NETWORKS OF NETWORKS IN DYNAMIC EVENTS:

The 2020 Lightning Complex Fires in Northern California

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Abstract

The transition from one level of operation to a next larger, more complex level while maintaining coherence as a system has stymied organizational theorists for decades. Drawing on concepts from systems theory, network analysis, and collaborative governance, we address the question of transition in rapidly escalating, massively complex, urgent events to focus explicitly on the form of intelligence networks as it applies to extreme hazards. This analysis examines the transition process in a rapidly escalating wildfire event as a case study in dynamic adaptation among multiple organizations as they seek to achieve the shared goal of containing the fire and protecting communities at risk. We use data from Incident Reports filed by California Department of Forestry and Fire Protection (CalFire) field personnel to create a preliminary system dynamics model that simulates the interaction among the key components active in the 2020 Santa Clara Unit (SCU) Lightning Complex Fire. We conclude that systematic integration of human, signal, imagery, and open-source forms of intelligence regarding the emergence and escalation of hazards would provide invaluable support to decision makers in confronting extreme events, enabling them to manage transitions in large-scale, complex operational systems more effectively.

Managing Rapidly Escalating Events

The increasing frequency, scale, and scope of large-scale, catastrophic events over the past three decades have underscored a long-standing, persistent problem in crisis management. *How do crisis managers scale their actions in response to threat from one level of operation to another under dynamically changing conditions, while maintaining effective performance as a system*? This question has drawn the attention of organizational theorists for decades. Initially framed as the 'edge of chaos,' Kauffman (1993:174) characterized this transition from routine performance at one level to innovative action in a larger, more complex, uncertain environment as requiring "sufficient structure to hold and exchange information, but sufficient flexibility to adapt to changing conditions." This transition increases in difficulty as the number of actors, severity of potential destruction, and diversity of impacts upon communities and the environment expands in rapidly escalating events (Solé, 2011). As the degree of uncertainty and number of unknown factors increase, the likely effectiveness of previously designed rules and procedures decreases, and crisis managers face a challenging situation in which they must act with imperfect and ambiguous information (Klein et al., 2003). Finding the balance between structure and flexibility is difficult in each distinct area of operation but aligning the balances achieved at separate levels of operation into an overall system of effective performance to bring a massive threat under control is the critical task.

The United States, as most countries, has invested substantially in emergency management and preparedness to reduce risk to its population, infrastructure, and continuity of operations (Waugh, 2015). In an iterative process, the U.S. has developed a set of five national planning frameworks to guide decision processes and prepare communities, states, and regions across the nation to cope with recurring hazards (FEMA, 2016). Yet, the substantial investments in equipment, training, and personnel have been exceeded year after year as the inexorable consequences of climate change has led to increasingly frequent and severe hazard events across the country, and indeed, across the globe (CA Governor's Office, 2019; CalFire, 2021; Rozsa, 2022).

The structured planning frameworks developed at the federal level in the U.S. have created a common terminology, language, and training programs to develop basic sets of skills in managing emergencies that can, in theory, transfer easily across local, county, state, and regional jurisdictions to create national capacity for managing hazards (Sylves, 2020; McEntire, 2015; Waugh & Tierney, 2007). Yet, the sheer scope, scale, and frequency of recurring hazards, with the cumulative burden of damage to environment, infrastructure, and mounting economic costs compels a continuing search for improved means of managing risk. While specifying a legal structure and rules for coordinating action across multiple jurisdictions and operational scales is fundamental to building capacity for managing complex operations to reduce hazard risk, the process of doing so in actual events is much more dynamic and uncertain, subject to sudden shifts in external conditions and unexpected, cascading consequences from actions taken – or not taken (Hardy and Comfort, 2014; Comfort, 2019).

While crisis events pose challenges for managers at every operational level, these challenges are even greater at the local level for communities that confront potentially catastrophic events. With lives and infrastructure at risk, local communities often have the least resources, limited equipment, and fewer skilled personnel to cope with massive destructive events (Nelson and Stenberg, 2021). In urgent conditions, responsible managers necessarily activate wider networks of assistance to manage the threat (Vale and Campanella, 2005). This process of activation brings access greater resources, but also requires realignment of new actors, absorption of new information, resolution of potential conflicts with existing procedures that adds a burden of integration, synthesis, and redefinition of strategies for action (Cohen and Levinthal, 1990). In effect, transitions between operational scales create new demands for information, adaptation, and realignment of action strategies that are often not anticipated nor recognized as crises escalate in scale and scope (Solé, 2011). Unrecognized, such misalignment may trigger dysfunctional performance that leads to cascading crises, worsening the overall capacity to respond.

Organizational theorists have repeatedly sought to identify the terms and conditions that define successful adaptation in rapidly changing, urgent conditions, but the exact balance between structure and process proves elusive and is necessarily redefined in actual events (Weick, 1995; Weick and Sutcliffe, 2007). Prior research has focused on network structure but, to a lesser extent, on the processes that characterize network change (Slaughter, 2017). This study focuses on the narrow region where the interaction between structure and process among multiple sub-networks shifts the entire operational system of systems into a different phase of macro-system performance. Lack of valid models of the dynamics of such transitions in large-scale, urgent events represents a major gap in administrative theory and practice.

