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Spatial optimization of operationally relevant large fire confine and point protection strategies: model development and test cases

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Abstract

This study introduces a large fire containment strategy that builds upon recent advances in spatial fire planning, notably the concept of Potential wildland fire Operation Delineations (PODs). Multiple PODs can be clustered together to form a "box" that is referred as the "response POD" (or rPOD). Fire lines would be built along the boundary of an rPOD to contain a large fire. Assets such as communities and infrastructure within an rPOD could be protected through "point zone protection." We develop a mixed integer program model to optimally aggregate PODs into an rPOD with an objective of coordinating containment and point protection to maximize net value change under different fire weather scenarios and resource availability constraints. This optimization framework leverages emerging fire risk assessment and response planning methods by considering factors that drive selection of the optimal rPOD including fire-related benefits and losses, the fire line construction effort required to contain fire, and the point protection requirement within the rPOD to reduce asset losses. The model could be used to support pre-fire assessment and planning, training, and incident response decisions. We use a portion of the Lolo National Forest in western Montana, U.S., as a study site for demonstration.

Keywords: decision support, mixed integer program, planning, risk assessment, wildland fire management

Introduction

Management of wildland fires presents a complex decision environment characterized by changing fire conditions, partial control, and uncertainty (Thompson 2013). In the United States, although nearly all ignitions (95-98%) are rapidly controlled (Short 2014), those rare fires that escape initial control efforts can often pose grave safety concerns, lead to significant damage, and account for the vast majority of area burned (Williams 2013). As these larger, longer-duration fire events evolve, fire managers face challenges when periodically reevaluating suppression strategies. Developing a strategy requires managers to consider a range of alternatives, weigh their respective probabilities of success, and balance multiple objectives relating to cost, responder exposure, and fire impacts (Dunn et al. 2017a; National Interagency Fire Center 2017). These types of decision contexts are ripe for decision biases to arise (Hand et al. 2015; Wibbenmeyer et al. 2013), but also present a rich space for application of decision support tools (Martell 2015; Thompson 2014).

Here we focus on evaluation of large fire consequences and alternative management strategies as critical steps in the fire manager's decision process (Thompson et al. 2017a). As motiving examples, we briefly consider two application-oriented decision support systems, WFDSS from the U.S. (Noonan-Wright et al. 2011; Zimmerman 2012), and AEGIS from Greece (Kalabokidis et al. 2016). Both systems offer functionality for fire behavior modeling and exposure analysis, overlaying fire spread probability contours with locations of values-at-risk. Both systems also offer support for certain types of decisions – WFDSS through provision of a framework to determine incident management organizational needs (equipment, personnel, etc.), and AEGIS through provision of tactically relevant information such as locations of water tanks, pumping stations, and helipads. However, neither system provides direct support to optimize fire management strategies, which is our focus here.

To begin we orient development and discussion of our decision support approach around management response to large fires in the U.S. The National Interagency Fire Center (2011) describes four generalized management strategies, briefly summarized below:

1. **Monitor**: the primary activity is to observe, collect and record fire-related data
2. **Confine**: restricting fire to a defined area using a combination of natural and constructed barriers to fire spread; often combined with burnout operations intended to create buffers of burned areas to hold the fire within the defined perimeter
3. **Point zone protection**: protecting specific points from fire while not actively trying to construct fireline
4. **Full suppression**: constructing fireline around fire to "put the fire out" as efficiently as possible

Fires may be managed under one or more of these strategies, effectively spanning a continuum from monitor to full suppression, and the relative balance of effort across strategies may change over time. For instance, fire managers may opt to pursue full suppression along one flank of the fire to protect a community while monitoring another flank as it burns into an area with low potential for damage or even ecosystem benefits (e.g., the 2012 Halstead Fire; see Hand et al. 2016). As concerns over responder safety, forest condition, and future hazard grow, managers face pressures to move away from full suppression as the dominant response (Calkin et al. 2015; North et al. 2015).

Despite shifting approaches for large fire management in the U.S., existing modeling approaches have generally assumed that full suppression to restrict fire growth is the chosen strategy. A natural question then arises over the degree to which such models can continue to provide relevant information to support on-the-ground decisions. Some models of coupled fire and suppression dynamics adopt user-defined stopping rules to cease fire growth based on factors like fire intensity thresholds, fire weather, or fire perimeter length relative to fireline construction (Fried and Fried 1996; Fried et al. 2006; Finney et al. 2011a; Petrovic et al. 2012). Recent modeling efforts have enhanced realism by considering fire arrival times and the timing and placement of suppression control activities (Belval et al. 2015, 2016). Those models, however, do not adequately capture essential elements of contemporary large fire management such as confining fire via indirect fireline and burnout operations using a combination of natural and constructed barriers (Thompson et al. 2016a). A recent optimization model (Minas and Hearne 2016) focuses on aggregating prescribed burn units into larger clusters to minimize the total perimeter of all clusters; their formulation is relevant but could result in multiple burn unit clusters and was not designed to support development of large fire confinement strategies. Another study from van der Merwe et al. (2013) developed a MIP model to study how suppression resources could be stationed and moved to support asset protection during an escaped fire. However, point protection is the only type of suppression effort considered in their study. Fire containment and point protection often need to be implemented together during large fire management. We therefore argue that a need exists for more contextually relevant decision support to facilitate evaluation of large fire confinement and point protection strategies.

To that end, here we turn to recent advances in operationally-driven spatial fire planning as a basis for enhanced decision support. Specifically we leverage the concept of Potential wildland fire Operation Delineations, or PODs, as a basis for summarizing risks and identifying fire management opportunities (Thompson et al. 2016b). PODs are polygons delineated by pre-identified potential fire control locations (O'Connor et al. 2016, 2017). Each POD is the fundamental analysis unit that can be aggregated to form larger fire containers (hereafter response PODs, or rPODs).

In this paper, we present a novel MIP formulation for large fire confinement and point zone protection strategies by adapting the concepts of PODs and rPODs. We leverage recent pre-fire risk assessment and response planning methods pioneered on National Forest System lands in the U.S. as key model design elements (Thompson et al. 2016b). The modeling method is intended to provide fire managers with a menu of plausibly efficient alternative fire management strategies as starting points towards reaching a practical solution, recognizing that information on suppression resource availability and productivity along with other conditions will need to be assimilated locally by the manager. The model could be used to support pre-fire assessment and planning, training, and incident response decisions. We present case study results for a landscape under National Forest System ownership in western Montana, U.S., and illustrate how solution characteristics vary with fire weather, suppression resource availability, and the impact of point protection emphasis to fire use towards ecosystem benefits. To conclude we describe model limitations, extensions, and opportunities for transitioning to effective operational use.

Methods

Model scope and justification

Fire incident decision making can be decomposed into a hierarchy of levels that vary in spatial and temporal scope. Noonan-Wright et al. (2011) describe tactical large fire decisions as relating to specific management actions made at a fine spatial scale over a short time horizon (1-3 days), and strategic decisions as relating to broader direction provided at a coarser spatial scale over a longer time horizon. Following this classification, our modeling approach is strategic in nature, aiming to spatially delineate rPODs and corresponding point protection needs at the landscape-scale as a guidepost for suppression actions that may unfold over the course of days to weeks.

Our model has many commonalities with a conceptual decision support framework for large fire management recently outlined by Dunn et al. (2017a), most notably the pre-identification of potential control locations and their aggregation into rPODs. Our model also shares a subset of objectives (net value change), decision variables (control line construction and point protection), and constraints (resource availability and fire behavior limiting control opportunities). The Dunn et al. (2017a) framework seeks to comprehensively describe multiple levels of large fire decisions, and therefore considers a broader range of decisions related to suppression resource acquisition and demobilization as well as tactical assignments to specific actions such as mop-up, hazard tree felling, and aviation use. These decisions are outside of the scope of our current model, although this framework will provide a useful roadmap for future model development as well as targeted monitoring to improve model parameterization.

To ground our model in reality, we reiterate that the concepts of mapping potential control locations and delineating PODs are being actively integrated into pre-fire planning efforts on National Forest System lands across the U.S. More relevantly, the POD concept was directly tested in the field during the 2017 fire season. To illustrate this point, Fig. 1 displays a network of predefined PODs overlaid with daily perimeters of the Pinal Fire on the Tonto National Forest in Arizona, U.S. Note that the fire perimeter lines up with the POD boundaries particularly well, as was the intention in managing the fire. Where the fire perimeter goes beyond the POD boundary on the southern edge corresponds to a ridgetop, which is another potential control location that could have formed a POD boundary. The figure also provides illustrative examples of point protection actions taken with the POD, confirming that managers will take such actions in areas where they otherwise intend to use fire for resource benefit. Although in this specific case the rPOD was a single POD (~3,000 ha), this example demonstrates the idea of creating PODs through pre-fire planning and then aggregating them in the response environment in a logical way to achieve objectives given conditions.

Data preparation

The diagram in Fig. 2 outlines the basic data requirement and analytical steps to prepare data, delineate PODs and set up the MIP model (highlighted in grey). Our objective is to build a MIP model to select the optimal rPOD, which is a cluster of PODs, to most efficiently achieve large fire management objectives under a given fire weather and suppression resource availability scenario. Point zone protection can be implemented in a selected rPOD to protect key economic features such as communities, infrastructure, and recreation sites.

Different methods may be used to delineate PODs on a landscape, ranging from the relatively simple and subjective (e.g., relying on local expert judgment; Thompson et al. 2016b) to the relatively complex and objective (e.g., building an empirical machine learning model to output a fire control probability surface; O'Connor et al. 2017). For a simple case, a given POD's boundary may be comprised of different features like a road segment, a ridge top, and a man-made fuel break etc. Containment effort would be scheduled along those boundaries.

Only after PODs have been spatially delineated can they be attributed with spatially-varying information on potential fire consequences and fire management effort. A range of approaches can be used to quantify and map potential fire consequences (e.g., Castillo et al. 2017; Thompson et al. 2015). Here we refer to fire consequences in terms of conditional net value change (*cNVC*; Scott et al. 2013), in that estimates are conditional on the occurrence of fire under the specified fire weather conditions. *cNVC* calculations reflect percent loss/gain values for each highly valued resource or asset (*HVRA*) included in the assessment, along with relative importance weights across *HVRAs* articulated by local leadership (Scott et al. 2013). Pre-calculated *cNVC* for every raster cell in a POD can be summed to calculate the *cNVC* of the corresponding POD. Because *cNVC* is a fire loss/benefit measurement calculated by weighting multiple *HVRAs*, maximizing *cNVC* in a MIP model is equivalent to running a multi-objective programming model with a set of preselected weights for different objectives. These weights express on-the-ground management priorities as articulated through agency mission, applicable statutes and regulations, local collaborative planning, and other factors. Exploring alternative weight spaces and their implications for alternative rPOD strategies is not relevant for our purposes here, but could be the subject of future work (see also Thompson et al. (2015) for sensitivity analysis of assessment results).

