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Short communication

Using cumulative NOAA-AVHRR spectral indices for estimating fire danger codes in northern boreal forests

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Abstract

In Canada, fire danger is rated by the Canadian forest fire danger rating system (CFFDRS). One of its components is the fire weather index (FWI) system, which has among others the drought code (DC). DC is used here as a surrogate of dead forest fuel moisture. DC values were computed from weather data acquired between 1993 and 1999 and compared to 10-day composite NOAA-AVHRR images acquired over Canadian northern boreal forests. They were yearly correlated with single compositing period and cumulative NDVI and surface temperature (ST) NOAA-AVHRR data. Correlations with cumulative spectral variables were stronger than with single compositing period variables and the best correlations occurred for the spring compositing periods (R between 0.57 and 0.80). Spring DC models using both single compositing period and cumulative spectral variables were established. Surface temperature-based indices were more often used in the models than NDVI-based indices. The models were stronger for dry or normal years than for wet years. Limitations and possible improvements of the models are discussed.

Keywords: NOAA-AVHRR; Surface temperature; NDVI; Boreal forests; Fire danger; Drought code

1. Introduction

In 2004, Canada recorded 6634 fires consuming 3,277,181 ha of the total 401,532,000 ha of forestland in the country (Canadian Interagency Forest Fire Centre, 2004). The fight against these fires costs nearly $1 billion annually (The State of Canada Forests, 2005). In Canada, fire danger is rated daily through the Canadian forest fire danger rating system (CFFDRS). One of the subsystems of the CFFDRS is the fire weather index system (FWI), which computes, through codes, numeric ratings of the moisture content of litter and other fine fuels (fine fuel moisture code, FFMC), of loosely compacted organic layers of moderate depth (duff moisture code, DMC) and the average moisture content of deep, compact organic layers (drought code, DC). The FWI system does not account for the difference in forest cover types and relies on interpolated point-source weather records.

As reviewed in Leblon (2005), satellite remote sensing could assist in fire danger mapping, as it offers large area coverage and data acquisition in remote areas on a regular basis. In previous studies, fuel moisture has been estimated primarily from NOAA-AVHRR normalized difference vegetation index (NDVI) images alone,

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or in combination with a NDVI-based index (relative greenness) (e.g., Paltridge and Barber, 1988; López et al., 1991; Illera et al., 1996; Burgan et al., 1998; Camia et al., 2003; Ceccato et al., 2003). Thermal infrared NOAA-AVHRR images have also been used in conjunction with NDVI images (e.g., Domínguez et al., 1994; Camia et al., 2003; Ceccato et al., 2003; Aguado et al., 2003; Oldford et al., 2003, 2006) because surface temperatures (ST) increase with drought levels (Pierce et al., 1990).

Both NDVI and ST images have a limited availability because of cloud contamination. In addition, the effects of directional and off-nadir viewing, atmospheric interferences, solar angle and shadows affect the usability of data. All these factors can be minimized by using maximum value composite (MVC) image techniques (Holben, 1986), assigning to each pixel the maximum NDVI of the composite period. NOAA-AVHRR composite NDVI and ST data are best correlated to FWI codes related to slow drying fuels, such as DMC, DC and the buildup index (BUI), over boreal forests and grasslands (Domínguez et al., 1994; Leblon et al., 2001) as well as over Mediterranean forests (Aguado et al., 2003). This relationship can be explained by the slow temporal change of the remotely sensed variables (10-day composite MVC NOAA-AVHRR images) and by the long time lag of slow drying fuel codes. Correlations between DC and NOAA-AVHRR spectral indices have been improved when spectral data of previous composite periods are used (Domínguez et al., 1994) or when cumulative NDVI (ΣNDVI) has been used (Leblon et al., 2001). Fire occurrence has been related to ΣNDVI or cumulative ST (ΣST) (Hartford and Burgan, 1994; Prosper-Laget et al., 1995; Illera et al., 1996).

