and policy on SARS-CoV-2 transmission over an entire seasonal cycle but also disentangle seasonality from within-season variability and investigate how factors affecting transmission could change with time.

Specifically, we fit our GAMs to daily, state-level R_t assuming a Gaussian distribution with a log link. For each time period of interest, our model has the form:

$$R_{t,s} \sim gaussian(\mu_{t,s}) \qquad \text{Equation 1}$$

$$log(\mu_{t,s}) = s(temperature_{t,s}) + s(humidity_{t,s}) + s(Google\ residential_{t,s}) + s(Google\ workplaces_{t,s}) + s(OxCGRT\ policy_{t,s}) + ti(temperature_{t,s}, humidity_{t,s}) + ti(\sigma(temperature)_s, humidity_{t,s}) + s(lagged\ cases_{t,s}) + s(state), \qquad \text{Equation 2}$$

where t is day; s is each Brazilian state or federal district; $lagged\ cases$ is the total number of confirmed COVID-19 cases during the preceding 30 days, which we include to account for autocorrelation; and $\sigma(temperature)$ represents the standard deviation of temperature, used as a proxy for daily temperature variability. Here, $s(...)$ represents smooths for a single variable, and $ti(...)$ is a tensor product interaction. All terms have a basis dimension of three (a larger basis could apply an overly complex model and thereby overfit the data). We use thin plate regression splines as the smoothing basis for each smooth term in Equation 2 besides the final term, for which we use random effects as the basis. These random effects account for states with higher or lower transmission due to random conditions beyond the fixed effects captured by the covariates in the model.

We quantified the importance of model terms in Equation 2 by calculating the accumulated local effects (ALE) of each term on R_t. The ALE are calculated as the change in modeled R_t over a small range of a given model term using all data samples within that range and centered around 0 such that the value of the ALE curve can be interpreted as the difference to the mean prediction. For example, if ALE = 0.05 at a temperature of 20°C, it means that, at this temperature, R_t is 0.05 higher than the average predicted value of R_t. Other ways to quantify feature importance from GAMs (e.g., partial dependence, partial effects) can be biased by correlation among input variables and may result in unrealistic combinations of input variables. ALE, on the other hand, are unbiased in their estimated feature effect.

Our analysis was conducted using R (version 4.0.3) with packages mgcv (version 1.8-38) (Wood, 2011), additive (version 0.0.3) (Badr, 2021), mgcViz (version 0.1.9) (Fasiolo et al., 2019), and vip (version 0.3.2) (Greenwell & Boehmke, 2020).

3 Results

By 31 August 2021, 20,785,196 COVID-19 cases and 580,763 deaths had been reported in Brazil. São Paulo had the highest number of cases (4,262,684) and deaths (145,836). The number of cases per capita exhibited substantial spatial variability, but we note that states in Brazil's sparsely populated North and Central-West regions had a higher number of cases per capita than the more densely populated coastal states (Figure 1A). The Northern state of Roraima, whose health care system has been strained by a recent influx of migrants and refugees from neighboring Venezuela (Doocy et al., 2019), had the highest case rate of all states: 20,468 per 100,000.

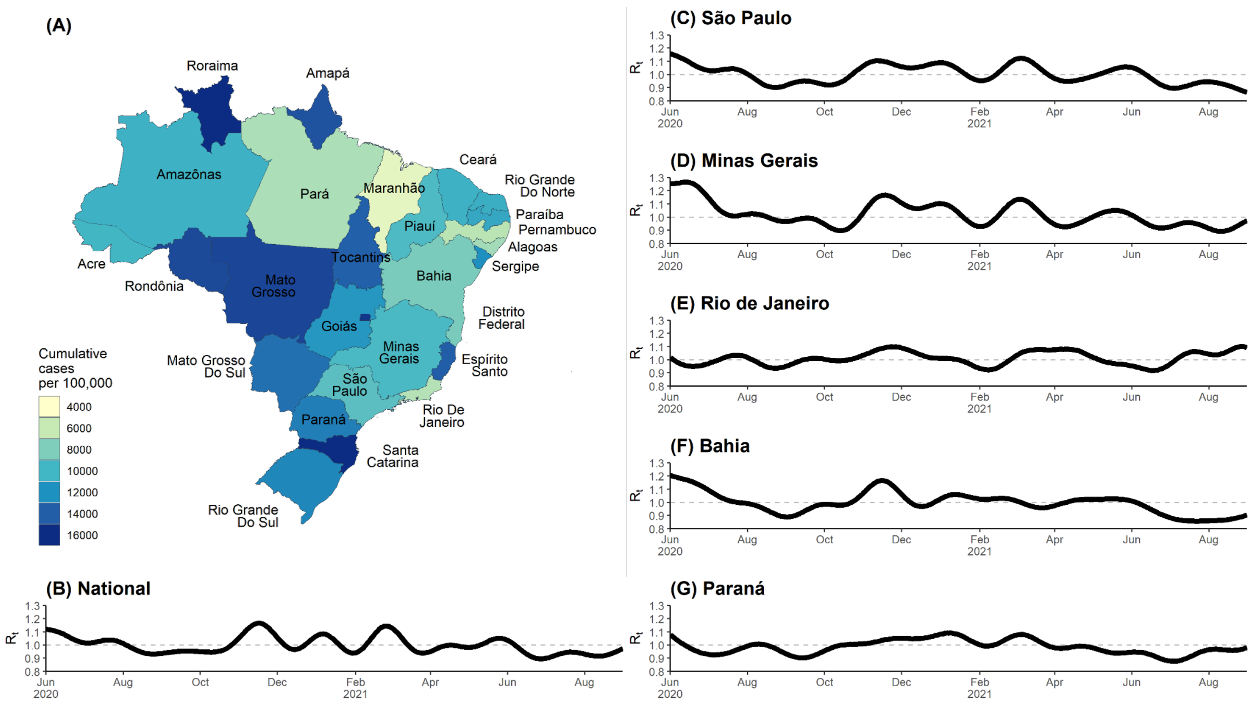

Figure 1. Cumulative cases of COVID-19 per 100,000 population as of 31 August 2021 in selected Brazilian states and time series of state-level R_t. Selected states represent five most populous states in 2021, and time series of additional states are shown in Figure S1. For contrast, the colorbar in (**a**) saturates at 4,000 and 16,0003

National-level R_t and R_t for individual states share some common features such as decreasing R_t at the beginning of our study period following the first wave and an increase in boreal winter (Figures 1B-G, S2). While the overall temporal variations in R_t are, at times, qualitatively similar between the national- and state-level time series, a closer inspection of R_t across these spatial scales highlights numerous differences that support our analysis of drivers of SARS-CoV-2 transmission at the state level.

