AGU100 ADVANCING EARTH AND SPACE SCIENCE

JGR

Journal of Geophysical Research: Atmospheres

RESEARCH ARTICLE
10.1029/2018JD028754

Evaluation of Gridded Precipitation Data and Interpolation Methods for Forest Fire Danger Rating in Alberta, Canada

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Key Points:

- Fire danger indices can be improved using regression kriging to combine gridded precipitation (Canadian Precipitation Analysis System) and weather station data
- We performed a weather station density sensitivity analysis to aid method selection for mapping fire danger on landscapes with heterogeneous station density

Supporting Information:

- Supporting Information S1

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Citation:
Cai, X., Wang, X., Jain, P., & Flannigan, M. D. (2019). Evaluation of gridded precipitation data and interpolation methods for forest fire danger rating in Alberta, Canada. *Journal of Geophysical Research: Atmospheres*, *124*, 3–17. https://doi.org/10.1029/2018JD028754

Received 2 APR 2018
Accepted 23 NOV 2018
Accepted article online 28 NOV 2018
Published online 3 JAN 2019

Author Contributions:
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Funding acquisition: Mike D. Flannigan
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Abstract The Canadian Forest Fire Weather Index System is the primary measurement of wildfire danger in Canada. Interpolating daily precipitation, one of the inputs for the Fire Weather Index System is a key challenge in areas without sufficient weather stations. This work evaluates the performance of gridded precipitation from the Canadian Precipitation Analysis (CaPA) System and six interpolation methods to achieve the best fire danger rating in Alberta, Canada. Results show that the CaPA System has only average performance due to limited radar coverage (10%) in the forested region; however, using the CaPA System as a covariate with regression kriging generates significantly better precipitation estimates. Ordinary kriging, regression kriging with elevation as a covariate, and the thin-plate smoothed spline are methods with similar performance. Fuel moisture codes of the Fire Weather Index System respond differently to precipitation amounts due to differences in their time constants for drying. Fine fuels with a short drying time (Fine Fuel Moisture Code) are best estimated by the CaPA System because of its enhanced skill in estimating small precipitation events. Compacted organic fuels with longer drying times (Duff Moisture Code and Drought Code) are best estimated by regression kriging with CaPA because it better predicts significant precipitation events. The dense fire weather station network in our study area (~3.0 stations/10,000 km^2) allows us to perform a sensitivity analysis, and we find that a threshold of >0.5 stations/10,000 km^2 is needed for regression kriging with CaPA to become appreciably better than the CaPA System.

1. Introduction

Wildfires are a dominant disturbance in the Canadian boreal forest ecosystem. Fire drives the physical and ecological dynamics of forest composition, density, productivity, and carbon cycling and storage (Rowe, 1983). Fire can also threaten communities in the boreal forest and cause damages measured in billions of dollars, such as the catastrophic fires in Slave Lake in 2011 (Flat Top Complex Wildfire Review Committee, 2012) and Fort McMurray in 2016 (MNP, 2017). In Canada, wildfires are suppressed when they threaten human life, infrastructure, and valuable natural resources. Accurate prediction of fire danger is essential for effective wildfire management (Taylor & Alexander, 2006; Wotton, 2009). Wildfires on the landscape are strongly influenced by weather/climate, fuel, ignition sources, and humans (Flannigan et al., 2005; Johnson, 1972). Of these factors, weather varies the most in space and time and is considered the best predictor of daily fire danger (Countryman, 1972; Flannigan et al., 2009), making fire weather prediction one of the most challenging but essential tasks in mapping fire danger.

Canadian scientists have worked on integrating weather information into fire danger rating since the 1920s, resulting in the development of the Canadian Forest Fire Weather Index (FWI) System (Van Wagner, 1987). The FWI System is a strictly weather-based system that relies on local noon observations of screen-level temperature and relative humidity, 10-m open space wind speed, and 24-hr accumulated precipitation. The FWI System produces three fuel moisture codes to represent moisture content in surface fine fuels (Fine Fuel Moisture Code (FFMC)), loosely compacted organic materials (Duff Moisture Code (DMC)), and a deep compacted organic layer (Drought Code (DC)). These fuel moisture codes are used to produce three fire behavior indices: the Initial Spread Index (ISI), Buildup Index (BUI), and Fire Weather Index (FWI). Specifically, FFMC and wind speed are combined to create ISI, which represents the rate of fire spread; DMC and DC are combined to give BUI, the total available fuel for burning; and finally, BUI and ISI are combined to create the FWI, the potential intensity of a spreading fire. The FWI fuel moisture codes are determined by the previous day's code values and current day's weather observations, and thus, the FWI System is essentially a dynamic bookkeeping system (Van Wagner, 1987). The FWI System has been used nationally and internationally (e.g., New Zealand, Indonesia, Portugal, Mexico, and the United States) to support the fire management daily decision-making process. The FWI System has also been used extensively in the research community, such as the study of the relationship between future wildfire activity and climate change (e.g., Flannigan et al., 2016; Wang, Parisien, et al., 2017).

Among the four input fire weather variables to the FWI System, precipitation is the source of the largest uncertainty when estimating fire danger across the landscape (Field et al., 2015; Flannigan et al., 1998; Flannigan & Wotton, 1989; Jain & Flannigan, 2017). Summer precipitation in Canada is often a result of convective storms and thunderstorms, which are difficult to resolve because they can vary over small spatial and temporal scales. In practice, precipitation and the other input weather variables of the FWI System are obtained from fire weather stations, which only operate during the fire season and are sparsely distributed in the boreal forest (Lawson, 1977; Lawson & Armitage, 2008; Turner & Lawson, 1978). Canadian wildfire management agencies use spatial interpolation methods, such as the inverse distance weighting (IDW) and thin-plate splines (TPS), to estimate fire weather variables and fire danger across the landscape (Englefield et al., 2000; Lee et al., 2002). Both IDW and TPS are based on relatively straightforward algorithms (Hofstra et al., 2008). IDW is a simple linear interpolation method based on a function of inverse distance (Shepard, 1968). Previous studies have shown that IDW cannot capture the high spatial variability of daily precipitation using the current fire weather station networks and result in poor estimates of the FWI System indices (Flannigan et al., 1998; Flannigan & Wotton, 1989; Hanes et al., 2017). TPS builds a spline surface by minimizing an energy functional subject to a user-specified smoothing parameter (Wahba, 1990), and has been used to interpolate monthly precipitation normals across Canada (Price et al., 2000). However, TPS may have difficulty in estimating daily precipitation over mountainous regions (Flannigan et al., 1998; Hutchinson et al., 2009). Therefore, an investigation of the performance of more robust interpolation methods in estimating daily precipitation is needed for more accurate fire danger mapping.

Geostatistical interpolation methods, such as ordinary kriging and regression kriging, have also been used frequently to interpolate climatic variables (Daly, 2006; Li & Heap, 2011, 2014). Kriging models the spatial covariance of the weather variable by building a semivariogram using the observed data (Diodato & Ceccarelli, 2005; Ly et al., 2011). Regression kriging combines observations of the climatic variable with additional covariates, such as elevation (Goovaerts, 2000; Jain & Flannigan, 2017) or gridded data that can include, for example, radar measurement (Bardossy & Pegram, 2017; Hasan et al., 2016). Haberlandt (2007) suggested that regression kriging outperformed conventional interpolation methods (e.g., ordinary kriging and TPS) when gridded radar precipitation data were used as a covariate. This is because regression kriging shows improved performance in addressing the spatial variability of summer precipitation by combining gridded precipitation and station data.

