Creating trusted extensions to existing software tools in bushfire consequence estimation

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ABSTRACT

Bushfire modelling has advanced with wildfire simulators such as Spark and Phoenix Rapidfire that can generate plausible fire dynamics and simulations that decision-makers can easily explore. With extreme weather impacting the Australian landscapes through the onset of droughts and heatwaves, it is becoming more important to make decisions rapidly from fire simulations. An element of this decision-making process is trust, in which the decision-maker feels empowered to make decisions from models of complex systems like fire. We propose a framework for decision-making that makes use of a fire emulator, a surrogate version of Spark, to facilitate faster exploration of wildfire predictions and their uncertainties under a changing climate. We discuss the advantages and next steps of an emulator model using the mechanisms and conditions framework, a powerful vocabulary and design framework that builds in trust to allow users of a technology to understand and accept the features of a system.

Keywords

Wildfires; trustworthiness; optimal decisions; affordance analysis; emulation;

INTRODUCTION

Bushfires in Australia have caused substantial damages both in terms of human life, and in terms of the value of economic losses. The 2019-2020 "Black Summer" fire season is the most recent severe fire season, occurring in drought conditions and resulting in multiple 'megafires'. The consequences of this mega-event resulted in 14.3 million hectares had been burnt, over 2779 homes, and at least 34 people killed (Wittwer et al. 2021; SBS 2020; Ladds et al. 2017). More difficult to quantify are the indirect economic impacts of fires, including those impacts in vulnerable groups (Williamson and Quinn 2021; Gibbs et al. 2020; Whittaker et al. 2015) and those that emerge and persist over time (Gibbs 2021). Further to directly measurable impacts, bushfires have environmental impacts on landscapes, species, and ecosystems, both local to Australia and further afield due to smoke transport (Dockrill 2019; Readfearn 2020a; Dickman 2020; Gramling 2021; Readfearn 2020b). Reactively measuring consequences and damage in each of these contexts post-event is an important exercise; equally important can be using tools to *predict* potential impacts in these contexts to support anticipation of specific challenges that occur during and after hazard events to improve planning and response decisions.

With bushfires now a relatively common and expected occurrence in the Australian landscape, there is a long history of mathematical and computational tools to support understanding of bushfire hazards (Griffiths 1999; Noble et al. 1980; Keetch and Byram 1968; Cheney et al. 1998; Cruz, J. S. Gould, Kidnie, et al. 2015; Anderson et al. 2015; Burrows et al. 2009; McArthur 1967; Sharples 2008; Sullivan et al. 2014; Rothermel 1972; Cruz, J. S. Gould, Alexander, et al. 2015). This research encompasses understanding conditions associated with high fire spread; to physics type models describing spread of fires in different vegetation, landscape types and conditions; to tools used to assess and communicate fire risk. Much of the information and knowledge from this research has been incorporated into bushfire characteristic solvers used in Australia such as such as Spark (Miller et al. 2015) and Phoenix Rapidfire (Tolhurst et al. 2012). Based on this foundation of research and experience, such solvers aim to model and predict how a fire-front will spread through time. These characteristic fire models also have some well-established contexts in which they are used to inform decisions. Contexts where these computational tools are used to support decisions range from operational planning purposes by fire agencies, to understanding landscape-scale fire consequence risk caused by electricity distribution where the goal is targeting and assessing preventative measures(IGNIS 2021a; IGNIS 2021b; IGNIS 2019; SA Power Networks 2019; Dunstall, Huston, et al. 2017; Dunstall, Towns, et al. 2017).

While these characteristic fire modeling platforms run reasonably quickly given particular parameterisations through specific landscapes, explorations of hundreds, hundreds of thousands, or even millions of scenarios to pre-inform decisions relating fire spread and consequence can take time. Further, uncertainty is not automatically considered when assessing whether a fire-front will progress in a particular direction or through a particular location conditional on variable weather inputs.

Despite the value of existing tools and their ability to incorporate key information about our understanding of fire behaviour, the threat posed by bushfires is evolving and likely increasing due to factors such as climate change (Canadell et al. 2021). Our understanding of further contexts where being able to assess landscape-scale risk, or assess fire behaviour is also increasing as society begins to measure more, and more complex facets of fire consequence. As the threat of fire increases, and our understanding of contexts of consequence, so too can our tools for addressing and understanding the risk (Neale et al. 2021; Owen 2018; Begg et al. 2021).

