Legacy effects in radial tree growth are rarely significant when accounting for inherent **biological memory**

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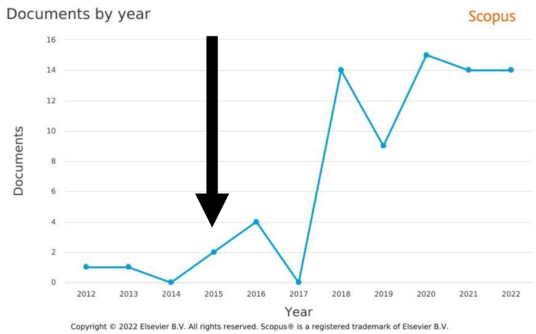
What are legacy effects? How are they calculated?

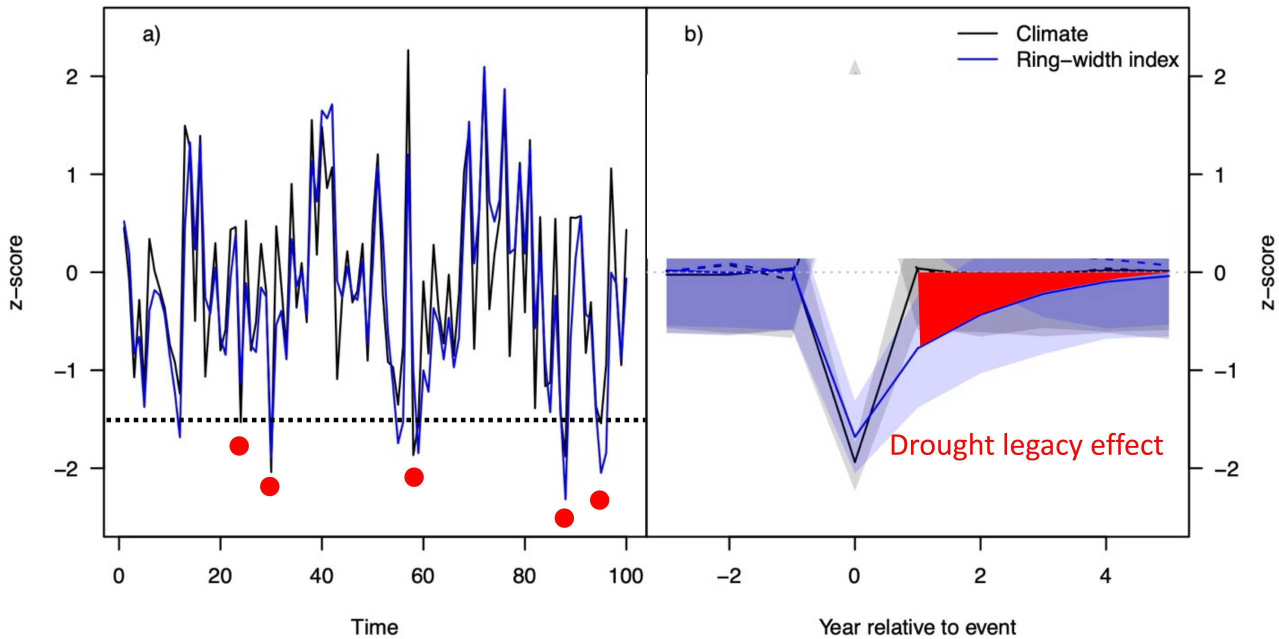
- Anderegg et al. (2015, Science): droughts negatively impact radial tree growth for up to four years

→ coined the term “**legacy effects**”

- Legacy effects = residuals of regression between tree-ring and climate time series, aggregated relative to a set of extreme events