The objective of this study is to analyze how multi-period spectral NOAA-AVHRR variables, like ΣNDVI and ΣST, can improve the spectral estimation of DC in northern boreal forests. DC is used here as surrogate for forest fuel moisture. The study used spectral and weather data acquired between 1993 and 1999, over boreal forests in northern Alberta and southern Northwest Territories, Canada. We developed multiple regression models between DC as the dependent variable, and single-period and cumulative spectral variables derived from 10-day composite NOAA-AVHRR NDVI and ST images, as independent variables. Because our study strictly focuses on northern boreal forests, it differs from previous ones that studied European Mediterranean forests (e.g., López et al., 1991; Illera et al., 1996; Camia et al., 2003; Ceccato et al., 2003; Aguado et al., 2003) or Western Canada boreal forest and grassland cover types (Domínguez et al., 1994). Our study is complementary

Fig. 1. Location of the study area in Canada (after Oldford et al., 2006).

to that of Oldford et al. (2006), who established relationships between DC and single period-based spectral variables using the same data set.

2. Materials and methods

2.1. Study area

Spectral and weather data used in the study were collected between 1993 and 1999 in northern Alberta and the southern Northwest Territories, Canada (54–62° north latitude and 110–115° west longitude) (Fig. 1). The approximately 250,000 km^2 study area includes forested and non-forested land cover types. It is within the Boreal Plains Ecozone of Canada including portions of the Taiga Shield, Taiga Plain and Prairie Ecozones (Rowe, 1972). More details about the study are provided by Oldford et al. (2006).

2.2. Materials and methods

As detailed in Oldford et al. (2006), spectral data were acquired by the AVHRR instrument on board NOAA-11 (years 1993 and 1994) and NOAA-14 satellites (years 1995–1999). From the raw images, 10-day ST and NDVI composites were produced and acquired from the Canada Center for Remote Sensing (CCRS). These images were processed by the "Geocoding and Compositing" (GEOCOMP) system at the Manitoba Remote Sensing Center, resulting in 140 images, 20 images per year. In order to avoid effects of representing the surface under heterogeneous illumination and viewing conditions, the images were first processed with the Atmosphere, Bidirectional and Contamination Corrections Version 2 Software System (Cihlar et al., 2004). Second, ST images were derived from the brightness temperature of NOAA-AVHRR channels four (10.3–11.3 μm) and five (11.5–12.5 μm). NDVI images were derived from NOAA-AVHRR channels two (0.725–1.10 μm) and one (0.58–0.68 μm). The images have a spatial resolution of 1 km^2 and are geo-referenced according to a Lambert conformal conic projection. Four forest cover classes were identified on NOAA-AVHRR images using a land cover map extracted from the 1998 Canada-wide cover map (Cihlar et al., 2003). They were: open coniferous, closed coniferous, open mixedwood, and closed mixedwood. Years were categorized into three classes (wet, dry and normal) using the rainfall accumulation between April and October with regards to the climatologic long-term averages. According to Oldford et al. (2006), 1996 and 1997 were 'wet' years, 1998 and 1999 were 'dry' years, and 1993, 1994 and 1995 were 'normal' years.

DC values were computed from weather station data, collected daily at noontime at 75 stations within the study area, using a SAS script provided by the Canadian Forest Service (Oldford et al., 2006). This DC calculation method does not take into account winter snowfall. Correlations between DC and spectral variables were computed using the median DC values of each compositing period, because medians are less sensitive to extreme values than are mean values.

NDVI, ST, and DC data were further processed using SAS and SigmaPlot software. ΣNDVI and ΣST were computed over the twenty 10-day compositing periods from each weather station and each year. These cumulative spectral variables were then correlated with DC values. Estimation DC models were established using single and cumulative NDVI and ST values through a forward stepwise multiple regression analysis using the PROC REG procedure of SAS (SAS Institute, 2001). A detailed description of study methodologies is given in Oldford et al. (2006). Model performance was compared using the adjusted R^2 instead of the simple R^2, because adjusted R^2 takes into account the sample size and the number of independent variables used in the model. Model performance was also compared using the root mean squared error (RMSE).