In this study, we generically refer to "containment effort" as activities such as constructing new fireline, reinforcing existing natural or man-made fuel breaks, and prepping for and implementing intentional burnout operations along POD boundaries. To model containment, we need information on the containment effort required for confining a fire using the boundary of an rPOD. The amount of required containment effort could vary along different rPOD boundaries. For example, less effort may be needed along a major road than a narrow stream. The total amount of required containment effort also depends on how PODs are clustered into an rPOD, and further requires the MIP model to ensure that effort along common (interior) edges of two adjacent PODs within an rPOD is not counted.

Besides containment effort, this model also needs data to quantify the point zone protection effort needed for successful asset protection. Allocation of point protection effort within a POD can lead to reductions in loss, making losses solution-dependent; this is indicated by the double-sided arrow in Fig. 2. We will refer the asset values that can be protected through point protection as *pNVC*. Examples of how to set up model parameters are demonstrated in the test cases later in this paper, and the model formulation is flexible to accommodate other measurement units or model parameterization processes if needed.

In summary, factors that drive selection of the optimal rPOD under each modeled fire weather and suppression resource availability scenario include the fire-related benefits and losses within each possible POD, the cumulative effort required along the perimeter of the rPOD, and point protection benefits and resource requirement within the rPOD. The modeling approach considers the POD within which the fire ignites as the "seed" to construct an optimal rPOD. The idea is that the model could be re-run in response to changing fire conditions, with the seed updated to be a cluster of PODs based on the current fire location and size; this approach is not unlike existing fire simulation models, such as FSPro (Finney et al. 2011a), used to update projections of possible fire spread based on the current perimeter (Calkin et al. 2011).

Mathematical formulation of the rPOD optimization model

Sets and indices:

- i or j indices for PODs

- (i, j) or (j, i) we use the indices of two adjacent PODs i and j to uniquely represent the shared edge between them. The value of the first subscript in the pair will always be smaller than the second, so that each edge is only represented by one pair of POD indices. In this model, we will use -1 to represent the area outside of the study site. Therefore, if the first subscript (either *i or j*) is *-1,* the edge (i, j) or (j, i) represents part of the study site boundary.
- $(i \to j)$ index of potential fire spread direction from POD i to its adjacent POD j. Note that i does not have to be smaller than j in this pair of indices.
- r index of suppression resource types, i.e. hand crew, engines, dozers etc.
- a_i index of the point protection locations within each POD i

Decision variables:

- X_i 0/1 variable, 1 if POD i is selected as part of the optimal rPOD. For the POD i^o that fire ignited from, the variable X_{i^o} would be set to one.
- $Y_{(i,j)}$ 0/1 variable, 1 if edge *(i,j)* is part of the rPOD boundary (control line location) constructed to contain fire; 0 if not.
- $H_{r,(i,j)}$ contiguous variable tracking the total time (i.e. hours) suppression resource type r spent along edge *(i,j).*
- O_{i,a_i} 0/1 variable tracking whether point protection would be applied at location a_i within POD i; 0 if not, 1 if applied.
- $B_{(i\to j)}$ 0/1 variable, 1 if fire would spread from POD *i to j*, 0 if not; *j= -1* representing fire spreads beyond the study site boundary.
- F_i an auxiliary contiguous variable like the "tail length" variables used by Önal and Briers (2006); it represents the sequence number of each POD being selected into the

optimal rPOD. This variable is necessary to require the model to form a contiguous cluster (or patch, or rPOD) starting from the fire ignition POD. For the POD i^o that fire ignited from, this variable F_{i^0} would be set to zero.

Parameters:

- i^o denotes the ignition POD
- $l_{r,(i,j)}$ the time (i.e. number of hours) required by using resource type *r* to build one unit length (i.e. meter) of containment line along edge *(i,j)*
- $cNVC_i$ conditional net value change within POD *i* under the modeled fire weather scenario; for this model formulation, positive value represents fire benefits; negative value represents fire losses
- $pNVC_{i,a_i}$ the benefit (avoided loss), in terms of *cNVC*, from successful point protection at location a_i in POD *i*
- k_{r,i,a_i} the time (i.e. number of hours) required by using resource type *r* to support successful point protection at location a_i in POD *i*
- $e_{(i,j)}$ the length of fire line that needs to be built along edge *(i,j)* to contain a fire under the modeled fire weather scenario
- d_r the total available hours of resource type *r* to spend on line construction and point protection during the large fire suppression operation
- M a large constant
- A_i the number of potential point protection locations in POD *i*

Mathematical equations

$$Max \quad Z = \sum_i cNVC_i \, X_i + \sum_i \sum_{a_i} pNVC_{i,a_i} O_{i,a_i} \tag{1}$$

Subject to.

$$X_{i^o} = 1 \tag{2}$$

$$\begin{cases} Y_{(i,j)} \geq X_i - X_j & \forall (i,j) \\ Y_{(i,j)} \geq X_j - X_i & \forall (i,j) \end{cases} \tag{3}$$

$$B_{(i \to j)} \leq X_i \qquad \forall (i \to j) \tag{4}$$

$$X_j \leq \textstyle\sum_i B_{(i \to j)} \qquad \forall j \neq i^o \tag{5}$$

$$\begin{cases} B_{(i \to j)} \leq 1 - Y_{(i,j)} & \forall (i \to j) \text{ when i < j} \\ B_{(i \to j)} \leq 1 - Y_{(j,i)} & \forall (i \to j) \text{ when i > j} \end{cases} \tag{6}$$

$$\begin{cases} X_j \geq X_i - Y_{(i,j)} & \forall (i \to j) \text{ when i < j} \\ X_j \geq X_i - Y_{(j,i)} & \forall (i \to j) \text{ when i > j} \end{cases} \tag{7}$$

$$\textstyle\sum_{a_i} O_{i,a_i} \leq A_i X_i \qquad \forall i \tag{8}$$

$$F_{i^o} = 0 \tag{9}$$

$$\begin{cases} F_j \leq F_i + M\left(1 - B_{(i \to j)}\right) + 1 & \forall (i \to j) \quad (10) \\ F_j \geq F_i - M\left(1 - B_{(i \to j)}\right) + 1 & \forall (i \to j) \quad (11) \end{cases}$$

$$e_{(i,j)} Y_{(i,j)} \leq \textstyle\sum_r l_{r,(i,j)} H_{r,(i,j)} \qquad \forall (i,j) \tag{12}$$

$$\textstyle\sum_{(i,j)} H_{r,(i,j)} + \sum_i \sum_{a_i} k_{r,i,a_i} O_{i,a_i} \leq d_r \; \forall r \tag{13}$$

The objective function (Equation 1) maximizes the total *cNVC* within the selected PODs to contain the fire, along with reductions in loss resulting from successful point protection at the selected locations within those PODs. Equation (2) ensures the POD containing the fire ignition location is included as part of the rPOD. Equation (3) uses a pair of equations to capture the logic that containment effort is needed between the boundary of POD *i* and *j* if and only one of the two adjacent PODs is burned; otherwise, no contain effort is needed along their boundary. Equation (4) ensures fire could spread out from POD *i* only if this POD has already burned. Equation (5) ensures that if POD i has burned, fire must spread into it from one of its adjacent PODs, unless i is the fire origin POD. Equation (6) is based on a model assumption that a fire would not spread across the boundary (e.g. $B_{(i \to j)} = 0$) after containment effort spent on it is beyond a predetermined threshold (e.g. $Y_{(i,j)} = 1$) depending on the boundary feature and the fire line intensity. Equation (7) ensures if fire is already in one of two adjacent PODs, the only way to prevent that fire from spreading into the adjacent POD is to contain fire along their boundaries. Equation (8) requires that point zone protection at any location a_i within each POD i could (and need to) be applied only when that POD is part of the selected optimal rPOD. Equations (9-11) use auxiliary variable F_i to ensure that PODs would be selected with certain sequence to form a contiguous container (or box) as the rPOD. These equations sequentially assign a number (see Fig. 3) to each selected POD. The POD that a fire started from would be assigned a sequence number of zero by Equation (9). Equations (10-11) increase the sequence number of POD i by one and assign it to its adjacent PODs if no required containment effort is spent along the boundary between them. Assigning a sequence number to every selected POD avoids creating disconnected clusters of PODs. Similar variables have been used to enforce raster cell connectivity in a reserve site selection model (Önal and Briers 2006). Equation (12) enforces that if edge *(i,j)* is selected as part of the containment boundary, the length of fire lines constructed by the joint efforts from multiple suppression resource types r need to cover the length of that edge. Equation (13) enforces the total fire management effort (e.g. measured by resource hours) upper bound for resource type r, including the containment efforts along the rPOD boundary and the point zone protection effort at the different locations within the rPOD. This constraint reflects a reality that there can be limited suppression resources available during large fire suppression operations.

Material and case studies

To test our model, we selected a portion of the Lolo National Forest in western Montana, U.S. (Fig. 4). The study site is approximately 60,000 ha with elevations ranging from 750m to 2100m, and primarily northern Rocky Mountain montane mixed conifer forests. Characteristic tree species include ponderosa pine, Douglas-fir, western larch, and lodgepole pine. All tests in this study assume the fire started from a single and arbitrarily selected POD (specifically POD #94) in the southwest portion of the study site. Fixing the fire starting location helps us focus on isolating differences due to changes in fire weather conditions and suppression resource availability.

We generated potential control locations and a topologically-linked network of PODs within our test area using GIS data and analysis techniques. For this test, we allowed potential control locations to be major roads, streams, or ridge tops. Our assumption is that fire containment efforts could be exerted along these geographic features to safely and more efficiently confine a large fire. We used GIS layers from the U.S. EPA and U.S. Geological Survey's NHDPlusV2 dataset (http://www.horizon- systems.com/NHDPlus/NHDPlusV2_home.php) for stream and ridge (catchment boundary) locations, and we acquired road GIS data from the Lolo National Forest. We analyzed the topological relationships of PODs and the boundaries between each pair of them using the "Polygon neighbors" tool in ESRI ArcGIS.

