ADVANCES IN FOREST FIRE RESEARCH

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Improved prediction of drought for wildland fire danger rating in Canada

Chelene C. Hanes^{*1,2}; Mike Wotton²; Douglas G. Woolford³; Laura Bourgeau-Chavez⁴; Stéphane Bélair⁵; David Martell²; Mike Flannigan⁶

¹Great Lakes Forestry Centre, Canadian Forest Service, Natural Resources Canada, 1219 Queen St. E, Sault Ste. Marie, ON, P6A 2E5, Canada {chelene.hanes@nrcan-rncan.gc.ca}

² Institute of Forestry and Conservation, John H. Daniels Faculty of Architecture, Landscape and Design, University of Toronto, 33 Willcocks Street, Toronto, ON M5S 3B3, Canada {mike.wotton,

david.martell}@utoronto.ca

³ Statistical and Actuarial Sciences, University of Western Ontario, 1151 Richmond St., London, ON, N6A 3K7, Canada {dwoolfor@uwo.ca}

4. Michigan Technological University, Michigan Tech Research Institute, 3600 Green Ct. Suite 100, Ann Arbor, MI 48105, United States {lchavez@mtu.edu}

5. Canadian Meteorological Centre, Environment and Climate Change Canada, 2121, route Transcanadienne, Dorval, Quebec H9P 1J3, Canada {stephane.belair@ec.gc.ca}

6. Natural Resource Science, Thompson Rivers University, 805 TRU Way, Kamloops, BC V2C 0C8, Canada {mflannigan@tru.ca}

*Corresponding author

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Abstract

Canadian fire management agencies track drought conditions using the Drought Code (DC). The DC is one of three fuel moisture codes in the Fire Weather Index System, which is part of the Canadian Forest Fire Danger Rating System. The DC represents the moisture of deep organic layers (15-18 cm nominal depth) and is used operationally to assess potential lightning ignition holdover, persistent deep smoldering, and mop-up problems. As the climate changes and drought conditions arise more frequently, our understanding of drought and how to measure it become more important. Determining what the DC means in areas without deep organic soils is a question commonly proposed by fire operations personnel. Recent studies have indicated that some more complex models (e.g. the Canadian Land Data Assimilation System – CaLDAS) may provide added intelligence about the fire environment and drought conditions, something that has not been explored in Canada. To shed light on these questions we carried out field studies in the provinces of Alberta and Ontario. Four field sites were included in our study, two in Alberta near Edson and Red Earth Creek, and two in Ontario near Dryden and Chapleau. At each of the seven plots within these four sites, we installed 8-12 water content reflectometry (WCR) probes at two different depths. The probes were installed from the surface through the organic layers, and in some cases, into the mineral soil. Overall, our results indicated that the simple DC model predicted the moisture content of the deeper organic layers (10-18 cm depths) well, even compared to the more complex CaLDAS model. The WCR probes at these depths, exhibited good agreement with how the DC model estimated moisture changes. The DC may therefore be representative of changes in moisture content in a wide range of depths and soil horizons. Issues with model inputs, particularly missed precipitation events and incorrect DC spring starting values, had a greater influence on DC model fit than other factors. Calibration and validation of the CaLDAS model to mineral soils may be the cause of its consistent under prediction of organic layer moisture.

1. Introduction

Throughout most typical fire seasons the principal day-to-day short-term indicators of fire danger, ignition potential and rate of spread, are of primary concern to fire managers. The moisture content of the litter layer and underlying fine to medium organic fuels heavily influence fire behaviour through their interaction with local weather and topography. Hot, dry and windy conditions can quickly dry out these layers, which can lead to more fire activity and more intense fires. Longer-term drought and continuous drying into deeper, denser organic fuels can make a challenging fire season quickly turn to something much worse.

Drought in the Canadian Forest Fire Danger Rating System (CFFDRS) is measured by the Drought Code (DC), one of three moisture codes in the Fire Weather Index (FWI) System. Similar drought indices used for fire danger rating exist in other jurisdictions, such as the Keetch-Byram Drought Index (Keetch and Byram, 1968) and the Palmer Drought Index (Palmer, 1965). One significant, but subtle difference is that the DC is designed to directly estimate the lack of moisture in denser organic layers rather than using hydrologic drought in the mineral soil as a proxy for fuel moisture deficiencies. The layer of the forest floor tracked nominally by the DC has depth of 15-18 cm and nominal fuel load of 25 kg/m², in keeping with the standard pine fuel on which the FWI System is based (Van Wagner, 1987).