Recently, Environment and Climate Change Canada (ECCC) have developed a gridded precipitation data set called the Canadian Precipitation Analysis (CaPA) System (Fortin et al., 2018; Mahfouf et al., 2007) to improve precipitation estimates in areas with sparse weather station networks. The CaPA System is a data assimilation system that produces 10-km gridded precipitation data in near-real time over North America by combining station observations, weather radar estimates, and numerical weather prediction (NWP) model forecasts. The CaPA System uses NWP forecasts as a background field. In areas with station observations, the differences between station observations and NWP forecasts are calculated and interpolated back to the NWP grids using a simple kriging method (Daley, 1991). In 2014, version 4.0 of the CaPA System successfully integrated radar estimates into the analysis (Fortin et al., 2015), resulting in a significant improvement in precipitation estimates in areas covered by radar. In addition, the CaPA System has greater confidence in areas closer to stations and a station density of 1.17/10,000 km^2 was required for the CaPA system to outperform the background NWP forecasts (Lespinas et al., 2015). Hanes et al. (2017) suggested that the precipitation estimates generated by the CaPA System improved the estimates of FFMC, ISI, and FWI in areas of radar coverage in Ontario, Canada. In this paper, we use version 4.0 of the Regional Deterministic Precipitation Analysis based on CaPA (RDPA-CaPA; Fortin et al., 2015), which we henceforth refer to as the CaPA System.

The objective of this study is to find the best approach in estimating daily precipitation and to therefore improve the accuracy of fire danger rating in areas without sufficient weather stations. We first compared the CaPA System with conventional and geostatistical interpolation methods to find the best precipitation

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estimation approach in radar and nonradar covered areas of Alberta, Canada. We then evaluated the impacts of different precipitation estimates on the FWI System indices. Finally, we examined the weather station density sensitivity of interpolation methods to optimize the selection of the best method for mapping fire danger across the landscape.

2. Data and Methods

2.1. Study Area

Our domain of study is the forested portion of Alberta, Canada (Figure 1), where active periods of the fire season are from May to August. Based on ECCC historical weather data, there is about 70% of the annual precipitation in Alberta falls from May to August from 2006 to 2016, much of which is the result of highly localized convective storms and thunderstorms (Strong & Leggar, 1992). Elevation ranges from ~3,500 m in the Rocky Mountains at the southwest to ~300 m in the boreal forest at north-central. To avoid extrapolation due to the lack of fire weather stations near the border, we buffered the study area inward by 75 km and partitioned it into a validation area and a buffer area (Figure 1a). We also partitioned the validation area into a radar area and a nonradar area using a 120-km Doppler range (Figure 1a), where the CaPA System estimates have greater confidence (Fortin et al., 2015).

2.2. Data

Fire weather station observations from Alberta Agriculture and Forestry (AAF) and the CaPA System outputs from ECCC during the 2014–2016 fire seasons were used in the analyses to accommodate the upgraded CaPA System, available since 14 July 2014 (Fortin et al., 2015). Compared to the 30-year historical normals, 2014 and 2015 were dry years and 2016 was a wet year.

Daily AAF fire weather observations were recorded from the fire weather station network (Figure 1a). We excluded observations from the Aviation Routine Weather Report (METAR) stations in the analyses because they are operated by ECCC and are inputs of the CaPA System (Lespinas et al., 2015). The AAF fire weather variables were cleaned to exclude unrealistic values, such as temperature >45 °C or < -45 °C, 24-hr accumulated precipitation >200 mm, relative humidity $>100\%$, and wind speed >150 km/hr. For missing values, when a station had ≤ 3 consecutive days of missing data, we interpolated the missing data using TPS based on the observations from the surrounding stations. When there were >3 consecutive days of missing data, the station was dropped. In total, there were 92, 79, and 89 fire weather stations left in the validation area for 2014, 2015, and 2016, respectively (Table 1). Although the 2015 fire season had ~15% lower station density in the validation area than that of 2014 and 2016, the weather station densities in areas with and without radar were similar for each fire season (Table 1).

The CaPA System (version 4.0) estimates, which combine ECCC weather station observations, radar precipitation estimates, and NWP model outputs, are obtained from ECCC (Fortin et al., 2015, 2018; Mahfouf et al., 2007). The ECCC weather station networks are independent of the AAF fire weather station network and are mainly distributed in the nonforested portion of Alberta (Figure 1b). Four ECCC weather radars overlapped with the study area and covered ~10% of our validation area (Table 1). The CaPA System outputs are the gridded 6-hr precipitation analyses (10-km resolution) produced at 00, 06, 12, and 18 UTC. The four 6-hr analyses were summed to generate the 24-hr precipitation estimates at 18 UTC (12 MST). ECCC stations are separate from the AAF fire weather station networks and are mainly distributed in the nonforested portion of Alberta (Figure 1b). Four ECCC weather radars overlapped with the study area and covered ~10% of our validation area (Table 1).

2.3. Evaluation Procedure for Precipitation Estimation Methods

Following previous studies, we selected six spatial interpolation methods to compare with the gridded CaPA System in estimating daily precipitation and the FWI System indices (Table 2). The six methods include IDW (Englefield et al., 2000), smoothed and nonsmoothed splines (Flannigan & Wotton, 1989; Price et al., 2000), ordinary kriging (Hofstra et al., 2008), regression kriging with elevation as a covariate (Goovaerts, 2000), and regression kriging with gridded precipitation data as a covariate (Haberlandt, 2007). In the latter case, we used the CaPA System as the covariate.

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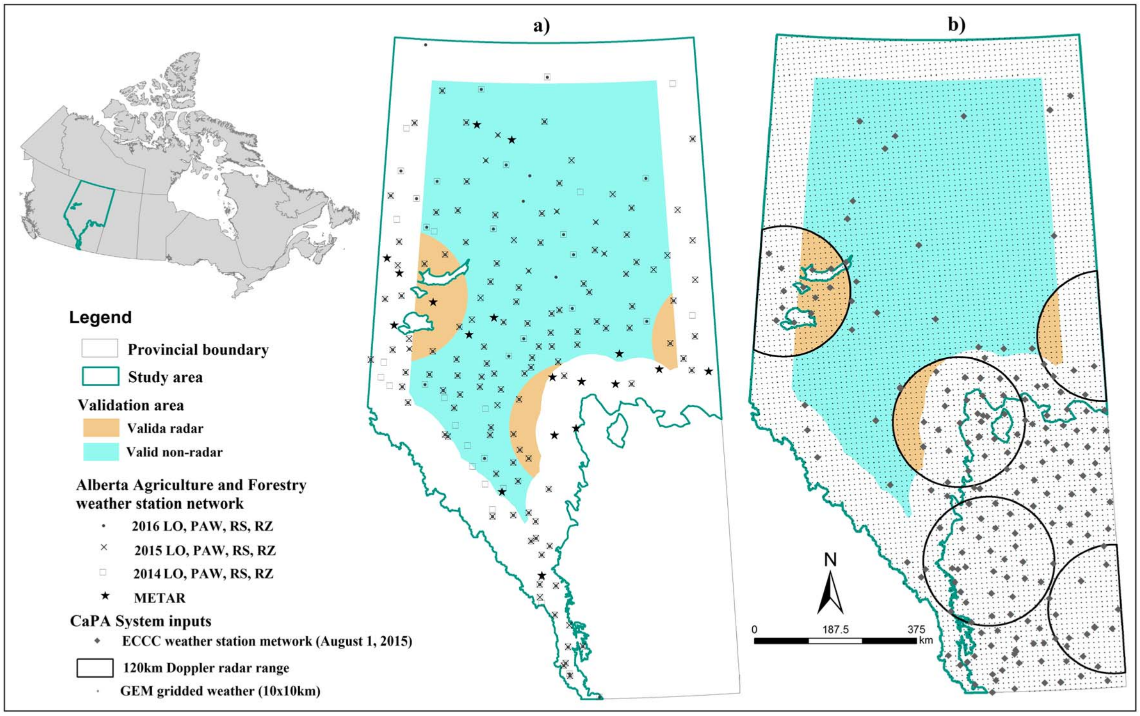

Figure 1. (a) Alberta agriculture and forestry (AAF) weather station network and (b) Canadian precipitation analysis (CaPA) system.

