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Meteorological factors’ effects on COVID-19 show seasonality and spatiality in Brazil

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ABSTRACT

The meteorological conditions may affect COVID-19 transmission. However, the roles of seasonality and macroclimate are still contentious due to the limited time series for early-stage studies. We studied meteorological factors’ effects on COVID-19 transmission in Brazil from February 25 to November 15, 2020. We aimed to explore whether this impact showed seasonal characteristics and spatial variations related to the macro-climate. We applied two-way fixed-effect models to identify the effects of meteorological factors on COVID-19 transmission and used spatial analysis to explore their spatial-temporal characteristics with a relatively long-time span. The results showed that cold, dry and windless conditions aggravated COVID-19 transmission. The daily average temperature, humidity, and wind speed negatively affected the daily new cases. Humidity and temperature played a dominant role in this process. For the time series, the influences of meteorological conditions on COVID-19 had a periodic fluctuation of 3–4 months (in line with the seasons in Brazil). The turning points of this fluctuation occurred at the turn of seasons. Spatially, the negative effects of temperature and humidity on COVID-19 transmission clustered in the northeastern and central parts of Brazil. This is consistent with the range of arid climate types. Overall, the seasonality and similar climate types should be considered to estimate the spatial-temporal COVID-19 patterns. Winter is a critical time to be alert for COVID-19, especially in the northern part of Brazil.

Keywords:
COVID-19
Meteorological factors
Climate
Seasonality
Spatiality

1. Introduction

COVID-19, caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in late 2019, has led to the worst public health and socioeconomic crisis the global population has ever faced (UN, 2020). The world is still struggling with this overwhelming catastrophe. Until September 20, 2021, there was over 200 million confirmed cases and 4 million deaths (WHO, 2021). Researchers predicted that the future dynamics of COVID-19 depend on multiple factors (e.g., meteorological conditions, population movement, political decisions), and surveillance about pandemic evolution should be maintained because of a possible increase in cases until 2024 (Kissler et al., 2020).

The meteorological factors affect COVID-19 spread in three ways (Hosseini, 2020). First, as the primary source of respiratory infections, the virus and its stability depend on ambient conditions such as temperature and humidity (Ahlawat et al., 2020). The in vitro experiments showed that SARS-CoV-2 exhibited strong stability at low temperature (4 °C) but decreased stability at higher temperature (37 °C) (Chin et al., 2020). Besides, humidity is likely to destabilise the virus by affecting the lipid membrane that protects it (Ahlawat et al., 2020). Second, the coronavirus is usually transmitted through the air via microdroplets and aerosols or through contaminated surfaces that humans touch (Bourouiba, 2020; Spicknall et al., 2010). In this case, meteorological factors such as air temperature, humidity, and wind speed, can affect the durability and stability of these potential carriers of the SARS-CoV-2 (Bourouiba, 2020). Third, as the hosts and distributors of SARS-CoV-2 (Liu et al., 2020), people with higher sensitivity and exposure are more likely to be infected (Anastassopoulou et al., 2020). Air pollution, which depends on meteorological conditions, can disrupt human immunity and increase vulnerability to adverse environments. Human activity patterns (e.g., travel rules, contact rates, and immune function) also depend on meteorological conditions and seasonality. These factors...
are known to exacerbate the epidemics (Tamerius et al., 2011).

Numerous studies have demonstrated the associations between COVID-19 transmission and meteorological factors such as temperature, humidity, rainfall, and wind speed (Briz-Redon and Serrano-Aroca, 2020; Shakil et al., 2020). However, few works were conducted regarding the effects of seasonality and the spatial pattern in a macro-climate context. For time series, most of the existing studies were focused on the early stage of the outbreak, with a limited time (Smit et al., 2020). The studies carried out in a short period, however, cannot reveal the seasonal impacts of meteorological factors on COVID-19. Large temporal analyses are needed to identify the response of COVID-19 to meteorological conditions (Smit et al., 2020). Regarding spatial analysis, many studies worked COVID-19 distribution itself (Martellucci et al., 2020; Weiss et al., 2020). However, linking meteorological conditions to the macro-climate context to analyse COVID-19 distribution is still lacking (Huang et al., 2020; Mendez-Arriaga, 2020).

