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Supplementary material

A simulation and optimisation procedure to model daily suppression resource transfers during a fire season in Colorado

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Section S1. Regression models to predict next-day engine and crew demands in each of the CO dispatch zones

The archived 2010-2013 ROSS data for daily engine and crew assignments are summarised in Figs S1 and S2. We first tested whether these daily engine and crew demands in each zone were stationary using the Dickey-Fuller test (Said and Dickey 1984). Test results showed that both the engine and crew demands in CRC, GJC and MTC were stationary, while the demands in DRC, FTC and PBC were non-stationary (Table S1). For the three zones with stationary resource demand data, we used regression models to directly predict the engine or crew demand at day *t* in each zone. For the other three zones with non-stationary resource demands, we built a first-difference model for each dispatch zone to predict the change in engine and crew demands from day (t – 1) to day *t* in that zone. We also evaluated the goodness of fit of those models using an out-of-sample R^2. To do this, we divided the four years into two sub-periods. The first sub-period was from 2010 to 2012, which was used for model fitting. The second sub-period consists of data from 2013, which was used to evaluate the forecasting performance of the fitted models by calculating the R^2 values. The following independent variables were initially tested for all models:

1) The one-day lagged number of engine or crew demands in each zone at day (t – 1). The coefficients of these variables were set to 1 if the first-difference models were used.
2) The change in engine or crew demands in each zone from day (t – 2) to (t – 1). The coefficients of these variables would not be zero if the first-difference models were used.
3) The number of new fires in day (t – 1).
4) A binary dummy variable indicating if the one-day PS outlook for day t was greater than or equal to 2. Because we were interested in one-day predictions of resource demands, we only used the one-day PS forecast. If the predicted fuel moisture for day t is low (the dummy variable is set to 1), we would expect higher resource demands.
5) A binary variable tracking whether there have been higher total resource demands (the total count of all engines, crews, air-tankers, helicopters and fire teams) from day (t – 2) to (t – 1). We used this binary variable to approximate the overall trend of fire suppression resource demands from day (t – 2) to (t – 1).

Positive coefficients were expected from all independent variables. After testing these variables using regression analyses, only independent variables with p-values ≤ 0.05 and having positive coefficients were kept in the prediction models. All model coefficients are displayed in Table S2 and S3.

We used R© (R Core Team 2013) to conduct the Durbin-Watson test (DW test; in Table S1) to check for serial correlation in prediction residuals for all of the prediction models in Table S2 and S3. Although Durbin's H test would be less biased than the DW test, we found the H-statistic is not well-defined for some of the models estimated in this study. The DW test did not reject the hypothesis that no autocorrelation is found in the prediction residuals.

Examining the prediction residuals (Fig. S3) with the daily resource demands (Figs S1 and S2) showed that prediction residuals are likely heteroscedastic, larger prediction residuals often occur during days with larger resource demands. Although the prediction errors do not cause bias in the estimation of the coefficients, heteroscedasticity could lead to overestimation of the goodness of fit for those models. Additional predictors and data could be added to improve these models during future studies.

For the in-sample tests using all data from 2010 to 2013, the R^2 values ranged from 0.8 to 0.97 for the engine demand prediction models, and from 0.81 to 0.96 for the crew demand prediction models (Table S1). We conducted out-of-sample tests by fitting the coefficients of the engine and crew demand models using historical data between 2010 and 2012, and then testing those models using the 2013 data. Out-of-sample tests gave us a range of R^2 values between 0.37 and 0.96 for engine demand predictions, and between 0.7 and 0.97 for crew demand predictions (Table S1). The lowest out-of-sample prediction accuracy was from the model predicting 2013 daily engine demand for FTC, potentially due to the model overfitting engine demand between 2010 and 2012. Including the 2013 data when fitting the final model should help with some of the overfitting issues. In the future, additional out-of-sample tests could also be conducted with ROSS data from 2014 and 2015 for further model improvement.

Each of the wildfires in our ROSS dataset only lasted a small portion of a fire season. We estimated a random effects version of a pooled data model in this study. We did not estimate fire-level (cross-sectional) fixed effects or day-level (time) fixed effects in these models. Exploration of more advanced models to fit those pooled data could be interesting future research.

