A Spatiotemporal Recommendation Engine for RxFire in the Southeast US

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- The RxFire recommendation engine
  - Statistical aspects of the model
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Climate change projected to reduce prescribed burning opportunities in the south-eastern United States

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Abstract. Prescribed burning is a critical tool for managing wildfire risks and meeting ecological objectives, but its safe and effective application requires that specific meteorological criteria (a 'burn window') are met. Here, we evaluate the potential impacts of projected climatic change on prescribed burning in the south-eastern United States by applying a set of burn window criteria that capture temperature, relative humidity and wind speed to projections from an ensemble of Global Climate Models under two greenhouse gas emission scenarios. Regionally, the percentage of suitable days for burning changes little during winter but decreases substantially in summer owing to rising temperatures by the end of the 21st century compared with historical conditions. Management implications of such changes for six representative land management units include seasonal shifts in burning opportunities from summer to cool-season months, but with considerable regional variation. We contend that the practical constraints of rising temperatures on prescribed fire activities represent a significant future challenge and show that even meeting basic burn criteria (as defined today) will become increasingly difficult over time, which speaks to the need for adaptive management strategies to prepare for such changes.

Additional keywords: coastal plain, piedmont, managed fire regimes, statistical downscaling, wildfire.

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Robust projections of future fire probability for the conterminous United States

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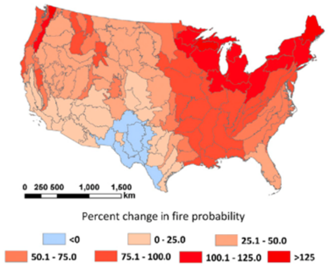
HIGHLIGHTS

- PC2FM is used to project shifts in 21st century fire regimes due to climate change.
- Fire probability is predicted to increase across the conterminous US.
- Increasing temperatures primarily account for projected rising fire probabilities.
- Pyrome analogs illustrate uncertainty in projections of future fire probability.
- PC2FM provides a useful compromise between empirical and processed-based fire models.

GRAPHICAL ABSTRACT



Projected changes (%) in annual fire probability from baseline (1971-2000) to late century (2070-2099) based on Greenhouse Gas Emissions Scenario RCP 8.5.

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ABSTRACT

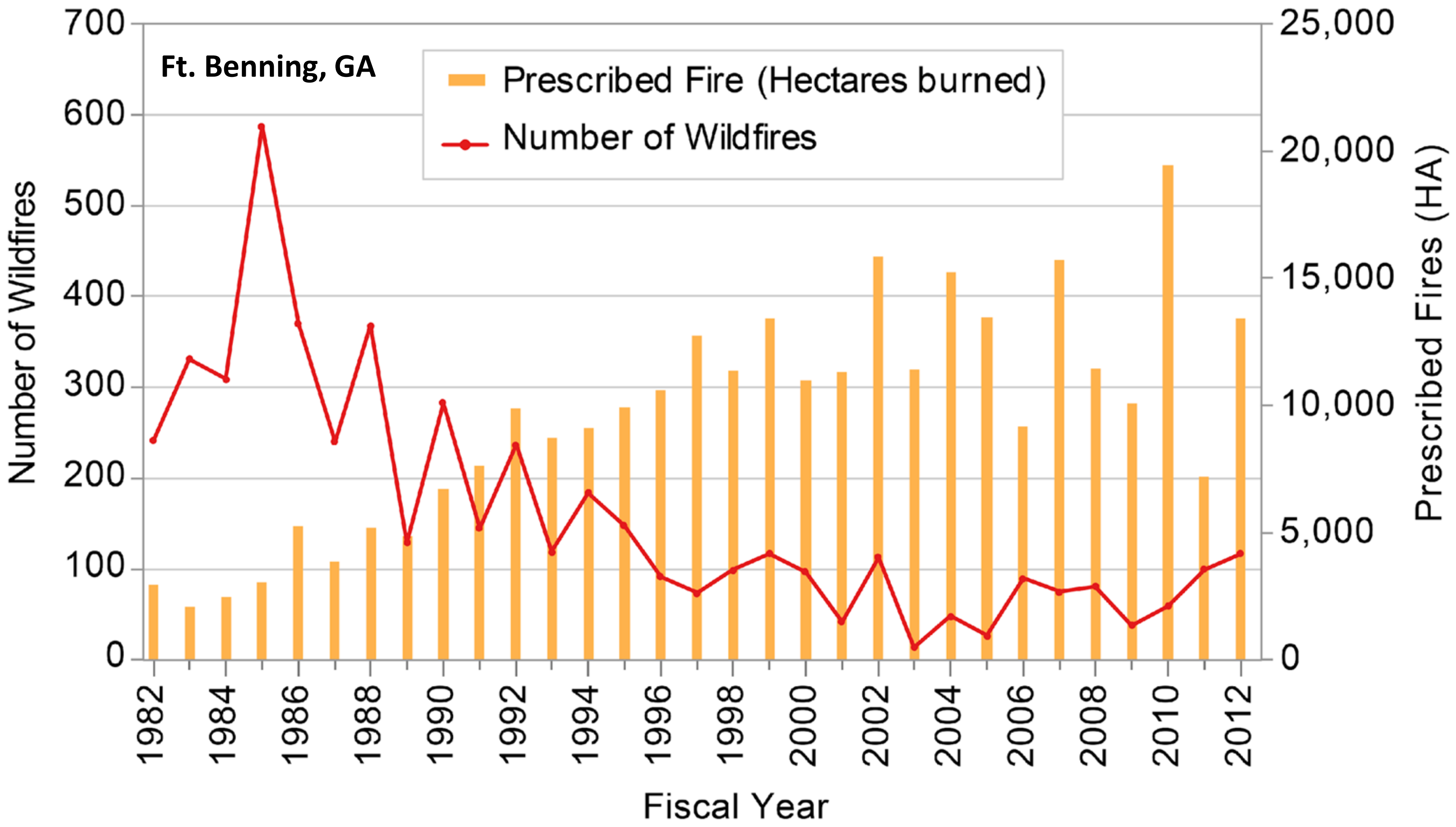
Globally increasing wildfires have been attributed to anthropogenic climate change. However, providing decision makers with a clear understanding of how future planetary warming could affect fire regimes is complicated by confounding land use factors that influence wildfire and by uncertainty associated with model simulations of climate change. We use an ensemble of statistically downscaled Global Climate Models in combination with the Physical Chemistry Fire Frequency Model (PC2FM) to project changing potential fire probabilities in the conterminous United States for two scenarios representing lower (RCP 4.5) and higher (RCP 8.5) greenhouse gas emission futures. PC2FM is a physically-based and scale-independent model that predicts mean fire return intervals from both fire reactant and reaction variables, which are largely dependent on a locale's climate. Our results overwhelmingly depict increasing potential fire probabilities across the conterminous US for both climate scenarios. The primary mechanism for the projected increases is rising temperatures, reflecting changes in the chemical reaction environment commensurate with enhanced photosynthetic rates and available thermal molecular energy. Existing high risk areas, such as the Cascade Range and the Coastal California Mountains, are projected to experience greater annual fire occurrence probabilities, with relative increases of 122% and 67%, respectively, under RCP 8.5 compared to increases of 63% and 38% under RCP 4.5. Regions not currently associated with frequently

