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Production and efficiency of large wildland fire suppression effort: A stochastic frontier analysis



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ABSTRACT

This study examines the production and efficiency of wildland fire suppression effort. We estimate the effectiveness of suppression resource inputs to produce controlled fire lines that contain large wildland fires using stochastic frontier analysis. Determinants of inefficiency are identified and the effects of these determinants on the daily production of controlled fire line are examined. Results indicate that the use of bulldozers and fire engines increase the production of controlled fire line, while firefighter crews do not tend to controlled fire line production. Production of controlled fire line is more efficient if it occurs along natural or built breaks, such as rivers and roads, and within areas previously burned by wildfires. However, results also indicate that productivity and efficiency of the controlled fire line are sensitive to weather, landscape and fire characteristics.

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1. Introduction

Public agencies from around the world devote substantial resources to manage and respond to natural hazard events and disturbances, such as floods, hurricanes, earthquakes, the spread of invasive species, and wildland fires. For example, expenditures on wildfire suppression by the U.S. Forest Service (USFS), the federal agency with the greatest responsibility for wildland fire management, totaled about \$10.2 billion (in 2012 dollars) over the decade ending in 2012. However, little is known about the productivity and efficiency of natural hazard management by public agencies or how control efforts affect the risks posed by natural hazards. In this paper we model the production of effective wildfire containment using Stochastic Frontier Analysis (SFA), and examine the determinants of estimated inefficiencies in containment production.

Wildland fire management provides an interesting setting for studying the productivity and efficiency of public agency responses to natural hazards. Thousands of wildfires occur each year

* Corresponding author. E-mail address: hari.katuwal@umontana.edu (H. Katuwal). within the United States, and increases in federal spending on large wildfire management has become a growing concern to Congress, state and federal agencies, and the public (Butry, 2009; Calkin et al., 2005; Gebert et al., 2007; Hesseln et al., 2010). Wildland fire management also fits within a broader class of hazard control problems that are characterized by spatiotemporal processes and a potential role for public management, such as biological invasions and public health epidemics (Epanchin-Niell and Wilen, 2012).

Suppression of large wildfires (greater than 121 ha) is a major component of wildfire management program. Less than 2 percent of wildfires escape initial containment efforts and become large fires, but these escaped fires account for 95% of total hectares burned and 85% of the total suppression expenditures (Donovan and Brown, 2005). Large fires are different than small fires in that these fires exhibit intense fire behavior and faster growth rate. When an ignition is identified, initial attack (IA) suppression resources are dispatched to immediately extinguish the fire using direct attack tactics. Once dispatched resources arrive on the fire, they build fireline around the growing fire perimeter. Once total suppression resource production exceeds the total perimeter of the growing fire, the fire is successfully contained. If the fire growth rate exceeds suppression



capacity the fire is declared escaped and typically a larger management team will be assigned to the event. Several IA models have been developed to support creation of dispatch rules for field application (Arienti et al., 2006; Fried and Fried, 1996; Ntaimo et al., 2013; Wei et al., 2015).

Large fire management is considerably more complex than initial attack of small fires. The increased size and more severe wildfire behavior that led to escape frequently requires a range of strategic objectives and tactical approaches. For large fires, line construction generally occurs simultaneously along multiple sectors, frequently involves construction of indirect line at a distance from the active fire edge, and may be accompanied by burnout operations (Finney et al., 2009). The efficiency and effectiveness of efforts to suppress large wildfires is not yet well understood (Butry et al., 2008; Finney et al., 2009; Holmes and Calkin, 2013), and it is not yet known how managers can improve operational efficiency of large wildland firefighting to reduce suppression costs or improve other outcomes (Holmes and Calkin, 2013).

The production of fireline to contain fire growth has been an important component of studies of optimal large fire management and suppression models.¹ Models of optimal suppression efforts have specified the production of stochastic fireline width that influences the likelihood of line containing fire growth (Mees and Strauss, 1992; Mees et al., 1994). The construction rates of fireline may be affected by a variety of conditions (Fried and Gilless, 1989), and variable construction rates play a role in determining the effectiveness of suppression efforts for containing fire size (Podur and Martell, 2007). However, few studies take an empirical approach to understanding the effectiveness of suppression resources for containing large fires.

Understanding the production and efficiency of wildfire suppression effort can help decision makers better allocate suppression resources to achieve fire containment objectives. After a fire has ignited, under-allocating resources for suppression may compromise efforts to minimize potential damages and costs associated with a large wildfire; conversely, over-allocating resources can increase costs and the exposure of personnel to risk and may tie up resources that could be productively used on other incidents. Results from the SFA model of wildfire containment could indicate the relative productivity of inputs used in suppression activities and identify conditions and characteristics of efficient suppression efforts.

The paper is organized as follows. Fire line productivity and effectiveness is discussed in the next section followed by theoretical background on stochastic frontier models. We describe the collection and interpretation of the data in Section 4 followed by the model results in Section 5. Conclusions and potential future research are presented in the last section.

2. Suppression effectiveness for large wildfires

Estimating production and efficiency relationships for wildfire management requires an understanding of the objectives and output of wildfire suppression efforts, which are complex and difficult to define and measure. The relevant measure of output may vary between fires and depend on several other factors associated with fire, landscape, and socio-political characteristics (Holmes and Calkin, 2013; Mendes, 2010; Plucinski et al., 2012). Measures of suppression effectiveness used in the past include the construction of fire line per unit time (i.e., a physical barrier to contain the spread of fire), success of initial attack (IA) (defined as the containment of a new ignition within about one day), area burned or protected, time until fire containment, and the probability of containment (Butry, 2009; Finney et al., 2009; Holmes and Calkin, 2013; Mendes, 2010; Plucinski, 2012).

For a majority of large fires, the objective is to limit the potential damage caused by the fire by containing and extinguishing it as quickly as possible. Thus, production of controlled fire line is a common objective for large wildfire suppression effort. Fire lines are constructed around the perimeter of the expected fire area to stop fire from spreading further. The objective of constructing fire line is to cut off the supply of fuel and stop the fire from spreading. Fire lines are made by cutting, scraping or digging with hand tools and/or other mechanized equipment such as bulldozers. Additionally, water or aerially delivered fire suppressants and retardant may be used to suppress fire perimeter and in some cases fire is intentionally used to burn out fuels in advance of a spreading wildfire to reduce available fuels and improve the likelihood that constructed fire line is not breached (Finney et al., 2009; Plucinski and Pastor, 2013).

Studies of suppression productivity and efficiency that use a production function approach have defined suppression output in various ways. Mendes (2010) suggests defining output as the number of burning hectares extinguished per unit time in a general microeconomic production model of wildfire suppression strategies. Hesseln et al. (2010) define the suppression objective as the minimization of economic losses, and the output of the suppression production process is defined as "avoided losses". This approach requires a subjective estimate of the losses that would have occurred had the fire not been suppressed, a highly complex undertaking. More relevant to this study, Holmes and Calkin (2013) used a Cobb–Douglas production function to estimate the production of contained fire line for large fire suppression.

