

A Bayesian Approach to Regime Assignment

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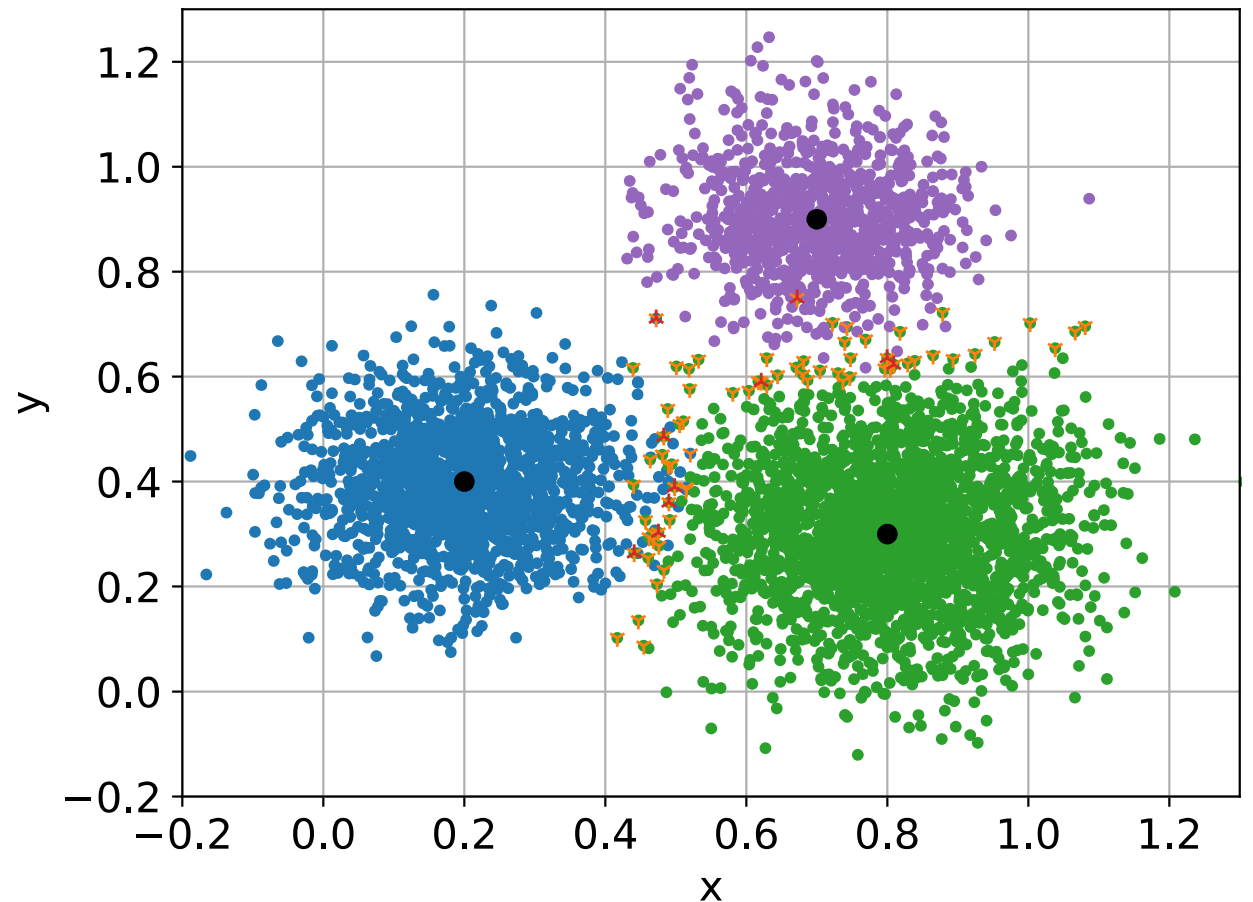
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Regimes, or clusters, are subsets of data which are similar within a regime, but different between regimes.