Data transformations are commonly applied to improve the interpolated precipitation estimates. In a preliminary analysis, we compared the square root transform (SRT), cube root transformation (CRT), and natural log transformation (LNT) and found that although all three transformations led to a similar decrease in prediction error, the SRT had the lowest bias. For this reason and also based on the results of a previous study (Hutchinson, 1998), we applied the square root transformation to five of the six interpolation methods (except in the case of IDW) to improve the interpolation accuracy, giving a total of 12 methods to compare as listed in Table 2. When using transformations, interpolated variables may be unbiased in the transformed space but introduce additional bias in the back-transformed space unless bias correction is applied (Cressie, 1993). Another preliminary analysis indicated that while applying bias correction for interpolation techniques

Table 1

Weather Station Network of Alberta Agricultural and Forestry (AAF) and Environment and Climate Change Canada (ECCC) From 2014 to 2016 in the Study Area, Validation Area, Radar-Covered Area, and Nonradar-Covered Area (see Figure 1 for More Details of These Areas)

		AAF Station Network		ECCC Station Network	
Regions	Years	No. of Stations	Station Density (Stations Per 10,000 km^2)	No. of Stations	Station Density (Stations Per 10,000 km^2)
Study area (505,964 km^2)	2014	170	3.3	51	1.0
	2015	132	2.6	71	1.4
	2016	145	2.9	51	1.0
Validation area (280,679 km^2)	2014	92	3.3	16	0.6
	2015	79	2.8	23	0.8
	2016	89	3.2	19	0.7
Nonradar area (252,669 km^2)	2014	84	3.3	14	0.6
	2015	71	2.8	20	0.8
	2016	80	3.2	17	0.7
Radar area (28,010 km^2)	2014	8	2.9	2	0.7
	2015	8	2.9	3	1.0
	2016	9	3.2	2	0.7

Table 2
The Gridded Precipitation Data and Spatial Interpolation Methods Evaluated in This Study

Type of the Methods	Methods	Transformation of Precipitation[a]	Abbreviation
Gridded data set	Canadian Precipitation Analysis System	N/A	CaPA
Conventional interpolation	Inverse distance weighting[2]	N/A	IDW
	Thin-plate smoothed spline[3]	N/A	TPS-S-SRT
		Square root	TPS-S-SRT
	Thin-plate nonsmoothed spline[4]	NA	TPS-NS
		Square root	TPS-NS-SRT
Geostatistical interpolation (univariate)	Ordinary kriging[b]	N/A	OK
		Square root	OK-SRT
Geostatistical interpolation (multivariate)	Regression kriging with elevation[c]	N/A	RK (elev)
		Square root	RK (elev)-SRT
	Regression kriging with CaPA[c]	N/A	RK (CaPA)
		Square root	RK (CaPA)-SRT

[a]Square-root transformation was applied to the precipitation observations before performing the interpolation, and a back-transformation was applied to the interpolated estimates. [b]A spherical model was used to build the semivariogram based on testing with several theoretical models and past studies (such as Ly et al., 2011). [c]Regression kriging first built a linear regression to the covariate (elevation or CaPA system estimates), then perform ordinary kriging with the regression residuals (Cressie, 2015). [d]A power parameter of 2 was used for the function of inverse distance following the current fire danger rating mapping approach of the Canadian wildland fire information system (Englefield et al., 2000). [e]A spline surface was fitted with the constraint of smoothing that is optimized by minimizing the generalized cross-validation (Wahba & Wendelberger, 1980). [f]A spline surface was fitted using the exact observations (Wahba & Wendelberger, 1980).

using the SRT led to a decrease in bias, it also led to an increase in errors. We therefore opted to not use bias correction in our reported results.

In this study, IDW was used as the benchmark for this study because it is the current interpolation method used by the Canadian Wildland Fire Information System to produce Canada-wide FWI System indices (Englefield et al., 2000). A three-step procedure was developed to evaluate the performance of the CaPA System and the interpolation methods.

Step 1. Generating precipitation estimates
The AAF weather station network was used in a leave-one-out cross-validation (LOOCV) procedure (Price et al., 2000; Stone, 1974) to generate precipitation estimates for each interpolation method. The LOOCV procedure removed one station at a time from the validation area (see Figure 1), and the daily precipitation at the removed station was estimated using the precipitation observations from the remainder of the station network. The removed weather station was then replaced into the data set, and the next weather station was removed, estimated, and replaced. This process stopped when all the stations in the validation area had been removed and replaced once. Precipitation estimates from the CaPA System were assigned to each station in the validation areas using a nearest-neighbor search. The LOOCV procedure and the extraction of CaPA System estimates were repeated daily during each fire season to generate continuous precipitation estimates for FWI System calculation.

IDW estimates the variable at a location by using the linear sum of observations, weighted by a function of inverse distance (Shepard, 1968). Following the current fire danger mapping approach of the Canadian Wildland Fire Information System, we used a power parameter of 2 for the inverse distance function (personal communication with Bo Lu). TPS with smoothing fits a thin plate spline surface with a smoothing parameter that represents the tension of the surface (Wahba, 1990). TPS without smoothing fits the spline surface with a smoothing parameter of zero (i.e., and thus is unbiased as it passes through the observations). Ordinary kriging is a geostatistical interpolation method that uses a semivariogram to model the spatial covariance of the variable of interest (Li & Heap, 2011). The resulting semivariogram can be fitted with various models such as Nugget, Exponential, Spherical, and Gaussian (Burrough & McDonnell, 1998). Based on a previous study (Ly et al., 2011), we selected the Spherical model to build a semivariogram model using daily observations of precipitation. Regression kriging is a multivariate geostatistical interpolation method that combines observations with additional covariates (Li & Heap, 2014). Here a linear regression is first performed between the precipitation data and a covariate (or covariates), and then ordinary kriging is performed with the residuals of the regression (Cressie, 2015). In this study, we used either elevation or CaPA System estimates as a covariate. Precipitation estimates for the geostatistical interpolation methods and IDW were generated using

Table 3
Evaluation Metrics Used in This Study

Type	Evaluation Metric	Formula	
Continuous[a]	Mean absolute error (MAE)	$\mathrm{MAE} = \frac{1}{n\times k}\sum_{i=1}^{n}\sum_{j=1}^{k}\left\|E_{i,j} - O_{i,j}\right\|$	Where $E_{i,\ j}$ is the estimates at weather station *i* on day *j* Where $O_{i,\ j}$ is the observations at weather station *i* on day *j*
	Mean error (bias)	$\mathrm{Bias} = \frac{1}{n\times k}\sum_{i=1}^{n}\sum_{j=1}^{k}\left(E_{i,j} -^{i,j} O_{i,j}\right)$	Where *n* is the number of valid fire weather stations and *k* is the number of days
Categorical[b]	Equitable Threat Score (ETS)	$\mathrm{ETS} = \frac{a-R(a)}{a+b+c-R(a)}$	Where R(a) = (a + b)(a + c)/(a + b + c + d) and *a*, *b*, *c*, and *d* are defined using the contingency table:
	Frequency Bias Index (FBI)	$\mathrm{FBI} = \frac{a+b}{a+c} - 1$	

	Observed (yes)	Observed (no)
Forecast (yes)	a (hit)	b (false alarm)
Forecast (no)	c (miss)	d (correct rejections)

[a]If a method had low values in both MAE and absolute bias, the method is considered a good performing method; if a method had low MAE but high negative/positive bias values, this method is still considered a good performing method but tends to underestimate/overestimate; if a method had high MAE values but low bias values, this method is not considered good because the low bias is a result of the canceling-out between underestimations and overestimations; and if a method had both high MAE and absolute bias values, this method is considered a bad performing method (Stanski et al., 1989). [b]ETS measures the fraction of correct estimates, ranging from $-1/3$ to 1; a perfect ETS score is 1 and ETS values <0 indicating no skill. ETS is insensitive to the climatology of the event (e.g., dryness and wetness). FBI measures the direction of errors; a positive/negative FBI value indicates a tendency of overestimation/underestimation. Note that we have subtracted 1 from the conventional definition of FBI so the perfect FBI score is 0 (Wilks, 2011).

the gstat package (Pebesma, 2004) in the R programming environment (R Development Core Team, 2016). Precipitation estimates for TPS were generated using the fields package (Nychka et al., 2016).

