Simulating the Expected Value of Changing Spatial Distributions of Wildfire Resources in Response to Wildfire Probability Outlooks

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Executive Summary

The scope of this research was to place an expected value on fire potential information given to wildfire managers by Predictive Services. Knowing that wildland fire managers pre-position suppression resources based on this information, a simulation was used to model Initial Attack (IA) operations and resulting fire size (and therefore, fire cost) to compare the potential cost savings that would occur given better positioning of IA wildfire suppression resources.

Fire behavior and wildfire suppression operations were simulated using Behave Plus fire behavior software over a hypothetical, wildfire-prone area. Suppression costs were determined through simulated output then a comparison was created to view the difference in suppression costs between 1) keeping resources in a status quo positioning (the arrangement of resources fire managers would use if area-specific fire potential information was not known) and 2) moving resources closer to potential fires based on Predictive Services information.

Prior research has shown well-planned initial suppression tactics are effective as a means of reducing overall fire suppression costs. In order to best allocate these resources, fire potential must be known. Fire potential outlooks are offered regionally and nationally by Predictive Services units positioned in Geographic Area Coordination Centers (GACCs) across the country. This paper specifically examines the Predictive Services 7 Day Fire Potential product. For the purposes of this paper, the value of this product is defined as the expected savings that occur from reducing fire size and suppression costs by pre-positioning suppression resources in the most efficient arrangement.

The hypothetical area used for this simulation was a stylized version of a multi-regional wildfire management area. The results show that once all regions were determined to have high risk days, there was a minimum 3.2% to 10% decrease in overall expected suppression costs. As wildfire threat levels in one or more sub-regions increased, so did the expected savings. With any combination of two sub-regions having severe fire potential, expected savings ranged from 16% to 17%. The highest expected savings ranged from 27.2% to 35.1% and occurred when one of the furthest sub-regions had a severe fire potential outlook while the others had lower levels of risk.

While it is believed this approach is valid in determining relative cost savings, many of the initial assumptions and parameters could be modified in order to develop a more dynamic, real-world environment. More analysis using this approach could include looking at expected suppression costs when probabilities of ignition vary over sub-regions or when numbers and types of suppression resources vary over sub-regions. Further analysis could delve into a 3-dimensional realm by implementing more accurate fire behavior software, allowing for geographic and fuel variability of sub-regions. It is believed additional extensions to the simple suppression model would yield more robust results on the savings fire managers could expect when they position suppression resources based on Predictive Services information.

Problem

Over-suppression of wildland fires on federal lands over the last sixty years is the result of a number of causes, including federal land management policies and regulations that emphasized protection of private property and complete suppression of wildfire. Because these fire suppression tactics have allowed for heavy accumulations of fuels on public lands, wildfires over the last few decades have been more likely to develop into large, devastating and expensive occurrences. A 2004 study by the Government Accounting Office stated that federal wildfire costs have exceeded the allotted budget every year since 1990 and recommended agencies improve their annual estimated budget (GAO, 2004). The Forest Service agreed with the GAO and in a response letter cited the best way to reduce their budget disparity was to minimize their annual expected suppression costs.

Initial Attack (IA) response times to wildfires heavily influence their ultimate size, thereby effecting firefighting operations costs. Reduction in this IA time enables crews to engage the fire sooner, thus limiting its growth by the rapidity of those initial efforts. The basic means to reduce response time consists of having suppression crews and equipment as close as possible to fire-prone areas. Given a limited budget for IA resources, firefighting agencies face the task of structuring placement of suppression resources over a large landscape such that these resources can respond to wildfire emergencies in a least-cost fashion. Wildfire threat for such a large landscape can vary greatly between its sub-regions and wildfires are random events, so completing this allocation task in an efficient manner requires foresight of fire potential for different sub-regions and proper positioning of IA crews with respect to those areas.

The Predictive Services (PS) unit, part of each Geographic Area Coordination Center (GACC), is a major provider of fire potential outlooks. They implement a three-pronged approach by utilizing intelligence specialists, fire weather meteorologists and fire behavior analysts to compile their products. PS facilitates both short-term and long-term decision support information by providing fire managers with products that include national, regional and smaller-scale outlooks over seasonal, monthly and weekly time periods. These outlooks provide information about fire suppression resource availability, fire weather and fire potential throughout a fire season. As factors affecting wildfire change, PS provides fire managers with daily updates to their 7 Day Fire Potential Outlook by sub-region, allowing managers to coordinate resources on a daily level. PS identifies both the unconditional probability of a fire starting as well as the conditional probability of a significant fire occurring in a specified area, defining a significant fire as one that *cannot* be contained given the area's available resources (Marsha 2008). The conditional probabilities are grouped according to severity and coded by color: green days = low fire potential, yellow days = moderate potential, brown days = high potential, brown days with a wind event or a high ignition risk = severe fire potential. Fire managers take note of these sub-regional outlooks updates across their jurisdictions and alter their mix of suppression resources accordingly.

But how much fiscal savings are realized by the use of Predictive Services information by wildfire suppression agencies? To answer this question we must look at the suppression costs under a status quo position, i.e. the initial arrangement of resources used if fire potential information is not known, verses suppression costs found under other possible pre-placements of resources that have the benefit of PS fire potential information. Positive differences between the status quo position and alternate allocations signal savings fire managers could expect by utilizing PS products.

The Decision Problem

The purpose of this paper is to determine the value of fire potential information provided to fire agencies by simulating the expected suppression costs found in a predefined wildfire–prone area, given a set of probabilistic fire events that could occur. A decision problem was developed to determine if a particular allocation of fire suppression resources is an efficient arrangement given a set of fire potential probabilities, its sum of all expected suppression costs per sub-region must be less than the expected suppression costs associated with all other possible allocations under the given fire potential scenario.

The decision problem utilizes several key assumptions.

1 Cost is positively related to the containment size of the fire.

2 Response time is proportional to the distance between an ignition and the location of IA resources.

3 Fire potential outlooks are interpreted as a change in the conditional probability of a significant fire in a set of well-defined areas.