We used the FlamMap fire modeling system (Finney 2006) to estimate flame length metrics that influence calculations of fire consequences along with containment effort and point protection effort requirements. We leveraged a modified national LANDFIRE fuels datasets (Ryan and Opperman 2013) that was developed via an expert opinion workshop to better represent local fuels conditions, and then generated fire behavior metrics for each 30m x 30m cell on the landscape. We developed six weather scenarios that vary in terms of wind speed, wind direction, and fuel moisture, using values drawn from a proximal Remote Automated Weather Station – the Pistol Creek RAWS station (id# PSTM8). Wind speed and direction were chosen based on historical frequencies of observed winds during the middle of the fire season (June – August). The most common wind speed and direction observed was 16.1 kilometers/hr winds (at 6.1m above ground), with an azimuth of 315 degrees. The most extreme winds observed were 40.2 kilometer/hour winds, with an azimuth of 225 degrees. For each wind scenario, we calculated the fire behavior for fuel moistures for the live woody, live herbaceous, 10, 100 and 1000 hour fuels representative of the 80th, 90th, and 97th observed percentile of energy release component (ERC). ERC measures the available energy (BTU) per unit area within the flaming front at the head of a fire. For writing purposes, we will use the ERC percentage to reflect the fuel moisture conditions in this paper.

To calculate *cNVC* we leveraged existing strategic risk assessment results generated locally by the U.S. Forest Service's Fire Modeling Institute in partnership with the Lolo National Forest based on the framework from Scott et al. (2013) and Thompson et al. (2015). Lolo National Forest fire managers and resource specialists identified eight categories of HVRAs to include in the assessment: communities, municipal watersheds, infrastructure, timber resources, ecosystems, critical wildlife habitat, recreation sites, and wilderness character. These HVRAs were further divided into 31 subcategories, each with its own loss/benefit function. Together with stochastic wildfire simulation outputs (Finney et al. 2011b) and HVRA importance weightings assigned by Lolo National Forest leadership, the spatial HVRA data were integrated to create an annualized ensemble-based *cNVC* surface across the landscape. To test our model for different weather conditions, we repeated the calculation of *cNVC* surfaces within our study area, substituting conditional fire intensity data from each of our six fire weather scenarios for the analogous simulation outputs used in the forest-wide assessment. In so doing, we produced condition-specific *cNVC* surfaces appropriate for the fire-specific suppression strategy. *cNVC* calculations assume that all burnable area within a selected POD does burn. To specifically model the need for, and benefit of, point protection, we also calculated the value that can be protected by point protection under each of the weather scenarios. We assume suppression resources could be allocated to protect valuable assets in the point protection zones, specifically communities, developed recreation sites, communication facilities and administrative sites within each POD. The value from those tangible assets is represented by *pNVC*.

The current MIP formulation allows us to model for multiple types of resources to build fire lines and for point protection, which, however, require intensive data collection and analysis (see Hand et al. 2017). To simplify the parameterization process when testing the prototype model, we will use only the 20-person Type I handcrew hour (referred to as "crew hour") to quantify fire containment and point protection effort. Referring to the production table in the Wildland Fire Incident Management Field Guide (National Wildfire Coordinating Group 2013), we assume a productivity rate that equates one crew hour with building 191m containment lines along major roads, or 98m along streams or ridge tops. These estimates correspond to a predicted fire flame length of 1.22m. If flame length increases, fire line width also needs to increase (see Andrews et al. 2011) to ensure containment. We adopt a study from Mees's et al. (1993; details in Appendix) to calculate the expected fire line width to contain a fire of certain flame length. We assume the expected crew hours to build one-unit length of fire line will be proportional to the required fire line width. Requirement for containment efforts could also vary by terrain and vegetation. If better data becomes available in the future, those relationships can be incorporated into the model through parameterization. We also address fire manager choices to avoid engagement in certain locations under certain conditions out of consideration for firefighter safety. For this study, we assume fire line will not be constructed along any POD boundary with flame length more than 2.44 meters (National Wildfire Coordinating Group 2013) under each modeled fire weather scenario.

Parameterizing the model for point protection resource requirement is also challenging due to limited data and research from the past. We referred to a graduate thesis from Marcille (2015) that describes a breakdown of suppression effort across suppression mission types on a set of nine large fires from 2010 to 2013 in the western U.S. This thesis calculates an average of 0.1463 ratio between point protection assignments to line construction assignments during large fire suppressions in that region. To use this data, we first calculated the total crew hours requirement to contain fires around the entire study site under a selected moderate-to-severe fire weather condition of 90th percentile ERC, northwest wind direction and 16.1km per hour wind speed. We then multiply the total crew hours for containment by 0.1463 to estimate the total crew hour required for point protection over the entire study site under the weather condition. The number of crew hours required to protect the assets in each POD is approximated by multiplying the total crew hours by the ratio of *pNVC* in that POD to the total *pNVC* of the study site. Under more severe fire weather, the *pNVC* in a POD might be higher, therefore the crew hours required for successful point protection in that POD would also increase. To simplify the data preparation process, we only modeled one point-protection location in each POD. Although modeling for multiple point protection locations (i.e. separated communities) in each POD is possible using the MIP model, it would require more detailed GIS analysis to delineate separated point protection zones in each POD. The above procedure used to parameterize the test case is for demonstration purpose. To make the analysis more relevant in the future, extensive local data collection, survey and field analysis would be necessary to quantify local point protection requirements.

Fire use and asset protection

The MIP formulation introduced so far (Equation 1 to 13) assumes a risk-neutral manager who would be willing to accept more loss so long as the benefits outweigh those losses. In practice, however, managers can exhibit tendencies for loss aversion and for minimizing short-term risks over long-term risks (Wilson et al. 2011). This may stem in part from the difficulties of balancing impacts to tangible assets like homes and infrastructures against ecosystem services (Venn and Calkin 2011), which is one principal reason to pre-calculate *cNVC* surfaces that can explicitly identify opportunities for beneficial fire. For pre-fire analysis, it would be useful to also clearly quantify such tradeoffs, and to provide alternative strategies to managers so they can evaluate the tradeoffs associated with different management approaches. In an attempt to explore how the concern of tangible asset losses would affect the benefit from fire use, especially under moderate fire weather, we conducted a set of model runs by: 1) multiplying the point protection crew hour requirement parameter k_{r,i,a_i} by a multiplier from one to 100 to represent a case when fire manager wants to spend more resources to protect communities and infrastructure, and 2) multiplying the point protection value $pNVC_{i,a_i}$by a multiplier from one to 100 to reflect a case when managers value tangible losses more than long-term ecosystem benefits.

Results

Influence of crew hour upper bound and fire weather

We ran the model with the same fire ignition location (POD #94) for all six fire weather scenarios at different crew hour upper bound limits and summarized the results in Fig. 5. The *cNVC* surfaces and the benefits of point zone protection (*pNVC*) underpinning each solution correspond to each unique fire weather scenario. For the moderate fire weather conditions (at 80% ERC level with both wind conditions), test results show as the available crew hour upper bound increases the optimal selection of rPOD increases the net fire benefit. Results under the slower wind (315-degree direction and 16.1 km per hour speed) and the 80% ERC show the slope of the net fire benefit curve is steepest between 100 and 300 crew hour upper limits; under the stronger wind (225-degree direction and 40.2km per hour speed) and the 80% ERC, results show the slope of the net fire benefit curve is steepest between 300 and 600 crew hour upper limits. Both curves flatten out thereafter, suggesting the model first finds PODs with highest net benefit and then options taper out. This also reflects increased potential for ecosystem benefit with moderate fire weather. Fire weather severity increases if wind speed increases (e.g. from 16km per hour to 40km per hour), or with higher percentile of ERC (e.g. from 80 to 97 percentile). At each modeled crew-hour upper bound, running the model with more severe fire weather would result in an rPOD with lower net fire benefit. The flatter curve under 97% ERC at wind speed of 16km per hour reflects the lower potential to achieve ecosystem benefits and higher potential for losses (Fig. 5a). Also note that the model may not find any feasible rPOD to contain the fire when fire weather is severe (see the missing curves and missing points for the "Total net fire benefit" in Fig. 5b).

We mapped the optimal rPODs under one moderate fire weather condition (wind direction of 315 degrees, wind speed of 16.1 km per hour, and the fuel moisture conditions calibrated under the 80% ERC level) in Fig. 6. The four panels illustrate how the size and shape of the optimal rPOD varies under four limits on crew hours (100, 300, 600, and 1000). Results show that, under this fire weather condition, increasing the crew-hour limit allows creation of a larger rPOD with greater benefits (Fig. 6a to 6d). At the 1000 crew-hour upper bound most of the test site would be included in the rPOD (Fig. 6d), which represents an extreme case when fire is used to provide more ecosystem benefits while it can still be controlled within a large "box" by using available suppression resources.

Relationship between rPOD perimeter, area, and number of PODs

Fig. 7 summarizes the total length of rPOD boundaries requiring containment effort for all fire weather and crew-hour limit scenarios. The general trend is that containment effort will be allocated along longer rPOD boundaries as the crew-hour upper bound increases. Fig. 7 panel (1.b) indicates that the model either cannot find a feasible solution (under 97% ERC) to contain the fire, or will build relatively smaller rPODs to avoid losses associated with the higher (40km/hour) wind speed.

The area of the optimal rPOD also generally increases with additional crew-hours (Fig. 7 panel 2). In all cases the rPOD area is the greatest under 80% ERC. The exception to increasing rPOD area is panel (2.a) and (2.b) under higher ERC levels, where the optimal solutions begin to flat out or decrease in size once suppression availability reaches certain threshold. Panel (3) displays the total count of PODs within each rPOD solution, and results track rPOD area results in panel (2) very closely. We might expect different results if the underlying distribution of POD area was more skewed.

The overall positive correlations between increasing crew-hour availability, longer rPOD perimeter, and larger rPOD area are not strictly held in all fire weather conditions. It is easy to understand that under the most severe fire weather, the model would attempt to minimize the size of a contained fire even if additional suppression resources were available. By increasing the crew hour upper bound, the model could also form rPODs with different shapes. Polygons with the same area but different shapes can have different perimeter lengths depending on the perimeter-to-area ratio. This model does not restrict the shape of the rPOD selected, nor explores the perimeter-to-area ratio of the rPOD, which could be relevant to some ecological criteria, but is not relevant to *cNVC* and its corresponding underlying spatial pattern of losses and benefits.