Prescribed Fire is a Critical Management Tool in the Southeast

More acres intentionally burned per year in SE than in any other region

Two Primary Goals

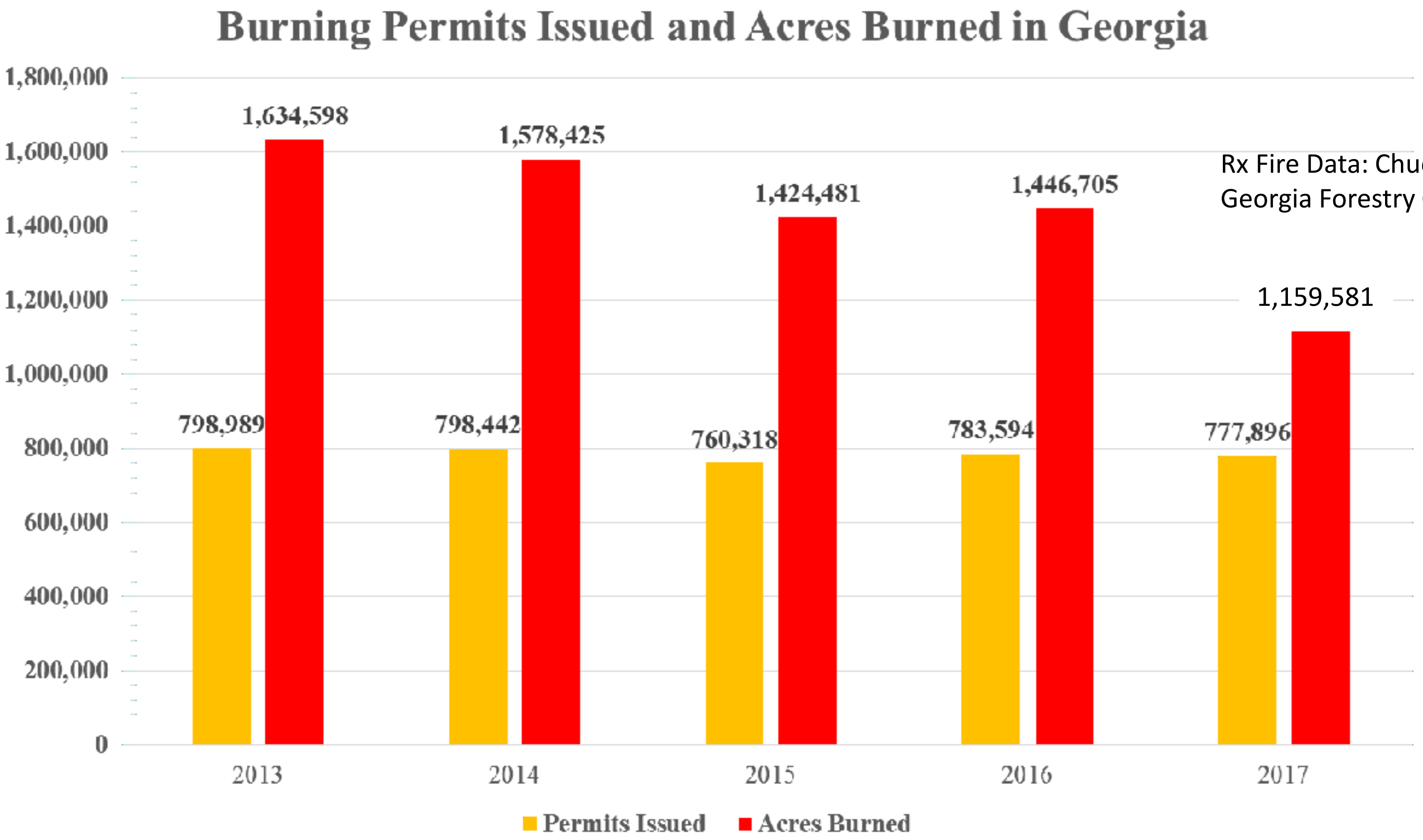
Habitat Management



Wildfire Risk Reduction

Figure 19.19 Carter et al. (2018)

Permitting and Acres Burned



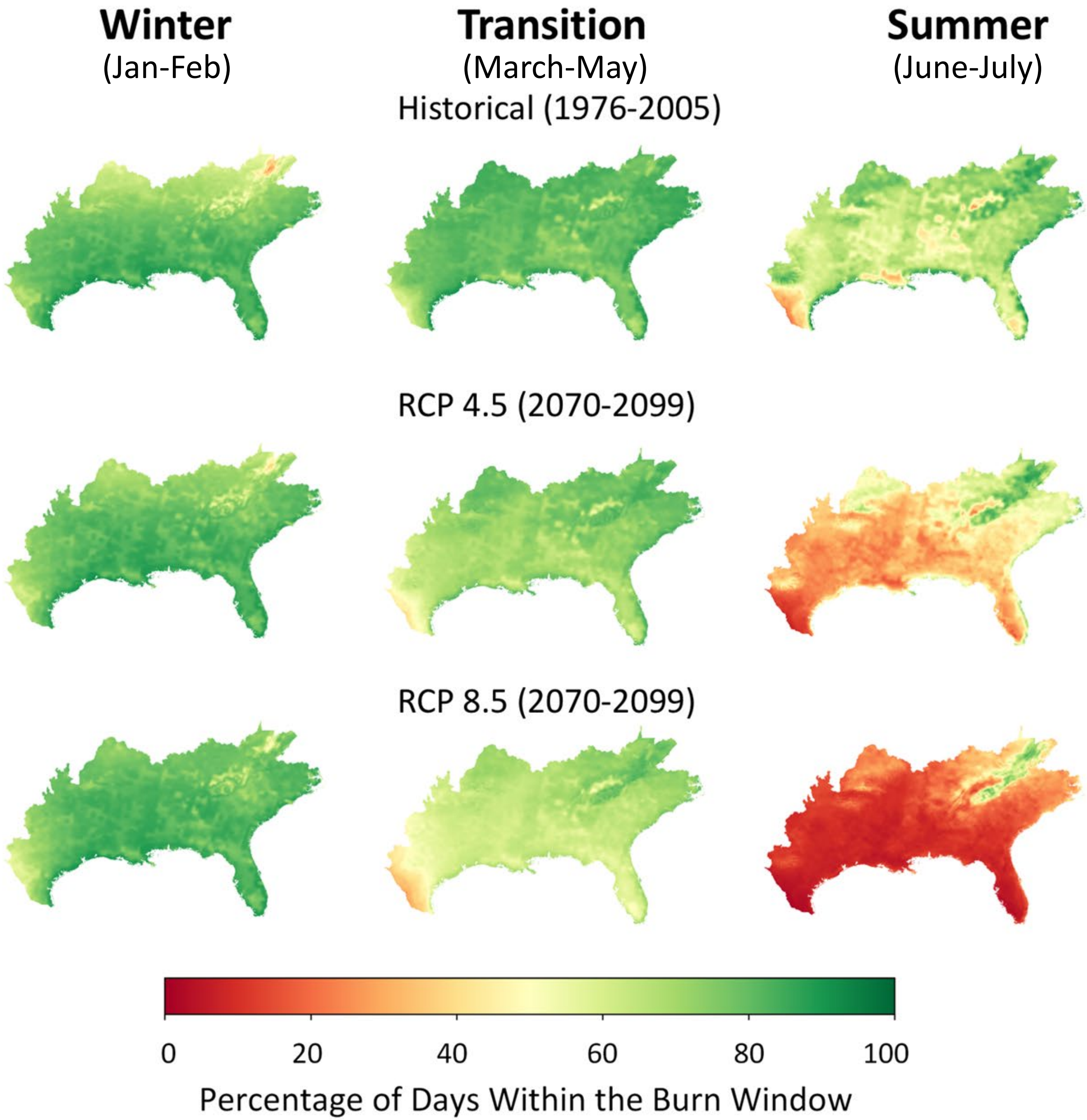
Rx Fire Data: Chuck Williams – Georgia Forestry Commission

Fire Management is sensitive to climate variability and change

How could projected changes in climate affect prescribed burning opportunities in the Southeast?

Literature-based meteorological criteria for burning

- Temperature 0-32.5^oC (32-90.5^oF)
- Relative Humidity > 30%
- Average Daily Wind Speed 2.25-8.0 m/s (~5-18 mph)


Winter
(Jan-Feb)
Transition
(March-May)
Summer
(June-July)
Historical (1976-2005)
RCP 4.5 (2070-2099)
RCP 8.5 (2070-2099)
0
20
40
60
80
100
Percentage of Days Within the Burn Window

Can prescribed fire managers adapt to a warming climate in a way that still allows them to accomplish their short-term, medium-term, and long-term objectives?

Project title: Development of an early warning system to identify changing prescribed burn opportunities across Southeast US fire-adapted habitats.