In this paper we present work in progress of an *emulator* of characteristic fire behaviour which we hope is a next step in decision making toolsets used to understand and plan for bushfire hazards. While this emulator is currently under development, we recognise the importance of developing it collaboratively with planners and end users so that the opportunities provided by decision and AI tools based on it are understood and adopted broadly in the fire community. An emulation approach implicitly derives fire characteristic information in a different way to models like Spark which explicitly encode information about our current scientific and physical understanding of fire behaviour. As such, this paper will also explore how the emulator enables and constrains the types of outputs that can be created in different ways to the Spark predictive model on which it is based. There are challenges implicit in this, as emulated results are similar but not identical to those of the models on which they are based. At the same time, this emulator will 'afford' us new frameworks for application, especially if an efficient decision framework for it can be embedded as part of the overall artificial intelligence (AI) being developed.

Discussion to this point has been focused towards the development and understanding of an emulator as a fire characteristic solver. There is a decision making element to the development of such solvers that can often be overlooked at the development and research stage. At 'completion' the outputs are often left for decision makers like emergency services and first responders to determine how they should be used to act upon and make decisions.

Decision-making is tricky across all aspects of our working and personal lives and it is often challenged by how the circumstances present and how we interact with those circumstances. The same is true with the technologies we use and develop, like our emulator, and how we interact with those technologies to achieve an outcome and a corresponding decision. These decisions can be especially important and sensitive in a hazards context where lives and livelihoods can be at stake. In addition to introducing our emulator approach to fire characteristic estimation, this paper will focus on how Machine Learning and Artificial Intelligence (MLAI) can benefit decision-making. This is achieved through identifying smarter ways of characterising the physical processes that we wish to model and then connecting them with relevant formal *decisions* frameworks that enable optimal decisions. We consider this joint research path of emulator and decisions in the context of how AI technology 'affords' where the emulator provides information on which to make a choice. Such a principled approach to decision-making can take into account both the affordances of the model and decision making objectives. To demonstrate, we consider a toy scenario in which the reader explores the complexity of even a 'simple' decision-making problem and how decisions can change based on different model affordances, and can be improved through formal decision frameworks. Finally, we discuss improvements to existing decision-making methods for complex situations and provide a framework and pathway forward to enable better decisions to be formalised in the context of wildfire management using machine learning.

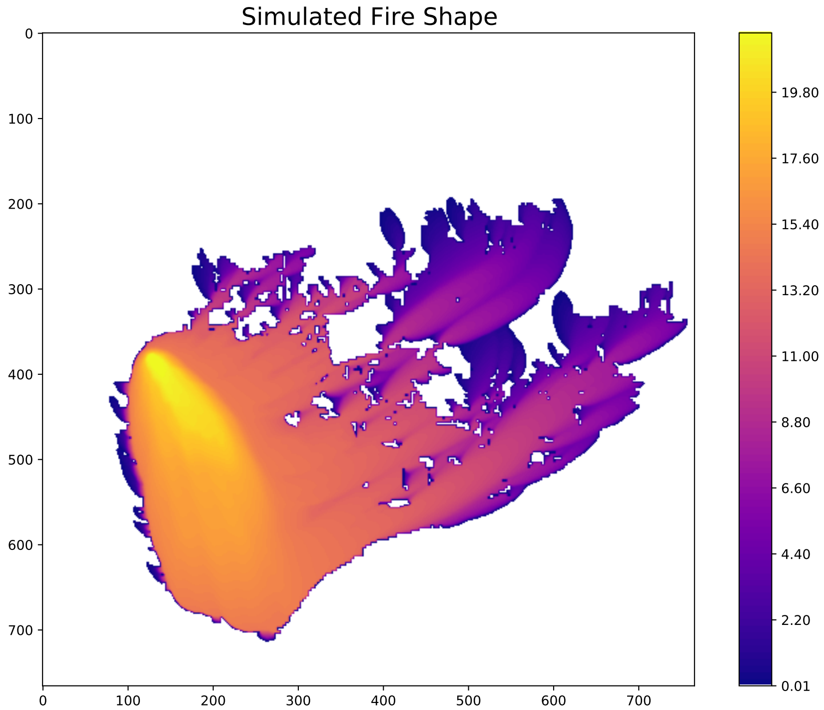

Figure 1. Fire arrival times as estimated in a Spark fire simulation. Yellow indicates earlier arrival times, purple, later arrival times.

METHODS

Wildfire modelling and emulation

As mentioned above, fire characteristic models such as Spark (Miller et al. 2015) and Phoenix Rapidfire (Tolhurst et al. 2012) are physics based in the sense that they incorporate our best understanding of fire spread. For example, much of the information about rate of spread is based on physical experiments of fire spread in different fuels, summarised in a resource like (Cruz, J. S. Gould, Alexander, et al. 2015). Basic physical knowledge and constraints such as fire not spreading in water is obviously also incorporated.