The predictive power of our GAMs was evaluated with several performance metrics (Figure S1). The temporal correlation between EpiStem2 and modeled R_t for different three-month seasons was strong, generally ~0.7, indicating that our modeled R_t provides an excellent temporal fit to R_t from EpiStem2. We do note that, despite this strong correlation, the GAMs slightly underpredict R_t for all time periods. Additionally, the model performance is worse for DJF 2020-2021 and subsequent three-month periods compared with JJA and SON 2020, which may stem from increased underlying immunity with time or events that alter behavioral patterns and therefore COVID-19 transmission (e.g., Carnaval, Natal/Christmas).

Temperature emerges as a significant ($p<0.05$) predictor for all periods but JJA 2021 (Table S1). Increasing temperatures are associated with a decrease of R_t relative to the mean for the first four three-month periods of our study; however, during JJA 2021 and for the full study period, JJA 2020-JJA 2021, we found essentially no change in R_t with temperature (Figure 2A). The largest temperature effects on R_t of ~0.05 occurred in JJA 2020. The magnitude of these effects is roughly half the magnitude of the daily variability of R_t ($\sigma(R_t) = 0.10$). We note, though, that the ~9°C range of temperatures over which we observe this change is not commonly encountered in many Brazilian states besides a handful in Brazil's south (e.g., Mato Grosso do Sul, Paraná, Rio Grande do Sul; Figure S3A).

Increased specific humidity was generally associated with an increase in R_t except during MAM 2021, which exhibits an inverted U-shaped relationship (Figure 2B). The effect of specific humidity on R_t is significant for all study periods except MAM 2021 (Table S1) and roughly double in magnitude compared with temperature's effect; for example, the largest increase in R_t relative to the mean associated with variations in specific humidity is ~0.1, observed during JJA 2020-JJA 2021 (Figure 2B). As with temperature, most states have a tight range of specific humidity and do not experience daily variations in specific humidity equivalent to the range over which we observe this 0.1 effect (Figure S3B).

The ALE of the OxCGRT policy and Google-derived mobility variables are generally equivalent or slightly larger in magnitude than the effects of meteorological variables. However, in contrast to the generally consistent conclusions we draw regarding the sign of temperature and specific humidity effects on R_t, the OxCGRT policy and Google-derived mobility variables generally have inconsistent effects on R_t across three-month study periods and the full study period. Specifically, the ALE of OxCGRT policy reverses direction between nearly every period (Figure 2C), and the direction of the residential and workplace mobility in SON 2020 and MAM 2021 differ from other periods in our study (Figure 2D-E).

The lagged cases term, which gauges the trajectory of the pandemic, has the largest effect on R_t (Figure 2F) and is significant in every time period of our study (Table S1). Its ALE are several times larger than that of the meteorological or policy- and mobility-related terms (note the scale in Figure 2F). The direction of this relationship, indicating that more cases in the previous 30 days are associated with lower transmission, likely reflect a reduction in the size of the susceptible pool following periods with a high number of cases. While our model accounts for the cumulative number of cases in the previous 30 days, we have also tested how examining the number of cases for longer periods (60 days) impacts results and found no substantive difference in key conclusions (not shown).

In our model we included a term to test R_t differences in states with tropical (small daily variations in temperature) versus temperate (large variations) climates ($\sigma(temperature)$; Equation 2). Since this term consists of 1 value per state per time period compared with other continuous variables shown in Figure 2 we present the ALE differently and show their distribution in Figure S4. These results reveal that the ALE of temperature variability on R_t is larger in states with the largest daily variations in temperature, although the average impact of temperature variability on R_t is not consistently positive or negative (Figure S4). This effect of temperature variability on transmission could explain some of the differences in COVID-19 cases between Brazil's tropical states with fewer COVID-19 cases (e.g., Pará, Maranhão; Figure 1A) and temperate states with more COVID-19 cases (e.g., Rio Grande Do Sul, Santa Catarina).

The significance of model terms and their effect on R_t (Table S1, Figure 2) are somewhat different concepts than importance. We next explore how each term's relative influence on model prediction by adopting the root-mean-square error (RMSE) as an indicator of importance, with a higher RSME representing greater importance of a model term. Figure 3 shows that the random effects term, which accounts for unexplained state-level heterogeneity, and the total number of confirmed COVID-19 cases in the preceding 30 days are clearly the most important terms in our model.