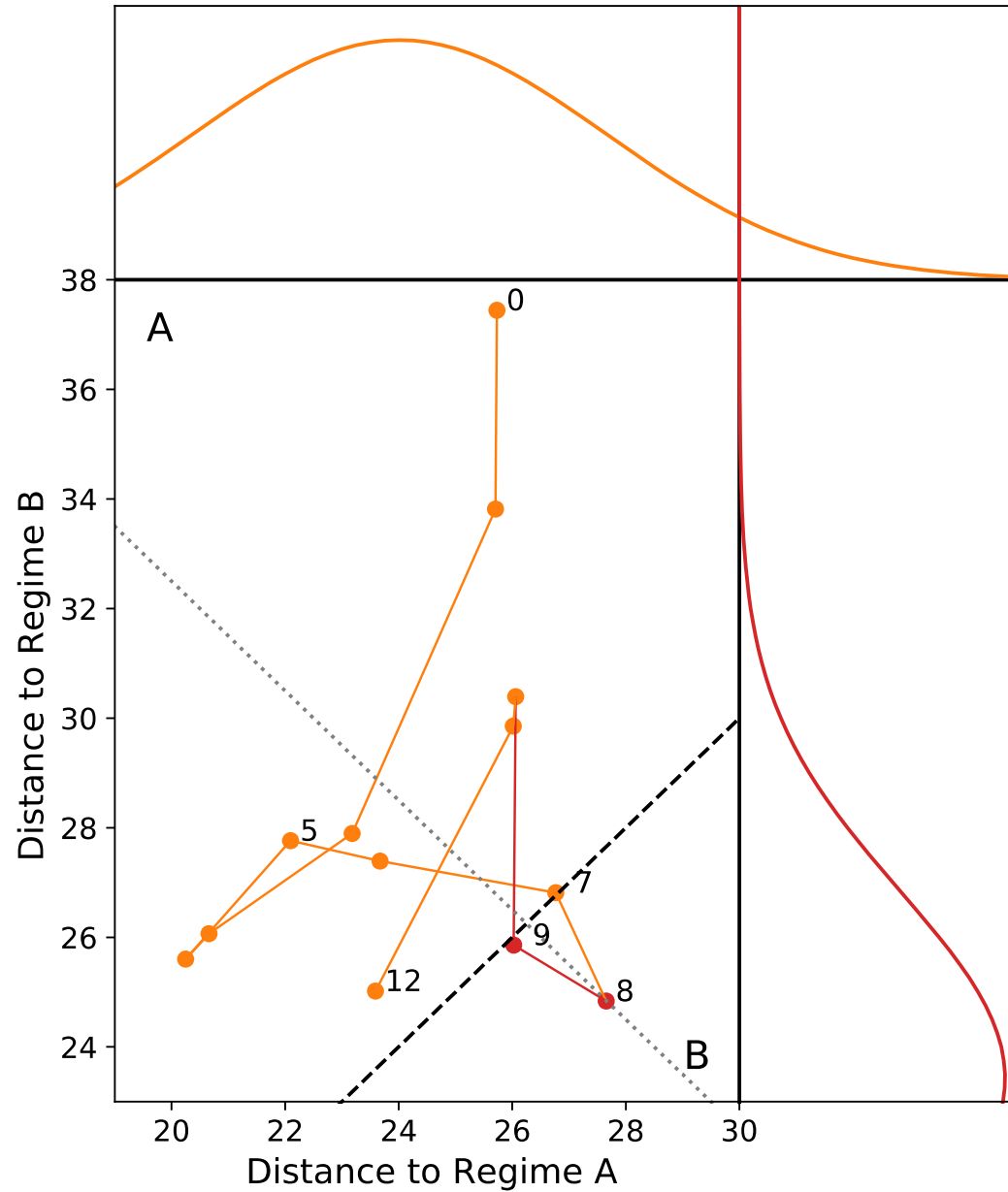
K-means clustering:
Split the data in k
clusters or regimes

