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# The influence of incident management teams on the deployment of wildfire suppression resources

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**Abstract.** Despite large commitments of personnel and equipment to wildfire suppression, relatively little is known about the factors that affect how many resources are ordered and assigned to wildfire incidents and the variation in resources across incident management teams (IMTs). Using detailed data on suppression resource assignments for IMTs managing the highest complexity wildfire incidents (Type 1 and Type 2), this paper examines daily suppression resource use and estimates the variation in resource use between IMTs. Results suggest that after controlling for fire and landscape characteristics, and for higher average resource use on fires in California, differences between IMTs account for ~14% of variation in resource use. Of the 89 IMTs that managed fires from 2007 to 2011, 17 teams exhibited daily resource capacity that was significantly higher than resource use for the median team.

**Additional keywords:** fixed effects, resource demand, suppression effort.

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## Introduction

Resources used to manage wildfires are scarce, particularly during times of heavy fire activity. Use of wildfire management resources is also costly and carries risks for personnel involved in fire management activities. Despite the large annual commitment of resources by public agencies for wildfire management in the United States, relatively little is known about how efficiently and cost-effectively wildfires are managed (Butry *et al.* 2008; Finney *et al.* 2009; Holmes and Calkin 2013; Katuwal *et al.* 2016; Thompson *et al.* 2016). At a most basic level, there is a need to better understand which factors determine when and where suppression resources are assigned.

Several factors may explain incident-level variation in the deployment of wildfire management resources, such as crews, personnel and equipment. Expenditures on large wildfire management are associated with fire size, landscape and geographic characteristics, weather, and sociopolitical influences (Gebert *et al.* 2007; Liang *et al.* 2008; Donovan *et al.* 2011; Yoder and Gebert 2012; Hand *et al.* 2014*a*), indicating that managers respond to different conditions by altering the amount and type of resources deployed on an incident. Managers also make strategic decisions to manage fires more or less aggressively, decisions that are related to the total amount and time-path of expenditures (Gebert and Black 2012). Yet wildfire expenditure models leave a significant portion of the variance in expenditures unexplained, particularly between geographic regions (Hand *et al.* 2014*b*).

Understanding how wildfire managers make decisions during an incident, and how decisions can vary among managers, may help explain variations in resource deployments. A variety of social, psychological and institutional factors may affect incident decision-making (Thompson 2014). Responses to and perceptions of risk are important determinants of manager decisions (Wilson *et al.* 2011; Wibbenmeyer *et al.* 2013) and are related to incident expenditures (Canton-Thompson *et al.* 2008). Further, strategy choices appear to be partially determined by expected fire behaviour and institutional expectations (Calkin *et al.* 2013). However, managers have varied experiences and preferences for managing fires, suggesting that resource use may vary widely between different types of incidents, management objectives and assignment of incident managers.

The broad goals of the present study are to better understand the factors that influence the use of fire management resources during wildfires, and to examine how resource assignments vary among managers. A primary research question is how much variation in the use of suppression resources is due to incident and landscape characteristics, and how much is due to differences between the teams and personnel who manage wildfires. The former case indicates how managers respond to conditions that can affect resource needs and effectiveness. The latter case describes how differences in manager experiences, preferences and perceptions affect decisions.

## A utility-theoretic model of suppression resource orders

Wildfire management in the United States is conducted primarily by public agencies, with the US Forest Service, Department of Interior and a handful of states (e.g. California) having the most significant responsibilities for managing wildfires. Often, the discussion of how to use resources efficiently focuses on the actions and decisions of these agencies. Yet fire management at the incident level is largely a decentralised endeavour, with individual managers and teams having significant autonomy to conduct operations without centralised interference. This suggests efforts to understand resource use may be well served by focusing on the managers who make day-to-day decisions to manage wildfire incidents.

We limit this analysis to managers of incident management teams (IMTs), who have specialised training and experience in managing wildfires. Agency administrators, such as National Forest System Forest Supervisors, identify the overarching objectives for the incident and the IMT is then responsible for implementing strategies and tactics to achieve those objectives. For our purposes, we assume these administrators generally define objectives to minimise the expected sum of suppression costs plus the net value change (losses minus benefits) to resources and assets (Donovan and Brown 2005), although heterogeneity among agency administrators could influence incident objectives and resource use decisions. Whereas Donovan and Brown (2005) built a theoretical model around decisions of agency administrators, here we apply the same utility-based theory to empirically examine decisions made by managers of IMTs.

We model manager choices of resource orders and use over the course of wildfire incidents in an expected utility-theoretic framework, based on the specification of manager utility in Donovan and Brown (2005). We extend this model in two ways: first, we allow manager decisions to be based on expectations of stochastic fire conditions. Second, we recognise that in some (but not all) situations, managers may face resource constraints (if not budgetary constraints). We apply the model to actual incident resource use data. These innovations allow additional explanations for why resource use may vary between different IMTs.

As in Donovan and Brown (2005), we assume that manager utility in a fire management environment is affected by the exposure of firefighters to harm ($F$) and damage caused by the fire ($D$). Managers select the amount of suppression resources to use on an incident, expressed as the personnel and equipment capable of building fire line that is actively engaged in fire management ($c$), given characteristics of the institutional environment ($\alpha$, e.g. strategic direction from agency administrators) and conditions of the fire environment ($\omega$, e.g. terrain, weather, vegetation).[1] The manager utility function is:

$$U = f(F(c,\alpha,\omega), D(c,\alpha,\omega)). \quad (1)$$

Increased risk to personnel is assumed to reduce utility, and reduced damage is assumed to increase utility. The relevant partial derivatives of the utility function are:

$$\frac{\partial U}{\partial F} < 0, \frac{\partial F}{\partial c} > 0$$

$$\frac{\partial U}{\partial D} < 0, \frac{\partial D}{\partial c} < 0.$$

Conditions of the fire environment ($\omega$) are taken as given but not known with certainty before a manager orders suppression resources. For simplicity, $\omega$ is indexed such that increases in $\omega$ are associated with increases in personnel exposure and increases in damage associated with a wildfire incident. Characteristics of the institutional environment may have positive or negative effects on firefighter exposure and damage; these characteristics are assumed to be known by managers when ordering suppression resources.

Given stochastic fire environment characteristics, managers must make resource order decisions based on expectations of conditions when resources arrive at some point in the future. The manager's problem is to select a level of $c$ (the resource order) to maximise expected utility ($E(U)$) conditional on the expected conditions of the fire environment. Resource orders are constrained by the total amount of resources available ($K$) in the suppression resource system at any given time. Managers are assumed to know the distribution of $\omega$ and the value of $K$ when they select their resource orders.[2] Thus, the utility maximisation problem is:

$$\max_c E(U) = \int_{\omega-}^{\omega+} \varphi(\omega) f(F(c,\alpha,\omega), D(c,\alpha,\omega))d\omega, c \leq K, \quad (2)$$

where $\varphi(\omega)$ is the probability distribution for $\omega$, and $K$ is the total available resources in the suppression resource system when the order is placed. The inequality constraint imposes that resource orders are strictly positive but can be less than total available suppression resources.[3] The expected utility evaluation assumes that for a given choice of $c$, managers evaluate utility over the entire range of $\omega$. The optimal level of $c$ (denoted $c^*$) is the one where the probability-weighted sum of utility evaluations over $\omega$ is maximised.

The conditions for a maximum are:

$$K - c^* \geq 0 \quad (3)$$

[1]The utility function is based on the use of firefighting resources for suppression activities, although there are a variety of fire management activities beyond fire-line construction, including point protection, conducting burnout operations, mopping up line and monitoring.

[2]Future extensions of this model could consider ordering behaviour when $K$ is unknown, but managers update their expectations of $K$ based on experience during an incident, and the likelihood of receiving ordered resources depends on the actual resources available.

