BUSHFIRE MONITORING FROM SPACE: AN AUSTRALIAN DISASTER

Aliénor Franck de Préaumont
Fachhochschule Kufstein
2010837068@stud.fh-kufstein.ac.at

Smoke billows from an Australian bushfire [9]

Keywords : *Fire Radiative Power, Lasso and Ridge Regression, SVM, MODIS, AMS, fire size, sub-pixel retrievals*

Abstract

Fire can be recognized as an essential climatic variable (according to GCOS, 2011) [3]. Particularly disastrous in Australia during the Black Summer, authorities are trying to monitor the negative effects of the fire activity. A main indicator regarding the intensity of a fire is the Fire Radiative Power (FRP). In this paper, a prediction of the FRP value will be conducted, using a NASA dataset. Then an overview of the long term influence of this value will be done. Afterwards, in relation to fire prevention, the correlation between the size of the fire and the FRP value will be studied. Finally a more precise analysis of the FRP value can be done using a sub-pixel-based calculation of the FRP value.

Introduction

On the 30th of January 2020 the BBC reported 33 people killed and more than 11 million hectares burnt: a state of emergency was declared in the Australian Capital Territory.[1] Fires in Australia were devastating and this period (2019-2020) will forever be known as the *Black Summer.*

Nasa is interested in the phenomenon and gave free access to some satellite data related to severe bushfires in Australia between 01.08.2019 and 11.01.2020. The instrument used for collecting these data is MODIS (Moderate Resolution Imaging Spectroradiometer) and is processed on 2 satellites: Aqua and Terra. A visualization of the entire earth is available in 1 or maximum 2 days. MODIS is composed of 36 spectral bands between 0,405 and 14,385µm, and thus MODIS offers ocean and land visualizations of the earth. [5]

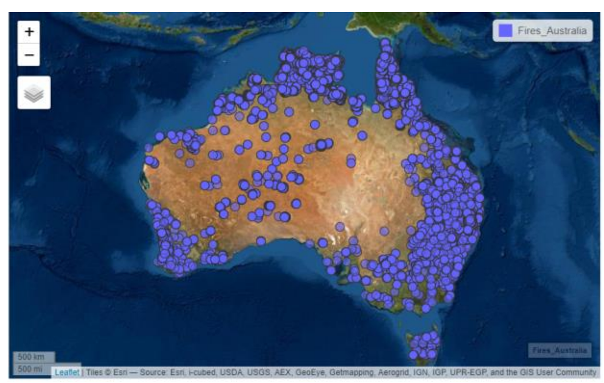

Figure 1: Fires in Australia between 01.08.2019 and 11.01.2020

1- A prediction of the FRP value and the impacts involved

a - Monitoring fires from space: detecting key trends

Firstly Satellite Data offer a complete geographical overview of the Australian disaster. It enables a full coverage of the bushfires: for example, Figure 1 shows all the bushfires which happened in Australia between 01.08.2019 and 11.01.2020. Satellite images allows us to cover areas which are difficult to access or for which there is not a lot of information available. Thanks to satellite images, like the one provided by MODIS, trends can be analyzed and discussed. As shown in Figure 2, the Fire Radiative Power depends on the brightness produced by bushfires; the fire radiations measured in Mw are usually higher during the day, than in the night, we see that both satellites are giving the same type of data on the plot below.

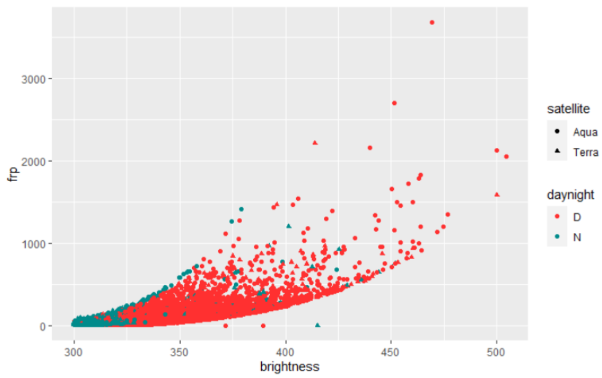

Figure 2: Brightness positively correlated to Fire Radiative Power depending on satellite type according day and night feature