The definition of fire line as the output of the suppression production process is convenient because it is a readily observable (with appropriate data) and the factors of production are known and often can be observed constructing fire line. A few studies have investigated fire line production rates. Observations of fire line construction have been used to develop standard linebuilding rates used as a reference guide by fire managers (Broyles, 2011). Whereas, Hirsch et al. (2004) used data obtained from expert judgment to estimate production rates for a subset of suppression resources. However, data to understand the complex interaction of constructed fire line with an actively spreading large wildfire are not systematically collected for wildfires within the US. Holmes and Calkin (2013) used daily reports of percentage contained and area burned to calculate fire line output, and noted that collection of more accurate operational data could help identify the important factors that contribute to productivity and inefficiency.

Accurate measurement of the fire perimeter's progression has been a barrier to estimating the production of fire line and efficiency of suppression efforts. In this study, detailed geospatial data on the progression of fires provide an opportunity to overcome this difficulty. Similar to Holmes and Calkin (2013), we assume that the objective of large fire suppression efforts is to arrest the growth of fires using fire line to contain their spread. The output associated with this objective is controlled fire line, defined as perimeter segments that did not burn over at a later time. Observations of daily fire perimeters over the course of a fire are used to identify those perimeter segments that succeeded in containing the fire (i.e., they did not burn over at a later time). In a production framework, daily observations of controlled fire line are associated with suppression inputs that can be used to construct fire line and other factors that may affect the production or efficiency of the suppression effort.

¹ Thanks to an anonymous reviewer for pointing this out.

3. Econometric methods and empirical models

3.1. Stochastic frontier analysis

The empirical analysis of wildfire suppression using SFA draws on a common approach used to examine production efficiency. Simultaneously introduced by Aigner et al. (1977) and Meeusen and Den Broeck (1977), SFA has been developed and applied to examine the efficiency in several fields in economics such as agriculture, health, manufacturing, and education (Aigner et al., 1977; Battese and Coelli, 1992, 1995; Greene, 2004, 2003; Hadri et al., 2003; Meeusen and Den Broeck, 1977).

Across natural hazard contexts there is limited understanding of production and efficiency relationships for public agency management efforts to control the damage of natural hazards. The ability to respond to and control hazards is an important component of models that assess tradeoffs in the management of wildfires (Huang et al., 2013; Penman et al., 2013), invasive species (Grimsrud et al., 2008; Kovacs et al., 2014), flood incidents (Dawson et al., 2011), and emergency response times (Mitsakis et al., 2014). Yet to our knowledge there have been few attempts to model the management of natural hazards by public agencies in an economic production framework (Holmes and Calkin (2013) being an exception); the application of a production and efficiency model to wildfire suppression is an attempt to fill this gap in the literature.

The SFA can also improve understanding of the relative roles of natural and man-made factors as determinants of wildfire containment efficiency. Environmental conditions (e.g., soil quality) have been found to be associated with farm production efficiency using SFA (Latruffe et al., 2004; Wadud and White, 2000), and various environmental and socio-political factors have been associated with the efficiency of public water utilities (Carvalho and Marques, 2011; Zschille and Walter, 2012). Wildfire managers often account for variations in expected weather and landscape features (such as fuel types and rivers), the presence of man-made features (such as roads), and previously burned areas that may affect fire behavior. This study seeks to quantify the degree to which such characteristics contribute to the efficiency of containment efforts.

The production analysis consists of two components in SFA. The first component estimates the production frontier (maximum attainable output observed for given sets of inputs) and the second component incorporates exogenous variables that influence the production performance or technical inefficiency (Kumbhakar and Lovell, 2003). In a stochastic frontier model, the error term is divided into two random components: a one-sided component that captures the effects of technical inefficiency and a traditional random error that captures the effects of measurement error. The production function is specified as,

$$y_{it} = \alpha + x'_{it}\beta + v_{it} - u_{it}, \tag{1}$$

where y_{it} is the logarithm of output, x_{it} is a vector of the set of inputs (in logs), α is a constant and β is a vector of production parameters to be estimated. v_{it} is the random error ($v_{it} \sim N(0, \sigma_v^2)$), and u_{it} is the one-sided error term representing inefficiency. It is also assumed that v_{it} and u_{it} are independent and u_{it} is independent of x_{it} . A variety of distributions are proposed for the distribution of u_{it} .

There are two approaches to associate determinants of efficiency in the stochastic frontier model: a one-step and a two-step approach. In the two-step approach, inefficiency (the one-sided error term) is estimated first without including any exogenous influences; inefficiency estimates are then regressed against explanatory variables in the second step. However, the estimates from the two-step procedure are biased if variables in the production function and variables in the inefficiency effects components are correlated (Battese and Coelli, 1995; Kumbhakar and Lovell, 2003; Liu and Myers, 2009).²

The one-step method (which is used in this study) simultaneously estimates relationships in the production process and the factors that explain inefficiency. We follow Battese and Coelli (1995) and assume that u_{it} are independently distributed at truncation zero of the $N^+(\mu_i, \sigma_u^2)$ where μ_i is the mean inefficiency of each production unit. Explanatory variables that are expected to influence the technical inefficiency are included in the inefficiency effects component of the frontier model (Battese and Coelli, 1995). The inefficiency effects model is specified as,

$$u_{it} = z_{it}\delta + w_{it},\tag{2}$$

where z_{it} is a vector of explanatory variables expected to influence technical inefficiency and δ is the parameter vector of the inefficiency variables.

Combining Equations (1) and (2) yields the empirical SFA model,

$$y_{it} = \alpha + x'_{it}\beta + v_{it} - u_{it}(z_{it},\delta).$$
(3)

Parameters of the stochastic frontiers and the inefficiency model are estimated simultaneously using the maximum likelihood method. Technical efficiency, the ratio of the observed output to the corresponding frontier output, can be calculated using,

$$TE = E\left(e^{-u}\right). \tag{4}$$

The marginal effect of explanatory variables (e.g. landscape characteristics, weather etc.) on efficiency can be estimated by calculating the partial derivative of the expectation of -u conditional on x_i and z_i (Liu and Myers, 2009; Olsen and Henningsen, 2011),

$$\frac{\partial [E(y_i|x_i, z_i)]}{\partial z_{ik}} = \frac{\partial [E(-u_i|x_i, z_i)]}{\partial z_{ik}}$$
(5)

The partial derivative in the above equation is the partial effect of z_i on y_i as well as partial effect of z_i on efficiency u_i that can be interpreted as the percentage change in expected output or efficiency when the exogenous variables in the inefficiency effects model change by one unit.

