CSIRO PUBLISHING

International Journal of Wildland Fire **2017**, *26*, 642–653
http://dx.doi.org/10.1071/WF16162

Studying interregional wildland fire engine assignments for large fire suppression

Erin J. Belval[A,E], *Yu Wei*[A], *David E. Calkin*[B], *Crystal S. Stonesifer*[B], *Matthew P. Thompson*[B,D] *and John R. Tipton*[C]

[A]Department of Forest and Rangeland Stewardship, Warner College of Natural Resources, Colorado State University, Fort Collins, CO 80523, USA.
[B]USDA Forest Service, Rocky Mountain Research Station, 800 East Beckwith, Missoula, MT 59801, USA.
[C]Department of Statistics, Colorado State University, Fort Collins, CO 80523, USA.
[D]Present address: USDA Forest Service, Rocky Mountain Research Station, 240 W Prospect Road, Fort Collins, CO 80526, USA.
[E]Corresponding author. Email: erin.belval@colostate.edu

Abstract. One crucial component of large fire response in the United States (US) is the sharing of wildland firefighting resources between regions: resources from regions experiencing low fire activity supplement resources in regions experiencing high fire activity. An important step towards improving the efficiency of resource sharing and related policies is to develop a better understanding of current assignment patterns. In this paper we examine the set of interregional wildland fire engine assignments for incidents in California and the Southwest Geographic Coordination Areas, utilising data from the Resource Ordering and Status System. We study a set of multinomial logistic models to examine seasonal and regional patterns affecting the probabilities of interregional resource assignments. This provides a quantitative and objective way to identify the factors strongly influencing interregional assignments. We found that the fire activity in the regions significantly affects response probabilities, as does the season and the national preparedness level. Because our models indicate significant unexplained variation, even when accounting for fire activity, seasonality and resource scarcity, we hypothesise that the existing system could benefit from future research.

Additional keywords: fire management, modelling

Received 24 August 2016, accepted 4 April 2017, published online 19 May 2017

Introduction

Managing wildland fires is a crucial and increasingly expensive task in the United States (US). In 2015, for the first time in its history, the US Department of Agriculture (USDA) Forest Service ('the USFS') spent over half of its budget on fighting wildland fire, and costs are expected to continue to rise (USDA Forest Service 2015). Large wildland fires comprise the majority of these wildland fire costs (US Department of Agriculture, US Department of the Interior, and National Association of State Foresters 2003): less than 2% of the fires managed by the USFS are responsible for over 30% of the wildland fire suppression costs incurred by the USFS (USDA Forest Service 2015). Managing large wildfires is not only costly but is also complex, requiring cooperation of several types of resources (e.g. crews, engines, airplanes, helicopters and management teams) from multiple agencies and regions. The US wildland firefighting system relies on resource sharing across geographic regions to respond to these large fires, particularly in periods of significant fire activity: areas with a resource surplus may supplement areas with a deficit of resources (National Interagency Coordination Center 2016). This sharing necessitates significant travel by firefighting resources, which increases firefighters' exposure to travel-related hazards. Of the fatalities incurred by wildland firefighters as recorded by the National Interagency Fire Center (NIFC) from 1990 to 2015, 21.4% were due to a vehicle accident (National Interagency Fire Center 2015). Beyond increasing exposure to travel hazards, travel is also costly. While sharing and moving resources between geographic regions may be less expensive than paying for a surplus of firefighting resources for each region, in a period of ever-rising wildland fire expenditure, saving money on travel could be valuable. In addition, long travel times may result in missed suppression opportunities on large fires, which may lead to increased wildfire damages. When compared with a lengthy engagement in large fire suppression, timely initial attack that keeps fires small may minimise suppression costs and values lost; however, successful initial attack cannot be completed if resources responsible for initial attack are unavailable because they are in travel status or responding to fires elsewhere.

Interregional resource assignments in the US are governed by a complex system of resource sharing between numerous jurisdictions (e.g. private, state, federal) and a range of governmental scales (e.g. local, municipal, regional, national). The numerous local resources frequently meet suppression needs, but resources are shared between regions when fire activity exceeds local response thresholds. Such interregional resource sharing is guided by regional and national mobilisation guides (e.g. California Wildland Fire Coordinating Group 2016; National Interagency Coordination Center 2016; Southwest Coordinating Group 2016), typically adhering to a 'nearest neighbour' rule. However, with the exception of episodes of significant national resource scarcity, local and regional entities may choose whether to allow their resources to be sent to other regions. Some of these restrictions on resource sharing are clearly stated in the local and regional mobilisation guides, others are determined on a day-to-day basis by local and regional fire managers. Because there are multiple facets to such decisions, many of the considerations regarding whether or not to share resources remain undocumented.

A particularly important resource used in wildland fire management is the wildland fire engine. These engines transport crews to the incident and provide the capacity to build wet line fireline created using water to wet flammable material (National Interagency Fire Center 2016*a*). Such wet line may be utilised to directly extinguish the fire or reduce the intensity of the flaming front by applying water directly to the flames. The water may also be used to create a temporary area of wet materials before the arrival of the flames to reduce the intensity of the fire or halt the fire's spread. On average, wildland engine assignments comprised 56% of the total assignment time of ground-based line-building resource assignments (for crews, engines and bulldozers) on large fires managed by one of the three main types of US large fire incident management teams (i.e. Type I, II or national incident management organisation) (calculated using 2007–2013 data from the National Interagency Resource Ordering and Status System, ROSS). In 2013, there were over 1000 wildland engines in the US that were given the status of available or on-incident for use on interregional assignments at some point during the year (as recorded in 2013 ROSS data). A majority of these engines are managed by a federal agency (83%). The non-federal engines are generally provided by states (14%); these state-provided engines have a variety of owners including state agencies, counties and local fire departments. The rest of the wildland engines are provided by a variety of sources including non-profit organisations, Native American tribes and private contractors.

A prerequisite step towards improving the efficiency of resource sharing and related policies is to develop a better understanding of current assignment patterns and the variables that influence them. The implementation of ROSS and the subsequent archival process has created a dataset that tracks where and when wildland firefighting resources have been assigned (Lockheed Martin Enterprise Solutions and Services 2012). In this study we used the ROSS dataset to characterise interregional movements of wildland engines for US fire suppression activities, specifically examining assignments to incidents in the California (CA) and Southwest (SW) Geographic Coordination Areas (GCAs). We selected these specific GCAs for three primary reasons. First, and most simply, we wanted to compare the differences in resource use and sharing patterns between neighbouring rather than remote GCAs. Second, large fire response in CA is characterised by relatively high resource use and suppression expenditures (Hand *et al.* 2014; Hand *et al.* 2017), which might suggest limiting external sharing. Last, the fire season in the SW is typically more temporally predictable relative to that in CA (National Wildfire Coordinating Group 2014), which might suggest different seasonal variations in resource sharing.

We used multinomial logistic models to examine and identify the effects of three main drivers (fire activity, seasonality and the scarcity of resources nationwide) on interregional wildland engine assignments, resulting in a deeper understanding of interregional assignments in the US. While this paper specifically examines regions within the US, the methods we describe have significant potential utility to other suppression resources (e.g. crews) and other regions within the US, nations with similar resource allocation challenges (e.g. Canada) (Tsang and Larson 2013) and Italy (Fiorucci *et al.* 2011), or between-nation resource sharing (see Jurvélius 2008 and European Policy Evaluation Consortium 2010 for several examples). This method allows for a quantitative and objective way to examine if policy directives are being followed and identify the factors strongly influencing the interregional assignments.