Since the development of the DC, most efforts to account for carrying-over drought from fall into spring and its impact on fire activity in Canada has focused on how to establish the starting spring values and field validation of the DC using destructive sampling methods (Otway et al., 2007, Stocks, 1979, Alexander, 1982, Lawson and Dalrymple, 1996). Most of Canada is snow covered, or receives significant precipitation during the winter months. More recent studies have developed correlations with organic soil moisture using electronic moisture probes (Terrier et al., 2014, Elmes et al., 2018, Keith et al., 2010). Such methods are less time consuming and allow greater temporal and spatial variability in measurements. Those instruments rely on soil dielectric properties, which can vary with soil composition, clay content and organic content (Bourgeau-Chavez et al., 2010, Kellner and Lundin, 2001). Despite good correlations with the measurements produced with these probes, questions remain operationally around probe installation and use and what layers best correlate with the DC.

The DC has also been shown to have strong correlation to C-band (~6 cm wavelength) Synthetic Aperture Radar (SAR) backscatter in low-biomass areas (Bourgeau-Chavez et al., 1999, Bourgeau-Chavez et al., 2007). An algorithm developed by Bourgeau-Chavez was shown to be useful to initialize DC start-up values in Alaska. Further work by Bourgeau-Chavez using polarimetric C-band SAR (Radarsat2) was successful at improving the soil moisture estimation in higher biomass areas (Bourgeau-Chavez et al., 2013). Although such research demonstrates the potential use of earth observation to map organic soil moisture, there remain limitations to remote sensing of soil moisture in forested regions (Jin et al., 2017, Magagi et al., 2013, Pan et al., 2016).

More sophisticated land surface models may alleviate some of the remote sensing issues; studies in other regions have shown improved drought estimation by incorporating land surface modelling outputs (Vinodkumar and Dharssi, 2019, Cooke et al., 2012, Yang et al., 2015) into fire danger methods to represent soil moisture changes. This approach has not been explored for the dense boreal forests in Canada. Inclusion of earth observations from an existing product, like the ECCC's (Environment and Climate Change Canada) Canadian Land Data Assimilation System (CaLDAS) (Carrera et al., 2019, Carrera et al., 2015) is an emerging area for fire science in Canada. CaLDAS integrates information from L-band satellite SMOS (Soil Moisture Ocean Salinity) as well as the geostationary satellite GOES (Geostationary Operational Environmental Satellite) with high-resolution land surface modelling and ground level observations to produce estimates of soil moisture across Canada every three hours. To further explore what organic depths the DC is tracking and determine the potential added intelligence electronic soil moisture content probes and land surface modelling data could provide, a field-based study was conducted in the provinces of Alberta and Ontario. This study had the following three objectives:

- 1. Determine how well the DC correlates to organic soil moisture and at which depths, using WRC (water content reflectometry) probes.
- 2. Explore the use of land surface models (CaLDAS) to represent moisture changes in these deep organic layers.
- 3. Determine if CALDAS estimates of soil moisture can be used to estimate/correct the DC.

2. Methods

We installed 8-12 WCR probes at depths of 10 and 18 cm in seven forest plots (Figure 1), from the surface through the organic layers, and in some cases, into the mineral soil. We compared these observed moisture contents with the DC model estimates of moisture and CaLDAS estimated Volumetric Moisture Content (VMC). DC values were estimated from nearby fire weather stations. The version of CaLDAS used included short-range forecasts calculated from ECCC's High Resolution Deterministic Prediction System every three hours. Precipitation within the model was assimilated from the Canadian Precipitation Analysis (CaPA)

(Mahfouf et al., 2007), in addition to other atmospheric variables, using an Ensemble Kalman Filter methodology. The land surface model was built around the SVS (Soil, Vegetation and Snow) scheme also developed by ECCC (Alavi et al., 2016, Husain et al., 2016). Daily soil moisture outputs from CaLDAS were obtained from ECCC for our analysis.

The field measurements of moisture content observed at depths of 10 cm and 18 cm were compared to the following: 1) daily DC values, converted to VMC, 2) CaLDAS VMC estimates at all three depths (0-5 cm, 5-10 cm and 10–20 cm) and 3) daily DC values (expressed as VMC) to CaLDAS VMC at three depths. All analysis were first conducted on daily time series of VMC during the fire season from late spring (May) until early fall (September) for 2019-2021 where available. The hydroGOF R package was used to calculate goodness of fit statistics for these time series comparisons including: R² (Coefficient of Determination), RMSE (Root Mean Square Error), Pbias (Percent Bias), and NSE (Nash Sutcliffe Efficiency; Nash and Sutcliffe, 1970). Goodness of fit statistics were first calculated for the entire 2019-2021 time series (May through September), then again for each individual year separately to show annual variations.