Balancing Structure with Flexibility in Complex, Dynamic Systems

Kaufmann's (1993) initial framing of transition between operational states captures the tension between structure and flexibility that is inherent in dynamic systems (Comfort, 2019). This tension increases as the system scales in size, complexity, and danger. Organizations, seeking reliability, structure performance through rules, procedures, and policies codified through a formal process to represent general acceptance of best practice for a given place and time, and further, translate such policies into values for the constituencies they serve.

Yet, in the flux of social change, rules need to be modified, updated, and adapted to shifting conditions to maintain functional performance in a dynamic society. Continual tension exists between maintaining the structure needed for stable performance and enabling the dynamics of innovation essential to adapt to changing conditions, reflecting the rate of change in the operating environment (Kauffman, 1993; Comfort, 1999; Berthod et al. 2016). This tension leads to the formation of networks as organizing units that link formal authority with dynamic sources of information about the changing state of threat and enable rapid comprehension of risk and timely, collective action (Comfort and Zhang, 2020; Comfort and Rhodes, 2022).

The tension between structure and flexibility is most acute during crisis operations that require continual awareness, adjustment, and active attention. Monitoring and measuring the rate of change in environmental, technical, and social conditions affected by crisis operations are critical steps in maintaining an effective balance in an escalating event. Used judiciously, indicators of change in specific conditions may inform corrective interventions before a crisis occurs; if ignored, the cumulative array of even minor changes across a complex system may signal potential disruption and transition to dysfunction (Solé, 2011; Argyris, 1993; Nelson & Winter, 1985). Access to technical support from advanced information and communications technologies offers an invaluable resource to managing the complexity of interacting sub-systems of temperature, wind, land cover, energy, transportation, and community activity, but it is not fully integrated into crisis decision processes at the system-wide level.

Transitional Forms in Multi-scale, Complex Environments

This study draws on three streams of literature in public policy and administration that have addressed transitions involved in scaling operations across different levels of complexity, authority, and risk; yet each has theoretical and methodological roots in a different discipline. All three streams of literature – systems thinking, network analysis, and collaborative governance –address modes of analysis for managing tensions across different scales of space, time, and scope of operations, analytical skills especially critical in crisis operations.

The first stream, **systems thinking**, has intellectual roots in engineering and is shaped by mathematical models developed to identify, quantify, and model change largely in technical systems operating in uncertain conditions (Davidson et al. 2015; Glass et al. 2011; Hollnagel, 2011, 2012; Beck, 1986/1992). With an engineering focus, these researchers sought to solve emerging problems in real time by using mathematical models to identify the critical components of an operating system and estimate the patterns of interaction among them that lead to successful performance or failure. The proliferation of desktop computers in the mid-'eighties enabled a generation of engineers to develop computational models that could be used to abstract real-world problems to solvable equations. Systems thinking allowed the engineers to design functioning systems that crossed boundaries of space and time, enabling advanced technical solutions for complex problems, such as metropolitan transportation systems, electrical grid systems, and global networks of communications. Yet, the systems approach often overlooked or ignored the human decision makers who were managing the technical systems, leaving the designed systems vulnerable to human error, even as the models focused on technical operations (Committee on Science and Technology, 99th Congress, 1986; Glass, 2009). Even worse, dynamic technical systems may exhibit unplanned and undesirable outputs that would be counterintuitive (Daellenbach et al., 2017).

In contrast, the second stream of literature, **network analysis**, has intellectual roots largely in the social sciences and focuses on identifying recurring interactions among individuals or units that represent a structure of recurring patterns in human decision making and action

(Steelman et al. 2022; Agranoff, 2007; Kapucu, 2006; Meier and O'Toole, 2001; Feiock et al., 2012). Researchers have used network analysis to identify interactions among actors in many types of activities, but there has been a notable focus on response networks to identify key actors and their interactions following urgent events (Comfort, 2019; Moynihan, 2009; Kapucu et al., 2010). In such events, crisis response involves the rapid mobilization of actors and resources in life-threatening situations where time is short, risk is high, and consequences of error are deadly. Network analyses in these studies have focused on identifying the patterns of interaction among varied actors at different levels of authority, using the metrics of frequency, centrality, density, and betweenness. Yet, while recognizing the role of communication and information exchange in such interactions, these studies have largely not examined the technologies through which these interactions occur – or fail.

Within the broad stream of network analysis applied to emergencies, researchers have identified three different types of networks: planned, emergent, and operational (Comfort and Zhang, 2020). Planned networks are formal networks established by public authorities and given legal responsibility and resources to engage in specified programs to reduce risk of hazards, such as the national planning frameworks developed by FEMA that serve as templates for organizing action at state, county, and municipal entities in the U.S. (FEMA, 2016) or the Standardized Emergency Management System (SEMS) adopted by the State of California (CalOES, 2022). Emergent networks, in contrast, are the spontaneous, self-organized groups of volunteers that offer services and assistance to community residents who have been injured or have suffered losses in a hazardous event (Drabek & McEntire, 2002). Operational networks bridge planned and emergent networks in practice. Defined as a set of interacting organizations that "employ a continual process of communication, feedback, and adaptation in practice," operational networks facilitate coordination among multiple actors at different levels of authority to achieve a shared goal of risk reduction *in real time* (Comfort and Zhang, 2020: 984). Granted authority and resources under official plans, operational networks use the tools of information and communications technologies to adapt those plans to the immediate demands of a dynamically evolving situation, engaging local actors that have specific knowledge of the conditions and constraints shaping the crisis. Operational networks have proven most effective in managing events of moderate size where communications can easily facilitate coordination among recognized actors.