Methods

Interregional assignments, fire activity and preparedness level data

ROSS was commissioned in 1995 to track the dispatch of firefighting resources from nationwide interagency dispatch centres. It provides a nationally standardised approach to resource order and dispatch-related recordkeeping; archived national data are available from 2007 to the present (Lockheed Martin Enterprise Solutions and Services 2012). Both the CA and SW GCAs use ROSS to request, mobilise and demobilise resources from outside regions (California Wildland Fire Coordinating Group 2016; Southwest Coordinating Group 2016). From ROSS data we obtained information regarding interregional wildland engine assignments from 2007 to 2013, including the GCA in which the incident occurred (the 'incident' GCA), the GCA from which the engine responded (the 'home' or 'response' GCA), when the resources arrived at the incident (mobilisation date) and the daily number of fires being managed by an Incident Management Team or Incident Commander in each GCA (we refer to these fires as 'large fires' and 'uncontained fires' in this paper). Each request was linked with fire activity and national preparedness level (PL) on the day before the mobilisation date (specifically, expected time of arrival) of the resource. The PL is a measure of fire activity and resource scarcity throughout the US ranging from one to five and determined by the National Multi-Agency Coordinating Group at NIFC according to the guidelines in the National Mobilisation Guide (National Interagency Coordination Center 2016); a PL of one indicates low fire activity and high resource availability and a PL of five indicates high fire activity and low resource availability. We used historical archives of the NICC National Incident Management Situation Report to obtain the daily PL and classified it as either low (PL of one, two or three) or high (PL of four or five). We used the Fire Program Analysis Fire Occurrence Database (Short 2014, 2015) to obtain the daily number of new ignitions occurring in each GCA. Daily tallies of total new ignitions and ongoing large fires per GCA provided a measure of regional suppression demand.

Resource request and fire occurrence data were grouped by the GCA in which the incidents originated. Historically, there were 11 GCAs; however, in 2014, the Eastern Great Basin and Western Great Basin merged. In addition, the 2013 National Mobilisation Guide (National Interagency Coordination Center 2013) provided a specific directive for two pairs of coordination areas (the Californian GCAs and Great Basin GCAs), stating that 'Resource mobilisation and reassignments between Northern California Operations and Southern California Operations, and between the Western Great Basin and Eastern Great Basin do not require resource orders through NICC'. Thus, we chose to consider Northern and Southern California to be a single region and the Eastern and Western Great Basin as a single region, resulting in nine aggregated GCAs: Alaska (AK), CA, Eastern (EA), Great Basin (GB), Northern Rockies (NR), Northwest (NW), Rocky Mountain (RM), SW and Southern (SA). The spatial boundaries of these GCAs are shown in Fig. 1.

For the purposes of this study we used the definition of a wildland engine from the Interagency Standards for Fire and Fire Aviation Operations (National Interagency Fire Center 2016*a*), which is a tanked vehicle specified in ROSS as a qualified Type 3, 4, 5, 6 or 7 engine. These engines are designed specifically for fighting wildland fire and are thus rugged vehicles that may go off paved roads. They typically range from ~190 to 2800-L water tank capacities and carry crews of two to three firefighters (National Interagency Fire Center 2016*a*). Our analysis is concerned with interregional sharing; consequently, we only examine filled requests for which the engine's home GCA differs from the incident GCA, that is, when the resources within a GCA cannot meet the region's demand. The number of intra- and interregional assignments archived in ROSS for 2007–2013 are summarised in Table 1 by incident and response GCA.

Monthly circular migration plates (Sander *et al.* 2014) provide an effective visual representation of the volume and characteristics of the complicated regional movement of wildland engines by month. The number of interregional assignments occurring in each month were counted to determine the total number for each incident–response GCA pair. The total number of assignments from one GCA to the other is indicated

Fig. 1. A map of the geographic coordination areas examined in this paper. Adapted from data provided by the Predictive Services Agency, available at http://psgeodata.fs.fed.us/download.html (accessed 20 March 2016).

Table 1. Summary of interregional engine assignments 2007–2013

The total number of observations of interregional assignments for engines archived in the Resource Ordering and Status System from 1 January 2007 to 31 December 2013, categorised by the incident Geographic Coordination Area (GCA) and the engine GCA (AK, Alaska; CA, California; EA, Eastern Area; GB, Great Basin; NR, Northern Rockies; NW, Northwest; RM, Rocky Mountain; SA, Southern Area; SW, Southwest)

	Incident GCA									Total percentage (interregional)
Engine GCA	AK	CA	EA	GB	NR	NW	RM	SA	SW	
AK	304	0	0	0	21	0	0	0	0	0.2
CA	0	77781	0	825	21	134	141	168	329	13.3
EA	0	93	848	81	140	6	91	304	28	6.1
GB	0	678	0	15751	63	117	252	193	306	13.3
NR	0	462	11	455	5724	135	250	103	370	14.7
NW	0	1041	0	788	252	11432	128	15	154	19.6
RM	0	336	35	469	156	62	6366	281	193	12.6
SA	0	28	15	99	12	5	38	1685	19	1.8
SW	0	586	1	682	348	124	197	285	9346	18.3
Total percentage (interregional)	0.0	26.6	0.5	28.0	8.4	4.8	9.0	11.1	11.5	

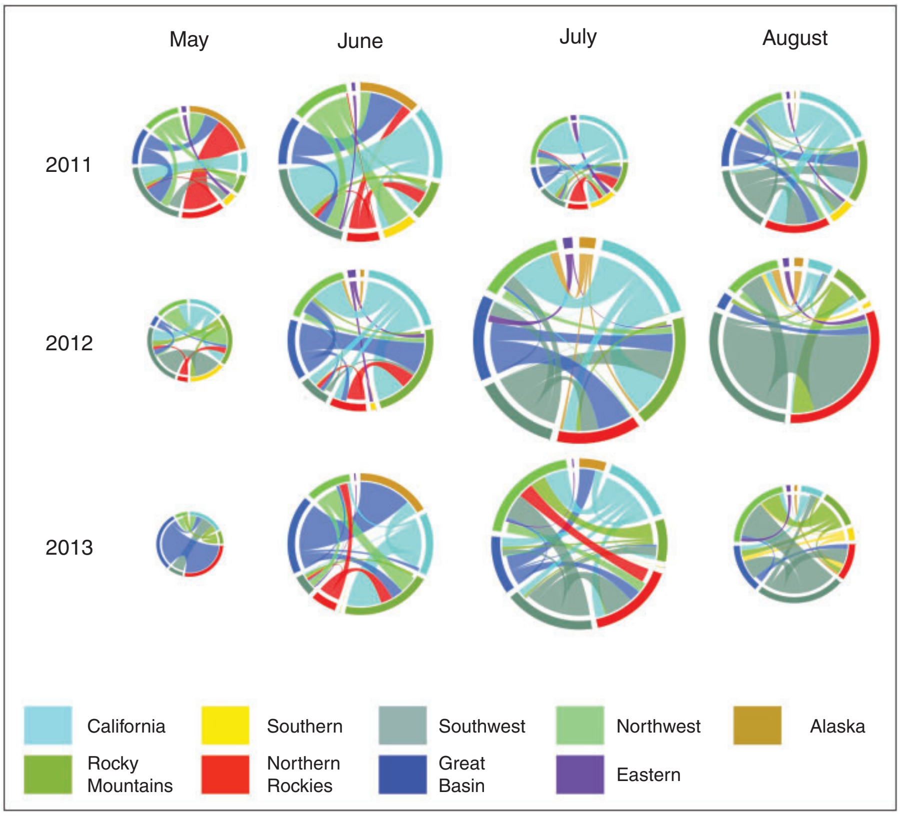

Fig. 2. Circular migration graphs showing a monthly summary of the interregional assignments of wildland engines for the summers of 2011–2013. The total number of assignments in each month across the US is proportional to the diameter of the circle. For scale, there were 222 total interregional engine assignments in July 2012 and 31 in May 2013. We refer to the arcs along the edge of each circular plot as the 'exterior arcs', and the arcs inside each circular plot as the 'interior arcs'. The total number of assignments from one GCA to the other is indicated by the width of each interior arc. Each of the interior arcs connects two exterior arcs: the exterior arc with the same colour as the interior arc indicates from which GCA the engines came; the exterior arc with a different colour as the interior arc indicates in which GCA the incident occurred.

by the width of each arc, and the total number of assignments in each month is proportional to the diameter of the circle (Fig. 2). We further describe and discuss these graphs in the Results section.

Multinomial logistic models

We used multinomial logistic models (see Hilbe 2009; Hosmer *et al.* 2013) to study the effects of several covariates on the likelihood that a resource from each of the home GCAs would respond to a request from incident GCAs. Multinomial logistic models are part of the group of statistical classification models. These models seek to classify responses into categories based on the supplied covariates. Multinomial logistic models predict the probability associated with each possible response category; the response category with the highest probability of occurrence may be interpreted as the prediction for the category of response. The multinomial logistic models fit in this paper were not created to predict future interregional engine responses but rather to study the effect that specific drivers have historically had on interregional assignments.

