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

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Abstract. Sharing fire engines and crews between fire suppression dispatch zones may help improve the utilisation of fire suppression resources. Using the Resource Ordering and Status System, the Predictive Services' Fire Potential Outlooks and the Rocky Mountain Region Preparedness Levels from 2010 to 2013, we tested a simulation and optimisation procedure to transfer crews and engines between dispatch zones in Colorado (central United States) and into Colorado from out-of-state. We used this model to examine how resource transfers may be influenced by assignment shift length, resource demand prediction accuracy, resource drawdown restrictions and the compounding effects of resource shortages. Test results show that, in certain years, shortening the crew shift length from 14 days to 4 days doubles the yearly transport cost. Results also show that improving the accuracy in predicting daily resource demands decreases the engine and crew transport costs by up to 40%. Other test results show that relaxing resource drawdown restrictions could decrease resource transport costs and the reliance on out-of-state resources. The model-suggested assignments result in lower transport costs than did historical assignments.

Additional keywords: fire management, modelling, planning.

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Introduction

Over recent decades, fire suppression has played an important role in protecting natural resources, human lives and properties from wildland fires in the United States (US). The US Forest Service (USFS) contained ~98% of fires reported between 1970 and 2002 before they grew to exceed 121 ha (~300 acres, a threshold commonly used to designate escaped fires in the US; Calkin *et al.* 2005). However, fuel accumulation, climate change and expansion of the wildland–urban interface have all contributed to a substantial increase in suppression costs in recent history. From fiscal year (FY) 1991 through FY 1999, federal fire expenditures averaged US$1.39 billion per year; since FY 2002, costs have increased to an average of US$3.51 billion per year (Headwater Economics 2013). In FY 2015, fire suppression costs comprised over half of the total annual USFS budget, which was ~US$4.8 billion (USDOI and USDA 2015*a*), and by 2025, fire suppression costs are projected to make up 67% of the agency's budget (USDA Forest Service 2015).

Studies show wildfires can significantly affect human populations and critical watersheds in Colorado (CO; Thompson *et al.* 2013; Haas *et al.* 2015; Liu and Wimberly 2015). Several fire seasons on the CO Front Range have set state records for the number of structures burned (Calkin *et al.* 2014). According to the 2015 State of Colorado House Joint Resolution, during the 1990s and early 2000s, the annual average area burned has tripled (State of Colorado 2015). CO's vulnerabilities to wildland fire incentivise the design and implementation of decision support models to study suppression resource assignments.

Allocating limited suppression resources to fires presents challenging decision problems (Petrovic *et al.* 2012; Martell 2015). Past models have been built to determine optimal seasonal resource stationing and dispatching for initial attack (IA; e.g. Haight and Fried 2007; Ntaimo *et al.* 2012, 2013; Lee *et al.* 2013; Gallego Arrubla *et al.* 2014; Wei *et al.* 2015), support suppression placement decisions on a single fire (e.g. Ntaimo *et al.* 2004; Alexandridis *et al.* 2011; Wei *et al.* 2011; Belval *et al.* 2015), allocate resources to home bases (Chow and Regan 2011), protect assets at risk using vehicle speed and road network data (van der Merwe *et al.* 2015) and integrate fuel management and suppression preparedness decisions to maximise areas covered by suppression resources (Minas *et al.* 2015). Each of these models examined an important aspect of fire management, but suppression resource sharing has not been systemically modelled.

In this study, we present a mixed integer program (MIP) to examine daily assignments of engines and crews for dispatch zones in CO over a fire season. Historical resource assignments and forecasts of fire activity provide a basis for our model design and test cases. A simulation and optimisation procedure assigns crews and engines to meet predicted next-day suppression demands at each dispatch zone in CO. Using this method, we examine how such assignments, and associated transfers of resources, may be affected by shift length, the accuracy of resource demand predictions, resource drawdown restrictions and the compounding effects of resource shortages. We also compare historical assignments with those suggested by the model. Our method provides a framework to support a state-wide decision process for allocating resources and allows us to examine the effect of several widely implemented fire suppression policies.

Material and methods

Data used for model parameterisation

CO houses six interagency dispatch centres, located in Craig (CRC), Durango (DRC), Fort Collins (FTC), Grand Junction (GJC), Montrose (MTC) and Pueblo (PBC; Fig. 1*a*). Each dispatch centre coordinates IA and resource mobilisation within its dispatch boundary (PIDC 2015). We used the name of the dispatch centre to represent the corresponding dispatch zone. Five of the dispatch zones are completely within CO. A portion of the PBC dispatch zone lies in Kansas. In this study, we only considered fires that originate within CO. Each crew or engine is owned by a federal or state agency, county, city, contractor or other individual, and is associated with a home base, the locations of which are shown in Fig. 1*a*. During a fire season, resources from outside CO are crucial in meeting suppression needs in CO, particularly during times of high resource demand. We treated any engine or crew moving into CO as though they were from a single external dispatch zone.

The Predictive Services (PS) program was developed in the US to support suppression resource allocation decisions, including providing predictions of significant fire activity (Predictive Services 2016). PS issues the 7-day climate- and weather-based Significant Fire Potential Outlook (a.k.a. 7-Day Outlook) on weekdays during the fire season for Predictive Service Areas (PSAs; Owen *et al.* 2012). Fig. 1*b* shows the PSAs within CO. A 7-Day Outlook value of 1 indicates 'moist', 2 indicates 'dry' and 3 indicates 'very dry' fuel conditions; values 4–9 are not scaled and indicate elevated fire potential due to factors such as lightning and atmospheric instability. A study by Riley *et al.* (2015) for the North-west and South-west Geographic Coordination Areas found that the 7-Day Outlook values are useful predictors of fire ignitions, fire escapes and large fire activities. We incorporated PS Outlook values into our analysis using regression models to predict zone-specific, next-day engine and crew demands.

The National Interagency Resource Ordering and Status System (ROSS), a database-driven dispatching program, is chartered by the National Wildfire Coordinating Group. ROSS supports resource mobilisation in ~400 interagency dispatch and coordination offices throughout the nation, including CO, by tracking resource requests and dispatching activities. Historically, ROSS was routinely used for fires that requested suppression resources beyond the local resource owner, for example, a national forest. IA activities involving only local suppression resources may not be reflected in historical ROSS records. Thus, ROSS data are appropriate for use in analyses examining interagency and interregional collaboration during suppression. Although ROSS does not include all fires in CO, it houses the most complete set of information on assignments involving multiple agencies and dispatch zones (NIFC 2016). We used ROSS records from 2010 to 2013, which include archived resource use information for 1036 fires in CO. For comparison, the Fire Occurrence Database (Short 2015) has records on 8721 fires in CO during this period, most of which did not require suppression resource assignments between multiple agencies and zones. The locations of the fires from ROSS are

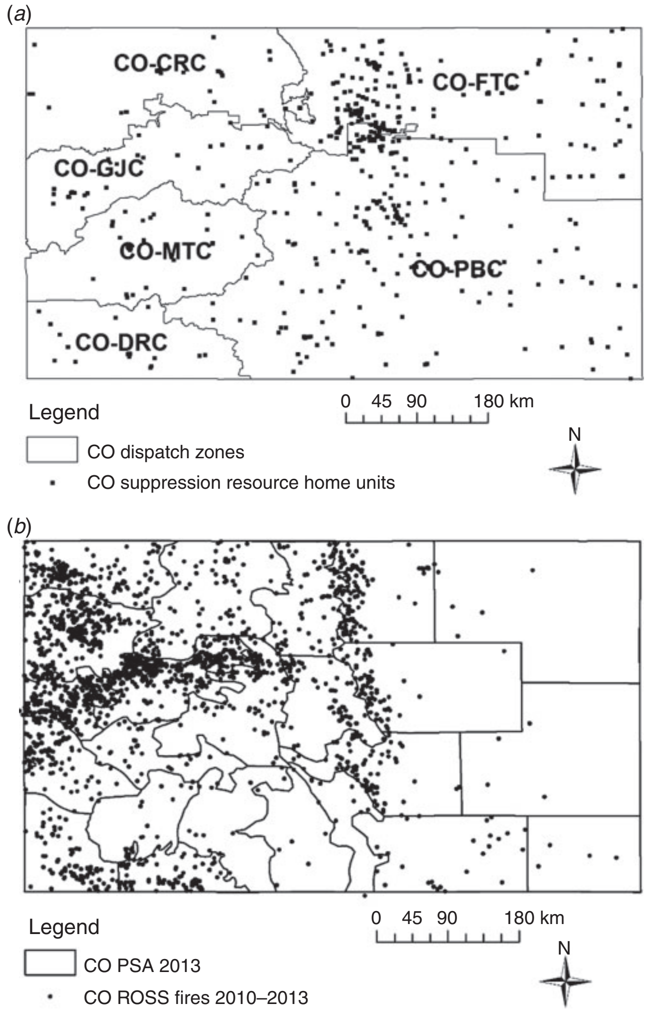

Fig. 1. Maps showing (*a*) the six dispatch zones in Colorado (CO) and the locations of suppression resource home bases (Craig, CRC; Durango, DRC; Fort Collins, FTC; Grand Junction, GJC; Montrose, MTC; Pueblo, PBC); (*b*) Predictive Service Areas (PSAs) in CO in 2013 and the Resource Ordering and Status System (ROSS) fire ignition locations from 2010 to 2013.

shown in Fig. 1*b*. We used the numbers of engines and crews that were assigned to all fires within a dispatch zone from ROSS records as the actual fire suppression demand on each day.