Fire characteristic solvers require an analogous set of inputs, including situational features that are consistent over a fire simulation such as topography and vegetation (with associated rates-of-spread). Other inputs, particularly related to meteorology can vary spatially and also temporally over the course of the fire. These include things such as wind-speed and direction inputs for different locations; temperature; relative humidity; drought estimates; fire danger estimates; and similar as needed.

We note that our list is not exhaustive of all inputs, particularly across different vegetation types. It merely provides an overview of some of the core types of spatial and spatio-temporal features that are used as inputs to the rate-of-spread and similar formulae that are used to inform fire characteristic solvers.

Collectively, such inputs that inform dynamics of our physical fire characteristic models are used as a basis for fire simulations at a start location. These solvers then create outputs such as arrival time maps. By selecting an arrival time, t, a characteristic fire perimeter, or active front at time t can be drawn. An example of arrival times taken from a set of Spark outputs is shown in Figure 1. This figure highlights the progression of a fire from its starting location (middle west, yellow) and progressing to the north east over the duration of the simulation and ending with the more recently burnt areas shown in purple.

Emulated Fire-Front

We propose an emulator of Spark, which creates spatial-temporal output of fire arrival times based on approximating the underpinning physics knowledge from Spark into the emulation system using machine learning. The emulator *learns* what a fire should look like based on the training data it is given. In this case, the training data comes from Spark simulation runs, but other training data could be created or sourced in future work and added to the library for training.

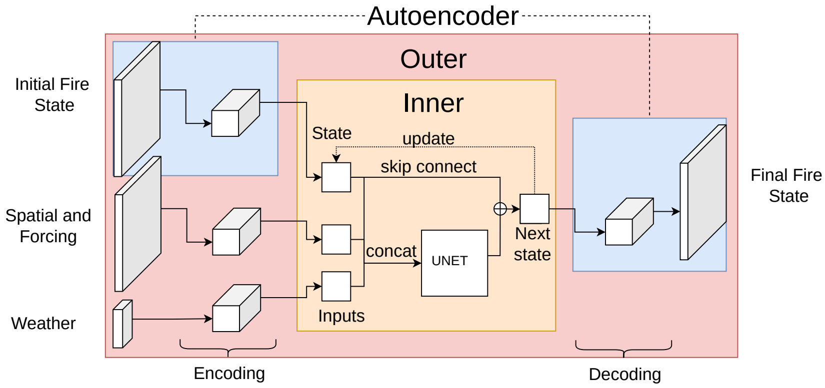

Figure 2. Overview of the emulator structure, highlighting the inner and outer components of the architecture that contributes to speedup of the emulated approach.

The basic structure of the emulator is visualized in Figure 2. This diagram shows two core learning steps termed the *outer* and *inner* components. The outer components comprise an *autoencoder* which encapsulates two key steps. First, it encodes input data into a lower dimensional latent (compressed) space. This is done to all of the inputs, including both explanatory variables, as well as fire arrival information taken from Spark outputs. It is this compression of information that can provide part of the computational speedup relative to the initial model. Balancing the encoding step is the decoding step. The purpose of the decoding step is to re-create an image in the same context and dimensionality as the original image. In this case, as our output of interest is the emulated fire arrival times, weather and spatial forcings are not decoded, just information about the final fire state.

The actual dynamics of fire are *learnt* in the inner portion of the emulator structure. This means that learning is taking place in the lower dimensional latent space. While not interpretable at a landscape-scale the way progression in Spark can be, this representation of fire dynamics is highly efficient and a source of speedup relative to the original model. Once learning/training is completed, the emulator can be used to create fast emulated fire results that can be interpreted in original spatial fire arrival time context once it is has been decoded. Further information about the neural net structure of the emulator can be found in (Bolt et al. 2022).

A comparison of an emulated fire-front taken at the end of a burn period, and a Spark fire-front simulated over the same time period is shown in Figure 3. Both methods for generating a fire- front give similar results, despite their different computational approaches. Additionally, the emulator has been able to learn and reproduce anticipated physical fire behaviours such as not burning through water bodies, fire fingering and capturing changes in spread rate as vegetation types change in the landscape.

Current work-in-progress for the emulator includes incorporating uncertainty into emulated outputs. We have considered two potential directions to achieve this. In early attempts, we have added variability to wind inputs to understand ways to visualize the output uncertainty for decision makers. This opportunity to create and demonstrate fast probabilistic emulations of fire-fronts through time will enable new uses for fire-front spread estimation that can be explored.