3. Results

Overall results indicated that the simple DC model did a good job of predicting the moisture content of the deeper organic layers (i.e. 10-18 cm) depths (Table 1), even compared to the more complex land surface model CaLDAS (Table 2). The WCR probes installed through the litter, fermentation and humus layers, and in some cases into the mineral soil, had good agreement with the DC model estimated VMC (Figure 2). Therefore, the DC may be representative of moisture changes in a wider range of depths, soil horizons and forest types. There was greater variability between different forest plots than between years and probe depths (Table 1). Model inputs, particularly precipitation and DC starting values had a large influence on DC model fit.

Differences in statistics and time series plots showed a clear trend that the DC had the best fit with the observed VMC in the wetter and deeper mixedwood Chapleau plot (Figure 2). In contrast, much poorer goodness of fit statistics were observed at the shallower and drier aspen plot also at the Chapleau site (Figure 2). Beyond those bookends there was no obvious indication of what is influencing overall organic moisture changes and the ability of the DC to represent them (i.e. duff depth, moisture regime, forest type); more advanced analyses may be required to investigate this further.

Results showed that better representation of precipitation is a simple way to improve DC tracking of forest floor moisture. This is not surprising as other studies have shown that FWI System codes and indices overall were improved compared to basic interpolation of stations with better precipitation inputs (i.e., gridded precipitation especially with radar) estimates (Hanes et al., 2017, Cai et al., 2019). Although the CaLDAS model includes high-resolution gridded precipitation products (Carrera et al., 2015) its outputs still consistently underestimated observed moisture contents (Table 2, Figure 3). It also had little skill in predicting DC values directly and consistently underestimated DC moisture content (Table 3, Figure 4). This strong bias is most likely due to the validation and calibration of CaLDAS to focus primarily on agricultural areas and mineral soil moisture (Carrera et al., 2019). This is similar to other remote sensing soil moisture calibrations/validations (Magagi et al., 2013, Pan et al., 2016). Although land surface models have been proposed as an alternative to drought modelling for fire danger in some areas (Vinodkumar and Dharssi, 2019, Cooke et al., 2012, Vinodkumar et al., 2017) the majority of studies assume mineral soil moisture as proxy measure of fuel moisture content. It is clear that overall, drier conditions are more conducive to fire, but it is the day-to-day changes in fine fuel moisture that are of primary importance, influencing daily variability in fire behaviour (Van Wagner, 1985). Many remote sensing and fire danger studies to date largely ignore the organic layer and focus only on "surface soils", which can include litter but are essentially mineral soil. Organic material contains more pore space and are therefore generally wetter than mineral soils (Otway et al., 2007). Therefore, to better model organic moisture directly, remote sensing retrieval algorithms and land surface models need to refine the soil dielectric models based on soil organic carbon properties (e.g., higher porosity and typically lower bulk density) (Jin et al., 2017). Organic soils typically have a lower dielectric content than mineral soil with same VMC (Jin et al., 2017, Bourgeau-Chavez et al., 2010). Integration of national maps of organic layer thickness (e.g., Hanes et al. 2022) into CaLDAS in combination with organic layer specific algorithms are needed to improve model skill for estimating drought indices for fire. Doing so would allow greater use of land surface models directly as additional sources

of fire intelligence, especially for regions without good weather station coverage; this would also allow fire managers to take advantage of the forecast capabilities of these complex models.

4. Conclusions

Our results indicate that the relatively simple DC model does a reasonable job of representing observed moisture changes in deeper organic layers over a wide range of forest types for depths of 10 to 18 cm. Electronic probes that use the dielectric content of soil moisture, installed at these depths, can be used to supplement or correct DC estimates. Physically based hydrologic models have been proposed because we have the capacity to use them (i.e., Johnson et al., 2013, Keith et al., 2010). Yet the simplicity of the DC model and ease of application without the necessity to parameterize to a specific region still outweigh any validation improvements in moving to a more complex model. Although land surface models like CaLDAS hold much promise to integrate earth observation and high-resolution numerical weather prediction outputs into wildfire danger prediction, their bias to mineral soils limit their use at this time. We anticipate better performance in the future once organic soils are integrated into CaLDAS and the SVS land surface scheme. This is not to say the DC model is perfect. Much clarity could come from expanding the definition of what the DC model represents (i.e. beyond the elusive standard 15-18 cm depth in a standard pine forest). This may require a shift in the definition from an exact moisture value for a specific soil horizon towards a definition that includes a wider range of slower drying organic layers/fuels as data permits.