3. Results and discussion

3.1. Correlation analysis

Pearson's correlation coefficients between DC and single-period and cumulative NDVI and ST values are presented for all cover types in Table 1. As for the single spectral variables (Oldford et al., 2006), correlations were best in the spring season. The high correlation between DC and spectral variables in spring was explained by the fact that both types of variables increased during spring (Oldford et al., 2006). Indeed, DC and ST (and ΣST) increase because of increasing air temperatures, while NDVI (and ΣNDVI) increase because of vegetation green-up. High correlations in spring were consistent with results obtained over Mediterranean forests (e.g., Aguado et al., 2003). In the Mediterranean studies, the best correlation occurred for late summer and fall data, both seasons being characterized by dry conditions under Mediterranean climates. Under western Canada climate, the driest season is spring, because water is still in a solid phase (frost water or snow) and is thereby not available to moisten fuels.

In the spring, correlations of DC with cumulative NDVI variables (R between 0.39 and 0.80) were higher than with single-period NDVI values (R between 0.16 and 0.65) (Table 1). Similar improvements in the correlation with NDVI data was shown by Leblon et al. (2001) in the case of boreal homogenous coniferous stands located in the Northwest Territories, Canada. The correlations with cumulative ST data (R between 0.57 and 0.87) were also improved compared to single-period ST data (R between 0.45 and 0.56) (Table 1). Correlations with ΣST (R between 0.57 and 0.87) were higher than with ΣNDVI (R between 0.39 and 0.80) (Table 1). However, both cumulative variables were strongly correlated (R between 0.90 and 0.95) (Table 2).

Table 1
Comparison between Pearson's correlation coefficients[a] of DC with single-period and with cumulative NOAA-AVHRR variables for all the cover types

Temporal variable		NOAA-AVHRR variable				n
Season	Year	NDVI	ΣNDVI	ST	ΣST	
Entire year (periods 1–20)	1993	−0.04	**0.61**	**0.08**	**0.75**	816
	1994	**−0.42**	**0.64**	**−0.1**	**0.77**	813
	1995	**0.18**	**0.35**	0.06	**0.37**	790
	1996	**−0.07**	**0.30**	0.07	**0.45**	772
	1997	**0.15**	**0.52**	**0.17**	**0.58**	756
	1998	−0.06	**0.69**	−0.05	**0.73**	843
	1999	**0.15**	**0.78**	**0.08**	**0.83**	922
Spring periods (1–7)	1993	**0.55**	**0.80**	**0.56**	**0.87**	331
	1994	**0.16**	**0.39**	**0.45**	**0.57**	290
	1995	**0.65**	**0.75**	**0.46**	**0.78**	287
	1996	**0.49**	**0.61**	**0.56**	**0.69**	272
	1997	**0.43**	**0.55**	**0.46**	**0.60**	275
	1998	**0.51**	**0.69**	**0.5**	**0.75**	313
	1999	**0.47**	**0.63**	**0.51**	**0.76**	328
Summer periods (8–16)	1993	**−0.41**	**0.20**	**0.15**	**0.55**	452
	1994	**−0.58**	**0.36**	**−0.11**	**0.68**	475
	1995	**−0.09**	0.03	−0.06	0.02	440
	1996	**−0.47**	0.02	**0.16**	**0.35**	432
	1997	**−0.29**	**0.29**	**0.16**	**0.45**	431
	1998	**−0.29**	**0.39**	**−0.18**	**0.53**	457
	1999	**0.09**	**0.50**	0.07	**0.62**	518
Fall periods (17–20)	1993	**−0.46**	*0.35*	0.28	0.72	33
	1994	**−0.33**	*0.29*	0.13	*0.29*	48
	1995	−0.08	0.02	0.14	*0.28*	63
	1996	−0.18	0.15	−0.15	0.18	68
	1997	**0.29**	0.15	0.14	0.07	50
	1998	−0.01	0.05	−0.02	0.04	73
	1999	**0.39**	*0.27*	0.22	**0.50**	76

[a] Bold underlined font (e.g., **0.45**): significant at $\alpha = 0.001$; bold font (e.g., **0.45**): significant at $\alpha = 0.01$; italic font (e.g. *0.45*): significant at $\alpha = 0.05$; plain font (e.g., 0.45): not significant.