The relative ratio of probabilities of two different responses are called the 'odds'. For example, if the probability of getting outcome A is 10% and the probability of getting outcome B is 20%, then the odds of getting outcome A as opposed to outcome B is 1/2 (i.e. outcome A is exactly half as likely to occur as outcome B). The coefficients provided by the multinomial logistic model can provide 'odds ratios', which indicate the multiplicative change in odds based on a one-unit increase in the covariate's value. For example, if the odds ratio associated with a specific covariate was 1.06, with each single unit increase of that covariate, the odds of getting outcome A as opposed to outcome B will increase by 6%.

We included the following covariates in the model: the fire activity in the response and incident GCAs, the fire season and the national PL. These covariates were included in the model using alternative-specific coefficients, as fire activity in a specific GCA is likely to have variable effects on the probability of an engine response from each GCA. Fire activity was approximated using the number of large fires and new ignitions in each GCA. Because of the temporal variability in fire seasons across regions of the western US, particularly regarding resource availability, we tested four dummy seasonal covariates in the model indicating if the assignment took place from 15 April to 15 May, 16 May to 15 August, 16 August to 15 September or 16 September to 15 October. We referred to these in the covariates as early season, mid-season, mid–late season and late season. These dates were initially chosen to correlate with starting and ending dates of the time of greatest fire activity in multiple GCAs (see the GCA mobilisation guides, e. g. California Wildland Fire Coordinating Group 2016; and Southwest Coordinating Group 2016; also see National Wildfire Coordinating Group 2014). We chose to use discrete dates to reflect periods of specific GCA business operations rather than including any climatic analysis of seasonality; the climatic aspect should be captured by the fire activity covariates. We also included national PL as one of the factors. During periods of higher national PLs, GCAs across the US experience high fire activity and low resource availability leading to more interregional requests. This results in the NICC having a more active role in prioritising assignments and dispatching resources (National Interagency Coordination Center 2016); thus, a high national PL may be associated with different resource assignment patterns. To test this, we included another dummy covariate in each model to indicate if the national PL was low (i.e. PL of one, two or three) or high (i.e. PL of four or five).

Table 1 shows that from 2007 to 2013 over 95% of the interregional wildland engine assignments to SW came from five GCAs: CA, GB, NR, NW and RM. Similarly, over 95% of all assignments to CA came from five GCAs: GB, NR, NW, RM and SW. Thus, to avoid potential model over specification caused by small sample sizes, we excluded AK, EA and SA from the response GCAs.

We fit our model in a Bayesian framework using the RSTAN package, ver. 2.14.1, in R (R Foundation for Statistical Computing, Vienna, Austria, see http://www.R-project.org/, accessed 26 April 2017; Stan Development Team, see http://mc-stan.org, accessed 26 April 2017). For an introduction to Bayesian models, we refer interested readers to Hobbs and Hooten (2015). For $i = 1, \ldots, N$ fires, let y_i be the region from which a resource is shared (with y_i taking on the values $1, \ldots, K$). We define the multinomial data likelihood as:

$$y_i \sim \text{multinomial}(\mathbf{p}_i)$$

where $\mathbf{p}_i = (\mathrm{p}_{i1}, \ldots, \mathrm{p}_{iK})'$ is a K-dimensional vector with p_{ik} the latent probability that the ith fire in the incident GCA would receive wildland engines from the kth home GCA. The latent probabilities $\mathbf{p}_i$ are informed by the covariates using the logistic link function:

$$\mathbf{p}_i = \frac{\exp(\boldsymbol{\mu}_k + \mathbf{X}_{ik}\boldsymbol{\beta}_k)}{\sum_{k=1}^{K} \exp(\boldsymbol{\mu}_k + \mathbf{X}_{ik}\boldsymbol{\beta}_k)}$$

where a single category k' is chosen as the reference category with $\boldsymbol{\mu}_{k'} = \mathbf{0}$ and $\boldsymbol{\beta}_{k'} = \mathbf{0}$ (e.g. $\exp(\mathbf{X}_{ik'}\boldsymbol{\beta}_{k'} = 1)$. Thus, the other coefficients $\boldsymbol{\beta}_k, k \neq k'$, reflect the corresponding covariates' effect on the log-odds of a wildland engine response from a given GCA as compared with a response from the reference GCA. When exponentiated, the coefficients provide the odds ratio, which gives the multiplicative change in odds of a response from a GCA as compared with the reference GCA for a one-unit increase in the covariate. The choice of reference GCA does not affect the probabilities estimated by the model and the coefficients can be transformed to compare each GCA to another.

In our model, we use standardised covariates (e.g. centring and scaling $\mathbf{X}$ by the column means and standard deviations). Standardising the covariates has no influence on the model as the scale of the original coefficients can be recovered, but aids in prior specification and interpretation of the results. The intercept $\boldsymbol{\mu}_{k'} = \mathbf{0}$ is given a vague $\mathrm{N}(\mathbf{0}, 100 \times \mathbf{I})$ prior and is insensitive to this prior choice. To prevent overfitting and to facilitate the selection of covariates, we assign a Bayesian Lasso prior on the regression coefficients $\boldsymbol{\beta}_k \sim \text{Double} - \text{exponential}(0, \lambda \times \mathbf{I})$ and complete the model with a Uniform(0, 100) prior on the variance λ (Park and Casella 2012).

The main advantage of fitting the regression in the Bayesian framework is it allows us to estimate the uncertainty in the regression coefficients and predictions. For example, the widely used R package *glmnet* (Friedman *et al.* 2010) does not provide uncertainty estimates for the $\boldsymbol{\beta}_k$ nor the odds ratios derived from $\boldsymbol{\beta}_k$. Within the Bayesian model framework, we can obtain credible intervals for the odds ratios of interest from the posterior samples. Credible intervals function similarly to confidence intervals, although they may not be symmetric around the mean (Hobbs and Hooten 2015).

We used two classification methods to examine the model's classification accuracy on held-out data using 10-fold cross-validation. The first classification method calculates the percentage of observations for which the model correctly classifies the response GCA, where, for each posterior sample of the regression parameters in the model, we simulate 100 categorical predictions and calculate the classification accuracy over the replicates. We call this the 'request-based' classification accuracy as it classifies each observation independently. The multinomial logistic models assume that each observation is independent; however, if there are multiple requests on a given day, calculating the model's accuracy using a request-based method underestimates the daily classification accuracy. Because the multinomial logistic model is producing probabilities based on daily fire activity, an alternative way to evaluate the model performance is to determine the expected number of engines responding from each GCA given the number of requests occurring that day; we call this the 'daily' classification accuracy. We compiled the number of requests that had occurred each day and calculated the corresponding model-produced probabilities using historical records. We then simulated 100 samples of responses for each posterior sample and calculated the daily prediction accuracy. For example, on 23 July 2008, there were 21 interregional requests from CA. The model predicted 8.7, 22.9, 12.8, 44.9 and 10.7% chances of a response from SW, GB, NR, NW and RM. The historical assignment patterns from that day were one, four, four, eleven and one engines responding from these GCAs respectively. Thus, on average, the daily accuracy for that day can be summarised as 16.9 engines predicted correctly and 4.1 engines predicted incorrectly. The simulation routine was run for each day and the daily correct classifications were aggregated to determine the overall daily classification accuracy.

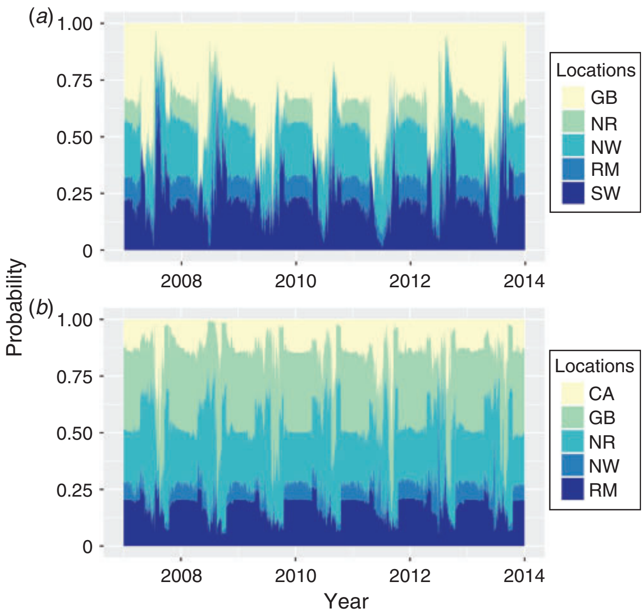

Fig. 3. The probabilities of responses of wildland engines from each Geographic Coordination Area as predicted by a multinomial logistic model for 2007 to 2013 (*a*) to incidents in California (CA) and (*b*) to incidents in the Southwest (SW). GB, Great Basin; NR, Northern Rockies; NW, Northwest; RM, Rocky Mountain.