The third research stream, **collaborative governance**, focuses on solving contentious issues for the benefit of the whole community. Collaborative governance studies seek to capture the interactions among different types of organizations focused on the same goal – for example, transportation, health care, land use planning, education, environmental protection -- from different sectors – public, private, and nonprofit -- in resolving conflicts among them in the public interest (Ansell & Gash, 2008; Emerson & Nabatchi, 2012; Moore et al., 2018; Ansell & Gash, 2018). Governance studies recognize the value in building a shared vision among the participants to facilitate the construction of workable strategies to resolve conflicts, resulting in innovative solutions and new knowledge informed by participatory dialogue that leads to viable results (Innes and Booher, 2018). Related studies have interpreted interaction between government and citizens in solving public problems as 'co-production' in which a public good, like reduced risk from hazards, was achieved through collaborative action between government and citizens, since neither sector could the solve complex problem alone (Alford, 2009; 2016). Such collaborative efforts among government agencies and actors in public and private sectors were evident during COVID-19 operations when actors shared the goal of preventing the spread of virus (Huang, 2020). Like network analysis, however, little if any attention is given to the technical means of communication and information exchange in governance platforms that support problem-solving interactions among the participating actors, groups, or sectors.

The common dimension underlying the three analytical approaches outlined above is the **flow of information and transfer of knowledge among multiple actors** in complex operating systems to support decision making on changing, contested issues. This dimension becomes even more critical in the transition between temporal and spatial scales of operation that involve shifts in juridical authority and allocation of resources. The complexity of such transitions is underscored by the frequency, intensity, and scale of massive hazard events that overwhelm existing capacity to mitigate and manage them. Such large-scale, catastrophic events require a different order of experience and innovation to manage the complex transitions between operational scales. This task leads logically to networked forms of organization to link wider types of knowledge to broader mechanisms of action.

Analyzing Operational Transitions

The imperative to scale operations quickly and effectively from one level of action to another in response to massive, urgent threats reveals an underlying gap in the integration of information regarding technical infrastructure, organizational procedures, and cultural values that characterize complex operations among diverse actors essential to produce coherent performance in real time. Shaping this gap is the phenomenon of *complex time*, a key concept that captures the dissonance among technical, organizational, and cultural performance among different groups (Krakauer, 2020; Comfort, 2022). That is, different actors perceive the same event through varying lenses of urgency, difficulty, costs, and rewards, and consequently, mobilize their actions to mitigate risk accordingly at different rates of change. The resulting differences in rates of cognition of risk, preparedness, and action produce coherent performance to perceived threat within sub-systems, but strain effective performance for the larger system.

The challenge lies in measuring the different rates of change in the performance of technical infrastructure, existing organizational procedures, and basic cultural values at different levels of operation to identify the areas of dysfunction that limit capacity of the whole system to integrate dissonant sub-units into functioning, coherent performance at a larger scale of operations in a dynamically changing environment. Enabling large-scale system performance at multiple levels of operation is no easy task; it requires the design of learning processes that strengthen integration in organizational capacity for adaptation, innovation, and self-organization at multiple levels of operation within a complex systems framework (Wilensky, 2015). This need calls for the explicit development of an intelligence function to guide system integration at micro, meso, and macro levels of system performance.

We borrow the basic concept of intelligence from the extensive literature on design, conduct, and uses of intelligence in security studies (Agrell and Treverton, 2015; Treverton and Wolf, 2007; Steele, 2006; Stonier, 1986; Kent, 1949), but redefine it in terms of the knowledge needed to inform decisions in rapidly changing, urgent, massively complex operations in response to catastrophic hazards. In classic military intelligence, officers seek four types of information from different sources as a means of improving the validity of information to mobilize operations in uncertain, changing conditions. First, Human Intelligence (HUMINT) is sought from knowledgeable people about the risk and its impact on the region. Second, Signal Intelligence (SIGINT) is gathered from sensors and electronic monitoring of changing conditions. Third, Imagery Intelligence (IMINT) provides information from satellite imagery of the geographic location at risk, or photos taken that provide graphic evidence or risk.

Finally, Open Source (OSINT) intelligence is gathered from newspapers, documents, reports, and plans that are available to anyone in public space (Agrell and Treverton, 2015). Honed by decades of practice to inform military operations, these four categories of information are equally relevant for Incident Commanders coping with catastrophic hazardous events.