Step 2. Calculating the FWI System indices
Daily precipitation estimated from the interpolation methods and the CaPA System, in combination with the AAF observations of temperature, relative humidity, and wind speed, were used to calculate the FWI System indices (Van Wagner, 1987) using the cffdrs R package (Wang, Wotton, et al., 2017). Due to the bookkeeping manner of the FWI System, errors in the precipitation estimates are carried-over from one day to the next (error propagation). Because we used LOOCV in this study, we have the option to allow the error propagation or to adjust the error propagation by using the previous day's observed fuel moisture codes. In the operational system (e.g., Canadian Wildland Fire Information System), the previous day's weather observations are not available in the areas without weather stations, so error propagation is inherent. We allowed the error propagation in the study since we want to simulate the operational system.

Step 3. Evaluating precipitation and FWI System estimates

Model performance was evaluated using the mean absolute error (MAE) and mean error (bias; Table 3). MAE measures the magnitude of average errors and bias measures the direction of the average errors (Stanski et al., 1989). In this study, we evaluated the methods based on four scenarios: (1) if a method had both low MAE and absolute bias values, we consider the method a good performing method (high accuracy and low bias); (2) if a method had a low MAE value but a high positive/negative bias value, we consider the method a relatively good performing method with the tendency to overestimate/underestimate; (3) if a method had a high MAE value but a low bias value, we do not consider the method a good method (as the low bias is a result of the canceling-out between underestimates and overestimates); and (4) if a method had both high MAE and absolute bias values, we consider the method to be a bad performing method. The equations of MAE and bias are shown in Table 3. We did not use the root-mean-square error for this study because it overemphasizes outliers (i.e., extreme precipitation events; Willmott & Matsuura, 2005), which are less frequent and problematic for fire danger rating. A stationary block bootstrapping resampling procedure was applied to generate 1,000 resamples (Lespinas et al., 2015; Politis & Romano, 1994). This resampling procedure takes into account the spatial and temporal autocorrelations, as well as nonnormality of the data by reconstructing a space–time resampling with the same length as the original data. The length of resampled blocks follows a geometric distribution with a mean block length. According to the averaged temporal autocorrelation of each variable, we selected a mean block length of 3, 4, 5, 10, and 20 days for daily precipitation, FFMC, FWI, DMC, and DC, respectively. To preserve the spatial correlation of precipitation and FWI System indices, we collected the observations and estimates at all weather stations for each resampled block. Confidence intervals for MAE ranks (1–12, from best to worst) and bias values, which were calculated from 1,000 resamples, were used to evaluate the performance of the examined methods.

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Minimum precipitation amounts of 0.5, 1.5, and 2.8 mm (referred to as effective precipitation) are assumed necessary to reduce the values of FFMC, DMC, and DC, respectively (Van Wagner, 1987). We therefore calculated the equitable threat score (ETS; the magnitude of errors) and frequency bias index (FBI; the direction of errors) with the following precipitation bins (0, 0.5), (0.5, 1.5), (1.5, 2.8), and (2.8, ∞) mm (Table 3). ETS measures the magnitude of errors while FBI measures the direction of errors for each precipitation category (Wilks, 2011). ETS and FBI were calculated for the top six performing methods based on MAE, as well as the IDW (used as a control group).

2.4. Weather Station Density Sensitivity Analysis

To examine the sensitivity of spatial interpolation methods to changes in weather station density in the context of fire danger rating, we developed a sensitivity analysis procedure. First, we randomly sampled 10, 25, 50, 75, and 90% of the AAF fire weather stations, respectively (see Table S1). We then applied the three-step performance evaluation procedure as described in section 2.3 to each of the subsamples and calculated the MAE value for each interpolation method. Lastly, we repeated this sensitivity analysis procedure 100 times for each weather station density (10, 25, 50, 75, and 90%) and calculated the mean of the 100 MAE values.

3. Results

3.1. Overall Method Performance and Impacts on the FWI System Indices

The performance of the examined methods was evaluated using the rank of MAE (Figure 2) and bias (Figure 3). In areas with radar (10% of the overall study area), regression kriging with CaPA had the lowest MAE rank for precipitation estimates; in areas without radar, regression kriging with elevation, ordinary kriging, and TPS smoothed had similarly lowest MAE ranks (Figure 2). Regardless of radar coverage, regression kriging with CaPA had the lowest MAE ranks for FFMC and FWI when the square root transformation was applied, and the lowest MAE ranks for DMC and DC when the square root transformation was not applied (Figure 2). Overall the CaPA System had a middle MAE rank (~6/12) for precipitation but had lower MAE ranks for precipitation, FFMC, and FWI in areas with radar. However, the CaPA System had the worst MAE ranks for DMC and DC regardless of radar coverage (Figure 2), which may due to the high negative bias values associated with the CaPA System (Figure 3). TPS related methods (e.g., TPS-NS-SRT) had low bias values (Figure 3) but they were not considered as good methods because the low bias is a result of the canceling-out between underestimating and overestimate as indicated by their high MAE ranks (Figure 2). Regardless of radar coverage, IDW had the highest MAE ranks and relatively high bias values and was considered the worst performing method. In addition, the square root transformation improved the MAE ranks for the interpolation methods (Figure 2) but resulted in a tendency of underestimation (Figure 3).

Overall, examples of the 24-hr gridded precipitation estimates (Figure 4) showed that regression kriging with CaPA had the best ability to address the spatial variability of daily precipitation among all the examined methods, and at the same time, it reduced the high negative bias associated with the CaPA System. These precipitation maps showed that regression kriging captured precipitation events identified by both the CaPA System and the AAF fire weather stations, and it was the only method that captured the precipitation events in the central northern region of the study area where the AAF weather stations are sparse. Precipitation maps produced by regression kriging also showed more detail, whereas the precipitation maps produced by TPS appeared to be oversmoothed and those from IDW showed the signature “bullseye” distribution that is not considered realistic for precipitation fields.

3.2. Method Performance in Estimating Effective Precipitation for Fuel Moisture Codes

The top-performing methods (regression kriging with CaPA, regression kriging with elevation, ordinary kriging, TPS smoothed, CaPA System) and IDW were better at predicting precipitation $<$0.5 mm and precipitation $>$2.8 mm than precipitation between 0.5 and 2.8 mm (the high ETS values in Figure 5a). The poor skill of these methods in predicting precipitation between 0.5 and 2.8 mm was due to high positive bias as indicated by the FBI (Figure 5b). In areas with radar, the CaPA System (as well as regression kriging with CaPA) resulted in higher ETS values than the other interpolation methods when predicting precipitation $<$1.5 mm, but it had the highest negative bias (underestimation) when estimating precipitation $>$2.8 mm (Figure 5b).