According to Partanen and Sofiev, in their paper *Forecasting the regional fire radiative power for regularly ignited vegetation fires:* “to date, no successful predictive model has been developed for short-term forecasting of fire occurrence” [6]. This leads us to ask: if it’s not possible to predict the likelihood of a fire, because it remains a random phenomenon, is a prediction of the Fire Radiative Power still possible using algorithms? If yes, how can this predicted value be used in the long term?

b- Forecasting Fire Radiative Power (FRP)

Fire radiative power refers to the rate of radiative energy emitted by the fire at the time of the observation. It is related to the heat, and can be defined as the rate at which fuel is being consumed (Wooster et al., 2005) [8].

Prediction model using regression.

The NASA Dataset is well adapted for modelling using regression models. One of the biggest challenges regarding forecasting FRP is to deal with overfitting. Therefore, it’s important to use simple models for example the multiple regression model or models such as Lasso and Ridge regression which are particularly well adapted to limit overfitting problems using L1 and L2 Regularizations.

Another interesting approach is to train the Support Vector for Regression. Usually used for classification, the principle of support vector machine modelling can be applied for regression, which can give us an interesting output.

model	train_rmse	train_mae	train_R2	test_rmse	test_mae
lm	8.037813	5.880793	0.8794324	7.778386	5.747422
lasso	8.141372	5.878233	0.8776763	7.914513	5.784903
ridge	8.037798	5.880752	0.8794328	7.778429	5.747452
glmnet	8.038155	5.872016	0.8794327	7.782171	5.743205
svm	8.352675	5.636934	0.8789503	8.074500	5.558073

Table 1: Results of the prediction algorithms

The results, after training the 4 different models are in the table above. The regularization approach enables us to choose, when needed between some bias over high variance. This trade-off between bias and variance enables us to avoid overfitting while modelling. The outcomes, shown in the table, are quite similar, which is not ideal for our modelling analysis.

The results of the Ridge Regression is slightly better. This can be explained by the fact, that the Ridge regression adds a penalty term (L2 penalty) and leads to a lower variance and a higher bias. Using Ridge regression allows us to reduce the complexity of the modelling.

The Lasso (Least Absolute Shrinkage and Selection Operator) adds penalty term to the cost function. The Ridge regression penalizes the sum of squared coefficients, but the lasso regression penalizes the sum of their absolute value (L1 penalty).

The R squared value of all of the four models is high (87 % of the variance is explained by the modelling), which is almost ideal.

The SVR model has the highest RMSE on the training set and as well as on the test set. However the Performance of the R2 is a bit better.

The variable importance is shown in the figure 3. The brightness has the most impact on the FRP prediction. Scan (pixel size) and acquisition time play an important role.

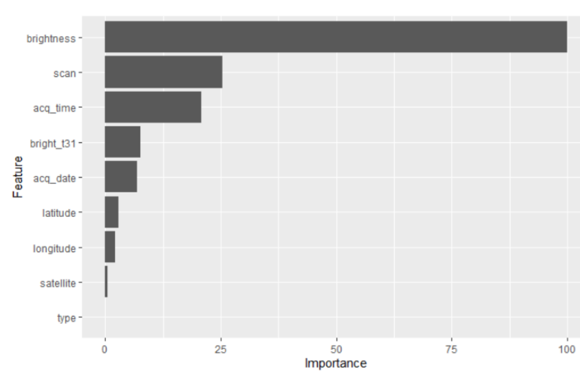

Figure 3: Variable Importance after training the SVR model

The SVR modelling is more complex than the regression one, the main goal of the SVR model is to reduce the error by customizing the hyperplane to maximize the margin.

c- FRP as a combustion process for forecasting biomass emissions

FRP is an estimator of the combustion of Biomass; we know that fires generate strong smoke pollution: plumes of black carbon travel miles away in the air and generate air quality issues. According to a CNN article, “the smoke from Australia’s fire will make ‘full circuit’ around the world”. [10] Let’s explain why the prediction and analysis of the FRP value is important for measuring air quality.