Following the mobilisation guides of the Arapaho-Roosevelt National Forest and Pawnee National Grassland (2015) and the Montrose Interagency Dispatch Center (2015), we defined the core fire season in CO to be from the 135th day of each year (14 or 15 May) to the 284th day of each year (10 or 11 October); consequently, we only examined assignments during this period. We modelled two categories of resources: crews and engines. Crews are groups of 18–20 firefighters who work as a team (NIFC 2016). Engines are tanked vehicles with specific pumping, tank capacity and crew requirements; these are classified as Type 1–7 (NIFC 2016). Because crews and engines are often dispatched under different geographic conditions (e.g. slope, roads and terrain), fire intensities and fuel types, and because past research is lacking in quantifying the potential substitution between the two resource types, we did not model any substitution between crews and engines.

Our model minimised the daily engine and crew transport costs incurred in CO. We used the geodesic distance measured in degrees between the centroids of each pair of dispatch zones to approximate the average transport cost for moving resources between zones (http://support.esri.com/en/knowledgebase/Gisdictionary/term/geodesic [Verified 6 October 2016]). These distances ranged from 1.01°–4.99° for the six zones (1° is ~110 km). For out-of-state resources, we arbitrarily assumed the transport distance was 6 degrees; this assumption guaranteed that the model would use all available resources in CO before calling on out-of-state resources. For resources assigned within a dispatch zone, we assumed the transport cost was half of the distance to the centroid of its closest adjacent dispatch zone; this incentivised the model to first use resources that are already within the dispatch zone in which the fire ignited. In future studies, the travel distances for resources from out-of-state locations or within each zone could be more precisely specified for better bookkeeping, but it would not influence the resource assignment decisions made by our model. The costs to move each resource between zones and to move out-of-state resources into CO were held constant for all model runs. Because of these assumptions, the model reported transport costs do not reflect real world costs; rather we compare the relative costs to examine the differences in assignments between model runs.

Prediction of the next-day resource demands

The simulation and optimisation procedure requires prediction of the next-day engine and crew demands from all dispatch zones to guide resource movement. Factors influencing resource demands are complicated and may include weather, vegetation, nearby housing, new and ongoing fire activity, fuel conditions, and resource commitment and availability (NMAC 2008; Preisler *et al.* 2011; Hand *et al.* 2016). Some of these data are available in real time; others also rely on predictions. In this paper, we used ROSS data to build linear regression models to predict the next-day engine and crew demands for each zone. The details of these regression models are explained in the online supplementary material. Predicting suppression resource demands is a challenging task because of the stochasticity of wildland fire occurrence, wildland fires' various social, economic and ecological effects on human and natural systems, and the complexity and uncertainty inherent in the fire suppression decision making process. The regression models used in our work provide predictions required by the simulation and optimisation procedure to study the effect of imperfect prediction of next-day resource demands; these models could be enhanced through further studies.

Resource shift length

According to the Interagency Standards for Fire and Fire Aviation Operations (USDOI and USDA 2015*b*), assignments of suppression resources to incidents usually will not exceed 14 days. Additional documentation, approval and justification are required for any assignment that exceeds 14 days, and assignments for non-military resources cannot exceed 21 days. An engine or crew can be transferred from one dispatch zone to another as needed before the end of its shift. For our study, we used 14 days as the default shift length for which each crew or engine could be assigned before that resource had to return to its home zone. For comparison, we tested an alternative 4-day shift length, which is approximately the average historical shift length of crews and engines from 2010 to 2013 from ROSS data.

Drawdown levels and resource availability

Fire managers in the US often use the Preparedness Level (PL) to assist with resource assignment decisions. The PL is a scaled, numeric value between 1 and 5 that is determined by fuel and weather conditions, fire activity and resource availability (NMAC 2015); a PL of 1 indicates low fire activity and high resource availability, whereas a PL of 5 indicates high fire activity and low resource availability. PLs are available at the national and regional level, and each dispatch centre may determine a local PL, which can differ from the regional PL. Individual dispatch centres typically have mobilisation plans to guide resource deployment decisions within that centre's dispatch zone for each PL. We were unable to collect the historical daily local PL records in each dispatch zone for this study; instead we used the historical PL data from the Rocky Mountain Area Coordination Center (RMACC) to approximate resource scarcity. RMACC is responsible for the coordination of suppression resources in CO, Wyoming, South Dakota, Kansas and Nebraska.

We assumed the maximum number of engines and crews that have been assigned to fires from each dispatch zone historically is the total number of engines and crews available for dispatch from that zone (see Table 1). During a fire season, some engines and crews may be held in their home bases for IA assignments; this predetermined number of reserved resources is often referred to in the US as the 'drawdown' level. Resources held for drawdown are typically unavailable for use outside their local areas (NIFC 2016). Determining appropriate drawdown levels is a complex task (Martell *et al.* 1998). In this study, we modelled drawdown restrictions based on historical records of resource assignments at each PL. Table 1 shows the maximum number of engines or crews that were ever dispatched to fires outside their home zones at each PL by dispatch zone. We used these records to set the upper bound on the number of resources

Table 1. Estimates of resource availability in each dispatch zone at different Preparedness Levels

PLs; PL0–PL5 indicate levels 0–5. The 'Maximum # that has been dispatched out of home zone' column shows the maximum *actual* number of resources that have been dispatched outside each home zone at each PL. The 'Assumed # that could be dispatched out of home zone' column shows the *assumed* upper bound of the number of resources that could be dispatched out of each home zone at each PL used in the model. We assume that at higher PLs, managers dispatch fewer resources out of their home zone. Craig, CRC; Durango, DRC; Fort Collins, FTC; Grand Junction, GJC; Montrose, MTC; Pueblo, PBC

Dispatch zone	Resource category	Maximum # dispatched	Maximum # that has been dispatched out of home zone						Assumed # that could be dispatched out of home zone					
			PL0	PL1	PL2	PL3	PL4	PL5	PL0	PL1	PL2	PL3	PL4	PL5
CRC	Engine	24	9	6	8	12	10	14	14	14	14	14	14	14
	Crew	7	7	2	6	5	5	3	7	6	6	5	3	3
DRC	Engine	21	10	8	12	16	11	0	16	16	16	16	11	0
	Crew	7	7	4	6	7	4	2	7	7	7	7	4	2
FTC	Engine	96	43	13	46	45	45	21	46	46	46	45	45	21
	Crew	16	15	9	13	15	11	6	15	15	15	15	11	6
GJC	Engine	30	18	7	15	18	20	2	20	20	20	20	20	2
	Crew	4	4	0	2	4	1	0	4	4	4	4	1	0
MTC	Engine	12	6	4	6	5	7	5	7	7	7	7	7	5
	Crew	2	1	0	2	0	0	0	2	2	2	0	0	0
PBC	Engine	104	51	12	53	67	69	47	69	69	69	69	69	47
	Crew	15	13	8	10	13	11	3	13	13	13	13	11	3

that may be dispatched from each home zone to fires outside of each zone across all PLs (Table 1). We created model constraints to ensure that more resources are held in each home zone as the PL increases. The resources reserved for drawdown may be dispatched to any fire occurring within a home zone. To test the effect of these drawdown restrictions, we used an allowable drawdown level (ADL) multiplier, which ranged from 0 to 3. The ADL multiplier was multiplied by the upper bound on the number of engines or crews that could be dispatched out of their home zones at each PL (in Table 1) to create a range of alternative drawdown restriction levels. For example, if the ADL multiplier is set to 0, no resources may be shared between dispatch zones; if it is set to 1, the model uses the drawdown restriction levels directly from Table 1. Finally, if the ADL multiplier is set to 3, three times the number of resources in Table 1 may be shared between zones.

A resource assignment and transfer model for CO

We used an MIP network model to optimise daily resource assignments within and between zones in CO. Nodes in the network allow the model to track the number of resources available in each dispatch zone each day. Arcs are used to track the resource transfers between zones in CO and into a zone in CO from outside the state. Our MIP model minimises the resource movement distances (an approximation of transport cost) for the assignment and transfer of engines and crews in fire day t to meet the resource demand for fire suppression in day (t+1). Fig. 2 shows a diagram for an example network with two in-state dispatch zones and a single out-of-state zone. The indices, parameters and decision variables used to present this model are shown in Table 2. This model is run iteratively for each day through a fire season.