Role of point protection

Fig. 7, panel (4), shows that the model tends to allocate less crew hours on point protection under more severe fire weather conditions. This is because under more severe fire weather conditions, suppression effort is often spent on containing the fire smaller and outside of PODs with high asset loss potential; under moderate fire weather conditions to the contrary, the area of rPOD increases and more point protection is used to reduce loss within PODs that otherwise provide a net ecosystem benefit. When the crew hour upper bound increases, we can see a general trend of more crew hours being allocated to point zone protection in the selected rPOD. However, if the model decides to select a different set of PODs to form the rPOD with higher crew hour upper bound, the amount of crew hours spent on point protection could also decrease when the overall crew hour availability increases (panel 4.a; 90% ERC).

Another type of summary analysis shows the percentage of crew hours spent on point protection versus containment effort (Fig. 8). Results presented here are for wind direction 315 degrees and 16.1km/hour wind speed (see also Fig. 5a). With fire weather conditions moving from severe (Fig. 8a) to moderate (Fig. 8c), we can see the trend that higher percentage of crew hours will be spent on point protection. This is consistent with results presented in Fig. 7, panel 4.a, where under moderate conditions the model capitalizes on opportunities to include PODs to gain ecological benefit while investing in protection to reduce losses within those same PODs (we refer readers back to Fig. 1 for a real-world example of such a strategy).

Fire use and asset protection

Test results show under moderate weather condition, the model will seek larger rPODs to gain more net benefits, even if that means in some cases fire will be allowed to burn through a POD with home or infrastructure losses. If concern over tangible asset losses increases, or if the required resource hours for successful point protection increases, the model can either avoid selecting the PODs that require point protection when it forms rPODs, or it can allocate more crew hours to point protection rather than containment. Solutions under both cases could result in an rPOD with less ecosystem benefit. Fig. 9 shows that the total ecosystem benefits earned by managing a fire under moderate weather condition would decrease as we switch our management emphasis more towards protecting tangible assets. It shows that the ecosystem benefits from fire can decrease by 30% when both the value of assets to be protected and the cost of protecting them increases. This type of information can be generated and provided to fire managers before a fire season starts to help layout out tradeoffs between emphasizing fire use and tangible asset protection. Also note that the surface shown in Fig. 9 is not always smooth due to two reasons: first, most of the decision variables in the MIP model are either binary or integer variables; second, to save computation time, we stopped each model run when a solution is found within a 5% gap of the possible optimal solution.

Discussion and Conclusions

We demonstrated that the MIP model could support the development of operationally relevant large fire management strategies by optimally aggregating PODs, which can be predefined according to fire management objectives in a local planning unit. We leveraged existing analytical products like pre-calculated *cNVC* surfaces and predefined potential control points that are increasingly used by fire managers for planning purposes. We contend that fire containment and point protection are interrelated management operations that need to be jointly optimized to best achieve the fire management objectives, and believe the work presented here grounds decision support in the realities of contemporary large fire management.

The rPOD formulation in this study does not need to pre-identify candidate rPODs. Instead, the model automatically builds an optimal patch starting from a "seed" unit by using adjacency relationships between pairs of analysis units. Similar types of formulations likely could be used to form landscape level patches for ecological benefits. Opportunities for other landscape spatially explicit optimization uses depend largely on the analogies between analysis units and the possible "seeds" from which to construct an optimal patch.

Short-term approaches for operational use of this method could emphasize the building blocks of the MIP model itself. For example, spatial *cNVC* surfaces could be pre-calculated, archived, and combined with incident-specific fire behavior simulations (Thompson et al. 2017b). Similarly, predefined potential control locations could be archived in an atlas (e.g. O'Connor et al. 2017) for use in determining appropriately sized "boxes" for confine and contain strategies. Further, pre-season training and simulation exercises could generate a range of optimal rPOD solutions under different scenarios, and these could be archived and used to stimulate response strategy development. The end-goal could be integration of functionality into an existing system like WFDSS, which already provides functionality for computationally intensive fire behavior simulations at the incident command post through a web-based platform (Noonan-Wright et al. 2011).

In the Pinal Fire example, typical fire season weather conditions (90^{th} percentile ERC) were used to generate a network of predetermined PODs, based on *cNVC*-informed response strategies. This POD network for the whole of the Tonto National Forest was housed on the WFDSS platform for the 2017 fire season. Local fire managers who helped to design the POD matrix were aware of the limitations of using a forest-scale planning product based on a single fire weather scenario for incident decision making, and adapted their operational tactics to evolving conditions while using predefined POD boundaries and *cNVC* values to guide strategic response. This approach helped to communicate to the public the intention of managing a natural ignition for resource benefit, and allowed fire planners time to identify and prepare assets in need of point protection shortly after ignition (Fig. 1). Predefining an optimal POD area in advance of ignition facilitated the use of suppression resources and tactics to reduce fire severity, protect highly valued assets, reduce fuel loading, and contain the fire within an efficient, reduced-exposure footprint.

Several extensions are possible to improve model fidelity, many of which relate to better reflecting the dynamic fire environment. Perhaps most obvious is reevaluating optimal response strategies in relation to changed weather. As stated in the introduction, our model is currently set up for iterative use. Managers could rerun the model using the current fire footprint to reset the fire-starting POD, and using the predicted fire weather to recalculate the cNVC surface and the suppression efforts needed along each potential containment line. Multiple weather scenarios could be used, such that for instance a risk-averse containment strategy could be selected based on more severe forecast. Expanding further, we could rely on stochastic simulation driven by historical and forecasted weather rather than using static fire behavior model outputs based on a set of weather scenarios. The event set of many simulated fire realizations given the current ignition location (or fire perimeter) could then form the basis for a probabilistic evaluation of fire size, shape, and corresponding consequences. Similarly, the potential control locations along POD boundaries could be assigned probabilities of success given weather and fire behavior conditions, recognizing that fires can at times spread or spot over control lines. The model could also be converted into a stochastic programming formulation to simultaneously consider the influence of multiple future fire weather scenarios. Future study is still needed to understand the benefit and cost of building a more complex stochastic programming model to provide strategic large fire containment strategies.

Other possible extensions relate to safety and tactical concerns. For example, it may be possible to pre-identify responder safety zones and egress routes (e.g., Campbell et al. 2016), and embed them into the model directly. This could be captured through constraints on POD selection based upon user-defined tolerances for number of or distance to safety zones. Similarly, we could augment our model to consider the type and amount of responder exposure rather than just total crew hours. In this sense, we could create a new objective that combines suppression effort and responder exposure in a multidimensional metric, and we could seek efficient frontiers balancing *cNVC* with a hazard-weighted exposure score. Such a formulation would be most consistent with existing risk management protocols in the U.S. that direct federal fire managers to “engage the fire before it starts” by predetermining response strategies balancing protection of values at risk with fire responder exposure (National Interagency Fire Center 2017). Our immediate research aims are to head in this direction.

An updated modeling framework could also be expanded to consider a broader range of tactical decisions as well as linkages between strategic and tactical responses. It is conceivable that implementation of a specific rPOD containment strategy may prove infeasible given on-the-ground conditions or resource constraints, a phenomenon that also arises for instance when tactical harvest scheduling models with spatial constraints are used to meet long-term sustainable yields derived from strategic models (e.g., Weintraub and Romero 2006). At present we assume fire incident managers would make these tactical and time-specific decisions based on more detailed fire spread simulations and other site-specific information, and reiterate that our model is intended to be sufficiently rapid and flexible to allow multiple runs. If needed, a suppression task assignment model could be built to optimize those time-specific tactical decisions to assign suppression resources along the selected rPOD boundary for fire control, or within a selected rPOD for point protection (see Constantino et al. 2017). Ideally such a formulation could also incorporate relationships between simulated fire arrival times, timing of suppression activities, and fire-control line interactions. Additional monitoring of actual suppression operations (e.g., Katuwal et al. 2017; Holmes and Calkin 2013) will likely be necessary to improve parameterization of crew hours and especially point protection effort.

Better parameterizing the model to fit local fire confinement and containment needs will ultimately be dependent on enhanced research to reduce uncertainties surrounding suppression operations. For example, the MIP formulation introduced here allows us to consider multiple resource types, but we built simplified test cases by using crew hours to measure suppression efforts due to the lack of localized data. Future research is needed to estimate the productive capacity of different suppression resources engaged in different missions, the moderating effects of suppression activities on fire spread, and conversely the amplifying effects of fire weather on resistance to control (Duff and Tolhurst 2015; Finney et al. 2009; Holmes and Calkin 2013; Katuwal et al. 2016). Collectively these uncertainties present significant barriers to building and parameterizing realistic models of suppression strategies, and will rightly be the subject of continued fire management research (Dunn et al. 2017b).

The locus of an increasing focus on pre-fire assessment and planning, an increasing emphasis on reducing unnecessary firefighter exposure, and an increasing recognition of the need to expand the footprint of the right type of fire, suggests that this modeling approach could have widespread application in the U.S. and elsewhere. We believe our model formulation has utility for preseason analysis, training, and real-time incident decision support. Our modeling approach emphasized reliance on pre-fire assessment and planning to help dampen time pressures, reduce uncertainties, expand options, and clarify risk-benefit tradeoffs (Thompson et al. 2016c). This modeling approach could dovetail nicely with for example research in Europe and elsewhere mapping suppression difficulty and evaluating the efficiency of suppression operations (Mitsopoulos et al. 2017; Rodríguez y Silva et al. 2014; Rodríguez y Silva and González-Cabán 2016). Continued research integrating suppression monitoring, fire modeling, and response optimization will ideally foster safer and more effective fire management.

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Appendix

Mees et al. (1993) modeled the relationship between average flame length *m* and the probability *p* of a fire line holding with a line width of *x*. They suggest if line width is less than certain threshold, the probability of it holding would be zero. If line is wider than a threshold, the probability of a line holding can be calculated through mathematical formulations. The formulation they used to calculate the probability of line holding can be inversed to calculate the required line width *x* with a targeted line holding probability of *p* when the average flame length is m.

$$x = \left(\frac{(T-h) * \log(1-p)}{\log 0.15} + h\right) * m$$

h (generally ≤1) and *T* (generally ≥1) are user defined parameters. *h* is selected such that the chance of holding is zero until the fire line width *x* exceeds *h*m*. Their study also suggests the value of *h* should vary depending on flame length m. *T* is selected so that the probability of holding is 0.85 when the line width equals *T*m*. To build our test case, we set a targeted probability of line holding of 0.99 and setting up the value of *T* and *h* according to the suggestion from the paper to calculate the required line width. The following calculations is used in our test cases.