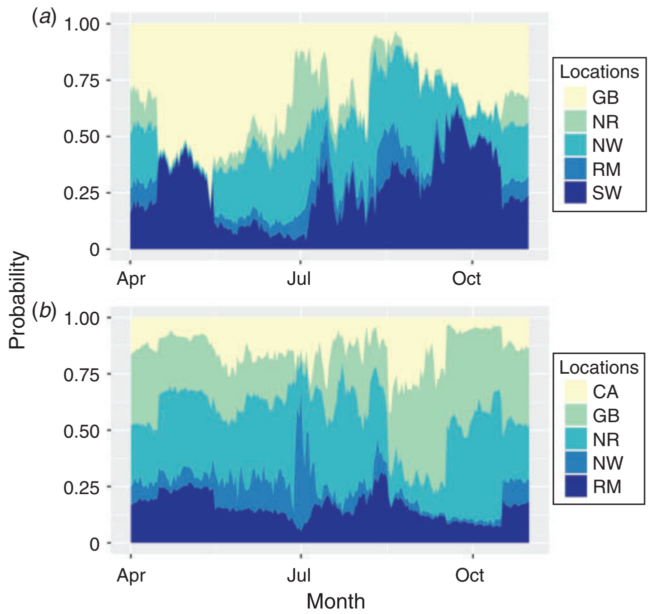

Fig. 4. The probabilities of responses of wildland engines from each Geographic Coordination Area as predicted by a multinomial logistic model for 2012 (*a*) to incidents in California (CA) and (*b*) to incidents in the Southwest (SW). GB, Great Basin; NR, Northern Rockies; NW, Northwest; RM, Rocky Mountain.

We compare the daily classification accuracy that was calculated using model-produced probabilities to the daily classification accuracy produced by using two other probability distributions. First, we used a uniform random distribution every day (assuming 20% probability for each response GCA). However, there may be an inherently different response rate from each GCA; for example, neighbouring GCAs may respond more frequently than non-neighbours. Thus we also used a probability distribution corresponding to the average percentage of responses provided by each GCA from 2007 to 2013. For incidents in CA, this distribution of responses was 22% from GB, 15% from NR, 33% from NW, 11% from RM and 19% from SW. For incidents in the SW, this distribution of responses was 24% from CA, 23% from GB, 27% from NR, 12% from NW and 14% from RM. We do not include seasonality in these two probability distributions as we would like to compare the performance of the multinomial logistic model with naïve probability distributions to examine the utility including the covariates we selected in the model.

We use the multinomial logistic regression models to first examine the implications of the coefficients regarding changes in the odds of a resource responding from a specific GCA. We also examine the implications of the classification accuracy measures. We then examine the seasonal trends and variation in model-produced probabilities of response for our case studies using historical fire activity and PLs from 2007 to 2013 (Fig. 3). In addition, we examine the variation in model-produced probabilities over the 2012 fire season (Fig. 4). The 2012 fire season was chosen as a case study because of a relatively high degree of resource use and fire activity in this year (National Interagency Coordination Center 2012). Last, we chose a fire day in 2012 with a high number of interregional responses (16 August and 14 June for the model of incidents in CA and in SW respectively) to demonstrate several patterns in resource responses to specific fire activity variables; we hold all but one covariate at the level from 16 August or 14 June, allowing us to isolate the effect of the number of new fires or the number of large fires in a single GCA on the engine response probabilities from the response GCAs (Figs 5, 6). The case studies in this paper provide examples of how the model results may be examined; other analyses and results can be obtained from the authors by request.

Results

The data in Table 1 demonstrate that interregional assignments are much less frequent than within-GCA assignments. Table 1 also shows that the interregional assignments mostly comprised resources from the six western GCAs in the continental US assigned to incidents in those same GCAs: CA, GB, NR, NW, RM and SW. EA, SA and AK combined provide less than 10% of the wildland engines used in interregional assignments. AK and EA also use very few outside resources. However, engine assignments to SA from all other GCAs comprise 11.1% of the engine assignment records. This is due, in part, to a particularly heavy fire season experienced in 2011 by the state of Texas, part of which is in the SA.

The circular migration plots in Fig. 2 show a monthly summary of interregional engine assignments for the summer months (May, June, July and August) of 2011, 2012 and 2013. The diameter of each circle is proportional to the total number of interregional assignments occurring each month. For scale, there were 222 total interregional engine assignments in July

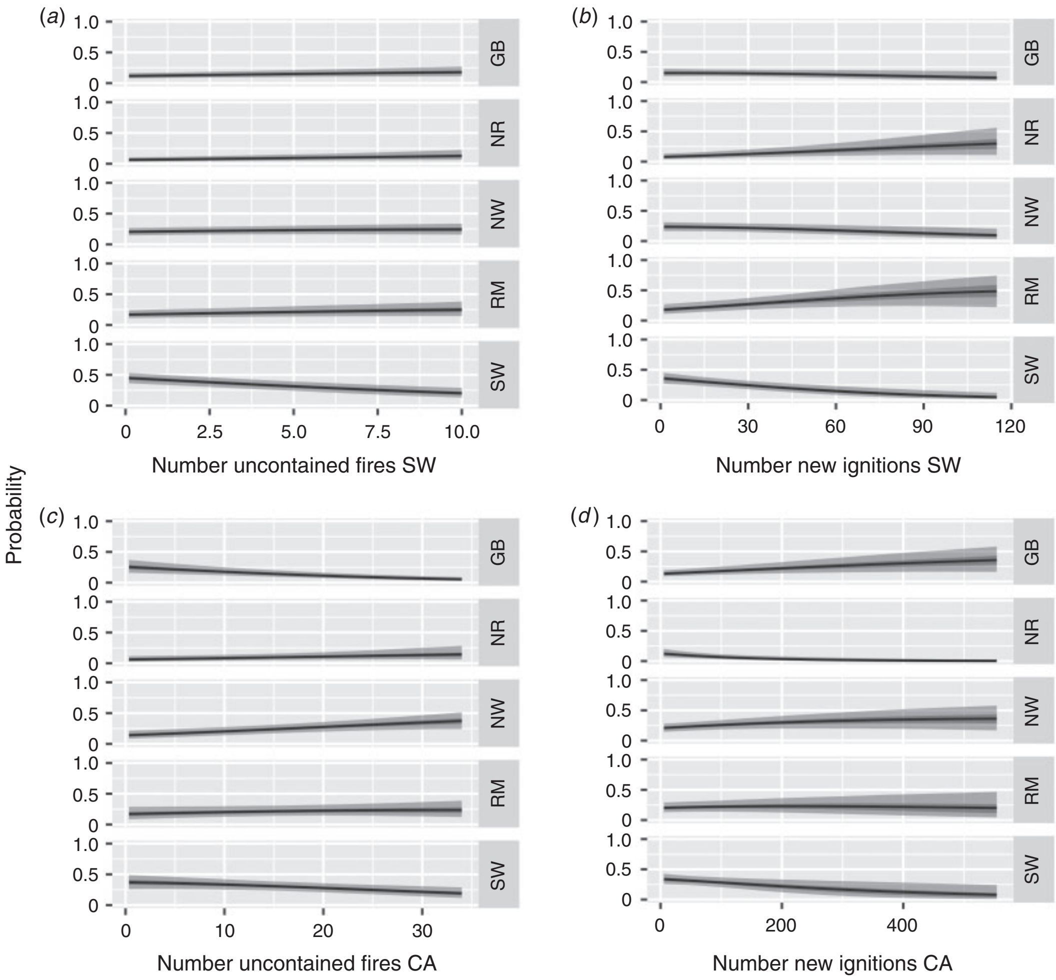

Fig. 5. The probabilities and associated uncertainty intervals for responses of wildland engines from each Geographic Coordination Area as predicted by a multinomial logistic model for 16 August 2012 for responses to incidents in California (*a*) varying only large fires (i.e., uncontained) in the Southwest, (*b*) varying only new ignitions in the Southwest, (*c*) varying only large fires (i.e., uncontained) in California and (*d*) varying only new ignitions in California. GB, Great Basin; NR, Northern Rockies; NW, Northwest; RM, Rocky Mountain.

