Modelling the drivers of natural fire activity: the bias created by cropland fires

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Abstract.   Wildland and cropland fires, which differ considerably in fire regime characteristics, have often been evaluated jointly to estimate regional or global fire regimes using satellite-based fire activity data. We hypothesised that excluding cropland fires will change the output of the models regarding the drivers of natural fire activity. We modelled MODIS fire activity data of western and southern Turkey for the years 2000–2015 using binomial generalised linear models in which many climatic, anthropogenic and geographic factors were included as predictor variables. For modelling, we used different datasets created by the exclusion of various cropland and vegetation land cover classes. More fire activity was observed as the number of cropland-dominated cells increased in a dataset. The explained deviance (%) of the binomial GLM differed substantially in the separate datasets for most of the variables. Moreover, excluding croplands gradually from the overall dataset resulted in a substantial decrease in the explained deviance (%) in the models for all variables. The results suggest that cropland fires have a significant effect on the output of fire regime models. Therefore, a clear distinction should be drawn between wildland and cropland fires in such models for a better understanding of natural fire activity.

Additional keywords: agricultural fire, climate, land cover, Mediterranean Basin, Turkey.

Introduction

Croplands constitute 11% of Earth's terrestrial surface, corresponding to nearly 40% of the Earth's surface suitable for crop production (Bruinsma 2003). The increasing demand for food supply is expected to impose an increase in crop production in the near future (Godfray *et al.* 2010; Tilman *et al.* 2011). Fire has been widely used in agricultural management during harvesting, post-harvesting or pre-planting periods since the Neolithic Revolution (Turner *et al.* 2010). Such agricultural fires are widespread, comprising ~10% of total fires on Earth (Korontzi *et al.* 2006), and are among the principal causes of wildland fires (Leone *et al.* 2009; Ganteaume *et al.* 2013). Despite increasing research on fire ecology and fire regimes during the last two decades, the patterns of agricultural fires have remained unclear (Tulbure *et al.* 2011). The most studied properties of agricultural fires are their contribution to air pollution (Stohl *et al.* 2006; Li *et al.* 2010) and atmospheric gas emissions (Andreae and Merlet 2001; van der Werf *et al.* 2010; McCarty 2011; McCarty *et al.* 2012).

Owing to development in satellite fire detection (Justice *et al.* 2002; Giglio *et al.* 2003), we have been able to observe fires anywhere on Earth since 2000. Using this technology, we have been able to document and understand fire regimes on a regional and global scale (Chuvieco *et al.* 2008; Archibald *et al.* 2013; Murphy *et al.* 2013; Pausas and Ribeiro 2013). Accordingly, a large number of cropland fires documented by satellite data have also been acknowledged in many regions (Korontzi *et al.* 2006; Chuvieco *et al.* 2008).

However, cropland fires have often been ignored in studies determining the drivers of fire activity and regimes on a regional or global basis, especially if satellite fire activity data are used (Murphy *et al.* 2013; Pausas and Ribeiro 2013; Curt *et al.* 2015). Consequently, in most cases, cropland and wildland fires have been evaluated jointly. However, wildland and cropland fires clearly differ in fire regime characteristics, such as season, frequency and severity of fire (Le Page *et al.* 2010; Amraoui *et al.* 2013; Benali *et al.* 2017). Wildland fires are mostly related to the weather and climatic factors, and have a relatively shorter fire season, whereas cropland fires are set by humans and have mostly longer fire season, depending on the type of the agriculture (Chuvieco *et al.* 2008). Since such differences exist in many regions, lack of differentiation between cropland and wildland fires in models of fire regimes may lead to an under-estimation or over-estimation of natural fire regimes. This drawback would also create a problem in predicting future fire regimes under different climate change scenarios.
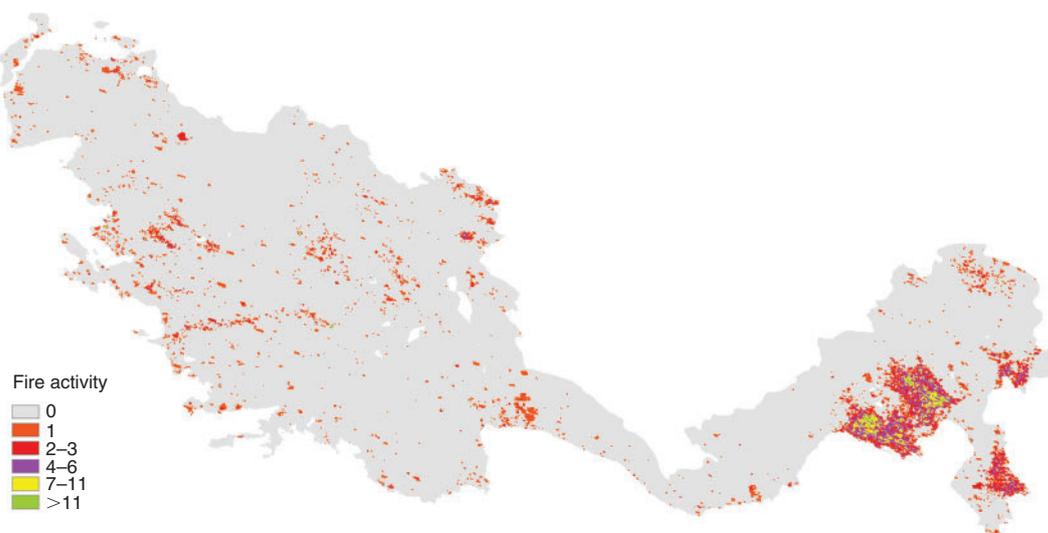
Fig. 1. Distribution and frequency of fire activity in the study area (based on Moderate Resolution Imaging Spectroradiometer (MODIS) fire activity data for years 2000–2015).