3.2. Adapting the stochastic frontier model for fire line production

The SFA model presented in the previous section was used to estimate production frontiers and examine inefficiencies for wildfire suppression. In the context of the production of controlled fire line, efficiency is the ratio of observed production to the best possible outcome observed from within the sample of fire line. Examination of efficiency requires the selection of a set of input and output combinations that defines production relationships and efficient output.

A wide array of firefighting resources is typically used during a

² The two step analysis is suggested to be problematic in that the explanatory variables in the inefficiency component are assumed to be uncorrelated with the variables in the production function component in the first step. If variables in these two components are correlated, the estimates are biased due to omitted variable bias. Consequently, coefficients of inefficiency in the second step are biased because the second step estimation is based on biased representation of the production frontier. Moreover, in the first step the expected value of the inefficiency is constant, but in the second state it is assumed to vary with the exogenous variables (Kumbhakar and Lovell, 2003; pp-264).

large wildfire suppression operation, and the production of controlled fire line depends on how and how many of these inputs are used. Additionally, fundamental determinants of fire behavior such as weather, vegetation and terrain characteristics may also affect the production of controlled fire line.

Following (Butry et al., 2008; Hesseln et al., 2010; Holmes and Calkin, 2013), we specified a general model of controlled fire line production using a Cobb–Douglas functional form and key predictor variables identified from previous research.³ Primary inputs in the production frontier portion of the model included crews, dozers, engines, helicopters, and air tankers. The basic production function was specified as,

$$\ln y_{it} = \beta_0 + \beta_1 \ln(crew) + \beta_2 \ln(dozer) + \beta_3 \ln(engine) + \beta_4(heli_air) + \beta_5 \ln(p_notheld_lag) + v_{it} - u_{it}, \qquad (6)$$

where y_{it} is the output measured as the length of the perimeter controlled or held (*p_held_daily*) for *i*th fire on *t*th day. Perimeter that was not controlled on the previous day (*p_notheld_lag*) was included to capture the growth of uncontrolled segments of the fire perimeter. crew, dozer, engine and heli_air are purchased inputs. The input variables *crew*, *dozer*, and *engine* are the number of handcrews, dozers, and engines per day, respectively. *heli_air* is sum of the number of helicopters and air tankers used on that particular day for the suppression. Crews, dozers, engines, helicopters and airtankers are suppression resources used to contain a fire by producing fireline and contributing in other suppression activities. Crews are typically groups of approximately 20 firefighters organized and trained for operational assignments on an incident. Wildfire engines are high-clearance ground vehicles equipped with water tanks and pumping systems of varying capacity, and are typically staffed with a crew of three to five people. Dozers are tracked vehicles with a front-mounted blade used for exposing and pushing mineral soil to produce firelines and are typically operated by one person. Helicopters and airtankers are aviation resources that drop chemicals or water to slow or halt fire progression usually in support of efforts by ground resources; the majority of helicopters are staffed with a crew of two and four people.

Several other factors that affect fire behavior may also affect the productivity and effectiveness of suppression efforts. Fire behavior (such as fire intensity and spread rate) is influenced by the interaction of weather, vegetation and terrain, and depends on variables such as temperature, humidity, wind speed, fuel type, slope, aspect, and elevation (Butry et al., 2008), which could affect the productivity of firefighting resources. However, there is no clearly defined theoretical justification that dictates the inclusion of these variables in production functions or inefficiency effects component production function (Battese and Coelli, 1995; Greene, 2005).⁴ We included weather and landscape-related variables as independent variables in the inefficiency component of the SFA to capture effect of these characteristics on productivity and effectiveness of suppression resources, rather than as productive inputs in their own right.⁵ The inefficiency effects was specified as,

$$u_{it} = \delta_{0} + \delta_{1}(max_gust_speed) + \delta_{2}(lag_max_rh) + \delta_{3}(timber) + \delta_{4}(river) + \delta_{5}(road) + \delta_{6}(full_suppression) + \delta_{7}(previous_fires) + \delta_{7}(relative_days) + w_{it},$$
(7)

where *max_gust_speed* and *lag_max_rh* are maximum gust speed and relative humidity of the previous day respectively. *timber* is a binary variable equal to 1 if the dominant fuel model is timber with grass and brush as the reference category; *river* and *road* are percentage of the daily fire perimeter held that is along rivers and roads; *full_suppression* is a binary variable equal to 1 if the suppression method is full suppression; *previous_fires* indicates percentage of fire line that occurs within a previously burned area, *relative_days* indicates the ratio of the current day to total duration of the fire.

Weather conditions have a significant effect on the spread and intensity of fires as well as the effectiveness of suppression activities (e.g. Arienti et al., 2006; Holmes and Calkin, 2013). Two variables, wind gust speed and relative humidity, were used to capture the effect of daily weather variables on fire behavior. Variation in forest fuel types is also expected to affect fire spread and intensity; previous literature suggests that suppression productivity is lower in timber fuels relative to grass and shrub (e.g. Hirsch et al., 2004; Holmes and Calkin, 2013). The total length of rivers along the controlled fire line was calculated and converted to the percent of the total controlled fire line along a river for a given day. Using a similar approach, road represents the percentage of road along the controlled fire line. Rivers and roads may affect the controllability of fire line due to the transition to unburnable fuels that can arrest fire spread. Additionally roads provide rapid access for fire suppression resources. Distance to roads and streams has been associated with the cessation of fire spread (Hirsch et al., 2004; Narayanaraj and Wimberly, 2011), although it is yet unknown how suppression effectiveness responds to these features.

A fire's burn severity and final size is influenced by previous wildfires on the landscape (Parks et al., 2014). We calculated percentage of fire line that occurred within areas previously burned by wildfires during the last 9 years (*previous_fires*) to examine the potential of previous fires to affect the production of controlled fire line. A binary variable (*full_suppression*) is included to capture the effect of adopting a full-suppression strategy (i.e., when suppression is vigorously attempted as opposed to less aggressive monitoring strategies) on efficiency. Lastly, efficiency may be associated with the length of time a fire burns. We included a measure of relative fire duration (*relative_days*) to examine whether fire line is more efficiently controlled as duration increases.

Production function (Equation (6)) and inefficiency effects models (Equation (7)) were simultaneously estimated using the stochastic frontier analysis tool in R (Coelli and Henningsen, 2011). We estimated and present three different specifications of the model: first, we included all the variables as major inputs; second, we included all major purchased input variables in the production function and other weather and landscape variables in the inefficiency component; and third, we included all the purchased variables and perimeter not held for the previous day in the production function component and other weather and landscape

³ Although we used a Cobb–Douglas production model, we note that there are several other candidates for the production function. We also estimated translog production function; interactions and squares of the variables were not significant, which argues for retaining the Cobb–Douglas form. Results available upon request.