4 The decision-maker allocates resources based on expected least-cost conditions given the information provided to them.

5 The sole source of information is provided by the GACC Predictive Services.

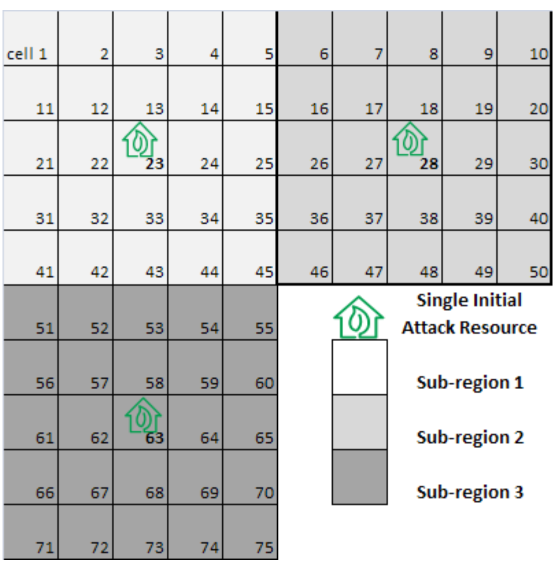
If the fire potential scenarios are differentials in the probable risk of fire among the sub-regions of the wildfire-prone area and there are a discrete number of resource allocations, then the objective function is to minimize the total expected suppression costs for the entire geographic area.

This paper addressed the issue as a least-cost allocation decision problem and used an approach drawn from cellular automata (Von Neumann 1966). Prior research has utilized cellular automation to look at spatial effects of wildfires (Donovan and Rideout 2003, Butry and Donovan 2008) and fire containment (Ntaimo et al 2004, Ntaimo and Hu 2008). The theory behind cellular automata converts the landscape to a grid where each cell within the grid is dictated by a set of rules or states. For this paper, a hypothetical area was constructed and divided into sub-regional areas. Each sub-region was equal in size and had a single suppression resource. Possible states for each cell included: 1) no fire event 2) a fire event 3) a significant fire event. Only a single fire event was assumed to occur at any given time, i.e. two fires could not occur simultaneously within the conceptual space. Each fire event received IA operations from all sub-regions. Each cellular event had an associated probability of occurring, and this probability changed as sub-regional fire potential changed. These probabilities were important not only for determining optimal pre-placement of suppression resources but also were critical for calculating expected suppression costs.

Simulated Methods

The hypothetical wildland area was divided into three sub-regions which were gridded into twenty-five cells, each fifteen square miles. The sub-regions were homogenous in geographic characteristic, fuel type and had the same probability of a fire ignition occurring [Figure 1]. This approach of restricting parameters has been used in prior research involving integer programming that optimized suppression resource allocation (Donovan and Rideout 2003) and was a requirement for the computer simulations which constrained fuel types, terrain and weather to be continuous over the landscape. A major difference between this paper's approach and the cited research was that for this paper the fires occurred within individual cells only and *were not* allowed spread to neighboring cells; hence, only IA actions for a single fire were simulated. Each region had a single resource assigned to it, and each resource had the same line construction rate. This line construction rate or production rate was defined as the ability to construction a break around the fire and was measured in chains per hour[1].

Figure 1: Hypothetical Wildland Area



Each fire's total acreage and burn time were calculated using BehavePlus 4.0 (Anderson 1986), a fire behavior software package developed by the U.S. Forest Service using Rothermel's algorithm of fire surface rate of spread (1972). Each fire's total burn time was affected by the combined IA response times, geographic and biologic variables and was directly related to the number of acres contained by the crews. IA costs were functions of the cellular burn time. The end of each simulation BehavePlus also determined whether or not the IA resources were able to contain the fire before a burn time limit of eighteen hours was reached. This burn time limit signaled the end of IA operations on the fire. Given the PS definition of a significant fire, the fire conditions were parameterized

[1] 1 chain = 66ft

so that the combination of responding resources was able to contain the fire before the burn time limited was attained under *most* fire potential conditions. Only severe fire conditions could result in uncontainable fires. If a fire was not contained by the resources, a maximum IA cost was reached and the fire remained uncontrolled and it was assumed additional resources were required for fire containment. In these severe fire events, the simulation stopped and an additional cost was incurred to account for the additional suppression actions that would be required.

Suppression crews' IA respond times were derived for each cell under all possible arrangements of resources across the regions and totaled ten allocations [Appendix Figure 1]. Using the lines between each cell as a road network, each crew had a specific response time that was proportional to the distance between the resource's staging cell and each fire cell within the grid. Each sub-region had one station cell located in the center of that sub-region. Crews placed within a sub-region were required to stage inside this station cell. The center cell was labeled the station cell because it was found to be the least-cost position under any myopic fire potential scenario where sub-regions received no suppression efforts from neighboring sub-regional crews. For each fire potential scenario, these response times were the *only* varying factors; hence, each cell contained ten different response time sets that corresponded with the various resource positions. All allocations were evaluated under each fire potential scenario in order to determine a least-cost arrangement. Fire potential scenarios consisted of all combinations of outlooks that could occur between the three sub-regions. For example the first scenario set each sub-region with an equally low threat of fire. The twenty-fourth fire potential scenario set sub-region one's potential to high, and sub-regions three's potential to moderate, and kept second sub-region's fire potential outlook at a low threat level. Refer to Table 2 in the Appendix to view each sub-regional outlook under all the fire potential scenarios.

An initial allocation was considered with all resources in their respective jurisdictions staged in their station cells located in the center cell of each sub-region. This initial allocation was considered the status quo for all fire potential scenarios and is a typical arrangement of resources found at the beginning of the fire season. As fire potential changes through a season over sub-regions it was assumed a regional fire manager would alter the suppression resource organization to mitigate potential threats. For this reason alternative staging allocations were considered within the gridded landscape [Appendix Figure 1]. Computationally this was done by systematically changing the resource IA response times to reflect different staging options. As stated earlier, staging options could only be the possible combinations of resources staging in the sub-regional station cells since traveling resources normally require support when out of their sub-region; therefore, no other cells within the sub-regions were considered for pre-placement. Different allocations resulted in different suppression costs across sub-regions, and when the conditional probabilities (i.e. fire potential outlooks) for a large fire changed between sub-regions, those costs began changing dramatically leading to least-cost allocations that were different from the status quo.