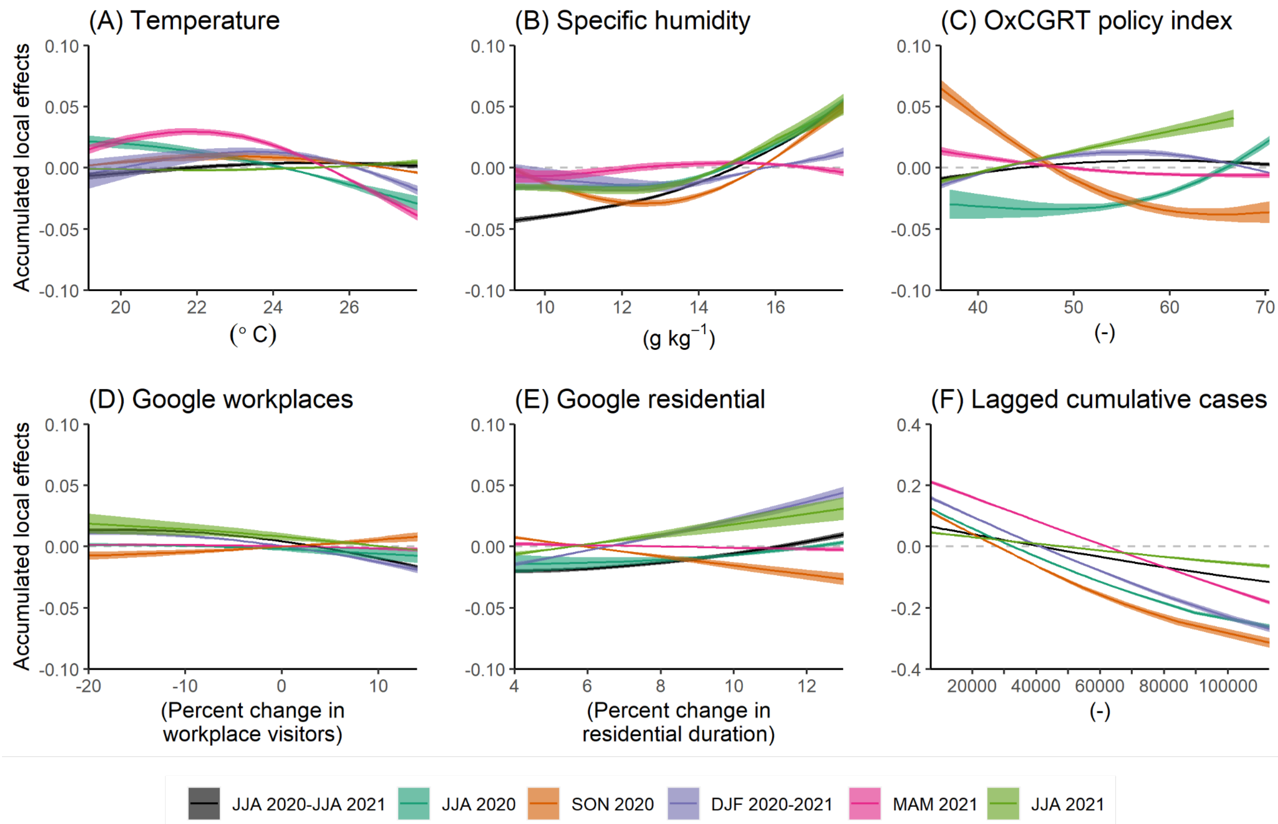

Figure 2. Accumulated local effects (ALE) of (**a**) temperature, (**b**) specific humidity, (**c**) the OxCGRT policy index, (**d**) Google workplaces mobility, (**e**) Google residential mobility, and (**f**) the number of cumulative cases in the preceding 30 days. Effects of model terms are shown for values between each term's 10th and 90th percentiles. Shaded bands for each curve denote the 95% confidence interval. Note the different scale of the vertical axis in (**f**).

Figure 3 also highlights the evolving role of model terms on R_t. While specific humidity and OxCGRT policy are generally the most important terms in our model after the random effects and lagged cases terms, the precise order of importance changes for different time periods. During MAM 2021, temperature is the third most important term in our model (Figure 3), which is consistent with the large ALE of temperature during this time period (Figure 2A); however, for other periods (e.g., JJA 2021), temperature is the least important.

Given the importance of state-level random effects in Figure 3, we also show how these random effects impact R_t. The ALE of the random effects have spatial structure, and these effects are consistently positive in Brazil's South and Southeast Regions and negative in the North (Figure S6). The spatial structure of this map roughly resembles Brazil's population density as well as gross domestic product per capita, and the random effects could be accounting for conditions related to sociodemographics.

4 Discussion

As one of the countries hardest hit by the COVID-19 pandemic, there is an acute need to characterize the drivers of SARS-CoV-2 transmission in Brazil to inform policy and other mitigative measures for future surges in cases. Earlier attempts to answer this question in the literature were often limited by short temporal record, methodological frameworks that were prone to the biases of input data and could not account for nonlinear relationships, and conclusions that raised questions the generalizability and robustness of their policy-relevant conclusions to different time periods. Our study leverages fifteen months of data within a flexible, nonparametric regression model, allowing us to understand drivers of transmission over an entire seasonal cycle, and investigates how the relationships between transmission and meteorology, policy, and human mobility change from season to season.

The changing sign and magnitude of drivers of SARS-CoV-2 transmission (e.g., Figures 2-3), also demonstrated in Yin et al. (2022) could explain the inconsistencies between our work and other studies on COVID-19 in Brazil and, more broadly, the variability in the published literature. Two studies focused on COVID-19 in Brazil in early- to mid-2020 (Pequeno et al., 2020; Rosario et al., 2020) found increased temperatures were associated with decreased severity, similar to our findings for JJA 2020 (Figure 2A). However, we have shown that this negative relationship between temperature and transmission does not persist later in 2020 or in 2021. This finding demonstrates the importance of analyzing each season separately. For example, considering the full study period might lead to the conclusion that temperature has a statistically significant but essentially null impact on transmission (Table S1, Figure 2A), while temperature bears a larger association with transmission in most of the three-month periods.

The relatively small impact of policy and mobility was surprising, given that at the early stage of the pandemic when transmissibility was high and immunity was low, disease control interventions are believed to have a stronger impact on transmission than any environmental driver (Carlson et al., 2020). There are at least two potential reasons for this finding. One explanation could lie in the evolving behavioral responses to the pandemic. Using the correlation between R_t and the OxCGRT policy and Google workplaces and residential variables as a proxy for behavioral responses during periods of increased versus decreased transmission, we find considerable spatiotemporal variability between these variables and R_t (Figure S5). Another explanation could be related to what these terms precisely measure and the data from which they are formed. The OxCGRT policy index measures how the government has implemented health and containment measures but does not show whether policy has been implemented *effectively* or measure *compliance to* policies. It is likely that the variability in restrictive measures over time by states and municipalities and the continued urban public transit, even during high periods of transition, favored population mobility and consequently the circulation of the virus (Castro et al., 2021; Kortessis et al., 2020). Brazil's federal government not only underestimated the impact of COVID-19 but also did not coordinate efforts, at times even trying to influence state and municipal governments against measures of social distancing (Castro et al., 2021). Governmental responses are also reactive and might not have a substantial effect if enacted in response to a surge in cases. Additionally, the Google mobility terms also derive from cell phone usage and internet access, which vary across Brazil (Instituto Brasileiro de Geografia e Estatística, 2018) and are unequally distributed among socioeconomic groups.