Brazil has the third-highest number of reported COVID-19 cases worldwide, with confirmed cases still growing at a rate of more than 10,000 a day by the end of September 2021 (WHO, 2021). Brazil also has a globally representative climatic context spanning both hemispheres. Brazil’s long pandemic period and diverse climate conditions make it suitable for examining the associations between COVID-19 and meteorological factors. The objectives of this study are to analyse: 1) the effects of meteorological factors on COVID-19 transmission in Brazil from February 25 to November 15, 2020; 2) the temporal and seasonal differences of these effects, and 3) the effects’ spatial distribution at a macro-climate level. This study can promote the understanding of seasonality and spatiality of meteorological factors’ effects on the pandemic.

2. Materials and methods

2.1. Study area

This study included Brazil’s 27 state capitals. Brazil is the fifth largest country worldwide, covering latitude from 5° N to 33° S and longitude from 35° W to 74° W. Brazil has diverse topography from the Amazon basin in the north and west to the Brazilian Highlands in the southeast. Brazil’s landmass is in a tropical, subtropical, and semi-arid zone. Almost all of Brazil is humid, while Eastern Brazil suffers from regular drought (Alvares et al., 2013). Brazil’s diverse geographical features make this region feasible to examine the COVID-19 transmission in different seasons and climate zones.

2.2. Data collection

COVID-19 and meteorological data from the 27 state capitals of Brazil were collected from February 25 (the first COVID-19 case was confirmed) to November 15, 2020. Daily COVID-19 confirmed cases were collected from Brazil’s National Ministry of Health (Secretarias de Saúde das Unidades Federativas, 2020). Daily meteorological data, including daily average temperature (T_ave, °C), maximum temperature (T_max, °C), minimum temperature (T_min, °C), relative humidity (RH, %), minimum relative humidity (RH_min, %), wind speed (m/s), and precipitation (mm) were collected from the National Institute of Meteorology authority in Brazil (INMET, 2020) (Table 1).

2.3. Statistical and spatial analysis

Data modelling was carried out as follows. First, we assessed the descriptive statistics. Since linearity is necessary for model accuracy, we transformed the values of variables using a natural logarithm. Assessing the dataset stationarity properties is key to avoiding spurious statistical interpretations. Therefore, we performed IPS (Im-Pesaran-Shin) and Fisher unit root tests (Pesaran, 2007) on natural logarithmic transformed data.

| Variable                      | Obs | Mean | Std. Dev. | Min | Max |
|-------------------------------|-----|------|-----------|-----|-----|
| T_max (daily maximum temperature, °C) | 6065 | 30   | 8         | 1   | 41  |
| T_ave (daily average temperature, °C) | 5692 | 24   | 8         | 3   | 33  |
| T_min (daily minimum temperature, °C) | 6060 | 20   | 4         | 3   | 31  |
| RH (relative humidity, %) | 5825 | 72   | 14        | 17  | 98  |
| H_min (daily minimum humidity, %) | 6055 | 49   | 16        | 7   | 95  |
| W (wind speed, m/s) | 5406 | 2    | 1         | 0   | 12  |
| P (precipitation, mm) | 5825 | 4    | 11        | 0   | 166 |
| DDC (daily confirmed cases, persons) | 5199 | 251  | 459       | 0   | 7063 |

Data period: February 25 to November 15, 2020.

Note: 'Obs' shows that in 27 capitals during all study period, variables have a different number of observations due to missing values recorded by meteorological stations, thus forming unbalanced panel data.

Second, we applied the Hausman test to select the appropriate model (Davidson and MacKinnon, 1993). The Hausman test results showed a chi-square statistical value of 16.83 (p = 0.018). Therefore, the null hypothesis was rejected at the significance level of 5%. In this case, the fixed-effect model was more suitable for our dataset. To consider both individual (inter-state) differences across Brazil and commonly missed variables that varied over time (e.g., the government’s control policy on COVID-19), the time fixed-effect λ_t was introduced to build a “Two-way fixed-effect” model. The model adopted the log-log estimation and made stepwise regression through the “general to specific” modelling method. This means that all explanatory variables were put into the model at first, and then insignificant explanatory variables were gradually eliminated. The model performance was assessed using the R^2, Akaike information criterion (AIC), and Bayesian information criterion (BIC). A model with higher R^2 and lower AIC and BIC was considered more accurate. The complete regression models are described in equation (1).