To date, several approaches have been used to detect cropland fires from satellite fire activity data. One approach considers the characteristics of fires or fire regimes, such as the frequency of fires, the duration of individual fires, the length of fire season and inter-annual variability in fire seasons. This approach has been used to define fire activity dominated by cropland fires (Chuvieco *et al.* 2008; Archibald *et al.* 2013) or to classify individual fires as cropland fires (Amraoui *et al.* 2013). Using this approach, for example, Chuvieco *et al.* (2008) were able to reveal the relative importance of cropland fires in different biomes and ecoregions. It is also possible to monitor and detect cropland fires by coupling satellite fire activity data and a land cover dataset (Korontzi *et al.* 2006; Le Page *et al.* 2010; van der Werf *et al.* 2010; Tulbure *et al.* 2011; Magi *et al.* 2012; Murphy *et al.* 2013; Curt *et al.* 2015; Rabin *et al.* 2015; Hall *et al.* 2016; Xie *et al.* 2016). The latter approach allows us to detect cropland fires from satellite data by considering fire activity on croplands. Korontzi *et al.* (2006) showed that global agricultural fire activity data revealed with this methodology is consistent with regional agricultural practices and crop production data, and therefore, is reliable.

The aim of our study is to understand the effect of considering cropland fires on the results of modelling of drivers of natural fire activity using satellite fire data. Considering the difference of cropland fires in frequency and season in comparison with wildland fires, we hypothesised that excluding cropland fires will change model output significantly. To test this hypothesis, we selected a region comprising various fire regimes, including wildland and cropland fires in the Mediterranean Basin, and used a modelling approach based on the exclusion of various vegetation and cropland land cover classes.

Methods

Study area

The study area is located in western and southern regions of Turkey and covers 199 935 km^2 in the eastern Mediterranean Basin (between 35.8 and 40.4°N and 26.2 and 36.8°E). The climate is typical Mediterranean, with dry summers and mild winters. Moreover, it shows substantial variability in temperature and precipitation within the study area (Bekar 2016). Mediterranean Turkey includes various vegetation types, such as sclerophyllous shrublands, coniferous forests (*Pinus brutia*, *P. nigra*, *Cedrus libani*, *Abies cilicica*) and sub-alpine grasslands (Atalay 1994). Moreover, the study area has been subjected to intense human activity for millennia, resulting in a significant impact on the landscape (Kaniewski *et al.* 2007; Şekercioğlu *et al.* 2011), including human-induced fires for transforming naturally vegetated areas to pastures and croplands (Kaniewski *et al.* 2008).

Data

We used an 8-day summary of fire activity data for cells ~1 km^2 in size (*MOD14A2*) obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) instruments on the *Terra* satellite for the years 2000–2015 (Fig. 1). MODIS fire activity data have been proved a good proxy of active fires on Earth (Csiszar *et al.* 2006; Pausas and Ribeiro 2013).

We used several variables to explain the distribution of fire activity data throughout the study area, including climatic, anthropogenic and topographic variables (Table 1; Fig. 2). We obtained the agricultural land area size, livestock population size and human population size from the Turkish Statistical Institute at the district level (minimum, mean, and maximum district sizes were 5524, 11761, and 20177 km^2) for the year 2015 (see http://www.tuik.gov.tr/, accessed 31 July 2016), and OpenStreetMap road network data for 2016 (Haklay and Weber 2008), as indicators of the human impact. To transform district-level data into GIS layers, data were first imported into ArcGIS (ver. 10.3.1, ESRI, Redlands, CA, USA). Subsequently, an interpolation technique was applied using the Inverse Distance Weighting tool in ArcGIS. GlobCover land cover data was transformed into ~1 km^2 (30 arc seconds) using ArcGIS

Table 1. Variables used in the models

All data were transformed to GIS layers at ~1 km^2 pixel resolution using ArcGIS. BIOCLIM, bioclimatic variables from the WorldClim database; PET, potential evapotranspiration; NDVI, Normalised Difference Vegetation Index