When flame length $m \leq 0.61$ meter, we will set *T=1* and *h=0.* The required line width *x* is calculated as:

$$x = \left(\frac{\log(0.01)}{\log 0.15}\right) * m = 2.427 * m$$

When $0.61 < m < 2.44\ meter$, we will set T=1 and $\mathrm{h} = (\mathrm{m} - 0.61)/m$

$$x = \left(\frac{(T-h) * \log(0.01)}{\log 0.15} + h\right) * m$$

According to the above formulation when flame length approaches 2.44 meter, the required line width will approach 3.31 meter. If $m \geq 2.44\ meter$, we will not allow lines to be built along the corresponding POD boundaries.

Figure 1. The Pinal Fire on the Tonto National Forest in Arizona was managed using a pre-defined network of PODs developed over the winter of 2016-2017. Planning POD boundaries used here are algorithm-informed potential control locations combined into PODs in a workshop with local fire managers. Daily fire progression demonstrates the use of POD to contain the fire for resource benefit and to concentrate containment resources along POD boundaries where they were most likely to be effective (c). Shortly after fire ignition, point protection teams were deployed to prep fire-sensitive assets within the intended footprint of the fire (b). A burn out operation was used to halt fire progression towards a community (a). The size, duration, and complexity of fuel types of the Pinal Fire demonstrate the potential for pre-season fire planning to improve fire season outcomes. Prior to the pre-season planning exercise, all ignitions on this landscape were aggressively suppressed.

Figure 2. Diagram of the modeling system components and interactions.

Figure 3: The sequence of polygons in which the model builds an rPOD by aggregating individual PODs beginning with the ignition POD (sequence number of zero). Fire lines only need to be constructed along the rPOD boundary (the bold line). The importance of the sequence numbers is they help the model create a contiguous patch including the ignition POD. Note that the sequence numbers do not reflect the sequence of fire spread into each POD; instead, they are the sequence in which an rPOD was built by the MIP model.

Figure 4. Study site location within the Lolo National Forest, Montana, U.S.

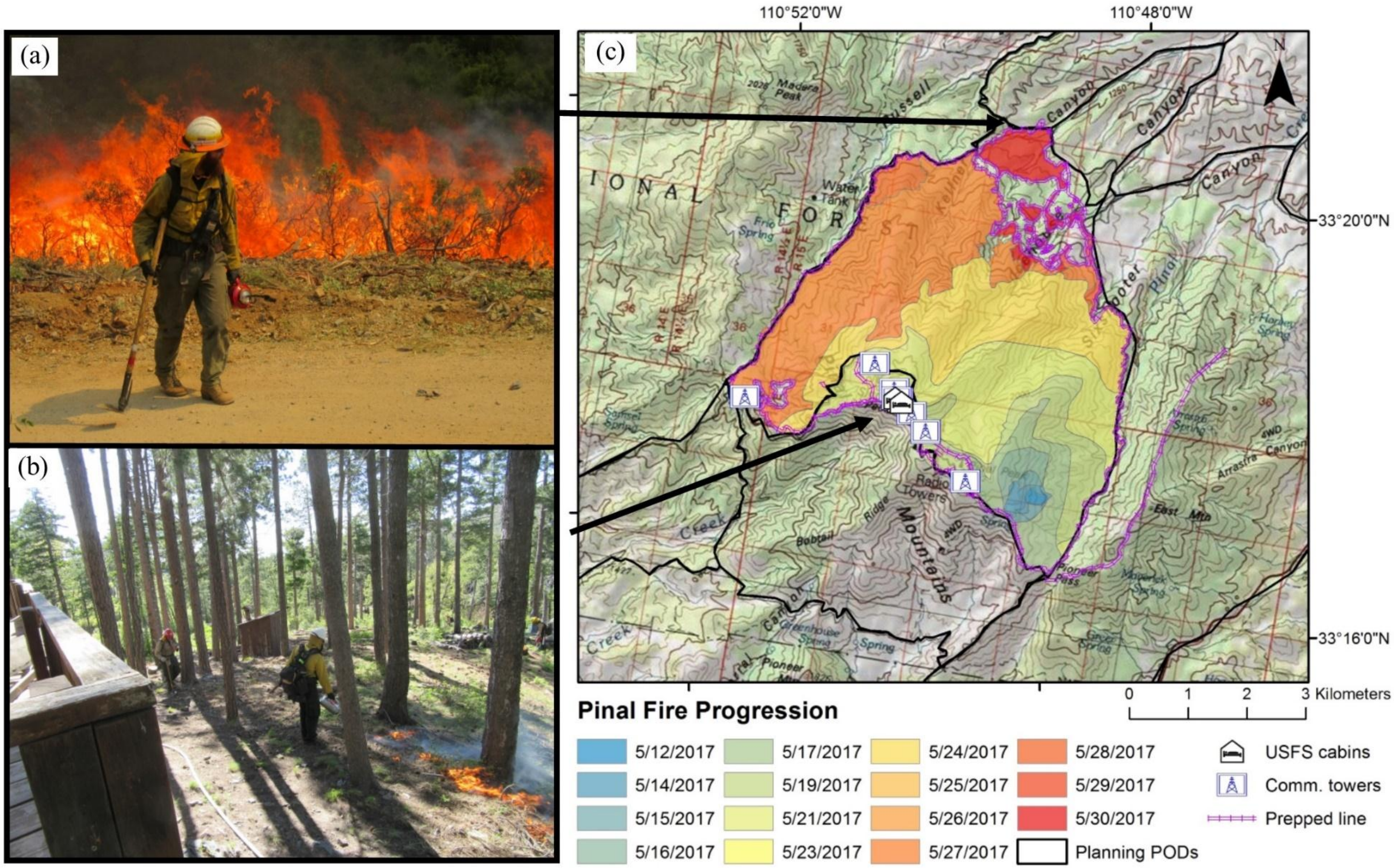
Figure 5. Total cNVC associated with the optimal rPOD under five fire weather scenarios (no feasible solution found for the sixth scenario), with the crewhour based suppression effort upper bound varying from 100 to 1000 hours. (a) wind direction 315 degree, 16.1km/hr wind speed, at 80%, 90% and 97% ERC; (b) wind direction 225 degree, 40.2km/hr wind speed, 80%, and 90% ERC.

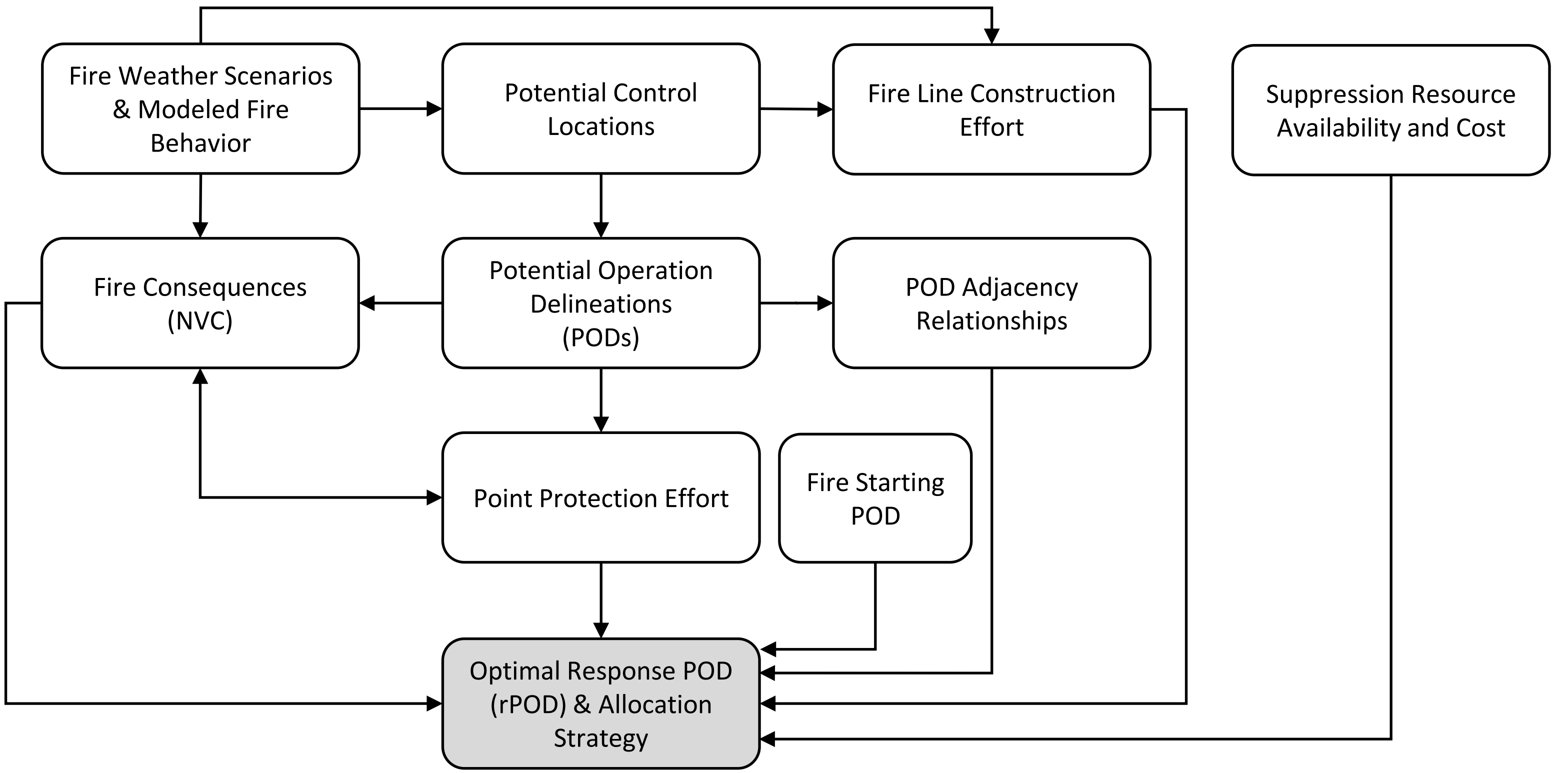
Figure 6. Changes in rPOD size and shape as they vary with budget constraints. "W80_315_16" represents a moderate fire weather condition at 80% ERC, 315 degree of wind direction and 16km/hour of wind speed, under which ecosystem benefits are possible across broad areas of the landscape. The figure shows the rPOD formed when the crew availability upper bound is set to be: (a) 100 hours; (b) 300 hours; (c) 600 hours; (d) 1000 hours.