Incident commanders confront similar barriers to decision making in extreme hazards, with incomplete information, uncertainty, ambiguity, and dynamic interaction among key elements in an environmental context outside of their control. We define intelligence as the production of knowledge needed to inform decisions to mobilize action in environments of high risk and uncertainty. Just as military officers acknowledge the limits of their assessments and seek confirmatory information from multiple sources and disciplines in situations of high risk, Incident Commanders operating in urgent contexts where time is critical and lives are at stake seek similar types of intelligence (Nowell and Steelman, 2016). The concept of 'unified command' implemented in disaster operations illustrates this principle in practice (CalOES, 2016). Yet, the size, scale, and scope of catastrophic hazards have exceeded prior methods of risk assessment, underscoring the need to rethink the intelligence function in managing extreme hazards.

Managing Catastrophic Hazards in Real Time.

In a classic example of large-scale threats requiring system adaptation at multiple levels of action, California is experiencing the consequences of climate change with dramatic shifts in weather patterns, drought conditions continuing over multiple years, and extended wildfire seasons leading to catastrophic mega-wildfires (Cal Fire, 2021). Five of the 20 largest wildfires in California's history occurred within one year, 2020 (CalFire, 2020 Fire Siege, 2021:37). Recognizing mounting losses from increasing frequency, scale, and scope of wildfire in the last decade, California has countered this threat by making significant investments in building capacity for mitigating wildfire risk through increased funding not only for equipment and personnel, but also for research, technologies, and training to increase organizational intelligence in managing wildfire risk (Governor's Strike Force Report, 2019). Doing so has extended responsibility for decision making to wider networks of public, private, and nonprofit organizations tasked with building resilience to wildfire risk statewide. This process has forged a concept of network intelligence as a basic component of managing risk in uncertain conditions (California Governor's Office, Task Force, 2021).

The fundamental challenge posed by wildfire risk in California and other states and countries lies in the sobering potential for catastrophe. That is, when the demands posed by actual hazard events exceed the scope and scale of planned operations with limited capacity, knowledge, and collective resources/skills for urgent response under tight time constraints, the situation triggers high losses of lives, property, livelihoods, and further cascading events. Such demands overwhelm the current operating capacity of other networks engaged in emergency response, threatening collapse of the wider social system. The potential for catastrophe requires a fundamental reconceptualization of the phenomena of hazard emergence that occur at different rates of change in multiple scales of operation and action simultaneously in actual hazard events.

Realigning Scale, Scope, and Time in Network Performance.

The relationships among people, jurisdictions, organizations/institutions, technologies, and risk need to be redesigned as functional networks capable of learning, redesign, and recalibration both in reciprocal response to participating actors and to the physical environment in which they operate. An initial effort to re-imagine functional networks includes systematic efforts to design sets of networks that can realign the scale, scope, and timing of their operations to fit the demands of the environment in which they are operating. It means creating the capacity for sub-units to gain a system's view through visualization of operations at multiple levels that enable the adaptation and adjustment among local sub-units needed for coherent performance. One means of facilitating this process of adaptation and adjustment is dispatching specialized Interagency Incident Management Teams (IIMTs) to provide expert support at vulnerable points of micro level performance that would strengthen macro performance of the whole operational system. IIMTs are select teams of firefighting personnel who receive special training in the cross-disciplinary aspects of managing complex, dynamic response operations (NWCG, 2022), and represent the most experienced level of managers assigned to aid decision processes in urgent, dynamic events.

The question is whether the IIMTs alone provide sufficient support to the transition between scales of complex operations in large-scale events, or if other methods of visualizing rapidly changing operational conditions could engage a wider audience to facilitate collective cognition and strengthen system performance for the whole community at risk. This study represents a preliminary effort to examine the processes of realignment and adaptation supported by intelligence networks to make transitions between different scales of space and time, using actual events from the 2020 Santa Clara Unit (SCU) Complex Lightning Fire in Northern California.

The Lightning Complex Fires in Northern California, August 2020.

The Context. On August 17, 2020, an extraordinary meteorological event ignited hundreds of wildfires simultaneously in northern California. More than 12,000 dry lightning strikes were recorded over two days, August 17-18, 2020, throughout northern California (CalFire, 2021). The lightning struck in hot, parched grasslands and forests with trees dying from prolonged drought in highly combustible wildlands bordering urban centers. Small fires, whipped by high winds, merged into larger fires. Three of the largest wildfires burned simultaneously in eight of the nine counties in the San Francisco Metropolitan Bay Area, home to seven million residents. Only the small, urban county of San Francisco escaped the wildfires.

The Santa Clara Unit (SCU) Complex Fire initially spread in three southern counties – Santa Clara, Alameda, Contra Costa, but stretched over to adjacent San Joaquin, Stanislaus, and Merced Counties – burning 396,622 acres and destroying 222 structures. The LNU Complex fire ignited in the northern counties of Solano, Napa, and Sonoma, spreading north to Lake County and east to Yolo County, burning 363,220 acres and destroying a larger number of structures, 1491, in a more populated area. The CZU Complex Fire ignited in San Mateo County and adjacent Santa Cruz County, destroying old growth sequoias in Big Trees State Park, and threatening the University of California, Santa Cruz campus. The next day, August 18, the Woodward Fire, ignited in Marin County, burning a smaller acreage but distracting attention and resources from the larger fires (CalFire, 2021). By any measure, the simultaneity of these fires created a massive demand on the existing fire-fighting capacity of emergency response organizations at micro, meso, and macro levels of operation.

