Stochastic Environmental Research and Risk Assessment (2021) 35:1759–1770
https://doi.org/10.1007/s00477-021-02043-8

ORIGINAL PAPER

Spatio-temporal analysis of fire occurrence in Australia

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Accepted: 3 June 2021 / Published online: 8 June 2021

Abstract

Fire is one of the most notorious hazards in Australia, with important economic impacts and damage to ecosystems. There is a concern of worsening fire conditions under climate variability, but there is little understanding of the variability in fire occurrence related to climate patterns. We present a statistical decomposition for spatio-temporal analysis of changes in fire occurrence in Australia and its association with climate factors. We found evidence of variability in the trend results for fire occurrence, and also some evidence that this variation is related to climate patterns. Our approach has applicability to other climate-related issues, providing a useful tool to identify possible changes in the intensity of occurrence over time, capturing long-term changes, and also seasonal and cyclical effects.

Keywords Australia · Climate variability · Fire occurrence · Spatio-temporal models · Trend-cycle decomposition

1 Introduction

There are evidence that climate and weather are important drivers of wildfire events, among different regions of the world, such as North America (e.g., Gillett et al. (2004); Westerling et al. (2006); Chen (2007); Le Goff et al. (2009); Wotton et al. (2010); Gedalof (2011)), Europe (e.g., Reinhard et al. (2005); Lozano et al. (2017)), as well as in Oceania (e.g., Williams et al. (2001); Pitman et al. (2007); Clarke et al. (2013)). In the most systems, it is climate that controls the amount of fuel available to burning, and also determines the flammability of the available fuel and the continuity of the fire. Anthropogenic factors may also exhibit influences on fire, directly by starting and managing fires or indirectly through anthropologically driven climate changes (Aldersley et al. 2011). In Australian ecosystems, fire plays an important role, influencing and determining the vegetation, due to factors such as floral composition, topography, and climate (Rahman et al. 2018). In the savannahs of northern Australia, intense fires dominate whereas massive fires in the arid zone occur after periods with above-average rainfall, with relatively less frequency. On the other hand, in the temperate forests of the south, large and intense fires occur, but is less extensive and also less regular (Moritz et al. 2014).

The relationship between fire occurrence and the climate factors in Australia has been explored in the literature (Verdon et al. 2004; Russell-Smith et al. 2007; Mariani et al. 2016; Dowdy 2018). In particular, the most important Australian climate drivers are the El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and Southern Annular Mode (SAM), causing spatio-temporal variations of temperature and rainfall (Hendon et al. 2007; Risbey et al. 2009), and therefore affecting the Australian fire behaviour. Additionally, some studies have identified some trends in the variables underlying fire indices. It has been observed an increase in the temperature extremes in Australia, with a particular increase in the number of record warm days while the number of record cold days has decreased (Alexander et al. 2007). Some studies have also found that Australian rainfall patterns have changed, with a significant decrease in rainfall in the southwest of Australia and a signicant increase in the proportion of total precipitation from extreme events in eastern Australia (Timbal et al. 2006; Gallant et al. 2007).

As a consequence of climate patterns, current and potential future changes in fire activity might pose threats to ecosystems and human health (Abatzoglou and Williams 2016), and understanding the patterns of fire occurrence is important to avoid loss and facilitate management decisions. The fire weather index is a common methodology

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used to assess the fire danger and to explore the effects of climatic indices in the Australian fire danger. In particular, several studies have adopted the McArthur Forest Fire Danger Index (FFDI) to find evidences of the variability of fire weather in Australia, and also to assess the linkages between climate drivers and FFDI (Verdon et al. 2004; Clarke et al. 2013; Harris and Lucas 2019). However, there is an important drawback related to the fire weather index methods. Usually these indexes are calculated based on weather monitoring station data, which may limit the analysis due to the fact that this kind of data may not be ideal for understanding the aspects of the spatial variability (Dowdy 2018). In order to be complementary to previous studies (Dowdy 2018) have proposed to assess the long-term variations in fire weather conditions based on gridded data, and have found that changes in fire weather conditions in southern Australia are related to anthropogenic climate change. However, while there is an increased concern of worsening fire conditions under climate change and variability, there is still little understanding of the relationship between the spatio-temporal changes of Australian fire occurrence and climate factors.

In order to contribute to this literature, we propose an alternative way to verify the existence of changes in the patterns of the fire activity, through the estimation of long-term and periodic components, using statistical tools to decompose the observed data into trend, seasonal, and cycle components. In addition, since fire occurrence can be associated with their spatial coordinates and temporal instant, to take into account the spatial heterogeneity of climate effects, we propose to combine elements of structural time series decomposition with spatio-temporal models with continuous spatial random effects, which can be thought as a process of decomposing geostatistical time series into a sum of persistent and mean-reverting components (Laurini 2019; Valente and Laurini 2020).

Therefore, in this study we will analyze the variability in the patterns of the fire occurrence in Australia within spatio-temporal point process framework, through a structural decomposition (e.g., Harvey (1990)) in spatio-temporal point pattern data. In particular, we extent the trend-cycle decomposition in spatio-temporal models to spatio-temporal point pattern data, by proposing to use a dynamic representation of a Log Gaussian Cox process (LGCP) where the intensity function is modeled through the decomposition of components into trend, seasonality, cycles, covariates and spatial effects (Laurini 2019; Valente and Laurini 2020). This is a useful formulation to identify possible changes in the intensity of occurrence over time, being capable to capture seasonal and cyclical effects, and to identify long-term changes in the fire events, that may be associated with climate variability.

We present here, the results of analyzing data for fires in Australia, from 2003 to 2019, using two different model specifications, with and without covariate effects, in order to assess the relationship of the variability in the patterns of fire events and climate factors. In addition to the above, we were also interested in assessing the possible variability in the maximum temperature and rainfall in Australia, evidencing the relationship between the changes in patterns of fire events and the seasonal, internannual and longer-term climate variability. In summary, results indicate an increase in the trend component of the fire occurrence, when the covariate effects are not included. On the other hand, when we included explanatory variables to control the main fixed effect related to climate patterns, the trend component remains relatively stable, which may suggests that the variability in the fire occurrence is attributable at least in part to climate factors. In addition, the results also give support to the increase in the trend component of the observed maximum temperature series.