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Can prescribed fire managers adapt to a warming climate in a way that still allows them to accomplish their short-term, medium-term, and long-term objectives?

The RxFire recommendation engine

A statistical tool with two components:

1. Fail-state estimation model
2. Optimal allocation algorithm for burn parcels

The RxFire recommendation engine

- Goal: Given weather conditions and information on burn plots, give expected utility/parcel benefit of burning each parcel
- Identifies ‘best’ parcels to burn in a 3-day window
- Help the decision-making process by providing options with the highest likelihood of success

Literature-based meteorological criteria for burning

- Temperature 0-32.5^{o}C (32-90.5^{o}F)
- Relative Humidity > 30%
- Average Daily Wind Speed 2.25-8.0 m/s (~5-18 mph)
- We define a fail-state as the ‘probability that burn criteria are not met’.

Fail-State Estimation

- Input: 3-day weather forecasts from the National Weather Service (National Digital Forecast Database or NDFD)
- Output: calibrated forecasts with uncertainty estimates
- Model: Bayesian hierarchical model (BHM) that jointly estimates Tmax, Tmin, Relative humidity, windspeed, and precipitation.
- Benefits of the BHM:
  - Uncertainty estimates: *`The 2-day forecast of Tmax is 80, and according to the model, the observed Tmax has a 95% probability of being within 78-82.5'*
  - Joint model: The weather variables are correlated, and the BHM takes that into consideration

Fail state estimation

- Alongside estimates like:

'*The 2-day forecast of Tmax is 80, and according to the model, the observed Tmax has a 95% probability of being within 78 - 82.5*'

- We can also compute estimates like:

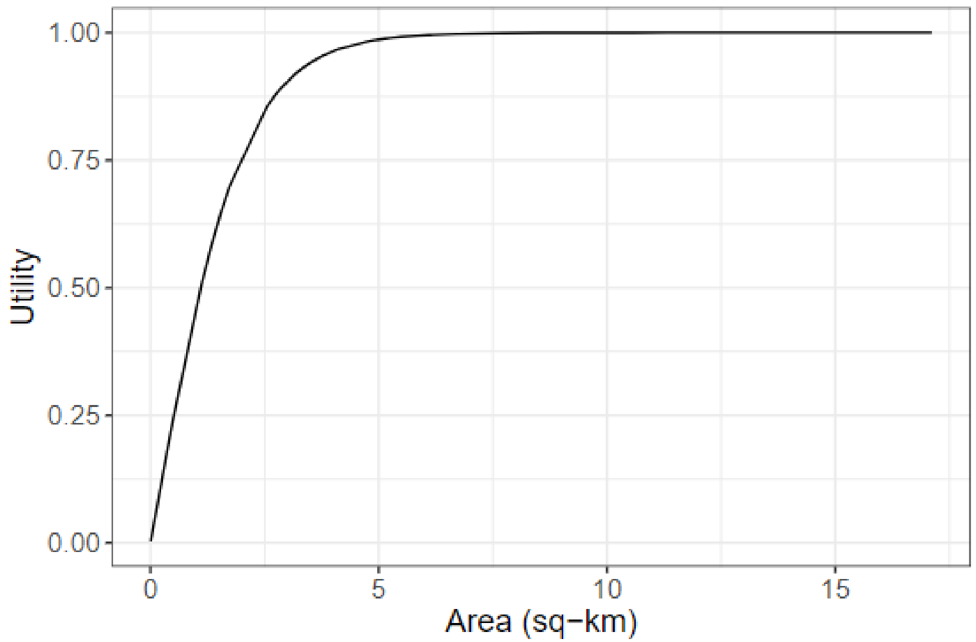
'*The 2-day forecast of Tmax is 80, and according to the model, the observed Tmax has a 99.3% probability of being < 90.5*' (i.e. within threshold),

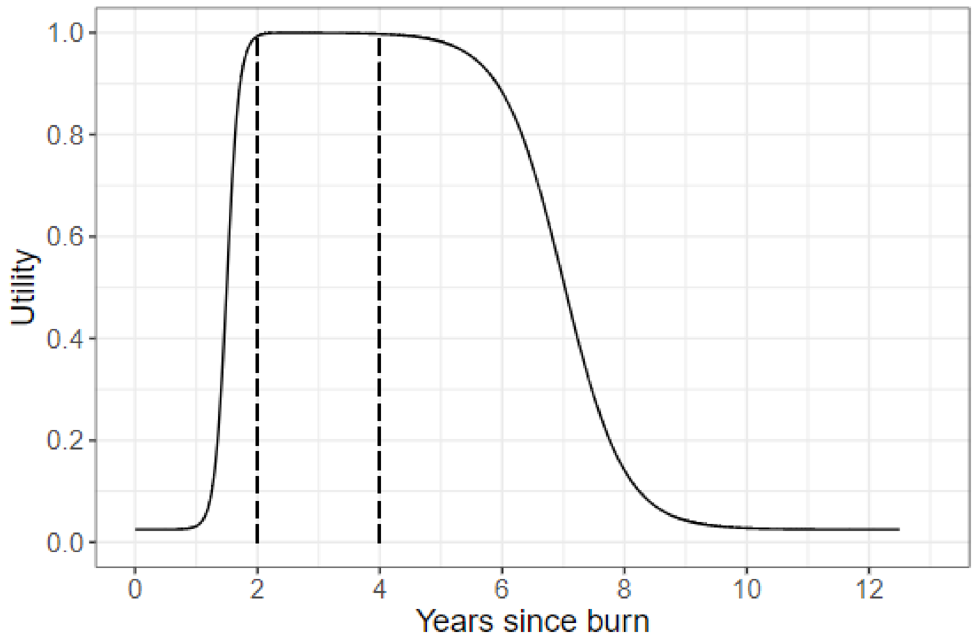
- and '*there is a 92.5% probability that all variables will be within threshold*'
- This way, we can essentially assign a burn viability score to every burn parcel based on 1-day, 2-day, and 3-day forecasts

Utility functions

What other things matter when scoring burn parcels?

- Area of the parcel
- Years since last burn





Utility function for years since burn

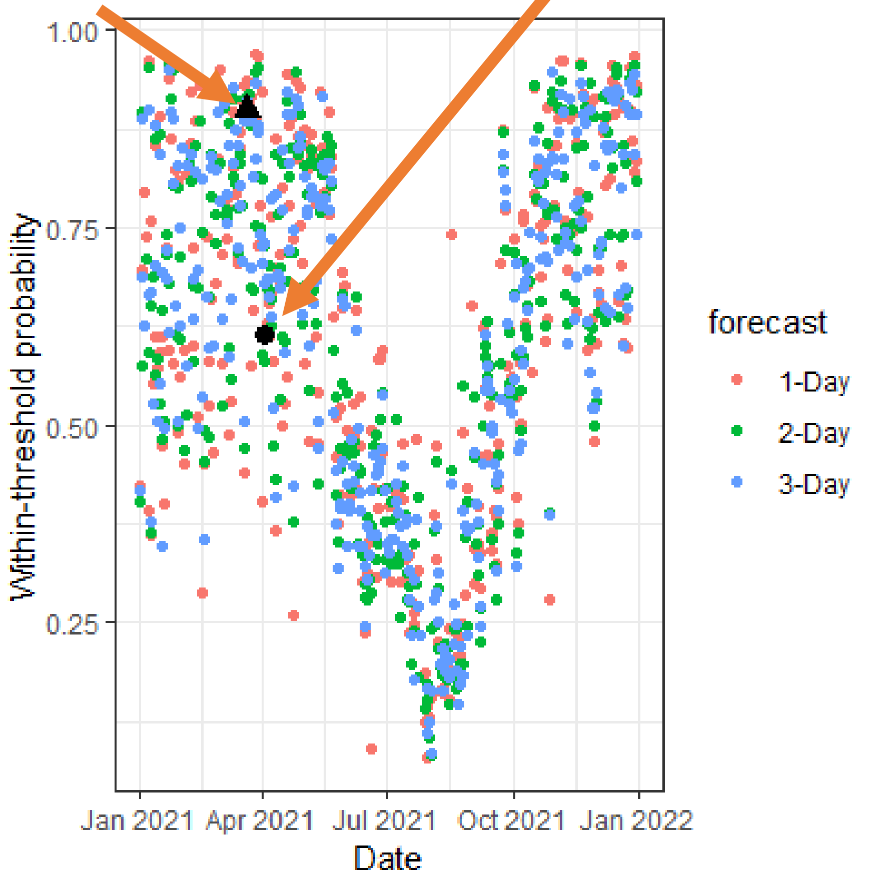
- Use a utility function to capture/quantify primary objectives
- Chose to use 'Years Since Burn' since it aggregates objectives related to habitat condition/quality, wildfire risk, and (potentially) efficacy/efficiency/cost
- Can also build spatial utility functions of interest including area, distance to the wildland urban interface, distance to nearby tracts etc.

