Question of Interest

What about time?

Granger "causality"

A variable X Granger-causes another variable Y if X values help predicting the future of Y

$$\mathbb{P}[Y(t+1) \in A | \mathcal{I}(t)] \neq \mathbb{P}[Y(t+1) \in A | \mathcal{I}_{-X}(t)]$$

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Not true causality

(as claimed by Granger himself)

Association level on causality ladder

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Not true causality

(as claimed by Granger himself)

Association level on causality ladder

Limitations:

- No instantaneous effects
- Mostly for linear relationships (VAR models)

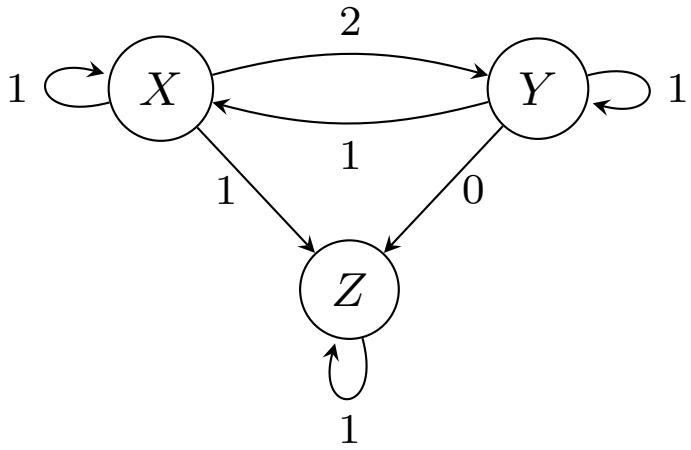
Temporal causal model

Functional causal model (FCM)

$$X_t := f_X(X_{t-1}, Y_{t-1}, \varepsilon_X)$$
$$Y_t := f_Y(Y_{t-1}, X_{t-2}, \varepsilon_Y)$$
$$Z_t := f_Z(Z_{t-1}, X_{t-1}, Y_t, \varepsilon_Z)$$

with noise terms $\boldsymbol{\varepsilon}$ jointly independent

(summary) Temporal causal graph



Joint probability distribution

$$P(X, Y, Z)$$

Temporal causal model

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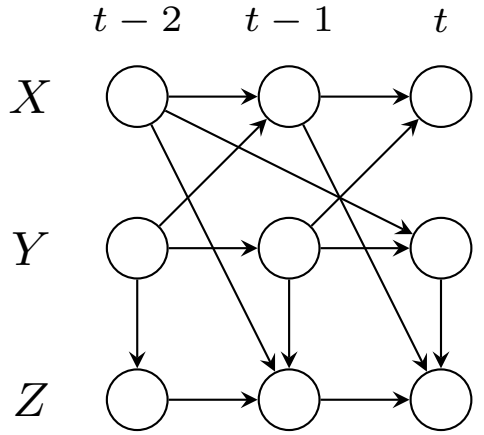
(window) Temporal causal graph



Joint probability distribution

$$P(X, Y, Z)$$

Time series setup challenge

Non-i.i.d. data

(independence testing, likelihood computation…)

Delay identification

Non-stationarity

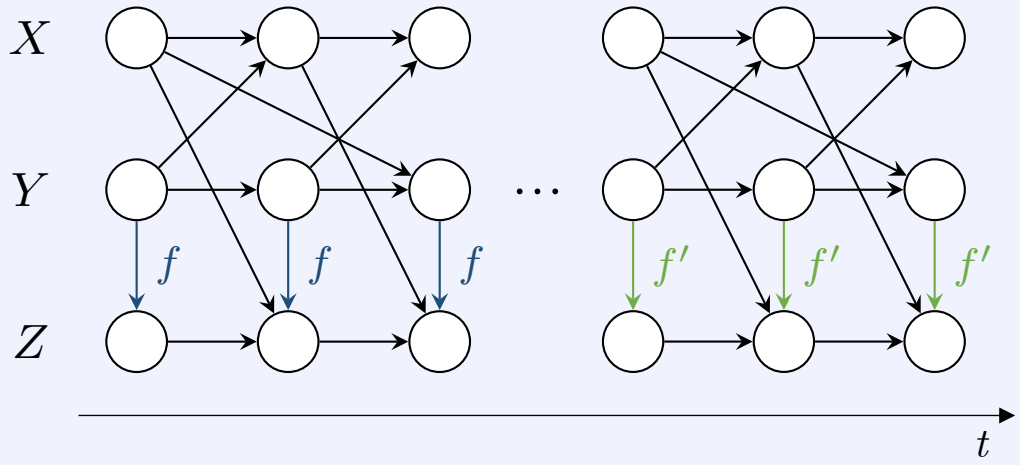
Non-stationarity under causal perspective