[3]Allowing $c$ to equal zero is a straightforward modification, but for the purposes of this study, it suffices to limit our attention to cases where managers have made the decision to place an order. Requiring $c$ to be strictly positive is equivalent to assuming that $\frac{\partial E(U)}{\partial c} > 0$ when $c = 0$. Although there may be a portion of the distribution of $\omega$ where $\frac{\partial E(U)}{\partial c} < 0$, implying that managers would prefer to reduce orders ex post for some values of $\omega$, these instances are assumed to be outweighed by potential utility improvements for realisations of $\omega$ where $\frac{\partial E(U)}{\partial c} > 0$. This assumption implies that $-\frac{\partial U}{\partial D}\frac{\partial D}{\partial c} > \frac{\partial U}{\partial F}\frac{\partial F}{\partial c}$ when $c = 0$.

$$\frac{\partial E(U)}{\partial c} \geq 0 \tag{4}$$

$$(K - c^*) \times \frac{\partial E(U)}{\partial c} = 0 \tag{5}$$

Satisfying these conditions implies that the first-stage solution can be characterised by one of three cases:

$$\text{case 1} : c^* < K, \frac{\partial E(U)}{\partial c} = 0$$

$$\text{case 2} : c^* = K, \frac{\partial E(U)}{\partial c} = 0$$

$$\text{case 3} : c^* = K, \frac{\partial E(U)}{\partial c} > 0.$$

The first case suggests that the constraint is non-binding, and managers can place an order that maximises expected utility. In the second case, the order is utility-maximising, but the constraint is just binding. The third case implies that managers could improve expected utility by ordering more, but are prevented from doing so by the resource constraint.

The solution to the utility maximisation problem implies an optimal resource demand function that depends on the distribution of $\omega$ ($\varphi(\omega)$), characteristics of the institutional environment ($\alpha$), the system resource constraint ($K$), and parameters of the utility function ($\beta$), or:

$$c^* = f(\varphi(\omega), \alpha, K, \beta) \tag{6}$$

This solution assumes that managers and the IMTs they lead are homogeneous in utility parameters, risk preferences and the distribution of potential fire conditions they will face.

A source of potential variation in resource demand is that expected conditions vary between fire incidents. Managers may face different distributions of $\omega$ depending on where and when a fire occurs, leading to different expected utility evaluations even if managers are otherwise homogeneous in how they respond to fire conditions. It is also possible that preference heterogeneity (i.e. the $F$ and $D$ functions vary in the manager population) can account for differences in orders in the first stage and optimal resource use in the second stage. Heterogeneity suggests that managers vary in how they evaluate and weigh potential outcomes for firefighter safety and damage. Preference heterogeneity could be derived from multiple sources, including different approaches to management, levels of professional oversight and external pressures.

Managers also likely vary in their perceptions of and responses to risk. Risk preferences are a factor in determining the strategic choices managers make during an incident (Wibbenmeyer *et al.* 2013; Hand *et al.* 2015), and common decision-making biases related to risk are likely important as well (Maguire and Albright 2005; Wilson *et al.* 2011). For example, heterogeneity of risk aversion could result in heterogeneous resource orders even if preferences and the distribution of fire conditions are homogeneous.

To account for these various sources of heterogeneity, the resource demand function can be altered to allow individual-specific parameters and distributions of $\omega$:

$$c^* = f(\varphi_i(\omega), \alpha, K, \beta, \pi_i) \tag{7}$$

This general specification of resource demand allows for individual-specific distributions of $\omega$ ($\varphi_i(\omega)$), which could occur if managers have different perceptions of risk) and individual-level idiosyncratic effects, $\pi_i$, that may capture differences in risk preferences or other unobserved heterogeneity between managers.[4]

## Empirical approach and model

Eqn 7 provides the basis for analysing orders of suppression resources by IMTs and the degree to which variations in orders are attributable to differences among IMTs.

The general identification strategy proceeds by assuming that preferences, risk attitudes and professional incentives are constant over time for a given IMT, but may vary across teams. This assumption is likely reasonable in the short term, i.e. over the course of a given incident, when team personnel and experience is fixed. Across multiple incidents and years, personnel turnover and experience may change the team-level preferences and attitudes. However, as a practical matter, teams tend to have stable personnel over the course of the time period studied here. Current landscape characteristics and conditions can vary on a daily basis for a given incident, and are observable by IMT personnel. However, managers may form expectations of conditions in the future that may be unobservable or uncertain in the current period.

IMTs may be assigned to multiple incidents in a given fire season and over the course of several years. Thus, we observe resource orders as $c_{ijt}|\omega_{ijt}$. That is, resource orders are observed in a panel format, where resource orders are observed for IMT $i$ on incident $j$ on day $t$ conditional on a vector of associated characteristics. Teams are assumed to order resources by observing the contemporaneous (same-day) fire conditions and predicted or expected future conditions, conditional on characteristics of the institutional environment and available resources. Decisions may also be affected by recent incident events, the stage of the incident and how management processes are structured (MacGregor and González-Cabán 2008). Daily resource orders vary from day to day as teams update orders based on observable fire environment conditions and expectations ($\omega_{ijt}$).

### *Regression model and hypotheses*

Based on the theoretical model presented in Eqn 7, we estimate a simple linear model to examine the factors that influence the use of suppression resources. Demand for suppression resources is modelled as:

$$l_{ijt} = \vartheta + x_{jt}\beta + \varepsilon_{it} \tag{8}$$

where $l_{ijt}$ is production capacity of all the resource ordered by $i$th team for $j$th fire on $t$th work days, $x_{jt}$ is a vector of factors

[4]It is also possible that managers have varying utility function parameters ($\beta$), although this topic is left for future research.

(e.g. landscape, weather, and fire characteristics) that are expected to influence use of the resources, $\beta$ is a vector of utility function parameters to be estimated, and $\vartheta$ is a regression constant. $\varepsilon_{it}$ is a random error term that is assumed to be identically and independently distributed (IID) with zero mean and constant variance i.e. $\varepsilon_{it} \sim (0, \sigma^2)$. In practice, estimates of Eqn 8 recognise that $\varepsilon_{it}$ may not be homoscedastic by correcting parameter standard errors to allow for non-IID disturbances.

The model specified above can accommodate individual-specific effects by specifying a fixed-effects model. A fixed-effects model introduces an individual-specific constant term in the regression equation that controls for unobserved factors affecting suppression resource demand that vary between individuals (IMTs in this case) but not within individuals across time (Hsiao 2014):

$$l_{ijt} = \vartheta + x_{it}\beta + \mu_i + \varepsilon_{it} \tag{9}$$

where $\mu_i$ is the individual team effect, i.e. fixed effect associated with different IMTs. The fixed effects represent the average values of the dependent variables for individual teams after controlling for potential covariates. The magnitude of the estimated fixed effects can provide insight into the variation in the demand for suppression resources that is explained by differences between teams after controlling for landscape, weather and fire characteristics.

In Eqn 9, the parameter estimates for fire and landscape characteristics (the $\beta$ vector) are of interest, as are the magnitudes of the team fixed effects. We use the parameter estimates to test several hypotheses:

- H1: Daily observed fire and landscape characteristics and expected conditions in part determine resource orders, with indicators of greater potential damage and fire growth potential positively associated with the size of resource orders.
- H2: Conditional on fire and landscape characteristics, overall suppression resource scarcity, high seasonal fire activity and differences in regional availability of resources will affect the size of resource orders teams receive during an incident.
- H3: Resource orders depend on when a team is assigned during a fire, when during the fire orders are placed, and how the fire had been managed at the initial assignment of an IMT to the incident.
- H4: After controlling for other factors, unobserved differences between IMTs (measured by the vector of fixed effects, $\mu_i$) do not account for significant differences in resource orders between teams.

Under our primary null hypothesis, the vector of fixed effects ($\mu_i$) will not be significantly different from zero, indicating that on average IMTs do not exhibit individual differences in resource orders after controlling for other factors.

### *Data description*

The primary source of resource ordering and use data is drawn from the Resource Ordering and Status System (ROSS). ROSS is a comprehensive database of all orders for Federal fire management equipment and personnel. Individual resource orders (e.g. for an engine with its crew to be assigned to a particular fire) contain information on the mobilisation date, demobilisation date and details about the resource type and personnel associated with each resource. For a given incident, all resource orders can be gathered based on date of assignment and release from the incident.