Application

To simulate resulting fire size and costs, BehavePlus 4.0 software was utilized. This software is an industry standard, used by Fire Behavior Analysts (FBAN) to calculate fire behavior, as well as resource strategy and cost. In practice, BehavePlus has been shown to adequately model wildfire behavior. For this research an FBAN was consulted to accurately simulate the fire behavior and suppression tactics that would occur in the hypothetical area. Once a fire was initiated in a cell of the grid, BehavePlus generated output on the fire's size, the containment size and status, the number of resources required for suppression as well as the IA cost for the fire. In order to simulate each fire event, BehavePlus required certain information about the area which was to be burned. The following list provides the parameters used to simulate a wildfire event using BehavePlus.

BehavePlus Inputs

Fuel model(s) used	:	FM2, FM6
Coverage of fuel model 2 (%)	:	60
Coverage of fuel model 6 (%)	:	40
1 hour fuel moistures (%)	:	3, 5, 8
10 hour fuel moistures (%)	:	4, 6, 9
100 hour fuel moistures (%)	:	6, 8, 11
Live fuel moistures (%)	:	30
Mid-flame windspeed (mph)	:	2, 4
Slope (%)	:	0
Elapse time till fire was reported (hr)	:	0.5
Resource type	:	Type I handcrew
Suppression tactic used	:	Direct rear attack
Line production rates (ch/hr)	:	36
Line construction offset (ch/hr)	:	0
Resource duration (hr)	:	18
Resource hourly cost (2008 $)	:	$513.78
Arrival times of the resources (hrs)	:	0 – 6.5

The dual fuel model used was tailored after the Western Great Basin Predictive Service Area 6 (Humboldt Basin); however, this simulation technique is well suited for any type of wildfire-prone area. The one, ten, and hundred-hour fuel moisture ranges corresponded to historic values found in PSA 6 under the various fire potential threat levels. The values used for fuel moistures depended on the threat level of the associated sub-region [Appendix Table 1]. The live fuel moisture was held constant at 30% to account for time period which was considered (June through August) when much of the live vegetation had become dormant. The midflame windspeed was set constant at two miles per hour unless a wind event was predicted, in which case it was increased to a constant four miles per hour. Each sub-region had a single Type I handcrew that responded to all fires using a direct rear attack and could attack the fire for no longer than eighteen hours in order to reflect IA operations only. Resource IA times for each cell ranged from zero to six and a half hour and depended on their staging location with respect to the cell that was evaluated. This was the only variable that changed over different allocations within a fire potential scenario. As different fire potential scenarios were evaluated, the outlooks between sub-regions changed to reflect differentials in wildfire risk. Appendix Table 2 depicts the values of the probabilities associated with the outlooks.

Results

The results showed that of the sixty-four fire potential scenarios evaluated, twenty-one (33%) resulted in the least-cost allocation being the status quo arrangement. It was determined forty-three scenarios (67%) had a least-cost allocation different from the status quo. The least-cost savings can be generalized into four distinct categories:

1. Status quo allocations : 0% savings
2. Low risk differentials between sub-regions : 0.9% - 3.4% savings
3. Multiple sub-regions having severe fire potential outlooks : 10% - 16.8% savings
4. Only one sub-region having a severe outlook : 27% - 35% savings

Figure 2 shows the expected savings found over for fire potential scenarios in which savings occurred by reallocating resources from the status quo, with each plateau representing a group of similar reallocation scenarios. In scenarios where the status quo was determine the most cost effective organization, no saving resulted because the fire manager had arranged the resources to the best organization by default. As the threat levels of the sub-regions increased, reallocation was required once a conditional threshold in the fire potentials was reached. A threshold was reached when at least one of the sub-region's fire potential was great enough to require additional resources to stage inside its boundaries, conditional on other sub-regions' levels of risk.

Take, for example, in half of the equal probability scenarios (i.e. no difference in risk between sub-regions) the status quo was the least-cost positioning of suppression resources. Figure 3 illustrates this point by showing the suppression cost for all allocations under the first scenario. It shows that all other arrangements of resources resulted in higher suppression costs than the status quo. However there existed a threshold for these equal probable cases and when crossed, the optimal positioning differed from the status quo. The results showed that once all sub-regions had brown outlooks, then a least-cost allocation was achieved by moving two resources to the middle sub-region and leaving one crew in either of the outer sub-regions, yielding a savings of 3.2% over the status quo. This positioning allowed for rapid response to the middle region while minimizing the respond time to the outer two regions. Since both outer regions had brown outlooks and were the same distance from the middle sub-region, placement of the final resource was arbitrary. Conversely, in the case where all regions had outlooks of a brown day with a wind event, the least-cost allocation required pooling all crews to the middle region and yielded a 10% savings over the status quo. Thus the area's fire manager would expect a 10% savings if he reallocated his resources based those particular sub-regional outlooks. A brown, windy outlook had the highest fire potential associated with it, and without all suppression efforts directed in an area of severe risk, any resulting fire would not be containable with the resources available. The results suggested that under this equally severe case, all suppression resource efforts must be utilized in the severely at-risk region that minimizes the distance between neighboring jurisdictions.

Other scenarios where the status quo was the least-cost allocation include scenarios with small differences in probable risk among sub-regions and all wildfire risk was relatively low. For example any combination of green and yellow outlooks required no reallocation. However, if sub-region one and two's outlooks remained green and sub-region three's outlook was updated to a brown then a 2% savings resulted when resources were moved to an allocation that reduced response times to the higher risk area. This scenario is an example of a conditional threshold that exists in the outlook differentials. In other words, conditional on the first two sub-regions remaining green, if sub-region three's outlook becomes brown the fire manager will reallocate resources away from the status quo organization. As other sub-regions' outlooks transitioned to brown, savings from reallocation increased. The first tier of Figure 2 represents the group of scenarios where reallocation initially becomes cost effective. This tier ends when both outer sub-regions were determined to have severe fire threat and the middle sub-region's outlook was green (scenario forty-one). Conversely, since under severe outlooks it took all the resources to contain a wildfire, if both outer sub-regions had brown, windy outlooks, no possible arrangements of the three crews were able to adequately cover both sub-regions due to the distance that had to be covered to response to a fire in the other areas. Under these scenarios, the allocation arrangement transitioned back to the status quo. Nevertheless, had the decision problem allowed for the available number of regional crews to increase, a savings through reallocation would be expected.