Table S1. Dickey Fuller tests (DF tests) show stationary engine and crew demands in Craig (CRC), Grand Junction (GJC) and Montrose (MTC), and nonstationary demands in the other three zones (Durango (DRC), Fort Collins (FTC), Pueblo (PBC))

The Durbin Watson test (DW test) exams the autocorrelation of prediction residuals from either the first difference models for nonstationary demand data or the direct 1-day lagged prediction model for stationary data. The out-of-sample R^2 is used to evaluate the structure of each model; for these tests, model coefficients are fit using the 2010 to 2012 data, and each model is tested by only using the 2013 data. (S) stationary data; (N) nonstationary data

Zone and Res. type	DF test	In-sample R^2	DW test	Out-of-sample R^2
CRC				
Engine	–5.97 (S)	0.80	2.11	0.83
Crew	–5.40 (S)	0.85	2.15	0.86
DRC				
Engine	–2.36 (N)	0.97	1.97	0.96
Crew	–2.98 (N)	0.95	2.02	0.97
FTC				
Engine	–2.42 (N)	0.97	2.18	0.37
Crew	–3.10 (N)	0.96	2.08	0.70
GJC				
Engine	–5.54 (S)	0.84	2.08	0.78
Crew	–5.82 (S)	0.81	2.00	0.82
MTC				
Engine	–5.12 (S)	0.85	2.00	0.86
Crew	–4.84 (S)	0.86	1.88	0.87
PBC				
Engine	–3.13 (N)	0.95	2.04	0.93
Crew	–3.05 (N)	0.95	2.12	0.94

Table S2. Coefficients of the linear regression models fit using 2010 to 2013 data to predict the next day engine demands in each zone (Craig (CRC); Durango (DRC); Fort Collins (FTC); Grand Junction (GJC); Montrose (MTC); Pueblo (PBC))

The number of observations includes only fire days from 2010 to 2013. The numbers inside parentheses are the standard errors for the corresponding coefficients. The coefficient for 'Engine demands (t – 1)' is set to 1 when the first-difference model is used

	Dependent variable:					
	Engine Demands (t)					
	(CRC)	(DRC)	(FTC)	(GJC)	(MTC)	(PBC)
Engine demand (t-1)	0.842***	1.000	1.000	0.865***	0.882***	1.000
	(0.021)			(0.017)	(0.017)	
Demand change (t-2) to (t-1)	0.149***	0.269***	0.416***	0.253***	-0.112**	0.411***
	(0.040)	(0.041)	(0.037)	(0.040)	(0.043)	(0.037)
New fires (t-1)	0.066**					
	(0.032)					
PS dummy	0.537***					0.778**
	(0.177)					(0.393)
More resources in (t-2) than in (t-1)		0.999**		0.895***	0.808***	
		(0.427)		(0.219)	(0.132)	
Constant	0.012	-0.148	0.006	0.023	-0.001	-0.162
	(0.090)	(0.156)	(0.191)	(0.085)	(0.033)	(0.179)
Observations	596	596	596	596	596	596
Note:				*p<0.1; **p<0.05; ***p<0.01;		

Table S3. Coefficients of the linear regression models fit using 2010 to 2013 data to predict the next day crew demands in each zone (Craig (CRC); Durango (DRC); Fort Collins (FTC); Grand Junction (GJC); Montrose (MTC); Pueblo (PBC))

The number of observations includes only fire days from 2010 to 2013. The numbers inside parentheses are the standard errors for the corresponding coefficients. The coefficient for 'Crew demand ($t-1$)' is set to 1 when the first-difference model is used

	Dependent variable:					
	Crew Demand (t)					
	(CRC)	(DRC)	(FTC)	(GJC)	(MTC)	(PBC)
Crew demand (t-1)	0.856***	1.000	1.000	0.867***	0.901***	1.000
	(0.017)			(0.019)	(0.017)	
Demand change (t-2) to (t-1)	0.334***	0.186***	0.180***	0.150***		0.341***
	(0.038)	(0.044)	(0.043)	(0.040)		(0.038)
New fires (t-1)	0.048**			0.034**		
	(0.020)			(0.017)		
PS dummy (t-1)	0.275**			0.282***		0.536***
	(0.113)			(0.081)		(0.196)
More resources in day (t-1) than in (t-2)		0.406**	0.530**		0.278***	
		(0.167)	(0.237)		(0.077)	
Constant	0.018	-0.060	-0.066	-0.019	0.011	-0.111
	(0.058)	(0.059)	(0.078)	(0.046)	(0.021)	(0.089)
Observations	596	596	596	596	596	596
Note:						*p<0.1; **p<0.05; ***p<0.01;