Variable	Description	Original resolution	Format
Climatic variables			
BIOCLIM	Includes 19 bioclimatic variables (°C for temperature, mm for precipitation)	1 × 1 km	Raster
PET	Includes 12 monthly PET variables (mm)	1 × 1 km	Raster
Anthropogenic variables			
Human population size	Number of inhabitants	District	Excel
Livestock population size	Total number of sheep, goats, and cattle	District	Excel
Agricultural area size	Agricultural area (decare)	District	Excel
Road network	Total length of roads (km)	–	Polyline
Geographic variables			
Slope	Slope (°)	90 m	Raster
Aspect	Aspect relative to north	90 m	Raster
Elevation	Altitude from sea level (m)	1 × 1 km	Raster
Ruggedness Index	Terrain Ruggedness Index (m)	90 m	Raster
Solar radiation	Annual insolation (Wh m^{-2})	90 m	Raster
Productivity and vegetation variables			
NDVI	Includes 12 monthly NDVI variables	1 × 1 km	Raster
GlobCover	Categorical land cover data	300 m	Raster

resample tool. For climate data, we used 19 bioclimatic variables from the WorldClim database (BIOCLIM; Hijmans *et al.* 2005), and monthly potential evapotranspiration (PET) variables from the Global Aridity and PET databases (Consortium for Spatial Information 2016) for the period between 1960 and 1990. The Normalized Difference Vegetation Index (NDVI) dataset for 2015 (*MOD13A3*; National Aeronautics and Space Administration 2016) was used as a proxy of productivity and vegetation cover. Geographical variables, such as elevation, slope, solar radiation and terrain ruggedness index, were derived from the digital elevation model from the Consortium for Spatial Information database (Jarvis *et al.* 2008).

GlobCover land cover data (Bontemps *et al.* 2011) were used to create separate datasets by including or excluding cells (pixels) dominated by croplands or vegetation (based on United Nations Land Cover Classification System; Fig. 3). We used a simple exclusion method to create datasets, similar to the common technique of excluding cloud pixels from remotely sensed data (e.g. Zhu and Woodcock 2012). To create *dataset 2*, for example, 1 × 1-km cells classified as 'cropland' and 'vegetation–cropland mosaic' were excluded from *dataset 1*, which is the dataset that includes all cells in the study area. The same procedure was applied for creating the other datasets (Table 2). *Dataset 2* and *dataset 3* were created by excluding cropland-dominated cells in *dataset 1*, whereas *dataset 4* and *dataset 5* were created by excluding vegetation-dominated cells. As a consequence of the exclusion process, we obtained five datasets that differ in the land cover type that was included (Table 2). That is, the overall dataset (*dataset 1*), vegetation-dominated datasets (*dataset 2* and *dataset 3*) and cropland-dominated datasets (*dataset 4* and *dataset 5*).

Modelling

We modelled the contribution of anthropogenic, climatic, geographic factors and productivity to explain fire activity in the study area for each dataset. We considered two types of fire activity variables: the number of fires (count data with discrete structure) and the presence of fire (presence and absence data with binary structure) in the entire study period (years between 2000 and 2015). We used generalised linear models (GLMs) to elucidate the relative contribution of different variables in explaining fire activity in the study area. GLMs have many advantages over standard linear models or regression approaches; in particular, they are more flexible by assuming various families of probability distributions (Guisan *et al.* 2002; O'Hara and Kotze 2010). As the fire activity data had excess zeros, we used a zero-inflated negative binomial generalised linear model (ZINB-GLM) to handle zeros and over-dispersion in the count data (Zeileis *et al.* 2008; Brown *et al.* 2015). For presence and absence data, we used a binomial GLM. However, as preliminary analyses showed that ZINB-GLMs and binomial GLMs yielded similar results (Bekar 2016), we presented and interpreted only the results of the binomial GLM, as a simpler modelling approach (ZINB-GLM results are also given in Table S1). We considered the percentage of the explained deviance as the main model output when comparing different datasets for each variable, because all models yielded significant results ($P < 0.0001$ in most cases), even though the effect size is small due to the very large number of cells in the datasets.

Using the exclusion procedure summarised above, we compared model outputs for each variable in different datasets to reveal the effect of cropland fires on model results and the relative contribution of each variable to fire activity. All analyses were conducted using the R statistical software (ver. 3.2.0; R Foundation for Statistical Computing, Vienna, Austria, see https://www.R-project.org/, accessed 31 July 2016), and ZINB-GLMs were performed using the *pscl* package in R (Jackman *et al.* 2015).