The simulation and optimisation procedure

(1) Set $t = 0$; set the number of resources deployed to fires from home zone h to fire zone i to zero; set the initial resource shortage in each zone i to zero; set the number of resources with assignment length that have already reached the maximum shift length to zero:

$$a_{t=0,\,h,i,r} = 0 \quad \forall h, i \neq 0,\, r \tag{1.1}$$

$$s_{t=0,\,i,r} = 0 \quad \forall i \neq 0,\, r \tag{1.2}$$

$$e_{t=0,h,i,r} = 0 \quad \forall h, i \neq 0, r \tag{1.3}$$

Set $a'_{t=0,h,r}$ equal to the total number of resources r based in zone h (no resources have been dispatched to any fire yet).

(2) Run the MIP model for day t to find the most inexpensive way to assign resources to meet the predicted resource demand $p_{t+1,i,r}$ for the next day in each zone. The MIP model formulation is as follows:

$$\min_t \sum_h \sum_{i\neq 0} \sum_{j\neq 0} \sum_r c_{i,j,r} \times M_{t,h,i,j,r} + \sum_h \sum_{i\neq 0} \sum_r c_{h,i,r} \times N_{t,h,i,r} + \sum_h \sum_{j\neq 0} \sum_r c_{h,j,r} \times U_{t,h,j,r} \tag{2.1}$$

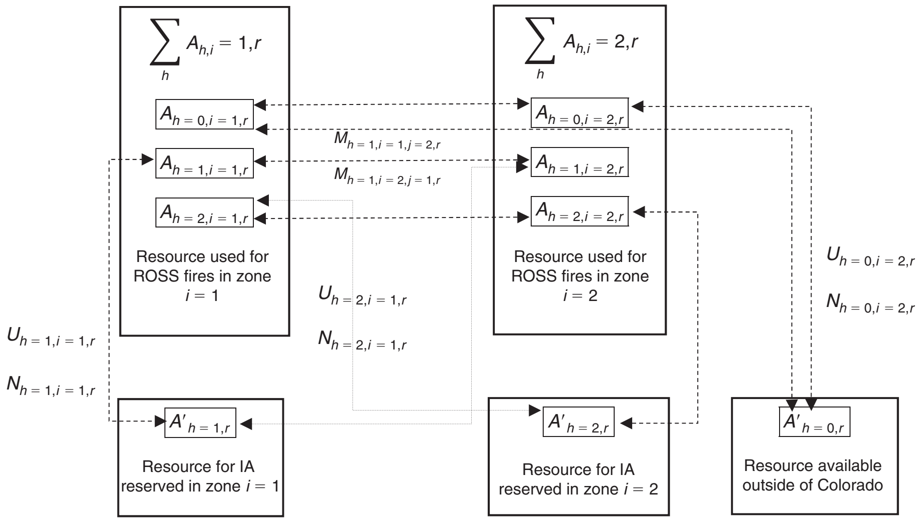

Fig. 2. A diagram to demonstrate the mixed integer program (MIP) model formulation for a state with two home dispatch zones ($h = 1$ and $h = 2$) and one out-of-state zone ($h = 0$); this shows the network model structure that is used to track how type r resources could be transferred on fire day t to meet the resource demands on day (t+1) in different zones (t is omitted in the subscript of all decision variables in this diagram). The arrow represents the resource transfer direction; IA is initial attack.

Table 2. Indices, decision variables and model parameters of the mixed integer program (MIP)

The denotations are used in the model to represent the dispatch of resources on fire day t to meet suppression resource demands in each dispatch zone on day t+1

Indices	
h, i, j	Indices of dispatch zones; h indicates the home zone of a resource ($h = 0$ indicates a resource comes from outside Colorado (CO)), i indicates the dispatch zone from which a resource transfers, and j indicates the dispatch zone into which a resource transfers
r	Index of resource type; e.g. crew or engine
t	Index of day; t denotes the current day; t+1 denotes the next day
Decision variables	
$A_{t+1,h,i,r}$	Number of type r resources from home zone h that would be used for fire suppression in zone i in day t+1; with $h = 0$, $A_{t+1,h=0,i\neq 0,r}$ tracks the number of resources from outside CO
$A'_{t+1,h,r}$	Number of type r resources that would not be dispatched to any fire in each home zone h on fire day t+1
$M_{t,h,i\neq 0,j\neq 0,r}$	Number of type r resources from home zone h transferring from a CO zone i to another CO zone j on day t; these will become available for fire suppression on day t+1
$U_{t,h,i\neq 0,r}$	Number of type r resources that would return to each home zone h from a CO zone i on day t
$N_{t,h,i\neq 0,r}$	Number of type r resources assigned from home zone h into a CO dispatch zone i on day t; each will become available for fire suppression on day t+1
Parameters	
$a_{t,h,i\neq 0,r}$	Number of type r resources from home zone h available for fire suppression in zone i on day t
$a'_{t,h,r}$	Number of type r resources reserved in home zone h on fire day t
l_t	Preparedness Level (PL) at day t
$a''_{h\neq 0,r,l_t}$	Maximum number of type r resources from each CO home zone h that may be dispatched outside h if PL is l_t on day t
$d_{t,i\neq 0,r}$	Actual demand for type r resources in a CO zone i at day t
$p_{t,j\neq 0,r}$	Prediction of next-day demand for type r resources in a CO zone j on day t
$c_{i,j,r}$	Transport cost associated with moving a type r resource from zone j to i, approximated by the distance between zones
β	Compounding factor for resource shortages
$s_{t,i\neq 0,r}$	Cumulative shortage of type r resources in a CO zone i on day t
$e_{t,h,i,r}$	Number of type r resources from home zone h that have reached maximum shift length; these resources are sent back to respective home zones on day t

and is subject to constraints:

$$A_{t+1,h,i,r} = N_{t,h,i,r} - U_{t,h,i,r} + \sum_{j\neq 0} M_{t,h,j,i,r} - \sum_{j\neq 0} M_{t,h,i,j,r} + a_{t,h,i,r} \quad \forall h, i \neq 0, r \tag{2.2}$$

$$A'_{t+1,h,r} = \sum_{i\neq 0} U_{t,h,i,r} - \sum_{i\neq 0} N_{t,h,i,r} + a'_{t,h,r} \quad \forall h, r \tag{2.3}$$

$$\sum_{i\neq 0 \text{ and } h\neq i} A_{t+1,h,i,r} \leq ADL \times a''_{h,r,l_t} \quad \forall h \neq 0, r \tag{2.4}$$

$$\sum_{i\neq 0} N_{t,h,i,r} \leq a'_{t,h,r} \quad \forall h, r \tag{2.5}$$

$$U_{t,h,i,r} + \sum_{j\neq 0} M_{t,h,i,j,r} \leq a_{t,h,i,r} \, \forall h, i \neq 0, r \tag{2.6}$$

$$\sum_{h} A_{t+1,h,i,r} \geq p_{t+1,i,r} + (1+\beta_r) \times s_{t,i,r} \quad \forall i \neq 0, r \tag{2.7}$$

$$U_{t,h,i,r} \geq \sum_{j^i} e_{t,h,j^i,r} \quad \forall h,\ i \neq 0, r \tag{2.8}$$

Eqn 2.1 is the objective function minimising the total transport cost on day t. Eqn 2.2 updates the next day's resource inventory at zone i, accounting for the transfer of resources in and out of that zone during day t and the inventory of total resources on day t. Resources from each home zone are tracked separately using index h. Any time a resource is released from fire suppression in dispatch zone i, it returns to its home zone h; these movements are tracked by $U_{t,h,i,r}$. Eqn 2.3 updates the number of resources kept in home zone h but not assigned to a fire during day t+1. Eqn 2.4 is the drawdown constraint used in this study; it limits the total number of type r resources from home zone h that can be dispatched out of h depending on PL. The ADL multiplier is set to 1 for most test cases. No drawdown restriction was modelled for the external zone ($h = 0$). Eqn 2.5 restricts the number of type r resources dispatched to fires from home zone h during day t to be no more than the number of resources still residing in h. Eqn 2.6 restricts the total number of type r resources from home zone h transferred out of a zone i to be no more than the number of resources currently dispatched in i. Petrovic *et al.* (2012) suggested that delays in suppression response may lead to increased disaster severity and thus greater demand for resources later. To account for this, we compound the current day's resource shortage by (1+β) and add it to the prediction of the next day's resource demand. Eqn 2.7 ensures that we fill the next day's predicted demand plus the demand created by the compounding of resource shortages for each zone i. Eqn 2.8 requires that all resources originally dispatched from home zone h to dispatch zone i that have been on assignment for longer than the maximum shift length are sent back to their home zone h from the zones (j^i) to which they are currently assigned. After the model is parameterised, we solve it using the MIP solver provided by IBM in their CPLEX software package, version 12.6. Intensive bookkeeping is implemented after the optimisation model has been solved to track where all resources are located after they have moved to their new assignments.