The set of incidents of interest are those that had a Type 1 or Type 2 IMT assigned at some point during the incident. The complexity of wildfire incidents is scaled from 5 to 1, from least to most complex. Highly complex incidents (Types 1 and 2) enlist formal incident management teams (IMTs), which follow a defined command-and-control structure. Type 1 and 2 teams typically manage fires with hundreds or thousands of resources assigned. The primary difference between Type 1 and Type 2 organisations is fire size and complexity; further, in Type 1 organisations, all command and general staff positions are filled by Type 1-qualified personnel who have completed additional training and certifications.

Incidents are identified by cross-referencing Incident Status Summary reports (referred to as ICS-209s), ROSS records and data contained in the Wildland Fire Decision Support System (WFDSS). A total of 372 incidents with 4079 days with IMT assignments were identified for fiscal years 2007 to 2011. This population of incident days excludes those where a team was assigned for less than 3 days or the assigned IMT could not be identified. From this population, 293 incidents comprising 3365 observed fire days could be linked to ROSS data and had complete ICS-209 data.[5]

Incidents and IMT assignments included in the estimation sample are summarised in Table 1. Incidents had teams assigned from 3 to 69 days. Several incidents had multiple teams assigned over the course of the entire incident; for longer-duration incidents, it is common for two or more teams to be assigned to an incident in succession. A total of 89 distinct teams were assigned to incidents in the dataset. From fiscal year 2007 to 2011, these teams were assigned to an average of ~3.7 incidents. The average length of each team assignment was 11.9 days.

### *Dependent variable: fire-line production capacity*

The various resources employed on a fire can be considered as human and physical capital that are used as inputs to produce 'fire management effort'. However, it is not always clear how the capacity to manage fires should be measured.

For this analysis, we define the dependent variable as the estimated capacity of a fire management organisation to directly suppress fires through the production of fire line. Although resources may be engaged in several activities other than fire-line production, estimated fire-line productive capacity is a convenient

[5]Sample selection tests for each model specification were estimated following Wooldridge (2010, ch. 17.7) to examine whether the sample of incident days where complete data are observed was non-randomly generated. Tests could not reject the hypothesis that the sample was randomly generated when selection was conditioned on incident duration, quarter of incident ignition and highest-complexity team type assigned to the fire ($P$ value $> 0.4$; results available on request).

**Table 1. Description of incidents included in estimates, by fiscal year (FY 2007–11)**

| FY | Number of fires | Number of fire days | Average length of team assignments (days) | Number of unique teams | Number of team assignments |
|---|---|---|---|---|---|
| 2007 | 101 | 1289 | 12.37 | 65 | 127 |
| 2008 | 85 | 883 | 10.88 | 53 | 97 |
| 2009 | 52 | 483 | 11.37 | 38 | 57 |
| 2010 | 26 | 281 | 12.52 | 22 | 29 |
| 2011 | 29 | 429 | 13.12 | 28 | 38 |
| Total | 293 | 3365 | 11.94 | 89 | 348 |

**Table 2. Production capacity rates by resource type and fuel model for line-producing resources with known production rates**

| Resource type | Description | Fuel model timber: FM 8–13 Brush or grass: FM 1–7 | Production capacity (PC) (m day$^{-1}$) |
|---|---|---|---|
| Type 1 crew | Team of 20 people with highest level of crew qualifications and at least seven full-time firefighters | Timber | 1051 |
| | | Brush or grass | 1238 |
| Type 1 crew – strike team | Similar to Type 1 crew but with a minimum of 27 personnel | Timber | 2100 |
| | | Brush or grass | 2476 |
| Type 2 crew | Team of 20 people made up of seasonal firefighters with basic firefighting qualifications | Timber | 563 |
| | | Brush or grass | 657 |
| Type 2 crew – strike team | Similar to Type 2 crew but with a minimum of 27 personnel | Timber | 1126 |
| | | Brush or grass | 1315 |
| Firefighter – single resource | An individual firefighter with qualifications to engage in specific firefighting tasks | Timber | 28 |
| | | Brush or grass | 32 |
| Type 1 helicopter | Largest-capacity rotor-wing aircraft | All fuel models | 724 |
| Type 2 helicopter | Medium-capacity rotor-wing aircraft | All fuel models | 482 |
| Type 3 helicopter | Smallest-capacity rotor-wing aircraft | All fuel models | 241 |
| Engine | Wildland fire engine with various tank capacities and pump pressures, staffed by 2–3 personnel | All fuel models | 422 |
| Engine – strike team | Team of five engines with between 11 and 21 total personnel | All fuel models | 2111 |
| Dozer | Tracked vehicle with a front-mounted blade for exposing soil for fire line or fire breaks | All fuel models | 2412 |
| Dozer – strike team | Team of two dozers with total of four personnel | All fuel models | 4824 |

measure for comparing different bundles of resource types on a fire in a commensurate unit – metres of fire line per day (Thompson *et al.* 2016). Resources capable of producing fire line include crews of personnel clearing vegetation with hand tools, bulldozers (‘dozers’) or other heavy equipment, engines and helicopters.

To estimate the fire-line production capacity of an IMT on a given incident, each resource type is assigned an estimated production rate that describes the amount of fire line each resource type can create in 1 day. These rates are found in the Wildland Firefighting Handbook, based on research by Broyles (2011) and calculated according to the method described in Holmes and Calkin (2013) (see Table 2). Productivity values have been converted from chains (66 feet, which is 1/80th of a mile or the length of a cricket pitch) to metres.

Table 2 lists the resource types that are considered as capable of producing fire line and the production rates for each resource type. For a given day, the number of each resource type assigned to an incident is multiplied by its respective daily production rate to yield a total estimated production capacity for each resource type, then aggregated across all resource types by day for a total production capacity for each day of the incident. Because production is not observed directly and different resources may vary in their productive ability across observable and unobservable conditions, the dependent variable is an estimate subject to random error. A necessary assumption is that random error in the dependent variable is IID, and thus can be subsumed within the model random error term $\varepsilon_{it}$ in Eqn 9.

### *Independent variables*

Wildland fires differ with respect to their potential to cause damage, including fire intensity, growth potential and potential risk due to weather, geographic and sociopolitical surroundings. Although the precise interactions among these characteristics that lead to damage to resources at risk or firefighter exposure to harm are not precisely known, we develop a vector of characteristics that can be considered proxies for fire potential to cause damage. These include current and expected fire and landscape characteristics, valuable assets threatened by fire, seasonal variations, controls for regional differences and the pattern of IMT assignments on an incident. Definition and descriptive statistics of the variables used in the empirical analysis are reported in Table 3.

We use several variables to control for current and expected fire and landscape characteristics. Fuel models reported in the