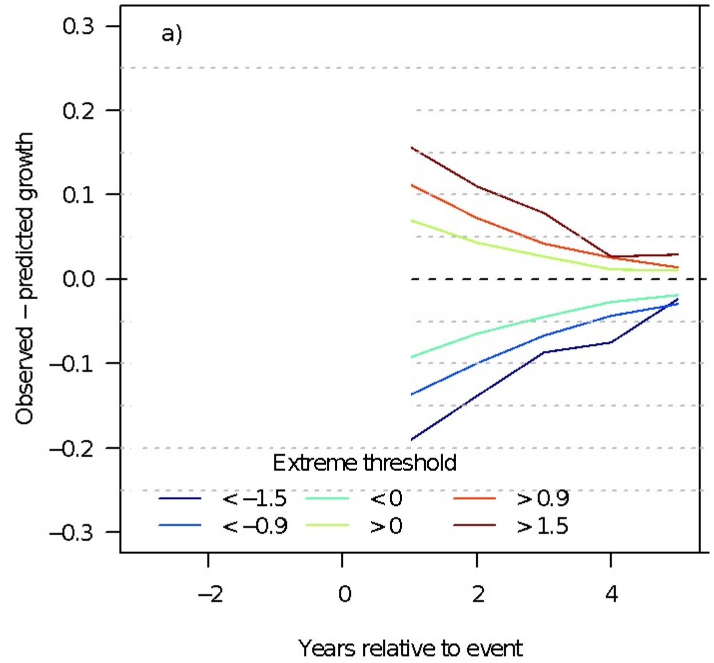


Search terms: „tree growth“ „drought legacies“



Drought legacy effects re-visited (~literature synthesis)

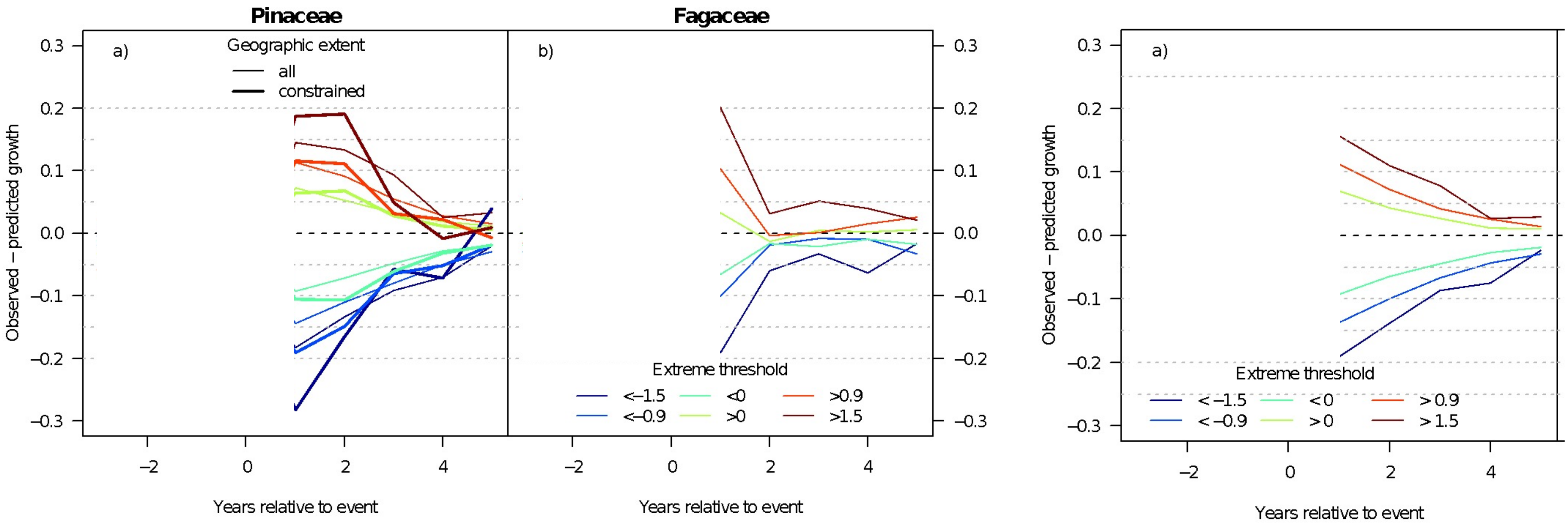
- Legacy effects scale with the chosen extreme threshold
- They are rather symmetric, i.e. similar in magnitude and shape after wet and dry extremes (Jiang et al., 2019 NatComm)
- Legacy effects scale with SD of chronologies (Gazol et al., 2020, JoE)
- Legacy effects are stronger at sites that have a higher correlation with climate (Anderegg et al., 2015, Gazol et al. 2020; Huang et al. 2018, GCB)



Drought legacy effects re-visited (~literature synthesis)