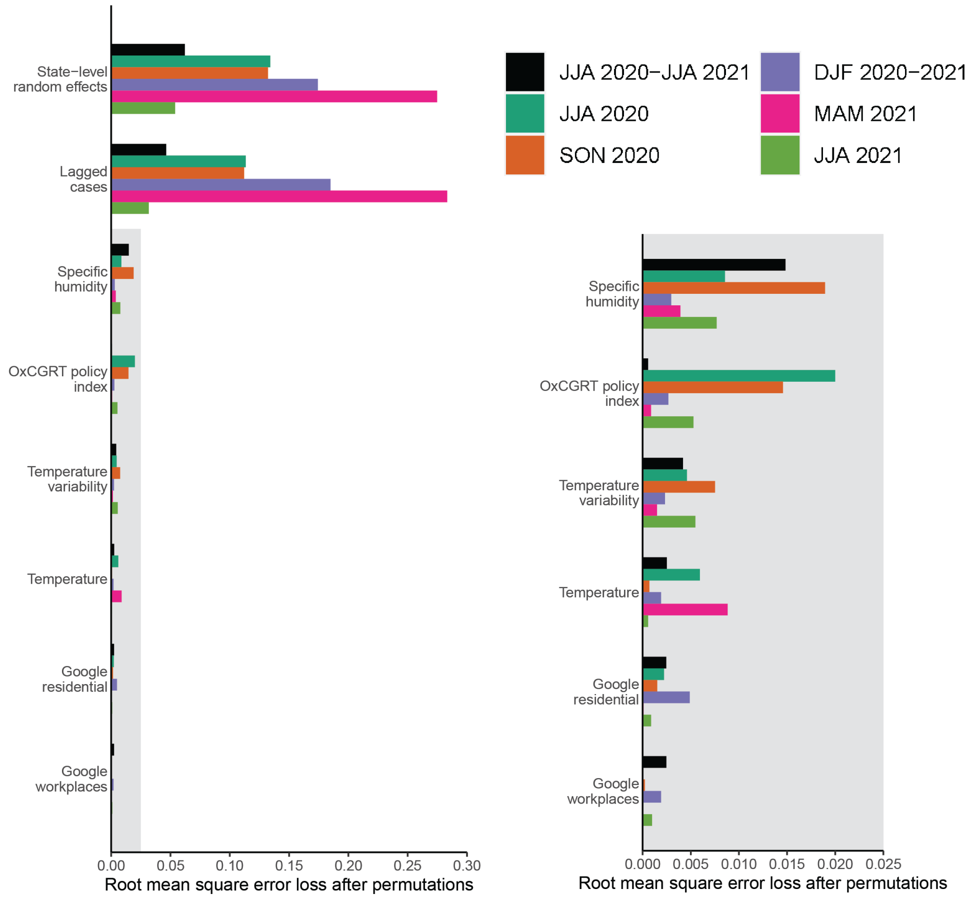

Figure 3. Permutation-based variable importance plot for GAM model terms using the root mean square error as the loss function. Larger values for a particular term indicate that removal of that variable causes the GAM to lose accuracy in its prediction. The zoomed-in version of the grey region in the left panel is shown on the right.

We chose a relatively small number of model terms (Equation 2) compared with other studies which have included air pollutants (Wu et al., 2020); sociodemographic data and additional mobility indicators (Colston et al., 2022; Nottmeyer & Sera, 2021); and additional meteorological variables (Colston et al., 2022; Ma et al., 2021; Zhang et al., 2022). Our selected meteorological terms have an established precedent for shaping respiratory virus seasonality (Lowen & Steel, 2014) and were most-commonly investigated in early studies on the meteorological drivers of SARS-CoV-2 transmission (Kerr et al., 2021). The policy and mobility terms represent plausible proxies for governmental responses and individual-level behavior that likely affect transmission. We acknowledge that including additional terms may further improve model performance or change the role purported impact of our chosen variables on R_t. However, additional terms could also lead to overfitting or decreased interpretability if no clear mechanism to tie a particular term to transmission exists.

In addition to the ecological fallacy that challenges studies investigating drivers of COVID-19 transmission, our study has several limitations. Our analysis was conducted at the state level rather than at the municipal level, the lowest level of political division, to provide the highest granularity possible without encountering missing data (e.g., the OxCGRT policy data does not have time series for all of Brazil's municipalities). This limitation is particularly relevant due to state and municipal alignments with the federal government which affected the intensity, duration, and timing of local responses against the disease (Castro et al., 2021). Brazil's mass vaccine campaign, which likely impacted underlying immunity and behavior, began in January 2021 and was not explicitly accounted for due to lack of information on vaccine rollout at the state level. Terms included in our model are not exhaustive, and other studies have highlighted additional drivers that bear a significant association with transmission. We also did not account for multiple SARS-CoV-2 variants and their different transmissibility; however, conducting our analysis in several three-month periods could partially mitigate this limitation.

5 Conclusions

In summary, we found that meteorological variables play a statistically significant, but relatively small, role in explaining spatiotemporal variations in SARS-CoV-2 transmission in Brazil. Higher temperatures were generally associated with decreased R_t, higher specific humidity with increased R_t, and increased total visitors in workplaces with decreased R_t (Figure 2), although these terms were not always significant in all time periods we examined (Table S1). On the other hand, the impact of governmental policies and time spent in places of residences were associated with both increases and decreases in R_t, depending on the time period (Figure 2). Most variations in R_t, though, were attributed to unexplained between-state heterogeneity and the trajectory of the pandemic (i.e., the number of recent cases; Figures 2-3).

Brazil is a global leader at administering COVID-19 vaccines. Its vaccination rate–an estimated 80% as of July 2022–exceeds that of the United States, Germany, the United Kingdom, and several other developed nations that had the earliest access to vaccines (Johns Hopkins Centers for Civic Impact, 2022). The rate of vaccinations in Brazil has been credited with preventing approximately 1,000,000 deaths from COVID-19 (Watson et al., 2022). While meteorology might weakly modulate transmission, we found no indication that daily or seasonal weather conditions alone will curb the virus in Brazil. At this point in time, disease control interventions and vaccines appear to be the greatest weapons to fight the pandemic in Brazil and throughout the world.

Acknowledgments

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Open Research

The Johns Hopkins unified COVID-19 environmental-epidemiological dataset, which contains the meteorological data and OxCGRT policy index used in this study, is publicly available at www.github.com/CSSEGISandData/COVID-19_Unified-Dataset/. Google's COVID-19 Community Mobility Reports are available at www.google.com/covid19/mobility/.