Drawbacks:

- Every data point has to be assigned to a regime
- Sensitive to small perturbations



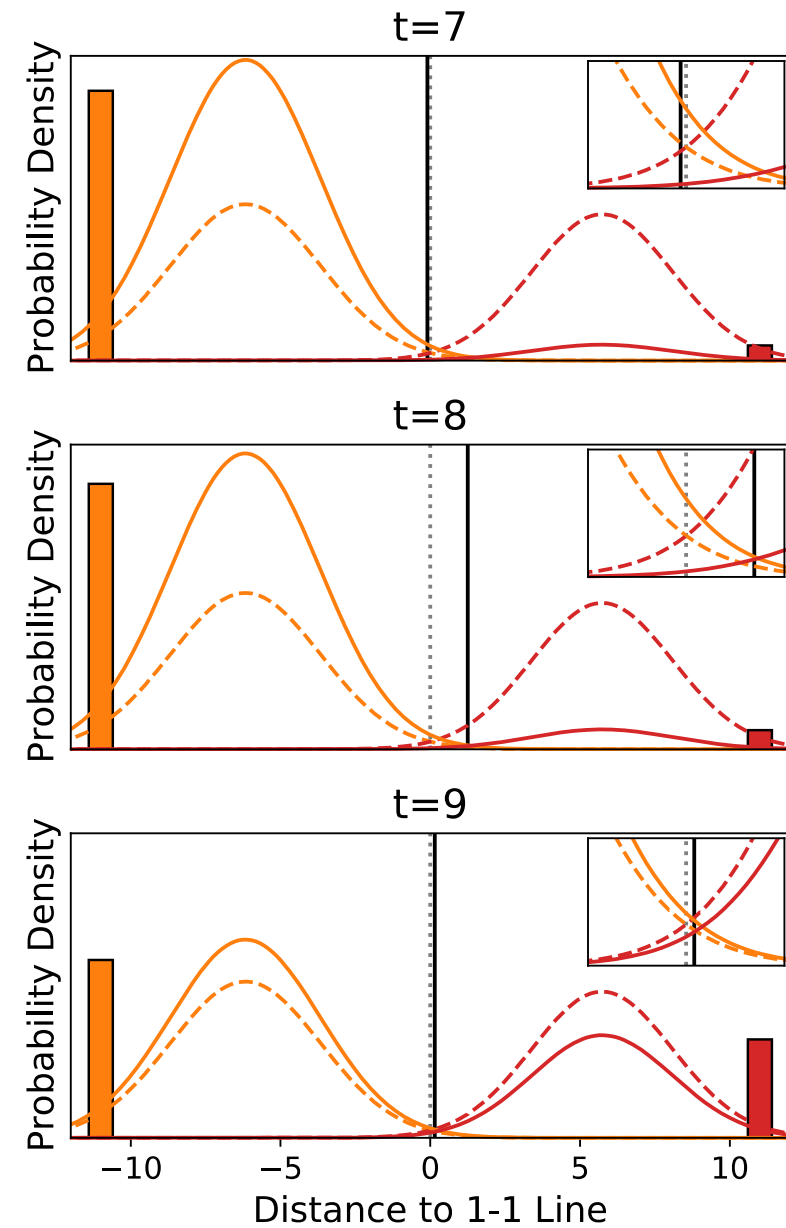
