Wildfire Fuel Treatments and Long-Term Carbon Storage in CA Forests

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BACKGROUND

- Forest Carbon Offsets in CA as a climate change mitigation tool
  - Paying forest owners for carbon stored in their forests
  - Incentivizes dense vegetation

- Increasing wildfire risk in CA Sierra Nevada
  - Fire suppression
  - Climate change

- Fuel treatments (mechanical thinning, prescribed burning, etc.)
  - Initial carbon loss, but reduces emissions from wildfire

CENTRAL RESEARCH QUESTION:

Can fuel-reduction treatments increase long-term net carbon storage by preventing wildfire in California mixed conifer forest?

SUB-QUESTION 1:

How do repeated fuel treatments (mechanical thinning, and/or prescribed fire) directly affect aboveground carbon stocks over time?

SUB-QUESTION 2:

How do repeated fuel treatments (mechanical thinning, and/or prescribed fire) affect predicted aboveground carbon stocks following modeled high-severity wildfire?

SUB-QUESTION 3:

How does the probability of wildfire affect net aboveground carbon stocks of treated forests?

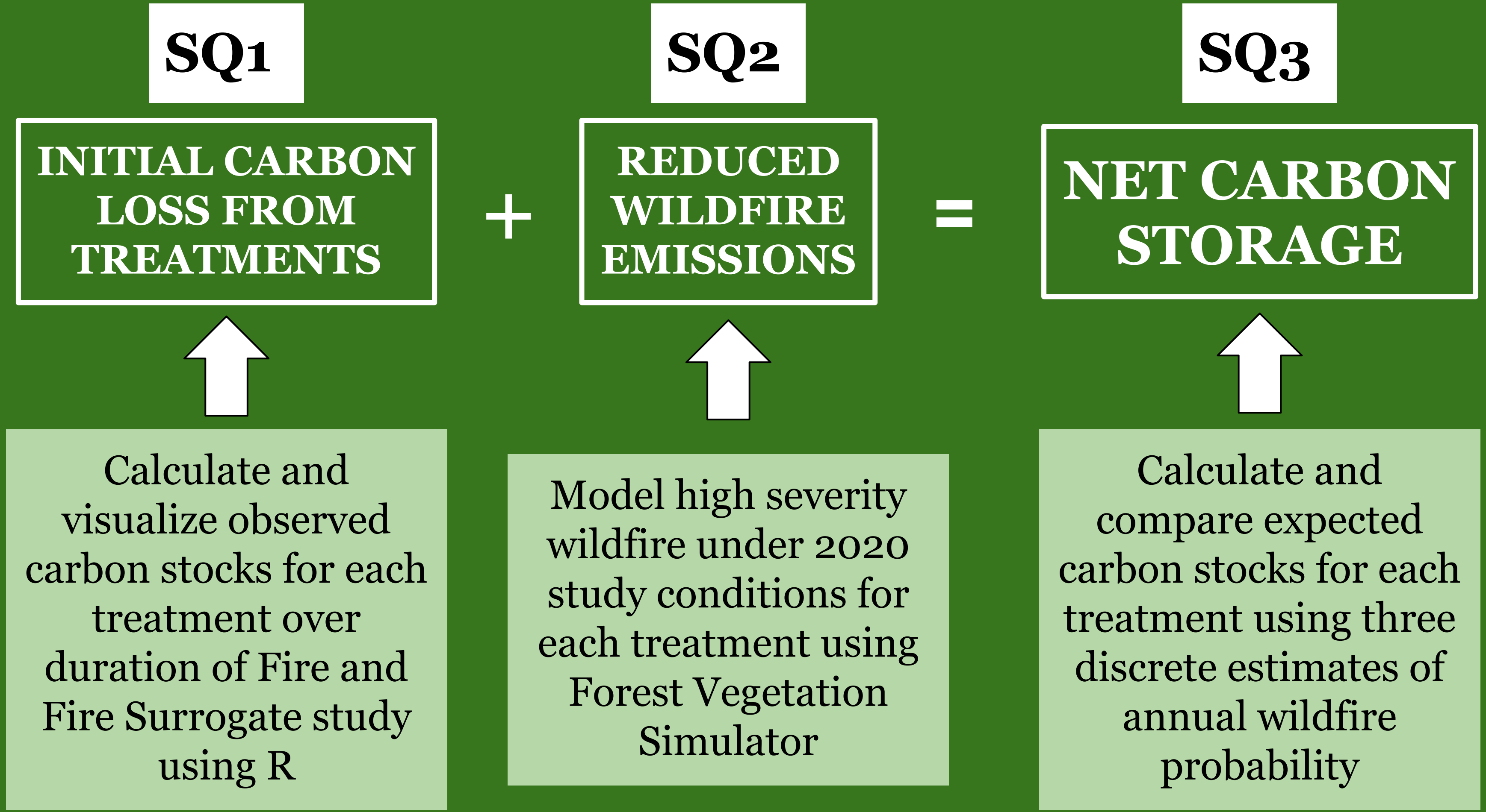
APPROACH

Blodgett Forest Research Station: Fire and Fire Surrogate Study (2001-2020)

TREATMENT TYPES:

- **Control:** no treatment