An Affordance Framework Applied To Fire-Front Emulators

All technologies enable and constrain in different ways, based on inbuilt features and how those features deploy in context. The opportunities and constraints of a technology are often referred to as ’affordances’–or how the features of a technology affect what we can do with it. (Davis and Chouinard 2016) and more recently, (Davis 2020) introduce the mechanisms and conditions framework of affordances, a design framework by which artefacts *request, demand, encourage, discourage, refuse and allow* certain outcomes. This framework can be applied to any technology as a way to examine and articulate how that technology operates in context. It is especially useful for grounding and organizing AI technologies with complex features, and for comparing technological systems to each other, as features and outcomes are mapped to a shared vocabulary (i.e., *request, demand, encourage, discourage, refuse, and allow*).

The mechanisms and conditions framework can thus productively apply to the wildfire emulator described above in order to explain its value vis-a-vis traditional predictive models. This clear articulation is vital, as uptake will require trust in the emulator system and understanding of the emulator’s relative benefits. Specifically, we can discuss emulator trade-offs and explore the relationship between emulators and the models they emulate to understand the

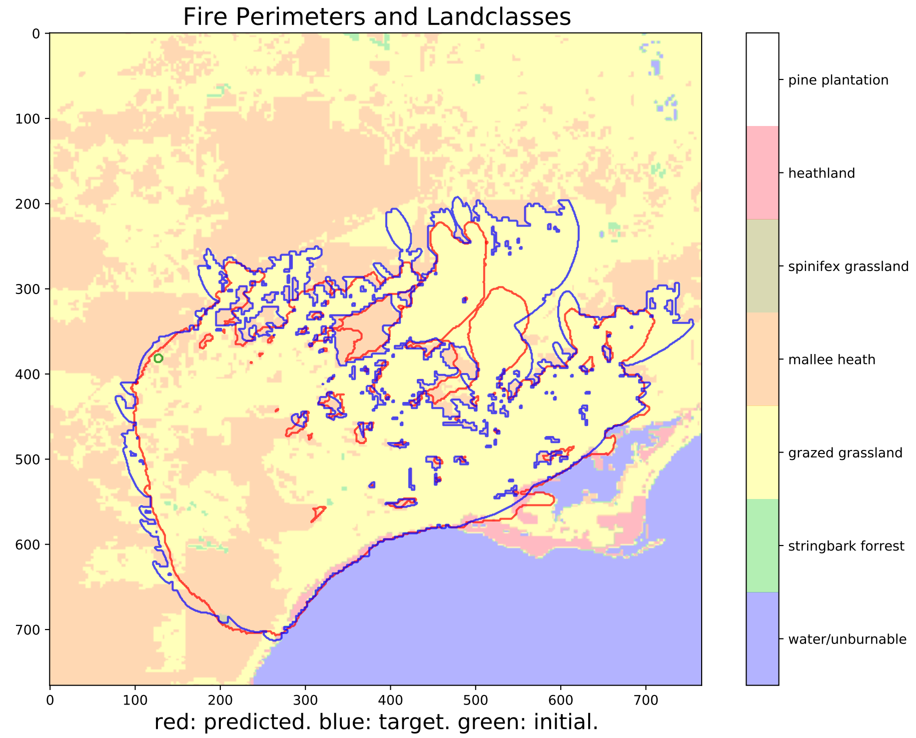

Figure 3. Comparison of Spark arrival time band (active fire-front) and emulator arrival time band at same simulated time point. Background is vegetation type which clearly impacts fire spread in both models. There are overall shape similarities between the Spark dynamic model and emulated results.

uses and benefits in certain types of situations. For example, the emulator *encourages* speed, operating system (OS) interoperability, and broad application, whereas the original wildfire model it was built on may be slower, *discourage* OS interoperability, and *demand* specific hardware and software. Of note, the emulator is not a replacement for the original model, but a supplement to it, such that trust in and reliance on the original model is a prerequisite, or *demand*, of a successful emulation. In short, this mechanisms and conditions framework helps clarify the utility of an emulator in the context of the original model and has the potential to bolster trust in the emulated version by showing its fidelity to the original model.

If emulators are embedded within a decision framework, this tech encourages optimal decision-making and allows more confident decisions to be made. This is particularly true where it is desirable to reflect uncertainty in outputs. This requires a faster, more efficient alternative to the original model as this decision framework demands flexibility and speed. In the context of the original model, they simply refuse or discourage the ability to connect with decisions and incorporate uncertainty in a timely or computationally feasible fashion and this may become unattractive to the decision-maker that wants decisions now.

EXPLORING DECISION-MAKING FOR WILDFIRES

There are many time scales to decisions that can be informed using results from fire-characteristic solvers like Spark or Phoenix Rapidfire, and, increasingly, by emulators like ours. The time scale and spatial scales of these decisions can vary depending on the application. For example, operational decisions are ones that are taken during the course of a fire. These can include firefighting suppression efforts, or decisions to evacuate suburbs or other communities.