2 Materials and methods

2.1 Data

We used daily data of fire occurrence in Australia from MODIS (Moderate Resolution Imaging Spectroradiometer) Thermal Anomalies/Fires product between January 2003 and December 2019 (Giglio and Justice 2015). The dataset, provided by NASA, includes information like fire occurrences (day/night), fire location (geographic coordinates), the criteria for the fire detection which are based on the apparent temperature of the fire pixel and the difference between the fire pixel and its background temperature, the detection confidence value which ranges from 0% and 100%, and other layers describing fire pixel attributes (Giglio and Justice 2015). In addition, in order to facilitate the visualization of the results, we used a quarterly aggregation of the daily data. To illustrate, we plot the number of fire occurrences in Australia by quarter (see Fig. 1) and the spatial distribution by quarter (see Fig. 2). In general, fires are observed in all quarters in Australia, although fire frequency is higher experienced during the last quarter of the year (summer/dry seasons), especially in Western Australia, Northern, and Queensland. The consistency of fire occurrence throughout the year in wealthier countries such as the United States and Australia is related to fuel management practices occurring during the cooler/wetter nonfire season, especially in highly populated areas (Earl and Simmonds 2018).

We also included some covariates that could be important in the fire observations since our data set includes fire occurrences of different causes, such as

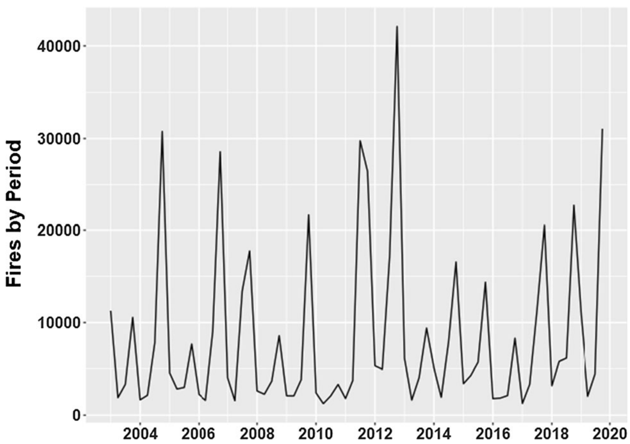


Fig. 1 Fires in Australia by quarter—From 2003 to 2019

human sources (deliberately or accidentally), and natural causes, that can be influenced by climate variables. As explanatory variables, we used monthly remote sensing data of maximum temperature and rainfall from AusCover data portal (http://www.auscover.org.au/) of Terrestrial Ecosystem Research Network (TERN), the distance from the geographic positioning of the sealed roads from National Topographic Database of Australia (GEODATA TOPO 250K series 3, available at https://data.gov.au/data/dataset/a0650f18-518a-4b99-a553-44f82f28b-b5f), and the geographical latitude. Temperature, rainfall and latitude are direct explanatory factors for the natural occurrence of fires, while the distance to sealed roads is a control for human influence in the occurrence of these events.

2.2 Spatio-temporal log gaussian Cox process

One way to deal with spatio-temporal point pattern data comes from spatio-temporal point processes. The Poisson process is a common structure used to model point process. However, this structure is limited even if one assumes a inhomogeneous distribution in space through a function of deterministic intensity. The limitations are related to the lack of possible sources of uncertainty and the fact that the Poisson process is conditionally independent. An alternative is to allow the dependency function to be a stochastic function, known as Cox process. In this paper, we used the structure of Log Gaussian Cox Process, which is a particular case of the Cox process, where the log-intensity function is a Gaussian random field. Additionally, to identify long term variability, and cyclical and seasonal effects, we adopted a decomposition of the intensity function into trend, seasonality, and cycle components along with spatial random effects.

Therefore, the model used in this work is a spatio-temporal formulation of point processes with stochastic intensity, using a decomposition of the intensity function into components that vary over time and space. The proposed model (Valente and Laurini 2020) can be written as follows:

$$\begin{aligned}
Y(s,t) &= Poisson(|e(s,t)|exp(\lambda(s,t)),\\
\lambda(s,t) &= \alpha + \mu_t + s_t + c_t + z(s,t)\beta + \xi(s,t)\\
\mu_t &= 2\mu_{t-1} - \mu_{t-2} + \eta_\mu\\
s_t &= s_{t-1} + s_{t-2} + \ldots + s_{t-m} + \eta_s\\
c_t &= \theta_1 c_{t-1} + \theta_2 c_{t-2} + \eta_c\\
\xi(s,t) &= \Phi\xi(s,t-1) + \omega(s,t)
\end{aligned} \tag{1}$$