- **Mechanical Thin Only (2001, 2017):** crown thinning and thin from below, slash masticated, masticated material distributed in clumps
- **Burn (2001, 2009, 2017):** prescribed burn
- **Mechanical and Burn (2001, 2017):** mechanical thin + prescribed burn of masticated material

Special thanks to Daniel Foster (Scott Stephens Lab) and Yihong Zhu (John Battles Lab) for trusting me with the cleanest dataset I've ever worked with


SQ1
INITIAL CARBON LOSS FROM TREATMENTS
+
SQ2
REDUCED WILDFIRE EMISSIONS
=
SQ3
NET CARBON STORAGE
Calculate and visualize observed carbon stocks for each treatment over duration of Fire and Fire Surrogate study using R
Model high severity wildfire under 2020 study conditions for each treatment using Forest Vegetation Simulator
Calculate and compare expected carbon stocks for each treatment using three discrete estimates of annual wildfire probability

PILOT STUDY SUMMARY

Plan: perform all methods (SQ1, SQ2, and SQ3) on control data only

Reality: only enough time for SQ1 :(

OCT 12: connected with Yihong at Battles Lab, who had just finished cleaning most recent FFS data for similar study

OCT 17: granted access to dataset

OCT 17 - NOV 9: worked with Yihong to understand data and previous work of FFS study researchers