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6. Figures and Tables

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Figure 1. Top: A map of North America with Canadian and United States borders highlighting the general area of our study region (box). Bottom: The four moisture probe field sites (shown as stars) in Alberta and Ontario; REC on this map designates the Red Earth Creek site. The number and vegetation type of each plot, within the different sites, are indicated in the orange boxes.

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Figure 2. Goodness of fit statistics and time series comparisons for each fire season (2019-2021) for the Chapleau site. Mixedwood (top row) is contrasted with aspen (bottom row). The black line is the observed (obs) Volumetric Moisture Content (VMC) (field measured at 18 cm). The grey line is the DC estimated VMC.

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Figure 3. Example of a better match between observed (18 cm) and CaLDAS (Canadian Land Data Assimilation System) volumetric moisture content (VMC) for 10-20 cm moisture for Chapleau, aspen plot (top row) and a worse match for the Chapleau, mixedwood plot (bottom row). Goodness of fit statistics and time series are shown for 2019-2021.

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Figure 4. Example of a better match between DC (Drought Code) VMC (volumetric moisture content) and CaLDAS (Canadian Land Data Assimilation System) moisture for the Edson, mixedwood plot (top row) and a worse match for Dryden, mixedwood plot (bottom row). Goodness of fit statistics and time series are shown for 2019-2021. The black dotted line is the DC VMC. The grey line is the simulated CaLDAS estimated VMC for 10-20 cm.

 Table 1. Goodness of fit statistics comparing field measured volumetric moisture content (VMC %) of the duff layer

 up to various depths compared to Drought Code (DC) estimated VMC calculated from the nearest fire weather station.

 Statistics listed (R², RMSE (Root Mean Square Error), NSE (Nash Sutcliffe Efficiency), Pbias (Percent Bias)) are for

 time series from 2019 – 2021, May until September, where field data permitted.

Site	Plot	Field Depth	R ²	RMSE	NSE	Pbias
		(cm)				
	A	10	0.55	11.93	-2.44	39.8
Chapleau	Aspen	18	0.53	13.85	-5.95	51.7
	Icolt nine	10	0.53	14.69	-5.28	58.2
	Jack pine	18	0.59	11.37	-1.57	37.5
	D1. 1	10	0.49	11.62	-2.37	37.1
	Black spruce	18	0.46	13.54	-5.81	48.6
	Mixedwood	10	0.74	9.64	-1.01	31.1
		18	0.83	5.99	0.70	9.6
D. 1.	Minadanaad	10	0.73	7.39	0.6	11.3
Dryden	Mixedwood	18	0.76	6.89	0.64	-8.3
Edson	Minadurand	6	0.68	10.86	-0.70	-18.4
	Mixedwood	10*	0.64	10.74	-0.56	-19.5
		30	0.69	16.05	-2.44	-28.3
DEC	Aanan	10	0.55	0.47	0.32	-11.3
KEU	Aspen	18	0.58	0.51	0.43	-9.1

*no data for 2019

 Table 2. Goodness of fit statistics comparing field measured volumetric moisture content (VMC %) of the duff layer

 up to various depths compared to Drought Code (DC) estimated VMC calculated from the nearest fire weather station.

 Statistics listed (R², RMSE (Root Mean Square Error), NSE (Nash Sutcliffe Efficiency), Pbias (Percent Bias)) are for
time series from 2019 – 2021, May until September, where field data permitted.