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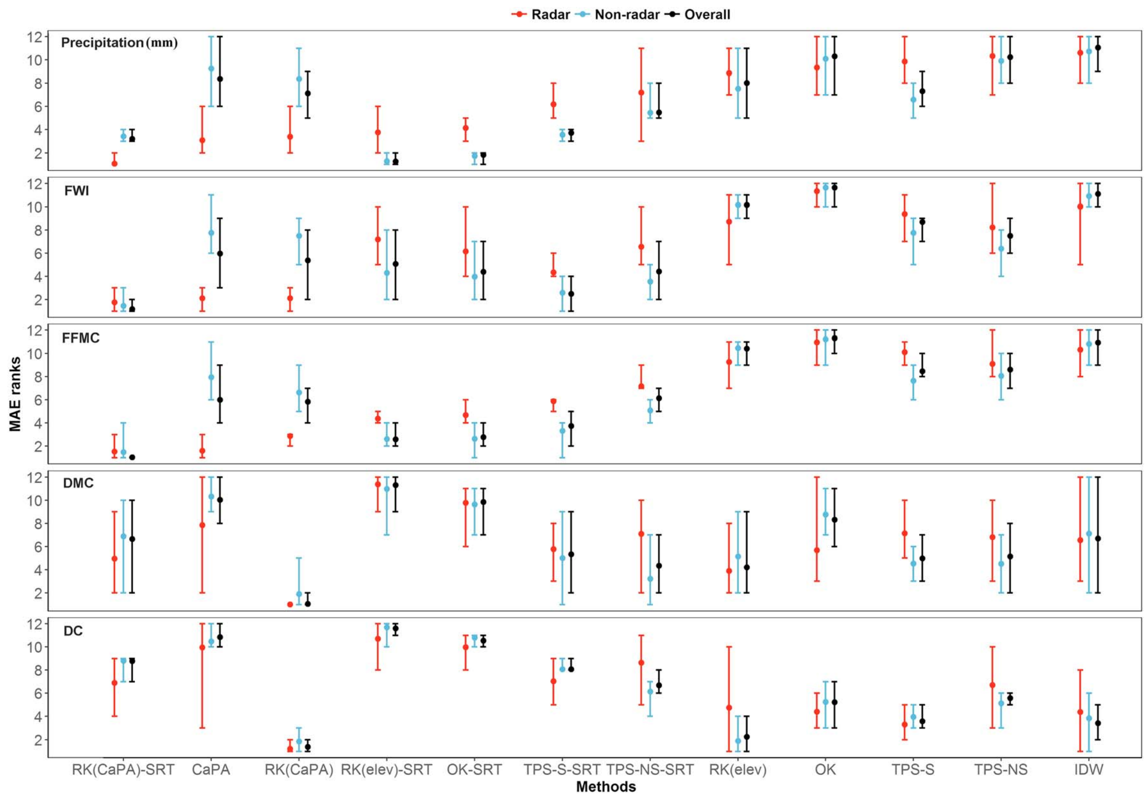

Figure 2. The 95% confidence interval of mean absolute error (MAE) ranks for daily precipitation, FWI, FFMC, DMC, and DC in areas with and without radar, and in the overall validation area averaged from 2014 to 2016. Abbreviations for interpolation methods are given in Table 2. Dots in the middle are mean rank values from 1,000 stationary block bootstrapping resamples. Methods are ordered from best/first (left) to worst/12th (right) according to the mean MAE ranks of precipitation in areas with radar. In the calculations for FWI system indices, temperature, relative humidity, and wind speed were kept unchanged from the observations.

Underestimating precipitation events $>$2.8 mm was especially problematic for DMC and DC as shown in Figure 6. Specifically, when a significant precipitation event of ~40 mm was underestimated at the beginning of the fire season at a location, all the fuel moisture codes were dramatically altered (Figure 6). The FFMC estimates recovered quickly after a few dry days, but DMC and DC remained overestimated for the remainder of the fire season. The CaPA System, which had the highest underestimation of the precipitation, resulted in the most overestimated DC. In contrast, regression kriging with CaPA (without square root transformation) produced the most accurate DC estimates (Figure 6) due to its ability to estimate significant precipitation events.

3.3. Sensitivity to Changes in Weather Station Density

All the interpolation methods produced poorer estimates of daily precipitation and the FWI System indices as weather station density decreased, while the performance of the CaPA System remained unchanged because the CaPA System is not dependant on the CaPA (Figure 7). For the interpolation methods to outperform the CaPA System, a minimum weather station density is required. In particular, for precipitation, a threshold of weather station density $>$ ~0.5/10,000 km^2 is needed for the regression with CaPA to become appreciably better than the CaPA System. This weather station threshold also applied to FFMC and FWI. For DMC and DC, regression kriging with the CaPA System was the best performing method regardless of the weather station density.

4. Discussion

This work assessed the performance of the CaPA System, standard interpolation methods (IDW, TPS, ordinary kriging), as well as regression kriging with CaPA as a covariate in estimating precipitation and the FWI System indices in Alberta, Canada. The CaPA System (version 4.0) integrates precipitation observations from the ECCC weather station network, radar precipitation estimates, and NWP model outputs (Fortin et al., 2015).

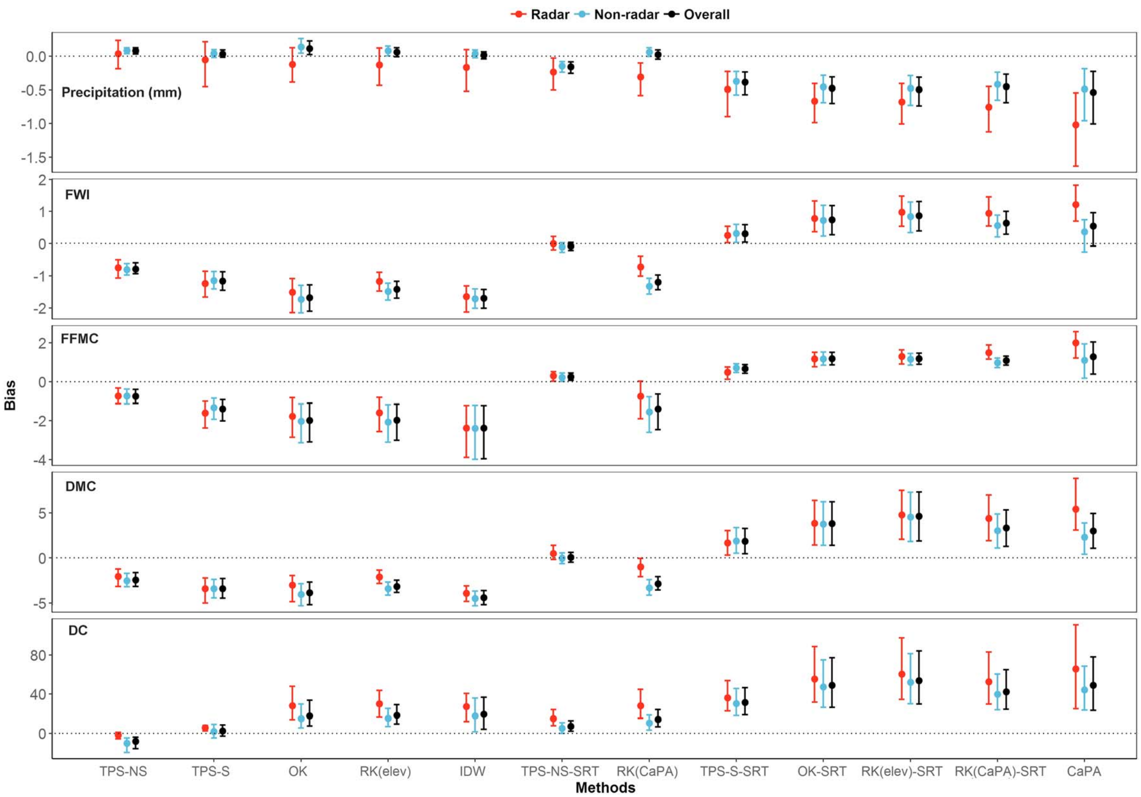

Figure 3. The 95% confidence interval of mean error (bias) values for daily precipitation, FWI, FFMC, DMC, and DC in areas with and without radar, and in overall validation area averaged from 2014 to 2016. Dots in the middle are mean values of the 1,000 stationary block bootstrapping resamples. Methods are ordered from best/first (left) to worst/12th (right) according to the absolute bias values of precipitation in areas with radar. In the calculations for FWI system indices, temperature, relative humidity, and wind speed were kept unchanged from the observations.

