Trends in wildfire burn severity across Canada, 1985 to 2015

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Supplementary Material 2

SM 2a. Residual cloud and shadow detection in burned area

When implementing the change detection algorithm in CanLaD for harvesting and fires, there were sometimes clouds and shadows that were not detected in the original images and appeared as a change when there was none. We therefore included a detection of shadows and clouds in the changealgorithm . For this project, we usedthe previously developed algorithm and improved the detection of shadows and clouds in burned area using new training specifically for that type of area.

SM 2b. Filling the gaps in the Landsat time series for the extended assessment of burn severity

Landsat data were missing in total for about 10% of *CanLaD* burned area for the first post-fire year required for the calculation of dNBR used for the extended assessment of burn severity. We refer to this post-fire year as t3 (as a reminder, t1 and t2 refers to the pre-fire and fire year, respectively, see Fig 2). We filled the t3 Landsat gaps using Landsat data from two years after the fire (t4) or occasionally from three years after the fire (t5) when t4 data were missing as well. We derived the missing t3 Landsat values for each of the spectral bands from band-specific linear regressions reported in the table S2.1. These regressions were adjusted using 1000 Landsat pixels randomly selected from the subset of *CanLaD* burned pixels for which Landsat data was available for all years from t2 to t5 inclusively (Table S2.1).

Table S2.1: Values of the parameters of the linear regression $B_{t3} = b + m\ B_{tx}$ where B represents the spectral reflectance value (x 1000) of a given band, subscript t3 represents the first post-fire year, while subscript tx represents either A) second post-fire year t4 or B) the third post-fire year t5. Also shown are the values of the coefficient of determination (R^2) and of the root mean squared error (RMSE).

A)

Band	m	b	R^2	RMSE
B3	0.66	138.87	55.54	80.69
B4	0.65	163.13	62.88	219.84
B5	0.66	453.22	47.45	206.22
B7	0.70	434.00	49.38	225.59

B)

Band	m	b	R^2	RMSE
B3	0.60	156.54	49.36	86.11
B4	0.57	195.84	47.86	272.00
B5	0.60	506.01	42.08	216.50
B7	0.71	447.77	49.90	224.42

SM 2b. Note on different normalization approaches

To reduce the noise inherent in the satellite images, there is a method called "offset" (Key and Benson 2006), which consists of taking areas outside the fire (within a maximum of 1km buffer distance approximatively) as a reference area for which the dNBR is calculated. As this dNBR should technically be 0, the difference between the value and 0 provides a correction coefficient that can be applied to the NBR inside the burned perimeters and normalising unburned pixels to 0. For each combination of scenes (one pre and one post scene), this factor must be calculated and applied to the portion inside the fire.

Initially, we had implemented the "offset" method but have encountered various problems and even mixed results in some places due to the nature of the Landsat mosaics and the surrounding landscape across Canada's forested land. The Landsat mosaics we are using are assembled built from several scenes and only the best pixel is chosen according to the clearest opacity of the atmosphere. When there is a cloud, the pixels in an area can be picked from different scenes. This results in several possible combinations of scenes within and around a single fire sometimes giving a very small number of reference pixels outside the fire. Thus the correction could be applied to a large area inside the fire with reference to a very small number of pixels outside the fire. In fact, recent work of Parks et al. (2018) suggests that the reference areas must be at the edge (within a distance from 180 m of the fire) but in Canada's landscapes and our mosaic type, it would frequently be many kilometers away.

More importantly, there are large areas of treed and non-treed peatlands, wetlands, and bare areas interspersed with forested areas which challenged our ability to locate appropriate reference areas, thereby making that solution difficult to apply. There are many wetlands in Canada, and these areas behave unpredictably in terms of reflectance because they are strongly influenced by water content from one year to the next. Bare environments are also common, with their radiometry varying also from year to year. It was therefore necessary to better select reference zones for the offset correction in order to target only coniferous stands, which are more stable. As we move northward through the study area, this definition of coniferous forest becomes very tenuous. This makes it difficult to control areas for correction and to ensure that there are enough pixels for each fire and good reference area around.   In fact, Parks et al. 2019, didn't use any offset for Canada, because the imprecision of the fire perimeters. In our case, even if we had good fire boundaries, the presence of wetlands, peatlands and bare areas makes challenging to apply.