⁴ In stochastic frontier literature, degree of competitiveness, ownership of the firm, and other managerial characteristics are included in the second component (i.e. inefficiency component) of the model (Kumbhakar and Lovell, 2003). For example, farmer's characteristics such as age, education levels etc. are included in the inefficiency component instead of control variables in the production in agricultural production function literature (Battese and Coelli, 1995). Weather and landscape variables could arguably be drivers of production if they are considered types of natural capital that can be leveraged as productive inputs.

⁵ It is also suggested that failure to account for such environmental variable can cause a correlation between some inputs and unobserved factors in the error tem and eventually produce bias estimates (Liu and Myers, 2009).



Fig. 1. Fires included in the analysis.

variables in the inefficiency component.

4. Data sources and description

An important feature of this study was the use of fire perimeters to observe the dependent variable: quantity of controlled fire line. Unfortunately, spatial data of actual fire line constructed on large wildland fires and the interaction with a spreading wildfire are not consistently available. Therefore, we utilized the progression of fire perimeters to define daily controlled fire line as those perimeter segments where the wildfire ceases to expand beyond that day's fire perimeter during the entire duration of the fire event. Geospatial data for the perimeters were identified from several sources, including Wildland Fire Decision Support System (WFDSS), National Interagency Fire Center (NIFC) fire reports, and Geospatial Multiagency Coordination (GeoMac), and matched with Incident Status Summary (ICS-209) reports for the incident corresponding to the day associated with each perimeter data point.^b The data set is comprised of large fires (>121 ha) for the calendar year 2010 and 2011 that contain information on the progression of the fire over multiple days. A large majority of the fires included in the analysis are from the western United States (Fig. 1).

Controlled fire line on a particular day was calculated retroactively from the final perimeter (after the fire is fully contained) that is, all segments of controlled fire line were part of the final fire perimeter; controlled fire line does not include perimeter that held on a specific day but later burned over (Fig. 2). Fire lines held on a specific day but burned over later may have some effect on delaying fire spread, and thus final fire size. Therefore, the use of final fire perimeter may undercount the effectiveness of suppression resources because the exclusion of fire line that may have delayed, but ultimately did not hold. We were not able to use the line that did not hold because of the unavailability of the data i.e. information on fire lines that were built but burned over later.

Several considerations were necessary to prepare the data for analysis. Fire perimeters were measured using different approaches (such as global positioning system, infrared mapping and ground based reconnaissance) and there is a great deal of variation in time of measurement for the final perimeter for a specific day. Since the period of highest fire growth typically occurs during the afternoon period, fire perimeters that were measured before 12:00 AM are considered as final perimeters for the previous day for the corresponding fire. Because a continuous progression of perimeters is required for our analysis, we dropped fire observations if more than one contiguous day is missing from a fire's set of perimeters. Additionally, fires with fewer than three continuous perimeter observations were not included.

Information on the purchased inputs (crews, dozers, engines, helicopters, and air tankers) for each day of each incident were drawn from the Resource Order and Status System (ROSS).⁷ Weather data (relative humidity, temperature, wind direction, wind speed) were obtained from the Remote Automated Weather Stations (RAWS) closest to the corresponding fire. On average, closest RAWS are 15.14 (minimum- 1.54, maximum- 43.29) kilometers from the ignition point of the fires. Natural lines or significant fuel breaks (e.g. river and road percentage) were drawn from various sources and calculated using geographic information

⁶ These sources are administrative weblinks/resources where information on wildfires are made available for decision support. The ICS-209 is a United States National Fire and Aviation Management web application that incident management teams use to report incident specific information significant incidents. WFDSS is a web based system that provides geospatial information about fire location, size, perimeter etc. in addition to other information to assists fire managers and analysts in making strategic and tactical decision for fire incidents. NIFC is the national coordinating center that mobilizes resources for wildland fires throughout United States. In addition to other fire related information, the incident information page of the center provides daily updates on large fires. GeoMAC is an internet based mapping application and provides fire perimeter data that is updated daily based upon input from incident intelligence sources, GPS data, infrared imagery and satellite platforms.

⁷ ROSS is a comprehensive data base for federal wildland fire management resources. It tracks all tactical, logistical, and support resources mobilized by the incident dispatch community.



Fig. 2. Progression map for the Schulz fire and calculation of perimeter held. Figure shows the progression of fire perimeter for the Shultz fire on the Coconino National Forest northeast of Flagstaff, Arizona that started on June 20, 2010 (day 1) and was fully contained on June 26, 2010 (day 7). The final perimeter and area of the fire were 66,900 m and 6100 ha respectively. The double line indicates final perimeter of the fire, red lines indicate the portion of the line that was burned over in subsequent days, blue lines indicate the perimeter that was held before the specific day, and green lines represent perimeter held on the specified day. Total sum of length of all portions of the perimeter held on each day is used as a measure of perimeter held on that specific day. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

system calculations. Information on rivers was drawn from Landscape Fire and Resource Management Planning Tools (LANDFIRE). Similarly, road data were obtained from Homeland Security Infrastructure Program (HSIP). Information on fuel model (grass, brush and timber) was drawn from ICS-209.

The final sample includes 63 fires and a total of 481 days. Summary and descriptive statistics of the variables used in the analysis are presented in Table 1. Average production of controlled fire line per day was 4694 m. Although highly variable, on average, 8 crews, 10 engines, and 1 dozer were employed per day. The average combined use of helicopters and air tankers is about 5 per day. Several zero values for all the major resources indicate that not all resources are used on a daily basis for all days. There is significant variation in fire size as indicated by perimeter not held. Multiple strategies (confine and contain, point or zone protection and full suppression) are used to manage large fire. Confine and contain implies a strategy to restrict the fire to a defined area, zone protection involves protecting specific point or zones from the fire and full suppression is a strategy to suppress the fire completely. About half of the fires included in the study were full-suppression fires. About two-thirds of the fires occurred in land with timber as a major fuel model.

Table 1

Descriptive statistics and definition of the variables (obs. = 481).

Variables	Definition	Mean ^a	Std. dev.	Max	Min
p_held_daily	Daily perimeter held (meter)	4694	7145	64,164	5.28
crew	Number of crews	7.99	7.37	32	0
dozer	Number of dozers	1.35	2.49	19	0
engine	Number of engines	9.98	12.85	65	0
heli_air	Sum of helicopters and air tankers	4.66	4.22	23	0
p_notheld_lag	Lag of perimeter not held (m)	23,364	26,226	162,889	0.56
max_gust_speed	Maximum gust speed (mph)	21.6	8.28	62	7
max_rh_lag	Lag of relative humidity	51.24	23.78	100	4
timber	Fuel model is timber $(1 = \text{Yes}, 0 = \text{No})$	0.68	0.47	1	0
rivers	Percentage of line that is built along the rivers	9.32	11.37	94.29	0
roads	Percentage of line that is built along the roads	16.57	26.44	100	0
full_suppression	Full suppression fires $(1 = \text{Yes}, 0 = \text{No})$	0.49	0.5	1	0
previous_fires	Percentage of line that is built on previously burned areas	6.53	19.57	100	0
relative_days	The ratio of the current day to total duration of the fire	0.56	0.24	1	0.04

^a Mean values of the resources indicate average number of corresponding resources per day per fire.