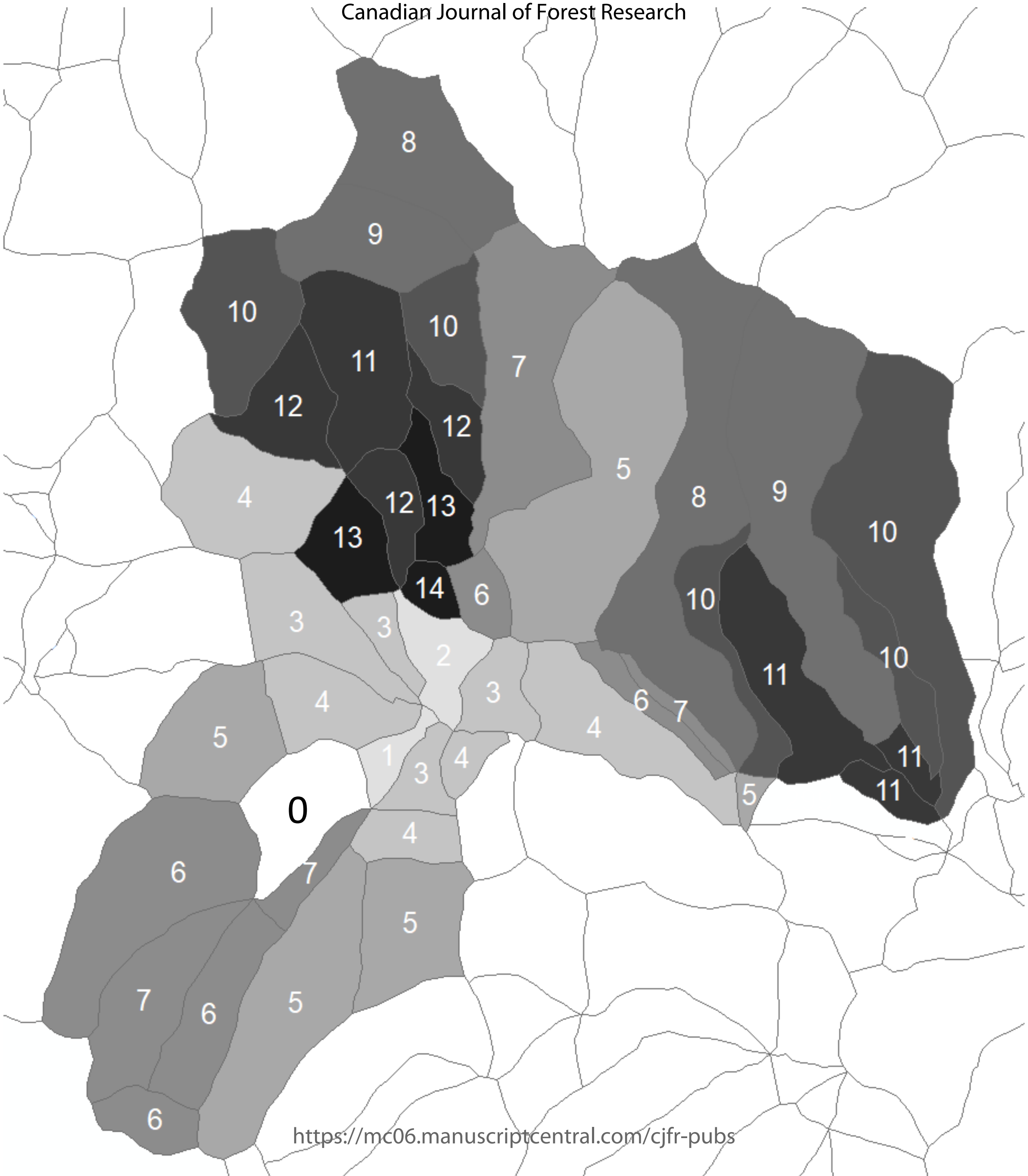
Figure 7. Panel (1) shows the area of the selected rPOD; Panel (2) shows the total length of fire lines needed to contain the fire; Panel (3) shows the total number of PODs in the selected rPOD; Panel (4) shows the crew hours allocated for point protection in the selected rPOD. Figures in column (a) represent model results under the weather condition of wind direction 315 degree, 16.1km/hr wind speed, and 80%, 90% and 97% ERC; figures in column (b) represent model runs with wind direction 225 degree, 40.2km/hr wind speed, and 80% and 90% ERC.

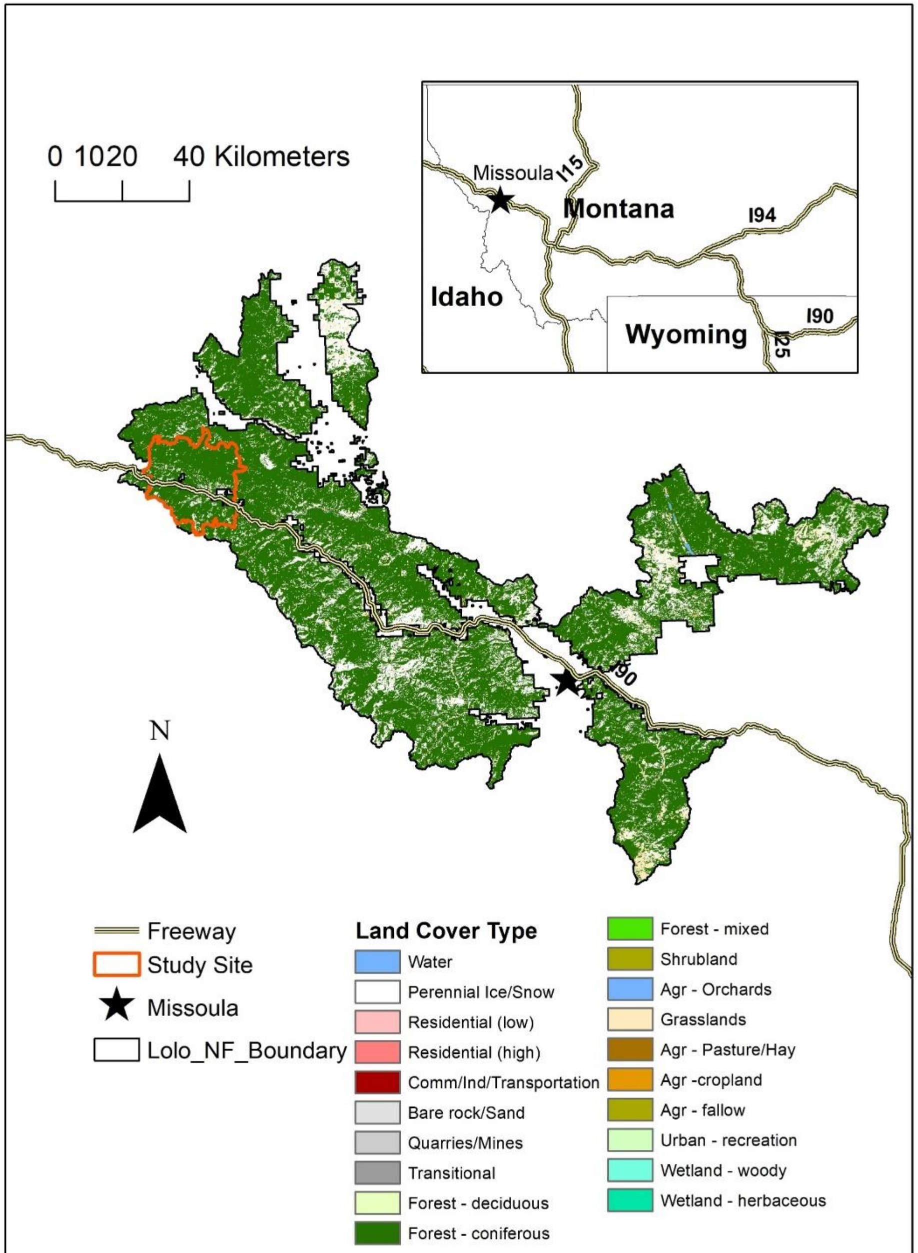
Figure 8. Percentage breakdown of crew hours spent on point protection versus on containment effort if wind direction is 315 degree, at 16.1km/hr wind speed when the suppression effort upper bound varies from 100 to 1000 crew hours at: (a) 97% ERC; (b) 90% ERC; (c) 80% ERC.