In their paper *Improving Forecasts of Biomass Burning Emissions with the Fire Weather Index,* the authors (di Giuseppe, Remy, Pappenberger and Wetterhall 2017) [2] explain that Data collected by the satellites Terra and Aqua related to the MODIS instrument, and particularly the FRP value are used by the Global Fire Assimilation System (GFA). They convert the FRP values into different kinds of emissions and air constituents. They manage to estimate 44 smoke constituents (for example CO, CO2, CH4, black carbon). Thanks to this process, air quality forecasts can be conducted at a global scale.

The Atmosphere Monitoring Service from Copernicus (CAMS) for instance provides an air quality forecast based on FRP values converted by the GFA. The CAMS is able to deliver near real time air quality indicators.

2- Challenges faced by the FRP value

a- Can the size of a fire be recognized using the FRP value? Is there any correlation between both variables?

If the size of a fire can be determined, then it can be useful in order to prevent the fire expanding. An analysis of the correlation between both variables is interesting in order to know if fire prevention can be done using the FRP value.

In their article *Varying relationships between fire radiative power and fire size at a global scale* (Laurent, Mouillot, Moreno, Yue, Ciais 2019) [4] the authors analyse if the relationship between fire patch size and front fire intensity (the study was published in 2018, before the Australian Black Summer) .
According to some studies (Pausas and Ribeiro, 2013; Luo et al., 2017), as the fire intensity grows, the fire occurrence increases until reaching a threshold.

The study is based on remote-sensing information from the Global Fire Emission Database (GFED; Giglio et al., 2013.) and the authors demonstrate that at one point the fire occurrence, which is defined as the number of remotely detected active fire in units of time per unit of area, does not increase any more.

As the fire season progresses, the fires tend to be more intense. This is detailed in the Fig. 4.

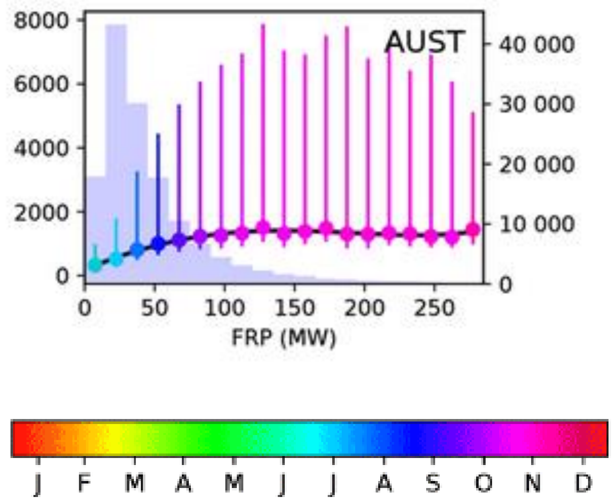

Figure 4: Median fire size vs. fire radiative power in Australia. [4]

The colors represent the average of the minimum burning dates of the fire patches, and the background histogram shows the number of fire patches in each FRP bin.

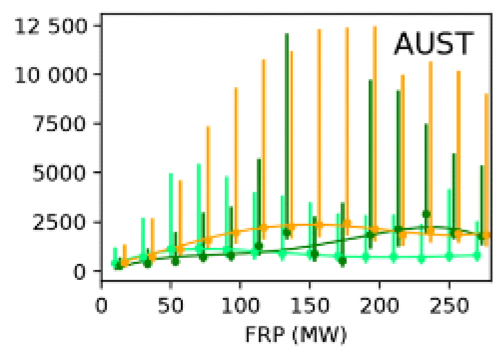

Figure 5: Median fire size in hectares vs. fire radiative power. [4]

The vegetation can be divided in 3 categories: forest, grassland/shrublands, savannah. In Australia, the savannah type is dominant, then comes forests and grassland.
According the study it seems that fires release more fire radiative power at the end of the fire season. It’s probably due to the fact, that energy is consumed by fuel moisture vaporization (Alexander, 1982; Pyne et al., 1996). Therefore the fire intensity and size are not so important at the beginning of the fire season.
As the season progresses, the fire radiative power increases and fires patches tend to propagate more (Sow et al., 2013; Sedano and Randerson, 2014; N'Dri et al., 2018). Over the time the fire size becomes limited due to scarcer fuel.