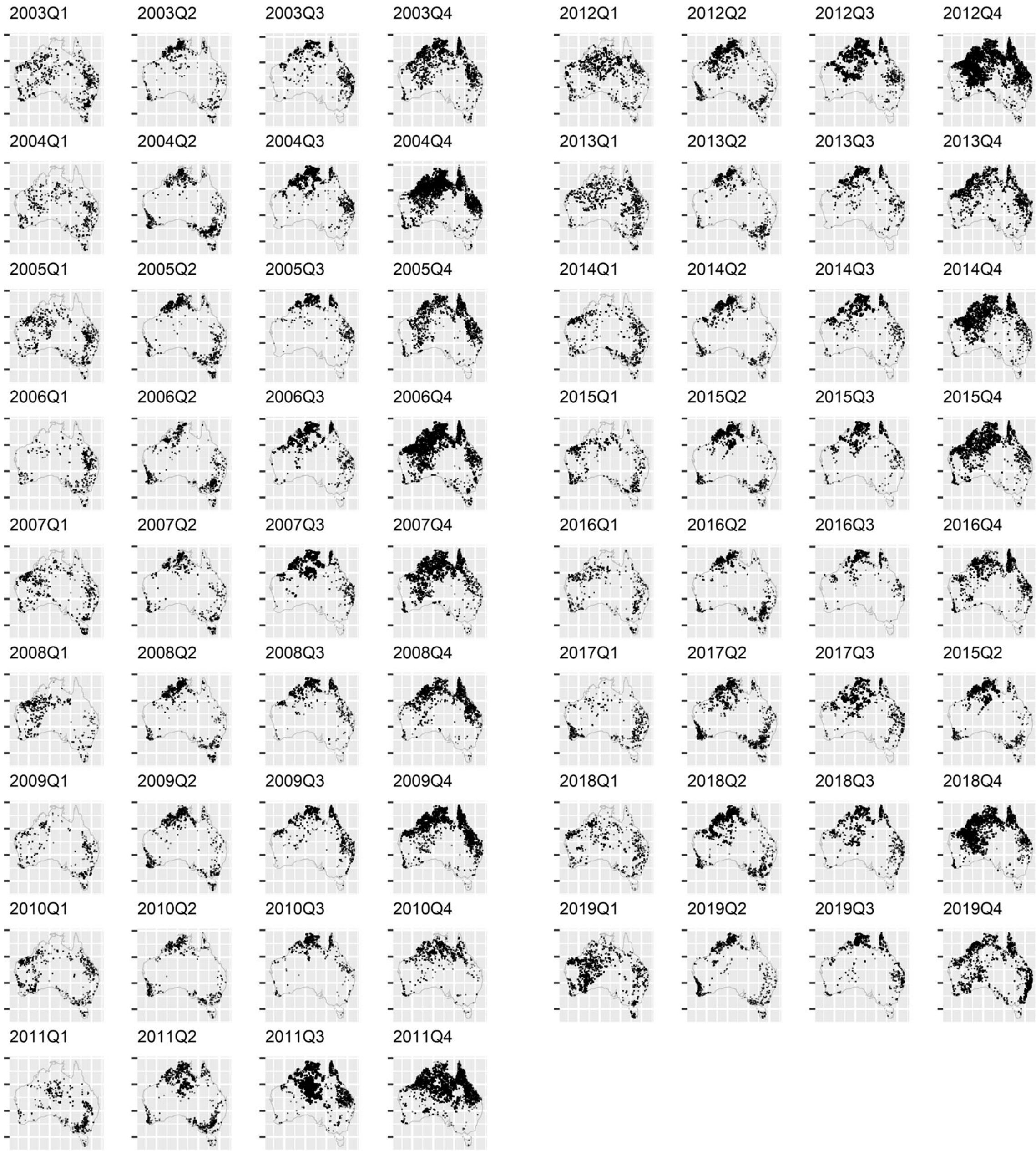
where $Y(s,\ t)$ is the number of occurrences in a region s in time t, $e(s,\ t)$ is the exposure offset for the region s, α is the intercept, μ_t is the long term trend modeled as a second-order random walk (RW2), which imposes a smoothness structure that is able to identify the trend component. In addition, the RW2 structure can be thought as a non-parametric trend structure since it can be related to spline models, which allows to identify in a more adequate way the persistent patterns of long-term variability. The s_t represents the seasonal components, c_t is a cycle component represented by an second-order autoregressive process with possibly complex roots. This component allows the reproduction of patterns with periodic (cyclic) components, which are appropriate for effects that are repeated over time (irregular periodicity) but eventually dissipate. In the problem in question, the cycle component is interesting since it allows to reproduce the effect of climatic variables that generate periodic patterns that last for more than a year, and thus climatic effects that are beyond pure seasonal components. The $z(s,t)$ is a set of covariates observed in the location s and period t, η_μ, η_c and η_s are nonspatial independent innovations with $\eta_\mu \sim N(0, \sigma^2_{\eta_\mu})$, $\eta_c \sim N(0, \sigma^2_{\eta_c})$ and $\eta_s \sim N(0, \sigma^2_{\eta_s})$. The $\xi(s,t)$ are the spatial random effects represented by the Gaussian process $\omega(s,t)$ continuously projected in space and given by

$$Cov(\omega(s,t)\omega(s',t')) = \begin{cases} 0 & \text{if } t \neq t' \\ \sigma^2 C(h) & \text{if } t = t' \end{cases} \quad \text{for } s \neq s'$$

where $C(h)$ is a covariance function of the Matérn class and σ^2 is the marginal variance. More detailed discussion about the method are available in Supplementary Information.

As the LCGP likelihood is analytically intractable, it is necessary to approximate the likelihood. To do this, one may use the SPDE approach (Lindgren et al. 2011), by using the approximation of SPDE solution as follows:

$$\omega(s,t) \approx \tilde{\omega}(s,t) = \sum_{j=1}^{n} w_j \varphi_j(s,t) \tag{2}$$



(a) 2003 - 2011 **(b)** 2012 - 2019

Fig. 2 Spatial distribution of fires in Australia—From 2003 to 2019

where n is the number of vertices of the triangulation, $\{w_j\}_{j=1}^{n}$ are the weights with Gaussian distribution and $\{\varphi_j\}_{j=1}^{n}$ are the basis functions defined for each node on the mesh. The idea is to calculate the weights $\{w_j\}$, which determine the values of the field at the vertices, while the values inside the triangles are determined by linear interpolation (Lindgren et al. 2011).

Replacing the Gaussian Field (GF) $\omega(s,t)$ by the Gaussian Markov Random Field (GMRF) approximation $\tilde{\omega}(s,t)$ in Eq. (1), and approximating the integral in the LGCP likelihood by a quadrature rule, it results that the approximate likelihood consists of $(n+n_t)T$ independent Poisson random variables, where n is the number of vertices and n_t is the number of observed point processes (see SI appendix for details). In addition, according to (Simpson et al. 2016), the LGCP formulation fits naturally within the Bayesian hierarchical modeling framework and are latent Gaussian models, therefore, it may be fitted using the Integrated Nested Laplace Approximations (INLA) approach of (Rue et al. 2009).

3 Results

Our analysis is based on a statistical model to decompose the temporal and spatial patterns of fire occurrence into long-term changes and transient effects. The model consists of a trend component, identifying persistent changes in fire patterns, transient components capturing cyclical and seasonal effects, and a spatial component capturing the territorial heterogeneity in the occurrence of these events. We performed the estimation of the parameters based on two different specifications, with and without covariates effects, which we call model M2 and M1, respectively. It is important to note that the formulation of model M1 is able to explain the spatio-temporal patterns of observed fire occurrence. However, we were also interested in to assess if the changes in the patterns of fire events can be related to climate variability. While maximum temperature and rainfall are related to climate factors, the location of the sealed roads provides evidence of intentional fire, since proximity to highways indicates accessibility and may provide evidence of human-induced fires. We use alternative formulations using unsealed roads, and the combination of sealed and unsealed roads. The specification with sealed roads had a slightly superior performance in terms of model fit, and so it is the form maintained in the model. We also included latitude as a covariate in this model, since there is evidence pointing to the dependence of fires regimes on this variable (Murphy et al. 2013; Williamson et al. 2016).