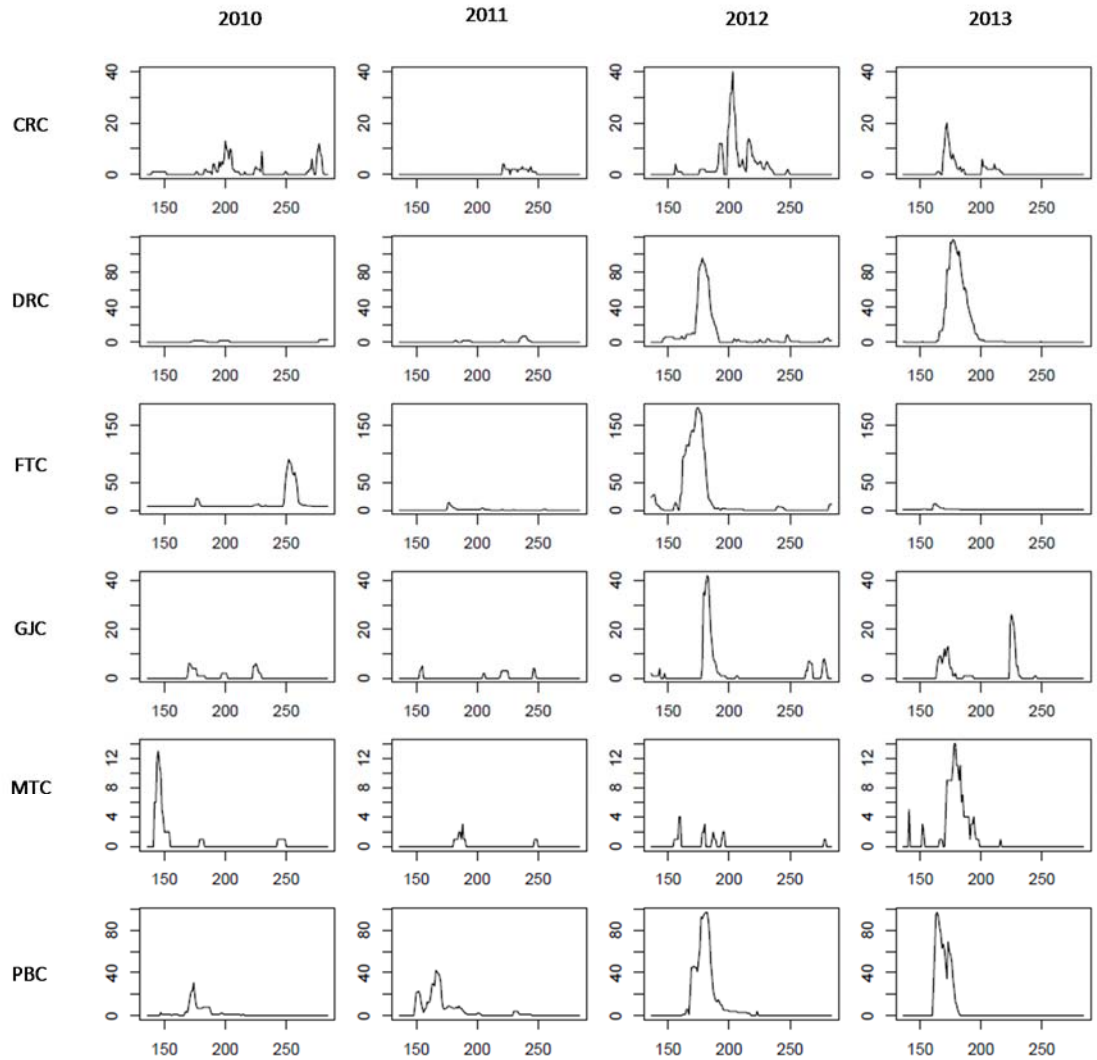

Fig. S1. The daily engine demands in each of the dispatch zones from 2010 to 2013. Each row represents one dispatch zone (Craig (CRC); Durango (DRC); Fort Collins (FTC); Grand Junction (GJC); Montrose (MTC); Pueblo (PBC)). Each column represents a year from 2010 to 2013. The y-axis represents the number of engines demanded; the x-axis represents the day of year.