Optimal allocation algorithm

- Inputs
  - List of burn tracts with locations and area
  - Weather forecasts for the region
- Assess probability of fail-states
- Determine utility functions for burn decisions
- Outputs
  - Probability of staying within prescription + expected utility of Rx burns at locations
  - Ranked list of locations with highest expected utility

When was the parcel actually burned?

What is the recommended day to burn?



Allocation algorithm example

- 3 locations, 3 days
- Say for plot 1:

Utility	Thresh prob	Area	Years since burn	Global
1-day	0.91	1	0.60	0.546
2-day	0.85	1	0.61	0.519
3-day	0.95	1	0.62	0.589

- $0.91 \times 1 \times 0.60 = 0.546$

- Now across all 3 plots, we have:

	1-day	2-day	3-day
Plot 1	0.546	0.519	0.589
Plot 2	0.613	0.600	0.615
Plot 3	0.309	0.442	0.600

- Which plot to burn on which day?
- Which combination of 3 values (one of each row) has the biggest sum?

Allocation algorithm example

Option A: Choose the largest value on day 1, then largest on day 2, and so on….

	1-day	2-day	3-day
Plot 1	0.546	**0.519**	0.589
Plot 2	**0.613**	0.600	0.615
Plot 3	0.309	0.442	**0.600**

Usually not the best option. In this case:

0.613 + 0.519 + 0.600 = 1.732

The Hungarian algorithm maximizes global utility

	1-day	2-day	3-day
Plot 1	**0.546**	0.519	0.589
Plot 2	0.613	**0.600**	0.615
Plot 3	0.309	0.442	**0.600**

In this case, the solution is:

0.546 + 0.600 + 0.600 = 1.746

Allocation algorithm example

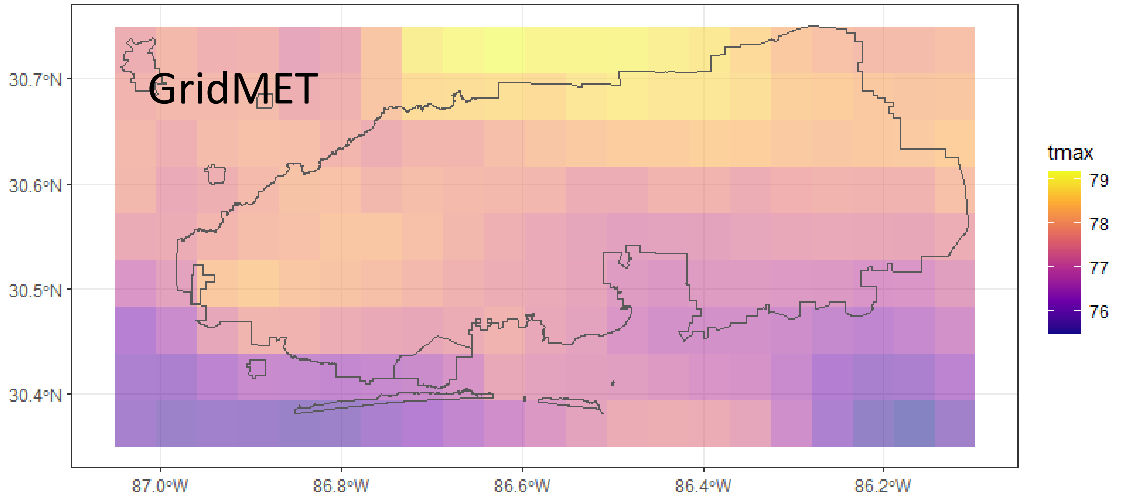
Utility	Thresh prob	Area	Years since burn	Global
1-day	0.91	1	0.60	0.546
2-day	0.85	1	0.61	0.519
3-day	0.95	1	0.62	0.589

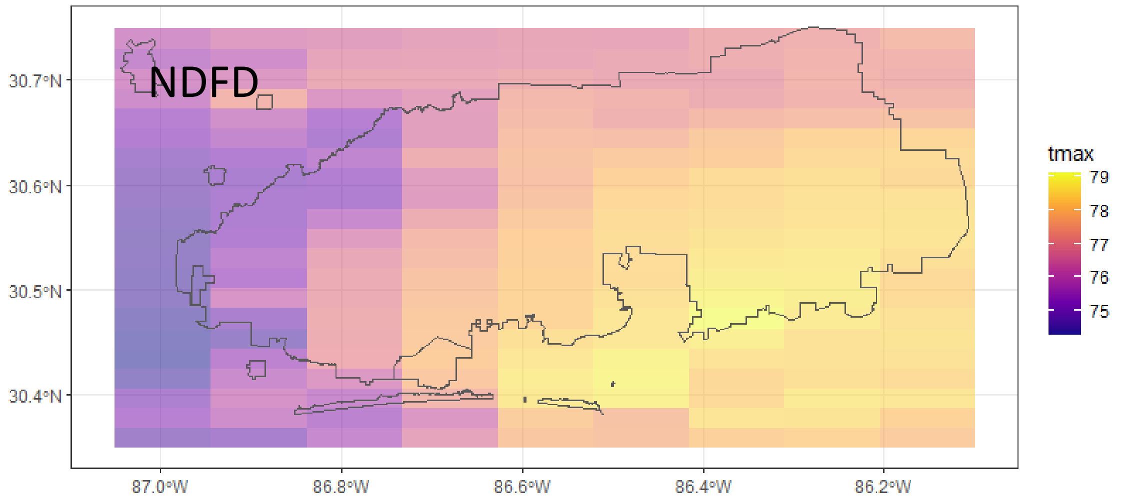
	1-day	2-day	3-day
Plot 1	0.546	0.519	0.589
Plot 2	0.613	0.600	0.615
Plot 3	0.309	0.442	0.600

- What if the burn manager decides that they will only consider plots which have a threshold probability of 90% or more? (i.e. < 10% chance of a fail state)
- Doesn't affect allocations, but it *could*
- For long periods, nothing will qualify for a burn
- The allocations happen over rolling 3-day windows
- Other, more nuanced decision making criteria considered in the tool

Eglin AFB Case study

- Detailed fire data available since the 1970s, including
  - Start and end dates
  - Shapefiles
  - Time since last burn
- 3-day weather forecast data from NDFD
- Observational weather data from GridMET (basis for downscaled climate model data for future phase of project)
- Model fitted for 2015-2020, validation and burn allocations for 2021.