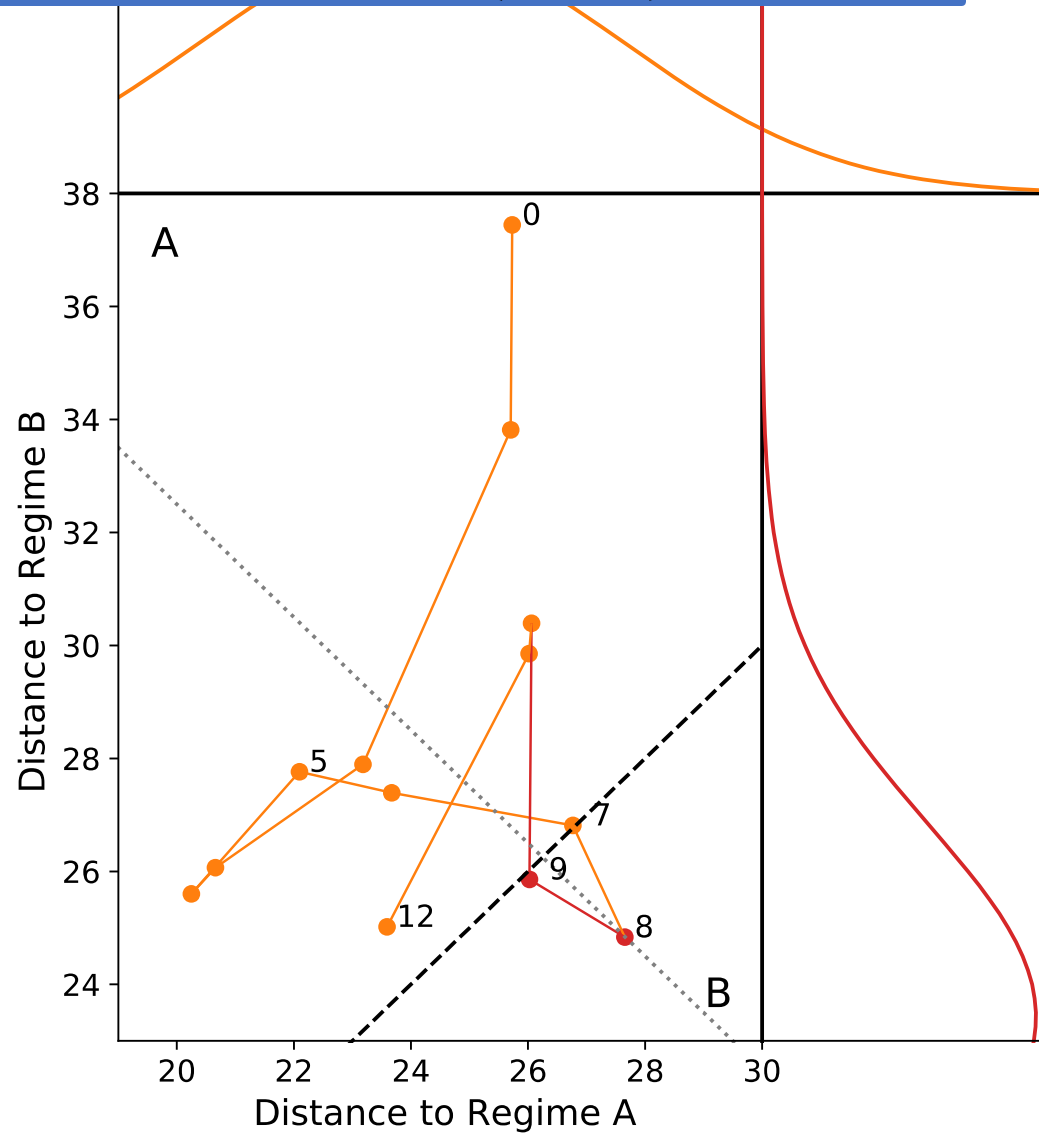
Noise can affect the distance to the regimes and this way alter the regime assignment.