The Challenge. The demands for response, coordination, and control in this set of actual events were unimaginably complex under urgent threat. The California Department of Forestry and Fire Protection (CalFire), the public agency with legal responsibility for managing wildfire risk, faced an excruciatingly difficult set of interrelated and escalating tasks in leading and organizing coherent response operations to an ever-shifting dynamic of field conditions. The only workable approach was to activate simultaneously networks of actors –personnel from fire departments statewide in California, federal agencies, and neighboring states; technical companies with advanced cameras and computational capacity; heavy equipment operators, meteorologists, emergency medicine physicians, helicopter pilots -- to provide the range of knowledge, skills, equipment, and personnel needed to mobilize rapidly escalating response operations. Yet, doing so across multiple jurisdictions that had widely varying access to resources and were constrained by health restrictions imposed by the COVID-19 pandemic presented a formidable challenge to agency personnel. This challenge is critical for California, with a GDP of $3.2 trillion, that ranks as the largest economy of all 50 US states and as the fifth largest economy in the world (www.forbes.com). Maintaining that economic ranking depends on the capacity of the state to manage wildfire risk, while also maintaining the environmental resources of the state that generate economic productivity and well-being for its population.

Research Design. This paper examines networks as learning mechanisms and explores linkages between different types of networks within a complex system of systems that generates transition to a more coherent mode of operation for the whole system. It focuses on the emerging role of *intelligence networks* that reinforce operational networks in mobilizing targeted, effective performance in multi-jurisdictional contexts under urgent, uncertain conditions. The 2020 SCU Lightning Complex Fire in Northern California serves as a field study to examine the rate of change in operations conducted for a rapidly escalating wildfire spreading to six counties and multiple municipalities within them, affecting millions of residents in near real time. The research questions are:

1. What mechanisms – social and technical – facilitated search, exchange, and updating of intelligence among different levels of operation in managing wildfire risk?
2. What mechanisms – social and technical – hindered collective management of risk among participating actors at different operational levels engaged in wildfire mitigation?
3. What functions served to integrate information regarding conflicting conditions to shift performance toward a coherent operational system for managing wildfire risk?

Methods, Data, and Analysis

Methods. The research method most appropriate for this complex policy problem is an initial exploratory case study to characterize the context, actors, and primary issues at risk (Yin, 2018). The first task is to identify the networks engaged in actual field operations in response to the SCU Lightning Complex wildfire. Four types of networks were observed in response operations for the SCU wildfire. These types are: 1) *planned networks* that represent the formal organizational structure of the Standardized Emergency Management System (SEMS) in which all California emergency response personnel are trained (California Office of Emergency Services, 2010); 2) *emergent networks* of local organizations and volunteers that responded spontaneously to the fire (Strandh and Eklund, 2017; Stallings and Quarantelli, 1985); 3) *operational networks* that integrated the first two types – planned and emergent – into a third type that supported reasonably coherent operations in practice (Comfort and Zhang, 2020); and 4) *intelligence networks* that included the Interagency Incident Management Teams (FEMA, 2016), teams of experienced personnel from federal, state, regional, and county agencies that brought advanced skills and knowledge to support local personnel in coordinating operations that involved mobilizing resources from multiple agencies, organizations, and jurisdictions under critical time constraints. This study focuses on intelligence networks as a mechanism to aid the transition among micro, meso, and macro scales of operation in an extreme event.

Data. Access to incident data necessary to distinguish the four types of networks is not easily available. Presumably, all data pertaining to wildfire operations are public and available to interested parties. In practice, incident data are held by operational agencies and are not readily released. Officially, data can be obtained by filing a Public Records Request and specifying the data one wishes to access and the reason for study. However, there is no certainty that the data will be provided, nor any indication of when it might be available. The second option is to review all agency reports and press briefings that provide general information about the size, scale, and duration of operations, but largely avoid specific identification of agencies, jurisdictions, private or nonprofit organizations that were involved in response operations. The third alternative is to review news reports of operations that provide information about community organizations as well as public agencies, but that likely are not complete. This initial exploratory study will be based on data sources that are publicly available and are drawn largely from the 2020 incident action reports filed by CalFire, plans, reports, and official briefings from CalFire and the Governor's Office of Emergency Services, State of California.

Specifically, the data to analyze rates of change in key parameters in an effort to characterize the dynamic operations of an actual wildfire were drawn from the 209 Incident Reports filed by Cal Fire for the SCU wildfire from its point of ignition on August 17, 2020 to its point of containment on September 10, 2020, a total of 25 days. The 209 reports are filed from the field by the Incident Command staff to provide an ongoing record of fire operations in 12-hour intervals filed at approximately 0600 and 1800 hours, producing a total of 52 reports, with some initial reports for small fires merged into the larger SCU event. The reports provided a basic characterization of operating conditions and activities during those time periods, including conditions of terrain, temperature, wind speed, assets at risk, acreage burned, operational personnel on site, assisting organizations, equipment requested, per cent of fire contained, residents evacuated, and estimated costs.