Table 2
Pearson's correlation coefficients[a] between ΣNDVI and ΣST for all the cover types

Season	Year	n	R
Entire year (periods 1–20)	1993	1640	**0.95**
	1994	1640	**0.94**
	1995	1640	**0.96**
	1996	1640	**0.95**
	1997	1640	**0.97**
	1998	1640	**0.96**
	1999	1640	**0.96**
Spring (periods 1–7)	1993	574	**0.92**
	1994	574	**0.93**
	1995	574	**0.95**
	1996	574	**0.90**
	1997	574	**0.95**
	1998	574	**0.95**
	1999	574	**0.94**
Summer (periods 8–16)	1993	738	**0.78**
	1994	738	**0.76**
	1995	738	**0.81**
	1996	738	**0.80**
	1997	738	**0.89**
	1998	738	**0.81**
	1999	738	**0.86**
Fall (periods 17–20)	1993	328	0.02
	1994	328	**0.18**
	1995	328	0.03
	1996	328	**0.27**
	1997	328	0.03
	1998	328	0.07
	1999	328	0.10

[a] Bold underlined font (e.g., **0.45**): significant at $\alpha = 0.001$; bold font (e.g., **0.45**): significant at $\alpha = 0.01$; italic font (e.g., *0.45*): significant at $\alpha = 0.05$; plain font (e.g., 0.45): not significant.

3.2. Stepwise multiple regression analysis

Yearly stepwise multiple regression models were established using solely the spring period data because for this period, correlations with DC were the highest, both for the single-period (NDVI, ST, NDVI/ST, RGRE) and for the cumulative spectral variables (ΣNDVI, ΣST). The models were computed for each forest cover type and for all the cover types together. In each case, the regression was significant at the level of $\alpha = 0.001$ (Table 3). Spectral variables used in each variable are given in Table 3. ΣST was used in each yearly model more often than ΣNDVI (Table 3), suggesting that cumulative ST images are better indicator of drought conditions than cumulative NDVI images. Adjusted R^2 for the fitted models (adjusted R^2 between 0.39 and 0.77 for the *all forest cover types* case) were higher than those for the models derived by Oldford et al. (2006) (adjusted R^2 between 0.26 and 0.53