2012 and 31 in May 2013. We refer to the arcs along the edge of each circular plot as the 'exterior arcs', and the arcs inside each circular plot as the 'interior arcs'. The total number of assignments from one GCA to the other is indicated by the width of each interior arc. Each of the interior arcs connects two exterior arcs: the exterior arc with the same colour as the interior arc indicates which GCA the engines came from; the exterior arc with a different colour to the interior arc indicates which GCA in which the incident occurred. For example, in August 2012, the largest share of interregional engine assignments consisted of engines from SW being assigned to NR; this is indicated by the width of the grey interior arc stretching between the SW exterior arc (indicated by the grey arc along the perimeter) and the NR exterior arc (indicated by the red arc along the perimeters).

The monthly circular migration graphs in Fig. 2 show interesting patterns. Seasonal trends of interregional assignments are immediately obvious; for example, in May and June, wildland engines tend to move into SW and in July and August engines move out of SW. The diameters of the circles are proportional to the number of interregional assignments that occurred in each month. Months with more wildland engine assignments often line up with significant fire events. For example, in June 2011, SW experienced significant large fire activity including the Wallow Fire, which burned 217 720 ha and was at the time the largest single fire ever recorded in the contiguous US (National Interagency Fire Center 2016*b*), and the Horseshoe 2 Fire, which burned 90 225 ha (National Interagency Fire Center 2016*c*). The response to these fires is evident in the migration graphs; several GCAs including CA, GB, NW, RM and NR sent engines to respond to the shortage of resources in SW. Similarly, many GCAs sent engines to SA throughout the summer of 2011, when Texas was experiencing a particularly severe wildfire season.

The coefficients and associated credible intervals associated with the standardised covariates of the multinomial logistic models are presented in Tables 2 and 3 to illustrate how engines were assigned to incidents in CA and SW respectively from each of the other GCAs. For the model of engines responding to

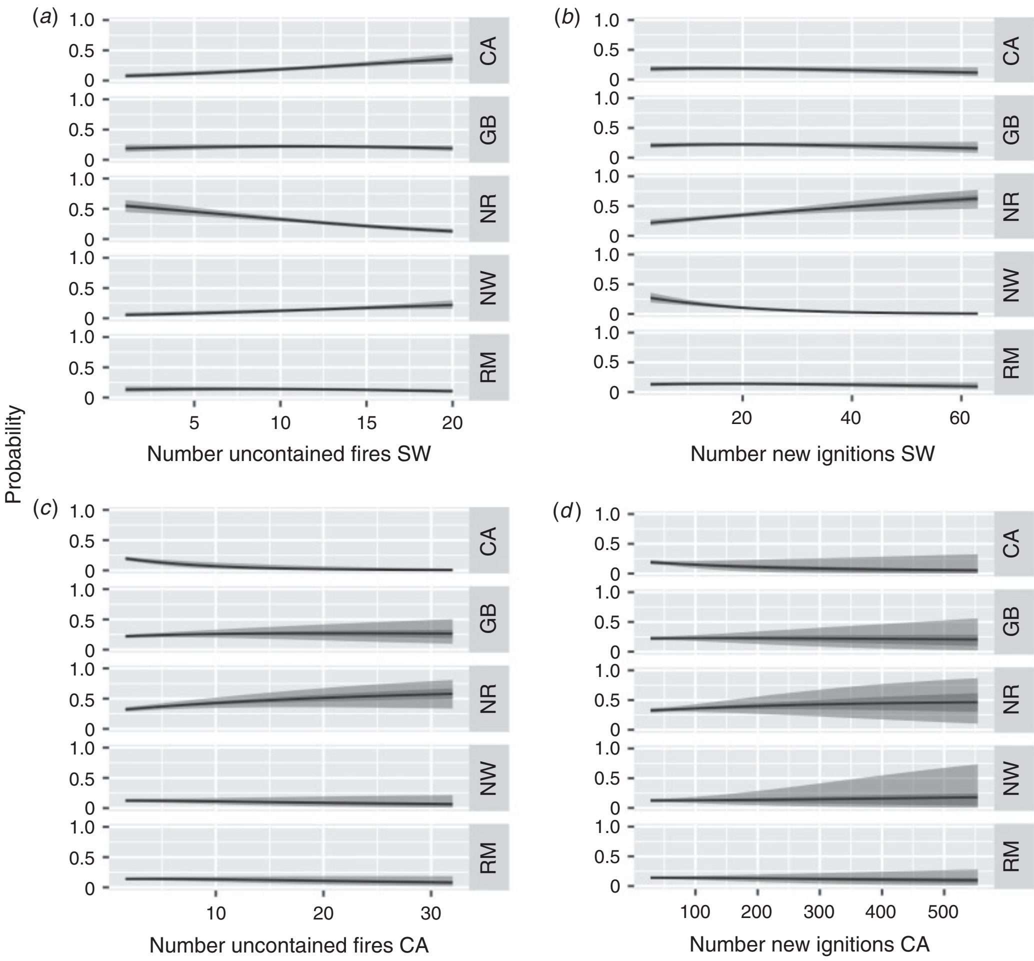

Fig. 6. The probabilities and associated uncertainty intervals for responses of wildland engines from each Geographic Coordination Area as predicted by a multinomial logistic model for 14 June 2012 for responses to incidents in the Southwest (*a*) varying only large fires (i.e., uncontained) in the Southwest, (*b*) varying only new ignitions in the Southwest, (*c*) varying only large fires (i.e., uncontained) in Californiaand (*d*) varying only new ignitions in California. GB, Great Basin; NR, Northern Rockies; NW, Northwest; RM, Rocky Mountain

incidents in CA we set the reference GCA to be SW (Table 2) and for the model of engines responding to incidents in SW we set the reference GCA to be CA (Table 3). The coefficients presented in Tables 2 and 3 can be exponentiated to produce the odds ratios discussed in the paper.

Some of the patterns revealed by the model coefficients are intuitive: for example, in the model describing how engines respond to incidents in the SW, the model coefficient for the number of large fires in CA results in an odds ratio of 116.8% (95% CI 106.4–130.5%), indicating an increase in the odds of an engine response from GB versus a response from CA for each additional large fire occurring in CA. Similarly, in the model of engines responding to incidents in CA, the coefficient for the number of large fires in SW corresponds to an odds ratio of 121.9% (95% CI 115.0–129.2%), indicating an increase in the odds of an engine response from GB rather than SW for each additional large fire occurring in SW. Given this and other numerous examples, we observe that fire activity in a GCA decreases the odds of an engine responding from that GCA versus a different GCA. We also observe some possible second order effects of geographic constraints. For example, for the model describing how engines respond to incidents in CA, the odds ratio indicates that each large fire occurring in NW decreases the odds of an engine response from GB versus from SW (odds ratio of 97.2%; 95% CI: 94.3–99.9%). This may be because as large fire activity in NW increases, GB rather than SW is more likely to send engines to NW, which may increase the odds that SW responds to a request in CA.