The fire radiative power and the size of a fire are positively correlated. Fire Radiative Power does not completely influence the fire patch size.

Can the FRP value be more precise?

b- To coarse pixel resolution

As explained previously, the FRP value is used in order to estimate smoke plume emissions. The MODIS instrument enables scientists to conduct analysis at a pixel level.

In their paper called *A sub-pixel-based calculation of fire radiative power from MODIS observations: 1 algorithm development and initial assessment* (Peterson, Wang, Ichoku, Ambrosia, Hyer 2013) [7] explain that the pixel resolution offered by MODIS tends to be too coarse. This can lead to errors, because small intense fires, and large low intensity fires can't be properly distinguished.
This issue can also lead to errors in the aerosols released from the patch fires, which is not ideal for estimating the air quality.

A solution needs to be found in order to conduct a detailed analysis. In their paper the authors are trying firstly to develop an algorithm for retrieving sub-pixel fire information for MODIS, then they assess the MODIS hot spot sub pixel detection algorithm. Finally they try to calculate the sub-pixel based FRP value.

The airborne Automous Modular Sensor (AMS) collects data while flying abord the NASA Ikhana Unmanned Airborne System (UAS). Using these high resolution data enables us to make a comparison with MODIS sub-pixel retrieval. The AMS is able to support Day and Night operations. The Ikhana flies over the same fire several times and it then collects a "mosaic" of data regarding the same event.

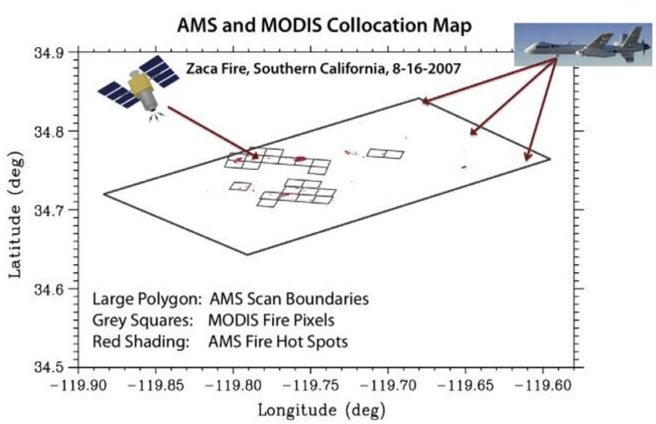

Figure 6: Example AMS and MODIS collocation map for the large Zaca Fire in August 2007. There is approximately an hour time lag between the MODIS overpass and the AMS flight [7]

For the study, data from August to October 2007 have been used. day, night, nadir, and off-nadir MODIS observations are collected. Overlapping pixels and need to be removed in order to avoid duplicates. Thanks to an interchannel comparison test (ICT), all the points that are not fire hot spots are removed.

A comparison between the sub pixel FRP and the MODIS FRP can be done. The aim is to assess the consistency of the sub pixel FRP value. The model shows that the correlation is high: figure 7 shows that the R= 0.93, which seems to be very satisfactory.

It means that the sub pixel values are acceptable (even at a pixel level). The authors underline that there might be errors which counteract each others. This suggests that the high accuracy does not necessarily mean that there are no errors. According to the author the retrieved values still need to be used cautiously.