An interesting finding occurred in the fire potential scenario where sub-region one was determined to have a yellow outlook, sub-region two had a green outlook, and the third sub-region had a brown outlook[2]. Though a reallocation was necessary, the least-cost position put two crews in the sub-region with the brown outlook and the last resource in sub-region two, leaving sub-region one (which had a higher threat level that sub-region two) without a suppression crew. In this instance it was found to be more cost effective to stage a resource in a less at-risk sub-region. Similar to the scenarios where both outer sub-regions had brown, windy outlooks, for this scenario the distance factor of the second sub-region outweighed the first sub-region's higher level of risk due to the fact that the suppression costs under yellow outlooks were not drastically more expensive than those found under green outlooks. Given the first sub-region's location in relation to the other two, the responding suppression resources arrived in sub-region one's cells in less than three hours on average. Conversely for that scenario, other allocations where sub-region two was left unprotected, it took some IA resources up to six and a half hours to reach a fire located there. This illustrates the trade-offs a fire manager faces between minimizing IA resource distance to all protection areas while considering individual fire threat levels.

The next group of least-cost reallocations occurred when multiple sub-regions were determined brown and windy. Any combinations of two sub-regions with severe fire potential yielded approximately 16.5% in expected savings over the status quo when repositioning occurred. Repositioning was such that the resources were divided among the most risky sub-regions while minimizing the respond time to the sub-region of less risk. Figure 4 depicts the suppression costs for all allocations under a scenario where two of the three sub-regions had severe risk outlooks. Note there are several allocations that have less expensive suppression costs than the status quo. This means various allocations were found to be more cost efficient than the status quo with allocation three being the best alternative. Recalling assumption four, under this scenario fire managers were assumed to pre-position crews to allocation three.

The final group of least cost reallocations represents the highest savings found by using Predictive Service's 7 Day Fire Potential outlook. These optimal arrangements occurred when only one

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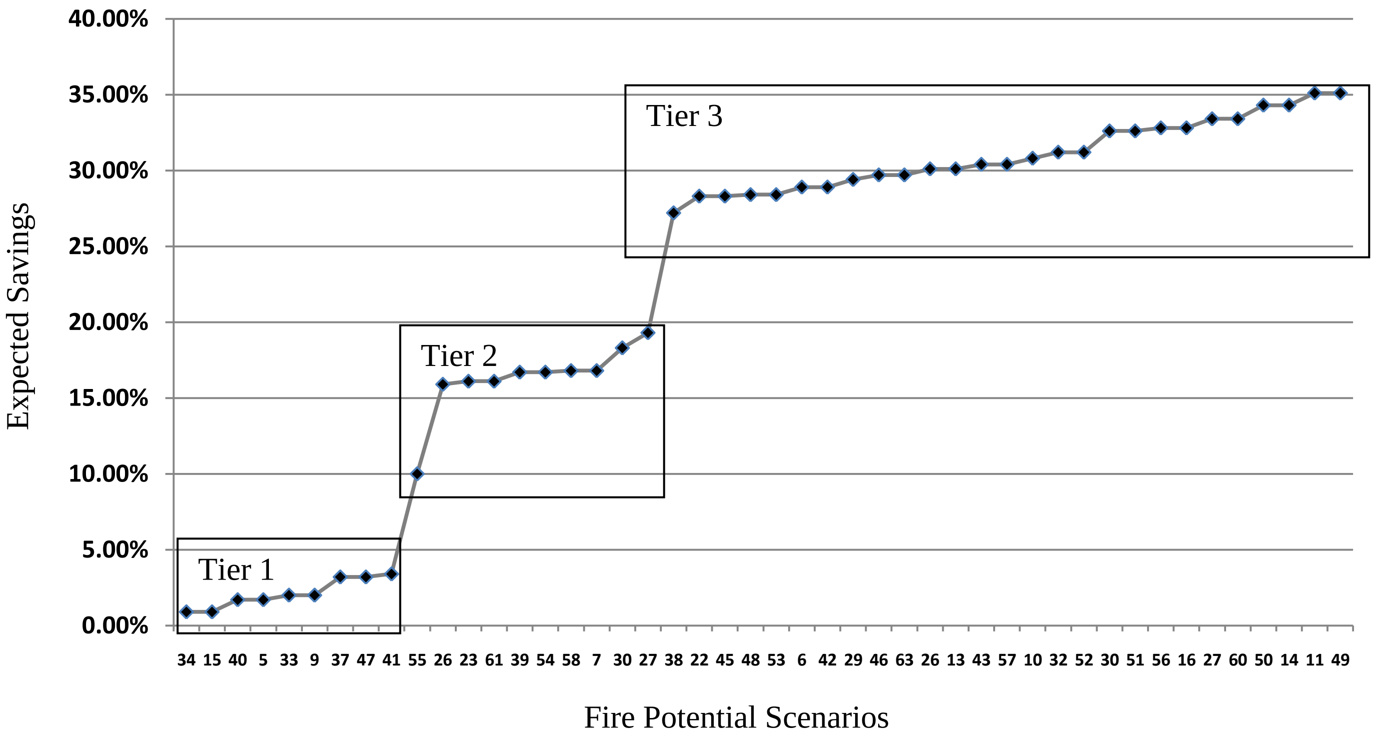
[2] Findings hold for the transposed scenario where region one had a yellow day outlook, region three had a green day outlook and the second region had a brown day outlook.

sub-region was projected to have severe fire potential. The savings started at 27.2% under scenario thirty-eight where sub-region one was determined to have a brown and windy day outlook and the others had brown day outlook. This savings steadily increased as the other two sub-regions' threat levels declined, reaching a maximum savings of 35.1% under scenario eleven and forty-nine[3]. This maximum savings were realized when one of the outer sub-regions was determined to have severe fire potential, and the other two were in the lowest threat level possible [Figure 5]. Table 3 in the Appendix lists all the least-cost allocations by fire potential scenario with their associated savings and outlooks.

Figure 2: **Expected Least-Cost Percent Savings through Reallocation by Fire Potential Scenario**



[3] These scenarios are transposes of each other.