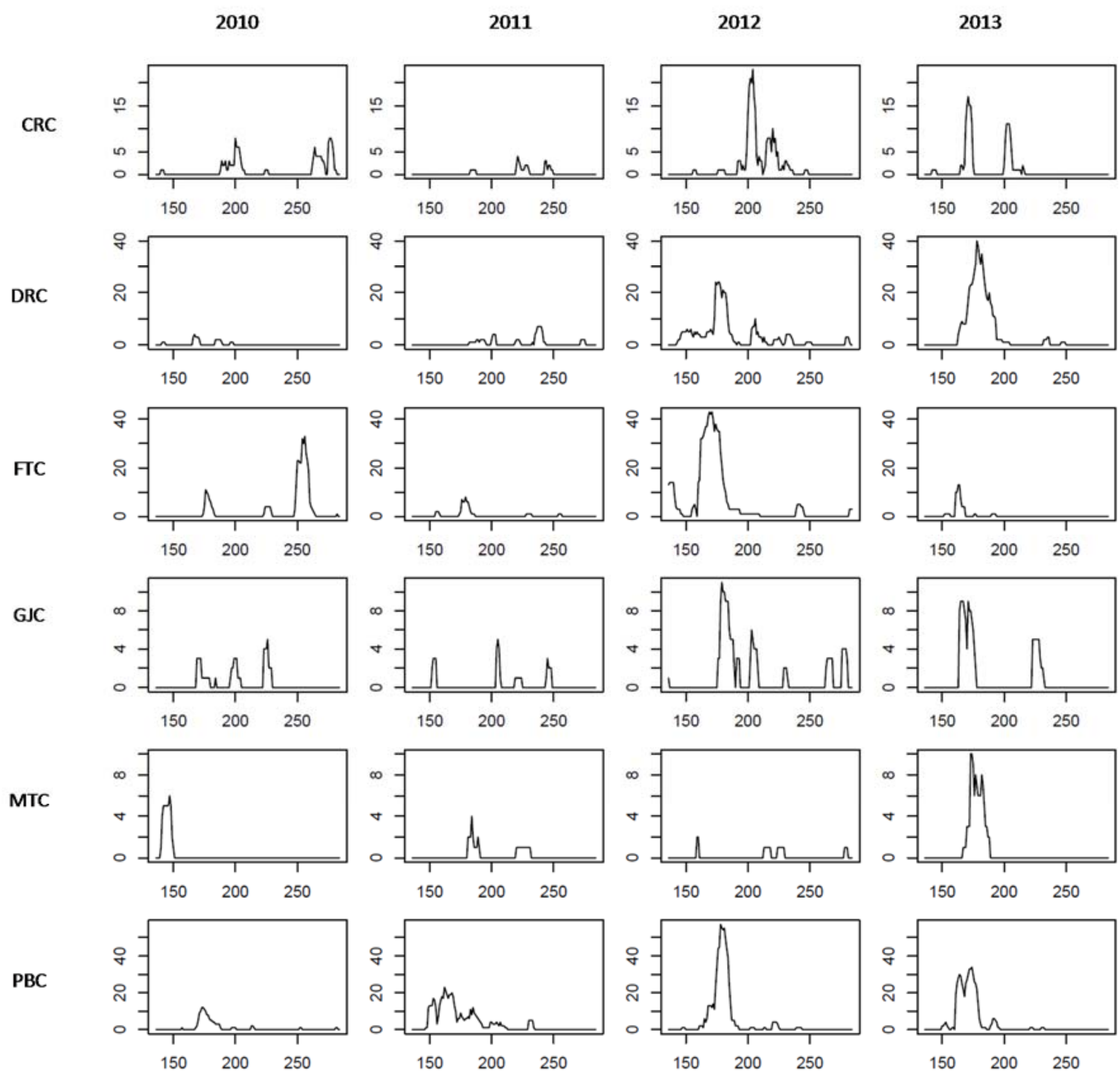

Fig. S2. The daily crew demands in each of the dispatch zones from 2010 to 2013. Each row represents one dispatch zone (Craig (CRC); Durango (DRC); Fort Collins (FTC); Grand Junction (GJC); Montrose (MTC); Pueblo (PBC)). Each column represents one year from 2010 to 2013. The y-axis represents the number of crews demanded; the x-axis represents the day of year.