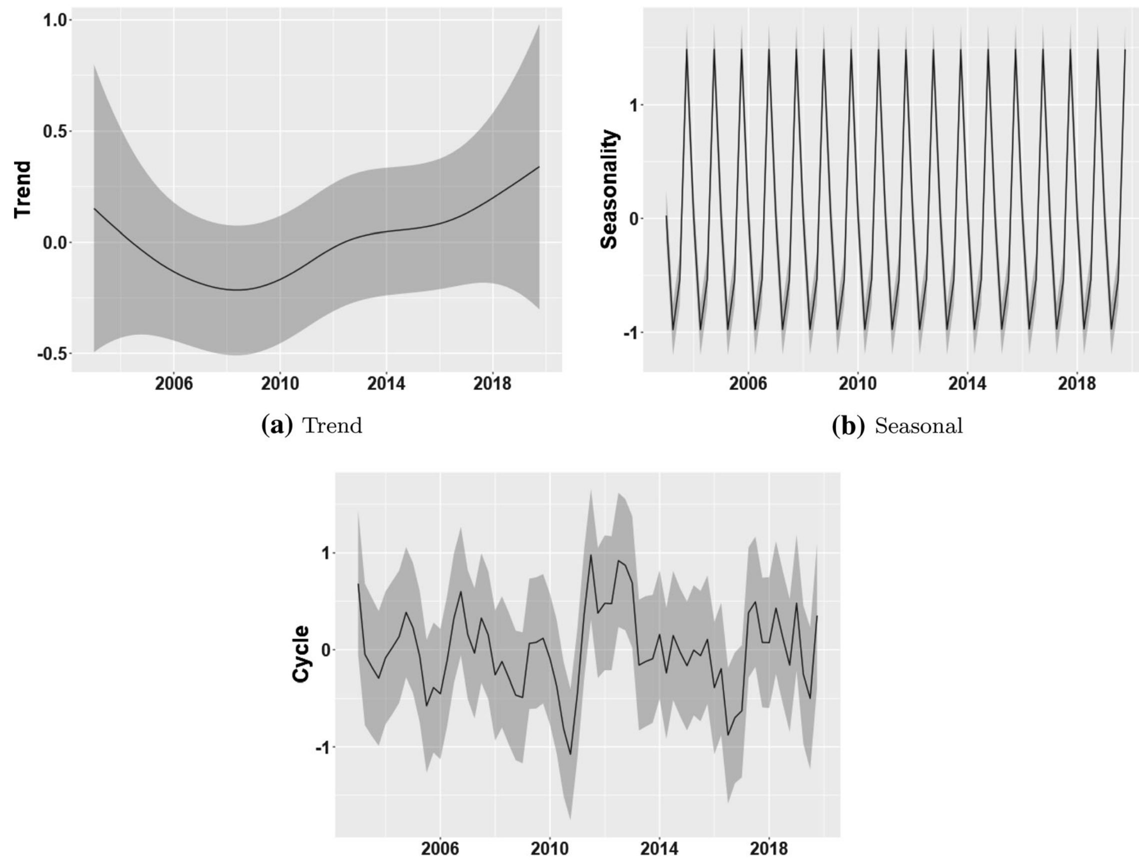
First, we estimated the parameters described in Eq. (1) without the effects of the covariates (model M1). In this case, the estimated parameters are the intercept (α), the precision of the trend component ($1/\eta_\mu$), seasonal component ($1/\eta_s$), and cycle component ($1/\eta_c$), the parameters of the second-order autoregressive process of the cycle (PACF1 and PACF2), the parameters of spatial covariance ($\log \tau$ and $\log \kappa$), and the parameter of spatial time dependence (Φ). The parameters $\log \tau$ and $\log \kappa$ are due to the parameterization proposed by Lindgren et al. (2011), which are better defined in SI appendix. In the second model specification (model M2) were included four explanatory variables namely, maximum temperature, rainfall, latitude, and sealed roads. In addition to the above, in this case, the estimated parameters include the parameters associated with the set of observed covariates (β).

The estimated precision parameters of trend, seasonal and cycle components under model M1 (see Supplementary Table A2) show a high precision associated with the seasonal component (estimated posterior mean equals 14267.626) as well as the trend component (estimated posterior mean equals 8379.048), whereas the cycle component shows a relatively minor precision (estimated posterior mean equals 2.228). The partial correlation parameters are related to the autoregressive parameters in the AR(2) representation of the cycle. The estimated parameters (0.194 and $-$ 0.044) indicate the presence of a cyclic component with the estimated period for the cycle component being equal 5.88 quarters.

Based on the estimated trend, seasonality, and cycle components of model M1 (posterior mean and 95% Bayesian credibility interval; Fig. 3), the most notable result is the trend component, which shows that there was a decrease in Australian fire occurrence from 2003 to 2010. This was followed by an upsurge in 2011, previously discussed in the literature (e.g., Giglio et al. (2013); Dutta et al. (2016); Earl and Simmonds (2017)). In addition, from 2011 to 2020, the fire levels exhibit a growth pattern. The seasonal component is stable with very tight credible intervals, which is consistent with the estimated precision parameter.

In order to assess if the variability in the patterns of fires can be associated with climate factors, we performed the estimation of model M2, which were included four explanatory variables. The estimated posterior means (see Supplementary Table A1) indicate a negative relation between fire events and rainfall ($-$ 0.002), and the distance from sealed roads ($-$ 0.007), as expected, and a positive relation between maximum temperature and fire occurrences (0.149). In addition, there are evidences of the influence of the latitudinal gradient in the fire activity, which is reflected in the weather conditions during the fire events (Williamson et al. 2016; Murphy et al. 2013). Based on these discussions, we included the geographical latitude as a covariate, which exerts a positive effect on the fire occurrence. It is possible to note that, under model M2 specification, the trend component is relatively stable after the upsurge in 2011 (Fig. 4).