Analysis. These data verify that four types of networks were operating in the SCU wildfire – 1) planned networks following the SEMS framework; 2) emergent networks identified as volunteers and personnel from private organizations joining field operations personnel; 3) operational networks that included local assisting organizations, and 4) intelligence networks that included the IIMT allocated to the SCU wildfire. These data documented the official number of personnel involved in the agency networks and the number of local assisting organizations that provided support and intelligence to the operational personnel. The 52 incident action reports recorded rates of change in key variables at 12-hour intervals. These reports were used to identify the basic parameters for a system dynamics model that included rates of change flowing through active networks engaged in wildfire response operations and that would characterize a learning system in real time.

Using data from the 209 Incident reports for five variables – acreage burned, operational personnel, acreage contained, assisting organizations, and estimated costs – we calculated the rate of change for each variable over the 25-day period, August 17 – September 10, 2020. We used a simple equation: actual record for the variable reported for a 12-hour period minus the record from the previous 12-hour report equals the change over the 12-hour period; change divided by the previous report x 100 = rate of percent change for that period. The rate of change varied considerably over the 52 report periods, so the average rate of change was not a valid measure. Instead, we found it more accurate to show the variation in rate of change with feedback loops between the variables documenting their interaction through a system dynamics model. These data were entered into a preliminary system dynamics model of operations that demonstrated the scaling of response operations from micro to meso to macro levels in an actual event, the 2020 SCU Lightning Complex Fire. Fig. 1, below, shows the initial model with the feedback loops showing the interactions among the variables.

Simulation Model

The simulation model is based on data from the 52 12-hour 209 reports submitted by CalFire and incorporates variables considered critical to identify the networks within the complex system of systems. The Anylogic simulation software was used to simulate dependencies among variables as represented in links (https://www.anylogic.com). The elements of the model are classified as stock, flow, dynamic variables, and parameters and these variables are defined below.

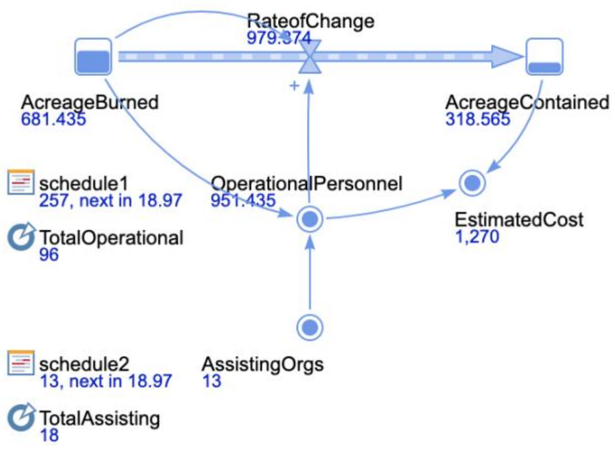

Fig. 1. Interacting variables in the SCU Lightning Complex Fire, 8/17 – 9/10/2020.
Model in AnyLogic software by Sae Mi Chang.

Stock. As a fundamental element of a system dynamics model, stocks represent the processes of the real-world. In this model, *AcreageBurned* and *AcreageContained* are set as stocks. The stock, *AcreageContained,* represents the simulated acreage that is derived from the actual variable reported for percent of the fire area that is contained. Thus, *AcreageBurned* diminishes as it moves to *AcreageContained* over time.

Flow. The flow defines how the stocks change over time to affect, in turn, the dynamics of the system. The *RateofChange* in this model is determined by the number of operational personnel engaged for the response activities. It is also determined by the average rate of change of percent containment which is 4.1% over 52 shift periods. This average rate of change is set as a baseline together with other variables that affect the rate of change.

Links. The links illustrate the dependencies among the elements in the system dynamics model. In this model, stocks, dynamic variables are linked to each other with arrows, depicting their dependent relationships. For instance, the number of *OperationalPersonnel* is in part dependent on *AcreageBurned* and in part the *AssistingOrgs.* In addition, the *EstimatedCost* is dependent on *OperationalPersonnel* and *AcreageBurned.* Such links between elements imply nonlinearity of the system.

Dynamic Variables. When variables change according to a certain formula that is composed of other variables, they are called dynamic variables. In this model, the dynamic variables are *OperationalPersonnel*, *AssistingOrg(anization)s*, and *EstimatedCosts*. The variable, *OperationalPersonnel*, represents the number of personnel engaged in field operations, while *AssistingOrganizations* represents the number of organizations that provide support to the operational personnel to contain the fire. *AssistingOrganizations*, in this model, provide local intelligence to the operational personnel who largely are mobilized from regions external to the fire site and may have little familiarity with the actual physical context of the fire. Finally, *EstimatedCost* includes both losses in structures, critical facilities damaged or destroyed by the fire, and costs of personnel, equipment, and materials used for fire suppression.

Parameters. The parameters represent characteristics of objects included in the model. This model employed *TotalOperationalPersonnel* and *TotalAssistingOrganizations* as parameters that describe what the changing values of dynamic variables - operational personnel and assisting organizations – stand for. The parameters are linked to the dynamic variables by means of the schedule function. The data showing the changing state for the two parameters, as reported in the 209 Reports, are listed in the Appendix.

Schedule. The schedule function is used to incorporate the difference in time of engagement between the *OperationalPersonnel* and *AssistingOrgs*. By employing schedule function to the model, it is possible to demonstrate the delay as seen from actual data. Based on the 12-hour incident reports, it was not until the 5th report that assisting organizations became involved in containment activities.