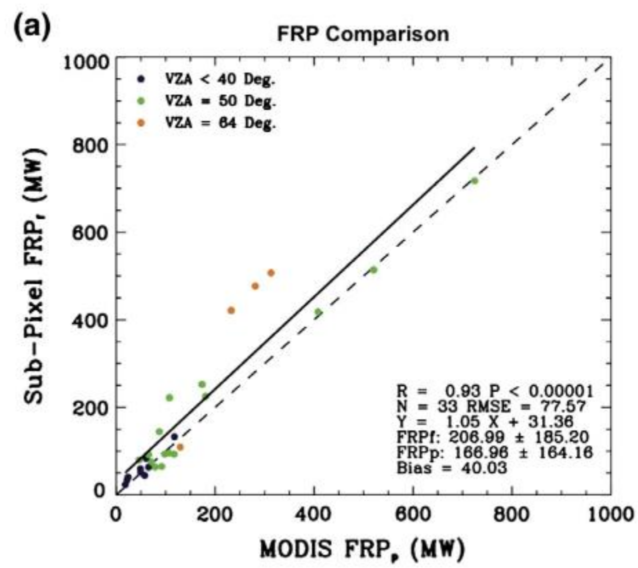

Figure 7: Pixel-level comparison between FRPp (Current MODIS pixel-based FRP) and FRPf (sub-pixel-based FRP) for all six cases. Solid line corresponds to the linear fit equation. [7]

Conclusion:

According to Pechony and Shindell (2010), climate change will cause an increase in bushfire activity[3]. This makes bushfire monitoring a key element for improving human wellbeing and limiting the negative impacts of fire on nature.
Thanks to satellite imagery, it's possible to analyze and predict the Fire Radiative Power values. This enables us then to estimate worldwide indicators such as air quality indexes.
Some authors are going further in the analysis (di Giuseppe, Remy, Pappenberger and Wetterhall 2017), they are for example studying the impact of weather indexes regarding biomass combustion. This

shows that fire monitoring is an accurate topic and research is ongoing.

REFERENCES

[1] BBC 2020 Australia fires: A visual guide to the bushfire crisis https://www.bbc.com/news/world-australia-50951043

[2] Di Giuseppe F., Rémy S., Pappenberger F., Wetterhall F. 2017 Improving Forecasts of Biomass Burning Emissions with the Fire Weather Index https://journals.ametsoc.org/view/journals/apme/56/10/jamc-d-16-0405.1.xml

[3] GCOS 2011. Systematic observation requirements for satellite-based data products for climate https://climate.esa.int/sites/default/files/gcos-154.pdf

[4] Laurent, Mouillot, Moreno Yue, Ciais: Varying relationships between fire radiative power and fire size at a global scale https://bg.copernicus.org/articles/16/275/2019/

[5] NASA Moderate Resolution Imaging Spectroradiometer https://modis.gsfc.nasa.gov/data/

[6] Partanen Tero M. Abril, Sofiev M. Forecasting the regional fire radiative power for regularly ignited vegetation fires 2021. https://nhess.copernicus.org/preprints/nhess-2021-262/nhess-2021-262.pdf

[7] Peterson D, Ichoku C., Wang J., Ambrosia V., Hyer E. A sub-pixel-based calculation of fire radiative power from MODIS observations: 1 Algorithm development and initial assessment

https://digitalcommons.unl.edu/cgi/viewcontent.cgi?referer=&httpsredir=1&article=1446&context=natrespapers

[8] Robert G., Wooster M. SEVIRI Fire Radiative Power (FRP) Dataset http://cedadocs.ceda.ac.uk/770/1/SEVIRI_FRP_documentdesc.pdf

[9] Thomson Reuters Foundation 2020 Burning issue: Australia debates risks of logging fire-damaged forests https://www.eco-business.com/news/burning-issue-australia-debates-risks-of-logging-fire-damaged-forests/

[10] Woodyatt A., 2020. Smoke from Australia's fires will make 'full circuit' around the world https://edition.cnn.com/2020/01/14/australia/nasa-smoke-full-circuit-intl-scli-scn/index.html

.