Figure 3: **Total Expected Suppression Costs for Scenario 1**

All sub-regions had green day outlooks

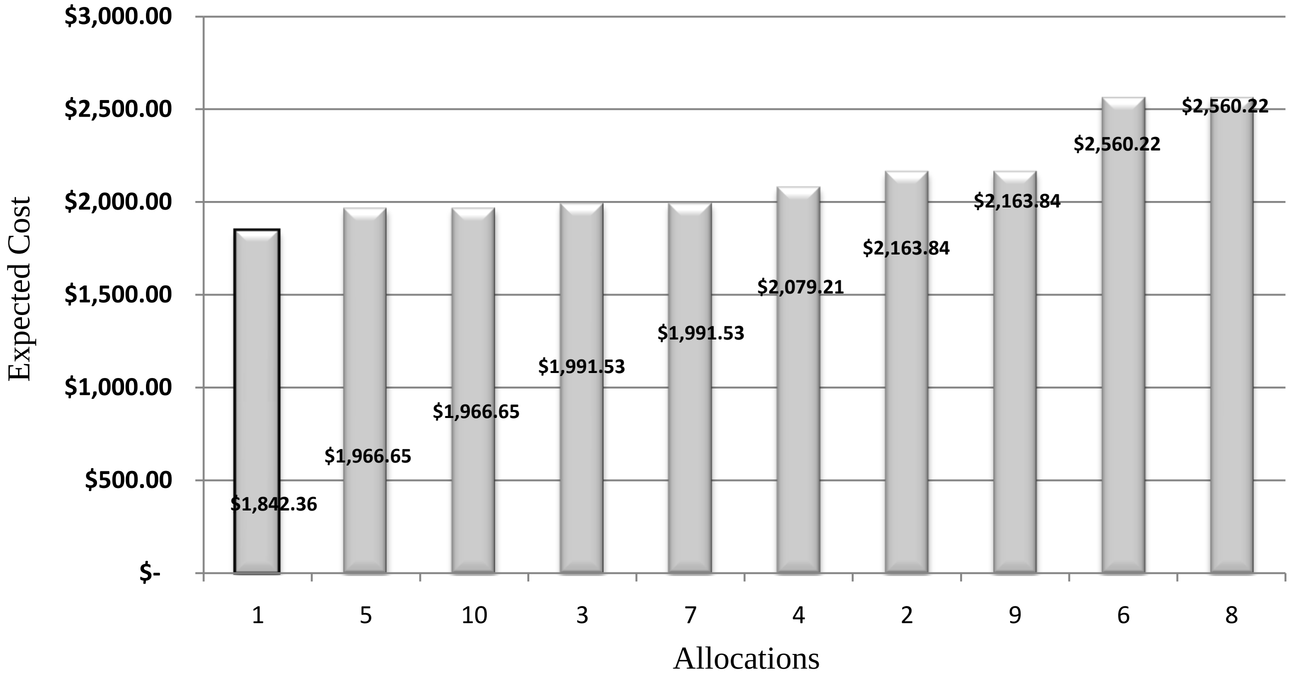


Figure 4: **Total Expected Suppression Costs for Scenario 7**

Sub-regions 1 and 2 had brown, windy day outlooks,
Sub-region 3 had a green day outlook

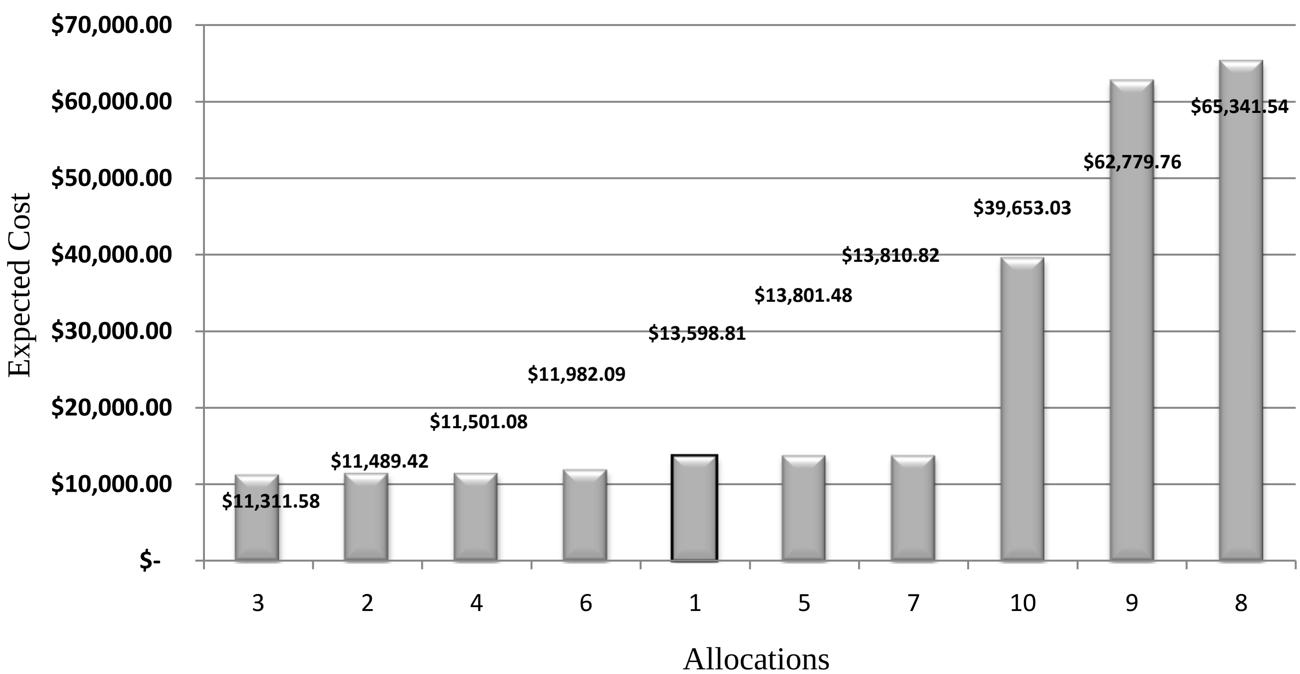
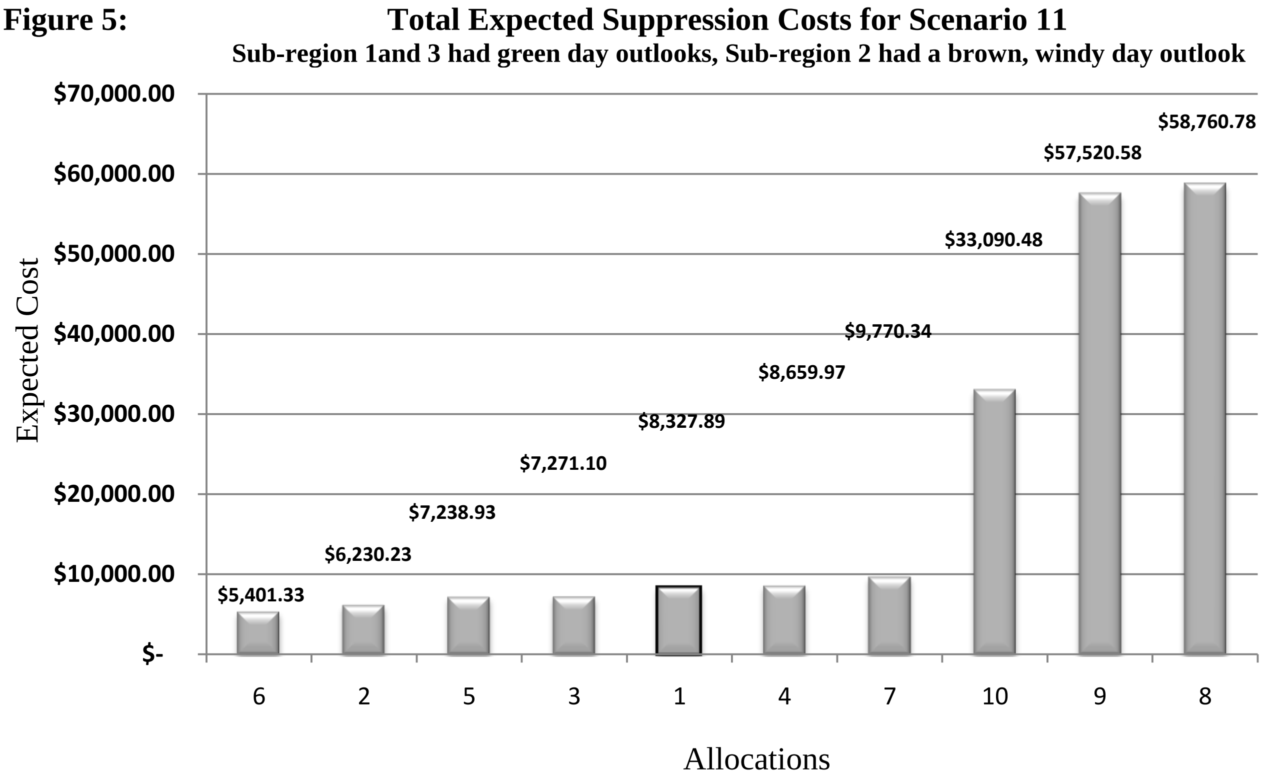