Results

In the study area, fire activity was observed in 7.4% of the cells (based on *dataset 1*). The percentage of cells in which fire activity
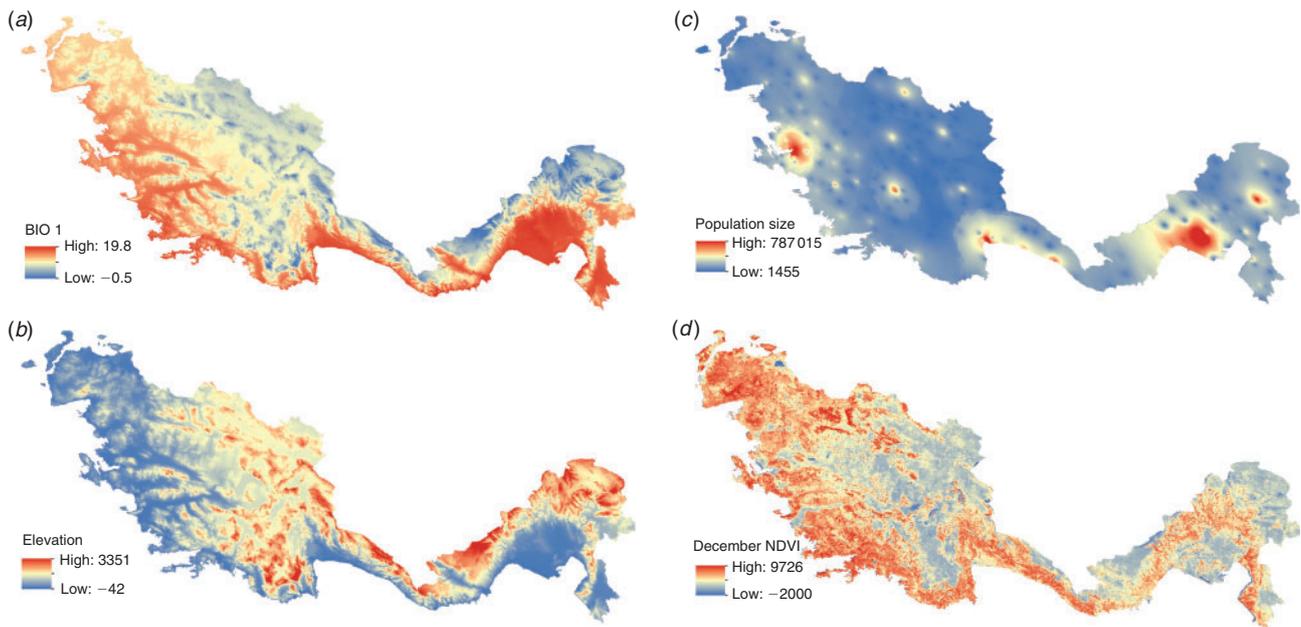
Fig. 2. Distribution of some of the explanatory variables representing climatic, anthropogenic, and topographic variables. (*a*) Annual mean temperature (BIO 1; °C), (*b*) elevation (m), (*c*) human population size, and (*d*) the Normalized Difference Vegetation Index (NDVI) of December.
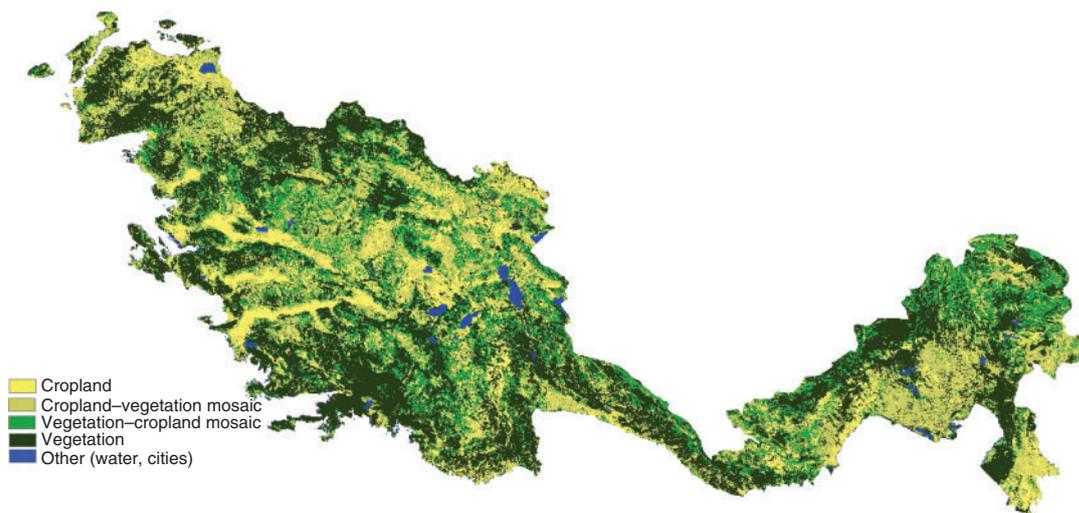

Fig. 3. Distribution of land cover classes (based on GlobCover land cover data).

was recorded decreased dramatically both in *dataset 2* (3.6%) and *dataset 3* (3.7%), whereas it increased slightly in *dataset 4* (8.8%) and markedly in *dataset 5* (12.0%) (Table 3). Consequently, both cropland and wildland fires were present in the study area; however, relatively more fire activity was observed as the number of cropland-dominated cells increased in a dataset.