Planning level decisions can occur well before a fire is experienced. Examples might include using simulations to understand potential financial consequence of fires to support better budget estimates and targeting of relief programs. Utility companies, who can be both causes and victims of wildfires, can use simulations to inform network planning for both preventative and protective actions.

Depending on the motivating problem, there are many complexities related to the decision making that can be supported with tools such a fire characteristic models, and emulators developed from them. Our work-in-progress emulator is at a point where it is a successful proof-of-concept around how, and that, fire characteristic models *can* be emulated relatively successfully. At this point we are exploring how to fine tune results of the current emulator

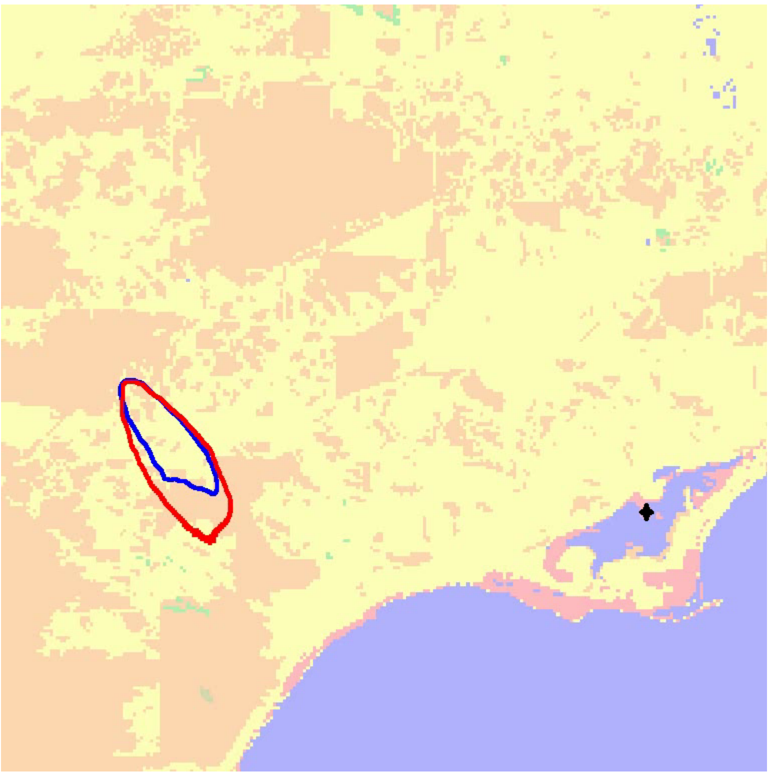

Figure 4. Early mapping of the fire threatening the holiday home (marked in black four-pointed star). Blue is Spark and red is emulator. Wind is traveling in a southerly direction.

and we are developing an extension that will allow results that better incorporate and report on uncertainty. There is a goal to make the emulator as useful a tool as it can be before either the single perimeter or uncertainty enabled versions are released for operational and planning purposes.

To facilitate thought and discussion around how our emulator, and its proposed uncertainty extensions will *afford* certain types of decisions, we explore emulated and original outputs using a simple motivating problem. While a relatively simple schema, we believe such an example can illustrate key decision processes and allow more complete understanding and articulation of some of the complexities related to decision making in a principled way.

For context, we posit that the reader has made a decision to go on an Australian beach vacation. The weather is balmy, and the forecast is for blue skies and no rain. After a few relaxing days, a bushfire starts nearby. The wind is coming from the north, and the most recent emergency prediction of the fire perimeter is as shown in Figure 4. There is a meteorology forecast that suggests the winds will change to a more westerly origin at some point in the next 12 hours. You, the holidaymaker, need to make a decision around whether to continue to enjoy your holiday, or whether to evacuate the area.

For the sake of simplicity when writing this paper, assume that you, the holiday maker have decided to stay in your beach house awaiting further information. The fire then progresses over the next 12 hours similar to what is shown in Figure 5.

Luckily the beach house you are sheltered in has not been directly impacted by the fire. We note that the location is currently cut off due to active fire front, and the holiday home could be at risk if there are further wind changes in the near future.

To understand the impact of incorporating uncertainty into decision making information, imagine the same scenario as above. However, instead of having one or two predicted fire perimeters on which to make a decision, there are a multitude. We create a toy set of emulations of this scenario in Figure 6. Here, the different emulated perimeters use the same base weather scenario, but small step changes in wind direction and wind-speed at each time point are introduced to loosely mimic uncertainty in real-world conditions.