The results of the request-based classification accuracy, the daily classification accuracy using daily probabilities produced by the multinomial logistic model, the daily classification accuracy produced by a uniform distribution and the daily classification accuracy produced by the non-uniform but constant probability distribution are shown in Table 4 and provide interesting comparisons. The request-based classification accuracy of the models is 27 and 23% for incidents in CA and SW respectively; these rates are higher than randomly selecting response GCAs for each observation. This demonstrates that

Table 2. Multinomial logistic model for engines responding to incidents in the California (CA) Geographic Coordination Area
The coefficients and associated credible intervals for a multinomial logistic model of engines responding to incidents in CA. The coefficients are the first number in each cell; the credible intervals are within the parentheses (refer to Table 1 for area abbreviations)

	GB	NR	NW	RM
Intercept	0.31 (−0.09, 0.71)	−0.87 (−1.39, −0.35)	−0.02 (−0.41, 0.36)	−0.95 (−1.47, −0.45)
New ignitions CA	0.00 (0.00, 0.01)	0.00 (−0.01, 0.00)	0.00 (0.00, 0.01)	0.00 (0.00, 0.01)
Large fires CA	−0.03 (−0.05, 0.00)	0.05 (0.01, 0.08)	0.05 (0.02, 0.08)	0.03 (0.00, 0.07)
New Ignitions GB	0.01 (0.00, 0.02)	0.00 (−0.01, 0.00)	0.01 (0.01, 0.02)	−0.01 (−0.02, 0.00)
Large fires GB	−0.09 (−0.13, −0.06)	0.04 (0.00, 0.09)	0.00 (−0.03, 0.03)	0.02 (−0.01, 0.06)
New ignitions NR	−0.01 (−0.03, 0.00)	0.00 (−0.01, 0.02)	0.00 (−0.01, 0.01)	0.00 (−0.01, 0.01)
Large fires NR	0.01 (−0.02, 0.04)	−0.07 (−0.13, −0.02)	−0.01 (−0.04, 0.02)	0.00 (−0.04, 0.04)
New ignitions NW	0.01 (0.00, 0.01)	0.01 (0.00, 0.01)	−0.01 (−0.01, 0.00)	0.00 (−0.01, 0.00)
Large fires NW	−0.03 (−0.06, 0.00)	−0.06 (−0.10, −0.01)	−0.16 (−0.20, −0.13)	−0.04 (−0.08, 0.00)
New ignitions RM	0.01 (0.00, 0.03)	0.00 (−0.01, 0.02)	0.01 (0.00, 0.02)	0.01 (0.00, 0.03)
Large fires RM	−0.05 (−0.17, 0.07)	0.06 (−0.11, 0.23)	−0.01 (−0.12, 0.09)	−0.07 (−0.24, 0.07)
New ignitions SW	0.01 (0.00, 0.03)	0.03 (0.02, 0.04)	0.01 (0.00, 0.02)	0.03 (0.01, 0.04)
Large fires SW	0.13 (0.07, 0.18)	0.15 (0.09, 0.21)	0.10 (0.05, 0.15)	0.12 (0.06, 0.18)
Early season	−0.08 (−1.01, 0.87)	−5.41 (−14.93, −0.86)	−6.02 (−16.14, −1.70)	−5.31 (−14.70, −0.92)
Mid-season	0.24 (−0.18, 0.71)	−1.38 (−2.16, −0.61)	−0.21 (−0.69, 0.22)	−1.15 (−1.86, −0.45)
Mid–late season	0.00 (−0.48, 0.49)	−1.85 (−2.87, −0.86)	0.81 (0.29, 1.33)	−1.16 (−2.00, −0.35)
Late season	−0.30 (−1.33, 0.67)	−4.57 (−13.77, −0.36)	−0.62 (−1.91, 0.51)	−5.08 (−14.33, −0.68)
High preparedness level	−0.66 (−1.03, −0.28)	0.28 (−0.15, 0.76)	−0.04 (−0.39, 0.30)	0.44 (−0.04, 0.94)

Table 3. Multinomial logistic model for engines responding to incidents in the Southwest (SW)
The coefficients and associated credible intervals for a multinomial logistic model of engines responding to incidents in SW. The coefficients are the first number in each cell; the credible intervals are within the parentheses (refer to Table 1 for area abbreviations)

	CA	GB	NR	NW
Intercept	−0.37 (−1.29, 0.54)	0.54 (−0.23, 1.40)	0.01 (−0.91, 0.84)	−0.99 (−2.28, 0.10)
New ignitions CA	0.00 (−0.01, 0.00)	0.00 (0.00, 0.01)	0.00 (0.00, 0.01)	0.00 (−0.01, 0.01)
Large fires CA	−0.13 (−0.24, −0.03)	0.03 (−0.01, 0.07)	0.04 (0.00, 0.09)	−0.01 (−0.07, 0.05)
New ignitions GB	−0.01 (−0.04, 0.00)	0.01 (−0.01, 0.02)	0.00 (−0.01, 0.02)	0.00 (−0.02, 0.02)
Large fires GB	0.02 (−0.06, 0.10)	−0.08 (−0.17, 0.00)	0.00 (−0.08, 0.06)	−0.01 (−0.11, 0.07)
New ignitions NR	0.00 (−0.03, 0.03)	0.00 (−0.03, 0.02)	0.00 (−0.02, 0.02)	0.00 (−0.03, 0.04)
Large fires NR	0.02 (−0.07, 0.12)	0.01 (−0.08, 0.11)	−0.08 (−0.20, 0.01)	−0.03 (−0.18, 0.08)
New ignitions NW	0.00 (−0.01, 0.02)	0.01 (−0.01, 0.02)	0.00 (−0.01, 0.01)	0.00 (−0.02, 0.02)
Large fires NW	0.05 (−0.03, 0.16)	0.05 (−0.02, 0.14)	−0.01 (−0.10, 0.06)	−0.14 (−0.36, 0.02)
New ignitions RM	0.00 (−0.01, 0.01)	0.00 (−0.01, 0.01)	0.00 (−0.01, 0.01)	0.00 (−0.01, 0.02)
Large fires RM	0.03 (−0.04, 0.13)	0.02 (−0.06, 0.12)	0.09 (0.01, 0.19)	0.13 (0.03, 0.23)
New ignitions SW	0.00 (−0.02, 0.01)	0.00 (−0.01, 0.02)	0.02 (0.01, 0.04)	−0.06 (−0.09, −0.04)
Large fires SW	0.10 (0.05, 0.14)	0.01 (−0.02, 0.05)	−0.06 (−0.11, −0.02)	0.09 (0.03, 0.15)
Early season	−0.65 (−1.68, 0.23)	−0.59 (−1.47, 0.15)	0.11 (−0.63, 1.02)	−0.07 (−1.14, 1.04)
Mid-season	0.18 (−0.58, 1.08)	−0.34 (−1.22, 0.31)	0.66 (−0.07, 1.58)	0.64 (−0.25, 1.97)
Mid–late season	1.49 (−0.06, 3.27)	0.39 (−0.86, 1.81)	0.53 (−0.86, 2.27)	−0.57 (−3.92, 1.56)
Late season	−1.70 (−9.56, 2.67)	1.29 (−1.45, 5.59)	2.76 (−0.12, 7.20)	−1.04 (−8.20, 3.48)
High preparedness level	0.04 (−1.11, 1.20)	−0.41 (−1.53, 0.51)	−0.29 (−1.31, 0.60)	0.99 (−0.41, 2.75)

the factors included in the model are influential in determining which GCA is likely to provide a response; however, for our purposes the daily classification accuracies are more informative. When using probabilities provided by the multinomial logistic models, the daily classification accuracies are 46.7 and 42.2% for incidents in CA and SW respectively. In comparison, a uniform probability distribution gives a daily classification accuracy of 36.3 and 27.8%, and the probability distribution reflecting the average percentage of responses from each GCA gives a 39.4 and 29.4% accuracy rate for incidents in CA and SW respectively.

Fig. 3 shows the daily modelled probabilities from 2007 to 2013 for engines responding to incidents in CA and SW. The effects of seasonal dummy variables are noticeable in Fig. 3*a*; in the period between 16 August and 15 September there is a noticeable drop in the probability that a resource will respond to an incident in CA from GB and a corresponding increase in the probability that a resource will respond from NW. This is also shown in the model coefficients; for example, if a request occurs in CA between 16 August and 15 September, the odds of a response from NW increases as compared with a response from

Table 4. Classification accuracy rates

The classification accuracy rates of the multinomial logistic regression models from Tables 2 and 3 calculated using a request-based method and a daily method. For comparison, daily accuracy classification rates are also presented for a uniform probability distribution and an average frequency-based probability distribution

	Southwest (%)	California (%)
Request-based accuracy	27.0	23.0
Daily accuracy: model-predicted probabilities	46.7	42.2
Daily accuracy: uniform probabilities	36.3	27.8
Daily accuracy: average frequency-based probabilities	39.4	29.4

GB. This indicates seasonal availability of resources, and that managers' perceptions of possible resource needs due to the fire season may have played an important role in resource response. The original data show that of the 1352 observations of interregional assignments to SW, 1215 (90%) took place between 16 May and 15 August. Thus, there are not many observations corresponding to other seasons, which may lead to the results of fire season being insignificant for engines responding to incidents in SW. The yearly trends in Fig. 3*b* are driven mainly by fire activity. The periodic mid-year peak in the probability that an engine will respond from NR to an incident in SW is driven by the fire activity variables rather than the seasonal dummy variables.