Probability of being within prescription

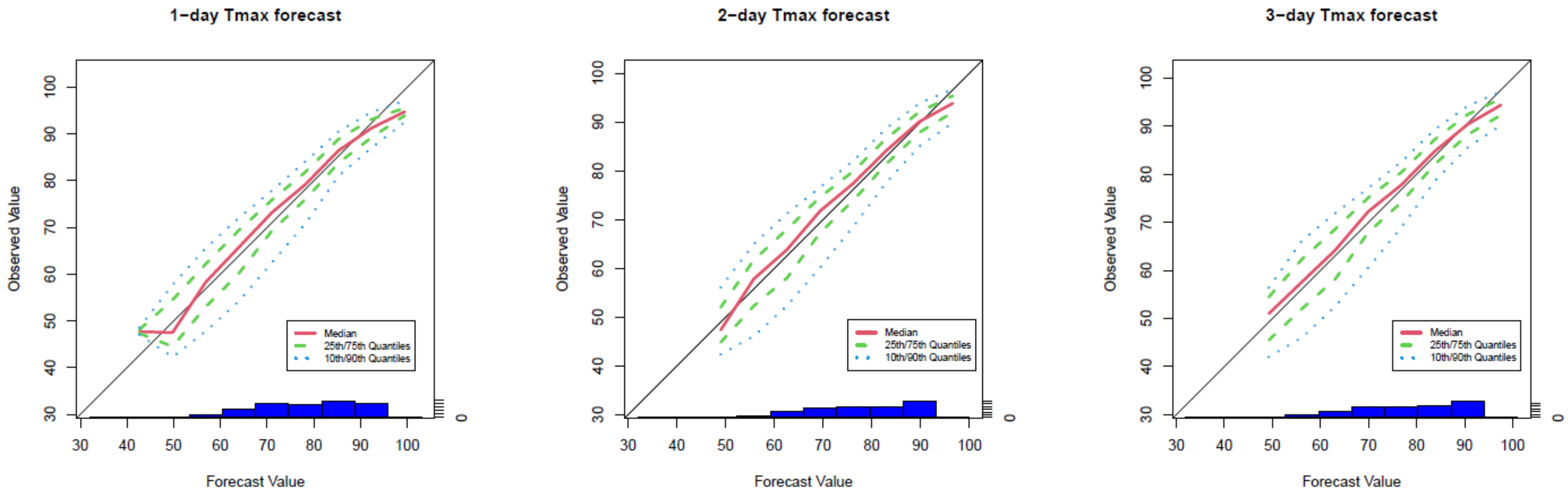
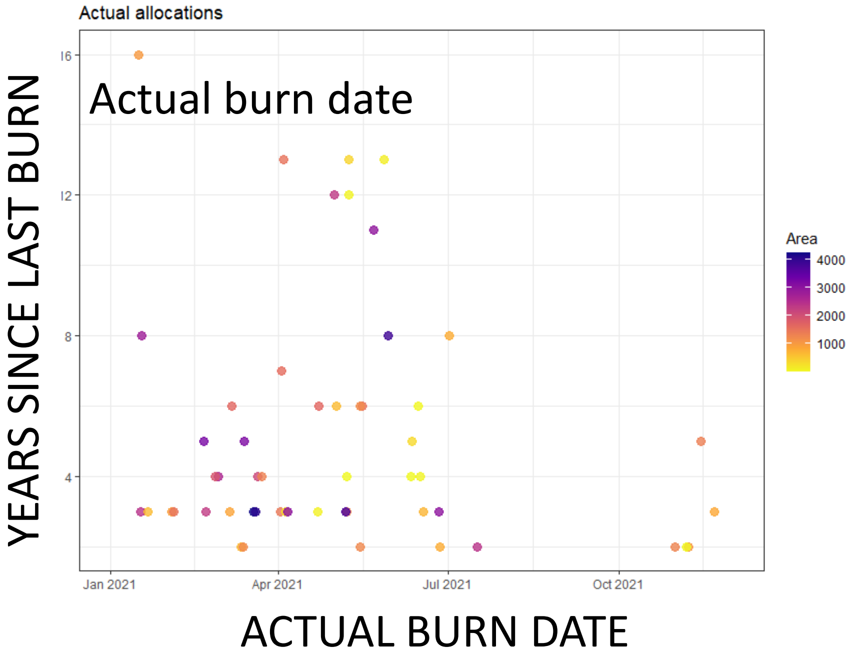


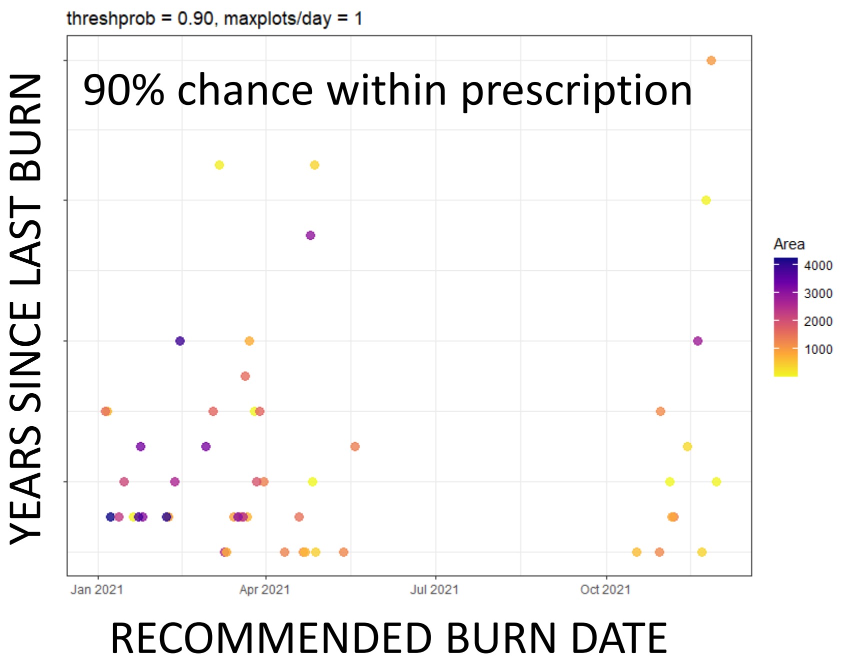
Figure 3: Forecast verification for 1, 2, and 3-day T_{max} predictions using CRPS, for data pooled across 88 locations.

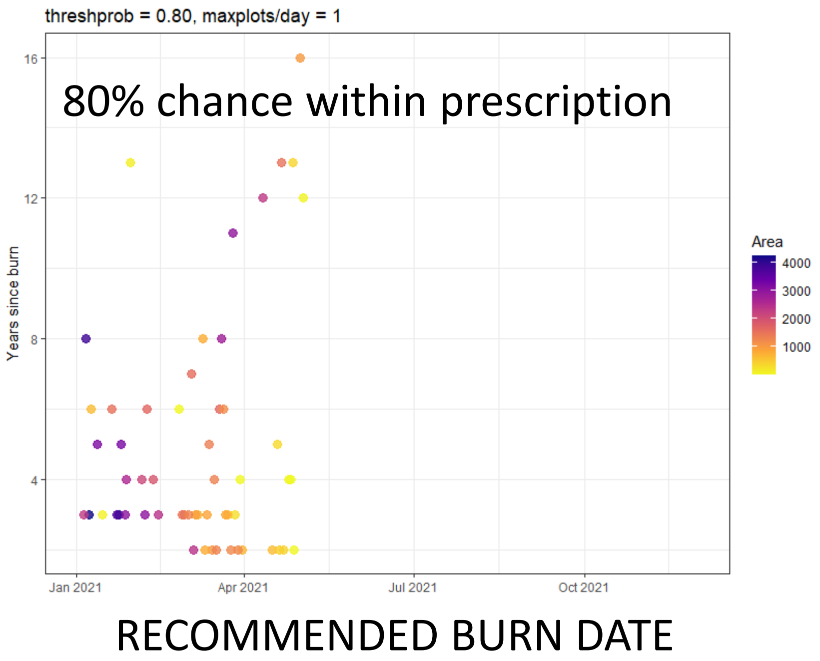
- Bayesian hierarchical model for joint forecast verification of prescription parameters
- Built-in uncertainty quantification