Fortunately, the decision to shelter was fortuitous in that the beach house location was not directly impacted by fire in any of the simulations. Imagine an alternate scenario though, where evacuation was chosen rather than sheltering at the house. Would the optimal/preferred evacuation pathway individuals chose be impacted by more

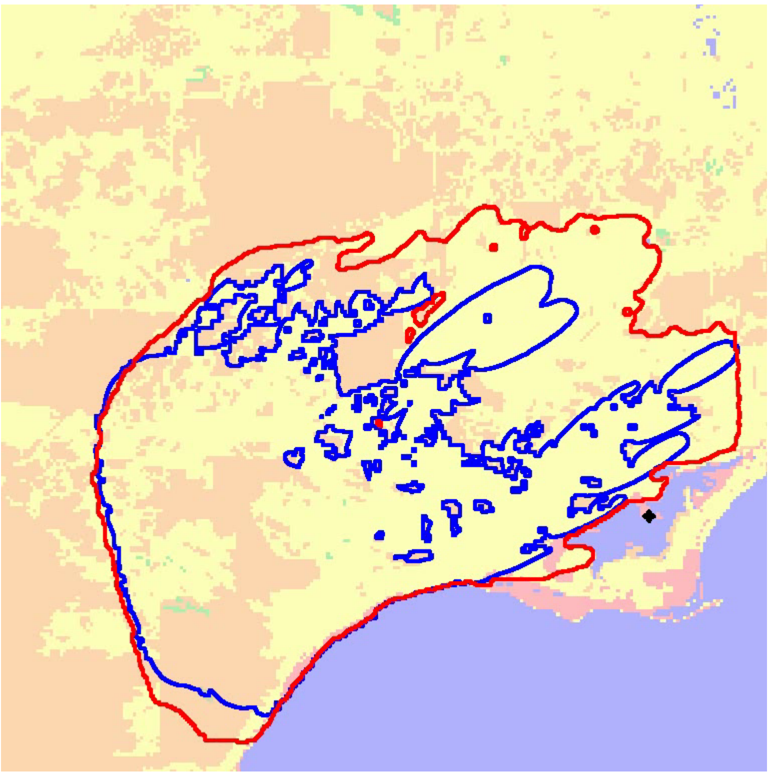

Figure 5. Final fire-front at midnight. Blue is Spark and red is emulator. Note that wind has changed to be a westerly, pushing the fire to the east. Beach house area is referenced by a black four-pointed star.

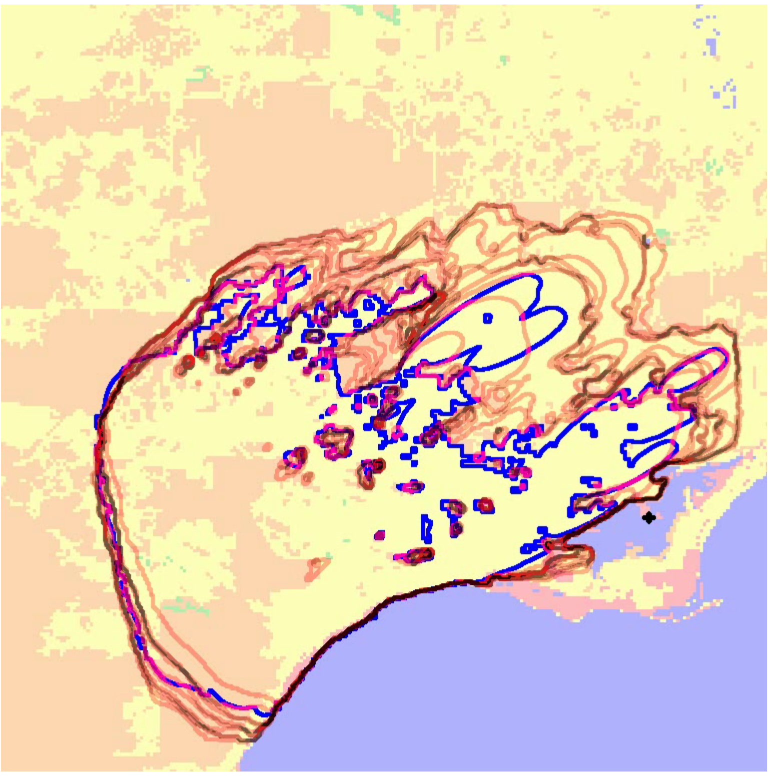

Figure 6. Ensemble emulator results with small uncertainty in wind and wind direction introduced. Blue is original Spark, various shades of translucent red are various emulated fires. The black four pointed star represents the location of the holiday beach-house.

information about potential uncertainty in the fire progression? Beyond being a holidaymaker who needs to shelter or escape, what other operational and planning decisions would/could be affected by what can be intuited from multiple emulated fire fronts instead of just one? In other words, what new types of decisions have been *afforded* by including uncertainty in our fireline reporting?