\[
\begin{align*}
\ln Y_{it} &= \beta_0 + \beta_1 \ln X_{it1} + \beta_2 \ln X_{it2} + \ldots + \beta_k \ln X_{itk} + \gamma T_{it1} + \gamma D20n + \gamma 3D3n + \ldots \\
&+ \gamma 1D2545n + u_i + e_t + c_i \quad (i = 1, \ldots , 27; \quad t = 1, \ldots , 254)
\end{align*}
\]

Where Y_{it} is the dependent variable (daily confirmed cases of COVID-19, DDC) for 27 state capitals ‘i’ over the period “t” from February 25 to November 15, 2020; X_{itk} is a vector that includes all explanatory variables (k is the lag order of the explanatory variables), i.e., daily maximum temperature (T_max), daily average temperature (T_ave), daily minimum temperature (T_min), relative humidity (RH), daily minimum humidity (H_min), wind speed (W), precipitation (P); β_k is the estimated slope coefficient; γD20n + γ3D3n + \ldots + γ254D254n is the time fixed-effects (take the first day as the base period); u_i is the individual fixed-effects controlling for specific characteristics of the state capitals that are fixed over the analyzed period; e_t is the panel error term permitted to be heteroskedastic; c_i is a constant.

Next, we considered the time lags that COVID-19 cases were affected by meteorological conditions. Clinical results showed that COVID-19 had an incubation period of approximately 4 days (Guan et al., 2020). Besides, testing and confirming cases also took several days (Pequeno et al., 2020). Accordingly, we considered a set of models with varying lagged days ranging from 1 to 20 days. Then, models were compared with AIC and model significance. The model with the lowest AIC and higher significance was the most accurate to choose the lagged days. We considered that the models were statistically significant according to the p level (p < 0.05). We ran the models with the STATA 15.0.

A Kernel density estimation (KDE) was applied to provide spatial density estimates for the meteorological factors’ influence on COVID-19 transmission. KDE was calculated according to equation (2):
Results of unit root test.

Table 2

| Variable          | Im-Pesaran-Shin unit-root test | Fisher-type unit-root test |
|-------------------|---------------------------------|-----------------------------|
|                   | Z-tilde-bar statistic p-value   | Modified inverse chi-squared statistic p-value |
| lnDCC             | –37.3817 0                    | 42.0299 0                   |
| lnT_ave           | –23.8005 0                    | 57.9291 0                   |
| lnT_max           | –33.3139 0                    | 79.3493 0                   |
| lnT_min           | –28.8948 0                    | 66.6314 0                   |
| lnRH              | –27.2499 0                    | 63.4732 0                   |
| lnRH_min          | –35.5659 0                    | 79.1530 0                   |
| lnP               | –35.3489 0                    | 91.9947 0                   |
| lnP               | –21.9246 0                    | 41.5735 0                   |

where $f(x,y)$ is the density estimation for the $(x,y)$ location, $n$ is the number of observations, and $h$ is the smoothing parameter. $K$ was a kernel function, and $d_i$ was the distance from the $(x,y)$ position to the observation position $i$. KDE was assessed using ArcGIS 10.2.

The Moran’s I index was used to analyse the global spatial autocorrelation of the meteorological factors’ influence on COVID-19 transmission. The Moran’s I was calculated according to formula (3):

$$ I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_i - \bar{X}) (X_j - \bar{X})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_i - \bar{X})^2} $$(3)

where $n$ is the number of observations; $X_i$ and $X_j$ are the meteorological factors’ influence on COVID-19 transmission in sites $i$ and $j$, respectively; $\bar{X}$ is the average influence coefficient; and $W_{ij}$ is the spatial weight matrix between sites $i$ and $j$. Moran’s I ranges from –1 to 1. Moran’s I greater than 0 indicates spatial clustering; the index less than 0 indicates a dispersed spatial distribution. Random distribution exists when Mor $s I$ equals 0.