Total of 56 plots that were burned at Eglin AFB in 2021

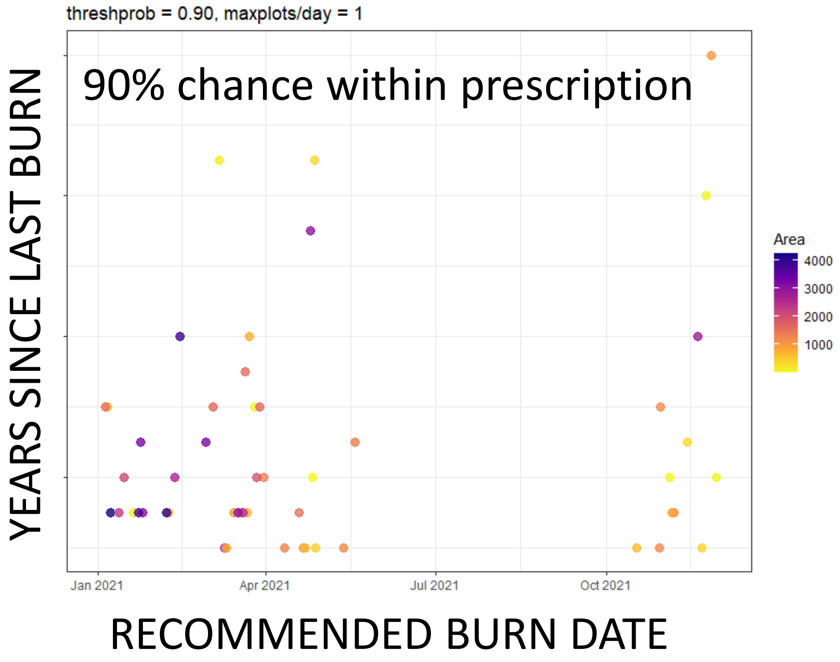
Example from 2021 burn season

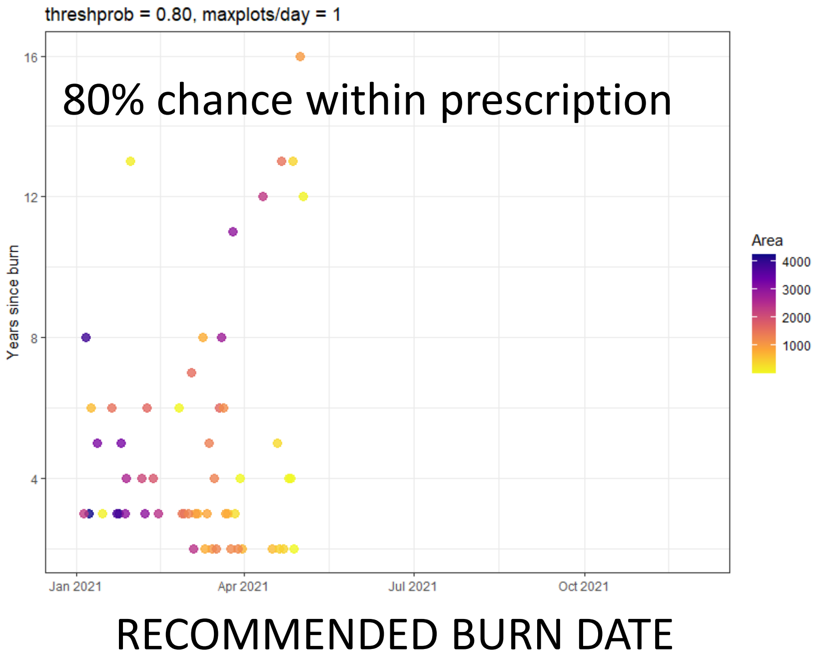


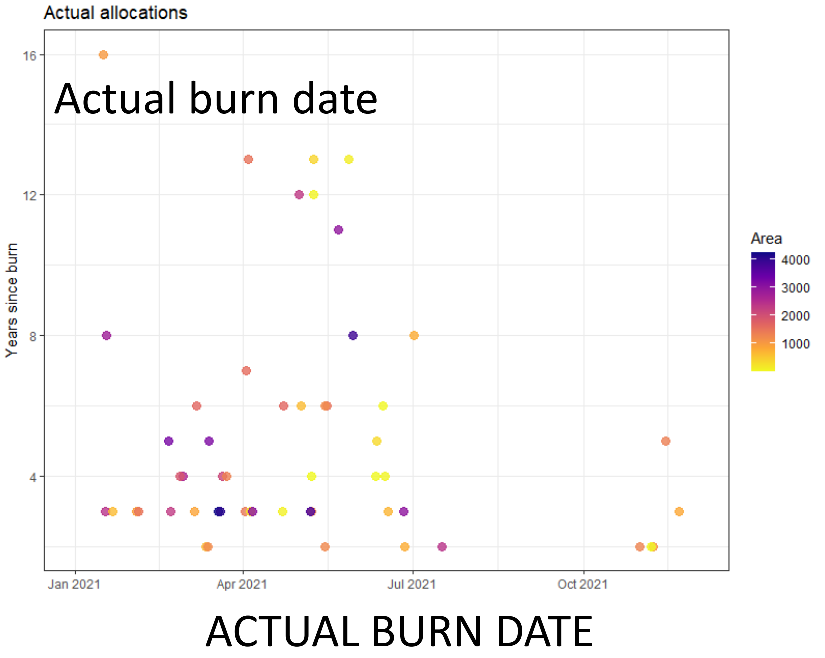


Higher threshold probability equates to more risk averse behavior

Example from 2021 burn season

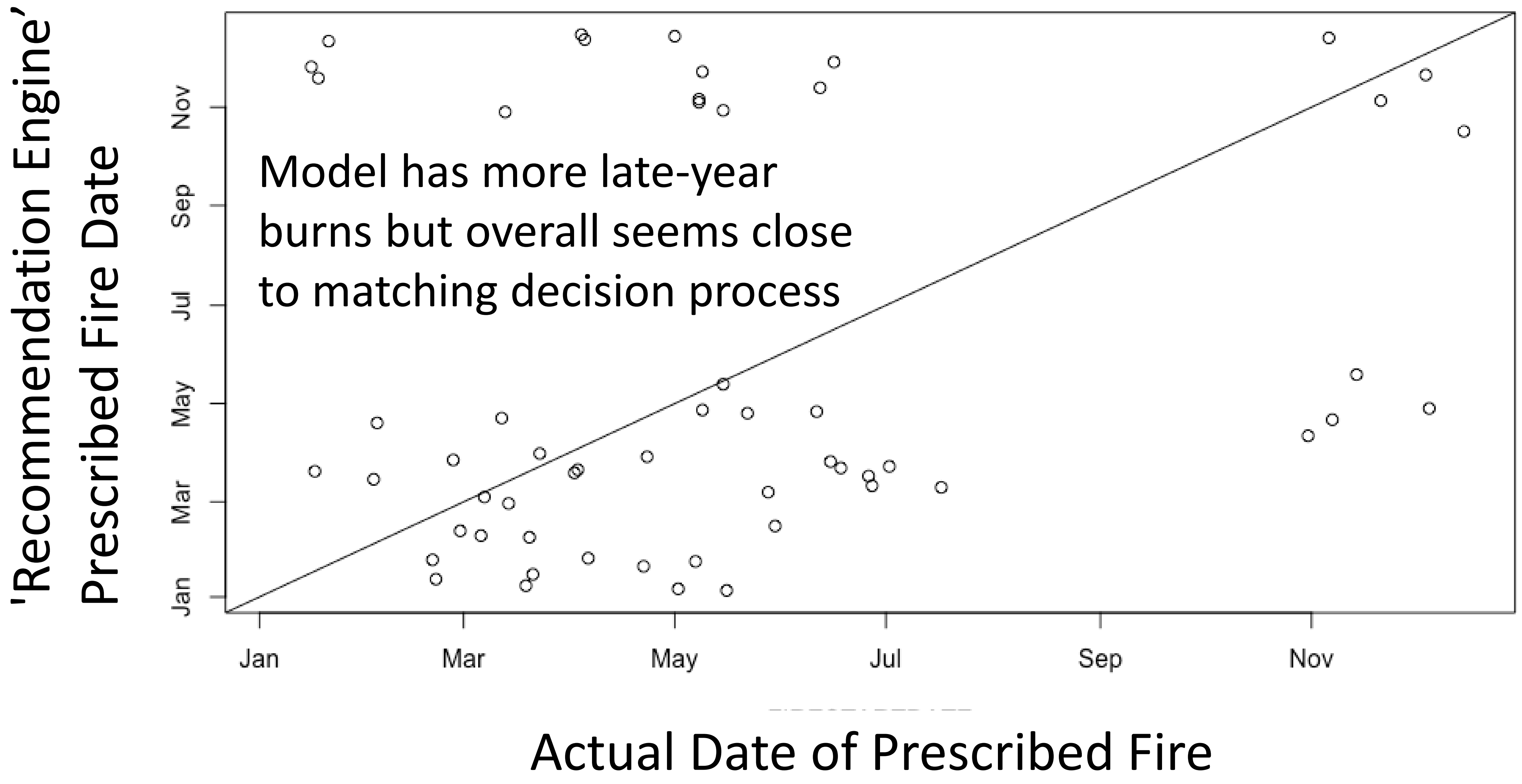




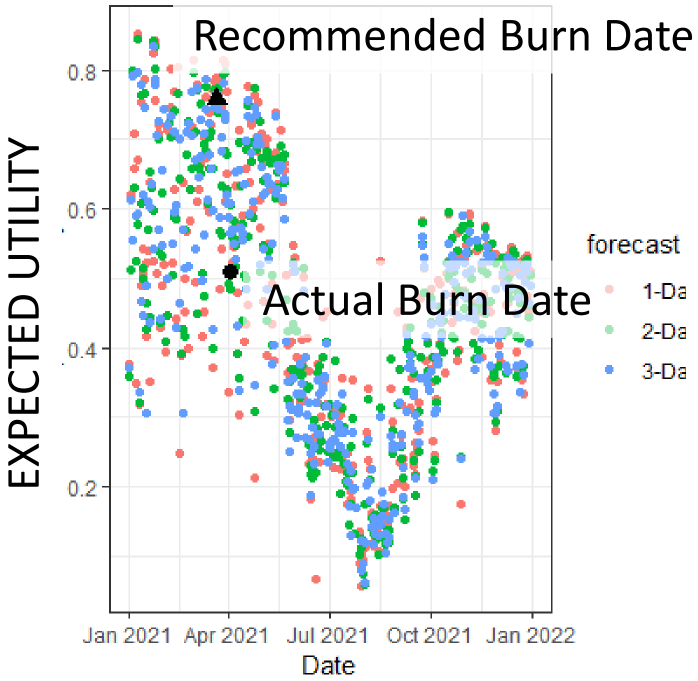


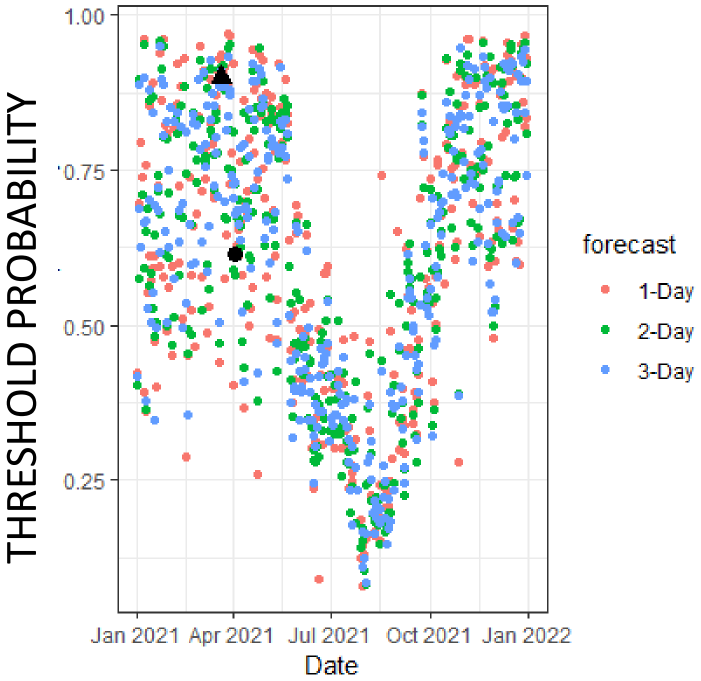