NOV 9 - NOW: SQ1 data analysis in R

PILOT STUDY RESULTS

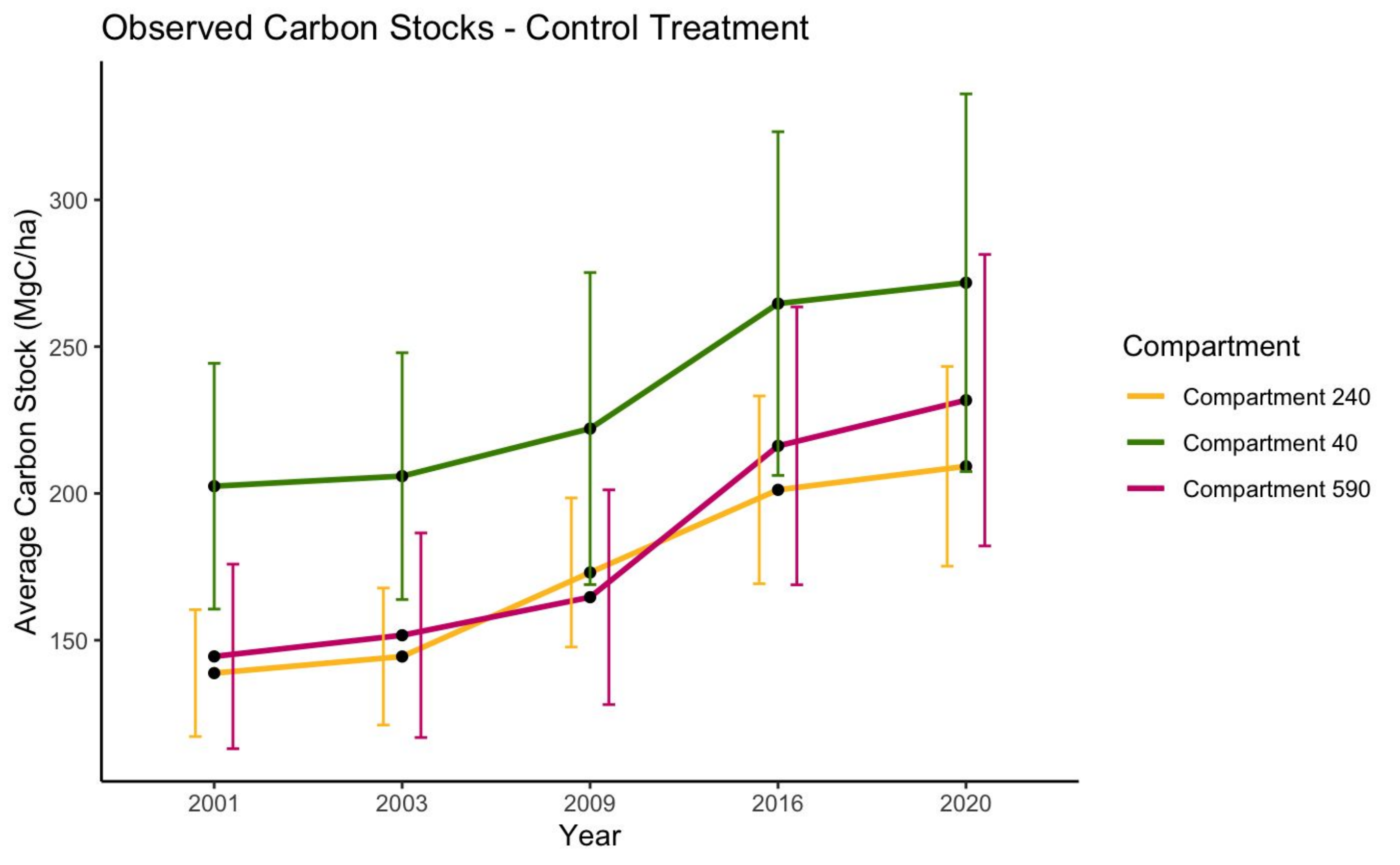
	treatment	compartment	plot	timestep	carbon	year
1	control	40	0040-00108	post_18	0.036643697	2020
2	control	40	0040-00108	post_18	0.220415808	2020
3	burn	340	0340-00006	post_18	0.130328797	2020
4	mech	490	0490-00104	pre_treatment	0.003861659	2001
5	mech	490	0490-00035	post_18	0.000027300	2020
6	mech	490	0490-00104	post_7	0.032630360	2009
7	burn	340	0340-00006	post_18	0.015340604	2020
8	mech	490	0490-00018	post_1	1.188373911	2003
9	mech	490	0490-00104	pre_treatment	0.214973106	2001
10	mech	490	0490-00104	post_18	0.000264285	2020
11	mech	490	0490-00120	post_18	0.000112274	2020
12	mech	490	0490-00120	post_18	0.000112274	2020
13	mech	490	0490-00120	post_18	0.000112274	2020
14	mech	490	0490-00120	pre_treatment	0.003861659	2001
15	control	40	0040-00108	post_18	0.020434726	2020
16	control	590	0590-00117	post_18	0.000810686	2020
17	control	40	0040-00108	post_18	0.093109520	2020
18	mech	490	0490-00018	post_7	0.861916126	2009
19	mech	490	0490-00018	post_1	0.504232932	2003

Showing 1 to 20 of 23,194 entries, 6 total columns

````
```{r}
#For each treatment, group by year, average carbon
control_comp_avg <- rbind(carbon40, carbon240, carbon590)
control_avg <- control_comp_avg %>% group_by(year) %>%
  summarise(year=year, treatment="control", avg_carbon=mean(avg_yr_carbon), sd=sd(avg_yr_carbon),
se=sd/sqrt(length(control_comp_avg)))
control_avg

mech_comp_avg <- rbind(carbon190, carbon350, carbon490)
mech_avg <- mech_comp_avg %>% group_by(year) %>%
  summarise(year=year, treatment="mech", avg_carbon=mean(avg_yr_carbon), sd=sd(avg_yr_carbon),
se=sd/sqrt(length(mech_comp_avg)))
mech_avg