- Legacy effects are stronger in Pinaceae compared to Fagaceae (Anderegg et al. 2015)

→ through stronger cross-correlation with climate and higher auto-correlation compared to Fagaceae

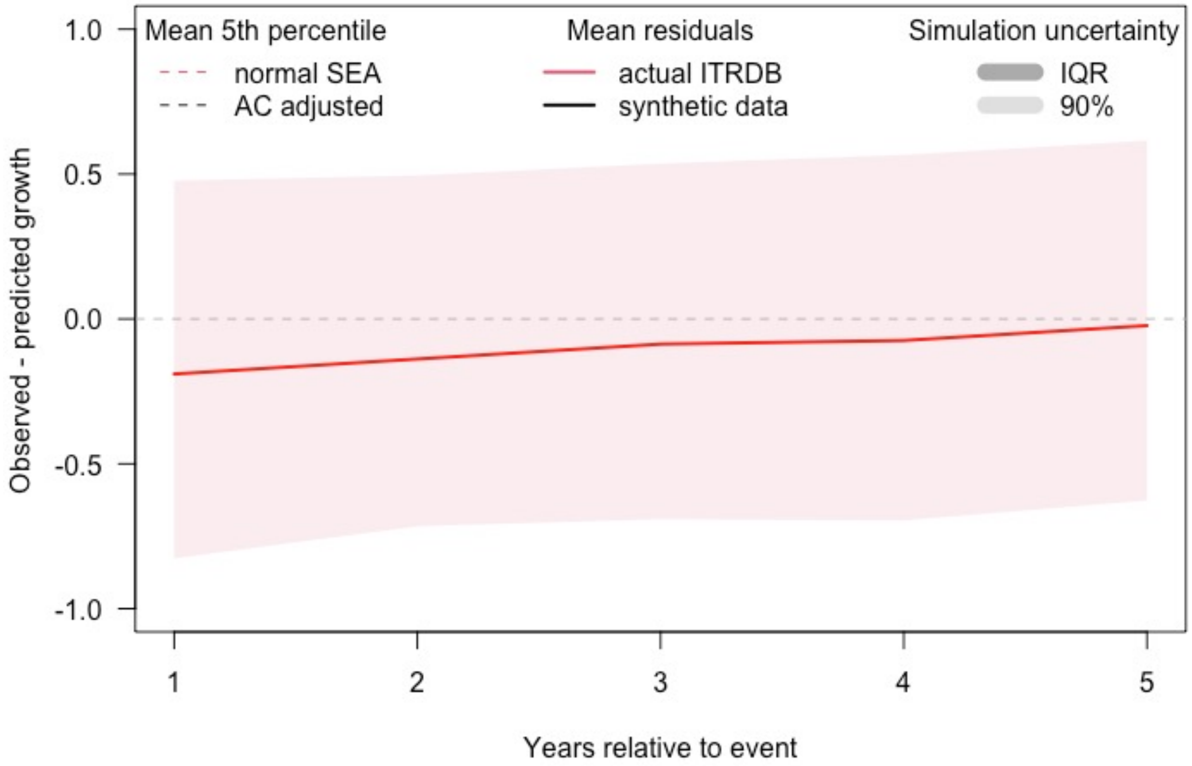


Individual legacy effects are very noisy!

- Statistical model explains only 8% of the variance of lag-1 effects (using climate-growth cross correlation and RWI auto-correlation)

Create white noise time series with n=100

→ add red noise to match observed cross-correlation and auto-correlation structure of tree-ring time series; repeat for all 2081 ITRDB sites



Legacy effects are predictable based on long time-series information !