Origin

- Functional mechanism change
- Varying cause-effect delay
- Cause-effect pairs deletion/addition/flip

How

- Drift vs. abrupt change
- Recurrent regimes



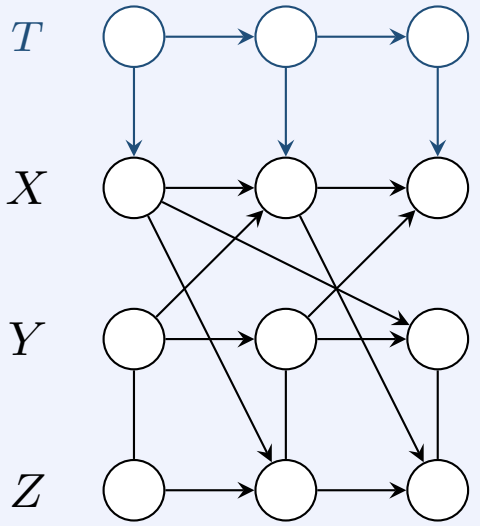
Constraint-based causal discovery from non-stationary TS

CD-NOD

- Based on conditional independence tests
- Use of a surrogate variable to model time (time index)
- Can handle non-stationarity if it can be expressed as smooth function of time

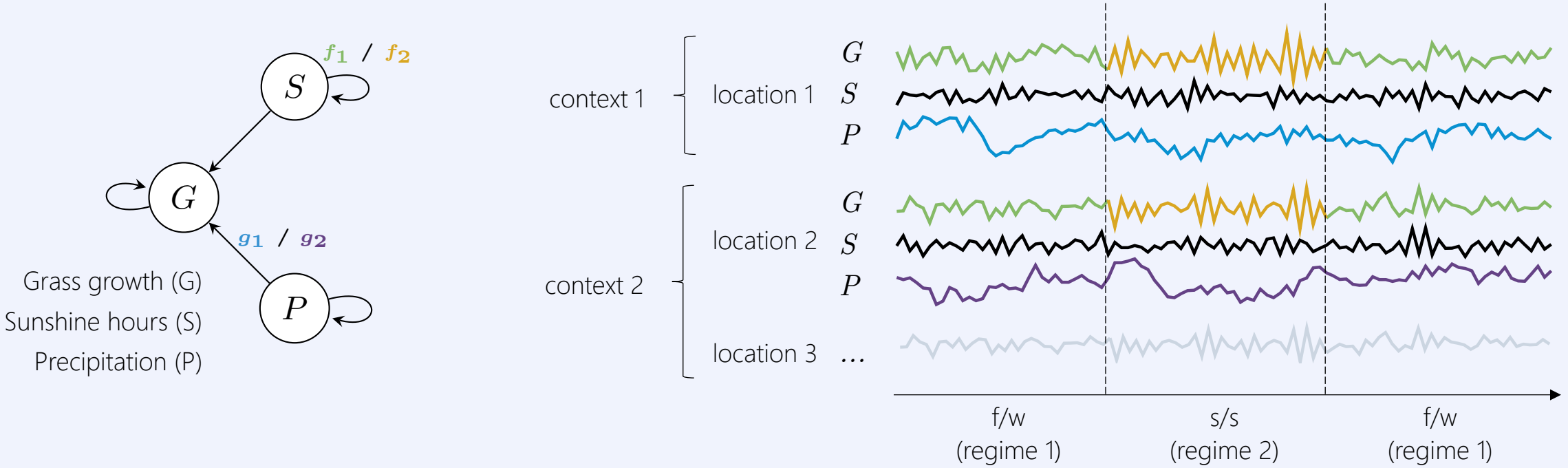
Limitations

- Partially oriented graph
- In practice, use conditional independence test designed for i.i.d. samples and multiple statistical testing problem



(Huang et al. 2020)