**Table 3. Definition and descriptive statistics and of the variables used in the analysis**

| Variables | Definition | Mean | s.d. | Maximum | Minimum |
|---|---|---|---|---|---|
| *pcdaily* | Daily productive capacity of all the resources used by a management team on a given incident (m) | 36 937 | 55 481 | 515 934 | 0 |
| *gacc_2* | Rocky Mountain geographic area[A] (1 = yes, 0 = no) | 0.03 | 0.16 | 1 | 0 |
| *gacc_3* | South-west geographic area (1 = yes, 0 = no) | 0.14 | 0.34 | 1 | 0 |
| *gacc_4* | East Great Basin geographic area (1 = yes, 0 = no) | 0.13 | 0.34 | 1 | 0 |
| *gacc_5* | Northern or southern California geographic area (1 = yes, 0 = no) | 0.27 | 0.45 | 1 | 0 |
| *gacc_6* | Northwest geographic area (1 = yes, 0 = no) | 0.18 | 0.39 | 1 | 0 |
| *gacc_8* | Southern geographic area (1 = yes, 0 = no) | 0.04 | 0.19 | 1 | 0 |
| *gacc_9* | Eastern geographic area (1 = yes, 0 = no) | 0.03 | 0.16 | 1 | 0 |
| *lhvalue* | Natural log of total housing value within 32 km (20 miles) of ignition | 18.53 | 5.79 | 26.01 | 0 |
| *brush* | Fuel model is brush[B] (1 = yes, 0 = no) | 0.25 | 0.43 | 1 | 0 |
| *timber* | Fuel model is timber (1 = yes, 0 = no) | 0.57 | 0.5 | 1 | 0 |
| *private* | Fire is in private jurisdiction (1 = yes, 0 = no) | 0.23 | 0.42 | 1 | 0 |
| *npl_2* | National preparedness level[C] is 2 (1 = yes, 0 = no) | 0.31 | 0.46 | 1 | 0 |
| *npl_3* | National preparedness level is 3 (1 = yes, 0 = no) | 0.19 | 0.39 | 1 | 0 |
| *npl_4* | National preparedness level is 4 (1 = yes, 0 = no) | 0.17 | 0.46 | 1 | 0 |
| *npl_5* | National preparedness level is 5 (1 = yes, 0 = no) | 0.23 | 0.39 | 1 | 0 |
| *gpextreme* | Growth potential is extreme (1 = yes, 0 = no) | 0.1 | 0.3 | 1 | 0 |
| *gphigh* | Growth potential is high (1 = yes, 0 = no) | 0.3 | 0.46 | 1 | 0 |
| *gpmedium* | Growth potential is medium (1 = yes, 0 = no) | 0.22 | 0.41 | 1 | 0 |
| *tobecontained* | Area of the fire to be contained (product of fire size and percentage to be contained) | 8.91 | 20.15 | 282.3 | 0 |
| *relfireday* | The ratio of the current day to total duration of the fire | 0.54 | 0.29 | 1 | 0.01 |
| *erc* | Energy release component calculated from ignition point using nearest weather station (0–100 scale) | 87.25 | 17.73 | 100 | 2 |
| *midseason* | Mid-season fire; July–August (1 = yes, 0 = no) | 0.5 | 0.5 | 1 | 0 |
| *lateseason* | Late-season fire; after September (1 = yes, 0 = no) | 0.28 | 0.45 | 1 | 0 |
| *team_2* | Second team assignment for the incident (1 = yes, 0 = no) | 0.14 | 0.35 | 1 | 0 |
| *team_3* | Third team assignment for the incident (1 = yes, 0 = no) | 0.04 | 0.21 | 1 | 0 |
| *team_4* | Forth team assignment for the incident (1 = yes, 0 = no) | 0.02 | 0.14 | 1 | 0 |
| *team_5* | Fifth team assignment for the incident (1 = yes, 0 = no) | 0 | 0.06 | 1 | 0 |
| *owngacc* | Team assignment is in the team's home geographic area (1 = yes, 0 = no) | 0.8 | 0.4 | 1 | 0 |
| *pcday1perha* | Productive capacity per hectare on day 1 for a team on a specific incident | 62.59 | 181.2 | 3533 | 0 |
| *contained* | Fire is 100% contained (1 = yes, 0 = no) | 0.18 | 0.38 | 1 | 0 |

[A]Geographic area refers to the Geographic Area Coordination Center (GACC) and is the location of a regional interagency operation centre for coordination and mobilisation of wildland fire management resources. For this study, the California – North Operations and California – South Operations GACCs were combined into a single category (*gacc_5*), as were the East Great Basin and West Great Basin (*gacc_4*, which are now operated as a single GACC). Northern Region (*gacc_1*) is used as a base category.
[B]Fuel models brush and timber are based on predominant fuels from three (Grass, Shrub and Timber) fuel models reported in ICS-209. Fuel model Grass is used as a base category.
[C]National preparedness levels, established by the National Multi-Agency Coordinating Group at National Interagency Fire Center, are dictated by burning conditions, fire activity and resource availability. Resource availability is the area of most concern. Preparedness level ranges from 1 to 5, Level 1 indicating virtually no fires and full availability of resources and Level 5 indicating high fire activity in several geographical regions and limited resource availability.

daily ICS-209 reports are used to control for the effect of different vegetation with categorical variables for each fuel type (brush, timber and grass). Energy release component (*erc*), a measure of potential burning conditions, is included to control for weather and fuel moisture conditions that affect the difficulty of suppression operations. IMT personnel report their assessment of fire growth potential, which may be related to potential for property damage and risks to firefighters, in daily ICS-209 forms as low, medium, high or extreme growth potential. Categorical variables for different growth potential (*gpextreme*, *gphigh*, *gpmedium*) are used to control for the effect of expected growth on the demand of suppression resources.

Fire size is an important determinant of suppression expenditures (Donovan and Brown 2005; Gebert *et al.* 2007; Liang *et al.* 2008), but fires of similar size with different levels of containment may require different amounts of suppression resources. We include an index variable (*tobecontained*) calculated as the product of area burned and the portion of perimeter of the fire that is yet to be contained (1 minus percentage contained) on each day. The square of the index (*tobecontained2*) is also used to capture the non-linear effect, if any, of the relative fraction of the fire already contained. We control for systematic effects on resource orders that may be related to the progression of time over the course of the fire by including a variable to measure the day of the fire relative to the total incident duration (*relfireday*).

Higher home values near a fire's ignition point have been shown to be associated with higher suppression expenditures

(Gebert *et al.* 2007; Liang *et al.* 2008) and we expect that demand for suppression resources is influenced by property value close to the fire. Natural log of total housing value within ~32 km (20 miles) of the ignition point (*lhvalue*) is used to account for the potential effect of risks to property values that are proximate to the fire.

Independently of housing value, land jurisdictions (e.g. private property, percentage of private land within burned area) are found to influence large wildfire suppression (Donovan *et al.* 2004), and we control for whether the fire ignited on private vs public ownership land (*private* = 1 if fire ignited in land under private ownership).

Categorical indicators of eight different geographic regions, corresponding to Geographical Area Coordination Centers (GACC), are used to capture the effect of geographic area on demand for suppression resources. Unobserved differences across geographic areas in ecological conditions, sociopolitical influences (including state partnerships with Federal agencies) and resource assignment protocols may affect the amount of resources teams use during an incident.

IMTs are often assigned to incidents outside of their home region (GACC). A dummy variable *owngacc* (= 1 if team was engaged in suppressing fire in its own geographic area coordination centre, 0 otherwise) is used to capture differences in resource orders for teams operating outside their typical geographic area.

Constraints on resource availability may affect the demand for suppression resources. National and geographic area preparedness levels are reported daily by the National Interagency Coordination Center in the daily Incident Management Situation Report (http://www.nifc.gov/nicc/sitreprt.pdf, accessed 23 March 2017). Preparedness levels are designed to indicate the overall fire activity and system-wide demand on suppression resources on a given day. National preparedness levels (NPLs) are used as proxies for the relative availability of suppression resources. We use a set of categorical variables for each NPL (*npl_1*, *npl_2*, *npl_3*, *npl_4* and *npl_5*) to capture the effect of resource availability on suppression resource orders.

We control for the seasonal fluctuation by incorporating fire season in our analysis. Although weather conditions in different regions can expand the fire season, the wildfire season generally runs from the beginning of May to the end of November. We created categorical variables *midseason* (= 1 if fire occurred during July and August, 0 otherwise), and *lateseason* (= 1 if fire occurred after August, 0 otherwise) to capture the effect of the seasonal fluctuations (relative to early-season fire occurrences).

Two or more teams are often assigned to an incident in succession for long-duration fire. Resource use could depend on the sequence of IMT assignments or the initial amount of resources ordered by each IMT. Categorical variables indicating the sequence of IMT assignments (*team_1*, *team_2*, *team_3*, *team_4*, *team_5*) for each incident are used to capture sequence effects. Productive capacity per hectare used on the first day (*pcday1perha*) by each IMT assignment for each fire is included to examine if initial resource use drives subsequent orders, and the interaction of total productive capacity on the first day and relative incident duration (*pcday1perha_relfireday*) is included to control for potential diminishing effects of the initial resource order over time.