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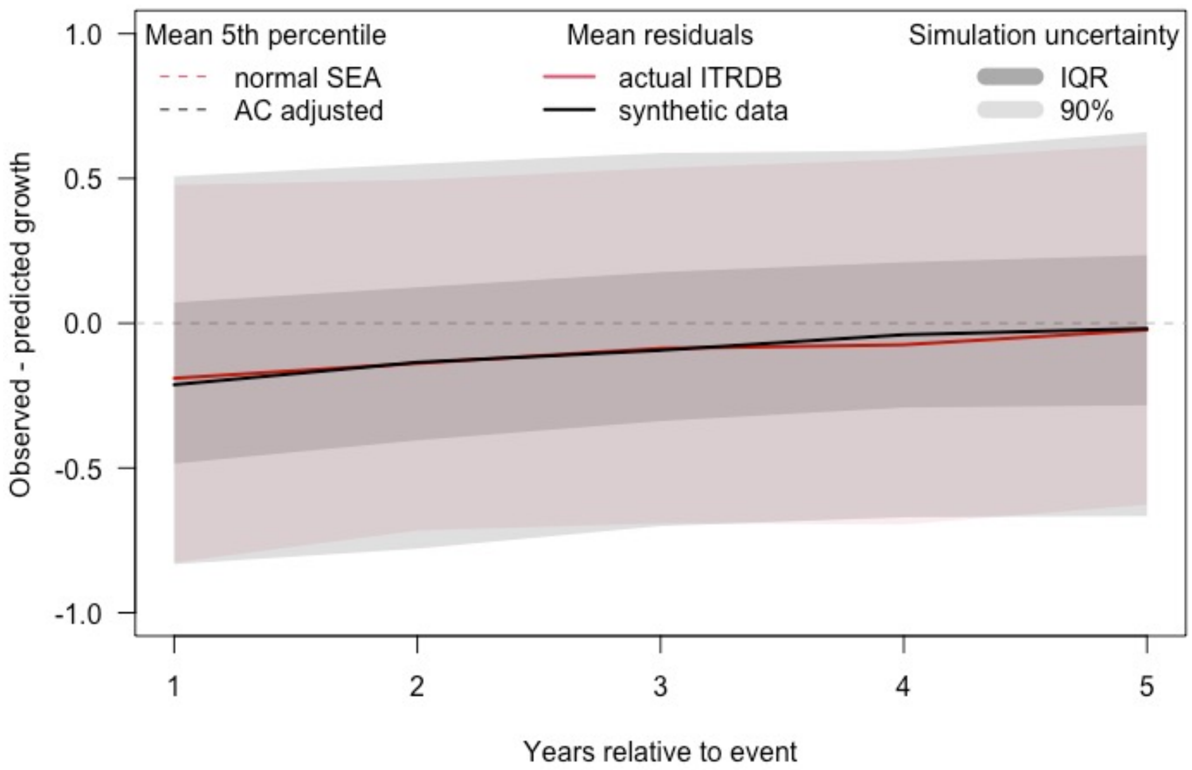

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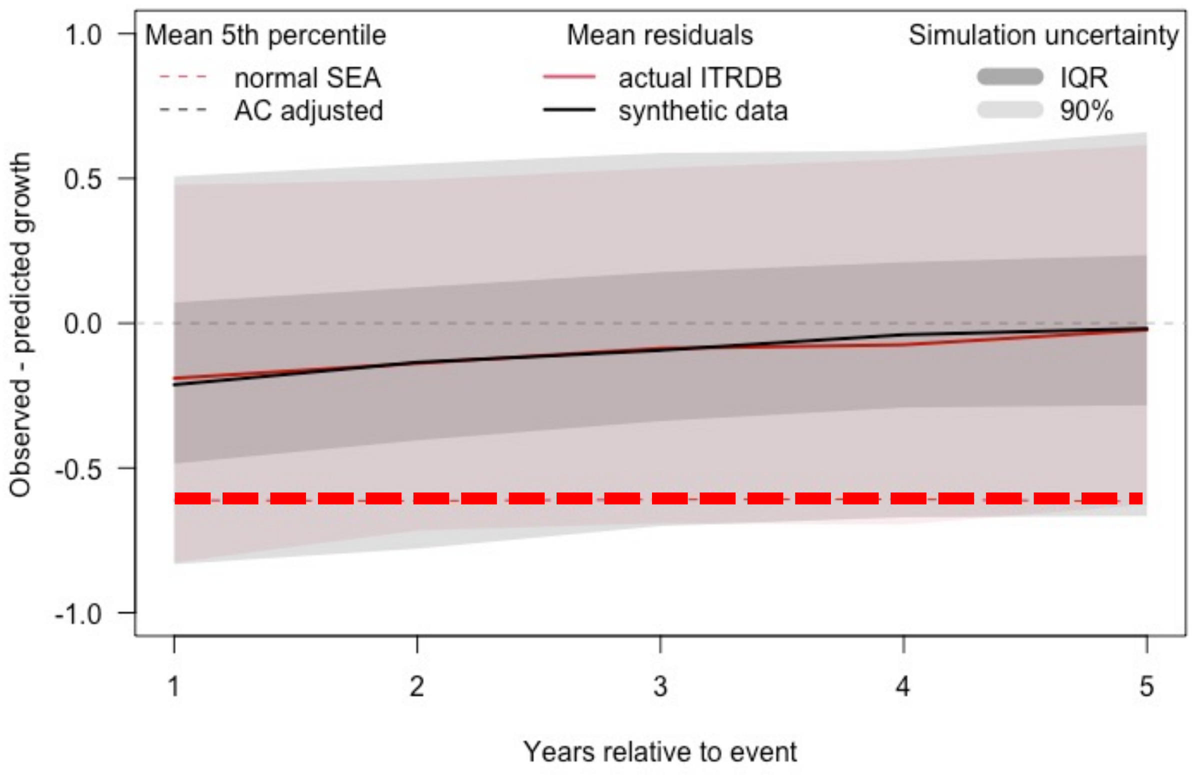
Classic SEA: 16% of lag-1 effects are significantly different from random ← INVALID ASSUMPTION