burn_comp_avg <- rbind(carbon60, carbon340, carbon400)
burn_avg <- burn_comp_avg %>% group_by(year) %>%
  summarise(year=year, treatment="burn", avg_carbon=mean(avg_yr_carbon), sd=sd(avg_yr_carbon),
se=sd/sqrt(length(burn_comp_avg)))
burn_avg

mechburn_comp_avg <- rbind(carbon180, carbon380, carbon570)
mechburn_avg <- mechburn_comp_avg %>% group_by(year) %>%
  summarise(year=year, treatment="mechburn", avg_carbon=mean(avg_yr_carbon), sd=sd(avg_yr_carbon),
            se=sd/sqrt(length(mechburn_comp_avg)))
mechburn_avg
```
````

*ONLY TREES! Still need to include understory and fuels, but tree carbon is the largest and thus most considerable pool

PILOT STUDY RESULTS



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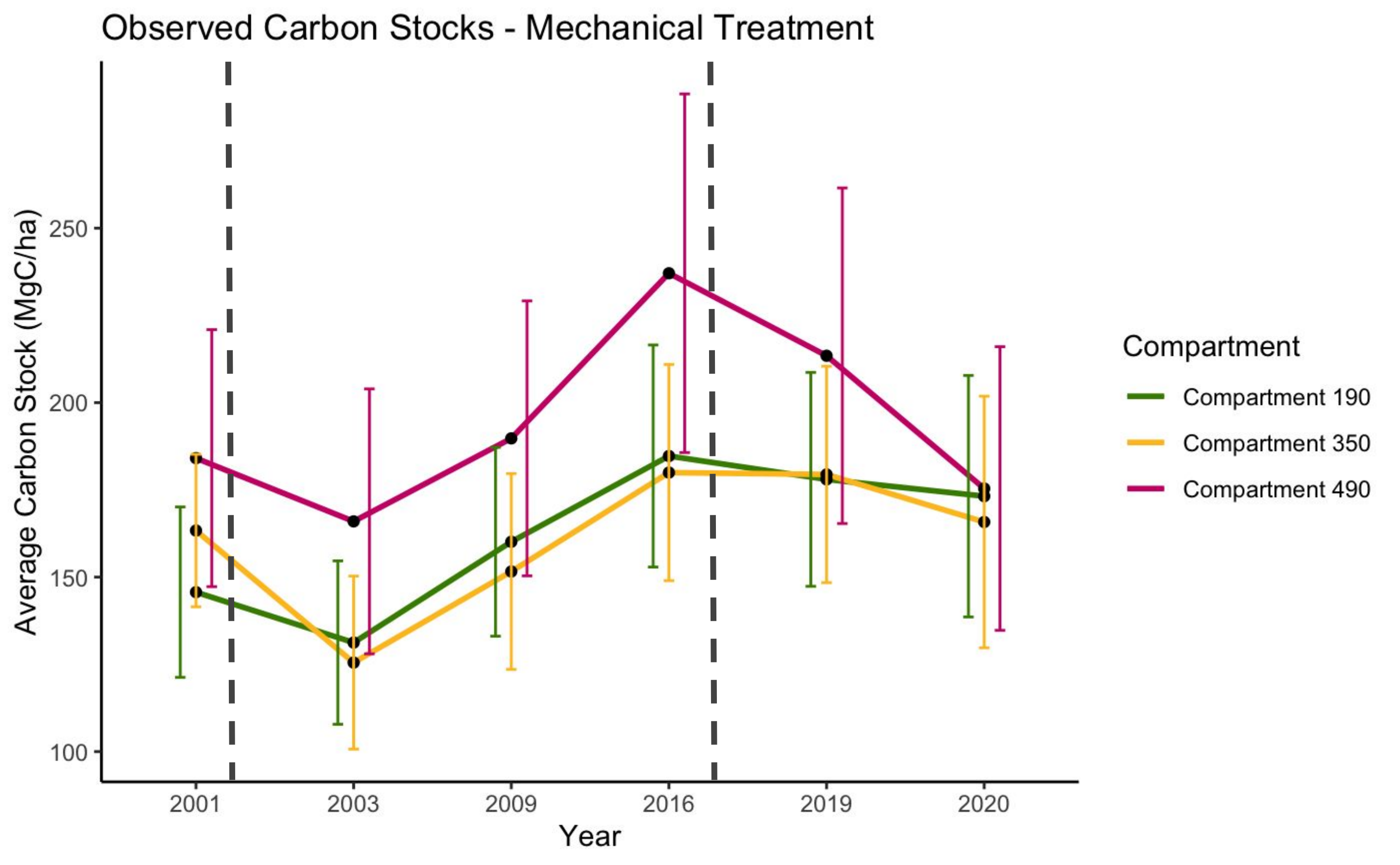