Finally, data suggest that significant resource orders were made even after the fires were reported as 100% contained. A categorical variable (*contained*) is used to control for the possibility that the demand for suppression resources is smaller after the fire is reported (in the ICS-209 report) as completely contained.

## Results

The total daily productive capacity of all resources (in metres per day) employed on a specific day is regressed on the independent variables discussed above and IMT-level fixed effects (based on Eqn 9). We tested for and found evidence of serial correlation in the error terms (Wooldridge 2010); as a result, all models are presented with standard errors that are robust to autocorrelation and heteroskedasticity and clustered by IMT (Table 4).

To examine the consistency of the results, we estimate three different specifications. Our basic specification (Model 1) includes geographic area (GACC) controls, fuel model variables, housing value, preparedness levels and the private ownership indicator. A second specification (Model 2) incorporates reported fire characteristics from the ICS-209 reports (growth potential, fire size and containment), energy release component (ERC), relative fire day and season controls. The third specification (Model 3) includes observable team characteristics (assignment sequence, origin GACC), first-day resource orders and a containment indicator. All three models are estimated with IMT-level fixed effects.

### *Factors related to resource orders*

Hypothesis H1 suggests that observable fire and landscape characteristics and manager expectations about characteristics affecting fire behaviour in part drive the size of resource orders made by IMTs. Results indicate that the primary characteristics that are related to resource orders include reported growth potential (i.e. managers' expectations of future fire behaviour), the value of housing in proximity of the fire and the area of the fire that remains uncontained. Indicators of fuel types (*brush*, *timber*), the measure of current fuel moisture and weather conditions (*erc*) and ignition on private land (*private*) do not appear to be significantly associated with resource capacity.

Reported extreme (*gpextreme*) and high (*gphigh*) growth potential are associated with larger resource capacity. Housing value in proximity to fires is also associated with greater resource use, which is consistent with studies showing greater expenditures on fires with greater housing values within a 32.2-km (20-mile) radius (Gebert *et al.* 2007; Hand *et al.* 2014*a*).

The area of the fire yet to be contained (*tobecontained*) exhibits a non-linear relationship with resource orders. Parameter estimates (in Models 2 and 3) indicate that a larger uncontained area (percentage uncontained times fire area) is associated with greater production capacity, although the effect decreases as uncontained fire size increases. The results imply increases in uncontained area are associated with increases in resource orders until uncontained area reaches ~60 300 ha; the effect of uncontained area on resource orders is the smallest for fires with very little uncontained area (e.g. when total containment is near 100%) and for fires with large areas uncontained (e.g. when large fires have low containment).

**Table 4. Regression results of fixed-effects models**

Dependent variable: metres of daily productive capacity. Significance codes: ***, $P = 0.01$; **, $P = 0.05$; *, $P = 0.1$. Numbers in parentheses indicate clustered standard errors

| Variables | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| *Constant* | 23 017** | −13 899 | −10 369 |
| | (10 980) | (13 735) | (12 693) |
| *gacc_2* | −9658 | 8948 | 8487 |
| | (7852) | (7754) | (7578) |
| *gacc_3* | −15 951** | −2825 | −4201 |
| | (6773) | (5221) | (7403) |
| *gacc_4* | −4404 | 433 | −2608 |
| | (5061) | (5589) | (5329) |
| *gacc_5* | 37 164*** | 45 553*** | 44 032*** |
| | (8242) | (7170) | (7203) |
| *gacc_6* | 4982 | 20 828** | 17 646** |
| | (8642) | (8350) | (8499) |
| *gacc_8* | −7781 | −928.1 | −1544 |
| | (8199) | (5241) | (5610) |
| *gacc_9* | −3611 | −11 972 | −8708 |
| | (8022) | (9409) | (10 086) |
| *lhvalue* | 578.8*** | 1559*** | 1475*** |
| | (207.5) | (382.1) | (367.1) |
| *brush* | −5508 | −7256 | −6827 |
| | (4628) | (4914) | (5173) |
| *timber* | −1747 | −1522 | −2602 |
| | (3113) | (2944) | (3178) |
| *private* | 5052 | 5467 | 6836* |
| | (3937) | (3899) | (4093) |
| *natl_pl2* | −2229 | −2091 | −1733 |
| | (5886) | (5634) | (5299) |
| *natl_pl3* | 5501 | 4696 | 5408 |
| | (7539) | (6983) | (6932) |
| *natl_pl4* | −2847 | −4228 | −4686 |
| | (6057) | (5961) | (5775) |
| *natl_pl5* | −5463 | −6240 | −5599 |
| | (7523) | (7018) | (6560) |
| *natl_pl3* | 5501 | 4696 | 5408 |
| | (7539) | (6983) | (6932) |
| *gpextreme* | | 14 540*** | 11 863*** |
| | | (4565) | (4504) |
| *gphigh* | | 10 384** | 7996** |
| | | (4063) | (3614) |
| *gpmedium* | | 8170* | 5389 |
| | | (4931) | (4135) |
| *tobecontained* | | 847.4*** | 959.2*** |
| | | (258.2) | (304.4) |
| *tobecontained2* | | −2.877*** | −3.227*** |
| | | (0.868) | (1.035) |
| *relfireday* | | 39 914*** | 43 597*** |
| | | (14 206) | (14 126) |
| *relfireday2* | | −71 562*** | −61 002*** |
| | | (12 300) | (12 271) |
| *erc* | | −84.05 | −80.25 |
| | | (71.52) | (69.10) |
| *midseason* | | 6400 | 5439 |
| | | (4336) | (4258) |
| *lateseason* | | 6783 | 7338 |
| | | (5756) | (5974) |
| *team_2* | | | −12 419* |
| | | | (7054) |
| *team_3* | | | −16 680* |
| | | | (10 083) |
| *team_4* | | | −20 940 |
| | | | (14 121) |
| *team_5* | | | −798.2 |
| | | | (10 318) |
| *owngacc* | | | −1155 |
| | | | (5326) |
| *pcday1perha* | | | 34.11 |
| | | | (36.57) |
| *pcday1perha_relincday* | | | −60.66 |
| | | | (57.79) |
| *contained* | | | −15 538*** |
| | | | (5547) |
| Number of observations | 3365 | 3364 | 3364 |
| $R^2$ | 0.538 | 0.645 | 0.657 |

Hypothesis H2 examines the possibility that resource scarcity, geographic area differences and seasonality may drive resource capacity. High preparedness levels (NPL = 4 or 5) indicate that fire activity (i.e. total number of fires at a given point in time) and overall resource demand are higher. However, results suggest that the effect of national preparedness levels is not statistically significant. Similarly, indicators of seasonality (mid-season and late-season fires compared with early season) are either marginally or not statistically significant.

Compared with the Northern Rockies (*gacc_1*), resource capacity is significantly larger for incidents in the California geographic area (*gacc_5*). There is also evidence that incidents in the Pacific Northwest (*gacc_6*) command more resources when other controls are included in the regression (Model 2 and Model 3). Resource use in the other geographic areas (Southwest, Great Basin, Southern Area and Eastern Area) are not statistically distinguishable from resource use in the Northern Rockies.

We also investigate whether IMTs operate differently when managing incidents outside their home region, perhaps owing to less familiarity with sociopolitical and management conditions in different regions. The *owngacc* indicator variable is not significantly different from zero, suggesting that managers approach resource orders similarly inside and outside their typical region.[6]

Hypothesis H3 asks whether characteristics of IMT assignments related to incident duration, sequence of team assignments and previous resource orders explain differences in

[6]We also explored whether IMTs might behave differently when operating within their own geographic area in some geographic areas but not others. For example, the *owngacc* variable was interacted with the *gacc_5* indicator to see whether IMTs based in California order resources in their home geographic area differently than IMTs based in other geographic areas. These exploratory regressions did not show any evidence that IMTs from some regions use different amounts of resources when working outside their home region. Results available on request.

resource orders. The primary effect related to duration and assignment sequence appears to be when orders are placed during an incident. Relative fire day (*relfireday*) exhibits a non-linear relationship with the demand for suppression resources. Increasing amounts of resources are ordered in the beginning of the incident as time progresses (positive and significant coefficient for *relfireday*), but orders start declining as relative fire day increases further (negative and significant coefficient for the square of *relfireday*).