Probabilistic
regime
assignment

$$P(\text{Regime}|\text{Data}) = \frac{P(\text{Data}|\text{Regime})P(\text{Regime})}{P(\text{Data})}$$

We use
Bayes
Theorem to
obtain a
probabilistic
regime
assignment.



Apply this approach to
atmospheric circulation
regimes.

Recurrent and
persistent patterns

Low-frequency
variability

Wintertime
Euro-Atlantic
sector

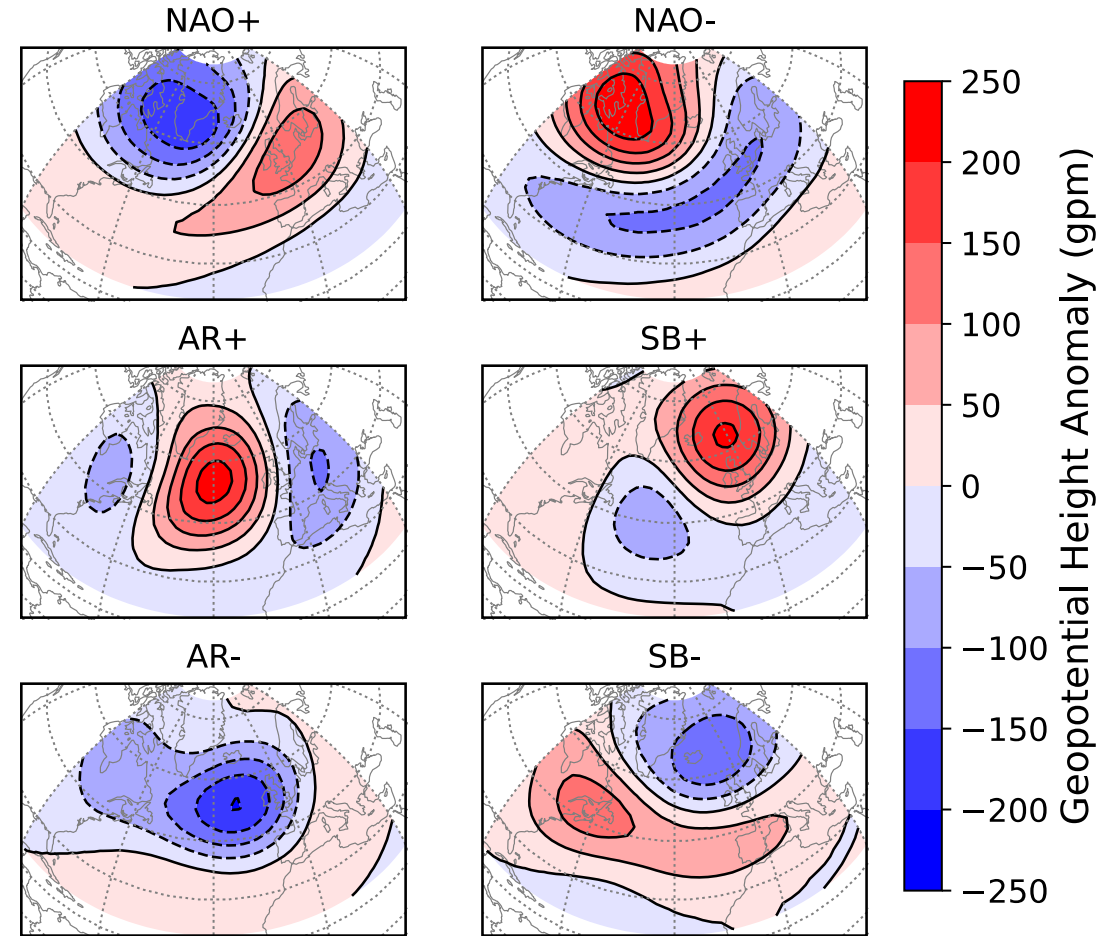
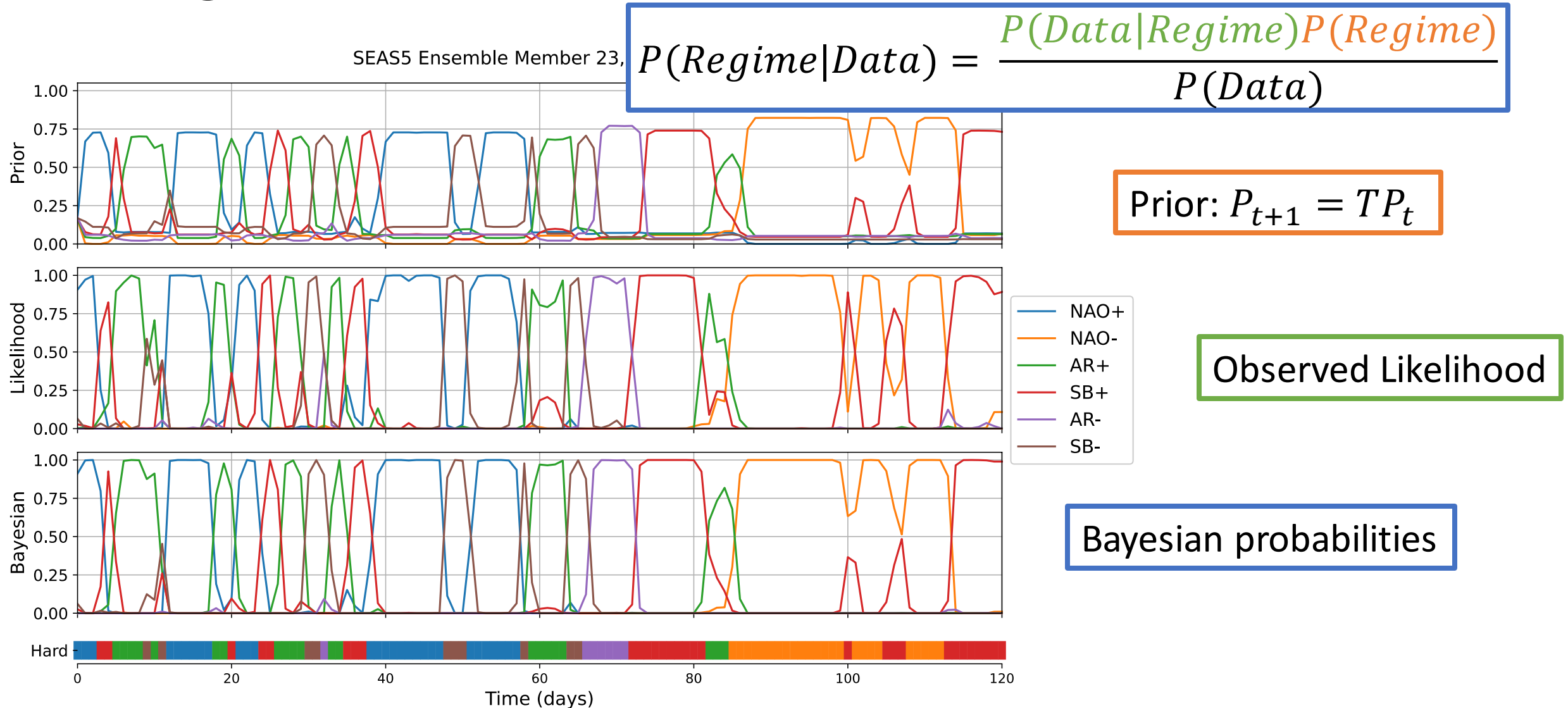
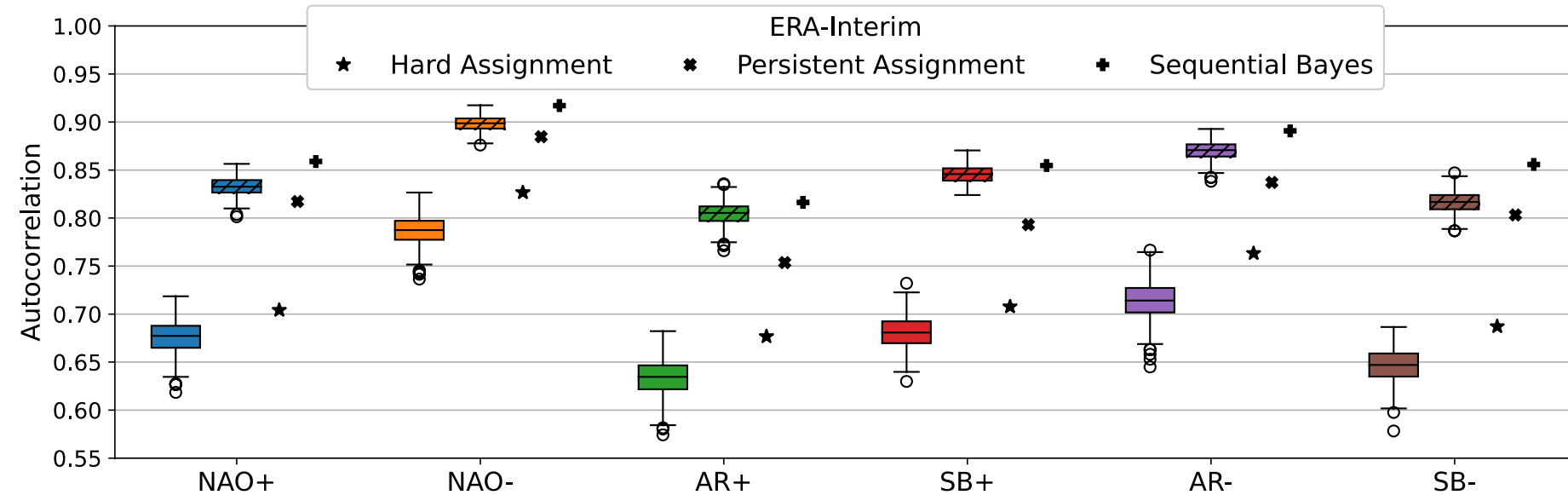
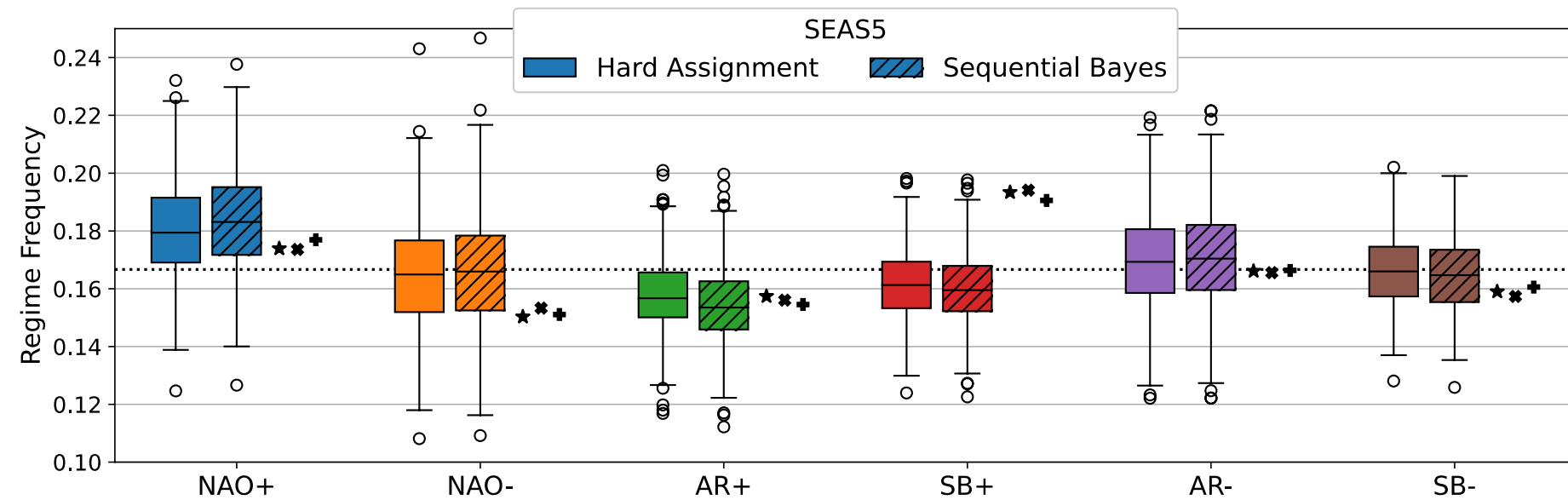