The explained deviance (%) of the binomial GLM substantially differed in different datasets for most of the variables (Table 3). In *dataset 2* and *dataset 3*, mean temperature of the wettest quarter (BIO 8) and the annual mean temperature (BIO 1) were the most explanatory climatic variables, whereas in *dataset 4* and *dataset 5*, the most explanatory variables were

mean temperature of the driest quarter (BIO 9) and mean temperature of the warmest quarter (BIO 10). The mean temperature of the coldest quarter (BIO 11) also explained a significant proportion of deviance in many datasets. The explained deviance (%) of the model of the human population size was twice as high in *dataset 4* as in *dataset 2* and *dataset 3*. Similarly, the explained deviance of the slope variable was also twice as high in *dataset 4* and *dataset 5* as in *dataset 2* and *dataset 3*. In all datasets, the most explanatory productivity variable was the NDVI of December. NDVI values of December in *dataset4* and *dataset5* were comparable with those in *dataset1*; however, NDVI values of July in the same datasets were

Table 2.   GlobCover land cover classes included in different datasets

'Cropland' refers to the cells (1 km^2) classified as irrigated or rain-fed cropland (without any vegetation), and 'vegetation' indicates the cells that are composed completely of vegetation and do not include any cropland. 'Cropland–vegetation mosaic' includes 50–70% cropland and 20–50% vegetation. 'Vegetation–cropland mosaic' includes 50–70% vegetation and 20–50% cropland. '+' and '−' indicate that a land cover class in a dataset was included or excluded

| | Land cover class | | |
	Cropland	Cropland–vegetation mosaic	Vegetation–cropland mosaic	Vegetation
The overall dataset				
Dataset 1	+	+	+	+
Vegetation-dominated datasets				
Dataset 2	−	−	+	+
Dataset 3	−	−	−	+
Cropland-dominated datasets				
Dataset 4	+	+	+	−
Dataset 5	+	−	−	−

Table 3.   Explained deviance (%) values (based on binomial generalised linear models, GLMs) for the best predictors of fire activity for each variable group in the study area for each dataset

T_{mean} refers to the mean temperature. All models are statistically significant ($P < 0.0001$ except for NDVI-July in *dataset2*, where $P = 0.001$). Total fire activity is the number of cells where fire activity was observed for years 2000–2015. Number of cells is the total number of cells within the study area in the corresponding dataset

| | Overall dataset | Vegetation-dominated datasets | | Cropland-dominated datasets | |
Variables	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5
Climatic variables					
T_{mean} – annual (BIO 1)	19.23	13.55	12.34	21.38	11.05
T_{mean} – wettest quarter (BIO 8)	15.81	14.42	13.62	16.44	6.99
T_{mean} – driest quarter (BIO 9)	19.35	12.83	11.32	21.62	12.35
T_{mean} – warmest quarter (BIO 10)	19.38	12.69	11.43	21.54	12.4
T_{mean} – coldest quarter (BIO 11)	15.37	11.39	10.67	17.17	8.02
Anthropogenic variables					
Human population size	8.76	5.26	4.00	10.48	4.48
Livestock population size	1.35	0.98	0.94	1.80	2.92
Geographic variables					
Elevation	14.81	11.81	11.56	15.28	8.69
Slope	11.70	5.27	4.55	14.54	9.07
Productivity variables					
NDVI-July	0.46	0.02	0.09	3.45	4.62
NDVI-December	5.15	1.38	2.15	4.98	4.47
Total fire activity	17168	5148	3234	12566	3157
Number of cells	231985	142093	88232	142209	26246

remarkably higher than those in *dataset1*. Moreover, the explained deviance (%) values of NDVI variables clearly differed between cropland-dominated and vegetation-dominated datasets (Table 3). Elevation was among the variables that have the most explained deviance (%) in all datasets except *dataset5*, as croplands are concentrated at lower elevations (Pekin 2016), and fire activity in natural vegetation is related to elevation (Bekar 2016) in the study region.

Excluding croplands gradually from the overall dataset resulted in a substantial decrease of the explained deviance (%) in the models for all variables. The decrease reached up to 8% in the mean temperature of the driest quarter (BIO9) and the mean temperature of the warmest quarter (BIO10), and 7% in the annual mean temperature (BIO1) and slope. On the contrary,

excluding vegetation-dominated cells resulted in an increase of the explained deviance (%) in most variables in *dataset 4*. However, *dataset 5*, which includes only croplands, had comparable or lower explained deviance (%) values than *dataset 1*.

Discussion

Our study showed that the explanatory power of predictor variables of fire activity data vary to a considerable extent in different datasets. The most apparent differences were between datasets including vegetation-dominated and cropland-dominated cells. This implies that cropland fires substantially affect the output of models including satellite fire activity data.

The possible problems that can be created by human-induced cropland fires in fire-regime modelling have already been

acknowledged (Archibald *et al.* 2013). However, the exclusion of agricultural fires in large-scale studies is problematic for fire modelling studies, because it is difficult to identify every agricultural practice on Earth by means of characteristics of fires. Characteristics of agricultural fires, such as season and duration, vary regionally, and a great deal of effort is required to distinguish agricultural fires from wildland fires globally using this methodology. Even though agricultural fires can be easily excluded from analyses when official fire statistics from national inventories are used, such a procedure cannot be applied in all cases, especially with fire activity data obtained from remote sensing. For example, Giglio *et al.* (2006) found that low fire radiative power is associated not only with areas of extensive croplands but also with heavily forested areas in some parts of the world.