The sequence of IMT assignments also matters, with later IMTs using fewer resources than the first-assigned team. And as expected, resource use is significantly lower after the fire is reported as 100% contained. However, resource use on the first day of an IMT assignment is not significantly associated with subsequent orders.

### *IMT-specific effects on resource orders*

Our final hypothesis (H4) is that after controlling for fire, landscape and assignment characteristics, IMTs do not exhibit significant differences in the size of resource orders due to unobserved team-specific characteristics. The effects of unobservable team characteristics on the use of suppression resources are captured by coefficients of individual team fixed effects after controlling for all other potential factors related to resource orders. Team fixed effects are included in all three models and reported by team number, ranked by the estimated magnitude of the team-specific effect in Table 5. Team numbers used to identify each IMT are randomly assigned to preserve the confidentiality of individuals associated with each team.

Overall, we reject the hypothesis that unobservable team-specific effects are unrelated to the size of resource orders. Significant variation in our model is explained by the team fixed effects. For example, the $R^2$ value (explanatory power of the model) increases by 14 to 17 percentage points when team fixed effects are included in the three models.

Results suggest that some teams consistently make significantly larger resource orders even after controlling for a variety of observable fire and management characteristics. Results are broadly consistent across different specifications, and the relative rankings of IMTs based on the magnitude of the estimated fixed effects change only slightly across the three models.

We use a series of descriptive analyses to examine the IMT rankings in more detail. We use results from Model 3 for further discussion. In Model 3, resource orders for 17 out of 89 IMTs were significantly greater than the median team, and for 14 IMTs were significantly less than the median team (Fig. 1).

Four out of the 10 lowest-ordering teams are based in California, and 8 out of 10 highest-ordering teams (i.e. those with the highest fixed effects) are also teams from California. All top-five resource ordering teams are Type-1 teams based in California. The teams from California in the least-resource-ordering category are Type-2 teams. Teams that do not order significantly more or less than the median team are mostly Type-2 teams. In sum, results suggest that the Type-1 teams from California in general appear to be ordering significantly more resources as compared with other teams. This result suggests that factors related to the suppression environment in California, and perhaps in particular related to incidents near large population centres, may play a role in team-level resource ordering behaviour.

We also compare IMTs at the top and bottom of the fixed-effects ranking to see if there is systematic variation based on the size and duration of fires these teams manage. Both size and duration are indirectly controlled for in the regressions through the *tobecontained* and *relfireday* variables respectively. However, it is possible that, for given values of *tobecontained* and *relfireday*, average size and duration could vary between teams. We do not detect any systematic relationship between the rankings and fire size and duration. For example, two out of top five resource-using teams were found to be managing fires that were smaller than the median size of fire. Similarly, three out of the top five teams that were using the least amount of resources managed fires that were larger than the medium size of fire in the sample.

It is also possible that the variables used in the regressions do not adequately capture variation in the degree to which large population centres may be threatened by the fires managed by IMTs at the top and bottom of the rankings. Housing value is highly correlated with population, but is a coarse indicator of values threatened by a fire and may not capture socioeconomic factors that drive suppression decisions (Donovan *et al.* 2011).

We compare the location of incidents managed by the five teams at the top and bottom of the IMT fixed-effects ranking to determine whether incidents managed by these teams tend to occur in more or less remote areas, indicating greater or lesser threats to populated areas. Thirteen incidents were managed by the five teams at the top of the rankings, and 17 incidents managed by the five teams at the bottom of the rankings. Table 6 lists these incidents for each group of IMTs and the population of the county where the fire occurred.

California fires account for all but one incident managed by these teams. Incidents managed by high- and low-resource-use teams occur in both high- and low-population areas, but the average county population for fires managed by the highest-resource-use teams is significantly higher. Although not a thorough test of the effect of population or other socioeconomic factors on the fixed-effects results, the population comparison suggests that more investigation into the source of IMT differences in resource use is warranted.

Our data are unbalanced panel data with significant variation in time series, i.e. number of days each IMT managed different fires. Sensitivity tests were conducted by estimating all the models, (1) excluding IMTs that managed fires for fewer than 10 days; (2) excluding IMTs that managed fire for more than 130 days; and (3) excluding both extreme categories; results and rankings did not change qualitatively from the full models presented above.[7] Further, there is also no apparent correlation between use of resources and number of assignments that an IMT received in our sample; teams assigned only once and those assigned multiple times are among the teams with the largest average resource orders.

[7]Results available from authors on request.

**Table 5. Fixed effects results from Model 1, Model 2 and Model 3**

Significance codes: ***, $P = 0.01$; **, $P = 0.05$; *, $P = 0.1$. Parameter values are expressed in metres of line. Numbers in parentheses indicate clustered standard errors

| Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|
| Team | Coefficient | Team | Coefficient | Team | Coefficient |
| t_6 | −64 525*** | t_6 | −56 719*** | t_6 | −56 345*** |
| | (11 225) | | (10 566) | | (10 580) |
| t_37 | −52 693*** | t_37 | −48 482*** | t_37 | −51 535*** |
| | (11 391) | | (9666) | | (9271) |
| t_59 | −50 059*** | t_59 | −36 085*** | t_59 | −34 996*** |
| | (9115) | | (7379) | | (7261) |
| t_8 | −48 476*** | t_8 | −34 178*** | t_8 | −29 925*** |
| | (12 013) | | (10 386) | | (11 289) |
| t_11 | −40 897*** | t_11 | −29 313*** | t_3 | −28 815*** |
| | (11 479) | | (9586) | | (6386) |
| t_7 | −40 470*** | t_7 | −25 460** | t_11 | −27 064*** |
| | (13 303) | | (10 763) | | (9422) |
| t_13 | −31 395*** | t_3 | −24 722*** | t_80 | −24 566*** |
| | (11 875) | | (7330) | | (7758) |
| t_48 | −27 150*** | t_14 | −22 231** | t_69 | −24 263*** |
| | (8986) | | (9838) | | (8397) |
| t_14 | −27 043** | t_13 | −21 656** | t_63 | −22 111*** |
| | (11 929) | | (9616) | | (8371) |
| t_29 | −26 825*** | t_63 | −21 412** | t_14 | −20 831** |
| | (8662) | | (8425) | | (10572) |
| t_5 | −26 727** | t_80 | −21 027** | t_7 | −20 399* |
| | (10 608) | | (8277) | | (11 557) |
| t_30 | −25 525** | t_69 | −20 975** | t_13 | −19 208* |
| | (10 458) | | (8970) | | (9885) |
| t_63 | −25 278*** | t_70 | −17 780*** | t_70 | −18 596*** |
| | (9675) | | (2063) | | (2253) |
| t_32 | −25 160*** | t_5 | −16 926* | t_43 | −16059 |
| | (8913) | | (8823) | | (10 073) |
| t_3 | −23 689** | t_86 | −15 919* | t_74 | −15 155** |
| | (9562) | | (8350) | | (6837) |
| t_36 | −23 354*** | t_43 | −15 135 | t_29 | −14 803** |
| | (8636) | | (10 123) | | (7336) |
| t_12 | −22 448** | t_36 | −12 968 | t_36 | −14 025* |
| | (10 652) | | (8499) | | (7983) |
| t_45 | −22 060** | t_56 | −11 998 | t_56 | −13 550* |
| | (10 842) | | (8047) | | (7159) |
| t_27 | −21 530* | t_51 | −11 691 | t_73 | −13 409*** |
| | (12 641) | | (7221) | | (3281) |
| t_49 | −20 108** | t_85 | −10 991 | t_86 | −13 079 |
| | (7868) | | (8467) | | (8295) |
| t_35 | −18 468* | t_12 | −10 710 | t_51 | −12 953* |
| | (10 703) | | (8839) | | (7284) |
| t_10 | −18 436** | t_29 | −10 585 | t_5 | −12 290 |
| | (8531) | | (8729) | | (9089) |
| t_85 | −18 178* | t_73 | −10 286*** | t_62 | −11 070 |
| | (9301) | | (3736) | | (8164) |
| t_69 | −18 128* | t_61 | −9825 | t_87 | −11 018* |
| | (10 103) | | (10 679) | | (6428) |
| t_54 | −17 589** | t_62 | −9721 | t_45 | −10 491 |
| | (8516) | | (8115) | | (10 882) |
| t_70 | −17 467*** | t_64 | −9701 | t_12 | −9744 |
| | (1401) | | (7705) | | (8639) |
| t_86 | −16 899* | t_74 | −9232 | t_61 | −9212 |
| | (9575) | | (8064) | | (10 541) |
| t_76 | −16 326* | t_87 | −9226 | t_54 | −8033 |
| | (8869) | | (7747) | | (8104) |
| t_74 | −16 253 | t_65 | −8967 | t_65 | −7811 |