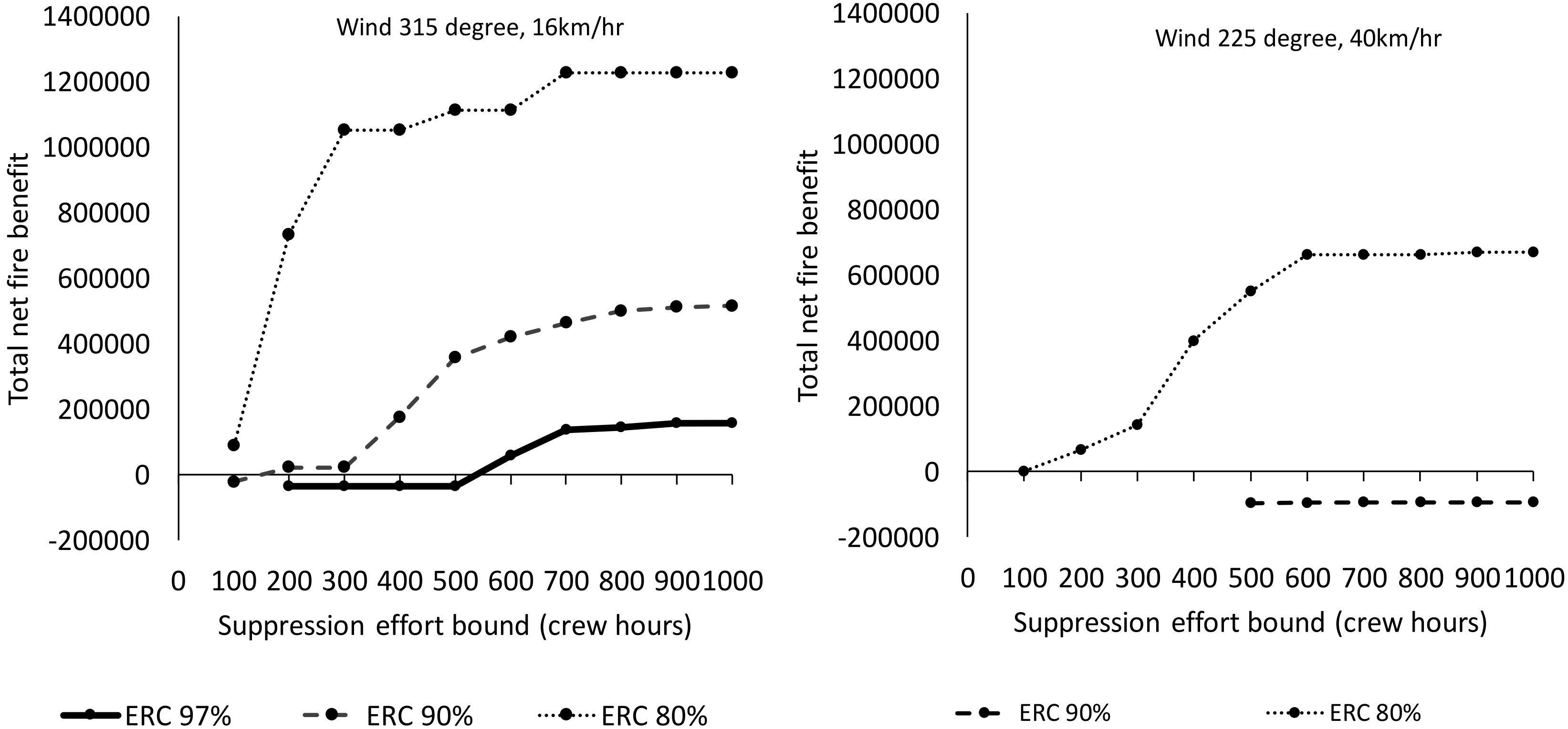
Figure 9. A response surface showing how the total ecosystem benefits from managing the studied fire would decrease as we switch our management emphasis more towards protecting tangible assets by 1) multiplying the point protection crew hour requirement parameter by a multiplier from one to 100, and by 2) multiplying the point protection value pNVC by a multiplier from one to 100.


(a)
(b)
(c)
110°52'0"W
110°48'0"W
33°20'0"N
33°16'0"N
0 1 2 3 Kilometers
Radio Towers
Mountains
Pinal Fire Progression
5/12/2017
5/14/2017
5/15/2017
5/16/2017
5/17/2017
5/19/2017
5/21/2017
5/23/2017
5/24/2017
5/25/2017
5/26/2017
5/27/2017
5/28/2017
5/29/2017
5/30/2017
Planning PODs
USFS cabins
Comm. towers
Prepped line

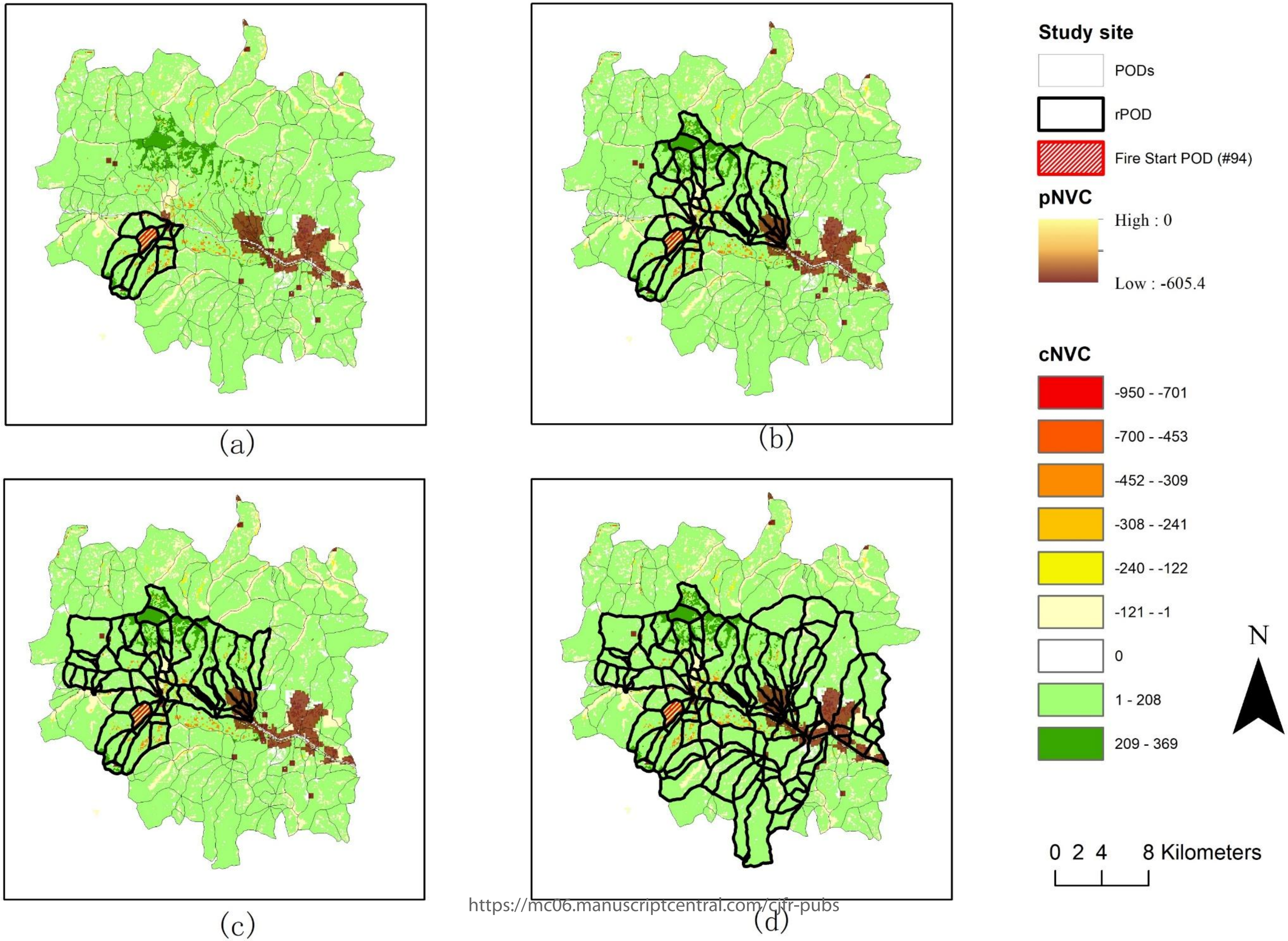

Fire Weather Scenarios & Modeled Fire Behavior
Potential Control Locations
Fire Line Construction Effort
Suppression Resource Availability and Cost
Fire Consequences (NVC)
Potential Operation Delineations (PODs)
POD Adjacency Relationships
Point Protection Effort
Fire Starting POD
Optimal Response POD (rPOD) & Allocation Strategy

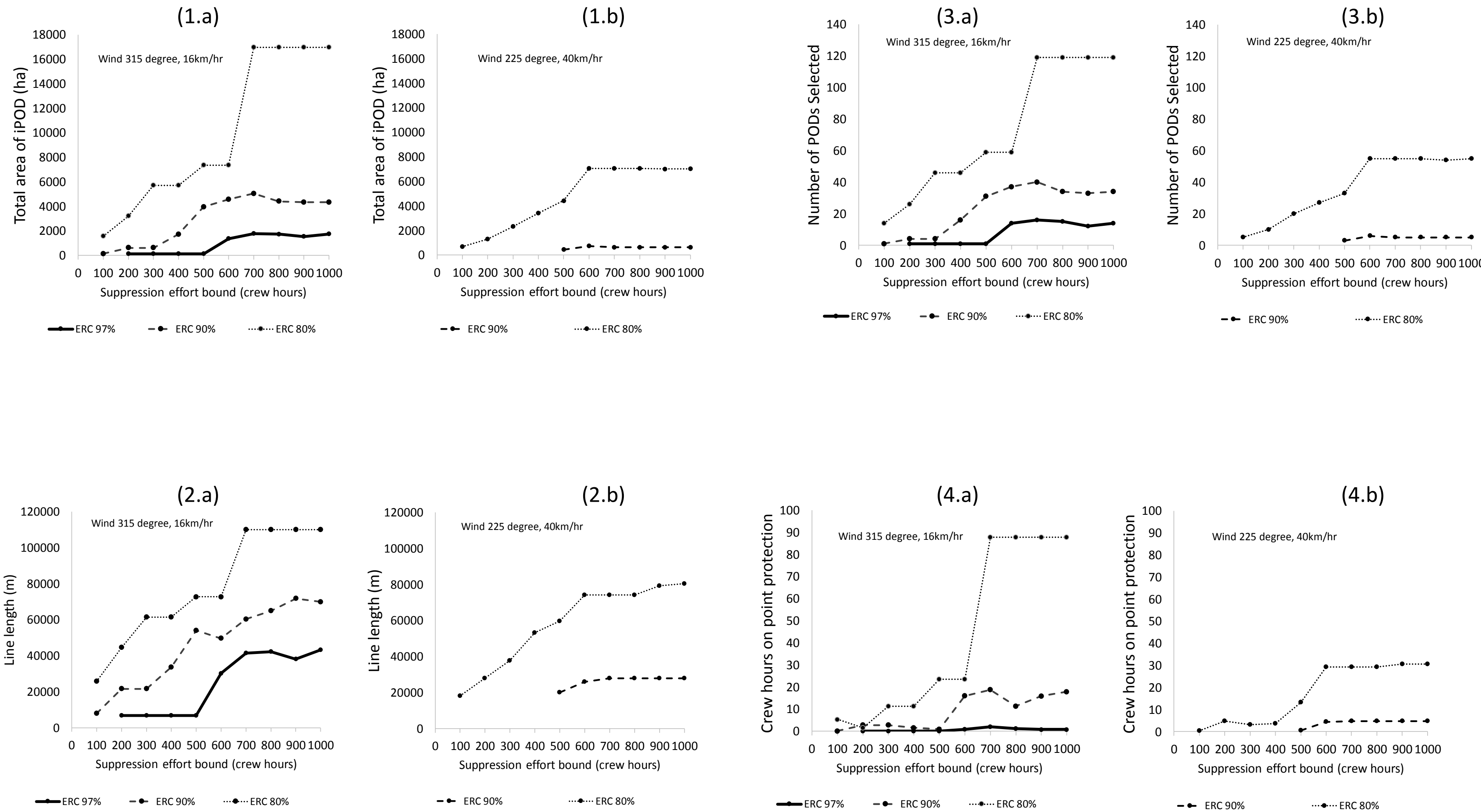

8
9
10
11
10
7
12
12
5
8
9
10
4
12
13
13
14
6
10
10
3
3
2
11
4
3
6
7
4
5
1
3
4
11
11
5
0
4
6
7
5
7
6
5
6