The spatial interpolation methods were based on the AAF fire weather station network, which is not currently assimilated into the CaPA System. We found that the CaPA System was only an average-performing method, except within the 120-km Doppler radar range. Lespinas et al. (2015) indicated that the cubic root transformation implemented in the analysis of the CaPA System could result in a large negative bias for the precipitation estimates, which may explain why the CaPA System did not perform the best. However, using the CaPA System as a covariate for regression kriging produced the best precipitation estimates compared to the rest of the examined interpolation methods (IDW, splines, ordinary kriging, regression kriging with elevation), particularly in areas covered by radar. This is the first study where the CaPA System was used as a covariate, and it demonstrates the advantage of using regression kriging to combine gridded precipitation and weather station data as noted by the previous studies (Bardossy & Pegram, 2017; Haberlandt, 2007; Hasan et al., 2016). On the other hand, using elevation as a covariate for regression kriging showed little improvements over ordinary kriging and smoothed splines. This may be because the majority of our study area is covered by the boreal forest, where the landscape is relatively flat, so that the correlation between elevation and daily precipitation is low (Goovaerts, 2000; Gundogdu, 2017). We found that IDW, the default interpolation method for the Canadian Wildland Fire Information System (Englefield et al., 2000; Lee et al., 2002), was the poorest performing methods in estimating precipitation. This result is in agreement with Flannigan and Wotton (1989), who suggested that interpolation methods such as IDW had difficulty in addressing the high spatial variability of summer precipitation due to the convective storms.

We found that the three fuel moisture codes of the FWI System responded differently to the evaluated methods, the reasons for which are twofold. First, predictive errors of the fuel moisture codes are carried-over from one day to the next (error propagation) as a result of the bookkeeping manner of the FWI System (Van Wagner, 1987). Second, the amount of time that is required for the fuels to lose its free moisture (drying

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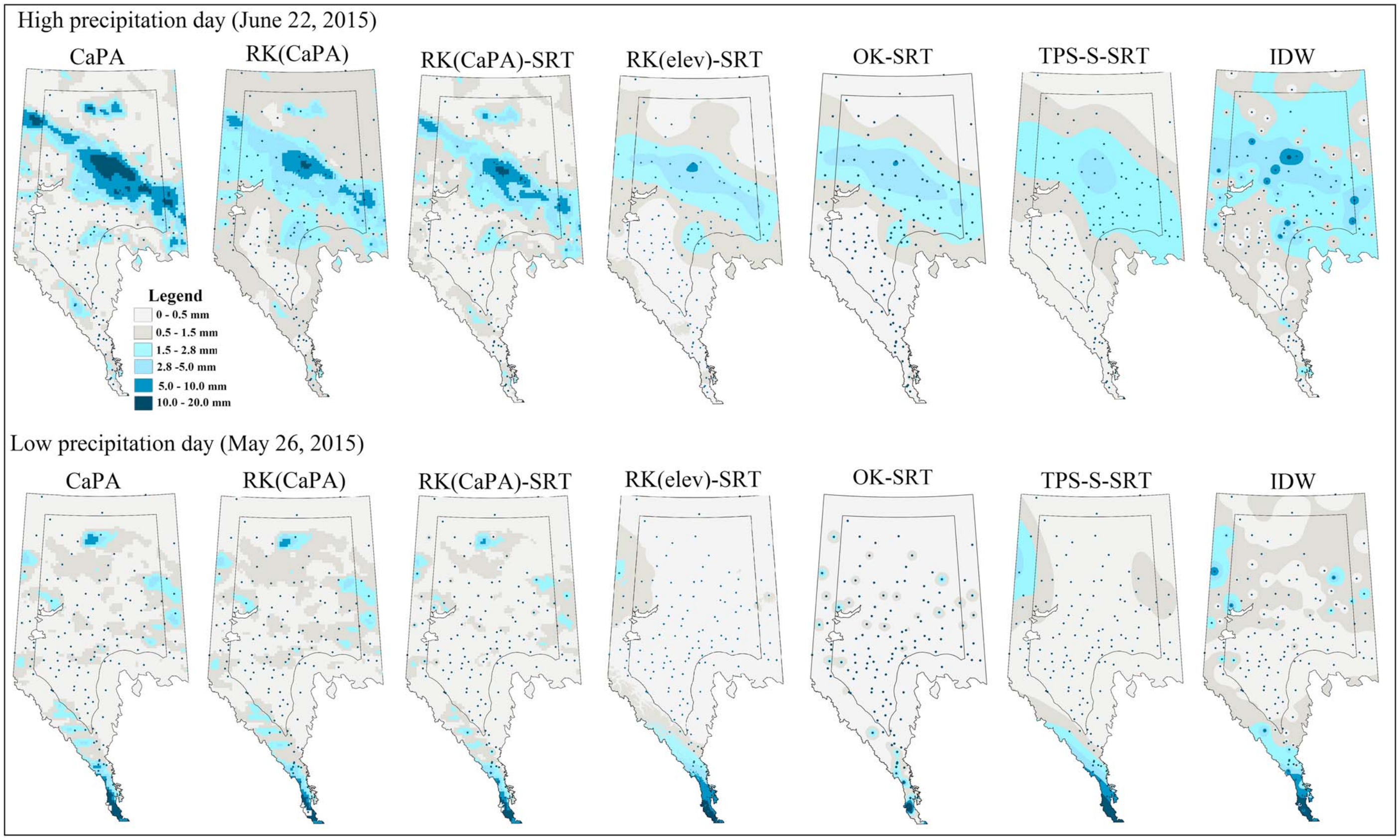

Figure 4. Examples of the 24-hr precipitation estimated using the top- to middle-performing methods and IDW on a light precipitation day (26 May 2015) and a rainy day (on 22 June 2015). Each dot represents a weather station.

time lags) is different for the three fuel moisture codes. FFMC, which has a shorter drying time lag of two or three days, could respond rapidly to precipitation events (Van Wagner, 1987) and, therefore, is less impacted by error propagation. Our results suggest that FFMC was best estimated using precipitation produced by the CaPA System and regression kriging with CaPA, particularly in areas with radar (Figures 2 and 5). This is because accurately estimating small precipitation events is critical for FFMC (Flannigan et al., 1989; Hanes et al., 2017). With the addition of radar precipitation estimates, CaPA System had better skill in predicting small precipitation events than the evaluated interpolation methods, therefore resulting in the best FFMC estimates. On the other hand, DMC and DC are highly impacted by the error propagation due to their long drying time lags of 12 and 52 days, respectively (Van Wagner, 1987). Our results showed that the methods which underestimated significant precipitation events (e.g., the CaPA System) always led to poor estimates of DMC and DC, which is problematic as noted by Horel et al. (2014). Ideally, error propagation could be corrected by calculating fuel moisture codes using the observed previous day's fuel moisture codes. However, this approach is not operationally feasible because observed previous day's fuel moisture codes are only available at the points of weather stations. Alternatively, the wildfire management agencies could correct the error propagation by interpolating previous day's DC and DMC values.