(*Continued*)

**Table 5. (Continued)**

| Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|
| Team | Coefficient | Team | Coefficient | Team | Coefficient |
| | (10 006) | | (8067) | | (7818) |
| t_58 | −16 240** | t_68 | −8709 | t_64 | −7723 |
| | (8026) | | (7079) | | (7092) |
| t_60 | −15 263 | t_88 | −8443 | t_60 | −7409 |
| | (12 339) | | (7639) | | (11 813) |
| t_72 | −15 196*** | t_60 | −8253 | t_85 | −6484 |
| | (5076) | | (11 795) | | (9076) |
| t_22 | −14 721 | t_35 | −7742 | t_38 | −4859 |
| | (12 487) | | (9669) | | (9559) |
| t_88 | −14 406* | t_27 | −7709 | t_88 | −4825 |
| | (8572) | | (10 279) | | (7603) |
| t_42 | −14 255 | t_44 | −6989 | t_35 | −4534 |
| | (9200) | | (10 013) | | (10 321) |
| t_62 | −14 064 | t_45 | −6346 | t_76 | −4443 |
| | (9283) | | (11 225) | | (6464) |
| t_4 | −13 094 | t_22 | −6254 | t_27 | −4226 |
| | (9383) | | (10 214) | | (10 498) |
| t_80 | −12 590* | t_89 | −5032 | t_89 | −4084 |
| | (7175) | | (9182) | | (9408) |
| t_61 | −12 211 | t_48 | −4703 | t_22 | −3409 |
| | (11 406) | | (8777) | | (10 588) |
| t_50 | −11 908 | t_66 | −3689 | t_44 | −2625 |
| | (7824) | | (8192) | | (9350) |
| t_53 | −11 847 | t_54 | −3349 | t_68 | −2200 |
| | (7952) | | (8295) | | (7364) |
| t_73 | −10 894*** | t_38 | −2408 | t_72 | −1371 |
| | (4160) | | (9652) | | (5051) |
| t_31 | −10 775 | t_42 | −2085 | t_53 | −1151 |
| | (8982) | | (7998) | | (6812) |
| t_65 | −10 549 | t_72 | −1391 | t_42 | −927 |
| | (9329) | | (5592) | | (8774) |
| t_66 | −10 370 | t_76 | 285 | t_66 | 829 |
| | (9459) | | (7656) | | (7890) |
| t_87 | −10 366 | t_79 | 983 | t_78 | 1080 |
| | (7954) | | (8658) | | (6461) |
| t_51 | −10 182 | t_53 | 1057 | t_77 | 1386 |
| | (7299) | | (7379) | | (6400) |
| t_9 | −8982 | t_10 | 1165 | t_9 | 2158 |
| | (9907) | | (8509) | | (8560) |
| t_52 | −8964 | t_9 | 2016 | t_82 | 3113 |
| | (9740) | | (8827) | | (6480) |
| t_64 | −7996 | t_46 | 2140 | t_40 | 3657 |
| | (8926) | | (9618) | | (8448) |
| t_43 | −7895 | t_24 | 2444 | t_83 | 3980 |
| | (9525) | | (10 116) | | (6025) |
| t_57 | −7223 | t_49 | 2993 | t_49 | 3998 |
| | (8556) | | (8382) | | (8445) |
| t_89 | −7141 | t_40 | 3330 | t_46 | 4462 |
| | (10 309) | | (8213) | | (9582) |
| t_79 | −7041 | t_58 | 3364 | t_24 | 4535 |
| | (9120) | | (7830) | | (10 371) |
| t_44 | −6904 | t_77 | 3532 | t_79 | 4661 |
| | (10 889) | | (7348) | | (9783) |
| t_24 | −6717 | t_78 | 5291 | t_58 | 5053 |
| | (12 050) | | (7512) | | (8491) |
| t_46 | −6237 | t_50 | 6061 | t_10 | 6308 |
| | (9196) | | (7995) | | (7458) |
| t_47 | −5911 | t_31 | 6093 | t_32 | 6469 |
| | (8486) | | (10 052) | | (12 349) |

(*Continued*)

**Table 5. (Continued)**

| Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|
| Team | Coefficient | Team | Coefficient | Team | Coefficient |
| t_41 | −4658 | t_37 | 6594 | t_57 | 7322 |
| | (8792) | | (7482) | | (8528) |
| t_78 | −4377 | t_47 | 7264 | t_47 | 7734 |
| | (8564) | | (8447) | | (7915) |
| t_68 | −3662 | t_83 | 7614 | t_50 | 8101 |
| | (7861) | | (7001) | | (8568) |
| t_40 | −3189 | t_4 | 7679 | t_31 | 8248 |
| | (8382) | | (10 318) | | (13 414) |
| t_56 | −2340 | t_57 | 8963 | t_41 | 11 464 |
| | (7684) | | (9413) | | (8773) |
| t_82 | −766 | t_41 | 10 803 | t_48 | 12 253 |
| | (8559) | | (8697) | | (10 268) |
| t_77 | 956 | t_32 | 11 165 | t_71 | 12 960** |
| | (8310) | | (12 057) | | (5696) |
| t_38 | 2329 | t_55 | 12 003 | t_34 | 13 494* |
| | (9194) | | (7878) | | (7605) |
| t_81 | 2335 | t_67 | 13 049* | t_4 | 13 497 |
| | (9156) | | (7106) | | (13 212) |
| t_71 | 7377 | t_30 | 13 219 | t_81 | 13 881* |
| | (7693) | | (12 396) | | (7526) |
| t_83 | 7795 | t_81 | 14183* | t_55 | 15 766* |
| | (7918) | | (8177) | | (9477) |
| t_67 | 11 776 | t_71 | 16 168** | t_17 | 17 384* |
| | (7908) | | (7279) | | (10 550) |
| t_55 | 12 093 | t_34 | 16 638* | t_30 | 18 323 |
| | (8563) | | (8492) | | (18 986) |
| t_39 | 15 227* | t_52 | 18 454 | t_52 | 18 560 |
| | (8954) | | (12 103) | | (12 006) |
| t_18 | 15 409 | t_84 | 18 526** | t_75 | 19 079** |
| | (10 869) | | (7330) | | (9590) |
| t_34 | 15 810* | t_17 | 19 768* | t_67 | 20 043** |
| | (8801) | | (10 270) | | (8425) |
| t_33 | 20 064** | t_39 | 20 188** | t_84 | 21 548*** |
| | (8751) | | (9253) | | (6834) |
| t_84 | 20 120** | t_18 | 20 985** | t_18 | 26 258*** |
| | (8293) | | (9171) | | (9365) |
| t_28 | 21 432 | t_75 | 23 257** | t_39 | 27 597*** |
| | (13 040) | | (10 189) | | (10 613) |
| t_75 | 23 393** | t_28 | 31 431*** | t_28 | 33 871*** |
| | (9865) | | (11 315) | | (12 388) |
| t_17 | 32 841*** | t_2 | 39 143*** | t_2 | 48 791*** |
| | (11937) | | (7717) | | (7973) |
| t_15 | 36 721*** | t_15 | 42 118*** | t_15 | 48 840*** |
| | (11 844) | | (9586) | | (10 298) |
| t_21 | 40 406*** | t_21 | 48 808*** | t_21 | 51 488*** |
| | (13 193) | | (11 516) | | (12 693) |
| t_2 | 50 781*** | t_33 | 49 318*** | t_33 | 56 202*** |
| | (7487) | | (9903) | | (11 393) |
| t_26 | 51 501*** | t_25 | 61 709*** | t_26 | 57 003*** |
| | (13 019) | | (10 414) | | (10 669) |
| t_25 | 55 371*** | t_26 | 63 071*** | t_25 | 60 794*** |
| | (12 611) | | (10 439) | | (10 866) |
| t_16 | 71 119*** | t_16 | 67 052*** | t_16 | 70 827*** |
| | (11 723) | | (10 742) | | (11 610) |
| t_20 | 88 888*** | t_20 | 85 777*** | t_20 | 82 573*** |
| | (12 669) | | (10 974) | | (11 332) |
| t_23 | 93 113*** | t_23 | 95 200*** | t_23 | 95 555*** |
| | (12 316) | | (10 189) | | (10 172) |
| t_19 | 210 280*** | t_19 | 166 870*** | t_19 | 173 263*** |
| | (12 897) | | (14 338) | | (15 094) |