Table 3
DC stepwise regression models for the spring season for each year

Cover	Year	Intercept	NDVI	RGRE	TS	NDVI/TS	∑TS	∑NDVI	R^2	Adjusted R^2	n	RMSE	p
All cover types	1993	10.30	−86.89				1.67	20.09	0.77	0.77	331	27.51	<0.0001
	1994	40.85					2.60	−27.63	0.39	0.39	290	40.39	<0.0001
	1995	−54.65				1620.74	1.57		0.64	0.63	287	44.18	<0.0001
	1996	29.85	−182.05	0.89	1.43	238.15	0.54	14.57	0.54	0.53	272	31.67	<0.0001
	1997	18.80					0.70		0.37	0.36	275	33.23	<0.0001
	1998	−21.89	227.18	−1.00	−2.45		2.33	−29.26	0.58	0.57	313	49.07	<0.0001
	1999	0.86					1.73	−17.22	0.60	0.59	328	38.12	<0.0001
Closed coniferous	1993	−140.89	178.42					45.31	0.82	0.81	36	21.55	<0.0001
	1994	−21.59			5.43		0.77		0.45	0.41	32	32.60	<0.0001
	1995	−182.52	649.25	−4.00	−2.74		2.30		0.92	0.91	39	20.68	<0.0001
	1996	−330.69		−1.98	12.96	5852.08	1.07		0.69	0.63	29	22.53	<0.0001
	1997	−87.72	269.39	−1.21			2.64	−61.44	0.80	0.77	32	19.37	<0.0001
	1998	−249.60	659.76	−2.19			2.15	−39.54	0.67	0.64	49	40.82	<0.0001
	1999	−21.86						43.05	0.48	0.46	43	36.26	<0.0001
Closed mixedwood	1993	77.58	−272.10				1.07	51.47	0.90	0.90	60	19.29	<0.0001
	1994	−180.21			17.47	1957.94	2.43	−57.60	0.46	0.42	58	41.56	<0.0001
	1995	−15.73					1.85		0.77	0.77	66	38.09	<0.0001
	1996	30.93					0.59		0.30	0.29	51	32.91	<0.0001
	1997	24.46		−1.12			0.50	29.65	0.48	0.45	64	27.62	<0.0001
	1998	97.88			−5.94		3.80	−57.18	0.80	0.79	62	34.06	<0.0001
	1999	17.86		−2.40			2.10	16.73	0.76	0.75	65	30.25	<0.0001
Open coniferous	1993	26.33	−130.21				2.13	12.09	0.75	0.75	170	29.10	<0.0001
	1994	54.89			−3.10		2.93	−24.59	0.42	0.41	142	43.71	<0.0001
	1995	29.08			−2.31		1.57		0.51	0.51	137	49.14	<0.0001
	1996	21.51	−80.99	0.78			1.00		0.64	0.63	151	30.55	<0.0001
	1997	63.95	−199.71	1.10			0.73		0.41	0.40	143	33.82	<0.0001
	1998	11.46					1.33		0.48	0.48	160	57.07	<0.0001
	1999	5.28					2.16	−34.70	0.63	0.63	178	37.42	<0.0001
Open mixedwood	1993	−8.99					1.06	23.73	0.81	0.80	65	25.88	<0.0001
	1994	83.18				−624.90	1.65	−13.86	0.49	0.47	58	26.87	<0.0001
	1995	−28.71		1.44			1.09		0.82	0.81	45	33.31	<0.0001
	1996	123.68		1.45	−3.22	−3367.63	−0.82	43.13	0.74	0.70	41	21.80	<0.0001
	1997	−29.55	190.74						0.37	0.36	36	33.64	<0.0001
	1998	−9.89					1.60		0.80	0.79	42	31.51	<0.0001
	1999	83.85	−409.62	2.27			1.55		0.92	0.91	42	17.55	<0.0001

for the *all forest cover types* case), suggesting that the inclusion of cumulative spectral variables in the regression models significantly improved the estimation accuracy of DC.

Graphs comparing DC estimated from the regression equation versus observed DC values showed model fits closer to the 1:1 line than with single-period variables (Oldford et al., 2006), but there was still some saturation occurring at high DC values (Fig. 2). The saturation was more pronounced in the wet years, i.e., 1996 and 1997 (Fig. 2d and e) than for the dry years, i.e., 1998 and 1999 (Fig. 2f and g). One reason explaining the saturation during wet years is that NDVI is high during wet years (more leaf area index), but the definition of NDVI leads to that the upper limit of NDVI values is 1 over vegetation.

When cover type was included in the analysis (Table 3), models generally were better for mixedwood forests than for coniferous forests, for which saturation occurred at lower DC values. This was particularly true for the open coniferous category, as was the case with single-period spectral variables (Oldford et al., 2006). Oldford et al. (2006) explained the open coniferous poor model performance by the fact that this cover type,