Site	Plot	CaLDAS	Field Depth	\mathbf{R}^2	RMSE	NSE	Pbias
		Depth (cm)	(cm)				
		0-5	10	0.27	11.89	-2.19	-37.5
			18	0.28	9.25	-2.10	-32.3
	Aspon	5-10	10	0.34	11.2	-2.03	-37.1
-	Aspen		18	0.35	8.92	-1.88	-31.7
		10-20	10	0.46	11.94	-2.45	-41.0
			18	0.48	9.65	-2.37	-36.0
	Jack pine	0-5	10	0.11	7.72	-0.74	-22.2
			18	0.05	11.30	-1.53	-32.4
		5-10	10	0.14	7.65	-0.71	-22.7
			18	0.07	11.24	-1.51	-32.8
		10-20	10	0.18	7.92	-0.83	-25.0
C 1 1			18	0.11	11.55	-1.65	-34.8
Chapleau		0-5	10	0.18	11.00	-4.61	-35.7
			18	0.17	14.46	-4.24	-42.2
	Black spruce	5-10	10	0.20	10.95	-4.56	-35.7
			18	0.19	14.43	-4.22	-42.2
		10-20	10	0.24	11.32	-4.94	-37.4
			18	0.24	14.81	-4.50	-43.7
	Mixedwood	0-5	10	0.05	10.02	-1.17	-22.2
			18	0.10	15.94	-1.10	-35.0
		5-10	10	0.04	8.55	-0.58	-15.0
			18	0.08	14.49	-0.74	-28.9
		10-20	10	0.10	8.89	-0.71	-19.7
			18	0.18	14.94	-0.85	-32.9
Dryden	Mixedwood	0-5	10	0.10	17.40	-1.22	-41.8
			18	0.04	23.16	-3.06	-52.0
		5-10	10	0.11	17.38	-1.22	-41.7
			18	0.05	23.12	-3.05	-52.0
		10-20	10	0.11	17.63	-1.28	-42.7
			18	0.05	23.40	-3.15	-52.8
Edson	Mixedwood	0-5	10*	0.61	20.69	-4.80	-48.2
			30	0.44	29.52	-10.65	-56.2
		5-10	10*	0.58	19.23	-4.01	-44.2
			30	0.40	28.30	-9.71	-53.6
		10-20	10*	0.61	19.04	-3.91	-43.6
			30	0.41	28.16	-9.60	-53.3
REC	Aspen	0-5	10	0.04	30.20	-5.51	-61.5
			18	0.04	28.81	-5.53	-60.4
		5-10	10	0.19	29.01	-5.01	-59.6
		-	18	0.22	26.82	-4.87	-57.7
		10-20	10	0.33	29.49	-5.21	-61.1
			18	0.36	28.06	-5.20	-59.9
REC	Aspen	10-20 0-5 5-10 10-20	$ \begin{array}{r} 30 \\ 10^{*} \\ 30 \\ 10 \\ 18 \\ 10 \\ 10 \\ 18 \\ 10 \\ 10 \\ 10 \\ 18 \\ 10 \\ $	$\begin{array}{c} 0.40\\ 0.61\\ 0.41\\ 0.04\\ 0.04\\ 0.19\\ 0.22\\ 0.33\\ 0.36\\ \end{array}$	28.30 19.04 28.16 30.20 28.81 29.01 26.82 29.49 28.06	-9.71 -3.91 -9.60 -5.51 -5.53 -5.01 -4.87 -5.21 -5.20	-53.6 -43.6 -53.3 -61.5 -60.4 -59.6 -57.7 -61.1 -59.9

*does not include 2019

Site	Plot	CaLDAS Depth (cm)	R ²	RMSE	NSE	Pbias
Chapleau	Aspen	0-5	0.04	22.27	-6.87	-55.3
		5-10	0.07	21.98	-6.66	-55.0
		10-20	0.15	22.82	-7.26	-57.8
	Jack pine	0-5	0.01	20.61	-5.95	-50.8
		5-10	0.01	20.62	-5.95	-51.1
		10-20	0.03	21.06	-6.25	-52.6
	Black spruce	0-5	0.01	20.48	-5.99	-50.8
		5-10	0.01	20.43	-5.95	-50.9
		10-20	0.02	20.82	-6.23	-52.1
	Mixedwood	0-5	0.19	16.78	-3.67	-40.7
		5-10	0.08	15.21	-2.83	-35.2
		10-20	0.29	15.82	-3.14	-38.8
Dryden	Mixedwood	0-5	0.02	21.44	-4.97	-51.1
		5-10	0.02	21.38	-4.94	-51.1
		10-20	0.02	21.65	-5.09	-51.9
Edson	Mixedwood	0-5	0.43	19.75	-2.31	-44.4
		5-10	0.46	18.65	-1.95	-41.1
		10-20	0.53	18.48	-1.9	-40.8
REC	Aspen	0-5	0.09	20.19	-1.5	-49.4
		5-10	0.35	18.774	-1.16	-46.3
		10-20	0.34	19.21	-1.27	-47.8