Meaningful discussions with emergency and hazard planning and response expertise would provide the best insight into how the different types of results (fire characteristic, single emulation, emulated uncertain ensemble) request, demand, encourage, discourage, refuse and allow certain decisions and uses. This is especially relevant because our Spark emulator is still in a developmental process. Now is the opportune time to have multiple structured and collaborative conversations about how the emulator could be used, considering viewpoints from many relevant decision making contexts. . On one hand, this creates opportunity to discuss and learn which emulator features and affordances are most useful in different decision making contexts. Having collaborative discussions with decision-makers who could be supported by the technology will also create a richer picture of the potential affordances provided by Spark and emulated versions of it. It can also lead to better trust and understanding of outputs from emulators and their advantages and disadvantages relative to the original Spark model.

CONCLUSION

In the broader context of climate change, risk and damages from natural hazards such as wildfires are increasing. Currently, there are a number of well established computational fire characteristic behaviour tools that embed physical and scientific knowledge about fire spread, such as fire-front rate-of-spread equations. Given the escalating risk of such events, we have built a prototype emulator of the Spark fire-front solver as an additional tool that can be used to explore potential fire consequence scenarios. A particular goal currently being progressed in the research and development of the emulator is more natural handling and reporting on potential uncertainty in fire-fronts at a given time.

Beyond establishment of the tool itself, we recognise the importance of conducting research to improve the uptake and understanding of the fundamental technology. This can involve a give and take in terms of understanding both what new types of decision emulation might afford, and how the emulator and its reporting can take feedback such that it permits desired interfaces and decisions. This is discussed in the context of the language of an affordance framework for AI as a structured path to facilitating this dialog between potential end-users and decision makers and AI and algorithm developers. To illustrate some of the affordances provided by the uncertainty being developed for the fire-front emulator, a simple example is discussed. Particular questions around how uncertainty might afford different decisions than one or two fire perimeter predictions were posed. We posit that facilitating such discussions with a shared affordance language and framework is an integral step to developing trusted AI systems for operational usage.

REFERENCES

Anderson, W. R., Cruz, M. G., Fernandes, P. M., McCaw, L., Vega, J. A., Bradstock, R. A., Fogarty, L., Gould, J., McCarthy, G., Marsden-Smedley, J. B., et al. (2015). "A generic, empirical-based model for predicting rate of fire spread in shrublands". In: *International Journal of Wildland Fire* 24.4, pp. 443–460.

Begg, D. C., Dwyer, D. G., Neale, D. T., and Pollock, D. I. (2021). *Established and emerging uses of predictive services in Victoria*.

Bolt, A., Dabrowski, J. J., Huston, C., and Kuhnert, P. (2022). *An Emulation Framework for Fire Front Spread*.

Burrows, N., Ward, B., Robinson, A., et al. (2009). "Fuel dynamics and fire spread in spinifex grasslands of the Western Desert". In: *Proceedings of the Royal Society of Queensland, The* 115, p. 69.

Canadell, J. G., Meyer, C., Cook, G. D., Dowdy, A., Briggs, P. R., Knauer, J., Pepler, A., and Haverd, V. (2021). "Multi-decadal increase of forest burned area in Australia is linked to climate change". In: *Nature communications* 12.1, pp. 1–11.

Cheney, N., Gould, J., and Catchpole, W. R. (1998). "Prediction of fire spread in grasslands". In: *International Journal of Wildland Fire* 8.1, pp. 1–13.

Cruz, M. G., Gould, J. S., Alexander, M. E., Sullivan, A. L., McCaw, W. L., and Matthews, S. (2015). *A guide to rate of fire spread models for Australian vegetation*. Australasian Fire et al.

Cruz, M. G., Gould, J. S., Kidnie, S., Bessell, R., Nichols, D., and Slijepcevic, A. (2015). "Effects of curing on grassfires: II. Effect of grass senescence on the rate of fire spread". In: *International Journal of Wildland Fire* 24.6, pp. 838–848.

Davis, J. (2020). *How artifacts afford: The power and politics of everyday things*. MIT Press.

Davis, J. and Chouinard, J. (2016). “Theorizing affordances: From request to refuse.” In: *Bulletin of science, technology and society* 36.4, pp. 241–248.

Dickman, C. (2020). “More than one billion animals killed in Australian bushfires”. In: *The University of Sydney News*.

Dockrill, P. (2019). “Fires in Australia just pushed Sydney’s air quality 12 times above hazardous levels”. In: *ScienceAlert*.

Dunstall, S., Huston, C., Towns, G., and Stephenson, A. (May 2017). *PBSP Risk Reduction Model — Mathematics and Computation*. Tech. rep. CSIRO Data61.