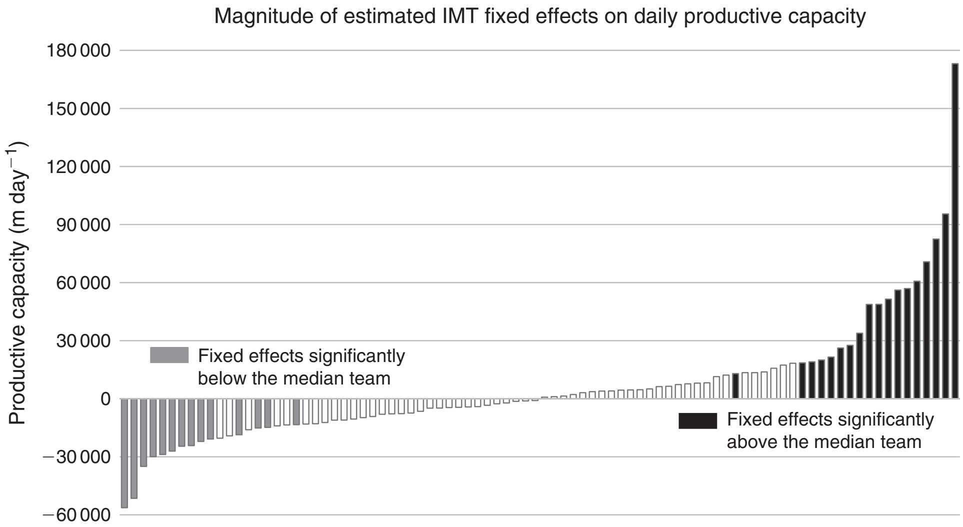


**Fig. 1.** Estimated fixed effects from Model 3. The height of the bars indicates the average daily productive capacity used by each incident management team (IMT), relative to the median team, after controlling for fire and landscape characteristics. Note: significant fixed effects are those different from zero with 95% confidence level.

**Table 6. Population of counties where fires occurred that were managed by the top five and bottom five resource-using IMT**
Source: US Census Bureau (2011)

| Incidents managed by top-five resource-using IMTs | | | Incidents managed by bottom-five resource-using IMTs | | |
|---|---|---|---|---|---|
| County | Number of incidents | Population in 2010 | County | Number of incidents | Population in 2010 |
| San Diego (CA) | 2 | 3 095 313 | San Diego (CA) | 1 | 3 095 313 |
| Los Angeles | 2 | 9 818 605 | Riverside (CA) | 1 | 2 189 641 |
| Ventura | 1 | 823 318 | San Bernardino (CA) | 1 | 2 035 210 |
| Santa Barbara | 2 | 423 895 | Tulare (CA) | 3 | 442 179 |
| Kern (CA) | 1 | 839 631 | Madera (CA) | 1 | 150 865 |
| Monterey (CA) | 1 | 415 037 | Mono (CA) | 1 | 14 202 |
| Santa Clara (CA) | 1 | 1 781 642 | Colusa (CA) | 1 | 21 419 |
| Mariposa (CA) | 1 | 18 251 | Butte (CA) | 1 | 220 000 |
| Yuba (CA) | 1 | 72 155 | Plumas (CA) | 1 | 20 007 |
| Plumas (CA) | 1 | 20 007 | Tehama (CA) | 1 | 63 463 |
| | | | Trinity (CA) | 2 | 13 786 |
| Average (all incidents) | 13 | 2 357 261 | Del Norte (CA) | 1 | 28 610 |
| | | | Skamania (WA) | 1 | 11 066 |
| | | | Average (all incidents) | 17 | 542 583 |

## Discussion

The objective of this study was to examine the factors associated with wildfire suppression resource orders and determine whether unobservable characteristics of wildfire IMTs account for variation in resource orders. We extended a utility-theoretic model of suppression resource demand to explain resource use for wildfire management operations. A key insight from this model is that individual-level differences between teams, e.g. differences in risk perceptions, or other unobserved characteristics, can account for differences in resource demand even when fire and landscape characteristics do not vary across incidents. Additional factors also account for a portion of the variation in resource orders, including growth potential of the fire, nearby housing values, the sequence of team assignments and regional differences.

Results suggest that unobservable characteristics and heterogeneity among IMTs remain as important determinants of the demand for suppression resources. Using the preferred model specification (Model 3), 31 of the 89 IMTs included in the analysis exhibit orders that are significantly different in magnitude from the median team at the 95% or greater confidence level (14 teams lower than the median, 17 teams higher than the median). These differences can be large; the difference between the highest- and lowest-ranked teams in terms of resource order size is ~2200 km of line-producing capacity per day. Depending on the types of resources ordered, this amounts to dozens of crews and potentially hundreds of personnel.

The results have implications for land-managers and policy-makers seeking to reduce wildfire management expenditures and the exposure of personnel to harm. Thus far, studies on wildfire suppression cost consider fire and landscape characteristics, potential values at risk and even socio-political factors as determinants of suppression expenditures, yet comparatively little attention has been paid to the role of individual manager and team effects. The magnitude difference in resource use between teams at the top and bottom of the ranking suggests that team-level differences are not trivial. These results are consistent with (though not directly comparable with) research that suggests that manager preferences and institutional factors, in addition to site characteristics, affect prescribed burning costs (González-Cabán 1997).

A limitation of the approach and results is that the models do not account for differences in management objectives, and we do not observe whether different amounts of suppression resources are effective at achieving objectives. It is possible that IMTs vary in the types of objectives they pursue, and the results do not shed light on whether teams are more effective or efficient than others with the resources they order. Future research may benefit from a consideration of incident-level objectives associated with different teams, although data currently available (primarily through the WFDSS) often preclude associating specific objectives with a particular IMT assigned to a fire.

A second limitation is that several of the independent variables used in the models are, at best, proxies for factors that determine the potential for a fire to cause damage and expose firefighters to risk. Much remains to be learned about how the proxy measures interact in a fire management context and how managers respond to those interactions. Further, the dependent variable – fire-line production capacity – is measured with errors; some variation unexplained by the model could be the result of this component of the error rather than model error.

Understanding the differences in suppression resource demand could also benefit from focusing on decisions to use suppression resources in an operational context. This study has focused solely on resources that are ordered and arrive at an incident; we do not attempt to analyse when, how often, how intensely or for what purpose these resources are used to manage a fire. Detailed operational data are currently available for only a small handful of incidents (see Thompson *et al.* 2016 for a case study example), although more complete geospatial and tactical information at the incident level is increasingly collected.

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