H. Katuwal et al. / Journal of Environmental Management 166 (2016) 227-236

Table 2

Results of stochastic frontier models (dep. var. = natural log of meters of controlled fire line; obs. = 481).

Variables	Model 1	Model 2	Model 3
constant	3.219*** (0.7728)	7.480*** (0.7728)	5.257*** (0.4681)
crew_d	-0.0861 (0.2621)	-0.1897 (0.2179)	-0.1771 (0.2062)
dozer_d	0.2642 (0.2522)	0.6813*** (0.1974)	0.6047*** (0.1783)
engine_d	1.038*** (0.2331)	0.75*** (0.1927)	0.789*** (0.1835)
heli_air_d	-0.6343^{**} (0.2685)	$-0.3736^{*}(0.2147)$	$-0.4544^{**}(0.2082)$
lcrew	-0.6195^{***} (0.1587)	-0.3439^{***} (0.1587)	-0.4805^{***} (0.1261)
ldozer	0.2298 (0.1399)	0.2716** (0.1076)	0.3128*** (0.1016)
lengine	0.5645*** (0.127)	0.6906*** (0.0978)	0.6044*** (0.096)
lheli_air	0.1349 (0.1777)	0.0968 (0.1504)	0.1438 (0.1414)
		Inefficiency Model	
lp_notheld_lag	0.3611*** (0.0574)	-0.5284(0.479)	0.2745*** (0.04)
			Inefficiency Model
max_gust_speed	0.0146* (0.0079)	-0.0293 (0.0414)	-0.0299(0.0476)
max_rh_lag	-0.0072^{**} (0.0029)	0.0734 (0.0458)	0.0342** (0.0134)
timber	0.1318 (0.1663)	-0.8841(1.447)	-0.6705 (0.1663)
rivers	0.0065 (0.005)	-0.1127 (0.1164)	-0.0705 (0.0606)
roads	0.0059** (0.0026)	-0.013 (0.0122)	-0.0096 (0.0026)
full_suppression	0.445* (0.2532)	-0.9529(1.234)	-1.737 (1.064)
previous_fires	0.0104*** (0.0036)	-0.0515 (0.0512)	-0.0495 (0.0352)
relative_days	1.151*** (0.2692)	-4.089(3.624)	$-4.694^{*}(2.648)$
sigmaSq	1.611*** (0.1677)	9.056 (5.842)	6.38** (2.64)
gamma	0.1875** (0.09)	0.9311*** (0.0403)	0.9164*** (0.0291)
AIC	1564	1567	1531
BIC	1648	1650	1614
Mean efficiency	0.6776	0.4815	0.4701

Significance codes: '***' 0.01 '**' 0.05 '*' 0.1.

Numbers in parentheses indicate standard errors.

lcrew, ldozer, lengine, and lheli_air indicate natural log of the purchased input variables crew, dozer, engine, and heli_air respectively. crew_d, dozer_d, engine_d, and heli_air_d are dummy variables for crew, dozer, engine, and heli_air such that the value of the dummy variable is 1 if the value of the corresponding resource variable is zero.

5. Results

We estimated the production functions presented in Equations (6) and (7) using SFA. The test on the appropriate functional form of the production function indicated that Cobb–Douglas model best represented the production function.

5.1. Stochastic frontier model results

We estimated three stochastic frontier models. In our first model (Model 1) we included all the variables as major inputs and control variables for the Cobb–Douglas production function with no variables included for the inefficiency effects model. In our second model (Model 2) we included all the major purchased inputs as explanatory variables for the production function, and weather and landscape characteristics in the inefficiency effects component. We also included the perimeter not held on the previous day in the inefficiency effects component of the frontier model. In our final model (Model 3) we included perimeter not held on previous day as a control variable and weather and landscape characteristics in the inefficiency effects component of the model.

Several input variables included zero values for multiple days in our data set. We used a dummy variable approach to estimate unbiased coefficients for the explanatory variable in the production function (Battese, 1997). Dummy variables (*crew_d*, *engine_d*, *dozer_d*, and *heli_air_d*) are included in the model to account for all of the observations when no resources were used at all.⁸ Maximum likelihood estimate results for all three models are presented in Table 2. Statistically significant values of gamma (γ), the share of deviation from the frontier attributed to inefficiency, in all three models, and other coefficients of the variables in the efficiency effects model indicate that inefficiency is persistent and inclusion of the efficiency effects model was justified (Battese, 1997). Additionally, the null hypotheses that the technical efficiency effects in the model were not random and that the explanatory variables in the model for the technical inefficiency effects have zero coefficients were strongly rejected by the significant coefficients of several variables in the efficiency effects of the model (Battese and Broca, 1997). Based on the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC), model 3 was the best performing model. We refer to model 3 for our further discussion.

The estimated coefficients for dozers (*ldozer*) and engines (*lengine*) are positive and significant, indicating that the use of these inputs is positively associated with the production of controlled fire line. The negative and significant coefficient for *lcrew* indicates that less fire line is controlled on days when greater numbers of crews are assigned, a result that was counter to expectations. Air resources (helicopters and air tankers) did not appear to have a significant relationship with controlled fire line.

The negative coefficient for *lcrew* could result from several possible circumstances suggesting that ground crews may be substantively engaged in activities other than creating fire line directly along a wildfire's perimeter. Within the large fire environment fire suppression crews engage in a range of activities including mop up and holding (that is working along or within an already burned area to assure that the fire does not expand beyond the current perimeter), development of contingency lines that are only engaged if primary fire lines fail to contain fire spread, large scale burn out operations that may require multiple days of preparation before the activity is initiated and fire growth is checked, and point protection of site specific individual resources values. It is also possible that fire lines produced by crews on a particular day were more likely to

⁸ Following Battese (1997) we create dummy variable for zero-resources such that $crew_d = 1$ if crew = 0 and $crew_d = 0$ if crew > 0. Log of the resources variables are created using: $ln(crew) = ln(Max(crew, crew_d))$.

burn over on later days. Similarly, the insignificant coefficient for air resources may be indicative that aerial missions may be associated with activities other than the production of controlled fire line; however mission objectives are currently not recorded (Calkin et al., 2014). A lack of information about the specific use of resources for line construction, point protections or other assignments prevents us from analyzing the contribution of crews and other inputs exclusively for the production of controlled fire line.