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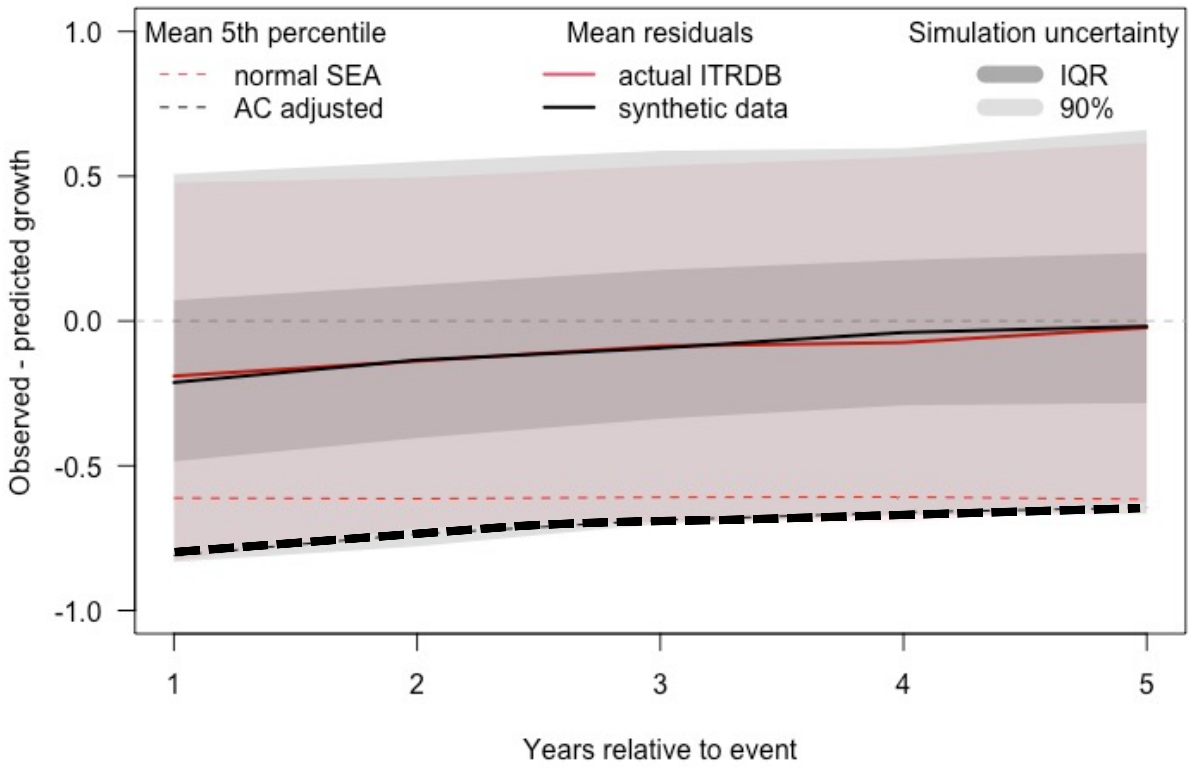
RIGHT ASSUMPTION: residuals are not random!