Figure 5:


Total Expected Suppression Costs for Scenario 11
Sub-region 1and 3 had green day outlooks, Sub-region 2 had a brown, windy day outlook
Expected Cost
$70,000.00
$60,000.00
$50,000.00
$40,000.00
$30,000.00
$20,000.00
$10,000.00
$-
$5,401.33
$6,230.23
$7,238.93
$7,271.10
$8,327.89
$8,659.97
$9,770.34
$33,090.48
$57,520.58
$58,760.78
6
2
5
3
1
4
7
10
9
8
Allocations

Conclusion

Given current budget restraints, it seems prudent to plan for a scarcity of suppression resources over many geographic areas. Given scarcity, it then becomes important to understand not only how fire managers decide to deploy IA resources but the value of the information upon which those decisions are made. Fire suppression models have long confirmed the notion that IA response times affect a wildfire's final size and overall suppression costs, but more importantly, we have determined that knowledge of future fire conditions and acting on this knowledge significantly affects total dollars spent on fire suppression.

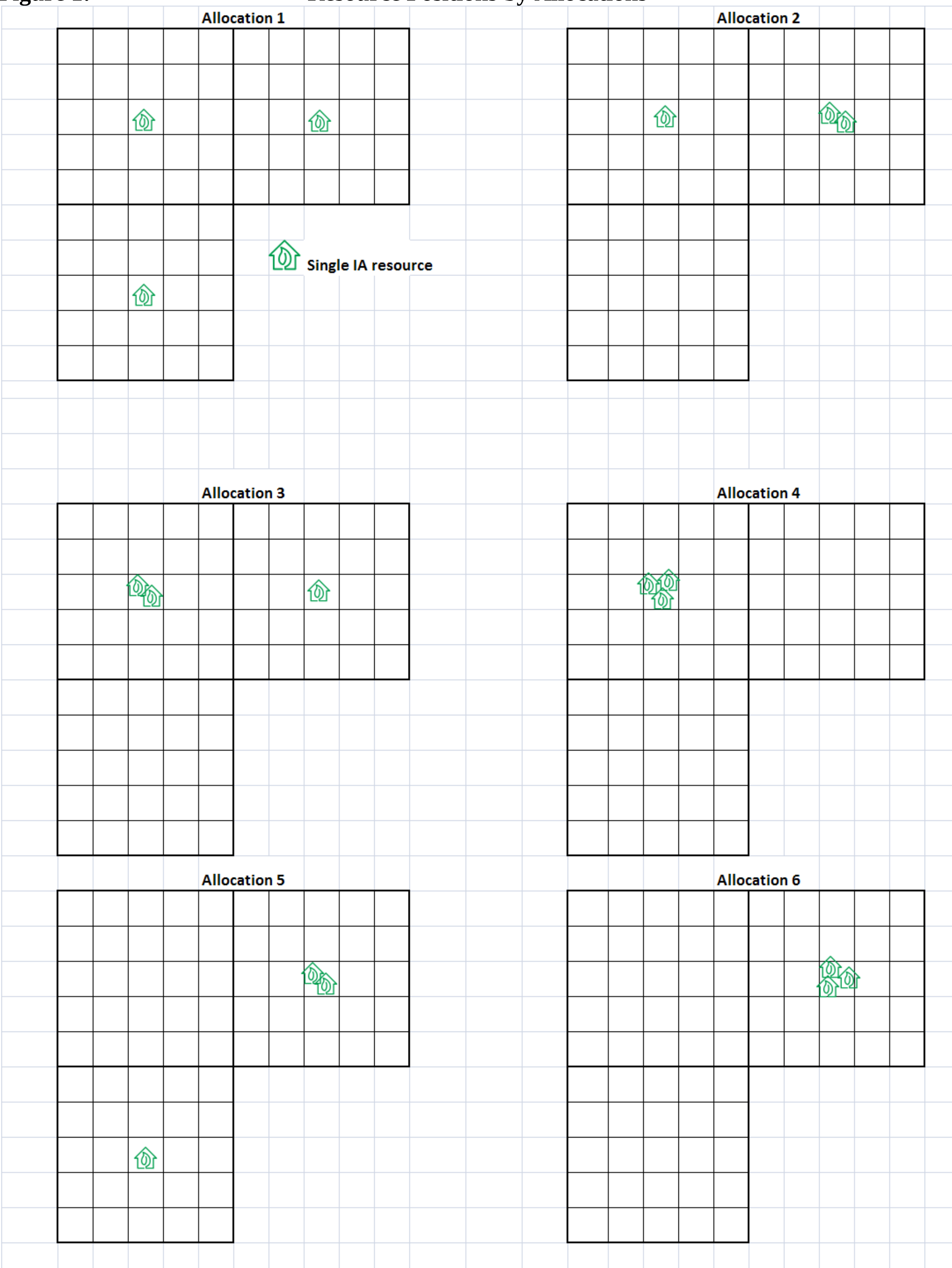
Results of this study are similar to that of prior research: optimal allocation of suppression resources is determined by proximity to areas of greater fire threat (Haight and Fried 2007). However the location of an at-risk area in relation to other locales also plays an important role in determining optimal pre-placement of resources. This study shows that optimal positioning is not just about being closer to areas of greater risk, but also about minimizing distances to all protection areas. Most importantly, within the context of the stylized landscape it was found that using Predictive Services' 7 Day Outlook can reduce fire agency suppression costs by up to 35% if optimal positioning is implemented.