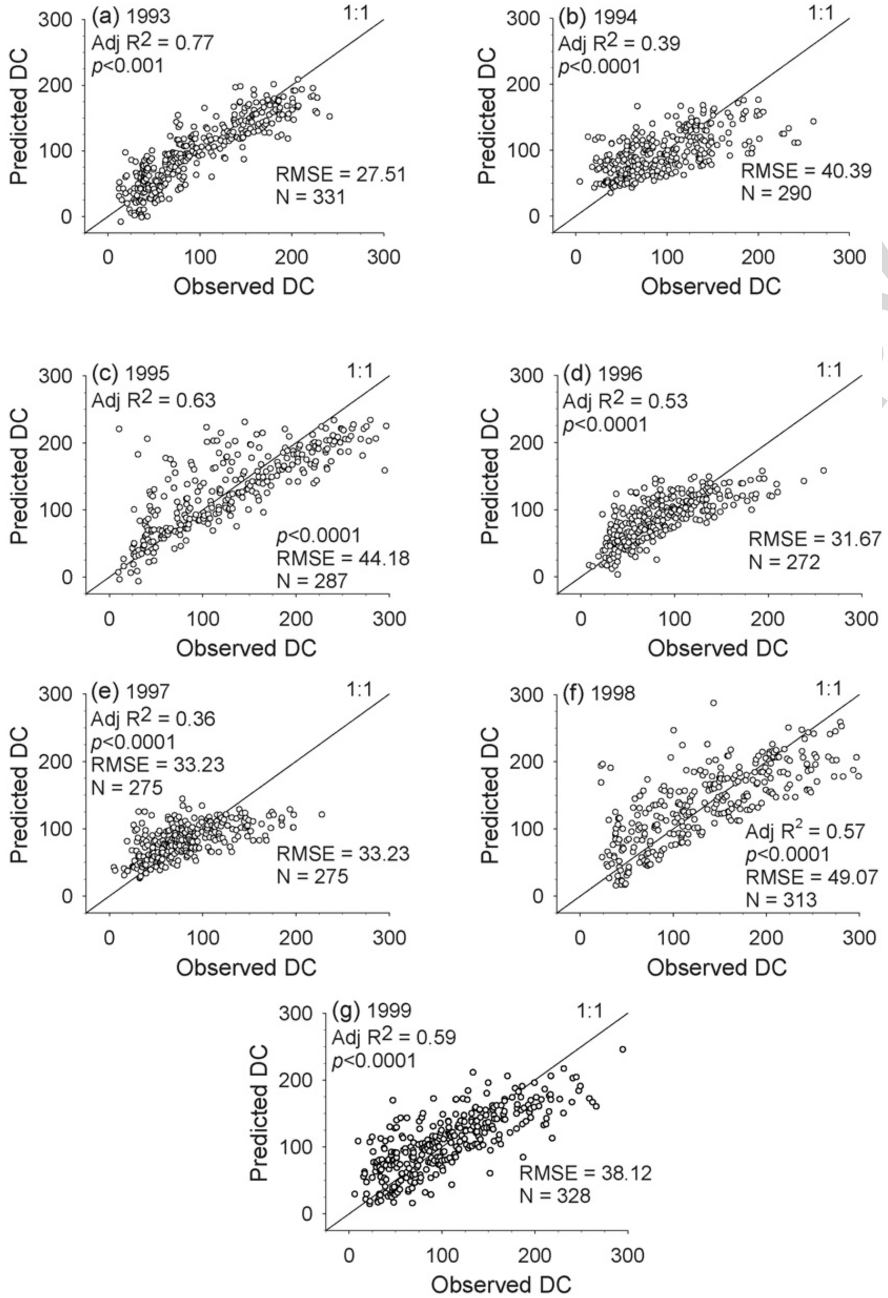

Fig. 2. Observed vs. predicted DC for the spring periods and for all the forest cover types. DC is estimated using the models listed in Table 3. Solid line is the 1:1 relationship.

which occupied the majority of the study area, was composed of a mixture of shrub, moss, lichen, and soil, leading to highly variable spectral values. The better performance of models for mixedwood forests can be explained by the sensitivity of the considered spectral indices to vegetation green-up, which is stronger over mixedwood forests during the spring season. For this type of cover types, models were better for the dry years than for the wet years (Table 3), particularly in the case of the closed mixedwood stands. The regression coefficient for the ST variable was stronger in the case of the dry years than in the case of the wet years, suggesting the sensitivity of this spectral variable to dry conditions.