5% is on par with the adjusted null hypothesis



The way forward Pt1:
Re-adjust expectations

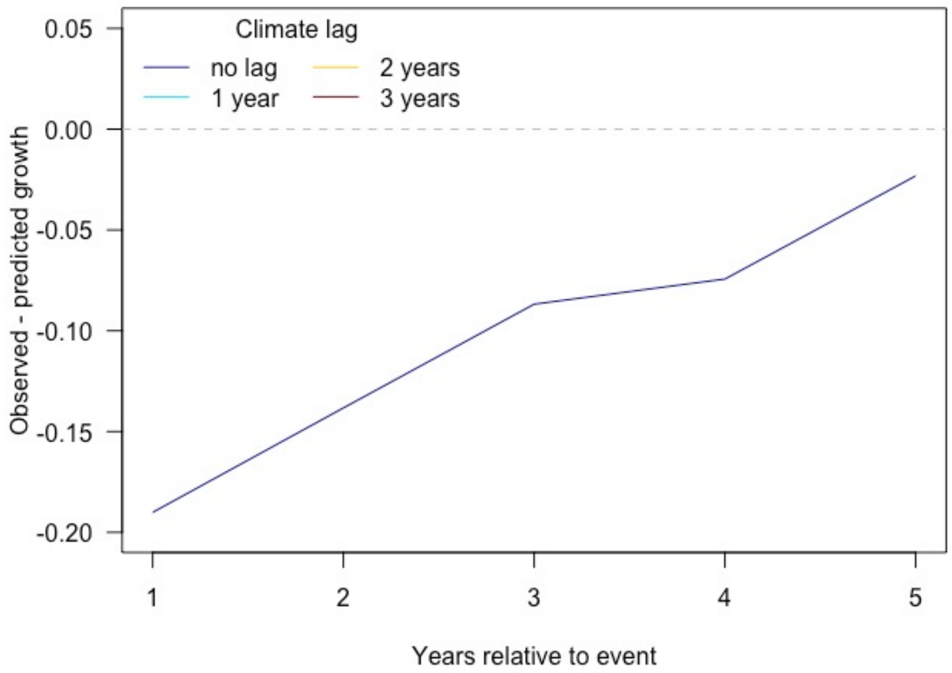
- Use synthetic data to adjust the null hypothesis, adjust the expectations based on **long time-series information**!

- **Strong consequences** for interpretation of other extreme event analyses (Lloret)
- Lower recovery and resilience values to be expected with series that correlate stronger to drought index, have higher AC, and higher year-to-year variability (SD).
- Incomplete recovery (line of full resilience) has to be the rule if we account for auto-correlation

The way forward Pt2: Change the growth model

- Use **distributed lag models** (e.g., antecedent stochastic modeling, Ogle et al., 2015) to ***a priori*** account for auto-correlation

- RW~ climate t



The way forward Pt2: change the growth model

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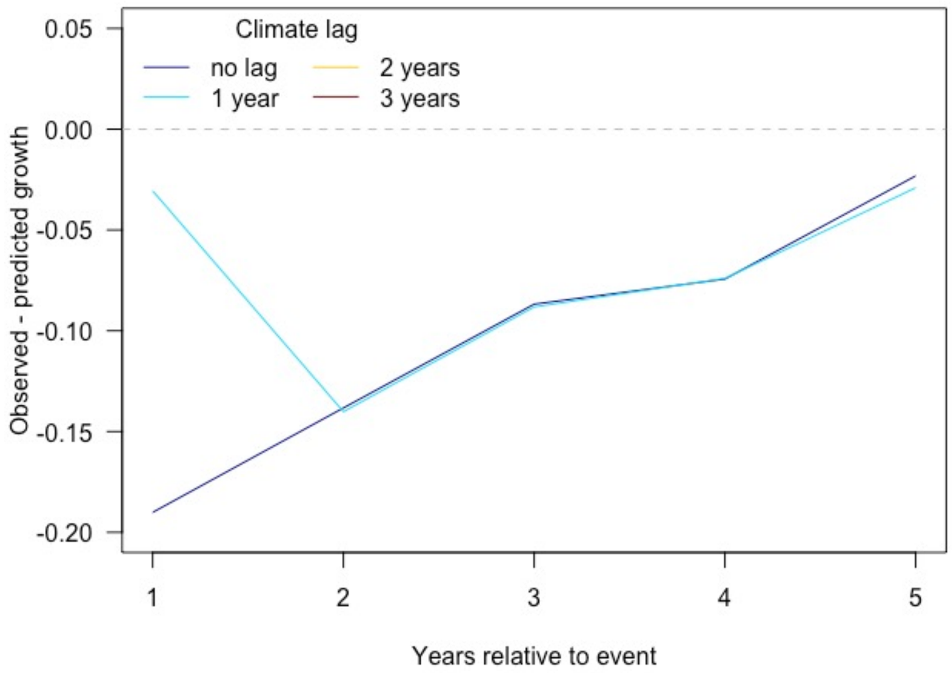
- RW~ climate t + climate t-1