The positive and significant coefficient of log of dozer indicated that dozer's contribution is positive and significant towards the production of controlled fire line. Similarly, positive coefficient of log of engine indicates that greater usage of engines was associated with more fire line controlled along the final perimeter. The results also revealed that the amount of fire line not held on previous day was positively associated with line held on the current day.

In addition to the determinants of efficiency, unit-specific efficiencies are of interest to assess the distribution of efficiency. **Table 3** shows the distribution of efficiency of fireline production based on efficiency calculated from Model 3. Efficiency results suggest that mean efficiency is 47 per cent indicating significant potential for further improvement in efficiency. Results also suggest that technical efficiency varies significantly across fires. Results show that technical efficiency ranges from as low as 17 per cent to as high as 74 per cent. Efficiency distribution shows that 55.56 of the fires have less than 50 per cent efficiency. Ranking of efficiency and coefficient of inefficiency models suggest that fire line that occurs along natural breaks using a full suppression strategy are more efficient.

5.2. Inefficiency effects results

For any management action, inefficiency is the deviation of observed or actual outcome from the potential best possible outcome. For large wildfire management the objective is often to produce controlled fire line with the given resources that arrests and contains the spreading fire. The inefficiency effects component of the SFA provides measurement on deviation of actual output from maximum possible output.

Determinants of inefficiency include maximum wind gust speed, lag of relative humidity, fuel model, percentage of river, percentage of road, and percentage of line that occurred within previous fire scars. Positive coefficients are interpreted as having a positive relationship between the corresponding variable and inefficiency. In other words, a positive coefficient indicates that an increase in the variable is associated with reduced efficiency.

The estimates of inefficiency effects component are reported in Table 2 – Model 3. In the following discussion we will refer to effects of each variable on efficiency. Results indicate that gust speed does not have any significant effect on efficiency, and the lag of relative humidity has a negative effect on efficiency. The negative association of lagged relative humidity with efficiency might be due to the fact that high relative humidity on previous days slowed down the growth rate of the fire resulting in less available fire line

Table 3

Distribution of technical inefficiency based on Model 3.

Efficiency class	No. of fires	Percentage of fires	
<20	1	1.59	
20-30	4	6.35	
30-40	9	14.29	
40-50	21	33.33	
50-60	15	23.81	
60-70	12	19.05	
>70	1	1.59	

Table 4

Marginal effects of control variables on efficiency of controlled line production from Model 3.

Variables	Marginal effects		
max_gust_speed	0.0456		
max_rh_lag	-0.0521		
timber	1.0210		
rivers	0.1074		
roads	0.0146		
full_suppression	2.6460		
previous_fire	0.0754		
relative_days	7.1510		

Note: Marginal effects indicate percentage change in efficiency when corresponding variable changes by one unit. Positive values indicate increases in the variable are associated with increases in efficiency.

to control. Fuel model does not appear to have any effect on efficiency. Although only marginally significant, natural breaks show positive effect on efficiency. Production of controlled fire line is more efficient if the fire line is along rivers.⁹ Similarly, percentage of roads has a positive effect on efficiency, which implies that fire line is more likely to be controlled when it occurs adjacent to roads. This result is consistent with the finding from previous studies such as Hirsch et al. (2004) and Narayanaraj and Wimberly (2011). Previous fire (*previous_fires*) has positive but marginally significant effect on efficiency (p~ 15%), suggesting that wildfire fire suppression is more efficient if fire line is constructed within previous wildfires. This result is in line with the argument that the growth and intensity of fire may be less severe within previous fire scars due to reduced fire line intensity that can allow safer and more effective fire suppression strategies. It supports the hypothesis that the existence of previously burned areas may have a protective effect and influence the wildfire size (Butry, 2009; Prestemon et al., 2002). As expected, the marginally significant (p~10%) negative coefficient of full_suppression indicates that efficiency increases when the wildfire strategy is to fully suppress all aspects of the fire. Finally, results indicate that efficiency increases with the duration of the fire (relative_days). Suppression effort is more efficient as it approaches full containment, and could indicate that there are benefits from experience during an incident and learning by doing. Fires escape initial attack because of adverse weather conditions and weather might not be favorable during initial stages of the fire. Thus, it is possible that weather tended to be more favorable as fires approach full containment and suppression effort is more effective during the period. It also possible that increased efficiency is because of backfiring during later stages of the fire where backfires are more frequently used and perimeter held is more efficient.

5.3. Marginal effect results

Estimates from the inefficiency model provide the direction of the influence of the corresponding variables to efficiency. However, these coefficients do not provide magnitude of the effect and cannot be interpreted as such. Marginal effect of these variables on efficiency provides the magnitude of these partial effects. We extend and examine sources of inefficiency by calculating the marginal effect of these sources on efficiency. Results are presented in Table 4.

Although only marginally significant, results from marginal effects of the inefficiency model indicate that efficiency increases if

 $^{^9}$ The coefficient of these natural breaks are significant at very generous and marginal level e.g. river percentage is significant at p~24% and roads percentage is significant at p~26%.

fire lines occur along natural break. However, the marginal effects are fairly small. Previous fires seem to play a significant role in increasing efficiency of controlled fireline production. Again, marginal effects are fairly small. Relative day seems to be one of the strongest factors that influence efficiency. Every one day increase fire days increases the efficiency by about 7 percentage points. Efficiency gain is highest for full suppression fire strategy. In general, our results suggest that the largest marginal gains in efficiency are associated with fuel type (*timber*), suppression strategies, and the duration of the fire.

6. Discussion and conclusion

The objective of this paper was to examine the determinants of efficiency of controlled fire line production for large wildfire suppression efforts. Wildfire management represents a class of public agency responses to natural hazards that have received little attention in an economic production framework. We used stochastic frontier analysis to examine production relationships and the determinants of inefficiency for creation of controlled fire line to suppress wildfires. The study builds on previous efforts to analyze the efficiency of wildfire suppression efforts, such as Holmes and Calkin (2013), by using geospatial data to observe controlled fire line as the productive output and estimating a parametric inefficiency model. Our results indicate that crews of firefighters, who tend to work with hand tools without heavy equipment, do not tend to contribute to the production of controlled fire line along the final perimeter of the fire. This may be because of our definition of the output of the production process. which is the length of perimeter held along the final perimeter for that day. On the other hand, bulldozers and fire engines appear to be effective at producing controlled fire line. It has been suggested that large fires are sensitive only to weather and landscape characteristics and do not respond to active wildfire management (Butry et al., 2008). The results presented here provide some evidence of an association between the use of suppression resource inputs and the control of fire lines, after controlling for weather and landscape characteristics.