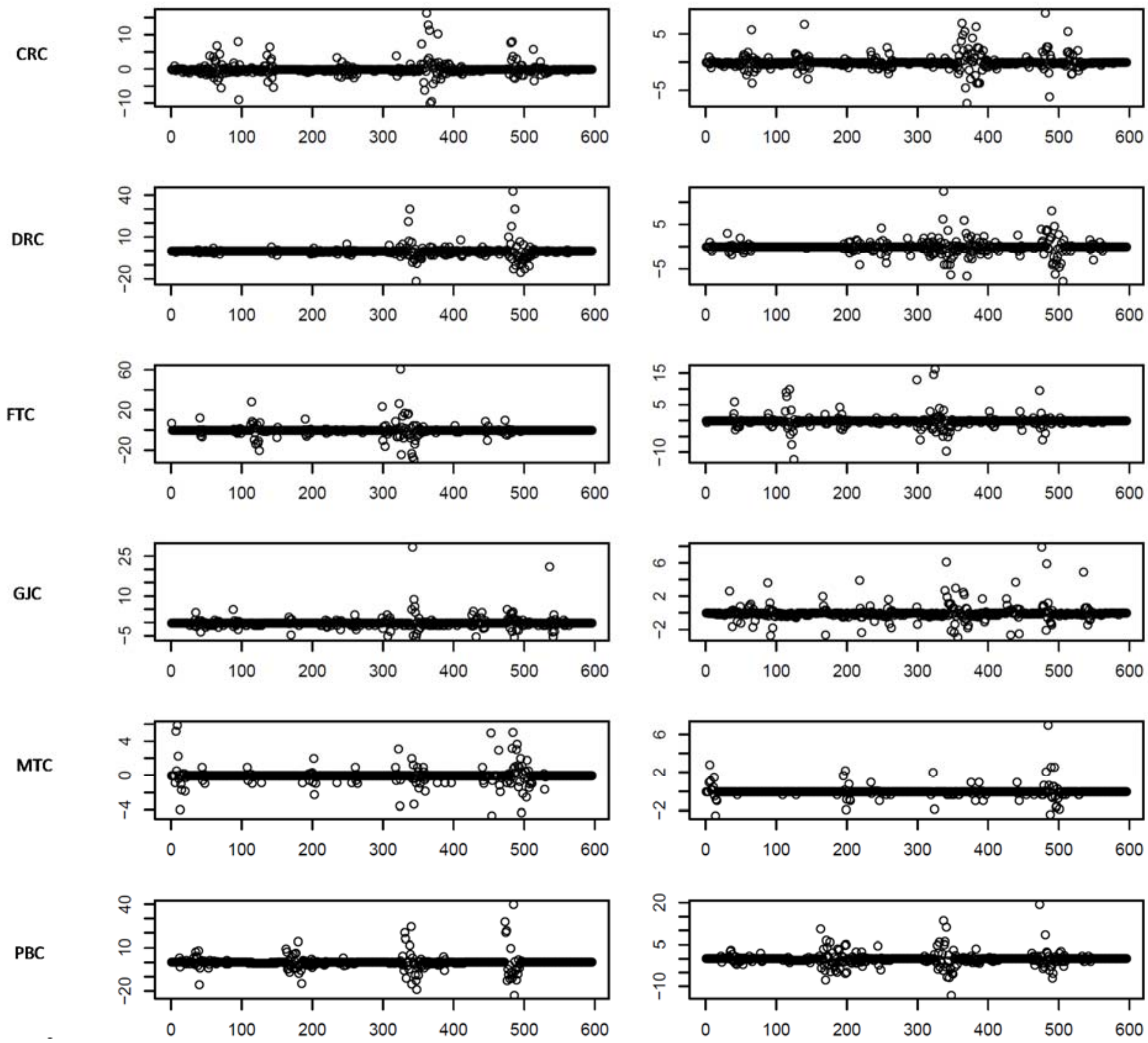

Fig. S3. The residuals for each of the prediction models. Each row represents one dispatch zone (Craig (CRC); Durango (DRC); Fort Collins (FTC); Grand Junction (GJC); Montrose (MTC); Pueblo (PBC)). The left column shows the residuals of engine demand prediction following the sequence of days during the fire seasons from 2010 to 2013 (days outside of fire seasons are omitted); the right column includes the residuals from crew predictions.

References

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