(3) Move forwards a day: day (t+1) becomes the new day t; update the resource inventory in all dispatch zones. We use Eqn 3 to calculate the realised resource shortage $s_{t,i,r}$ on day t:

$$s_{t,i,r} = \max\{d_{t,i,r} + (1+\beta) \times s_{t-1,i,r} - \sum_h a_{t,h,i,r}, 0\} \quad \forall i \neq 0,\ r \tag{3}$$

After all the parameters are updated, we go back to step (2) and resolve the MIP model for day t to find the most inexpensive way to transfer resources to meet resource demands for the next day.

Eqn 3 does not account for any potential benefits of having a surplus of resources for any zone on any day. In reality, when extra resources are available they may be used in building additional fire line, preparing for IA or conducting fuel treatments. However, the benefit of having extra resources is difficult to estimate and may vary between days. For example, if the fire activity in a dispatch zone is low after a fire day t, the benefit of having extra resources on day t might be substantially less than a day on which fire activity on the following day is high. Conversely, fire activity may be so extreme that engagement in fire suppression by ground resources would be deemed unsafe; thus no extra benefit of additional crews and engines would potentially be observed. Due to the variable nature of such benefits, we chose not to include them in this model.

Test cases and results

Our first test case acts as the 'baseline' case (named BL14; 14 indicates the maximum shift length), which we compared with other test cases to examine the effects of a shorter shift length (the BL04 case), 'perfect predictions' of resource demands (the PP case) and a larger compounding factor for resource shortages (the β0.5 test case). These effects are quantified by the objective function values (i.e. total transport cost of engines and crews), the number of resource transfers into CO from outside the state and the number of resource transfers between dispatch zones. We also used the model to examine the effect of drawdown restrictions. Finally, we compared the model-suggested assignments with records from ROSS.

The baseline test case (BL14)

In our baseline test case (BL14, we examined resource assignments assuming a 14-day shift length, no resource shortage compounding ($\beta = 0$), historical drawdown levels (ADL = 1) and imperfect next-day demand predictions from the regression models in Table S1. Table 3 summarises these results.

Reflecting the variation in resource demands each year, the model suggested substantially different yearly engine (Fig. 3) and crew (Fig. 4) transfers between dispatch zones. In 2011, there were no engine transfers between zones because the demand for engines in each zone was fully met by within-zone engines. Resource needs were slightly higher in 2010, requiring two engine transfers from GJC to MTC; however, no out-of-state engines were required. Engine demand in 2012 was the

Table 3. A summary of simulation and optimisation model runs using different parameter settings by year simulated

For comparison, the last row for each year shows the actual resource transfers from historical Resource Ordering and Status System (ROSS) records. '# out-of-state dispatch' is the number of engines or crews called in from outside Colorado (CO); '# in-zone dispatch' is the number of engines or crews dispatched within their home zones; 'n/a' is not applicable

Name of test case	Prediction method	β	Shifts (days)	Total transport cost		# out-of-state dispatch		# in-zone dispatch	
				Engine	Crew	Engine	Crew	Engine	Crew
Year 2010									
BL14	Regression	0	14	307	142	0	0	336	104
BL04	Regression	0	4	658	284	0	0	618	167
PP	Perfect	0	14	252	122	0	0	278	87
β0.5	Regression	0.5	14	347	293	0	2	389	115
Actual	n/a	n/a	n/a	1322	769	36	49	265	71
Year 2011									
BL14	Regression	0	14	135	193	0	0	159	119
BL04	Regression	0	4	243	311	0	0	279	191
PP	Perfect	0	14	123	115	0	0	137	91
β0.5	Regression	0.5	14	216	248	0	0	243	134
Actual	n/a	n/a	n/a	928	1249	21	70	269	87
Year 2012									
BL14	Regression	0	14	4388	1703	285	90	437	149
BL04	Regression	0	4	6281	3366	323	211	942	295
PP	Perfect	0	14	2881	1339	176	76	393	128
β0.5	Regression	0.5	14	5099	2326	300	134	522	172
Actual	n/a	n/a	n/a	6547	3205	422	223	401	104
Year 2013									
BL14	Regression	0	14	1005	1106	0	53	278	69
BL04	Regression	0	4	2277	3064	16	134	527	145
PP	Perfect	0	14	714	842	0	43	265	64
β0.5	Regression	0.5	14	1829	1349	34	67	306	79
Actual	n/a	n/a	n/a	3219	2100	184	137	209	61

highest of the 4 years studied (Fig. 3); not only did we observe more engine transfers between dispatch zones, there were also 285 assignments of out-of-state engines, indicating a higher reliance on out-of-state suppression resources. The largest number of engine transfers between zones during the 2012 fire season occurred from PBC to FTC due to the demand from the High Park Fire, which was the second-largest fire by area burned in recorded CO history at the time. Crew transfers (Fig. 4) followed similar trends; 2012 and 2013 showed more transfers than 2010 and 2011. The yearly variation in resource transfers highlights the challenges of building general, multi-year policies that guide engine and crew assignments in CO.

A shorter shift length test case (BL04)

For the BL04 test case, all modelled settings except shift length were the same as the BL14 case; we shortened the 14-day shift length to a hypothetical 4-day shift length. This change more than doubled the engine and crew transport costs in 2010 and 2013, and almost doubled the crew transport cost in 2012 (Table 3). For both 2010 and 2013, the shorter shift more than doubled the engine and crew transport costs; for the other 2 years, shorter shift increased the engine and crew transport costs by 43–98%. In the BL04 test case, engines and crews were dispatched more frequently from their home bases to fires within their home zones, and the number of requests for out-of-state resources also increased significantly for most years.

The perfect prediction test case (PP)

We revised the BL14 test case using the assumption that we can perfectly predict the next day's crew and engine demands. We compared this test case with the BL14 test case to examine the effect of prediction accuracy on our model results. A new Eqn 4 replaced Eqn 2.7 to provide the model with perfect predictions. Note that resource shortages do not occur in this test case because the model assigns resources using perfectly predicted resource demands, and we assume each zone can use unlimited out-of-state resources to meet its resource demand:

$$A_{t+1,i,r} \geq d_{t+1,i,r} \quad \forall i \neq 0, r \tag{4}$$

Results from the PP test case (summarised in Table 3) show that perfectly predicting resource demand can decrease the yearly engine transport cost; for example, when compared with the BL14 results, PP test case cost results are 9% lower in 2011 and 34% in 2013. The yearly crew transport cost also decreased with the PP test case, ranging from 14% lower in 2010 to 40% lower in 2011 when compared with the BL14 results. The benefits from accurate predictions are also reflected by model results that consistently use fewer out-of-state resources (Table 3). For example, in 2012, the number of out-of-state engine transfers decreased from 285 in the BL14 case to 176 in the PP case, whereas the number of out-of-state crew transfers decreased from 90 in the BL14 case to 76 in the PP case. In 2013,

2010	CRC	DRC	FTC	GJC	MTC	PBC
OUT	0	0	0	0	0	0
CRC	54	0	0	0	0	0
DRC	0	15	0	0	0	0
FTC	0	0	193	0	0	0
GJC	0	0	0	26	2	0
MTC	0	0	0	0	12	0
PBC	0	0	6	0	0	36

2011	CRC	DRC	FTC	GJC	MTC	PBC
OUT	0	0	0	0	0	0
CRC	12	0	0	0	0	0
DRC	0	15	0	0	0	0
FTC	0	0	41	0	0	0
GJC	0	0	0	25	0	0
MTC	0	0	0	0	4	0
PBC	0	0	0	0	0	62

2012						
OUT	0	66	128	0	0	91
CRC	56	6	16	0	0	0
DRC	0	76	0	34	2	8
FTC	0	0	211	0	0	41
GJC	18	23	0	33	0	0
MTC	0	10	0	0	10	0
PBC	0	17	80	11	0	51

2013						
OUT	0	0	0	0	0	0
CRC	31	14	0	15	6	0
DRC	7	49	0	1	5	0
FTC	0	13	35	0	8	24
GJC	3	21	0	45	2	1
MTC	3	11	0	8	14	7
PBC	0	123	0	0	0	104

Fig. 3. Modelled engine transfers between dispatch zones from 2010 to 2013 for the baseline test case (BL14). Row names are zones providing resources; column names are zones requesting resources. OUT, out-of-state; Craig, CRC; Durango, DRC; Fort Collins, FTC; Grand Junction, GJC; Montrose, MTC; Pueblo, PBC.

the number of out-of-state crew transfers decreased from 53 in the BL14 case to 43 in the PP case.

The increased resource shortage compounding case (β0.5)

We revised the BL14 test case by setting compounding factor β to 0.5 to examine the possible effects of delayed suppression on next-day resource demands due to resource shortages, and we named this new test case β0.5. This model parameterisation assumes any resource shortages on one day will make the next day's fire situation worse and will thus require 1.5 times the current day's shortage of crews (or engines) plus the actual demands predicted for the next day. Compared with the BL14 test case, setting β to 0.5 increased the yearly engine transport costs by 13–82% and increased the yearly crew transport costs by 22–106%. These model results suggest that the compounding effects of resource shortages may substantially increase engine and crew transport costs.