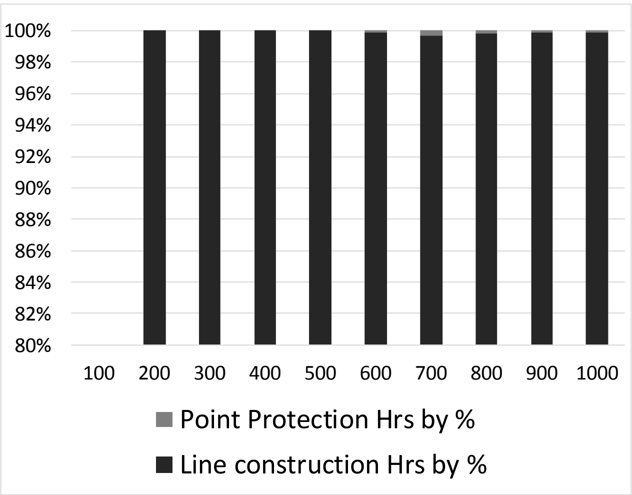

0 1020 40 Kilometers
Missoula
I15
Montana
I94
Idaho
I90
Wyoming
I25
N
Freeway
Study Site
Missoula
Lolo_NF_Boundary
Land Cover Type
Water
Perennial Ice/Snow
Residential (low)
Residential (high)
Comm/Ind/Transportation
Bare rock/Sand
Quarries/Mines
Transitional
Forest - deciduous
Forest - coniferous
Forest - mixed
Shrubland
Agr - Orchards
Grasslands
Agr - Pasture/Hay
Agr -cropland
Agr - fallow
Urban - recreation
Wetland - woody
Wetland - herbaceous


Wind 315 degree, 16km/hr
1400000
1200000
1000000
800000
600000
400000
200000
0
-200000
Total net fire benefit
0 100 200 300 400 500 600 700 800 900 1000
Suppression effort bound (crew hours)
ERC 97%
ERC 90%
ERC 80%
Wind 225 degree, 40km/hr
1400000
1200000
1000000
800000
600000
400000
200000
0
-200000
Total net fire benefit
0 100 200 300 400 500 600 700 800 900 1000
Suppression effort bound (crew hours)
ERC 90%
ERC 80%

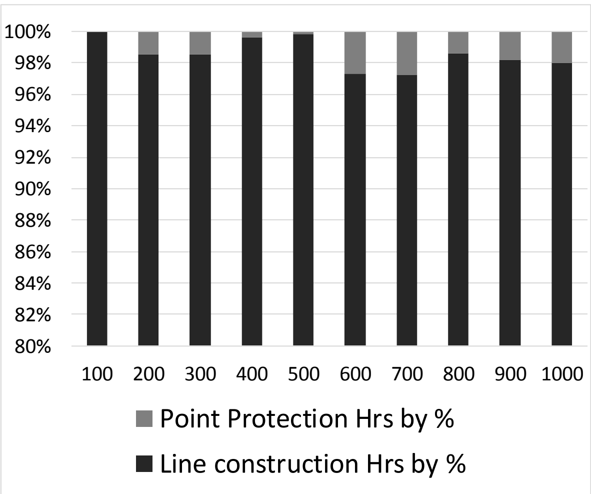
(a) (b)


(a)
(b)
(c)
(d)
Study site
PODs
rPOD
Fire Start POD (#94)
pNVC
High : 0
Low : -605.4
cNVC
-950 - -701
-700 - -453
-452 - -309
-308 - -241
-240 - -122
-121 - -1
0
1 - 208
209 - 369
N
0 2 4 8 Kilometers


(1.a)
Wind 315 degree, 16km/hr
Total area of iPOD (ha)
Suppression effort bound (crew hours)
ERC 97%
ERC 90%
ERC 80%
(1.b)
Wind 225 degree, 40km/hr
Total area of iPOD (ha)
Suppression effort bound (crew hours)
ERC 90%
ERC 80%
(3.a)
Wind 315 degree, 16km/hr
Number of PODs Selected
Suppression effort bound (crew hours)
ERC 97%
ERC 90%
ERC 80%
(3.b)
Wind 225 degree, 40km/hr
Number of PODs Selected
Suppression effort bound (crew hours)
ERC 90%
ERC 80%
(2.a)
Wind 315 degree, 16km/hr
Line length (m)
Suppression effort bound (crew hours)
ERC 97%
ERC 90%
ERC 80%
(2.b)
Wind 225 degree, 40km/hr
Line length (m)
Suppression effort bound (crew hours)
ERC 90%
ERC 80%
(4.a)
Wind 315 degree, 16km/hr
Crew hours on point protection
Suppression effort bound (crew hours)
ERC 97%
ERC 90%
ERC 80%
(4.b)
Wind 225 degree, 40km/hr
Crew hours on point protection
Suppression effort bound (crew hours)
ERC 90%
ERC 80%


100%
98%
96%
94%
92%
90%
88%
86%
84%
82%
80%
100 200 300 400 500 600 700 800 900 1000
Point Protection Hrs by %
Line construction Hrs by %

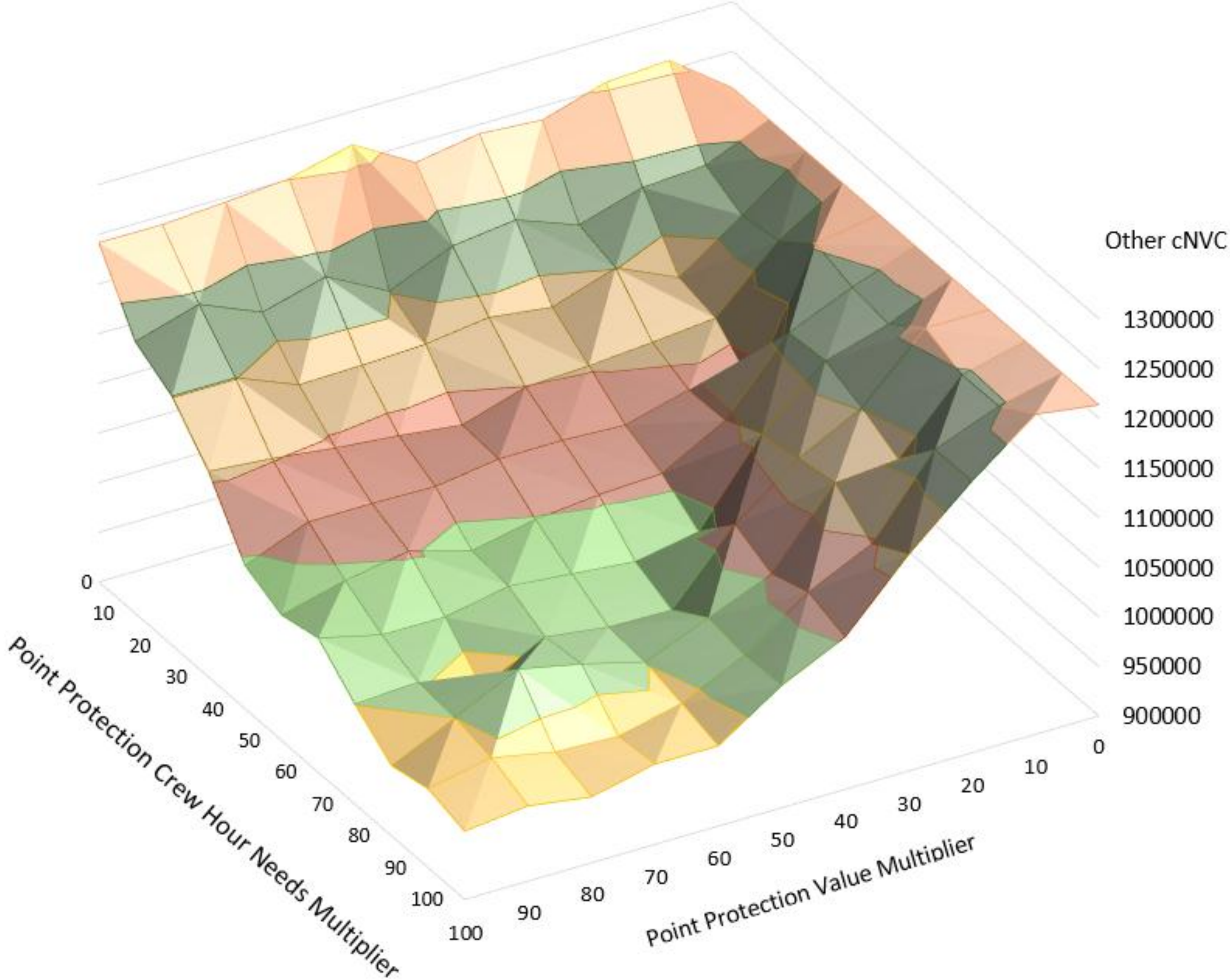
(a)


100%
98%
96%
94%
92%
90%
88%
86%
84%
82%
80%
100 200 300 400 500 600 700 800 900 1000
Point Protection Hrs by %
Line construction Hrs by %

(b)


100%
98%
96%
94%
92%
90%
88%
86%
84%
82%
80%
100 200 300 400 500 600 700 800 900 1000
Point Protection Hrs by %
Line construction Hrs by %

(c)


Other cNVC
1300000
1250000
1200000
1150000
1100000
1050000
1000000
950000
900000
0
10
20
30
40
50
60
70
80
90
100
Point Protection Crew Hour Needs Multiplier
0
10
20
30
40
50
60
70
80
90
100
Point Protection Value Multiplier