3. Results

3.1. Descriptive analysis

The descriptive statistics of COVID-19 and the meteorological data set are shown in Table 1. On average, $T_{\text{ave}}$ was 24°C, with $T_{\text{max}}$ 30°C and $T_{\text{min}}$ 20°C. The average RH was 72%, the average $W$ was 2 m/s, and the average $P$ was 4 mm from February 25 to November 15, 2020. As for COVID-19, the average $DCC$ was 251 persons.

Since non-stationary time series data fitting may cause a pseudo autocorrelation, it is necessary to test the data stationarity of each variable to ensure the validity of the model estimation. The IPS and Fisher unit root tests showed that the null hypothesis with a unit root was rejected with a significance level of 1% in all variables. Therefore, we assumed that the data series were stationary (Table 2).

To ensure the accuracy of the two-way fixed-effect model estimation, correlation test is necessary before the model simulation. We calculated Spearman’s correlation coefficients between the daily confirmed cases and meteorological factors across all cities and days. We used the p-value ($p < 0.05$) to determine the statistical significance of the correlation. The results showed that lnDCC had a negative and significant correlation with the lnT_max ($-0.104$, $p < 0.01$), lnT_ave ($-0.111$, $p < 0.01$), lnT_min ($-0.115$, $p < 0.01$), lnRH ($-0.103$, $p < 0.01$), lnRH_min ($-0.056$, $p < 0.01$) and lnP ($-0.108$, $p < 0.01$). And lnDCC showed positive correlation with lnW ($0.125$, $p < 0.01$).

3.2. Model estimation results

Four two-way fixed-effect models were constructed to analyse the meteorological factors’ effect on the daily confirmed cases of COVID-19 in Brazil (Table 3). We ran models to determine the lag time. The results suggested that as the lagged days increased from 1 to 20, models showed different significance, and the AIC value declined. The model had the largest significance with a 8-days lag. Therefore, we modeled the impact of meteorological conditions that were lagged 8 days on COVID-19 transmission.

The results showed that except for model 1, the fitting from model 2 to model 4 tended to be stable and significant. Model 3 was the best-fitted, with the largest $R^2$ and smallest AIC and BIC values. Also, the variable fitting in model 3 was more significant than other models. Model 3 showed that lnT_ave, lnRH, and lnW had a significant negative effect on the lnDCC, while the lnT_min and lnRH_min had positive effects on the lnDCC. Among all, the daily average RH showed the highest explanatory capacity to predict COVID-19 daily new cases. Every 1% decrease of humidity corresponded to an increase of 1.661% in COVID-19 cases. The average temperature was also an important factor aggravating COVID-19 transmission. With every 1% increase in temperature, the new cases increased by 0.919%. An increase of 1% in minimum temperature and minimum humidity produced increases of 0.571% and 0.336% in the COVID-19 new cases, respectively. Finally, the COVID-19 transmission was aggravated by 0.245% if wind speed decreased by 1%. Therefore, the COVID-19 daily cases increased faster under low humidity, temperature, and wind speed conditions (Table 3).

Time fixed effect (Fig. 1a) and individual fixed effect (Fig. 1b) controlled unobserved changes in variable inputs. Conceptually, state-fixed effect controlled for average state COVID-19 growth rates, and day-fixed effect for country shocks common to all states. The effects of time dummy variables on the daily confirmed cases showed an increasing trend, and most of them are statistically significant at the level of 1%. Since the time fixed effects represent the influence of the factors that are not included in the model on a specific day, it can be observed an increasing effect of variables on COVID-19 transmission that were not absorbed by the model, such as the lockdown/restriction
measures and health services’ input (Fig. 1a). Besides, the state-specific individual fixed effect that was not included in the model mainly distributed in Brazil’s northern and eastern states. This indicated that the pandemic situation in these states was mainly affected by social and demographic factors (Fig. 1b).