The spatial heterogeneity of the fire occurrences in Australia can be seen through the estimated spatial random effects under models M1 (see Supplementary Figure A2) and M2 (Figs. 5 and 6). In addition, to show the importance of the trend, seasonal and cycle components in the analysis of fire occurrence, we plotted the observed total fire count and the predicted value of fire count in each year given by the sum of the estimated trend, seasonal, cycle and intercept components of the models M1 (see Supplementary Figure A3) and M2 (Fig. 7). The results provide evidence that the latent components explain the most part of the variability observed in the total fires count since the prediction of the total count mostly lies inside the 95% credibility interval for the whole period. Also, the estimated intensity function and the observed fire occurrence (black dots) for models M1 (see Supplementary Figure A3) and M2 (Supplementary Figure A4) shows that the estimated log intensity function explains the spatio-temporal



(a) Trend **(b)** Seasonal

(c) Cycle

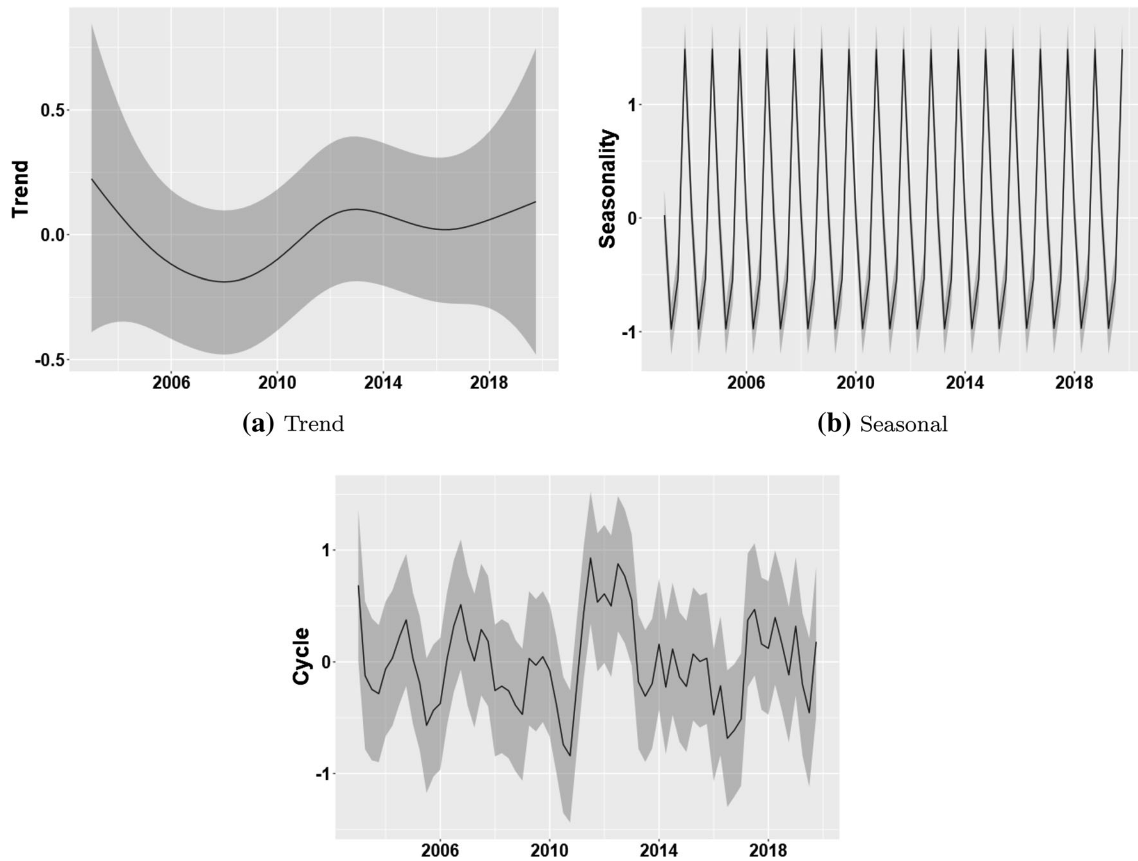
Fig. 3 Trend, Seasonal and Cycle decomposition of fire occurrence in Australia—Model without covariates (M1). The shaded areas in the graph represents the 95% Bayesian credibility interval

variation observed in the fire count, which suggests that the proposed model has a good fit. Supplementary Table A3 shows some fit measures for the two models (mean error (ME), root mean squared error (RMSE), mean absolute error (MAE) and mean percentage error (MPE)). In general, the models present a good fit in these measures, with a small negative bias in both models, but of very low magnitude, with mean percentual errors of -0.332% and -0.327% for models M1 and M2, respectively.

In order to support the evidence that changes in fire occurrences have been related to climate factors, we performed a similar method for decomposition of trend, cycle and seasonal components in spatio-temporal models to investigate the existence of variability in the patterns of the maximum temperature and rainfall from 2003 to 2019 in Australia. In summary, the central idea of the method is to decompose the time series in a similar way to a time series structural decomposition, with the innovation process in each location that contains an error component projected in the spatial continuum (Laurini 2019). For the observed maximum temperature our analysis show the presence of a tendency from 2010 to 2019 (see Fig. 8), evidencing the relationship between climate factors and fire occurrence in Australia, in agreement with previous results (e.g., Hughes (2003); Griffiths et al. (2005); Alexander et al. (2007)). On the other hand, the results obtained through the modeling carried out in this article do not indicate the presence of relevant changes in the trend of rainfall series (see Supplementary Figure A4). In addition, the proposed model was not able to capture a significant cycle component.

4 Discussion

Before moving to discuss our findings, it is worth spending a few words on what we consider the main limitations of this study. There is a meaningful limitation related to the selected covariates in our analysis. Since the proposed model performs a spatio-temporal analysis for the occurrences of a process observed continuously in space, the covariates must to be available at every location of the interest region within the observation window. Due to this methodological constraint, the number of available covariates are limited. In particular, in our paper, we were



(a) Trend **(b)** Seasonal

(c) Cycle

Fig. 4 Trend, Seasonal and Cycle decomposition of fire occurrence in Australia—Model with covariates (M2). The shaded areas in the graph represents the 95% Bayesian credibility interval

able to include only information in climatic patterns and measures of human presence.

The second limitation is more significant and difficult to overcome. As previously stated, our database contains only 16 years of data from fire occurrences in Australia and due to the limited data sample the results demand our attention. In other words, given data limitations, our results may be sensitive to uncertainty and caution is required in its interpretation. In fact, strongest results to provide baselines for assessing the long-term changes in the pattern of fire occurrence in Australia require longer time series. Although, we believe that the problem addressed in our paper is important and timely, and the proposed method can give some new insights to this subject, significantly contributing to the literature of statistical analysis of climate variability through spatio-temporal models. In addition, to highlight the potential of our approach, we discuss here about the validity of using statistical modeling for the analysis of relevant climate-related issues under data availability limitations, and also how the model can provide compelling evidence (although not conclusive) of the impact of climate patterns in the spatio-temporal variability of Australian fire activity.