The conceptual area is not entirely consistent with the real world. However, it serves as a basic foundation from which more complex situations can be modeled. Many assumptions were made regarding geographic, biologic and probabilistic factors. Some expenses like travel costs and property value were not taken into account. Further research should address these concerns, but more importantly it should look at variability in the number and types of resources available for IA, geographic features, fuel types and probabilities of fire events. For example, future research could simulate fires in sub-regions that contain different fuel types, topography and mixes of suppression resources. Each sub-region could have its own independent probabilities of wildfire events and simulations could take place using more complex fire behavior software like FARSITE. Such research would better look at the benefits and trade-offs that occur under the complex allocation decisions facing fire managers. Budgetary issues like determining best staffing levels could also be investigated through such an approach.

A major hindrance to this type of study is the lack of computational efficiency. In order to gather large numbers of fire observations under various conditions, hundreds of fire scenarios must be input into a fire behavior application. Given current fire behavior software, iterative simulations of fires are both tedious and prone to input errors. For example BehavePlus required simulations to be run and saved individually, and then data had to be converted and cleaned before analysis could begin. Admittedly this application was not designed for this type of analysis, though BehavePlus and other fire behavior software have a great potential to aid in such endeavors. If a fire behavior application allowed for batch simulations and more friendly data transfer to statistical programs, future research on expected suppression costs could have a major impact on federal fire agencies' expenditures.