Using land cover maps obtained from satellites presents a good solution to this problem. Recently, the increasing reliability of land cover databases has made them available for differentiating agricultural fires from wildland fires (Tulbure *et al.* 2011; Amraoui *et al.* 2013; Knorr *et al.* 2014). Similar approaches have successfully been used to estimate the percentage of burned areas in land cover classes (van der Werf *et al.* 2010) and to estimate post-fire regeneration of natural landscapes using satellite remote sensing data (Abdul Malak *et al.* 2015). Another approach may be the inclusion of agricultural areas within vegetation variables as a separate land cover class in order to understand the fire regimes of anthropogenic and natural origin in a region (e.g. Curt *et al.* 2015). However, such an approach will leave unanswered the question of what the drivers of natural fire regimes are, because this cannot be inferred from models including both agricultural lands and vegetation-covered areas. The issue of cropland fires may also affect the conclusions of future studies on fire regimes in relation to climate change, even if these studies are conducted at a lower resolution (e.g. Krawchuk *et al.* 2009). Since wildland and agricultural fires clearly differ in fire regime characteristics, such as intensity and season (Korontzi *et al.* 2006; Le Page *et al.* 2010; Benali *et al.* 2017), the differentiation of wildland and cropland fires in the evaluation of the drivers of fire regimes has the potential to improve fire regime models. Our study proved that land cover databases could be used for the purpose of differentiating agricultural fires from wildland fires when satellite-based fire activity data are used. The observed differences in the explained deviances of predictor variables in our models dominated by different land cover classes suggest that drivers of natural and agricultural fire activity can be distinguished by incorporating land cover.

In conclusion, our results suggest that cropland fires have a significant effect on the output of fire regime models. Therefore, a clear distinction should be drawn between wildland and cropland fires in such models for a better understanding of natural fire activity.

Conflicts of interest

The authors declare no conflicts of interest.

Acknowledgements

References

Abdul Malak D, Pausas JG, Pardo Pascual J, Ruiz LA (2015) Fire recurrence and the dynamics of Enhanced Vegetation Index in a Mediterranean ecosystem. *International Journal of Applied Geospatial Research* **6**, 18–35. doi:10.4018/IJAGR.2015040102

Amraoui M, Liberato MLR, Calado TJ, DaCamara CC, Coelho LP, Trigo RM, Gouveia CM (2013) Fire activity over Mediterranean Europe based on information from Meteosat-8. *Forest Ecology and Management* **294**, 62–75. doi:10.1016/J.FORECO.2012.08.032

Andreae MO, Merlet P (2001) Emissions of trace gases and aerosols from biomass burning. *Global Biogeochemical Cycles* **15**, 955–966. doi:10.1029/2000GB001382

Archibald S, Lehmann CER, Gómez-Dans JL, Bradstock RA (2013) Defining pyromes and global syndromes of fire regimes. *Proceedings of the National Academy of Sciences of the United States of America* **110**, 6442–6447. doi:10.1073/PNAS.1211466110

Atalay I (1994) 'Vegetation Geography of Turkey'. (Aegean University Press: İzmir, Turkey)

Bekar İ (2016) The role of anthropogenic and natural factors in shaping recent fire regimes in Mediterranean ecosystems. MSc thesis, Hacettepe University. [In Turkish with English summary]

Benali A, Mota B, Carvalhais N, Oom D, Miller LM, Campagnolo ML (2017) Bimodal fire regimes unveil a global-scale anthropogenic fingerprint. *Global Ecology and Biogeography* **26**, 799–811. doi:10.1111/GEB.12586

Bontemps S, Defourny P, Bogaert E Van, Kalogirou V, Perez JR (2011) GLOBCOVER 2009: Products Description and Validation Report. (Université catholique de Louvain and European Space Agency) doi:10013/EPIC.39884.D016

Brown CD, Liu J, Yan G, Johnstone JF (2015) Disentangling legacy effects from environmental filters of postfire assembly of boreal tree assemblages. *Ecology* **96**, 3023–3032. doi:10.1890/14-2302.1

Bruinsma J (Ed.) (2003) 'World Agriculture: Towards 2015/2030: an FAO Perspective'. (Earthscan Publishing: London, UK)

Chuvieco E, Giglio L, Justice CO (2008) Global characterization of fire activity: toward defining fire regimes from Earth observation data. *Global Change Biology* **14**, 1488–1502. doi:10.1111/J.1365-2486.2008.01585.X

Consortium for Spatial Information (2016) Global Aridity and PET Database. Available at http://www.cgiar-csi.org/data/global-aridity-and-pet-database [Verified 1 August 2016]

Csiszar IA, Morisette JT, Giglio L (2006) Validation of active fire detection from moderate-resolution satellite sensors: The MODIS example in Northern Eurasia. *IEEE Transactions on Geoscience and Remote Sensing* **44**, 1757–1764. doi:10.1109/TGRS.2006.875941