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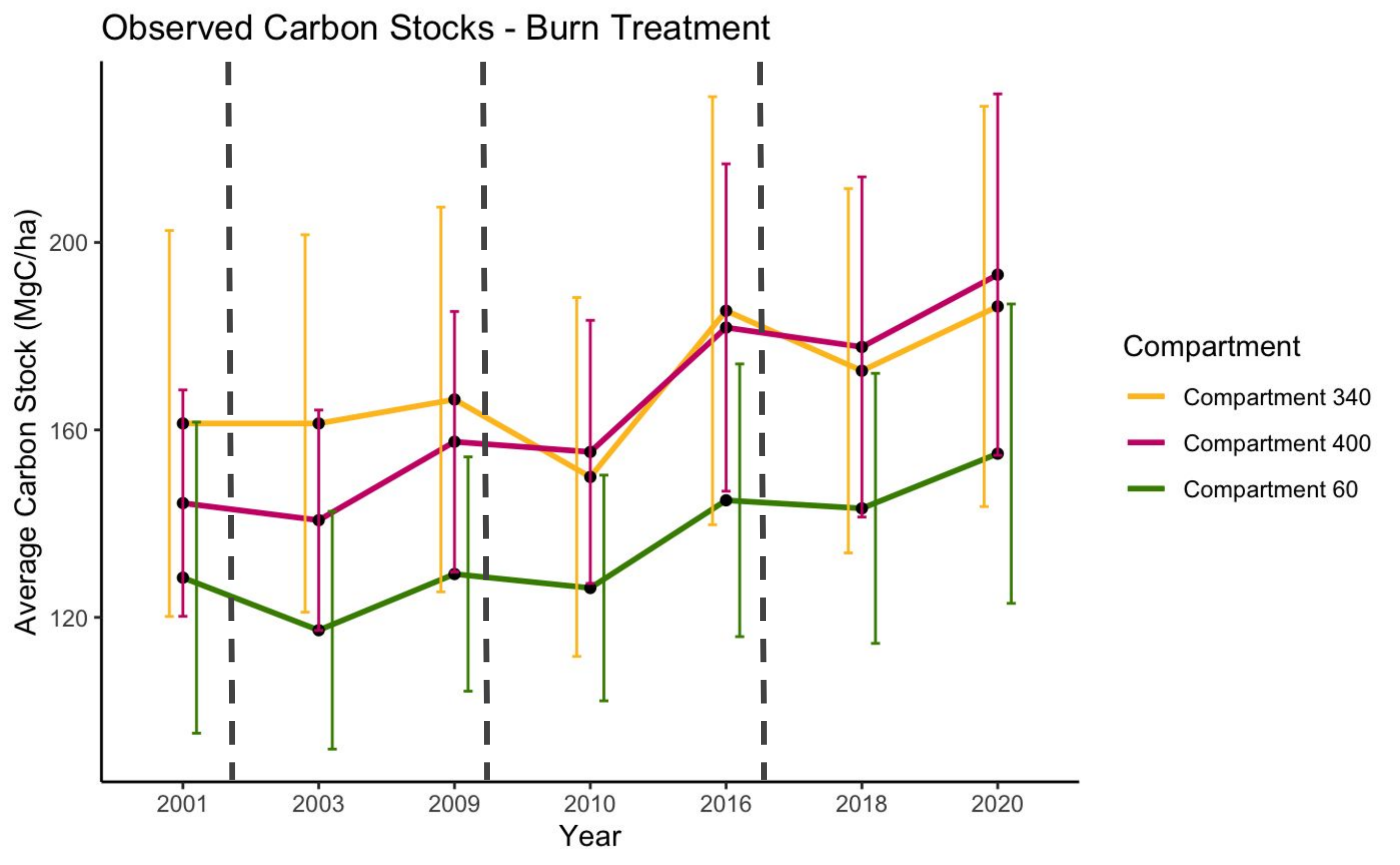