### 3.3. Time dynamics and seasonality

We modeled the monthly trend of the COVID-19 transmission affected by meteorological factors (Fig. 2). From March to November, the number of COVID-19 daily new cases was negatively related to humidity, while it fluctuated periodically with temperature and wind speed every 3–4 months. The turning points of these fluctuations were identified in May, August, and November, the period of seasonal change. Temperature’s effect on COVID-19 transmission was unstable in different months, in which 67% showed a negative correlation. This instability manifested periodic fluctuations in March-April-May, May-June-July-August, and August-September-October-November. Humidity negatively affected COVID-19 new cases from March to November, except for April and May, indicating that the dry condition may aggregate the COVID-19 transmission. Wind speed’s effect on the COVID-19 daily cases showed a fluctuation in different months, similar to the observed effect of temperature. Nevertheless, wind speed’s influence coefficient fluctuated around 0, indicating that wind speed had only a minor impact on the COVID-19 daily cases.

The results in Fig. 2 present that the effects of temperature, humidity, and wind speed on COVID-19 transmission were cyclical. Therefore, we aggregated the months in the different seasons to identify the seasonal characteristic (Fig. 3). Average temperature and relative humidity showed a significant positive effect on new cases from March to May (autumn), and a negative effect from June to August (winter) and September to November (spring). From March to May, an increase of 1% in temperature and humidity produced increases of 2.849% (P < 0.01) and 1.378% (P < 0.01) in the COVID-19 cases, respectively. From June to August, the new cases increased by 0.577% (P < 0.05) and 0.854% (P < 0.01) for every 1% decrease in temperature and humidity. From September to November, the new cases increased by 0.645% (P < 0.01) when the humidity decreased by 1%, not statistically significant for temperature (coef. = -0.008, P > 0.05). Wind speed showed no significant effect (P > 0.05) on COVID-19 transmission after season division.

### 3.4. Spatial analysis

The above results showed that temperature and humidity were the most influential variables on COVID-19 transmission. We further analyzed their spatial characteristics. Moran’s I was calculated to measure the overall spatial correlation of the influence of climatic factors (i.e., daily average temperature and relative humidity) on COVID-19 cases. The global Moran’s I showed a coefficient of 0.56, Z score of 4.33 and p-value of 0.001. Regarding the humidity’s influence on COVID-19, the global Moran’s I value was 0.25, with Z score 2.05 and a p-value of 0.033. A positive spatial correlation (clustered pattern), therefore, was statistically significant for the influence of temperature and humidity on the COVID-19 cases.

Fig. 4 presents the KDE spatial distribution and the result of Anselin Local Moran’s I analysis. The temperature’s influence on COVID-19 transmission formed a high-density area in the northeastern part of Brazil. Here, temperature’s impact on COVID-19 was stronger than other areas, especially those located in the west part of the country. The Anselin Local Moran’s I analysis showed that the spatial clusters of the negative relation, i.e., Low-Low (the low coefficient value surrounded by low coefficient value) between temperature and COVID-19, were also concentrated in the northeastern areas. In contrast, only several High-High (the high coefficient value was surrounded by high coefficient value) clusters and low outlier (the low value was surrounded by high value) were found in the south, north, and middle-west, respectively (Fig. 4).

The influence of humidity on the COVID-19 daily cases showed two high-density centres in Brazil’s northeastern and south-central parts. The Anselin Local Moran’s I analysis showed that Low-Low dominated
spatial clusters located in the central areas. A High-High cluster was found in the south and a high outlier (the high coefficient value surrounded by low coefficient value) located in the southeast.

4. Discussion

Our results indicated that the daily average temperature, relative humidity, and wind speed negatively affected the COVID-19 daily new cases. Cold, dry, and windless conditions may aggravate the spread of COVID-19, where humidity and temperature play a dominant role. In Brazil, autumn is from March to May, winter from June to August, and spring from September to November (INMET, 2020). The monthly trend indicated that the influences of temperature, humidity, and wind speed on COVID-19 transmission fluctuated every 3–4 months (in line with the seasons in Brazil), and the turning point of these periodic fluctuations occurred in the period of seasonal changes. The seasonal analysis demonstrated that the meteorological factors’ effects on COVID-19 spread varied with seasons and showed a consistent negative correlation in the winter.