Note that not all the factors that might contribute to containing the fire are incorporated into this simulation model. However, this model provides understanding about how different networks are interlinked to one another. That is, operational personnel working under the planned networks of the SEMS framework are first involved in response activities, followed by assisting organizations. The assisting organization support the exchange of local knowledge and experience throughout the process that informs and guides the decision processes of the operational personnel. This model clearly demonstrates that the rate of change is not merely determined by a single network but rather by the multiple networks that are interlinked with one another.

Interpretation of Results

The model represents a simulation based on actual data from the 209 Incident Reports, identifying links that influence, and are influenced by, variables that affect one another. In effect, the simulated network expands and contracts, adjusting to the scope and scale of the event as resources in knowledge, skills, and experience are mobilized to manage an expanding, increasingly dangerous, catastrophic event and bring it under control. Previous networks have generated the capacity to recognize the skills and resources needed to counter unexpected and unknown challenges as critical information becomes available and reveal possible alternative strategies for action. A system dynamics model identifies the threshold points of change in the system where performance lagging in one variable indicates potential weakness in the system, and where additional resources applied strategically would strengthen overall system performance. In environments of uncertainty, innovations in technology that monitor change in risk conditions in real-time are critical to maintaining a valid, current profile of risk that allows informed allocation of resources, skill, and time to mitigate potential damage and prevent cascading losses.

This simple model shows the key relationships between the rapid increase in acreage burned and the slow entry of operational personnel that reverses when the number of operational personnel increase and the acreage under fire is contained (representing percent contained tallied in the data). The estimated cost of the fire increases steadily throughout the 52 report periods, including losses incurred in buildings destroyed and infrastructure damaged as well as the cost of personnel and equipment used in fire suppression. Importantly, the relationship between assisting personnel and organizational personnel increases the capacity of the organizational personnel to contain the fire, as shown by the increase in rate of change in personnel. This increase shows indirectly that local intelligence provided by the assisting organizations enabled the operational personnel in the field to perform more effectively. In practice, the assisting organizations provided key insight, knowledge, and judgment from a local perspective that informed micro level operations to improve system performance. The model also reflects the impact of time on the evolving dynamic of operations personnel, as the delay in mobilization of personnel in the field accelerated the rate of acreage burned which, in turn, accelerated the costs of suppression.

Discussion

Returning to the research questions posed for this study, we first sought to identify what mechanisms – social and technical – facilitated search, exchange, and updating of intelligence among different levels of operation in managing wildfire risk. In this preliminary study, we relied primarily on publicly available data that provided an assessment of intelligence from the official perspective of the operational agencies but did not provide detailed data on other types of social and technical mechanisms used for intelligence collection, analysis, and exchange. While this is a preliminary study, the public data provided in the 209 Incident Reports by 12-hour periods nonetheless documented the fire's progression and containment, the expansion and contraction of operational personnel, and the interaction among the local assisting organizations as they moved to support the operational personnel. The trajectory of the fire slows as more organizations engage in operations and provide more intelligence support at the local level to augment the overall operations. The data available do not allow analysis of what types of intelligence the assisting organizations provided, but this is a promising direction for further research.

Regarding the second question – what mechanisms hindered collective management of risk at different operational levels – the simulation suggests that timely mobilization of resources, for both personnel and equipment, could have altered the progression of the fire. Although requests for equipment were included in the 209 reports, the allocation of equipment was not, so this variable was not included in the model. Again, detailed data are not available from the 209 Incident reports, but the lack of multi-way communication among agencies at successive operational levels is strongly suggested by the late mobilization of resources and personnel during the first seven days of fire operations.

Considering the third question – what functions served to integrate information to shift performance toward a coherent operational system – the systematic reporting of the fire's progression and the 12-hour tallies of operational personnel, assisting organizations, acreage burned, percent contained, and estimated costs were exchanged among field commanders, district personnel, and state personnel to provide a running account of basic measures of performance. While these measures are standard indicators used in wildfire management, they also provide data that can be analyzed in more detail, studied in comparison with other wildfire events, and modeled to develop alternative strategies to cope with the continuing threat of wildfire.

Conclusions, Limitations, and Future Research

This preliminary study likely suggests more questions than it answers. These findings confirm the critical role of intelligence in managing large-scale, rapidly evolving events like wildfire, but also illustrate the challenge of analyzing the information flow in such events in real time. Developing and implementing more systematic means of reporting field operations for such events will be essential to provide valid data for more detailed analysis. Supplemental research would probe more deeply into the types of intelligence that were provided by the different sets of organizations engaged in field and management operations. Interagency Incident Management Team 6 was assigned to the SCU wildfire, but there is little detail in the 209 Reports regarding what specific skills they provided to the On-scene Incident Commander, other than more experience, additional training, additional disciplinary skills. Conducting semi-structured qualitative interviews with members of IIMT 6 would be an important next step in identifying the types of intelligence they provided to on-site Incident Commanders and in analyzing the interactions among the different operational levels.