Appendix

Figure 1: Resource Positions by Allocations



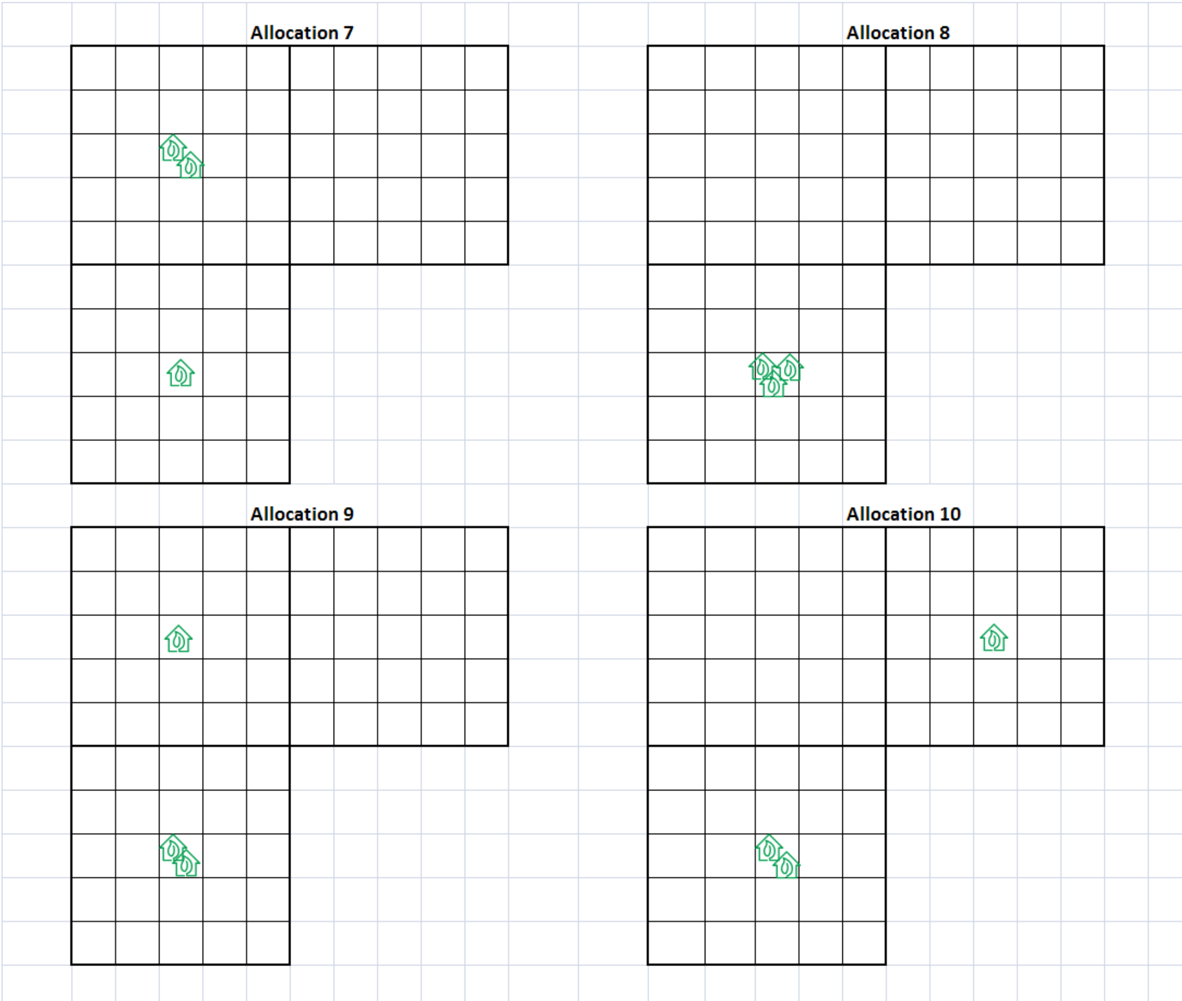


Table 1: **Fuel Moistures and Windspeed by Fire Potential Outlook**

Outlook Threat Level	1 hr fuel moisture (%)	10 hr fuel moisture (%)	100 hr fuel moisture (%)	Live fuel moisture (%)	Midflame Windspeed (mph)
Green Day	8	9	11	30	2
Yellow Day	5	6	8	30	2
Brown Day	3	4	6	30	2
Brown Windy Day	3	4	6	30	4

Table 2: **Probabilities of Cellular Fire Events by Fire Potential Outlook**

Outlook	Pr(Ignition)	Pr(No Ignition)	Pr(Significant Fire)*	Pr(Non-significant Fire)*
Green Day	0.014	0.985	0.02	0.98
Yellow Day	0.014	0.985	0.06	0.94
Brown Day	0.014	0.985	0.14	0.86
Brown Windy Day	0.014	0.985	0.20	0.80

*Note: These probabilities are conditional on an ignition occurring

Table 3: **All Least-Cost Allocation Expected Savings by Scenario**

G= green outlook, Y=yellow outlook, B=brown outlook, BW= brown, windy outlook

Scenario	Allocation	Difference From SQ	Percent Change	Region 1 Outlook	Region 2 Outlook	Region 3 Outlook
1	1	$ -	0.00%	G	G	G
2	1	$ -	0.00%	Y	G	G
3	1	$ -	0.00%	Y	Y	G
4	1	$ -	0.00%	B	Y	G
8	1	$ -	0.00%	B	G	G
12	1	$ -	0.00%	G	Y	G
17	1	$ -	0.00%	G	G	Y
18	1	$ -	0.00%	Y	G	Y
19	1	$ -	0.00%	Y	Y	Y
20	1	$ -	0.00%	B	Y	Y
21	1	$ -	0.00%	B	B	Y
24	1	$ -	0.00%	B	G	Y
25	1	$ -	0.00%	G	B	Y
28	1	$ -	0.00%	G	Y	Y
31	1	$ -	0.00%	Y	B	Y
35	1	$ -	0.00%	Y	Y	B
36	1	$ -	0.00%	B	Y	B
44	1	$ -	0.00%	G	Y	B
59	1	$ -	0.00%	G	BW	BW
62	1	$ -	0.00%	Y	BW	BW
64	1	$ -	0.00%	B	BW	BW
34	10	$ 9.68	0.90%	Y	G	B
15	5	$ 20.74	0.90%	Y	B	G
40	7	$ 21.63	1.70%	B	G	B
5	3	$ 46.35	1.70%	B	B	G
33	10	$ 21.10	2.00%	G	G	B
9	5	$ 45.23	2.00%	G	B	G
37	2	$ 100.61	3.20%	B	B	B
47	2	$ 92.61	3.20%	Y	B	B
41	2	$ 93.28	3.40%	G	B	B
55	4	$ 2,002.50	10.00%	BW	BW	BW
22	4	$ 2,213.77	16.10%	BW	B	Y
29	4	$ 2,213.77	16.10%	BW	Y	Y
26	4	$ 2,341.50	16.70%	BW	G	Y
32	6	$ 2,341.50	16.70%	B	BW	Y
23	3	$ 1,067.38	16.80%	BW	BW	Y
61	7	$ 2,287.23	16.80%	BW	Y	BW
39	2	$ 2,178.30	27.20%	BW	BW	B

54	9	$ 2,180.42	28.30%	BW	B	BW
58	7	$ 2,180.42	28.30%	BW	G	BW
7	3	$ 2,595.49	28.40%	BW	BW	G
30	6	$ 2,595.49	28.40%	Y	BW	Y
27	6	$ 1,019.96	28.90%	G	BW	Y
38	4	$ 2,185.63	28.90%	BW	B	B
45	4	$ 2,182.54	29.40%	BW	Y	B
48	6	$ 2,641.73	29.70%	B	BW	B
53	8	$ 2,641.73	29.70%	B	B	BW
6	4	$ 2,187.75	30.10%	BW	B	G
42	4	$ 2,187.75	30.10%	BW	G	B
46	6	$ 2,665.65	30.39%	Y	BW	B
63	8	$ 2,665.65	30.40%	Y	B	BW
13	4	$ 1,023.38	30.80%	BW	Y	G
43	6	$ 2,763.68	31.20%	G	BW	B
57	8	$ 2,763.68	31.20%	G	B	BW
10	4	$ 2,809.91	32.60%	BW	G	G
52	8	$ 2,809.91	32.60%	B	Y	BW
51	8	$ 1,332.98	32.80%	Y	Y	BW
56	8	$ 2,856.39	32.80%	B	G	BW
16	6	$ 2,833.84	33.40%	B	BW	G
60	8	$ 2,833.84	33.40%	G	Y	BW
50	8	$ 1,354.56	34.30%	Y	G	BW
14	6	$ 2,902.63	34.30%	Y	BW	G
11	6	$ 1,365.73	35.10%	G	BW	G
49	8	$ 2,926.56	35.10%	G	G	BW

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