Similarly, Sarkodie and Owusu (2020) reported that low temperature, low wind speed, and low humidity prolonged the activation and infectivity of the SARS-CoV-2. Lorenzo et al. (2021) observed that humidity was associated with lower COVID-19 cases. A negative correlation between temperature and COVID-19 cases was reported by Dogan et al. (2020). Reviews reported that most previous studies suggested the inverse forcing of temperature and humidity on the COVID-19 transmission (Briz-Redon and Serrano-Aroca, 2020; Byun et al., 2021). Therefore, the cold and dry air could increase COVID-19 new cases, and the winter was a hard time curbing COVID-19 (Smit et al., 2020). For example, while effectively controlling the outbreak, China also saw a resurgence of COVID-19 in the winter. China was vigilant against "environment-person transmission" in addition to previous
person-person transmission’ (Chinanews, 2020).

Seasonality affects many respiratory (Killerby et al., 2018; Lofgren et al., 2007; Stewart, 2016) and other infectious diseases (Fisman, 2012; Martinez, 2018), such as SARS, MERS, or influenza. Their infection peak occurred in the winter (Smits et al., 2020). For instance, in temperate regions, influenza infections showed a seasonal cycle: November to March in the northern hemisphere and May to September in the southern hemisphere corresponding to the winter (Tamerius et al., 2013). Similarly, COVID-19 initially broke out in China and then surged in East Asia, Central Asia, Europe and North America. All of them occurred in the coldest or changing season months of the year (Sajjadi et al., 2020; Smits et al., 2020).

Brazil has a humid tropical and subtropical climate except for a drier area in the Northeast (Alvarenga et al., 2013). The dominant-negative effect of temperature and humidity on COVID-19 transmission also showed a clear spatial aggregation in Brazil’s northeastern and central parts, consistent with the spatial range of tropical savanna climate and warm and semi-arid climate (see supplementary materials for the climate types in Brazil). This showed that the macro-climate may have an important influence on COVID-19 transmission (Sajjadi et al., 2020). Several studies also indicated that the climate and geographical background are likely to be fundamental driving mechanisms of the pandemic (Mendez-Arriaga, 2020; Sun et al., 2020). Moreover, some studies found that global climate change might interfere with the outbreak of COVID-19 and other infectious diseases (Anwar et al., 2019; Casadevall, 2020).

COVID-19 transmission was also affected by other environmental conditions (e.g., air pollution, mainly PM) (Marques et al., 2021; Marques and Domingo, 2022), as well as social factors such as population density, social activities, political options (e.g., lockdown measures) and vaccination (Li et al., 2020; Lu et al., 2021; Yin et al., 2021; Zaichick et al., 2020). We focused on meteorological factors without considering other related factors, which is a limitation of our work. In addition, human error may occur in the data chain under an overloaded data system and some governments may interfere with the actual data release (Dubrow, 2021). The daily reported case data, therefore, could underreport COVID-19 and affect the results as the dependent variable. Although the fixed-effect model we used can reduce the effect of unobserved factors (Ortiz-Bobea et al., 2021), the reporting accuracy of case data still limited studies related to COVID-19. So far, the relationship between meteorological conditions and COVID-19 transmission remains controversial. Meteorological factors can only weakly modulate COVID-19 spread amid non-pharmaceutical interventions (either government-enforced or voluntary) (Demongeot et al., 2020; Hassan et al., 2020).

Although more than two year passed, the COVID-19 pandemic is still spreading worldwide. It is predicted that COVID-19 may continue and resurge in the next several years (Kissler et al., 2020). Therefore, countries should normalise quarantine measures, accelerate vaccination, control social distancing, and promote wearing masks, especially in the cold and dry winter due to the high risk of transmission. Moreover, the COVID-19 spread showed spatial correlation and aggregation in a similar climate background as we observed in this work. Therefore, it is key to strengthening cooperation on containment measures between countries with similar climate backgrounds.

5. Conclusions

Our study examined the effects and spatial-temporal characteristics of meteorological factors on COVID-19 transmission in Brazil from February 25 to November 15, 2020. Overall, the results showed that: 1) Low temperatures, humidity, and wind speed aggravated COVID-19 transmission; 2) The temporal trends of COVID-19 transmission presented a periodic fluctuation and reflected the seasonal changes; 3) The spatial distribution showed a clustered pattern that coincided with same climate type. Our results suggest that seasonality and climate types should be considered to estimate the spatial-temporal trend of COVID-19, especially in the winter season.

Declaration of competing interest

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

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Appendix A. Supplementary data

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