Fig. 4 shows finer-scale observations of the modelled daily probabilities of interregional engine assignments during the 2012 fire season. The graphs show numerous examples of shifts in response probabilities as the dummy variables change value. In addition to the seasonal variables (see Fig. 4*a*, 15 May, 15 August and 15 September), the change in national PL plays an important role. For example, the national PL was high from 27 June to 17 July 2012 and from 8 August to 2 September 2012 (National Interagency Coordination Center 2012). The model reports smaller probabilities for an engine responding from GB to incidents in CA during this period of higher PL. This effect is also reflected in the coefficients of the model: a high national PL is associated with an increase in the odds of CA getting an engine from SW, NR, NW or RM rather than GB.

We also used the graphs in Fig. 4 to examine the joint effect of fire activity in multiple GCAs. Historical records show that during the first half of July 2012, fire activity in SW decreased while fire activity in NW increased; in the second half of July 2012, fire activity in the stayed about the same while fire activity in NW decreased. The model-produced response probabilities reflect this, with the probability of an engine responding from SW gradually increasing in the first half of July and decreasing through the second half; similarly, the probability of an engine responding from NW decreases over the first half of July and increases during the second half. Fig. 4 also demonstrates that the modelled response probabilities differ significantly between incident GCAs. For example, on 1 July 2012, the probability of an engine responding from NR to an incident in CA was near the highest of the year. On that same day, the probability of an engine responding from NR to SW was relatively low in comparison with the rest of the year.

After using the model to examine the interregional engine assignments in 2012, we further examined the effect of changing specific fire activity variables while fixing the other covariates using parameters from selected fire days; Figs 5 and 6 show the response probabilities for incidents in CA for 16 August 2012 and for incidents in SW on 14 June 2012, varying only the number of new ignitions or large fires in SW or CA. Fig. 5 demonstrates that increasing the number of new ignitions or large fires in SW decreases the probability of an engine responding from SW to incidents in CA; similarly Fig. 6 shows that increasing the number of new ignitions or large fires in CA decreases the probability of an engine responding from CA to incidents in SW. Fire activity also shows interesting effects on response probabilities from the other GCAs. For example, an increase in new ignitions in SW increases the probability of an engine response from NR to incidents in SW, but an increase in large fires in SW decreases the probability an engine responding from NR. This may occur because requests from large fires may be associated with a need for faster responses, incentivising managers to use resources from neighbouring GCAs.

Discussion

The data from ROSS provided us with many interesting insights into interregional wildland engine assignments. Interregional assignments mostly comprised resource sharing between the six western GCAs in the continental US: CA, GB, NR, NW, RM and SW. This may be due to factors such as the spatial locations of the GCAs and resource availability in the three other GCAs (AK, SA and EA) during the western GCAs' fire seasons. Similarly, barriers between GCAs such as mountains and access points between GCAs such as interstates and major highways might influence the frequency of resource sharing. We observed that interregional assignments are much less frequent than within-GCA assignments; however, this does not negate the importance of interregional assignments because such assignments can incur significant travel hazards and costs. For example, in July 2008, two engines from Michigan were assigned to the Iron Complex Fire in California, requiring over 6400 km of round-trip travel. Examining the interregional assignments aggregated on a monthly basis shows both seasonal trends (e.g. resources moving into and out of SW) and response to fire activity (e.g. significant fire activity in Texas in the summer of 2011). Examining these data using multinomial logistic models showed that fire activity, national PL and fire season are significant drivers of interregional movement. Our models provided higher classification accuracy rates for interregional engine response than using a uniform probability distribution or a probability distribution based on the historical average interregional response frequencies. However, our classification accuracy rates also indicate significant unexplained variation even after accounting for these drivers.

The multinomial logistic models indicated that, in general, increasing large fire activity corresponds to decreasing response probabilities from a GCA. However, the effect of large fire activity varies between regions. These differences are not limited to effects on the response region or incident region in which the fire activity takes place but also to effects on other regions due to indirect effects of regional resource sharing. We also found that high national PL can significantly affect engine response; it is associated with a decreased probability of a response from GB to an incident in CA and a corresponding increased probability of a response from the other four response regions. However, it is important to note that high PLs occur infrequently and when they do occur, this is during extended periods of time over which a few major fires occur in a specific region: that is, days of high PL are likely to have correlated resource use patterns as they are highly correlated in time. In the dataset we used there were only six periods of high PL. This translated to 132 days during which there were 1877 observations of interregional engine assignments to CA with a high national PL and 142 days during which there were 1226 observations of interregional engine assignments to CA with a low national PL. In comparison, there were 26 days during which there were 56 observations of interregional engine assignments to SW at a high national PL and 263 days during which there were 1296 observations of interregional engine assignments to SW at a low national PL. We note that because these observations only covered six periods of high PL, each of which had unique resource use patterns, these results may not be generalisable and may be overfitting to reflect the circumstances under which these periods of high PL occurred.

Our data and models also demonstrated seasonal trends in interregional assignments that are significant for some GCAs, but not for all. For example, we found a drop in the modelled probability that a resource will respond to an incident in CA from GB during the GB fire season. Seasonality is significant in changing the odds of a response from SW when compared with the other response GCAs for incidents in CA. However, the seasonal variable effects are not significant for the probabilities of engines responding to incidents in SW from other GCAs.

While many of the patterns revealed by our models are intuitive, others are not. For example, an increase in new ignitions in SW is associated with an increase in the probability that an engine will respond to incidents in SW from NR. This may occur because NR is off season when SW is on season; thus, the model associates the increase in new ignitions in SW with an increase in NR presence in the region. However, the same signal is not present for NW, which would also be off season. This indicates that SW may have different relationships with NR and NW. Determining if such relationships are efficient is left to future research.

Multinomial logistic models are appropriate when options 'can plausibly be assumed to be distinct and weighted independently in the eyes of each decision maker' (McFadden 1974). We believe this model form is appropriate for our study because of the spatial and temporal nature of this problem (i.e. each GCA is spatially distinct with unique fire seasons and differing fire activity patterns) with no GCA providing a nearly identical substitute for any other GCA. We compared the models derived from the Bayesian method to the models derived from a non-penalised maximum likelihood routine and found that the coefficients were similar. We used the non-penalised models to examine the Hausman–McFadden tests for independence of irrelevant alternatives (Hausman and McFadden 1984). For the model of engines responding to incidents in SW, we found no evidence that the independence of irrelevant alternatives assumption is violated. For the model of engines responding to incidents in CA, we found the assumption of independence of irrelevant alternatives may be violated based on the Hausman–McFadden tests. However, the Hausman–McFadden test has been found to reject the assumption of the independence of irrelevant alternatives even when the options are distinct (Cheng and Long 2007). Thus, because we believe the model is theoretically well specified, we choose to use the multinomial logistic models presented in this paper.

Although the models in this paper allowed us to examine the effect of fire activity, season and national PL on interregional movements, the models may still be further improved. For example, a more sophisticated seasonal variable or measure of national fire activity and resource scarcity could significantly enhance our model. Similarly, enhancements could potentially be made by accounting for the location of a fire relative to the boundary of a neighbouring GCA; for example, it may require less travel to send an engine to southern CA from south-western Arizona (located in the SW GCA) than from northern CA. We also assumed that each request could be filled by resources outside the GCA requesting the resource; however, in times of high resource scarcity, some requests for resources go unfilled. Examining these requests that were not filled is also important. Other enhancements to this model, or that future models might consider, include adding spatial granularity to support examining travel on a smaller scale; examining if there are policy differences between GCAs that create artificial barriers to interregional assignments or that encourage interregional resource sharing; examining other resources beyond wildland engines; and examining differences between resource providers (i.e. federal agency-owned engines versus contract engines).