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GeoHealth

Supporting Information for

Evolving Drivers of Brazilian SARS-CoV-2 Transmission: A Spatiotemporally Disaggregated Time Series Analysis of Meteorology, Policy, and Human Mobility

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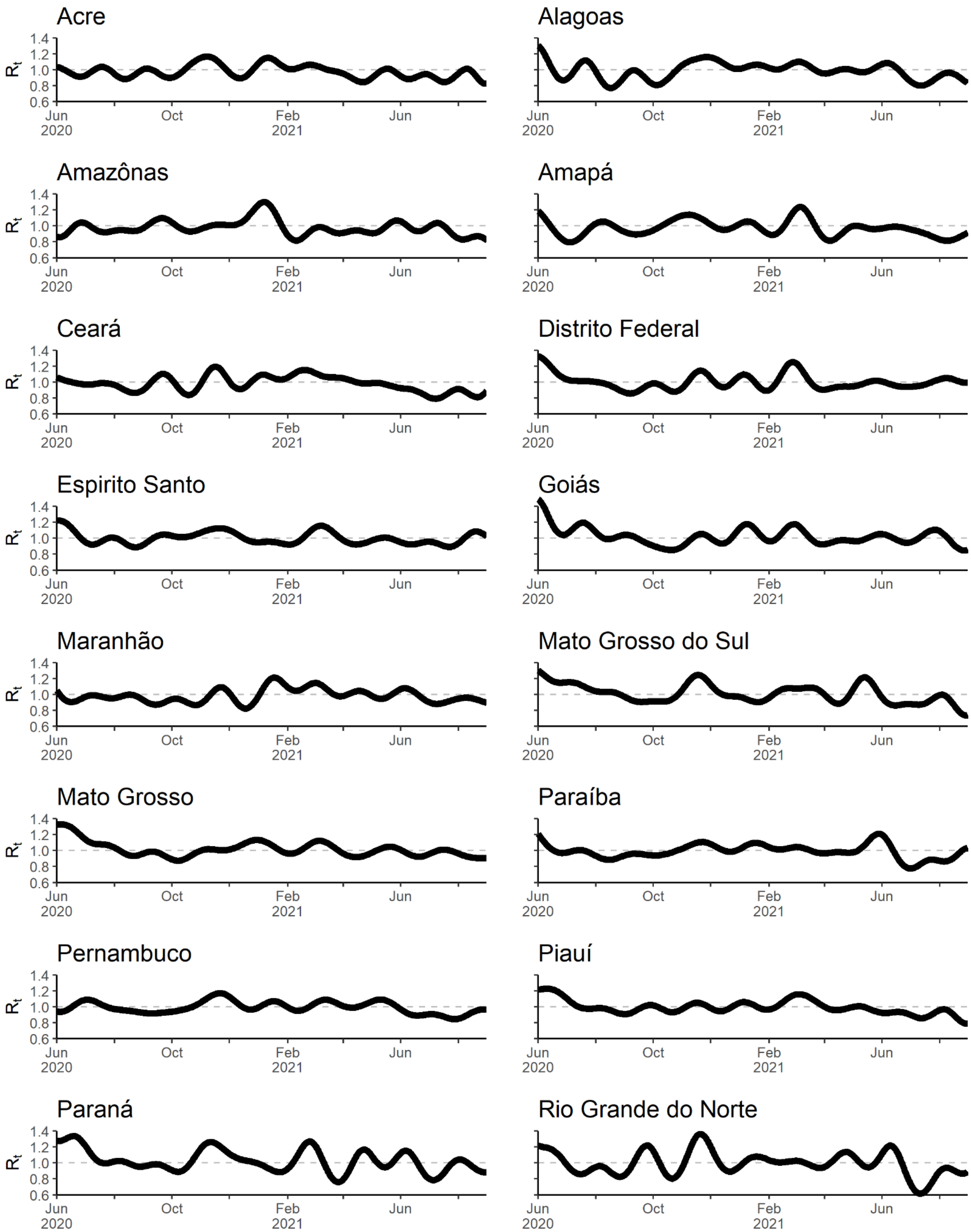

Figure S1. Same as Figure 1B-G in the main text but showing time series of R_t for other Brazilian states and the federal district.