Can include constraints like maximum # plots burnt/day OR maximum area burnt/day.

Example from 2021 burn season


Model has more late-year burns but overall seems close to matching decision process
'Recommendation Engine' Prescribed Fire Date
Jan
Mar
May
Jul
Sep
Nov
Jan
Mar
May
Jul
Sep
Nov
Actual Date of Prescribed Fire

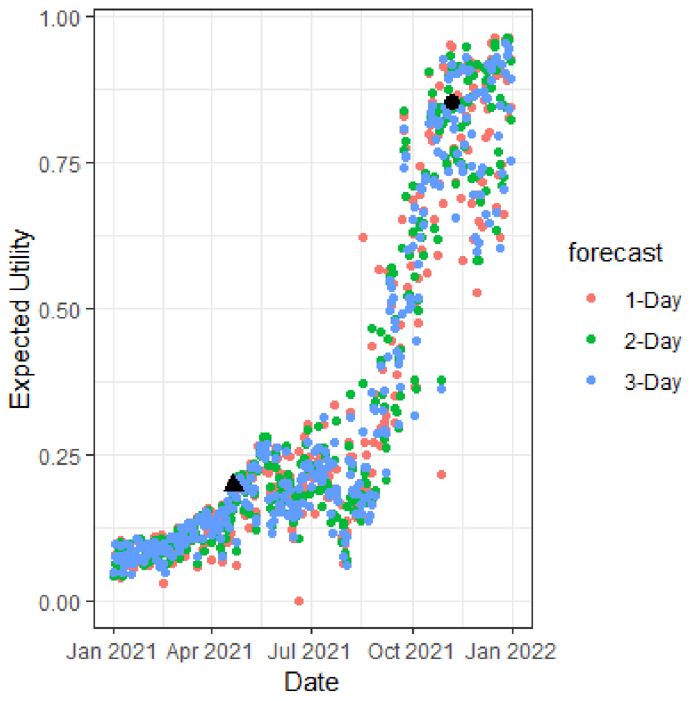
Burn allocation example 1

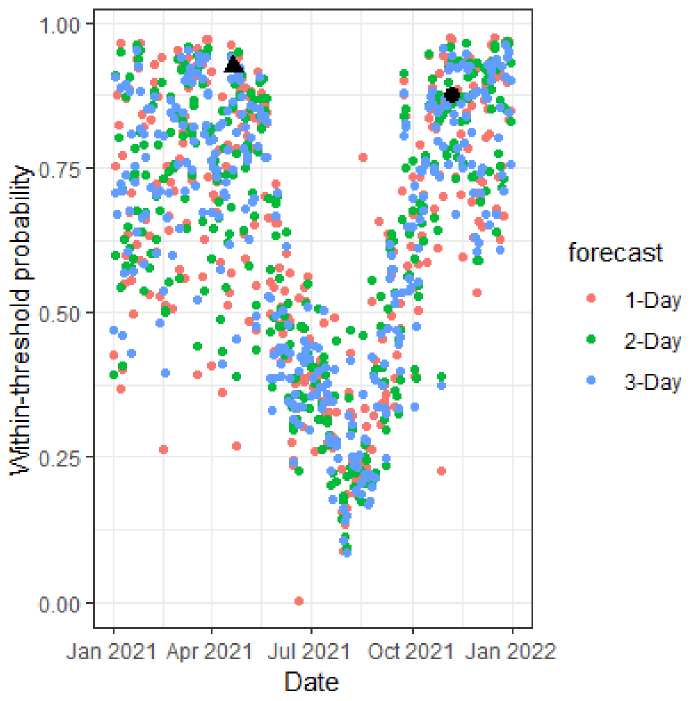




YSB = 7	Tmax	Tmin	RHmin	Windspeed	Rain
Actual	67	37	29.66	2.65	0
Estimate	70	46	34	5	0