In fact, the most relevant issue is the separation between long-term and transient effects of the fire occurrences, which is central in the interpretation of the model results. The trend component plays a crucial role, incorporating the persistent changes in the fire occurrence. In our model, the use of a random walk model imposes an statistical identification that ensures that the trend component only captures long-term changes, isolating the effects of short-term changes which are captured by the cycle and seasonality components, and also the spatial patterns. Thus, we are using interpretation features that are common to other statistical models that try to identify possible long-term movements in climate-related issues through non-stationary latent components, which comprises a rich literature of statistical models to analyze climate changes (e.g. Bloomfield (1992); Estrada et al. (2013); Laurini (2019); Valente and Laurini (2020)). After all, the whole idea is precisely imposing an identification structure that encompasses all the persistent changes in a common component, which aggregates all changes with relevant long-term

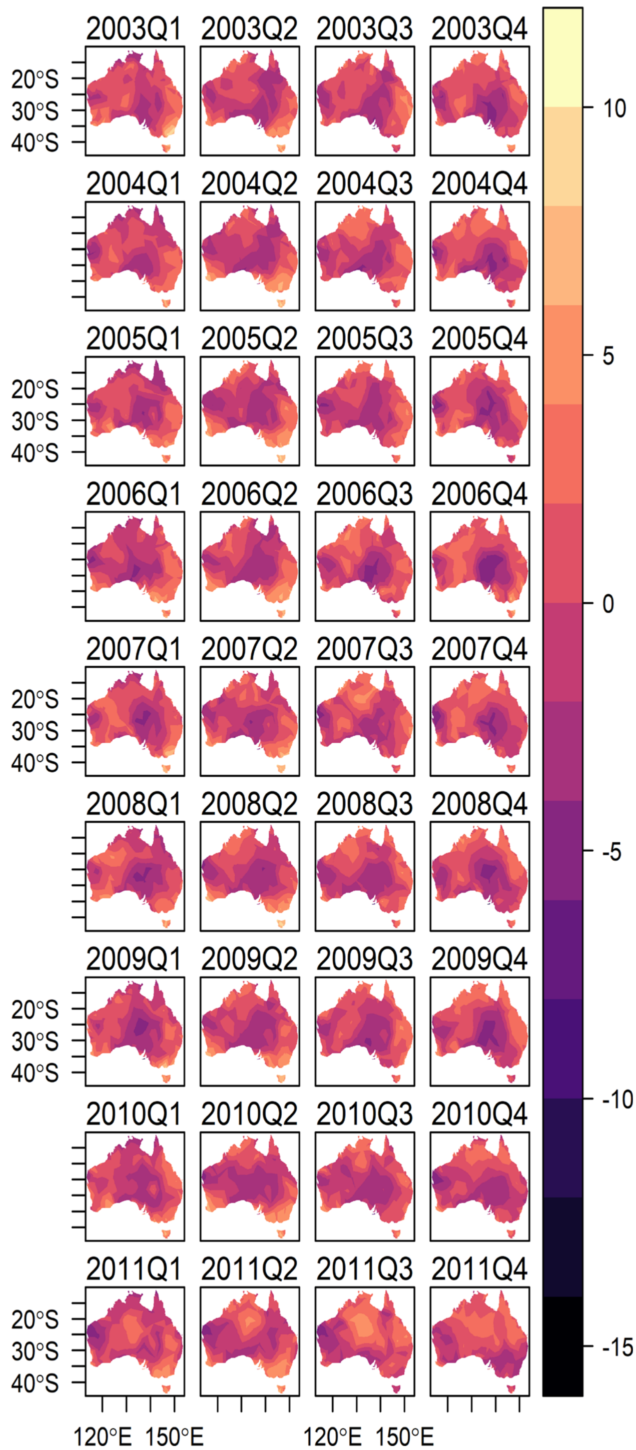


Fig. 5 Spatial random effects—Model with covariates (M2) 2003–2011

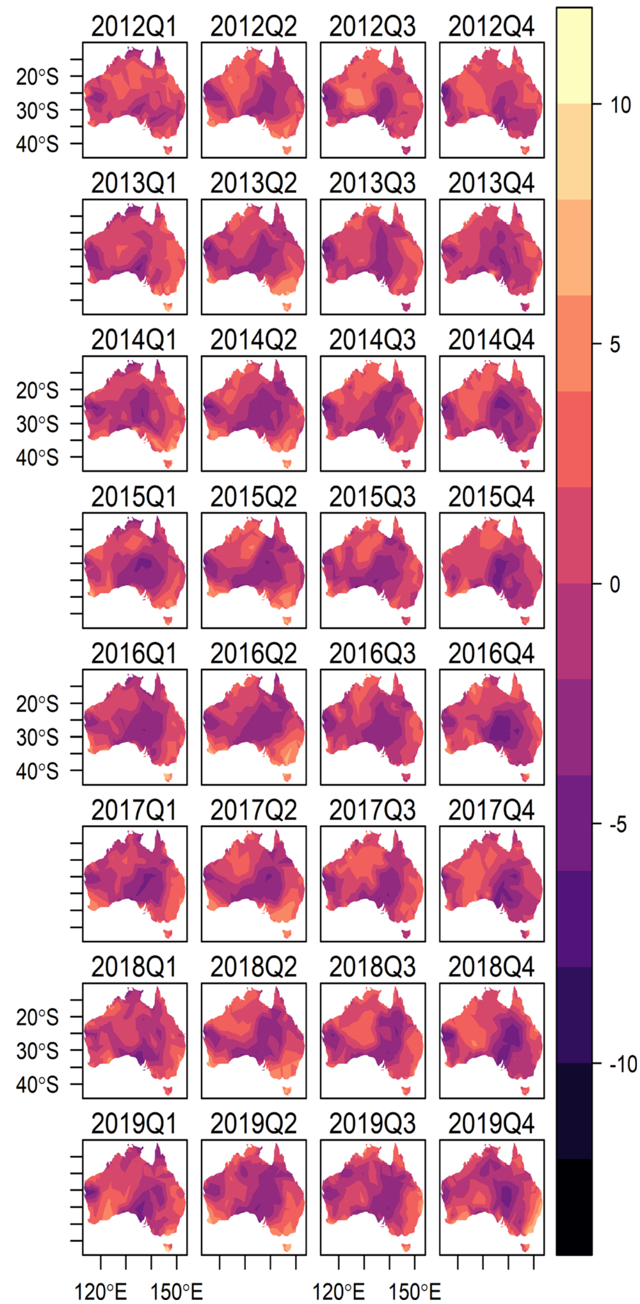


Fig. 6 Spatial random effects—Model with covariates (M2) 2012–2019

effects, which is in turn a way of estimating patterns of climate variability (or climate change, considering longer observed time series) using temporal and spatio-temporal models. In particular, in the presence of limited data it is necessary to impose restrictions in order to be able to separate long term and transient effects, which is also necessary due to the non-stationary nature of the long-term climate variability processes.