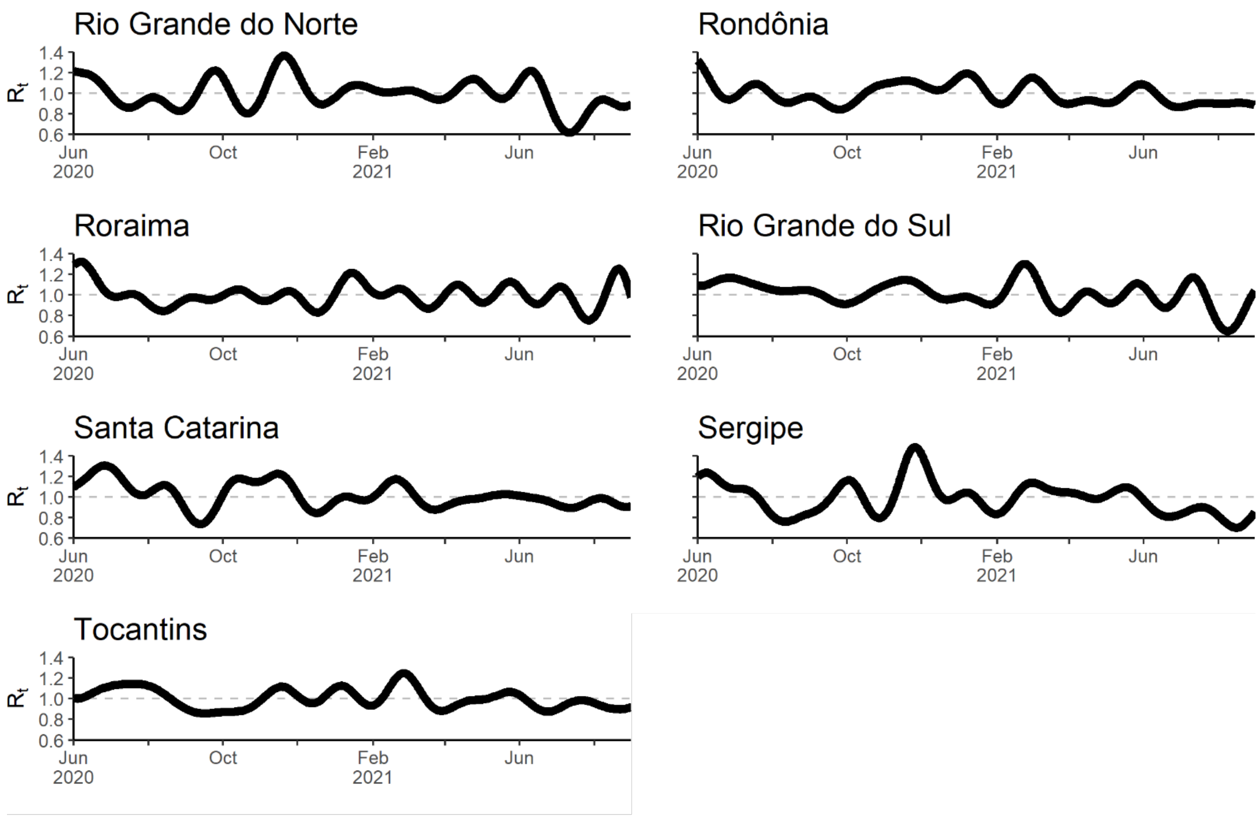

Figure S1 (continued).

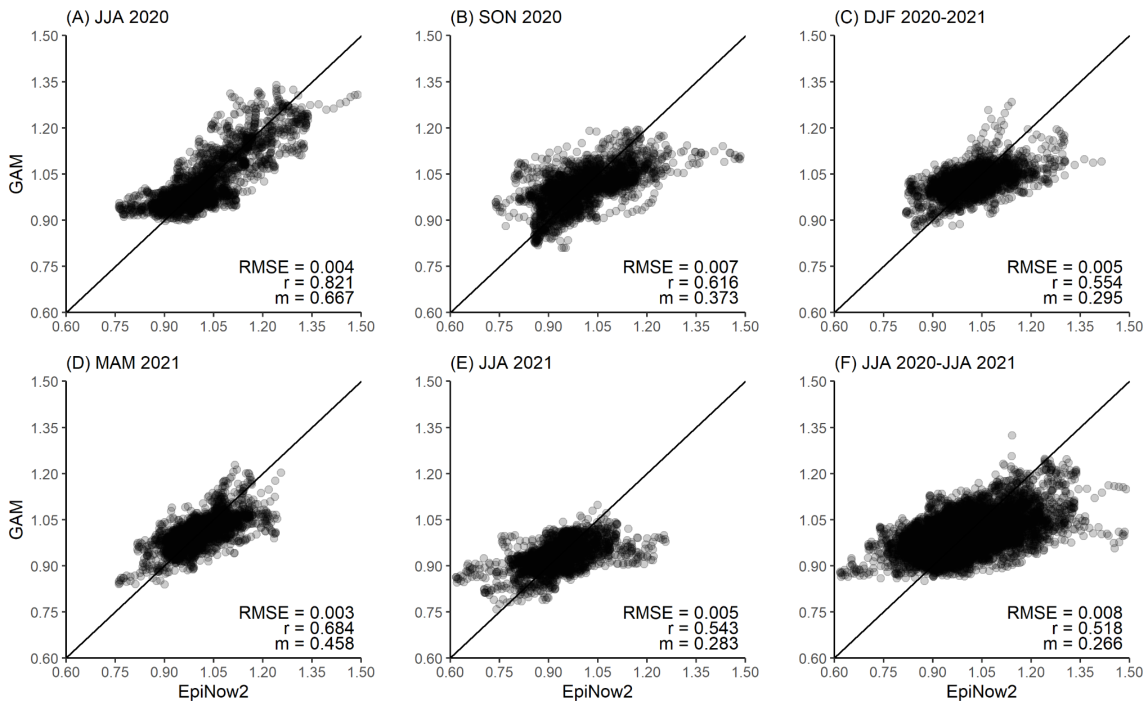

Figure S2. Scatter plot showing GAM-predicted versus EpiNow2-estimated R_t for different periods of interest. The solid line shows the 1:1 line. Inset text denotes the root mean square error (RMSE), Pearson correlation coefficient (r), and the slope of the linear regression fit (m), where GAM R_t is the dependent variable and EpiNow2 R_t is the explanatory variable.