The effect of drawdown levels

We revised the BL14 case by varying the value of the ADL multiplier between 0 and 3 to test the effect of drawdown restrictions. There are competing effects of increasing the ADL. Higher ADLs increase the ability for zones to collaborate, which may reduce reliance on out-of-state resources. However, in periods of high resource demand, allowing more resources to move out of their home zones may cause resource shortages in those zones. Days with high demand that occur after resources have been moved out of their home zones may require those resources to move back or create a need for out-of-state resources, which may increase transport costs.

The effect of ADL on resource transfers in 2010 and 2011 was minimal; we found no benefit in tightening or loosening drawdown levels in those years, likely due to lower suppression resource demands. However, changes in drawdown levels appear to have larger effects on costs during years with higher resource demands. We graphed four categories of engine and crew transport costs against the ADL multiplier for 2012 and 2013 (Fig. 5): the total yearly transport cost for engines or crews, the yearly transport cost for out-of-state engines or crews, the yearly transport cost of moving engines or crews between dispatch zones and the yearly transport cost of assigning engines or crews to fires within their home zones. Using Fig. 5, we observed that the total engine and crew transport costs in 2012 and 2013 generally decreased when drawdown restrictions were

2010	CRC	DRC	FTC	GJC	MTC	PBC
OUT	0	0	0	0	0	0
CRC	20	0	2	4	0	0
DRC	1	12	0	0	0	0
FTC	0	0	33	0	0	0
GJC	7	0	0	12	4	0
MTC	0	0	0	6	2	0
PBC	0	0	13	0	0	25

2011	CRC	DRC	FTC	GJC	MTC	PBC
	0	0	0	0	0	0
	15	0	0	6	0	0
	0	21	0	0	0	5
	0	0	12	0	0	21
	0	2	0	10	2	4
	0	0	0	2	4	2
	0	0	0	0	0	57

2012						
OUT	0	31	10	5	0	44
CRC	19	11	4	13	0	0
DRC	12	26	16	7	0	10
FTC	11	2	55	1	0	36
GJC	13	4	0	11	3	1
MTC	0	0	1	2	7	0
PBC	0	14	23	3	0	31

2013						
	0	14	1	20	2	16
	9	7	0	10	3	7
	8	15	0	4	12	7
	10	0	13	0	0	9
	7	14	0	4	9	7
	2	13	0	4	2	6
	4	21	0	0	7	26

Fig. 4. Modelled crew transfers between dispatch zones from 2010 to 2013 for the baseline test case (BL14). OUT, out-of-state; Craig, CRC; Durango, DRC; Fort Collins, FTC; Grand Junction, GJC; Montrose, MTC; Pueblo, PBC.

relaxed (higher ADL values), with some minor fluctuations. These fluctuations are attributable to the competing effects of increasing ADL that we mentioned earlier. We observed that the optimal drawdown strategies vary between years; an ADL multiplier of 3 is optimal for engines in 2012, 1.8 is optimal for crews in 2012, 0.6 is optimal for engines in 2013, and 0.9 is optimal for crews in 2013. These test results suggest that there is no single optimal drawdown level that can minimise resource transport costs across all years. Drawdown restrictions may need to be set dynamically based on factors beyond PL to better adapt to changing fire situations. Improved forecasting of longer-term resource demand potential (e.g. fire season severity) and short-term fire weather factors (e.g. lightning, wind and fuel dryness) might assist managers in adjusting drawdown restrictions efficiently.

Increasing the value of ADL in most cases decreased the costs from using out-of-state engines and crews because dispatch zones in CO were able to share more resources with each other. We found exceptions in 2012, where the out-of-state engine and crew transport costs occasionally slightly increased as the value of ADL increased. Studying the detailed daily model output suggests that this occurred when PL increased – for example from 4 to 5 – requiring certain dispatch zones to call resources back from their out-of-zone assignments (Table 1) before the end of their 14-day shift. This requires additional out-of-state resources to be requested to meet the demand gaps left by the recalled resources. The shortened shift length caused by the change in PL may be the reason we observe higher out-of-state engine transport costs in these cases. At higher ADLs, this likely occurs because more resources are already working out of their home zones.

Historical engine and crew assignments and transfers

We calculated yearly transport costs and the number of transfers based on the actual engine and crew assignments into and between CO dispatch zones from 2010 to 2013 using ROSS assignment records. We used the same transport cost assumptions that our models used so we could compare the model reported engine and crew transport costs with the transport costs calculated using historical data.

Certain data gaps exist in the historical ROSS records. For example, ROSS tracks which fire each resource was assigned to, but the system does not always record whether the resource was moved to that fire directly from another fire or from that resource's home base. We assumed that if a resource was dispatched to a fire within 48 h of demobilisation from another

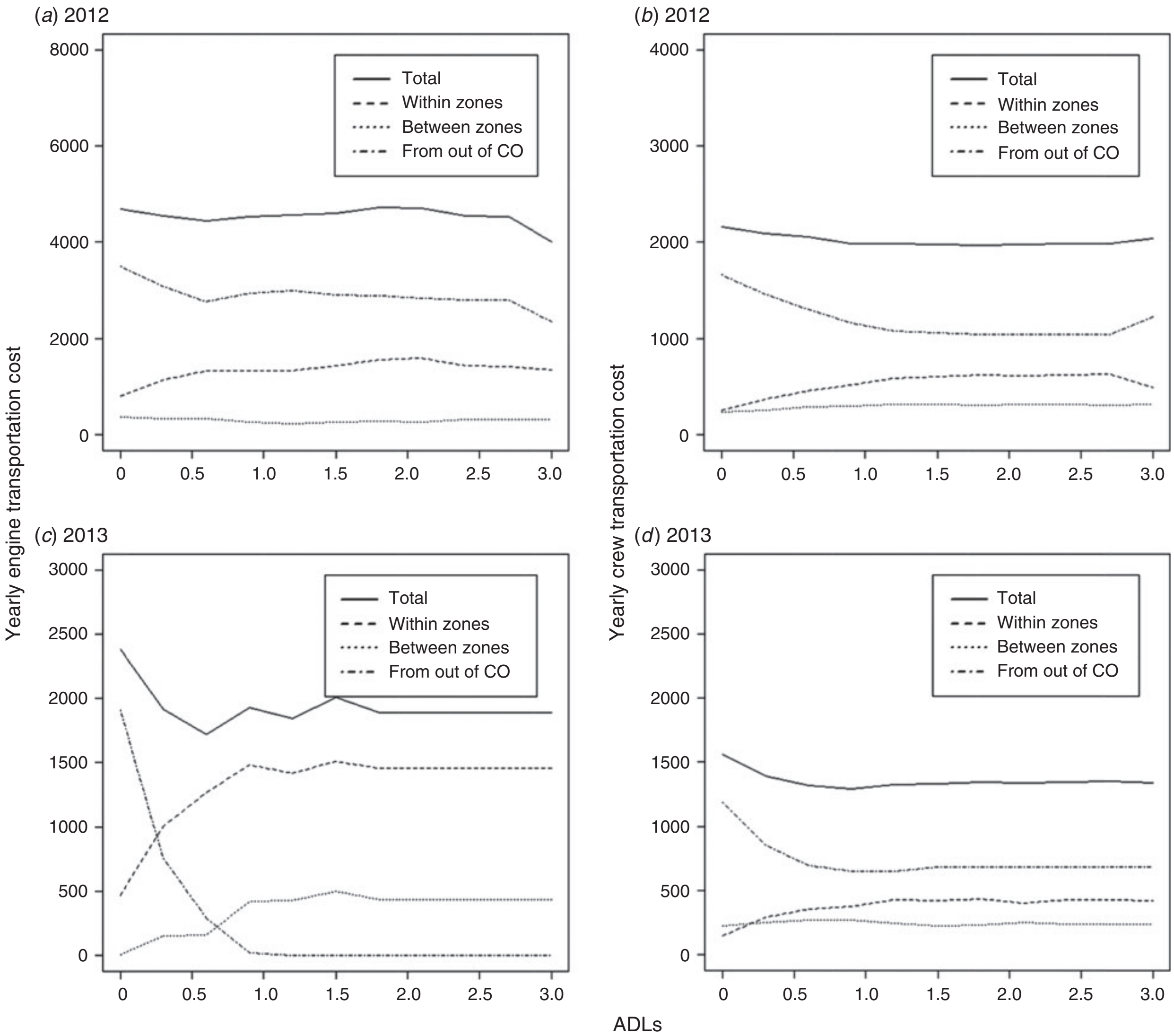

Fig. 5. Effect of allowable drawdown levels (ADLs) on different types of engine and crew transport costs in 2012 and 2013 using the baseline test case (BL14).

fire, then it moved directly from one fire to another; otherwise, it returned to its home base first before being sent to the next fire. This 48-h heuristic was necessary to estimate historical resource travel costs. Any potential bias from such estimates may need further study.