4. Conclusions

DC values were computed from weather data recorded during the 1993–1999 fire seasons and correlated to NOAA-AVHRR single compositing period and cumulative NDVI and ST data. The best correlations were found for the spring compositing periods. For these periods, correlations with cumulative spectral variables were higher than with single-period variables. Stepwise regression models were established by using both single-period and multi-period NDVI and ST variables. DC was better estimated in normal and dry years (adjusted R^2 between 0.39 and 0.77) than in wet years (adjusted R^2 between 0.37 and 0.54). Also, models established with data acquired over mixedwood forests (adjusted R^2 between 0.40 and 0.91) were generally better than those established with data acquired over coniferous forests (adjusted R^2 between 0.40 and 0.81).

We presented regression models to estimate DC values from both single compositing period and multiple-period NOAA-AVHRR NDVI and ST images. These regression models are still highly empirical and cover types and year of data acquisition have an influence on the model performance. Thereby, it was not possible to establish a single generalized model predicting DC values from NOAA-AVHRR spectral data whatever the year and the cover type. This limits the operational use of the study. Therefore, it would useful to try to develop a more physical-based approach, which can be more independent of the data set on which it is developed on.

Another operational limitation of the study is that the 1 km spatial resolution of these images may be too coarse to well represent the spatial heterogeneity of Canada's boreal forests. Therefore, it would be useful to test fine resolution images provided by new sensors-like MODIS in DC estimation. However, like NOAA-AVHRR, MODIS image availability is limited by cloud conditions, whereas SAR images like those provided by ERS-1/2, ENVISAT, and RADARSAT would not have this limitation. RADARSAT and ERS-1 data were already related to DC over boreal forests (Bourgeau-Chavez et al., 1999, 2001; Leblon et al., 2002; Abbott et al., in press) but these studies occurred over monospecies coniferous stands. Further work is needed to test these images over more heterogeneous areas, like the one considered in this study.

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References

Abbott, K.N., Leblon, B., Staples, G.C., Maclean, D.A., Alexander, M.E., in press. Fire danger monitoring in a northern boreal forest region using RADARSAT-1 imagery. Int. J. Remote Sens.

Aguado, I., Chuvieco, E., Martín, P., Salas, J., 2003. Assessment of forest fire danger conditions in southern Spain from NOAA images and meteorological indices. Int. J. Remote Sens. 8 (24), 1653–1668.

Bourgeau-Chavez, L., Kasischke, E.S., Rutherford, M.D., 1999. Evaluation of ERS SAR data for prediction of fire danger in a boreal region. Int. J. Wildland Fire 9, 183–194.

Bourgeau-Chavez, L.L., Nolan, M., Hyer, E., Brunzell, S., 2001. Analysis of SAR data for fire danger prediction in boreal Alaska. Final Technical Report ASF-IARC, NASA Grant NAS-98-129, available online at www.gd-ais.com.

Burgan, R.E., Klaver, R.W., Klaver, J.M., 1998. Fuel models and fire potential from satellite and surface observations. Int. J. Wildland Fire 8 (3), 159–170.

Canadian Interagency Forest Fire Centre, 2004. Canada report 2004, available online at: http://www.ciffc.ca/news/canreport.pdf.

Camia, A., Leblon, B., Carlson, J.D., Cruz, M., Aguado, I., 2003. Estimation of dead fuel moisture content. In: Chuvieco, E. (Ed.), Wildland Fire Danger Estimation and Mapping: The Role of Remote Sensing. World Scientific Publishing, London, (Chapter 3), pp. 63–90.

Ceccato, P., Leblon, B., Chuvieco, E., Flasse, S., 2003. Estimation of live fuel moisture content. In: Chuvieco, E. (Ed.), Wildland Fire Danger Estimation and Mapping: The Role of Remote Sensing. World Scientific Publishing, London, (Chapter 4), pp. 91–118.