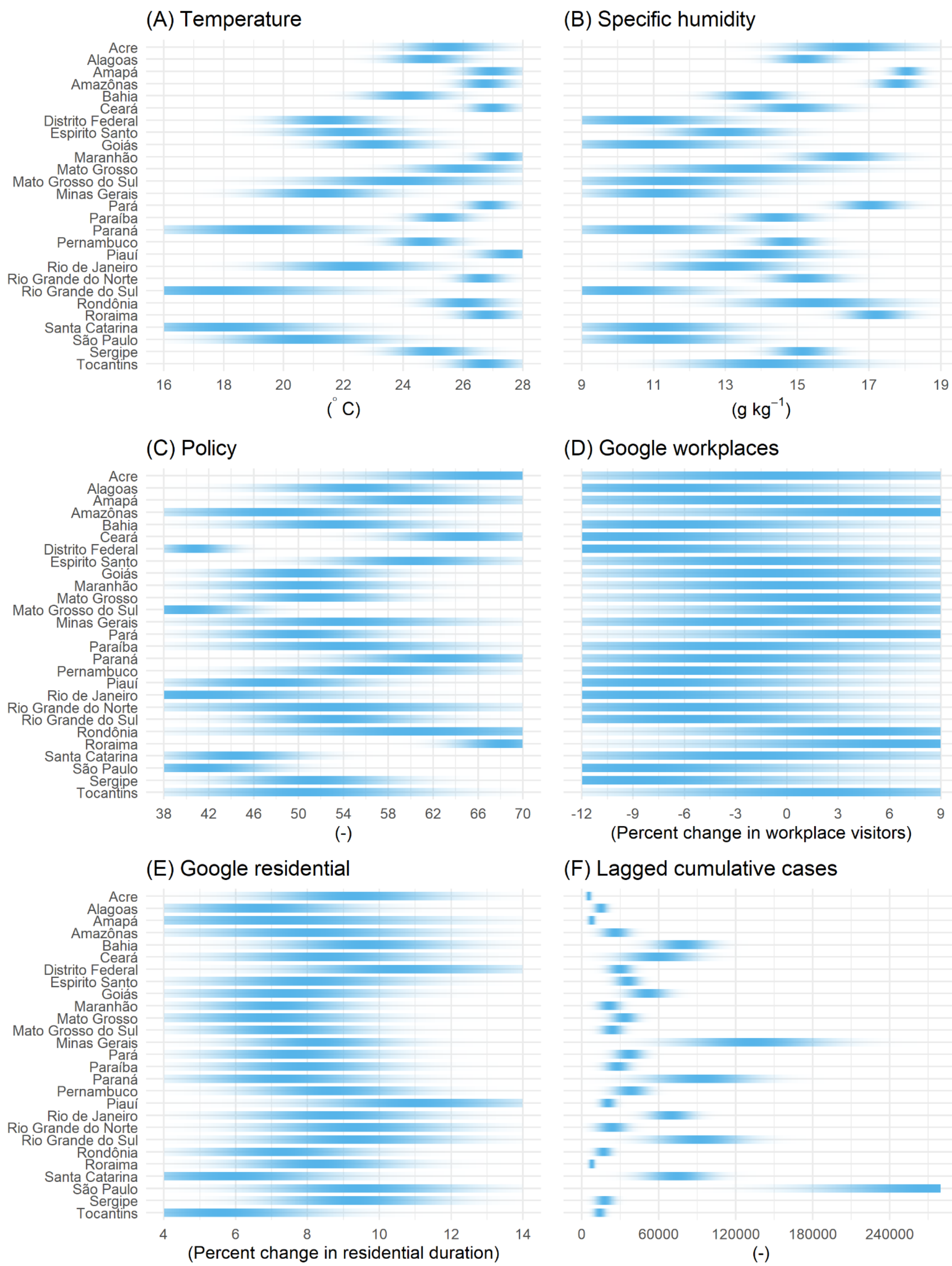

Figure S3. Distribution of state-level GAM model terms for the full study period, JJA 2020-JJA 2021. Bands show the 95% confidence interval generated from each model term and its margin of error.

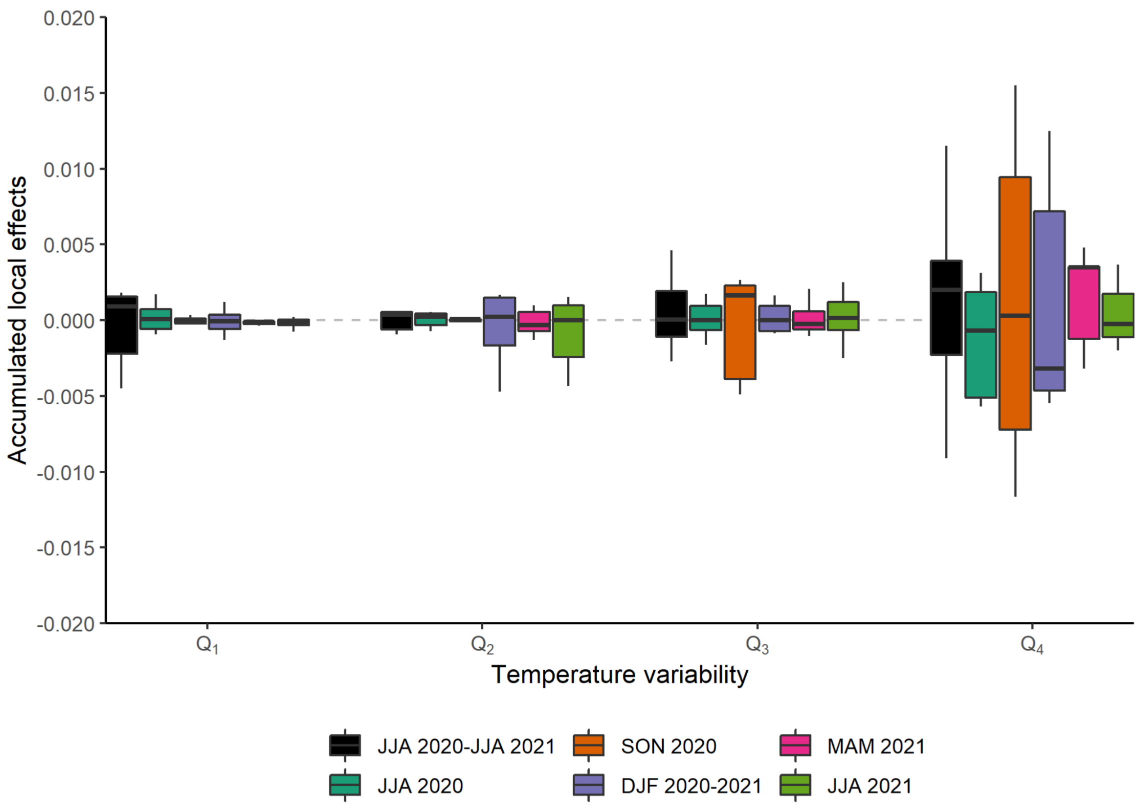

Figure S4. Distribution of the ALE for state-level temperature variability ($\sigma(\text{temperature})_s$ in Equation 2 in the main text). Different groups of boxes represent different quartiles of temperature variability: Q_1 represents states with temperature variability in the 0-25th percentile, Q_2 in the 25-50th percentile, Q_3 in the 50-75th percentile, and Q_4 in the 75-100th percentile. Individual box features, from bottom to top, denote the first quartile, the median, and the third quartile. Whiskers extend to ±1.5 times the interquartile range.