The calculated historical engine transport costs were 1.5–7 times higher than the costs reported for the BL14 test case, and the calculated historical crew transport costs were 1.9–6.5 times higher than the costs reported for the BL14 test case (Table 3). ROSS records also showed more out-of-state engine and crew assignments than the results from the BL14 test case: for example, 1.5 times as many out-of-state engine assignments and 2.5 times as many out-of-state crew assignments in 2012 (Table 3). The BL14 solutions did not require any out-of-state engines and crews in 2010 and 2011. Based on ROSS records, however, a substantial number of out-of-state engines and crews were used during both years. The difference was also substantial in 2013; although the model suggested no need for any out-of-state engines and only 53 assignments of out-of-state crews, the ROSS records show we used out-of-state engines 184 times and crews 137 times.

It is not a surprise that transport costs calculated directly from the archived ROSS records are higher than the model-suggested costs: the model-suggested resource assignments are designed to minimise the daily resource transport cost. However, other important management restrictions exist that are not included in the model. For example, workloads between crews or engines may need to be balanced. Similarly, resource transport may be impeded by road conditions or weather. Although these management concerns are not without significance and might be incorporated into future models, results from this study suggest that there is potential to further decrease transport costs and reduce the reliance on out-of-state engines and crews using more efficient assignments of fire suppression resources within CO.

Discussion and conclusions

This study developed a modelling approach to examine resource assignments and the resulting transfers to meet predicted next-day fire suppression resource demands in CO. An MIP model was used to optimise the daily response to resource demand over a fire season by moving resources between dispatch zones. Data needed to implement this method, such as the daily resource demand, the number of new ignitions, the PS Outlooks and the PL, were already collected or predicted daily at local, regional and national levels to support fire suppression decisions. This modelling approach allowed us to integrate these data to determine cost-efficient assignments for engines and crews on a daily basis.

Test cases using this method allowed us to examine potential effects of policy changes. Shortening assignment shift lengths from 14 to 4 days more than doubled the resource transport cost in some years. Providing accurate predictions of next-day resource demands substantially decreased the reliance on out-of-state resources and total resource transport costs. This suggests that improving the accuracy of suppression resource demand prediction models should be a priority for future studies. Here, we used regression models to predict next-day resource demands. Extending predictions beyond a single day could help further improve resource utilisation decisions, particularly in developing resource drawdown levels and for prepositioning decisions. Such improvements in resource demand prediction models might include tasks such as collecting additional data, selecting more suitable regression model forms or including other predictor variables such as human population densities and values to be protected from wildland fires in each zone.

Resource drawdown restrictions are commonly implemented by dispatch centres at local, regional and national levels in the US. Our work represents the first research effort to examine the effects of such policies. Our test cases demonstrated some of the potential effects of differing drawdown restriction levels on resource assignments. We found that relaxing drawdown restrictions generally decreased the overall transport cost and the reliance on out-of-state resources as it allowed for more resource sharing between dispatch zones. However, if the predictions of resource demands lack accuracy, moving resources more frequently between zones can also increase the overall transport cost. Test results showed drawdown levels that minimise transport costs could vary substantially between fire seasons and resource types. Determining a single optimal drawdown level for each PL may not be efficient. Improved longer-term predictions of resource demands may better inform decisions regarding allowances for out-of-zone resource dispatching.

In this paper, we assumed that resource assignments were driven by resource demands in each dispatch zone and were restricted by factors such as resource availability, assignment shift length and drawdown levels. We also assumed the observed engine and crew demands in a fire day in each zone were the actual suppression demands. This may not always be accurate: for example, risk-averse managers may order more resources than they actually expect to need (Maguire and Albright 2005). If this does occur, our model-estimated transport cost would be higher than necessary. However, determining the difference between the observed and actual demands is challenging. Surveys or field measurement may be required to quantify this difference. We also assumed that the maximum numbers of engines and crews that have been dispatched in each zone during a 4-year period represent the numbers of engines and crews available in that zone. Future studies may be needed to account for the variation of resource availability across a fire season (e.g. effects of seasonal firefighters). We used 4 years of ROSS records to derive the drawdown restrictions by PL in each zone. An alternative method would entail collection of zone-specific drawdown restrictions by contacting fire managers directly. Another potential enhancement could involve modelling the influence of drawdown in preventing fire escapes, which might be achieved by connecting our model to existing IA dispatch models or employing standard IA response rules (e.g. Haight and Fried 2007).

The approach presented here models crews and engines independently without allowing any substitution between the two resource types. In reality, sending an engine to fill a crew request might be preferable to sending no resources at all. Some ROSS records demonstrate historical unfilled crew requests that are followed immediately by filled engine requests, indicating that such substitutions may be occurring in the field. The model could be enhanced to include resource substitutions if additional studies could quantify the rate of substitution that occurs between crews and engines under differing fire situations, fuel types and topographic conditions.

In this work, we produced a system model based on archived resource assignment data from ROSS to help fire managers study fire suppression resource assignment, transfer and drawdown policies. Implementing such a system could help simplify and standardise dispatching procedures. This approach is also promising for national-scale analyses as a tool to study national level resource assignments, including examining inter-state and regional collaborations.

References

Alexandridis A, Russo L, Vakalis D, Bafas GV, Siettos CI (2011) Wildland fire spread modelling using cellular automata: evolution in large-scale spatially heterogeneous environments under fire suppression tactics. *International Journal of Wildland Fire* **20**, 633–647. doi:10.1071/WF09119

Arapaho-Roosevelt National Forest and Pawnee National Grassland (2015) Fire resource briefing packet. Available at http://gacc.nifc.gov/rmcc/dispatch_centers/r2ftc/documents/Briefing_Packet.pdf [Verified 26 March 2016]

Belval EJ, Wei Y, Bevers M (2015) A mixed integer program to model spatial wildfire behavior and suppression placement decisions. *Canadian Journal of Forest Research* **45**, 384–393. doi:10.1139/CJFR-2014-0252

Calkin DE, Gebert KM, Jones JG, Neilson RP (2005) Forest Service large fire area burned and suppression expenditure trends 1970–2002. *Journal of Forestry* **4**, 179–183.

Calkin DE, Cohen JD, Finney MA, Thompson MP (2014) How risk management can prevent future wildfire disasters in the wildland–urban interface. *Proceedings of the National Academy of Sciences of the United States of America* **111**, 746–751. doi:10.1073/PNAS.1315088111

Chow JYJ, Regan AC (2011) Resource location and relocation models with rolling horizon forecasting for wildland fire planning. *INFOR* **49**, 31–43. doi:10.3138/INFOR.49.1.031

Gallego Arrubla JA, Ntaimo L, Stripling C (2014) Wildfire initial response planning using probabilistically constrained stochastic integer programming. *International Journal of Wildland Fire* **23**, 825–838. doi:10.1071/WF13204

Haas JR, Calkin DE, Thompson MP (2015) Wildfire risk transmission in the Colorado Front Range, USA. *Risk Analysis* **35**, 226–240. doi:10.1111/RISA.12270

Haight RG, Fried JS (2007) Deploying wildland fire suppression resources with a scenario-based standard response model. *INFOR* **45**, 31–39. doi:10.3138/INFOR.45.1.31

Hand MS, Thompson MP, Calkin DE (2016) Examining heterogeneity and wildfire management expenditures using spatially and temporally descriptive data. *Journal of Forest Economics* **22**, 80–102. doi:10.1016/J.JFE.2016.01.001

Headwater Economics (2013) The rising cost of wildfire protection. Available at http://headwaterseconomics.org/wildfire/homes-risk/fire-cost-background/ [Verified 13 July 2016]

Lee Y, Fried JS, Albers HJ, Haight RG (2013) Deploying initial attack resources for wildfire suppression: spatial coordination, budget constraints, and capacity constraints. *Canadian Journal of Forest Research* **43**, 56–65. doi:10.1139/CJFR-2011-0433

Liu ZH, Wimberly MC (2015) Climatic and landscape influences on fire regimes from 1984 to 2010 in the western United States. *PLoS One* **10**, e0140839. doi:10.1371/JOURNAL.PONE.0140839

Maguire LA, Albright EA (2005) Can behavioral decision theory explain risk-averse fire management decisions? *Forest Ecology and Management* **211**, 47–58. doi:10.1016/J.FORECO.2005.01.027

Martell DL (2015) A review of recent forest and wildland fire management decision support systems research. *Current Forestry Report* **1**, 128–137. doi:10.1007/S40725-015-0011-Y

Martell DL, Gunn EA, Weintraub A (1998) Forest management challenges for operational researchers. *European Journal of Operational Research* **104**, 1–17. doi:10.1016/S0377-2217(97)00329-9

Minas J, Hearne J, Martell D (2015) An integrated optimization model for fuel management and fire suppression preparedness planning. *Annals of Operations Research* **232**, 201–215.