We want to make it absolutely clear that the results do not suggest that reducing the use of ground crews from large wildfire suppression operations will improve outcomes. Ground crews are considered a critical and necessary suppression resource. However, many of the actions in which they engage do not produce direct fireline that ultimately resides along the final fire perimeter on any given day. Ground crews often engage in indirect strategies such as burnout operations where the results of these efforts are not realized for several operational periods. Additionally, mopping up (extinguishing or removing burning material near control lines to prevent future spread) is critical in assuring that wildfires do not move beyond the existing period, but such activities are not credited within our definition of held fire lines since it occurs subsequent to the establishment of the fire perimeter. Further investigation is required to examine the effectiveness of suppression resources on these specific activities that are not included in this analysis. These results clearly confirm that those suppression resource production models used in a variety of IA models (such as Fried and Fried, 1996; Ntaimo et al., 2013; Wei et al., 2015) are not applicable to modeling large complex wildfire incidents. Fundamentally, suppression of large wildfires is not consistent with simple IA models of fireline production arresting a growing perimeter, confirm the findings of Finney et al. (2009) that large fire suppression is opportunistic. Wildfire perimeters are defined by a complex combination of environmental conditions, experienced weather, and management actions that require additional study.

There could be other variables that influence fire behavior and

efficiency of fire line production but are not included in our analysis. Extreme fire conditions may prevent crews from controlling fire line and increase the likelihood that existing fire line is burned over. Similarly, resources might have been used solely for point protection rather than building fire line. We are also unable to observe when firefighters use burnouts and back burns (i.e., "fighting fire with fire") to starve the fire of fuels and arrest fire spread. These techniques tend to increase the area burned and length of perimeter, but it is not clear how they affect the observed length of controlled line on a given day or subsequent days.

This study uses a simple Cobb-Douglas production function in the stochastic frontier analysis. A statistical model of fire line production is bound to mask many of the complex interactions that characterize the fire line production process. Future research could explore the application of other specialized production functions to examine the role of purchased inputs and other environmental factors on suppression effectiveness. Detailed field observations may also be useful for understanding interactions between tactical fire line activities and fire spread, intensity, and impacts to highly valued resources and assets. Such insights will be critical to expanding our knowledge regarding how large wildfires are managed and the efficiency of alternative strategies.

With these caveats in mind, our results suggest that production of controlled fire line is more efficient if they are built along the natural or man-made lines such as rivers and roads. However, the estimated effects on efficiency are only marginally significant and relatively small. Similarly, areas that were burned by previous fires are associated with greater efficiency in producing controlled fire line. Thus, efficiency analysis provides useful information in that it identifies the circumstances under which suppression effort (as defined in this analysis) is more efficient. This knowledge, even if it requires further development, would greatly benefit general firefighting operations. For example, such features could be highlighted within existing decision support tools (e.g., the Wildland Fire Decision Support System) to aid managers in planning suppression activities. Although the terrain and environmental variables are beyond the control of fire managers, the choice of how and where to deploy firefighting resources are controlled by managers of the suppression effort.

Wildfire management shares several characteristics with other types of natural hazards, including the deployment of resources to mitigate the impact of the hazard, a significant role for spatial processes and geophysical effects outside of management control, and the involvement of public agencies. To our knowledge this is the first attempt to estimate production and efficiency relationships in an application to public agency management of natural hazards. SFA holds promise for studying the management of a variety of natural hazard incidents, such as floods and invasive species spread. For example, understanding the production and efficiency of management efforts may help assess tradeoffs when managers can invest in both prevention and mitigation measures against endogenous hazards (Ranjan et al., 2008).

Results should be interpreted cautiously with regard to practical implications. The output indicator in our analysis is only one aspect of overall suppression efforts. Data constraints are an obvious restriction, although the use of geospatial data to measure controlled fire line is an improvement over previous efforts. Our result only examines fire line controlled as part of the final fire perimeter. Data do not allow us to examine efficiency in terms of other objectives of suppression efforts. For example, defending homes or structures and other valuable resources could be a major objective of some of the suppression operations included in the data set. Similarly, a significant amount of suppression resources could have been employed in indirect attack such as burn-out operations or to build firelines at a distance from the active fire edge that did not become a part of final perimeter of the fire. Because of a lack of specific information we were not able to examine these specific objectives in our analysis. Availability of more detailed and comprehensive data on actual fire line constructed and fire management objectives would allow one to examine efficiency for specific objectives of suppression efforts.

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References

- Aigner, D., Lovell, C., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econ. 6, 21–37.
- Arienti, M.C., Cumming, S.G., Boutin, S., 2006. Empirical models of forest fire initial attack success probabilities: the effects of fuels, anthropogenic linear features, fire weather, and management. Can. J. For. Res. 36, 3155–3166.
- Battese, G., Coelli, T., 1992. Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. J. Prod. Anal. 3, 153–169. Battese, G.E., 1997. A note on the estimation of Cobb-Douglas production functions
- when some explanatory variables have zero values. J. Agr. Econ. 48, 250–252. Battese, G.E., Broca, S.S., 1997. Functional forms of stochastic frontier production
- functions and models for technical inefficiency effects: a comparative study for wheat farmers in Pakistan. J. Prod. Anal. 8, 395–414.
- Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir. Econ. 20, 325–332.
- Broyles, G., 2011. Fireline Production Rate. USDA Forest Service, National Technology & Development Program, San Dimas, CA, pp. 1151–1805. Fire Management Report.
- Butry, D.T., 2009. Fighting fire with fire: estimating the efficacy of wildfire mitigation programs using propensity scores. Environ. Ecol. Stat. 16, 291–319.
- Butry, D.T., Gumpertz, M., Genton, M.G., 2008. The production of large and small wildfires. In: The Economics Forest Disturbances. Springer, pp. 79–106.
- Calkin, D.E., Gebert, K.M., Jones, J.G., Neilson, R.P., 2005. Forest service large fire area burned and suppression expenditure trends, 1970-2002. J. For 103, 179–183.
- Calkin, D.E., Stonesifer, C.S., Thompson, M.P., McHugh, C.W., 2014. Large airtanker use and outcomes in suppressing wildland fires in the United States. Int. J. Wildland Fire 23, 259–271.
- Carvalho, P., Marques, R.C., 2011. The influence of the operational environment on the efficiency of water utilities. J. Environ. Manag. 92, 2698–2707.
- Coelli, T., Henningsen, A., 2011. Frontier: Stochastic Frontier Analysis. R Package Version 0.997-2.
- Dawson, R.J., Peppe, R., Wang, M., 2011. An agent-based model for risk-based flood incident management. Nat. Hazards 59, 167–189.
- Donovan, G.H., Brown, T.C., 2005. An alternative incentive structure for wildfire management on national forest land. For. Sci. 51, 387–395.
- Epanchin-Niell, R.S., Wilen, J.E., 2012. Optimal spatial control of biological invasions. J. Environ. Econ. Manag. 63, 260–270.
 Finney, M., Grenfell, I.C., McHugh, C.W., 2009. Modeling containment of large
- Finney, M., Grenfell, I.C., McHugh, C.W., 2009. Modeling containment of large wildfires using generalized linear mixed-model analysis. For. Sci. 55, 249–255.
- Fried, J.S., Fried, B.D., 1996. Simulating wildfire containment with realistic tactics. For. Sci. 42, 267–281.
- Fried, J.S., Gilless, J.K., 1989. Notes: Expert opinion estimation of fireline production rates. For. Sci. 35, 870–877.
- Gebert, K.M., Calkin, D.E., Yoder, J., 2007. Estimating suppression expenditures for individual large wildland fires. West. J. Appl. For. 22, 188–196.
- Greene, W., 2003. Econometric Analysis. Prentice Hall, Upper Saddle River, New Jersey.
- Greene, W., 2004. Distinguishing between heterogeneity and inefficiency: stochastic frontier analysis of the World Health Organization's panel data on national health care systems. Health Econ. 13, 959–980.
- Greene, W., 2005. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. J. Econ. 126, 269–303.
- Grimsrud, K.M., Chermak, J.M., Hansen, J., Thacher, J.A., Krause, K., 2008. A two-