Not surprisingly, we found the performance of interpolation methods decreased with decreasing weather station density as noted by the previous studies (Chen et al., 2008; Herrera et al., 2012; Hofstra et al., 2010). What is novel in our study is that by examining the sensitivity of interpolation methods to station density, we were able to select the optimal methods for mapping fire danger on landscapes with heterogeneous weather station networks. For example, our study showed that the CaPA System was only an average-performing method for fire danger rating in Alberta, whereas Hanes et al. (2017) suggested that the CaPA System had improved performance in estimating precipitation and fire danger rating in the forested areas of Ontario. The conflicting result could be explained by the differences in weather station density between the two studies. Lespinas et al. (2015) suggested that the CaPA System has better performance in areas

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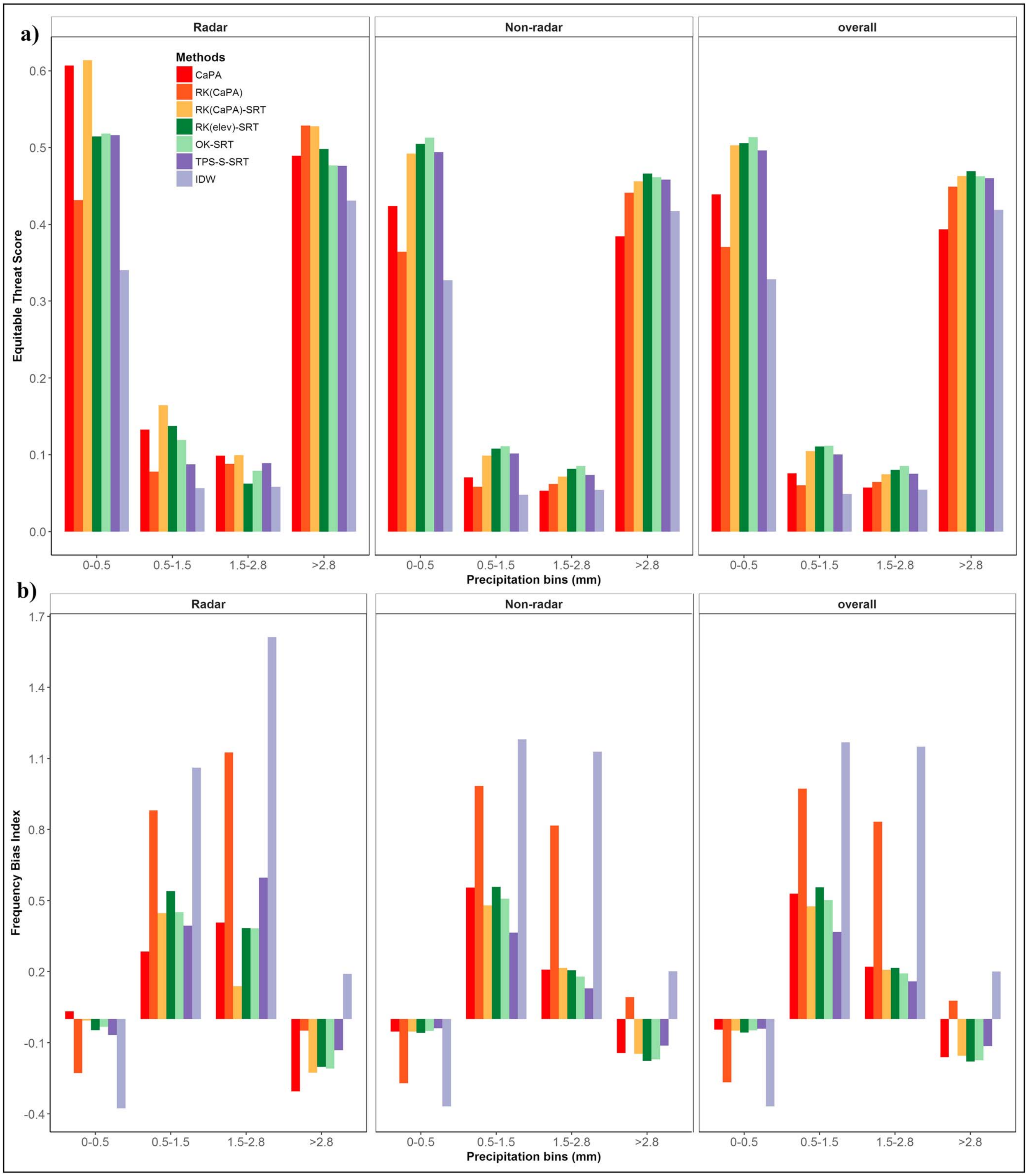

Figure 5. (a) Equitable threat score (ETS) and (b) frequency bias index (FBI) for the top- to middle-performing methods and IDW in areas with and without radar, and in overall validation area averaged from 2014 to 2016. The perfect ETS score is 1 and ETS values <0 indicating no skill. A perfect FBI score is 0 and a positive/negative FBI indicates overestimations/underestimations. Precip ≤0.5 mm has no effect to fuel moisture codes, 0.5 mm < precip ≤1.5 mm only affect FFMC, 1.5 mm < precip ≤2.8 mm only affect DMC, and precip >2.8 mm affect DMC and DC.

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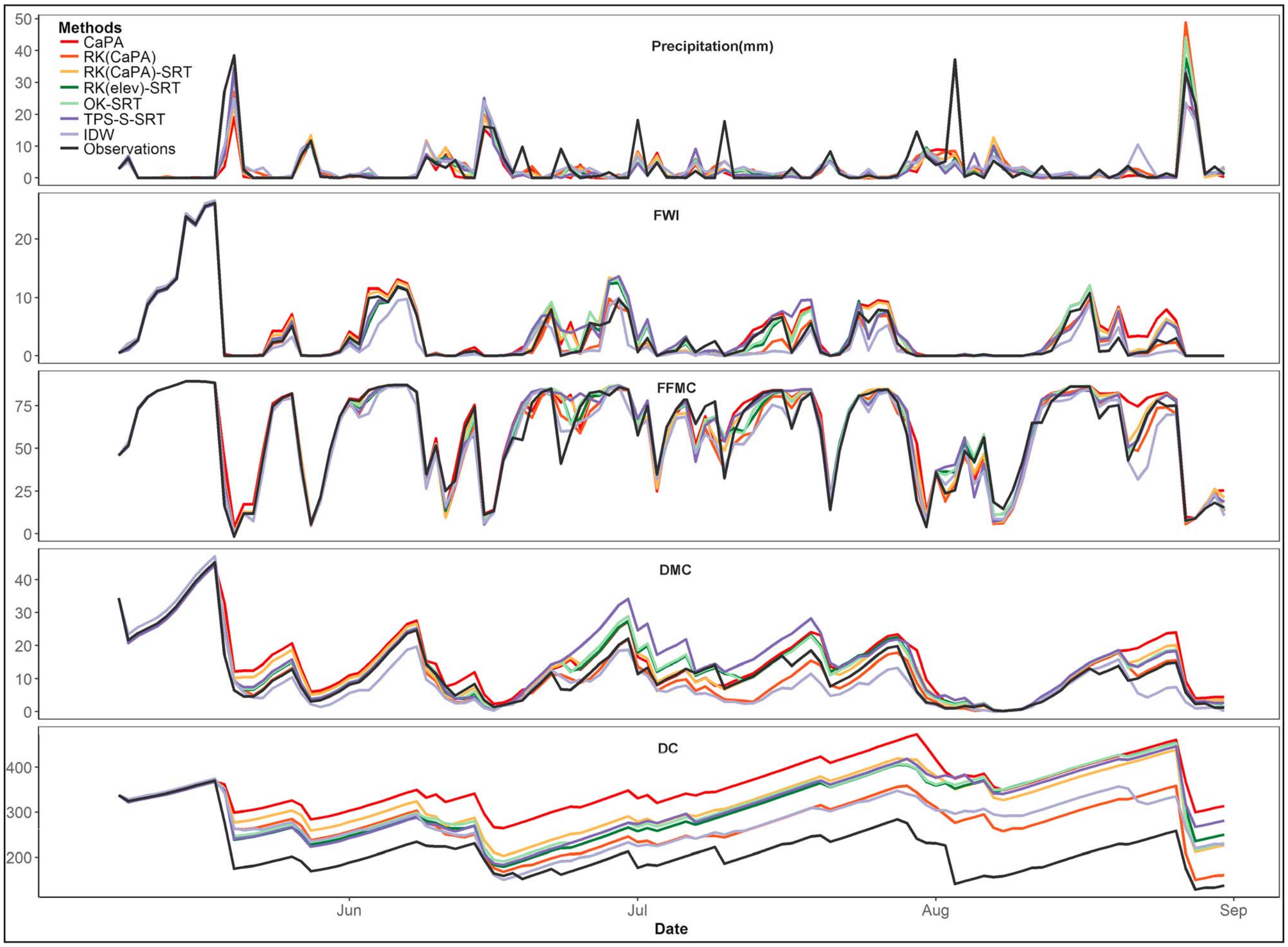

Figure 6. Time series plots of observations versus estimates for daily precipitation and the derived FWI system indices for the top- to middle-performing methods and IDW at Whitemud lookout tower in 2016 (116 days). Whitemud lookout tower is within the 120-km Doppler radar range.

with a denser weather station. Since the ECCC station network densities were 1.13 and 0.38/10,000 km^2 in Alberta and Ontario, respectively, we expected that CaPA (at least outside of radar regions) would produce better performance in Alberta. However, the AAF fire weather station density (3.1/10,000 km^2), which is a separate station network from ECCC, was much higher than the ECCC station network in Alberta and allowed some of the interpolation methods to outperform the CaPA System in Alberta. Our sensitivity analysis showed that when fire weather station density was below ~0.5/10,000 km^2, the CaPA System produced the best precipitation estimates, which is a result similar to Hanes et al. (2017). A better understanding of the sensitivity derived from weather station density will provide valuable information to aid the proper use and application of the FWI System.