With these caveats in mind we move on to discuss the findings. Our evidence suggests that there were an increasing trend of the intensity of fire occurrence in Australia since 2010. Yet, as previously discussed, mathematically, the estimated long-term component can be seen as the accumulation of all shocks that occurred in the past with non-transitory effects, and this is the reason why the level shift would correspond to persistent changes.

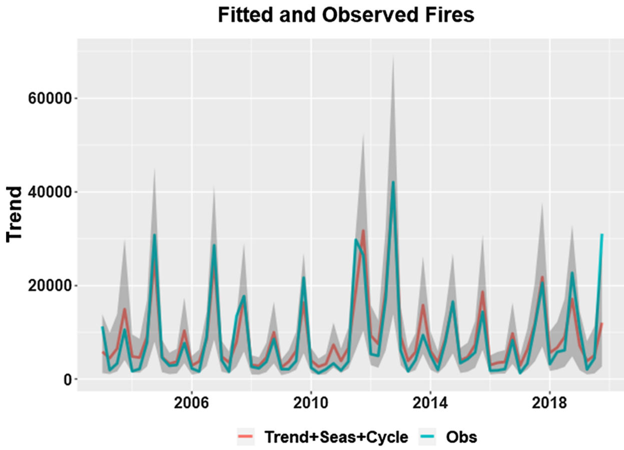
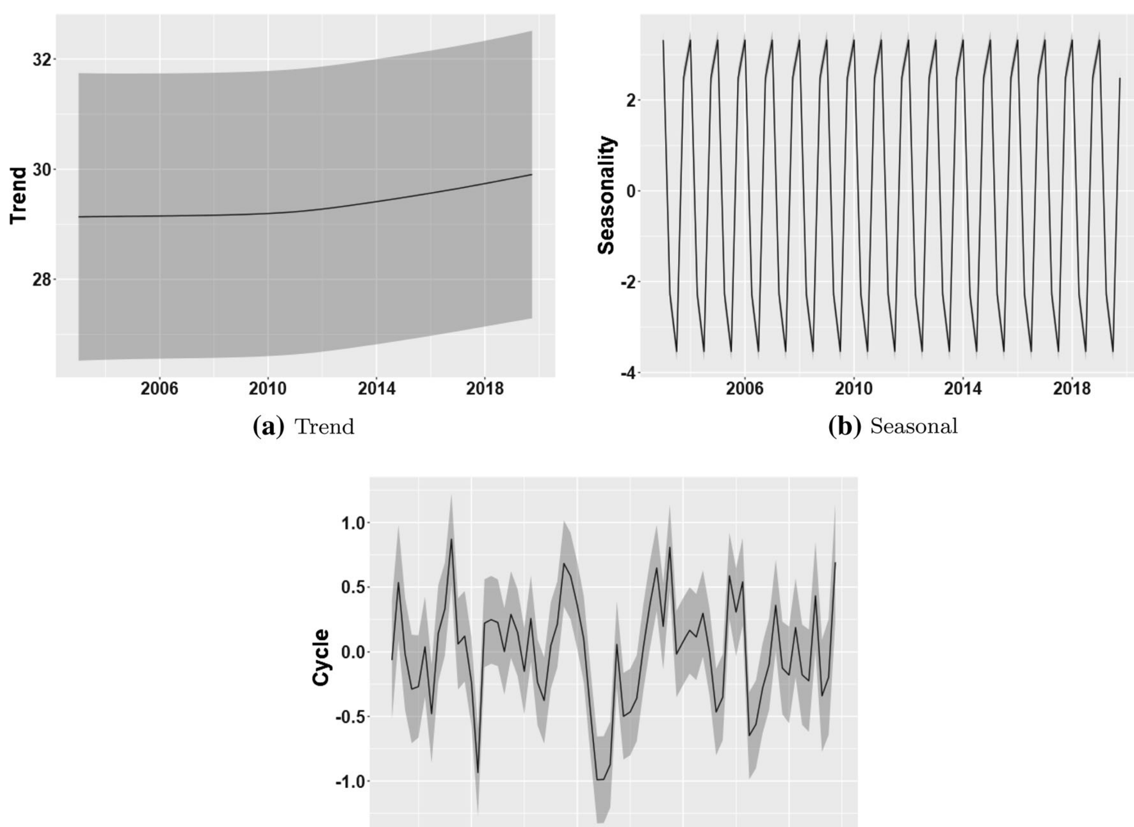


Fig. 7 Predicted fires by the sum of trend, seas and cycle components and observed fires—Model with covariates (M2). Shaded areas in the graph represent the 95% Bayesian credibility interval

However, despite the evidence of long-term changes in fire activity, given data limitation in this particular case, we cannot state with confidence that the observed variability in the estimated trend component corresponds to long-term changes. Indeed, since the decadal climate variability and climate change overlap, based on a short observed time series, it is difficult to distinguish between the two effects. Changes in fire weather over longer time scales have been widely discussed in the literature, and it have been associated with anthropogenic climate changes (Dowdy et al. 2016; Harris and Lucas 2019), but also with climate variability (e.g., Interdecadal Pacific Oscillation) (Verdon et al. 2004). On the other hand, it is worth noting that, for longer time series, our proposed model could be considered as an important tool to identify the distinct effects from climate change and climate variability, given the model ability to capture persistent and mean-reverting (seasonal and components with irregular periodicity) terms, taken into account the effects of covariates and the spatial heterogeneity.

Given the mean-reverting and irregular periodicity nature of the cycle component, it was possible to capture the effects of interannual and/or multi-year climate variability in the fire activity. As an example, based on the results, it is possible to observe that the estimated cycle component was able to capture the considerable decrease in the fire activity in 2010-11, which coincides with weak to moderate and moderate to strong La Niña events[1], being one of the



(a) Trend **(b)** Seasonal **(c)** Cycle

Fig. 8 Trend, Seasonal and Cycle decomposition of maximum temperature wettest calendar years on record for Australia, and also the lagged response from the same La Niña, which drove up fuel loads in central Australia, which consequently increase the fire activity.