Conclusion

The models developed in this study set a baseline, demonstrating how interregional assignments can be studied to reveal systematic patterns and determine which factors are drivers of the system. Once we understand how resources move across the country and what the drivers of this movement are, we can more efficiently direct that movement with clear fire management goals in mind. Because our models indicate substantial unexplained variation in the decisions regarding engine sharing, even when accounting for fire activity, seasonality and resource scarcity, we hypothesise that the existing system that is based upon informal rules and individual heuristics may be inefficient and could benefit from future research regarding how to balance expected travel and demand across the nation. In line with federal guidance (US Department of Agriculture and US Department of the Interior 2009), such research might investigate policies that allow for a range of management objectives, including the option to quickly suppress all fires. Similarly, policies could be investigated that more judiciously focus limited resources to quickly respond to new or ongoing ignitions in areas where fire for resource benefit cannot be tolerated due to proximity to human populations or high levels of values adversely affected by fire. Additionally, developing other models of resource movement could be valuable to examine alternative ways to meet management and allocation objectives while simultaneously minimising travel and the associated risk and expense.

The utility of these efforts is international in scope; these methods and models can be replicated in other countries or regions with similar resource allocation challenges such as multiple fire management regions, resource sharing between regions and the seasonal variations of fire activities and suppression resource demand in different regions. Such models based on historical data provide the foundation of understanding needed to begin to work towards increased efficiency and minimised firefighter risk when managing wildland fire.

Acknowledgements

This research was supported by Joint Venture Agreement 14-JV-11221636–029 between Colorado State University and the USDA Forest Service Rocky Mountain Research Station. The authors thank Ben Bird for his insights and expertise regarding multinomial logistic modelling. We also thank three anonymous reviewers whose suggestions and comments enhanced this paper.

References

California Wildland Fire Coordinating Group (2016) California interagency mobilization guide. Available at https://gacc.nifc.gov/oncc/mob_guide/index.html [Verified 26 March 2017]

Cheng S, Long JS (2007) Testing for IIA in the multinomial logit model. *Sociological Methods & Research* **35**, 583–600. doi:10.1177/0049124106292361

European Policy Evaluation Consortium (2010) Study on wild fire fighting resources sharing models: final report. (GHK Consulting: London, UK) Available at http://ec.europa.eu/echo/files/civil_protection/civil/prote/pdfdocs/future/Wildfire_Final_Report.pdf [Verified 26 March 2017]

Fiorucci P, Galardi M, Negro D, Gollino A (2011) The situation of forest fires in Italy. *Wildfire Magazine*. Available at http://wildfiremagazine.org/2011/01/italy-on-right-track-en/ [Verified 24 March 2017]

Friedman J, Hastie T, Tibshirani R (2010) Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software* **33**(1), 1–22. doi:10.18637/JSS.V033.I01

Hand MS, Gebert KM, Liang J, Calkin DE, Thompson MP, Zhou M (2014) 'Economics of Wildfire Management: the Development and Application of Suppression Expenditure Models.' (Springer Briefs in Fire, Springer: New York, NY, USA)

Hand MS, Katuwal H, Calkin DE, Thompson MP (2017) The influence of incident management teams on the deployment of wildfire suppression resources. *International Journal of Wildland Fire* **26**(7), 615–629. doi:10.1071/WF16126

Hausman JA, McFadden D (1984) Specification tests for the multinomial logit model. *Econometrica* **52**, 1219–1240. doi:10.2307/1910997

Hilbe JM (2009) 'Logistic Regression Models.' (Chapman & Hall Texts in Statistical Science, Taylor and Francis Group: Boca Raton, FL, USA)

Hobbs NT, Hooten MB (2015) 'Bayesian Models: a Statistical Primer for Ecologists.' (Princeton University Press: Princeton, NJ, USA)

Hosmer DW, Lemeshow S, Sturdivant RX (2013) 'Applied Logistic Regression', 3rd edn. (Wiley: Hoboken, NJ, USA)

Jurvélius M (2008) Legal frameworks for forest fire management: international agreements and national legislation. In 'Proceedings of the Second International Symposium on Fire Economics, Planning, and Policy: a Global View', 19–22 April 2004, Córdoba, Spain. (Ed. A. González-Cabán) USDA Forest Service, Pacific Southwest Research Station, General Technical Report PSW-GTR-208, pp. 127–135 (Albany, CA, USA)

Lockheed Martin Enterprise Solutions & Services (2012) ROSS analytical reports historical data dictionary. (Lakewood, CO, USA) Available at http://famit.nwcg.gov/sites/default/files/ROSS_AR_Historical_Data_Dictionary.pdf [Verified 26 April 2017]

McFadden D (1974) Conditional logit analysis of qualitative choice behavior. In 'Frontiers of Econometrics'. (Ed. P Zarembka) pp 105-142. (Academic Press: New York, NY, USA)

National Interagency Coordination Center (2012) Wildland fire summary and statistics annual report 2012. (NICC: Boise, ID, USA) Available at http://www.predictiveservices.nifc.gov/intelligence/2012_statssumm/2012Stats&Summ.html [Verified 26 April 2017]

National Interagency Coordination Center (2013) 2013 National mobilization guide. (NICC: Boise, ID, USA)

National Interagency Coordination Center (2016) 2016 National mobilization guide. (NICC: Boise, ID, USA)

National Interagency Fire Center (2015) Wildland fire fatalities by year. (NIFC: Boise, ID, USA) Available at https://www.nifc.gov/safety/safety_documents/Fatalities-by-Year.pdf [Verified 26 April 2017]

National Interagency Fire Center (2016*a*) Interagency standards for fire and fire aviation operations. (NIFC: Boise, ID, USA)

National Interagency Fire Center (2016*b*) Historically significant wildland fires. (NIFC: Boise, ID, USA) Available at https://www.nifc.gov/fireInfo/fireInfo_stats_histSigFires.html [Verified 26 April 2017]

National Interagency Fire Center (2016*c*) 1997–2016 Large fires. (NIFC: Boise, ID) Available at https://www.nifc.gov/fireInfo/fireInfo_stats_lgFires.html [Verified 26 April 2017]

National Wildfire Coordinating Group (2014) Fire behavior field reference guide. PMS #437. (NWCG: Boise, ID, USA) Available at http://www.fbfrg.org/ [Verified 26 April 2017]

Park T, Casella G (2012) The Bayesian lasso. *Journal of the American Statistical Association* **103**(482), 681–686. doi:10.1198/016214508000000337

Sander N, Abel GJ, Bauer R, Schmidt J (2014) Visualizing migration flow data with circular plots. *Vienna Institute of Demography Working Papers*, February 2014.

Short KC (2014) A spatial database of wildfires in the United States, 1992–2011. *Earth System Science Data* **6**, 1–27. doi:10.5194/ESSD-6-1-2014

Short KC (2015) Spatial wildfire occurrence data for the United States, 1992–2013 [FPA_FOD_20150323], 3rd edn. (Forest Service Research Data Archive: Fort Collins, CO, USA) doi:10.2737/RDS-2013-0009.3

Southwest Coordinating Group (2016) Southwest mobilization guide. (SWCG) Available at https://gacc.nifc.gov/swcc/dispatch_logistics/dispatch/mobguide/mobguide.htm [Verified 26 April 2017]

Tsang A, Larson K (2013) Resource sharing for control of wildland fires. In 'Proceedings of the Twenty-Seventh AAAI Conference on Artificial Intelligence', 14–18 July 2013, Bellevue, WA, USA. pp. 1355–1361. (AAAI Press: Palo Alto, CA, USA)

US Department of Agriculture, US Department of the Interior (2009) Guidance for implementation of federal wildland fire management policy. (USDA and USDOI) Available at https://www.nifc.gov/policies/policies_documents/GIFWFMP.pdf [Verified 26 March 2017]

USDA Forest Service (2015) The rising cost of wildfire operations: effects on the forest service's non-fire work. (USDA Forest Service) Available at https://www.fs.fed.us/sites/default/files/2015-Rising-Cost-Wildfire-Operations.pdf [Verified 26 March 2017]

US Department of Agriculture, US Department of the Interior, National Association of State Foresters (2003) Large fire cost reduction plan. Available at https://www.fs.fed.us/fire/ibp/cost_accounting/5100_LargeFireCostReductionAction_Mar_03.pdf [Verified 26 March 2017]