Curt T, Borgniet L, Ibanez T, Moron V, Hély C (2015) Understanding fire patterns and fire drivers for setting a sustainable management policy of the New-Caledonian biodiversity hotspot. *Forest Ecology and Management* **337**, 48–60. doi:10.1016/J.FORECO.2014.10.032

Ganteaume A, Camia A, Jappiot M, San-Miguel-Ayanz J, Long-Fournel M, Lampin C (2013) A review of the main driving factors of forest fire ignition over Europe. *Environmental Management* **51**, 651–662. doi:10.1007/S00267-012-9961-Z

Giglio L, Descloitres J, Justice CO, Kaufman Y (2003) An enhanced contextual fire detection algorithm for MODIS. *Remote Sensing of Environment* **87**, 273–282. doi:10.1016/S0034-4257(03)00184-6

Giglio L, van der Werf GR, Randerson JT, Collatz GJ, Kasibhatla P (2006) Global estimation of burned area using MODIS active fire observations. *Atmospheric Chemistry and Physics Discussion* **5**, 11091–11141. doi:10.5194/ACPD-5-11091-2005

Godfray HCJ, Beddington JR, Crute IR, Haddad L, Lawrence D, Muir JF, Pretty J, Robinson S, Thomas SM, Toulmin C (2010) Food security: the challenge of feeding 9 billion people. *Science* **327**, 812–818. doi:10.1126/SCIENCE.1185383

Guisan A, Edwards TC, Jr, Hastie T (2002) Generalized linear and generalized additive models in studies of species distributions: setting the scene. *Ecological Modelling* **157**, 89–100. doi:10.1016/S0304-3800(02)00204-1

Haklay M, Weber P (2008) OpenStreetMap: user-generated street maps. *IEEE Pervasive Computing* **7**, 12–18. doi:10.1109/MPRV.2008.80

Hall JV, Loboda TV, Giglio L, McCarty GW (2016) A MODIS-based burned area assessment for Russian croplands: Mapping requirements and challenges. *Remote Sensing of Environment* **184**, 506–521. doi:10.1016/J.RSE.2016.07.022

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A (2005) Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* **25**, 1965–1978. doi:10.1002/JOC.1276

Jackman S, Tahk A, Zeileis A, Maimone C, Fearon J, Jackman MS (2015) Package 'pscl'. Available at https://cran.r-project.org/web/packages/pscl/index.html [Verified 1 August 2016]

Jarvis A, Reuter A, Nelson EG (2008) CSI SRTM 90m Database. Available at http://srtm.csi.cgiar.org [Verified 1 August 2016]

Justice CO, Giglio L, Korontzi S, Owens J, Morisette JT, Roy DP, Descloitres J, Alleaume S, Petitcolin F, Kaufman Y (2002) The MODIS fire products. *Remote Sensing of Environment* **83**, 244–262. doi:10.1016/S0034-4257(02)00076-7

Kaniewski D, De Laet V, Paulissen E, Waelkens M (2007) Long-term effects of human impact on mountainous ecosystems, western Taurus Mountains, Turkey. *Journal of Biogeography* **34**, 1975–1997. doi:10.1111/J.1365-2699.2007.01753.X

Kaniewski D, Paulissen E, De Laet V, Waelkens M (2008) Late Holocene fire impact and post-fire regeneration from the Bereket basin, Taurus Mountains, southwest Turkey. *Quaternary Research* **70**, 228–239. doi:10.1016/J.YQRES.2008.04.002

Knorr W, Kaminski T, Arneth A, Weber U (2014) Impact of human population density on fire frequency at the global scale. *Biogeosciences* **11**, 1085–1102. doi:10.5194/BG-11-1085-2014

Korontzi S, McCarty J, Loboda T, Kumar S, Justice C (2006) Global distribution of agricultural fires in croplands from 3 years of Moderate Resolution Imaging Spectroradiometer (MODIS) data. *Global Biogeochemical Cycles* **20**, GB2021. doi:10.1029/2005GB002529

Krawchuk MA, Moritz MA, Parisien MA, Van Dorn J, Hayhoe K (2009) Global pyrogeography: the current and future distribution of wildfire. *PLoS One* **4**, e5102. doi:10.1371/JOURNAL.PONE.0005102

Le Page Y, Oom D, Silva JMN, Jönsson P, Pereira JMC (2010) Seasonality of vegetation fires as modified by human action: Observing the deviation from eco-climatic fire regimes. *Global Ecology and Biogeography* **19**, 575–588. doi:10.1111/J.1466-8238.2010.00525.X

Leone V, Lovreglio R, Martín MP, Martínez J, Vilar L (2009) Human factors of fire occurrence in the Mediterranean. In 'Earth Observation of Wildland Fires in Mediterranean Ecosystems'. (Ed. E Chuvieco) pp. 149–170. (Springer: Berlin)