Montrose Interagency Dispatch Center (2015) Montrose Interagency Dispatch Center mob guide. Available at http://gacc.nifc.gov/rmcc/dispatch_centers/r2mtc/Mobilizaton_Guide/MTC%20Mob%20Guide.pdf [Verified 26 March 2016]

National Interagency Fire Center (NIFC) (2016) National Interagency Mobilization Guide. Available at http://www.nifc.gov/nicc/mobguide/Chapter%2010.pdf [Verified 12 July 2016]

National Multi-Agency Coordination Group (NMAC) (2008) Support guide. Available at http://www.nifc.gov/nicc/administrative/nmac/index.html [Verified 25 March 2016]

National Multi-agency Coordination Group (NMAC) (2015) National Preparedness Levels. Available at https://www.nifc.gov/fireInfo/fireinfo_prepLevels.html [Verified 12 July 2016]

Ntaimo L, Seigler BP, Vasconcelos MJ, Khargharia B (2004) Forest fire spread and suppression in DEVS. *Simulation* **80**, 479–500. doi:10.1177/0037549704050918

Ntaimo L, Arrubla JAG, Stripling C, Young J, Spencer T (2012) A stochastic programming standard response model for wildfire initial attack planning. *Canadian Journal of Forest Research* **42**, 987–1001. doi:10.1139/X2012-032

Ntaimo L, Arrubla JAG, Gang J, Stripling C, Young J, Spencer T (2013) A simulation and stochastic integer programming approach to wildfire initial attack planning. *Forest Science* **59**, 105–117. doi:10.5849/FORSCI.11-022

Owen G, Mcleod JD, Kolden CA, Ferguson DB, Brown TJ (2012) Wildfire management and forecasting fire potential: the roles of climate information and social networks in the southwest United States. *Weather, Climate, and Society* **4**, 90–102. doi:10.1175/WCAS-D-11-00038.1

Petrovic N, Alderson DL, Carlson JM (2012) Dynamic resource allocation in disaster response: tradeoffs in wildfire suppression. *PLoS One* **7**, e33285. doi:10.1371/JOURNAL.PONE.0033285

Predictive Services (2016) Predictive Services Program Overview. Available at http://www.predictiveservices.nifc.gov/predictive.htm [Verified 12 July 2016]

Preisler HK, Westerling AL, Gebert KM, Munoz-Arriola F, Holmes TP (2011) Spatially explicit forecasts of large wildland fire probability and suppression costs for California. *International Journal of Wildland Fire* **20**, 508–517. doi:10.1071/WF09087

Pueblo Interagency Dispatch Center (2015) Pueblo Interagency Dispatch Center mob guide. Available at http://gacc.nifc.gov/rmcc/dispatch_centers/r2pbc/2015%20PIDC%20MobGuide.pdf [Verified 25 March 2016]

Riley K, Stonesifer C, Calkin D, Preisler H (2015) Assessing Predictive Services' 7-day potential fire forecast. In 'Proceedings of the large wildland fires conference', 19–23 May 2014, Missoula, MT. (Eds RE Keane, M Jolly, R Parsons, K Riley) USDA Forest Service, Rocky Mountain Research Station, RMRS-P-73, pp. 187–194 (Fort Collins, CO).

Short KC (2015) Spatial wildfire occurrence data for the United States, 1992–2013 [FPA_FOD_20150323]. 3rd edn. Fort Collins, CO: Forest Service Research Data Archive. Available at http://www.fs.usda.gov/rds/archive/Product/RDS-2013-0009.3/

State of Colorado (2015) House Joint Resolution: Concerning Requests to the Federal Government Regarding Support for Wildland Fire Suppression. LLS No. R15–0129.01, Ashley, Zimmerman x2291. Available at https://www.colorado.gov/pacific/sites/default/files/Wildfire%20RESOLUTION%20A%2015-0129.pdf [Verified 25 March 2016]

Thompson MP, Scott J, Langowski PG, Gilbertson-Day JW, Haas JR, Bowne EM (2013) Assessing watershed–wildfire risks on National Forest System lands in the Rocky Mountain Region of the United States. *Water (Basel)* **5**, 945–971. doi:10.3390/W5030945

USDA Forest Service (2015) The rising cost of wildfire operations: effects on the Forest Service's non fire work. Available at http://www.fs.fed.us/sites/default/files/2015-Fire-Budget-Report.pdf [Verified 25 March 2016]

USDOI and USDA (2015*a*) Fiscal year 2015 budget overview. Available at http://www.fs.fed.us/aboutus/budget/2015/FY15-FS-Budget-Overview.pdf [Verified 20 July 2016]

USDOI and USDA (2015*b*) Interagency standards for fire and fire aviation operations. Available at https://www.nifc.gov/PUBLICATIONS/redbook/2015/RedBookAll.pdf [Verified 20 July 2016]

van der Merwe M, Minas JP, Ozlen M, Hearne JW (2015) A mixed integer programming approach for asset protection during escaped wildfires. *Canadian Journal of Forest Research* **45**, 444–451. doi:10.1139/CJFR-2014-0239

Wei Y, Rideout DB, Halls T (2011) Toward efficient management of large fires: a mixed integer programming model and two iterative approaches. *Forest Science* **13**, 435–447.

Wei Y, Bevers M, Belval EJ, Bird B (2015) A chance-constrained programming model to allocate wildfire initial attack resources for a fire season. *Forest Science* **61**, 278–288. doi:10.5849/FORSCI.14-112

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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:

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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 Foundation for Statistical Computing, Vienna, Austria, see http://www.R-project.org/, accessed 25 March 2016) 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

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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. Probabilities are significant at: *, $P < 0.01$; **, $P < 0.05$; ***, $P < 0.001$

	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

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. Probabilities are significant at: *, $P < 0.01$; **, $P < 0.05$; ***, $P < 0.001$

	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

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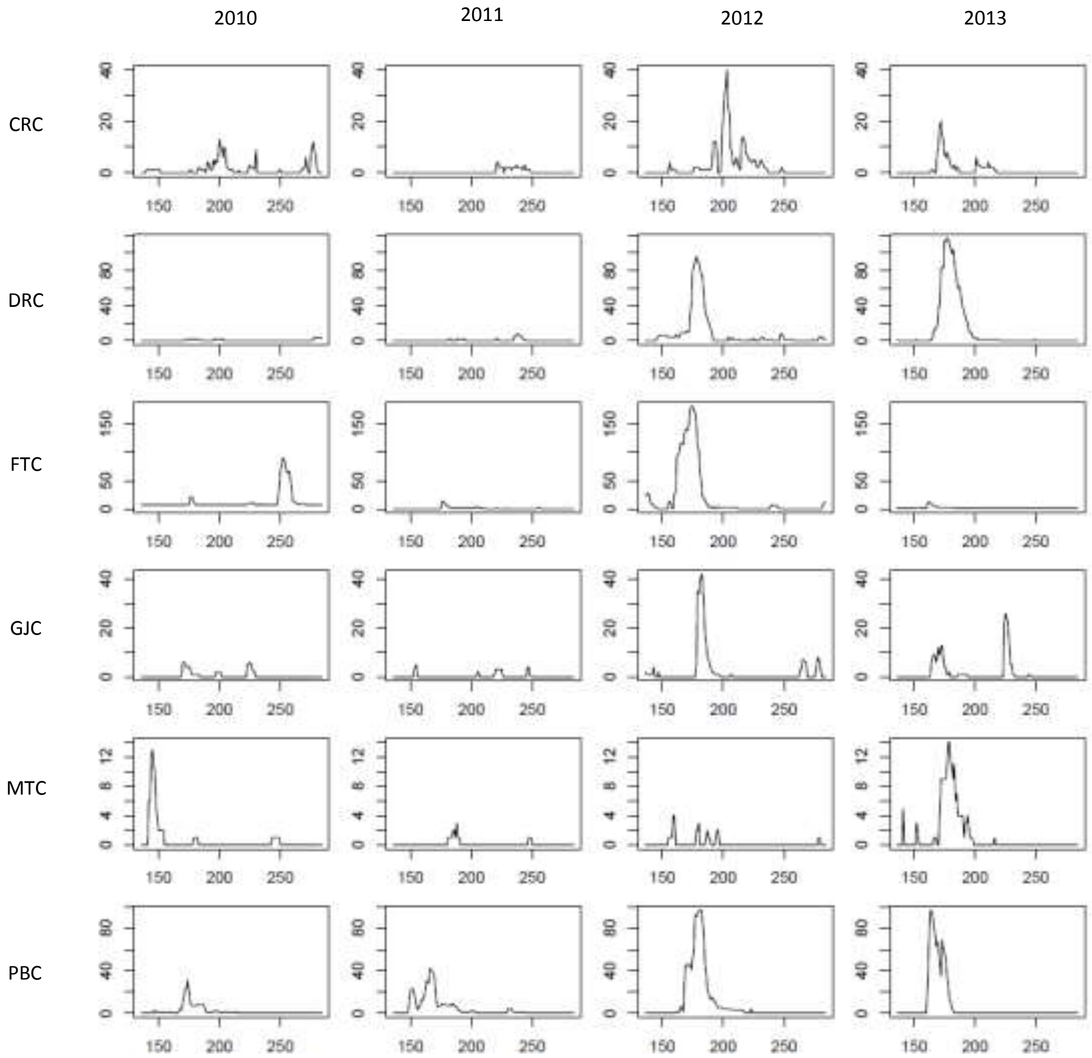