Another normalisation technique that is suggested in the literature (san Miguel et al. 2019) is to take a median values (of NBR for instance) from several images of the same pixels. We used this approach for the creation of the pre-fire mosaics in CanLaD (Guindon et al. 2017, 2018) but had to use three years to get enough images. In fact, as the study area have a very short growing season restricting us to use only July and August images as phenology has a strong impact on reflectance values than that of the different sensors (Chen et al. 2020). Thus, by using only July and August images there are very few scenes available. Considering that at least 3 pixels are needed to calculate a median, it would be impossible to calculate a median for 44% of all burned pixels in the country from 1985 to 2015. Some regions are also more affected than others by the frequency of cloud cover (or lack of available scenes) such as the Taiga East, where this number climbs to 65%. In summary, the final number of available post-fire pixels is only 2.9 for all period from 1985 to 1995, contrasting with results from southern areas in USA where the number of available pixels is ranging from 6 to 20 (Parks et al. 2018) with a mean of 11. In the light of our trials, no such normalisation was applied.

In the light of our trials, the difficulties of applying both the offset values and of calculating medians, defining a standardised approach covering the country was deemed impossible. We have opted for slightly more noise in the data but less inconsistency introduced by different approaches and for which it would be difficult to control due to regional differences and over time (one satellite, two satellite, one-half broken satellite). We felt that making no normalization was better than introducing bias that are difficult to control and assess. These corrections would have a minor impact on the final results other than reducing the range in values (change in quartile 1 and 3).

REFERENCE

Chen, D., Loboda, T.V. and Hall, J.V. 2020. A systematic evaluation of influence of image selection process on remote sensing-based burn severity indices in North American boreal forest and tundra ecosystems. ISPRS Journal of Photogrammetry and Remote Sensing, **159**: 63-77.

Guindon, L., Villemaire, P., St-Amant, R., Bernier, P.Y., Beaudoin, A., Caron, F., Bonucelli, M., and Dorion, H. 2017. Canada Landsat Disturbance (*CanLaD*): a Canada-wide Landsat-based 30 m resolution product of fire and harvest detection and attribution since 1984. doi:10.23687/add1346b-f632-4eb9-a83d-a662b38655ad.

Guindon, L., Bernier, P., Gauthier, S., Stinson, G., Villemaire, P., and Beaudoin, A. (2018). Missing forest cover gains in boreal forests explained. *Ecosphere*, *9*(1), e02094.

Key, C.H., and Benson, N.C. 2006 Landscape assessment (LA) sampling and analysis methods. General Technical USDA Forest Service General Technical Report. RMRS-GTR-164-CD.

Parks, S.A., Holsinger, L., Voss, M., Loehman, R., and Robinson, N. 2018. Mean composite fire severity metrics computed with Google Earth Engine offer improved accuracy and expanded mapping potential. Remote Sensing **10(**6): 879.

Parks, S.A., Holsinger, L.M., Koontz, M.J., Collins, L., Whitman, E., Parisien, M.-A., Loehman, R.A., Barnes, J.L., Bourdon, J.F., Boucher, J., and Boucher, Y. 2019. Giving Ecological Meaning to Satellite-Derived Fire Severity Metrics across North American Forests. Remote Sensing **11**(14): 1735.

San-Miguel, I., Andison, D.W., and Coops, N.C. 2019. Quantifying local fire regimes using the Landsat data-archive: a conceptual framework to derive detailed fire pattern metrics from pixel-level information. International Journal of Digital Earth **12**(5): 544-565.