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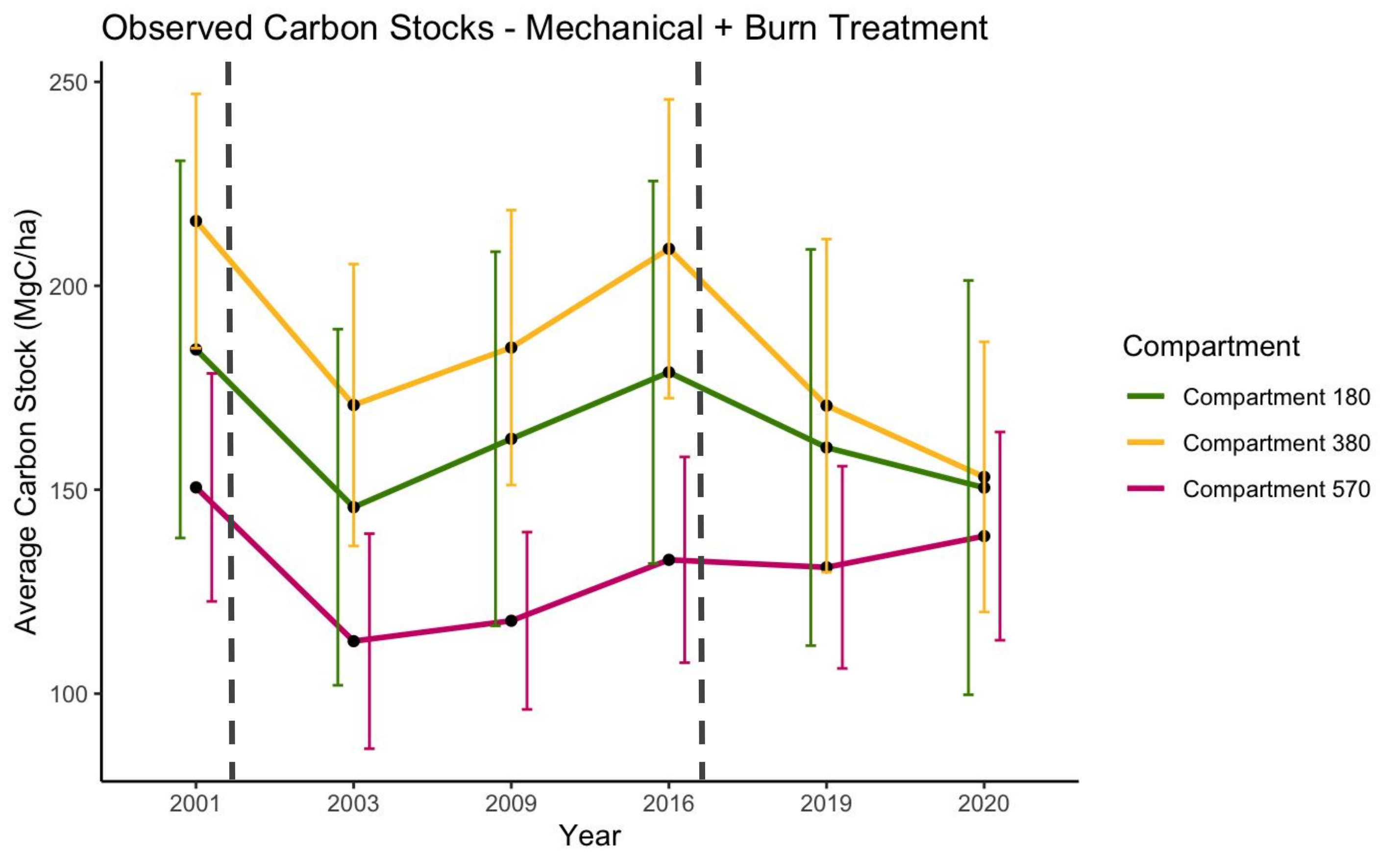