Fig. S1. The daily engine demands in each of the dispatch zones from 2010 to 2013. Each row represents one dispatch zone (Craig (CRC); Durango (DRC); Fort Collins (FTC); Grand Junction (GJC); Montrose (MTC); Pueblo (PBC)). Each column represents a year from 2010 to 2013. The *y*-axis represents the number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

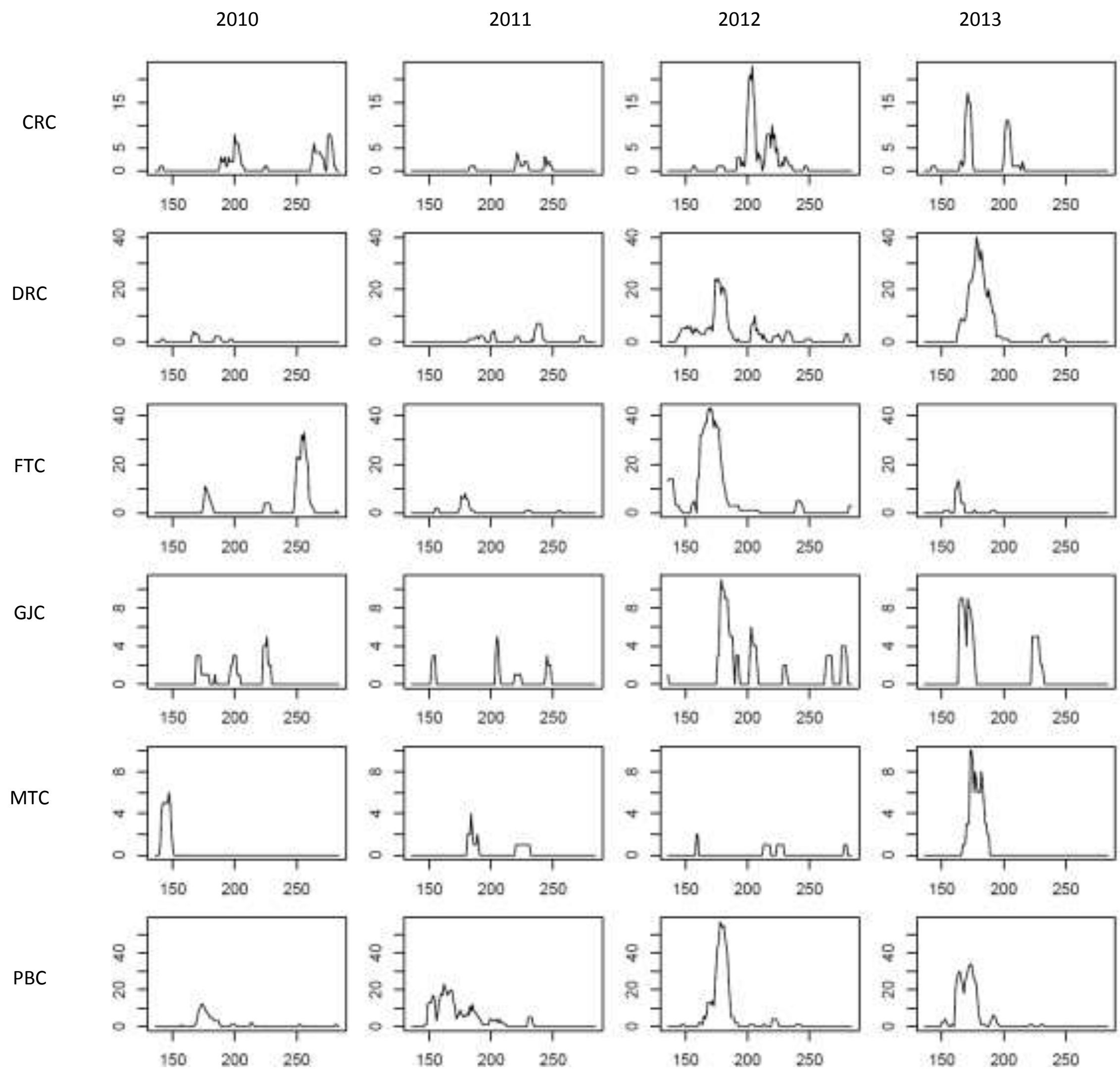

Fig. S2. The daily crew demands in each of the dispatch zones from 2010 to 2013. Each row represents one dispatch zone (Craig (CRC); Durango (DRC); Fort Collins (FTC); Grand Junction (GJC); Montrose (MTC); Pueblo (PBC)). Each column represents one year from 2010 to 2013. The *y*-axis represents the number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

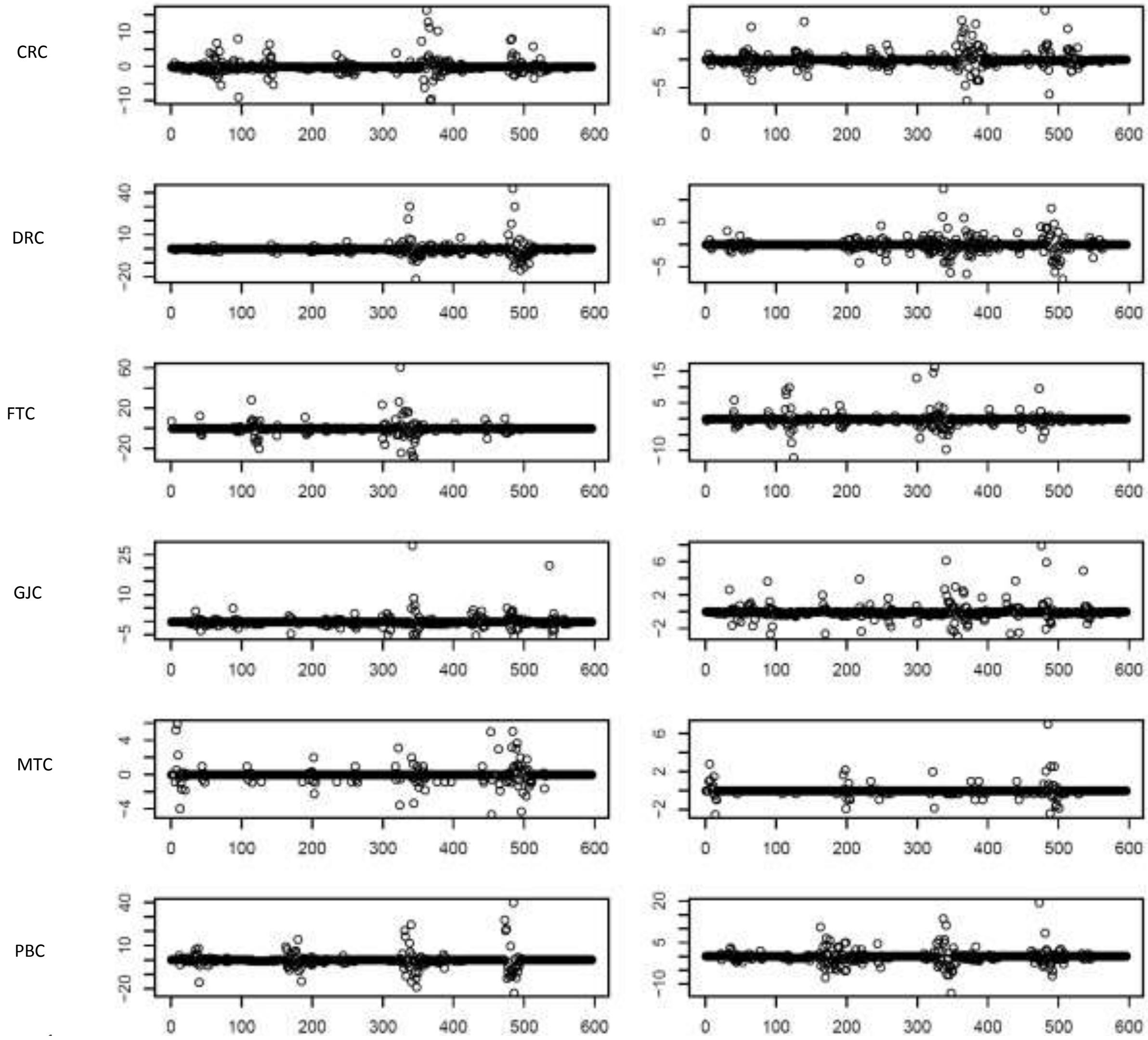

Fig. S3. The residuals for each of the prediction models. Each row represents one dispatch zone (Craig (CRC); Durango (DRC); Fort Collins (FTC); Grand Junction (GJC); Montrose (MTC); Pueblo (PBC)). The left column shows the residuals of engine demand prediction following the sequence of days during the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

References

Said SE, Dickey DA (1984) Testing for unit roots in autoregressive moving average models of unknown order. *Biometrika* **71**, 599–607. doi:10.1093/biomet/71.3.599