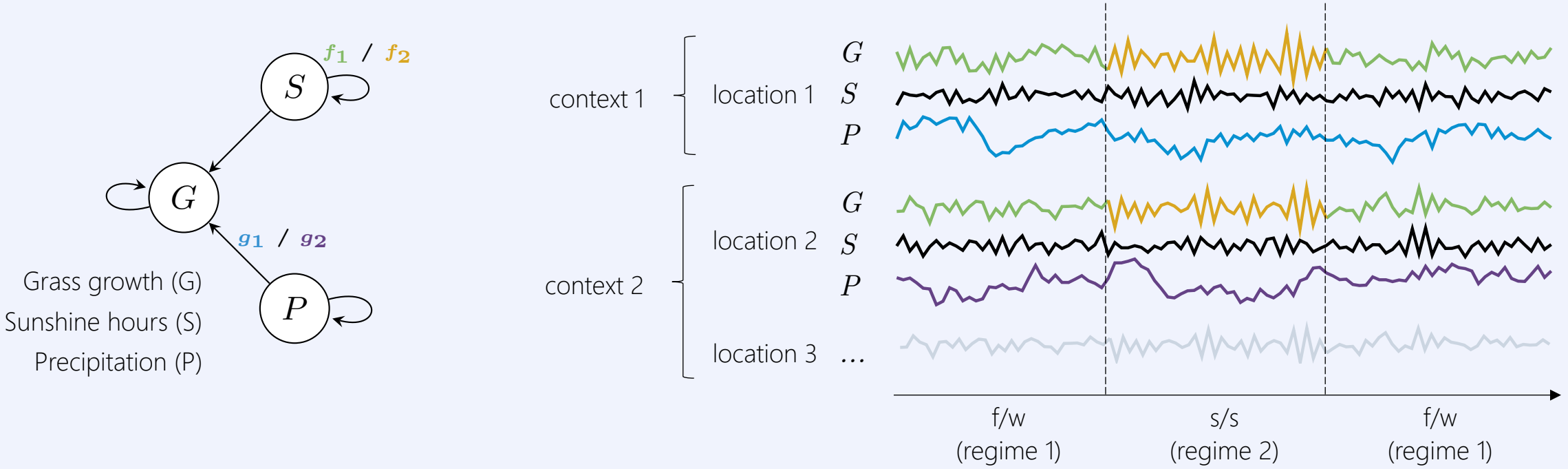
AIT-based causal discovery from non-stationary TS



SPACETIME

Times series with recurrent regimes and from heterogeneous contexts

AIT-based causal discovery from non-stationary TS



SPACETIME

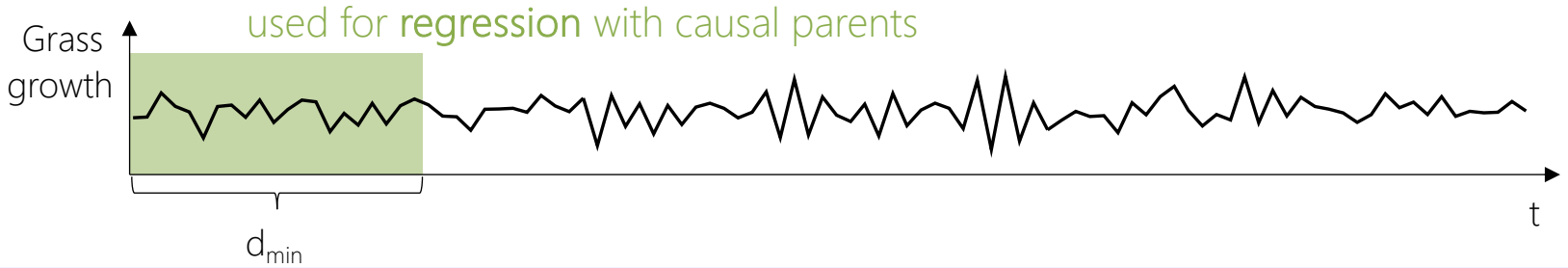
Times series with recurrent regimes and from heterogeneous contexts

Major assumption: the causal structure does not change

(Mameche et al. 2025)