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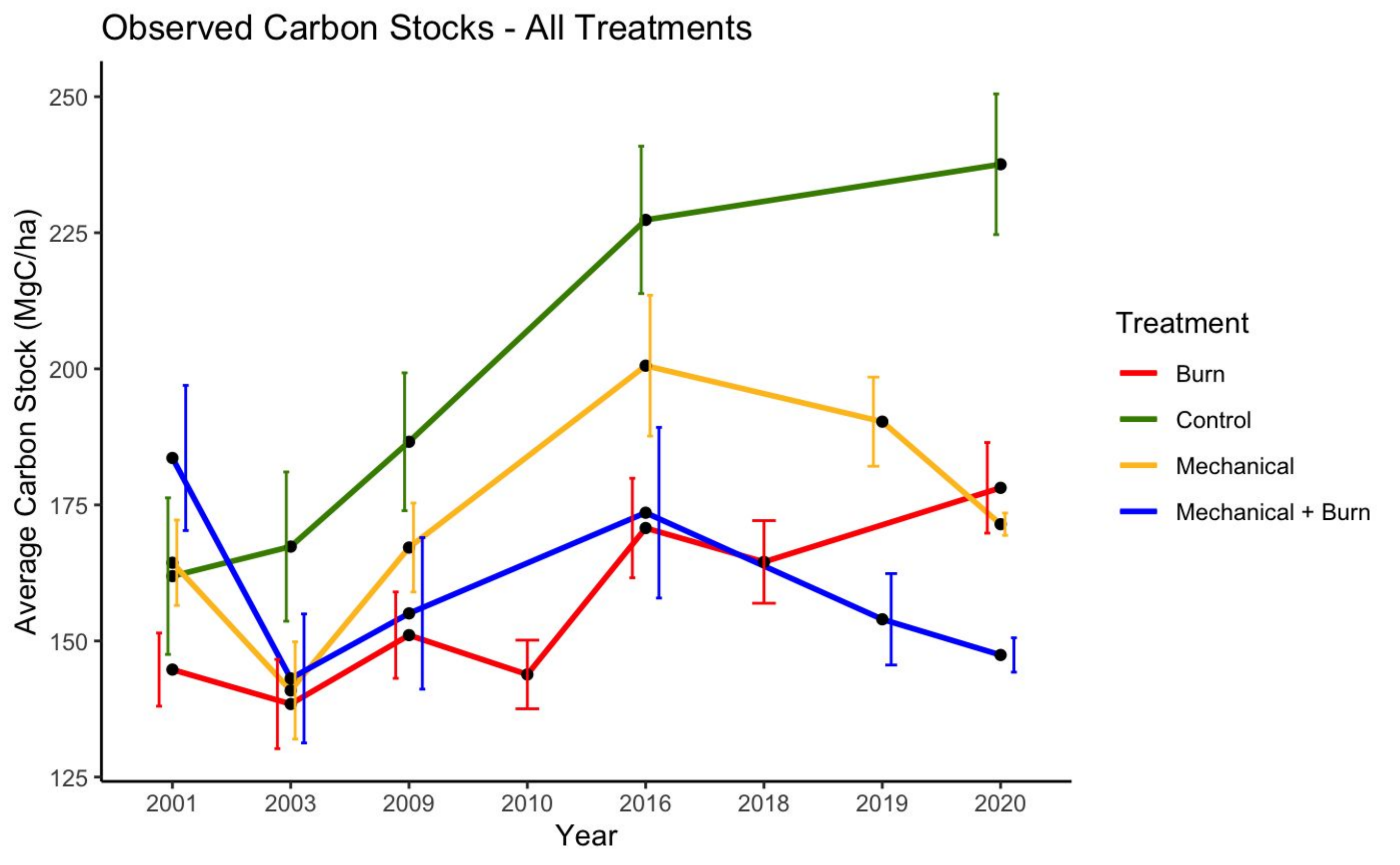

NEXT STEPS

SQ1: Wrap up loose ends with understory and fuels data

SQ2: Model high severity wildfire under 2020 study conditions for each treatment using Forest Vegetation Simulator

SQ3: Calculate and compare expected carbon stocks for each treatment using three discrete estimates of annual wildfire probability (calculations detailed in Methods draft)

NEW INSIGHTS: Time management, maybe minimize range of assumptions used in SQ3 to improve efficiency

THANK YOU!

Let me know if you have any questions!

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