Cihlar, J., Latifovic, R., Beaubien, J., Guindon, B., Palmer, M., 2003. Thematic mapper (TM) based accuracy assessment of a land cover product for Canada derived from SPOT VEGETATION (VGT) data. Can. J. Remote Sens. 29 (2), 154–170.

Cihlar, J., Latifovic, R., Chen, J., Trishchenko, A., Du, Y., Fedosejevs, G., Guindon, B., 2004. Systematic corrections of AVHRR image composites for temporal studies. Remote Sens. Environ. 89, 217–233.

Domínguez, L., Lee, B.S., Chuvieco, E., Cihlar, J., 1994. Fire danger estimation using AVHRR images in the Prairie Provinces of Canada. In: Proceedings of the 2nd International Conference on Forest Fire Research, 2 (17), Coimbra, Portugal, pp. 679–690.

Hartford, R.A., Burgan, R.E., 1994. Vegetation condition and fire occurrence: a remote sensing connection. In: Proceedings of the Interior West Fire Council Meeting and Symposium, Coeur d'Alene, USA, pp. 243–279.

Holben, B.N., 1986. Characteristics of maximum-value composite images from temporal AVHRR data. Int. J. Remote Sens. 7, 1417–1434.

Illera, P., Fernández, A., Delgado, J.A., 1996. Temporal evolution of the NDVI as an indicator of forest fire danger. Int. J. Remote Sens. 17 (6), 1093–1105.

Leblon, B., 2005. Using remote sensing for fire danger monitoring. Nat. Hazards 35, 343–359.

Leblon, B., Alexander, M.E., Chen, J., White, S., 2001. Monitoring fire danger of northern boreal forests with NOAA-AVHRR NDVI images. Int. J. Remote Sens. 22, 2839–2846.

Leblon, B., Kasischke, E.S., Alexander, M.E., Doyle, M., Abbott, M., 2002. Fire danger monitoring using ERS-1 SAR images in the case of northern boreal forests. Nat. Hazards 27, 231–255.

López, S., González, F., Llop, R., Cuevas, J.M., 1991. An evaluation of the utility of NOAA-AVHRR images for monitoring forest fire risk in Spain. Int. J. Remote Sens. 12 (9), 1841–1851.

Oldford, S., Leblon, B., Gallant, L., Alexander, M.E., 2003. Mapping pre-fire conditions in the Northwest Territories, Canada, using NOAA-AVHRR images. GeoCarto Int. 18 (4), 21–32.

Oldford, S., Leblon, B., MacLean, D.A., Flannigan, M., 2006. Predicting slow drying fuel moisture codes using NOAA-AVHRR images. Int. J. Remote Sens. 27 (18), 3881–3902.

Paltridge, G.W., Barber, J., 1988. Monitoring grassland dryness and fire potential in Australia with NOAA-AVHRR data. Remote Sens. Environ. 25, 381–394.

Pierce, L.L., Running, S.W., Riggs, G.A., 1990. Remote detection of canopy water stress in coniferous forests using the NS001 Thematic Mapper Simulator and the Thermal Infrared Multispectral Scanner. Photogram. Eng. Remote Sens. 56 (5), 579–586.

Prosper-Laget, V., Wigneron, J.P., Guinot, J.P., Seguin, B., 1995. Utilisation du satellite NOAA pour la détection des risques d'incendies de forêts. La Météorol. 8 (10), 28–38.

Rowe, J.S., 1972. Forest regions of Canada, Canada. Bulletin 123, Department of Northern Affairs and Natural Resources, Forestry Branch, p. 71.

SAS Institute Inc., 2001. The SAS System for Windows, version 8.02. SAS Institute Inc, Cary, NC.

The State of Canada Forests, 2005. Sparking discussion on forest fires. http://www.nrcan-rncan.gc.ca/cfs-scf/national/what-quoi/sof/sof04/sparking-discussion_e.html (accessed 16 February 2005).