Li H, Han Z, Cheng T, Du H, Kong L, Chen J, Zhang R, Wang W (2010) Agricultural fire impacts on the air quality of Shanghai during summer harvest time. *Aerosol and Air Quality Research* **10**, 95–101. doi:10.4209/AAQR.2009.08.0049

Magi BI, Rabin S, Shevliakova E, Pacala S (2012) Separating agricultural and non-agricultural fire seasonality at regional scales. *Biogeosciences* **9**, 3003–3012. doi:10.5194/BG-9-3003-2012

McCarty JL (2011) Remote sensing-based estimates of annual and seasonal emissions from crop residue burning in the contiguous United States. *Journal of the Air & Waste Management Association (1995)* **61**, 22–34. doi:10.3155/1047-3289.61.1.22

McCarty JL, Ellicott EA, Romanenkov V, Rukhovitch D, Koroleva P (2012) Multi-year black carbon emissions from cropland burning in the Russian Federation. *Atmospheric Environment* **63**, 223–238. doi:10.1016/J.ATMOSENV.2012.08.053

Murphy BP, Bradstock RA, Boer MM, Carter J, Cary GJ, Cochrane MA, Fensham R, Russell-Smith J, Williamson GJ, Bowman DMJS (2013) Fire regimes of Australia: A pyrogeographic model system. *Journal of Biogeography* **40**, 1048–1058. doi:10.1111/JBI.12065

National Aeronautics and Space Administration (2016) Vegetation Index. Available at http://go.nasa.gov/1UMSkgb [Verified 31 July 2016]

O'Hara RB, Kotze DJ (2010) Do not log-transform count data. *Methods in Ecology and Evolution* **1**, 118–122. doi:10.1111/J.2041-210X.2010.00021.X

Pausas JG, Ribeiro E (2013) The global fire-productivity relationship. *Global Ecology and Biogeography* **22**, 728–736. doi:10.1111/GEB.12043

Pekin BK (2016) Anthropogenic and topographic correlates of natural vegetation cover within agricultural landscape mosaics in Turkey. *Land Use Policy* **54**, 313–320. doi:10.1016/J.LANDUSEPOL.2016.02.029

Rabin SS, Magi BI, Shevliakova E, Pacala SW (2015) Quantifying regional, time-varying effects of cropland and pasture on vegetation fire. *Biogeosciences* **12**, 6591–6604. doi:10.5194/BG-12-6591-2015

Şekercioğlu ÇH, Anderson S, Akçay E, Bilgin R, Can ÖE, Semiz G, Tavşanoğlu Ç, Yokeş MB, Soyumert A, İpekdal K, Sağlam İK, Yücel M, Nüzhet DH (2011) Turkey's globally important biodiversity in crisis. *Biological Conservation* **144**, 2752–2769. doi:10.1016/J.BIOCON.2011.06.025

Stohl A, Berg T, Burkhart JF, Fjæraa AM, Forster C, Herber A, Hov Ø, Lunder C, McMillan WW, Oltmans S, Shiobara M, Simpson D, Solberg S, Stebel K, Ström J, Tørseth K, Treffeisen R, Virkkunen K, Yttri KE (2006) Arctic smoke – record high air pollution levels in the European Arctic due to agricultural fires in Eastern Europe. *Atmospheric Chemistry and Physics Discussion* **6**, 9655–9722. doi:10.5194/ACPD-6-9655-2006

Tilman D, Balzer C, Hill J, Befort BL (2011) Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences of the United States of America* **108**, 20260–20264. doi:10.1073/PNAS.1116437108

Tulbure MG, Wimberly MC, Roy DP, Henebry GM (2011) Spatial and temporal heterogeneity of agricultural fires in the central United States in relation to land cover and land use. *Landscape Ecology* **26**, 211–224. doi:10.1007/S10980-010-9548-0

Turner R, Roberts N, Eastwood WJ, Jenkins E, Rosen A (2010) Fire, climate and the origins of agriculture: Micro-charcoal records of biomass burning during the last glacial-interglacial transition in Southwest Asia. *Journal of Quaternary Science* **25**, 371–386. doi:10.1002/JQS.1332

van der Werf GR, Randerson JT, Giglio L, Collatz GJ, Mu M, Kasibhatla PS, Morton DC, Defries RS, Jin Y, Van Leeuwen TT (2010) Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009). *Atmospheric Chemistry and Physics* **10**, 11707–11735. doi:10.5194/ACP-10-11707-2010

Xie H, Du L, Liu S, Chen L, Gao S, Liu S, Pan H, Tong X (2016) Dynamic monitoring of agricultural fires in China from 2010 to 2014 using MODIS and GlobeLand30 data. *ISPRS International Journal of Geo-Information* **5**, 172. doi:10.3390/IJGI5100172

Zeileis A, Kleiber C, Jackman S (2008) Regression models for count data in R. *Journal of Statistical Software* **27**, 1–25. doi:10.18637/JSS.V027.I08

Zhu Z, Woodcock CE (2012) Object-based cloud and cloud shadow detection in Landsat imagery. *Remote Sensing of Environment* **118**, 83–94. doi:10.1016/J.RSE.2011.10.028