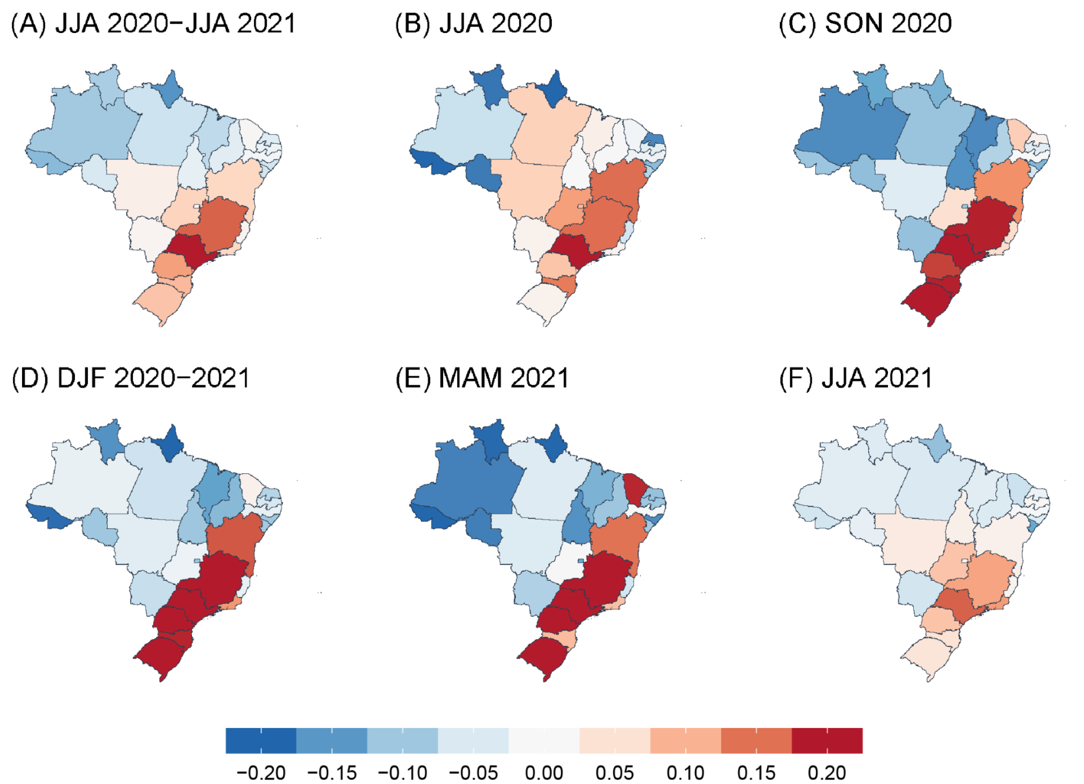

Figure S5. ALE of the state-level random effects. States with ALE>0 can be interpreted as states with higher propensity for transmission.

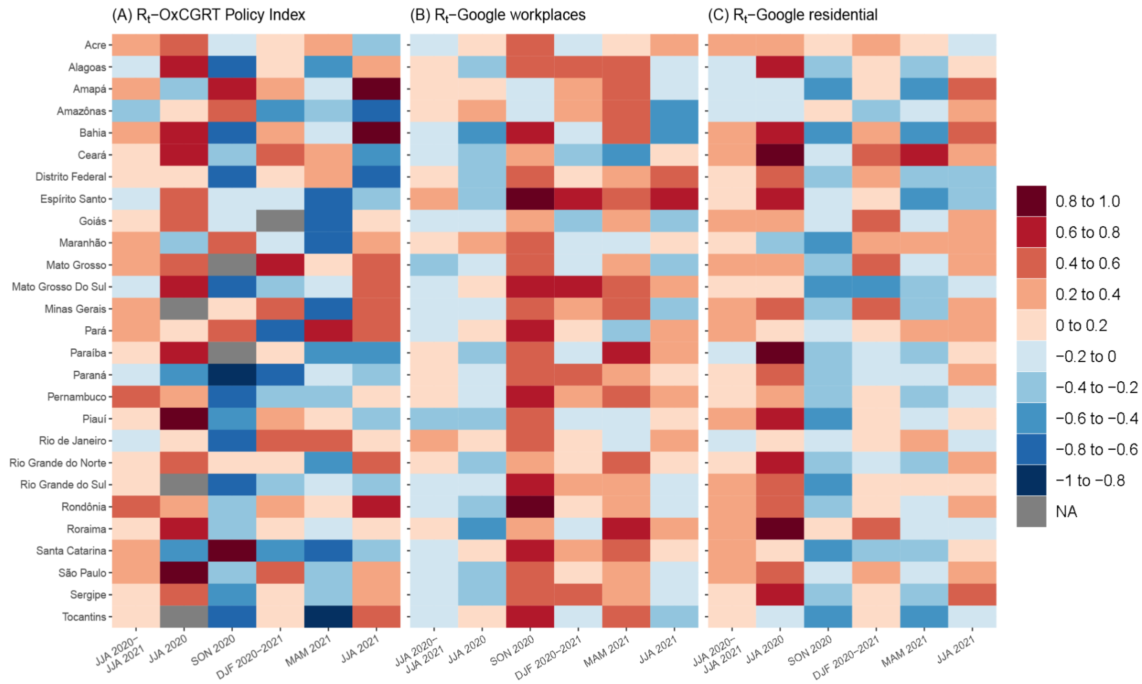

Figure S6. Spearman's rank correlation coefficient measuring the relationship between state-level R_t and (A) the OxCGRT policy, (B) Google workplaces, and (C) Google residential model terms for each study time period. States where the OxCGRT policy term has no daily variations for a particular period are denoted with the NA value.

Period	Deviance explained (%)	p-value								
		f(temperature)	f(specific humidity)	f(Temperature, Specific humidity)	f(Temperature variability, Specific humidity)	f(OxCGRT Policy Index)	f(Google workplaces)	f(Google residential)	f(Lagged cumulative cases)	f(state)
JJA 2020-JJA 2021	26.8	0.0025	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
JJA 2020	67.4	< 0.0001	< 0.0001	< 0.0001	0.0008	< 0.0001	0.0995	< 0.0001	< 0.0001	< 0.0001
SON 2020	37.9	0.0015	< 0.0001	0.5377	< 0.0001	< 0.0001	0.0075	< 0.0001	< 0.0001	< 0.0001
DJF 2020-2021	30.6	< 0.0001	0.0001	0.7890	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
MAM 2021	46.8	< 0.0001	0.1721	< 0.0001	0.1475	< 0.0001	0.0795	0.0842	< 0.0001	< 0.0001
JJA 2021	29.5	0.7750	0.0001	< 0.0001	0.0183	< 0.0001	0.0009	0.0003	< 0.0001	< 0.0001

Table S1. Generalized additive model (GAM) deviance explained and significance of smoothing parameters for each study period and terms. Here, JJA = June-July, SON = September-November, DJF = December-February, and MAM = March-May.