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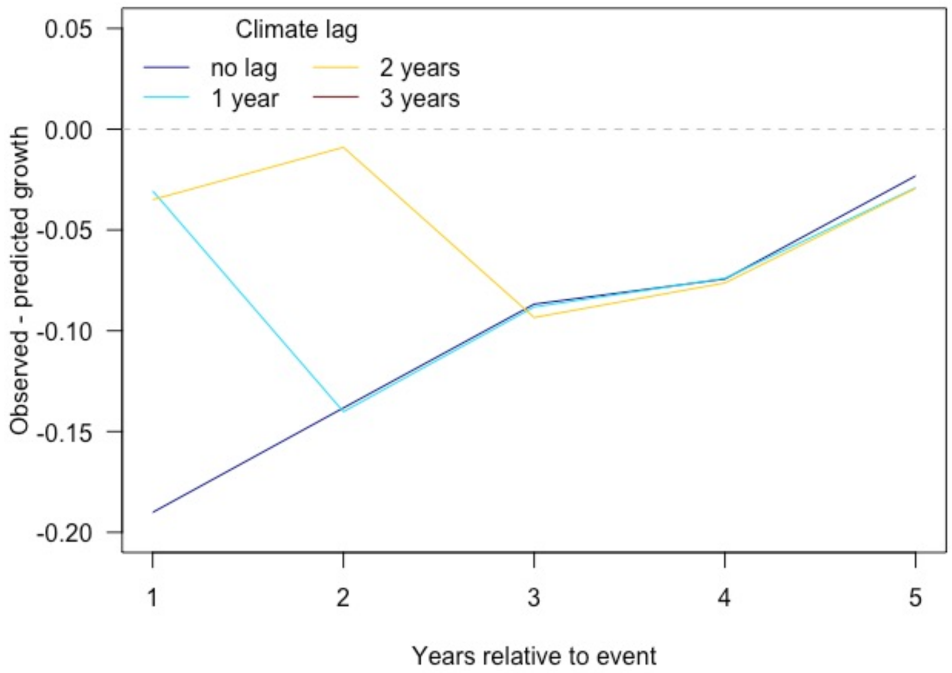
- RW~ climate t + climate t-1 + climate t-2