By including covariates in the model we were able to investigate the link between the increases in fire activity and anthropological activities and climate factors over time. Our findings suggest that climate patterns and human activities are underlying factors that have driven the upward trend of the fire occurrence. Fire requires sufficient biomass, biomass available to burn, ambient conditions conductive to spread, and ignitions (Bradstock 2010). These factors influence the spatio-temporal fire activity, and is strongly dependent on the meteorological conditions and how these conditions interact with the vegetation, or fuel, resulting in fundamentally different fire regimes across Australia. The anthropological influence may further complicate the influence of biophysical drivers, through land-use modification, human ignitions, and fire suppression (Andela et al. 2017). Supporting the evidence that the variability in the fire occurrence have been related to climate variability, our findings suggest a growth pattern of the trend of maximum temperature. This result is in agreement with some other studies, which have reported that the variability in fire occurrence conditions are consistent with observed changes in temperature and rainfall throughout Australia (Russell-Smith et al. 2007; Clarke et al. 2013; Dowdy 2018). On the other hand, the lack of meaningful results related to changes in the trend of rainfall series may be related to different patterns of precipitation throughout Australia. Many studies have analyzed Australian rainfall trends and have shown more regionally dependent variations (Hughes 2003). Thus, since we assessed the rainfall trend over a large area, it is too hard to capture the presence of a tendency for rainfall.

In addition, by including the geographical latitude as a covariate, our results corroborates previous analyses of spatio-temporal variability in fire activity over the entire country, pointing out the importance of the latitudinal information in shaping temporal patterns of fire activity (Murphy et al. 2013; Williamson et al. 2016). Our findings suggest that the latitude has a positive effect on fire intensity, in that by increasing the geographical latitude the fire frequency is more intense. It is worth noting that as the entire analyzed region is below the equator, the latitudes are negative, indicating that the higher fire frequency is concentrated along with the northern Australia. Indeed, as discussed by Murphy et al. (2013), the variation in Australian fire regimes is related to latitudinal gradient in season rainfall, driven by summer monsoon activity in the north and winter frontal activity in the south. The very reliable dry-wet cycle in the north allows the high fire frequencies to occur annually (mostly in the dry season, from April to November), and thereby limiting maximum fire intensities. On the other hand, in the south, as the influence of the summer monsoon rainfall diminishes, fire frequency becomes strongly constrained by the fire weather and fuel moisture (Bradstock 2010), and the coincidence of extreme fire conditions and abundant fine fuels might only occurs every 5–10 years, which in turn increase maximum fire frequencies, occurring mostly during the summer and autumn. In the arid zones, the fire activity is constrained by the lack of continuous fuels or slow vegetation grows, and is characterized by intermittent periods of fire activity, which occurs mainly after periods of high-rainfall, often associated with La Niña events(Murphy et al. 2013).

From the spatial perspective, there is evidence of the temporal variability of fire activity across different regions of the country. Such a knowledge is important for management and planning applications that requires to consider potential threats to human life and economic losses under natural hazards. Based on our analysis it is possible to observe that fire is most frequent in northern Australia, where tropical monsoon climate dominates. On the other hand, fire occurrence is less frequent in the arid (central) and temperate (southern) zones. Indeed, it is possible to observe an increase in the fire activity in the arid central zones in 2011, which reflects the lagged response of the La Niña event between 2010 and 2011, that caused periods of high-rainfall. The temperate southern Australia is characterized by infrequent but intense fires, which is associated with severe drought. In particular, based on the spatial random effects, it is possible to see that our model was able to capture the intense fire activity in southern Australia between 2003 and 2011, when the "Millennium Drought" (Van Dijk et al. 2013) was broken by the above average rainfall in 2010 and 2011. It is worth noting that the results of this spatio-temporal variability of the fire activity are also useful to highlight the influence of the climate variability in this kind of event. In particular, is possible to observe that spatio-temporal results are consistent with the expected variations under Australian climate influences, like the monsoon and the east to southeasterly winds in the northern areas of Australia, and also the frontal systems and blocking highs in the southern Australia. These kind of climate drivers are capable to affect weather variables, such as temperature and rainfall, influencing the fire activity (Dowdy 2018). Therefore, the spatio-temporal analyses of the variability of the fire events over Australia is a useful tool to understand the general patterns and temporal variability of the fire activity, and how climate drivers can influence it over space and time.

Evidence that climate patterns are responsible for the variability in fire occurrence in Australia has been

[1] See http://www.bom.gov.au/climate/enso/lnlist/index.shtml.

previously reported in the literature, however our approach provides a structural time series decomposition of fire occurrence in Australia into a sum of trend, seasonal, and cycle components plus the effect of additional covariates, taking into account the spatial heterogeneity. Our method reveals the fire occurrence behavior and its association with climate factors avoiding some problems usually faced by inference procedures on climate-related issues, such as the dimensionality of the data and the difficulty to include spatial information of climatic effects. Furthermore, our results enable a more comprehensive understanding of the variability of fire occurrences in Australia under climate variability and can better inform the management and policy decisions.

5 Conclusion

As a contribution to the understanding of Australian patterns of fire occurrence, we propose to use a dynamic representation of a Log Gaussian Cox process where the intensity function is modeled through a decomposition of components into trend, seasonality, cycles, covariates and spatial effects, which is useful to identify persistent changes in the intensity of occurrences over time, and to capture seasonal and cyclical effects, taking into account the spatial heterogeneity. Within this framework, our findings suggested the existence of the variability in the trend component of Australian fire activity, suggesting that this variation may be associated with anthropological activities and climate factors over time. Furthermore, we find a growth pattern of the trend of maximum temperature, evidencing the relationship between the variability in the fire occurrence have been related to climate patterns.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1007/s00477-021-02043-8.

Acknowledgements The authors acknowledge funding from CNPq (306023/2018-0), FAPESP (2018/04654-9), Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) - Finance Code 001 and Instituto Escolhas. We are also grateful for the excellent suggestions and criticisms of two anonymous referees.

Author Contributions F and ML designed research, performed research, and wrote the paper.

Declaration

Conflict of interest The authors declare that they have no conflict of interest.

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