Dunstall, S., Towns, G., Huston, C., and Stephenson, A. (May 2017). *PBSP Risk Reduction Model — Overview and Technical Details*. Tech. rep. Victorian Government and CSIRO Data61.

Gibbs, L., Molyneaux, R., Gallagher, H., Block, K., Richardson, J., Brandenburg, V., O’Donnell, M., Kellett, C., Quinn, P., Kosta, L., et al. (2020). *10 Years Beyond Bushfires Report 2020*. Tech. rep. University of Melbourne.

Gibbs, L. (2021). “More than a decade after Black Saturday fires, it’s time we got serious about longterm disaster recovery planning”. In: *The Conversation*.

Gramling, C. (2021). “Australian fires in 2019-2020 had even more global reach than previously thought”. In: *ScienceNews*.

Griffiths, D. (1999). “Improved Formula for the Drought Factor in McArthur’s Forest Fire Danger Meter”. In: *J. Australian Forestry* 62.2, pp. 202–206.

IGNIS (2019). *PROJECT IGNIS - Quantifying Catastrophic Bushfires milestone 2 close-off report*.

IGNIS (2021a). *Collaborating with the energy sector to protect communities*.

IGNIS (2021b). *Quantifying catastrophic bushfire consequence*.

Keetch, J. J. and Byram, G. M. (1968). *A Drought Index for Forest Fire Control*. Tech. rep. Research Paper SE-38, Asheville, NC. U.S. Department of Agriculture, Forest Service, Southeastern Forest Experiment Station.

Ladds, M., Keating, A., Handmer, J., and Magee, L. (2017). “How much do disasters cost? A comparison of disaster cost estimates in Australia”. In: *International Journal of Disaster Risk Reduction* 21, pp. 419–429.

McArthur, A. G. (1967). “Fire behaviour in eucalypt forests”. In.

Miller, C., Hilton, J., Sullivan, A., and Prakash, M. (2015). “SPARK – A Bushfire Spread Prediction Tool”. In: *Environmental Software Systems. Infrastructures, Services and Applications*. Ed. by R. Denzer, R. M. Argent, G. Schimak, and J. Hřebíček. Cham: Springer International Publishing, pp. 262–271.

Neale, T., Vergani, M., Begg, C., Kilinc, M., Wouters, M., and Harris, S. (2021). “’Any prediction is better than none’? A study of the perceptions of fire behaviour analysis users in Australia”. In: *International Journal of Wildland Fire* 30.12, pp. 946–953.

Noble, I. R., Gill, A. M., and Bary, G. A. V. (1980). “McArthur’s fire-danger meters expressed as equations”. In: *Austral Ecology* 5.2, pp. 201–203.

Owen, C. (2018). “How emergency services organisations can – and do – utilise research”. In: *Australian Journal of Emergency Management* 33.2, pp. 28–33.

Readfearn, G. (2020a). “Canberra experiences worst air quality on record as bushfire smoke from south coast sets in”. In: *Guardian Australia*.

Readfearn, G. (2020b). “Silent death: Australia’s bushfires push countless species to extinction”. In: *Guardian Australia*.

Rothermel, R. C. (1972). “A mathematical model for predicting fire spread in wildland fuels”. In: *Res. Pap. INT-115. Ogden, UT: US Department of Agriculture, Intermountain Forest and Range Experiment Station. 40 p.* 115.

SA Power Networks (2019). *Bushfire mitigation program CBA methodology*.

SBS (2020). “The numbers behind Australia’s catastrophic bushfire season”. In: *SBS News*.

Sharples, J. J. (2008). “Review of formal methodologies for wind–slope correction of wildfire rate of spread”. In: *International Journal of Wildland Fire* 17.2, pp. 179–193.

Sullivan, A. L., Sharples, J., Matthews, S., and Plucinski, M. P. (2014). “A downslope fire spread correction factor based on landscape-scale fire behaviour”. In: *Environmental modelling & software* 62, pp. 153–163.

Tolhurst, K., Duff, T., and Chong, D. (Jan. 2012). *PHOENIX Rapidfire: Under the Hood. Unpublished Guide*.

Whittaker, J., Eriksen, C., and Haynes, K. (2015). "More men die in bushfires: how gender affects how we plan and respond". In: *The Conversation*.

Williamson, B. and Quinn, P. (2021). "Unwelcoming and reluctant to help: bushfire recovery hasn't considered Aboriginal culture, but things are finally starting to change". In: *The Conversation*.

Wittwer, G., Li, K., and Yang, S. (2021). "The impact of the 2019-20 bushfires on Victoria". In: *Victoria's economic bulletin* 5.