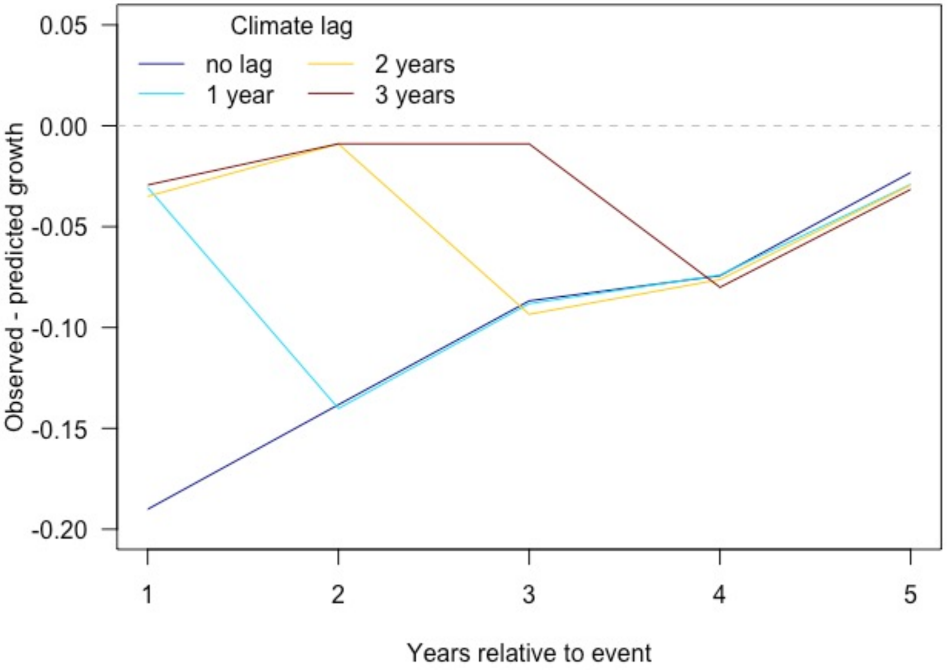


The way forward Pt2: change the growth model

- Use **distributed lag models** (e.g., antecedent stochastic modeling, Ogle et al., 2015) to ***a priori*** account for auto-correlation

- RW~ climate t + climate t-1 + climate t-2 + climate t-3

Legacy effects disappear!



Conclusion

to paraphrase Körner (2003):

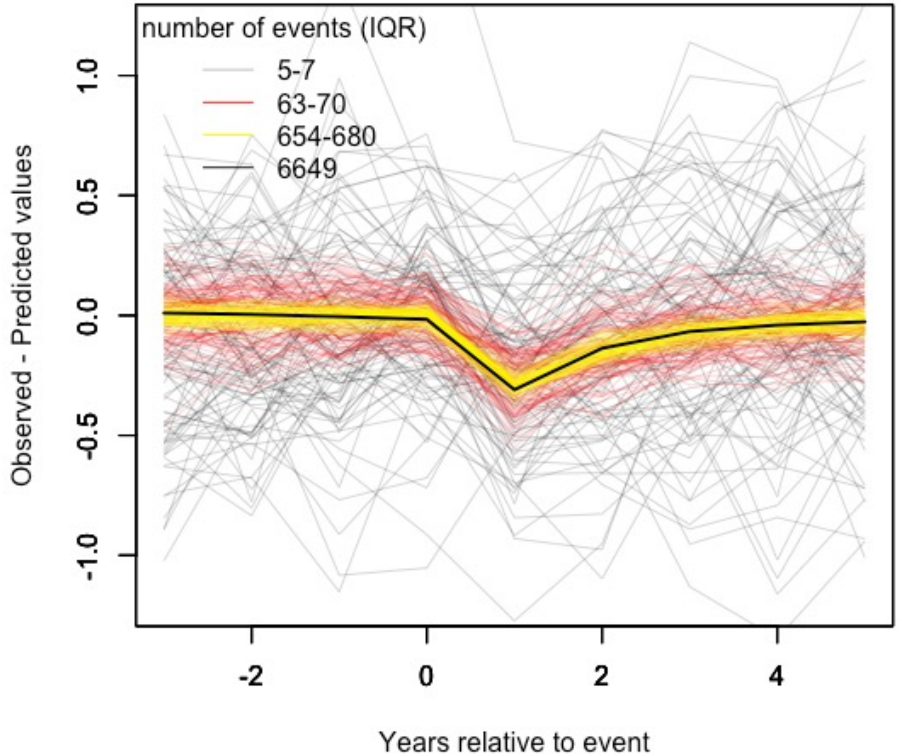
*The application of **invalid statistical assumptions** and **overly simplistic models** to estimate expected tree growth has given rise to a new word for “biological memory”.*

*The term “legacy effect” and its **interpretation as a physiological crisis** that is **only** induced by extreme droughts **is misguided**.*

Thank you for your attention!

Replication is key!

- Noise is common to extreme event analyses with low N (replications).
- We need about 500 observations (number of events per site * number of sites; yellow lines) to get a robust mean legacy effect estimation.



Replication is key!

If n is sufficiently high then:

- The contribution of rho (cross-correlation) and phi (AC1) on lag-1 effects is equal!
- Double the amount of auto-correlation (or cross-correlation)

  → double the amount of lag-1 effects