agent dynamic model with an invasive weed diffusion externality: an application to Yellow Starthistle (Centaurea solstitialis L.) in New Mexico. J. Environ. Manag. 89, 322–335.

- Hadri, K., Guermat, C., Whittaker, J., 2003. Estimation of technical inefficiency effects using panel data and doubly heteroscedastic stochastic production frontiers. Empir. Econ. 28, 203–222.
- Hesseln, H., Amacher, G.S., Deskins, A., 2010. Economic analysis of geospatial technologies for wildfire suppression. Int. J. Wildland Fire 19, 468–477.
- Hirsch, K.G., Podur, J.J., Janser, R.F., McAlpine, R.S., Martell, D.L., 2004. Productivity of Ontario initial-attack fire crews: results of an expert-judgement elicitation study. Can. J. For. Res. 34, 705–715.
- Holmes, T.P., Calkin, D.E., 2013. Econometric analysis of fire suppression production functions for large wildland fires. Int. J. Wildland Fire 22, 246–255.
- Huang, C.-H., Finkral, A., Sorensen, C., Kolb, T., 2013. Toward full economic valuation of forest fuels-reduction treatments. J. Environ. Manag. 130, 221–231.
- Kovacs, K.F., Haight, R.G., Mercader, R.J., McCullough, D.G., 2014. A bioeconomic analysis of an emerald ash borer invasion of an urban forest with multiple jurisdictions. Resour. Energy Econ. 36, 270–289.
- Kumbhakar, S.C., Lovell, C.A.K., 2003. Stochastic Frontier Analysis. Cambridge University Press, Cambridge.
- Latruffe, L., Balcombe, K., Davidova, S., Zawalinska, K., 2004. Determinants of technical efficiency of crop and livestock farms in Poland. Appl. Econ. 36, 1255–1263.
- Liu, Y., Myers, R., 2009. Model selection in stochastic frontier analysis with an application to maize production in Kenya. J. Prod. Anal. 31, 33–46.
- Mees, R., Strauss, D., 1992. Allocating resources to large wildland fires: a model with stochastic production rates. For. Sci. 38, 842–853.
- Mees, R., Strauss, D., Chase, R., 1994. Minimizing the cost of wildland fire suppression: a model with uncertainty in predicted flame length and fire-line width produced. Can. J. For. Res. 24, 1253–1259.
- Meeusen, W., Den Broeck, J. van, 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. Int. Econ. Rev. 18, 435–444.
- Mendes, I., 2010. A theoretical economic model for choosing efficient wildfire suppression strategies. For. Policy Econ. 12, 323–329.
- Mitsakis, E., Stamos, I., Grau, J.M.S., Aifadopoulou, G., 2014. Optimal allocation of emergency response services for managing disasters. Disaster Prev. Manag. 23, 329–342.
- Narayanaraj, G., Wimberly, M.C., 2011. Influences of forest roads on the spatial pattern of wildfire boundaries. Int. J. Wildland Fire 20, 792–803.
- Ntaimo, L., Gallego-Arrubla, J.A., Gan, J., Stripling, C., Young, J., Spencer, T., 2013. A simulation and stochastic integer programming approach to wildfire initial attack planning. For. Sci. 59, 105–117.
- Olsen, J.V., Henningsen, A., 2011. Investment Utilisation, Adjustment Costs, and Technical Efficiency in Danish Pig Farms. University of Copenhagen, Department of Food and Resource Economics.
- Parks, S.A., Miller, C., Nelson, C.R., Holden, Z.A., 2014. Previous fires moderate burn severity of subsequent wildland fires in two large western US wilderness areas. Ecosystems 17, 29–42.
- Penman, T., Collins, L., Price, O., Bradstock, R., Metcalf, S., Chong, D., 2013. Examining the relative effects of fire weather, suppression and fuel treatment on fire behaviour—A simulation study. J. Environ. Manag. 131, 325–333.
- Plucinski, M., McCarthy, G., Hollis, J., Gould, J., 2012. The effect of aerial suppression on the containment time of Australian wildfires estimated by fire management personnel. Int. J. Wildland Fire 21, 219–229.
- Plucinski, M.P., 2012. Factors affecting containment area and time of Australian forest fires featuring aerial suppression. For. Sci. 58, 390–398.
- Plucinski, M.P., Pastor, E., 2013. Criteria and methodology for evaluating aerial wildfire suppression. Int. J. Wildland Fire 22, 1144–1154.
- Podur, J.J., Martell, D.L., 2007. A simulation model of the growth and suppression of large forest fires in Ontario. Int. J. Wildland Fire 16, 285–294.
- Prestemon, J.P., Pye, J.M., Butry, D.T., Holmes, T.P., Mercer, D.E., 2002. Understanding broadscale wildfire risks in a human-dominated landscape. For. Sci. 48, 685–693.
- Ranjan, R., Marshall, E., Shortle, J., 2008. Optimal renewable resource management in the presence of endogenous risk of invasion. J. Environ. Manag. 89, 273–283.
- Wadud, A., White, B., 2000. Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. Appl. Econ. 32, 1665–1673.
- Wei, Y., Bevers, M., Belval, E., Bird, B., 2015. A chance-constrained programming model to allocate wildfire initial attack resources for a fire season. For. Sci. 61, 278–288.
- Zschille, M., Walter, M., 2012. The performance of German water utilities: a (semi)parametric analysis. Appl. Econ. 44, 3749–3764.