Fig. Six circulation regimes for the Euro-Atlantic sector (North Atlantic Oscillation (NAO) + and -, Atlantic Ridge (AR) + and -, Scandinavian Blocking + and -

How does the sequential Bayesian regime assignment work?





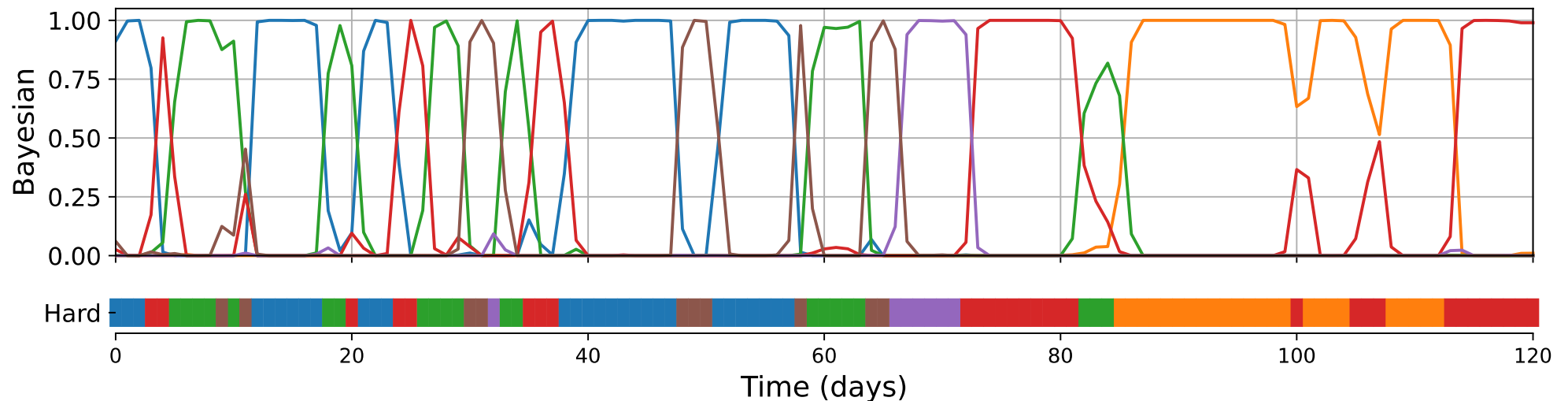
The sequential Bayesian approach yields more persistent regimes without affecting the regime frequencies.

The sequential Bayesian approach yields a more informative regime assignment compared to standard categorical methods.

Bayes Theorem:

$$P(\text{Regime}|\text{Data}) = \frac{P(\text{Data}|\text{Regime})P(\text{Regime})}{P(\text{Data})}$$

QUESTIONS?



A Bayesian approach treats the regime assignment in a probabilistic way

Posterior

Bayes Theorem:

$$P(r|D) = \frac{P(D|r)P(r)}{P(D)}$$

Prior: $P_t(r) = TP_{t-1}(r|D)$

Data: $P(D) = \sum_{r=1}^k P(D|r)P(r)$

$$\text{Observations: } P(D|r) = \frac{-\frac{1}{2}(D-\mu_r)^T \Sigma_r^{-1}(D-\mu_r)}{\sqrt{(2\pi)^k |\Sigma_r|}}$$