Reconceptualizing the intelligence function for managing wildfire operations necessarily means extending the sources, types, and mechanisms of information search, analysis, and exchange available to decision makers in system-wide operations. Variations on the four types of intelligence sought in military operations – HUMINT, SIGINT, IMINT, and OSINT – are likely available to onsite commanders in wildfire operations, but are they synthesized in readily available, timely formats that can be accessed easily by field personnel on a dynamic, urgent fireground? New technologies are rapidly developing in the use of edge computing to bring computational power directly to the operational field (Pandey et al., 2022). New methods of visualizing complex operations at multiple scales are under development (Soga et al., 2021; NCAR, 2022). Yet, the larger task of integrating multiple modes of intelligence into an actionable form that can be delivered timely to Incident Commanders in the field is not yet operational. Articulating the wider goal of intelligence needed to support real-time decision making in urgent events like massive wildfires is the first step toward producing this function in practice.

There is some indication that steps in this direction are being taken. The University of California has developed a *Disaster Resilience Network* to pool the talents, resources, and energies of the ten separate campuses, each of which is at risk from wildfire, to provide a statewide focus on wildfire for risk reduction (https://ucdrn.org/). This multi-campus, multi-disciplinary network of researchers, faculty, students, and wider alumni is still a nascent effort, but it is a broad, community-based initiative to explore, innovate, understand, and change the conditions that precipitate mega-wildfires in California. Reducing wildfire risk in California will necessarily involve social, technical, economic, and geographic types of analysis and a network of actors at multiple levels of operation, before, during, and after extreme events to collect data, analyze it, and produce intelligence to support collective action.

Additional documents are being evaluated for release from a Public Records Request that would provide a more detailed narrative of operations for the SCU wildfire, and documents to support a comparative analysis of the two other lightning complex fires that were burning simultaneously in the San Francisco Metropolitan Area, the LNU and the CZU wildfires. Conducting a comparative study among the three major fires that ignited on the same day, August 17, 2020, and burned for roughly the same period, will provide insight into the strain on the overall complex system of fire management in California and its implications for managing wildland fires in other states and countries.

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Appendix
Simulation: Dynamic Variables,
Data Source, CalFire 209 Reports, SCU Lightning Complex Fire,
August 17 – September 10, 2020

Schedule 1 – Operational Personnel

Time	Value
Day 1 19:15	96
Day 1 19:59	132
Day 1 19:55	120
Day 1 19:51	162
Day 1 20:00	522
Day 2 18:00	578
Day 3 05:58	578
Day 3 17:45	1008
Day 4 05:45	1036
Day 4 17:35	1114
Day 5 05:45	1114
Day 5 17:30	1179
Day 6 05:48	1179
Day 6 17:09	1232
Day 7 06:43	1232
Day 7 17:24	1336
Day 8 05:47	1336

Day 8 17:59	1393
Day 9 05:46	1393
Day 9 17:24	1655
Day 10 05:42	1655
Day 10 17:36	1903
Day 11 05:48	1903
Day 11 17:30	1935
Day 12 05:43	1935
Day 12 17:31	1991
Day 13 05:45	1991
Day 13 17:49	2025
Day 14 05:44	2025
Day 14 17:49	1934
Day 15 05:43	1934
Day 15 17:32	1773
Day 16 05:47	1773
Day 16 17:36	1609
Day 17 05:49	1609
Day 17 17:31	1561
Day 18 05:47	1561
Day 18 17:40	1462
Day 19 05:51	1362
Day 19 17:20	1234
Day 20 05:49	1234
Day 20 17:30	1143
Day 21 06:03	1143
Day 21 18:00	968
Day 22 05:51	819
Day 22 15:45	604
Day 23 06:01	597
Day 23 17:37	572
Day 24 05:45	320
Day 24 17:30	263
Day 25 05:45	263
Day 25 17:45	257

Schedule 2 – Assisting Organizations

Time	Value
Day 1 19:15	0
Day 1 19:59	0
Day 1 19:55	0
Day 1 19:51	0
Day 1 20:00	18
Day 2 18:00	18
Day 3 05:58	18
Day 3 17:45	27

Day 4 05:45	31
Day 4 17:35	31
Day 5 05:45	31
Day 5 17:30	32
Day 6 05:48	33
Day 6 17:09	33
Day 7 06:43	33
Day 7 17:24	33
Day 8 05:47	33
Day 8 17:59	33
Day 9 05:46	33
Day 9 17:24	33
Day 10 05:42	33
Day 10 17:36	59
Day 11 05:48	59
Day 11 17:30	59
Day 12 05:43	59
Day 12 17:31	59
Day 13 05:45	59
Day 13 17:49	59
Day 14 05:44	59
Day 14 17:49	59
Day 15 05:43	59
Day 15 17:32	59
Day 16 05:47	59
Day 16 17:36	18
Day 17 05:49	18
Day 17 17:31	18
Day 18 05:47	18
Day 18 17:40	18
Day 19 05:51	18
Day 19 17:20	18
Day 20 05:49	18
Day 20 17:30	13
Day 21 06:03	13
Day 21 18:00	13
Day 22 05:51	13
Day 22 15:45	13
Day 23 06:01	13
Day 23 17:37	13
Day 24 05:45	13
Day 24 17:30	13
Day 25 05:45	13
Day 25 17:45	13