Improved fire danger rating, as measured by the FWI System, will provide valuable contributions to both the fire management agencies and research community (Taylor & Alexander, 2006; Wotton, 2009). We propose that fire danger indices can be improved by using regression kriging to combine gridded CaPA System precipitation estimates and weather station data. Alternatively, we recommend that ECCC assimilates the AAF fire weather station network into the CaPA System for more accurate precipitation estimates as the two weather station networks are independent.

There are some caveats with this study. First, we compared the performance of the CaPA System and interpolation methods in radar and nonradar covered areas, but only 10% of our study area was covered by radar, which is not ideal for comparison. Second, the ECCC weather stations remained unchanged in the sensitivity analysis of weather station density. The density of the ECCC weather station network varies across the landscape (Lespinas et al., 2015). Therefore, the threshold weather station density (0.5/10,000 km^2) we had for

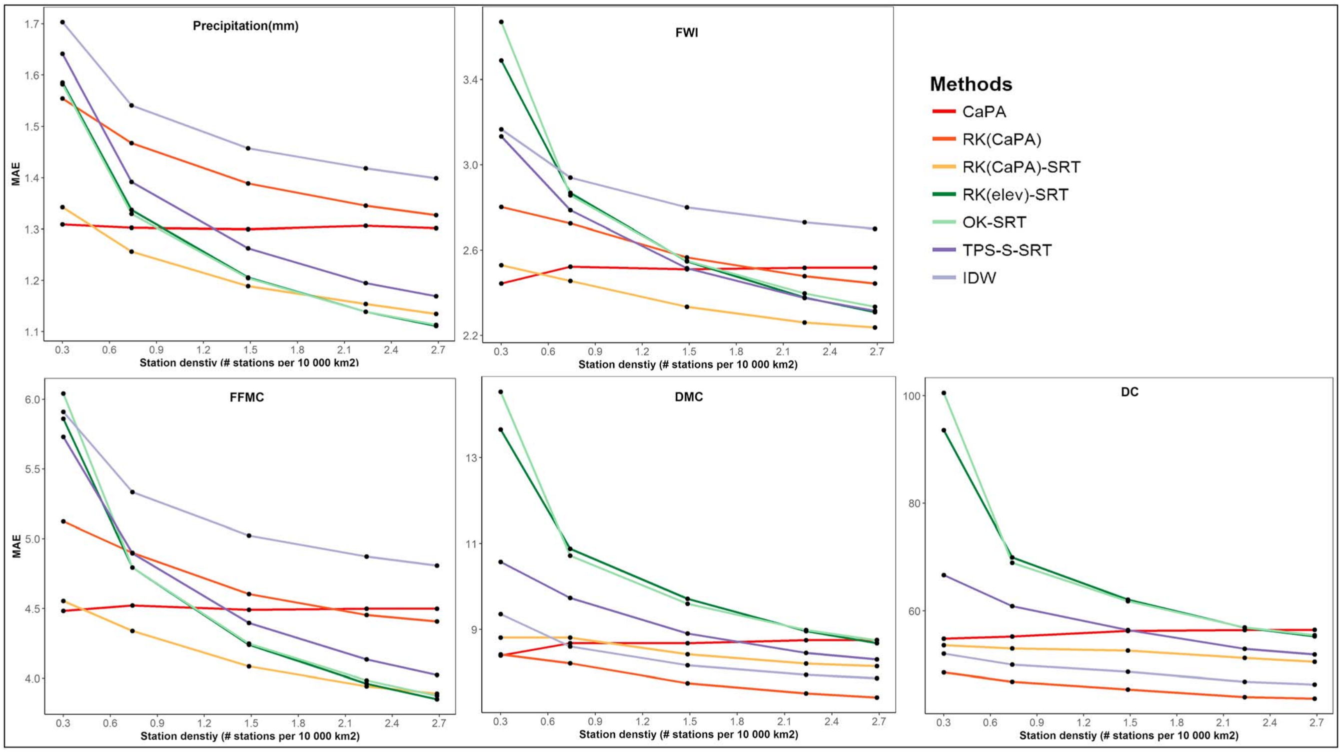

Figure 7. MAE values of precipitation and FWI system estimates for the CaPA system and the examined spatial interpolation methods in varying weather station densities. Dots are the mean MAE values resulted from the random resampling (n = 100) and are averaged for the years from 2014 to 2016 for each weather station density scenario.

Alberta may vary slightly in other areas according to the ECCC weather station density. Third, because the distribution of the AAF FW station network is irregular throughout the study area, there may be anisotropy in the spatial covariance of the observations. For future study, we therefore suggest evaluating the use of angular distance weighting (Hofstra & New, 2009) or anistropic kriging (Friedland et al., 2017) to deal with any anisotropy. Last, we evaluated a specific configuration of the CaPA System (version 4.0), which did not yet integrate satellite-based precipitation analyses. Work on integrating satellite-based precipitation analyses into the CaPA System is currently undergoing (Boluwade et al., 2017; Friesen et al., 2017). Future work on assessing fire danger using precipitation products should include evaluation of this newer version of CaPA as well as other satellite-based precipitation products such as the Global Precipitation Measurement (Smith et al., 2007), Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (Sorooshian et al., 2005), or the Global Precipitation Climatology Project (Huffman et al., 2009).

5. Conclusions

Improving our understanding of the FWI Systems will aid in its proper use and application. This work addressed one of the biggest challenges in mapping regional fire danger indices by comparing the gridded CaPA System with the six spatial interpolation methods in Alberta, Canada. We found that the CaPA System was only an average-performing method on its own, but resulted in the best precipitation estimates when used as a covariate for regression kriging. This is the first time of using regression kriging to combine gridded precipitation (i.e., the CaPA System) and weather station data in a fire danger mapping context. We believe that the addition of regression kriging and the CaPA System to the field of fire danger mapping will provide valuable information for both fire management agencies and the research community. We also performed a weather station density analysis to aid method selection for mapping regional fire danger. As the performance of interpolation methods increased with the increasing weather station density, we found that a threshold of 0.5 weather stations/10,000 km^2 or more was necessary for the regression with the CaPA System as a covariate to significantly outperform the CaPA System.

Acknowledgments

Historical fire weather station data are provided by Alberta Agriculture and Forestry and can be accessed by request (http://wildfire.alberta.ca/resources/historical-data/wildfire-weather-data.aspx). Historical CaPA System precipitation data are provided by Environment and Climate Change Canada and can be downloaded online from http://collaboration.cmc.ec.gc.ca/science/outgoing/capa.grib/. This research is funded by Alberta Agriculture and Forestry, as well as Flannigan's NSERC Discovery Grant. We are grateful to Bo Lu, Brett Moore, and Chelene Hanes for their valuable suggestions and discussion. We also thank Sean Coogan for commenting on the manuscript.

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