Detecting regime changes

1 Functional modeling



Detecting regime changes

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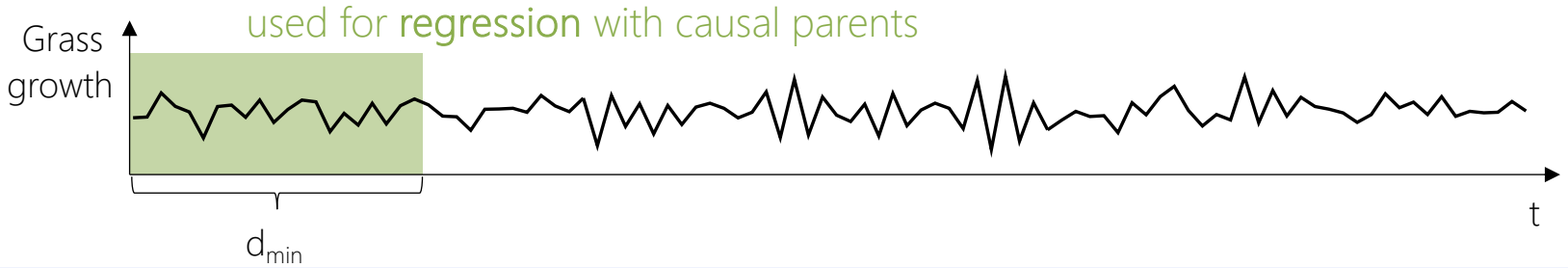
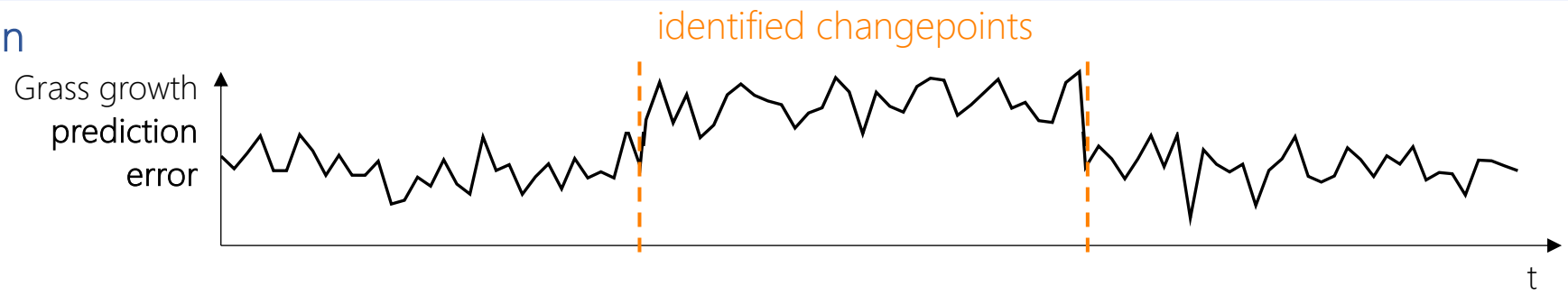


2 Changepoint detection



Detecting regime changes

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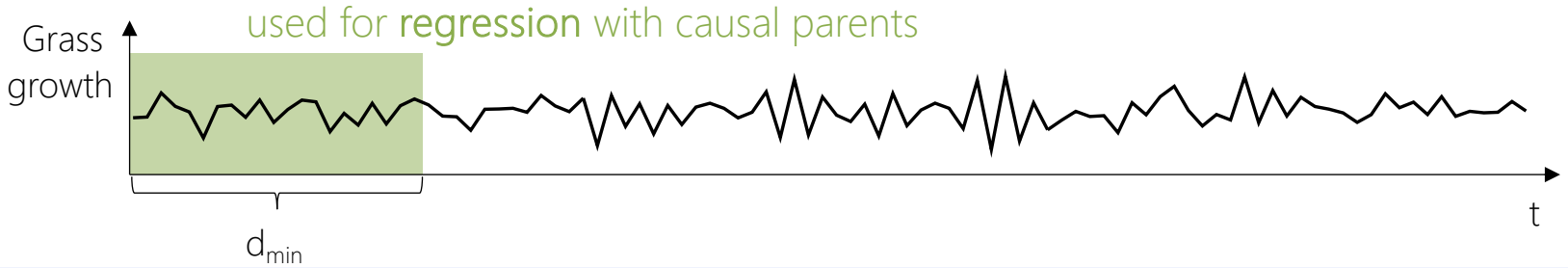

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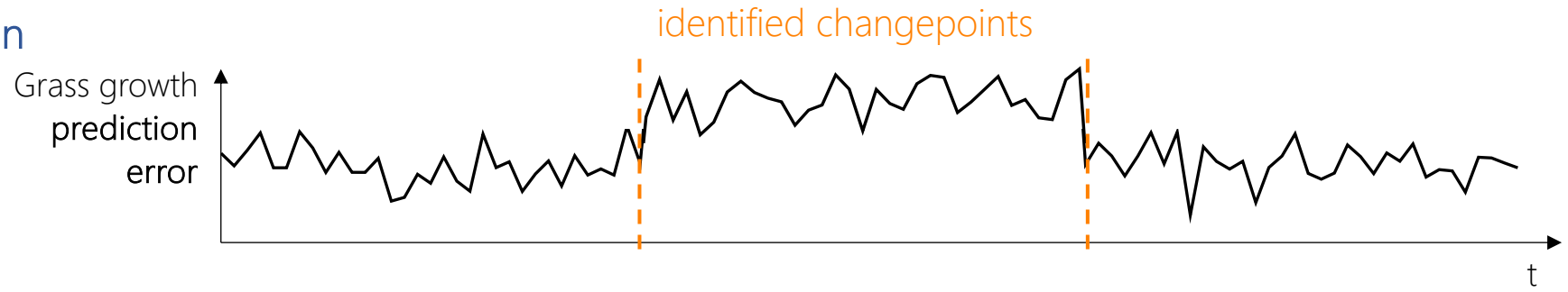

3 Regime partitioning