Burn allocation example 2

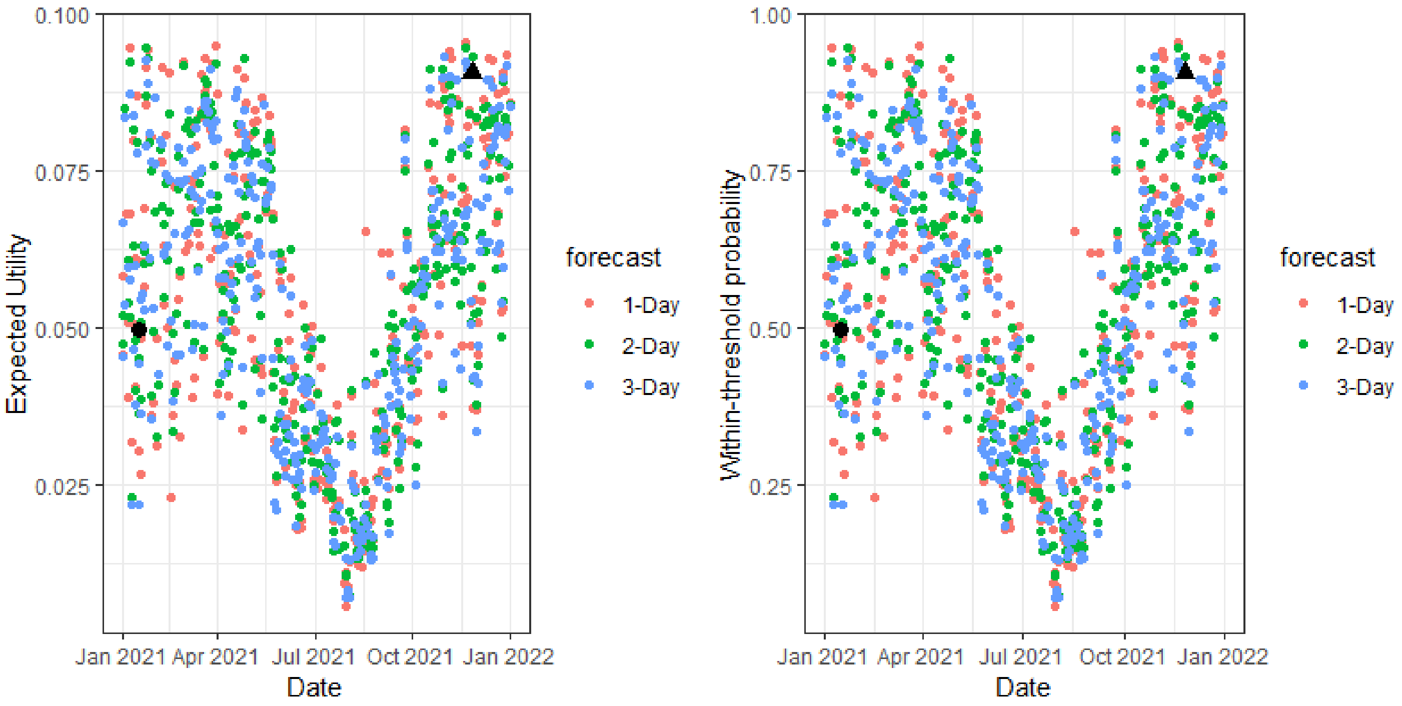




YSB = 2	Tmax	Tmin	RHmin	Windspeed	Rain
Actual	69	43	31	4.9	0
Estimate	74	47	37	5.6	0

Burn allocation example 3

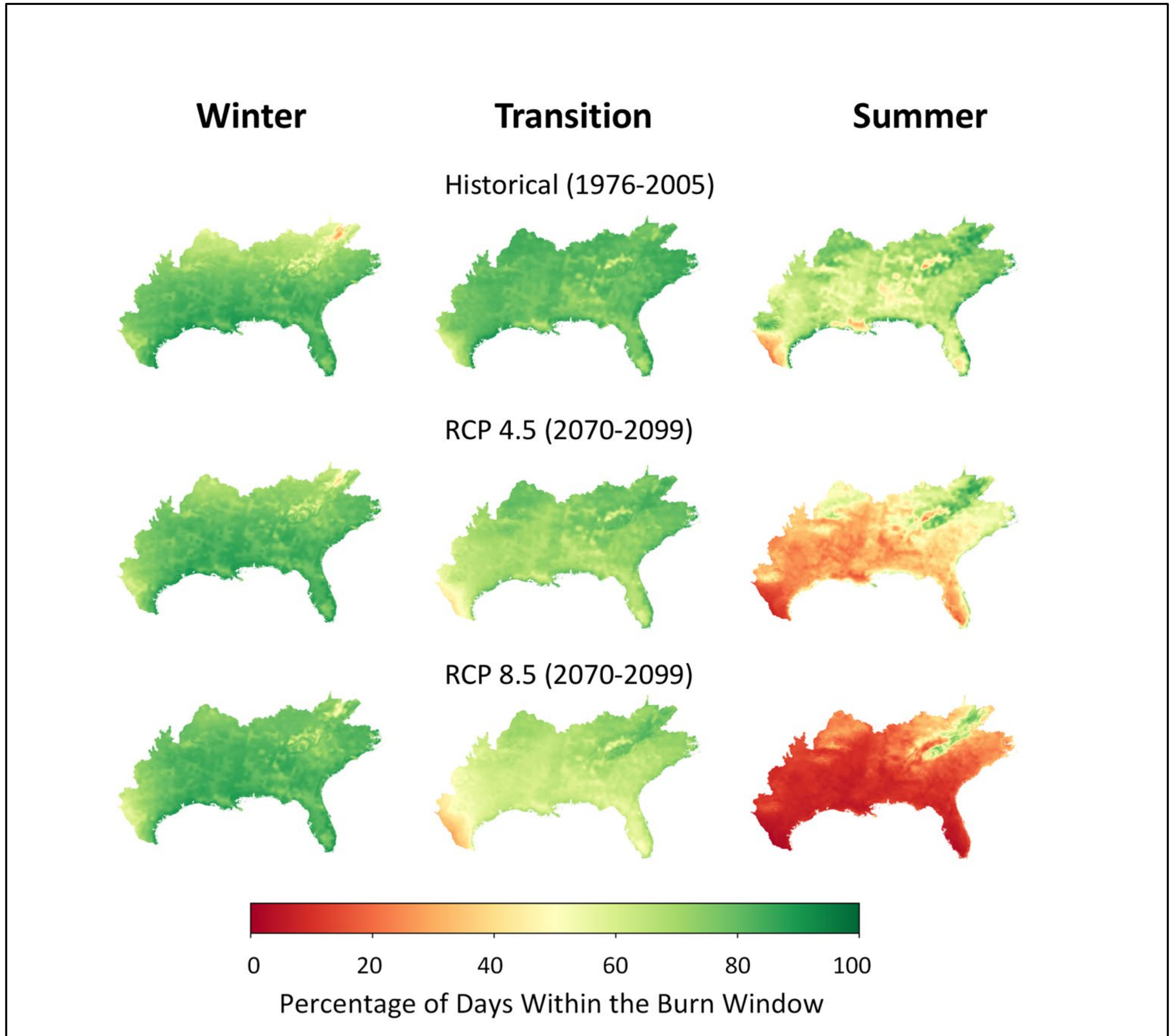
VERY LOW UTILITY



YSB = 16	Tmax	Tmin	RHmin	Windspeed	Rain
Actual	54	30	33	5.1	0
Estimate	62	33	47	5.5	0

What next?

Relax the fail-state constraints



Expand the set of utility functions

- Workshop conducted in 12/23 with fire practitioners from the Coastal Plains and Piedmont regions of North Carolina to elicit:
  - Additional constraints like cost/manpower in different management scenarios
  - Custom utility functions which depend on vegetation type/stakeholders

Quantify opportunity loss

- Use climate predictions (medium-term) or climatology (long-term) to estimate trends for available burn days
- Use the information in the tool to provide more context:

‘Both parcels A and B have same utility this year, but parcel A’s utility declines steadily from next year (if we don’t burn this year), while parcel B’s utility starts declining only after 2 years (if we don’t burn this year).

Operationalizing the tool

- The methodology is off-the-shelf, so a similar model can be developed for other regions
- Bayesian models can be updated to incorporate new information
- Archival weather forecast data and observed weather data is usually easily available for CONUS (needed to train the fail-state estimator)
- Supply your own utility function (or modify ours)