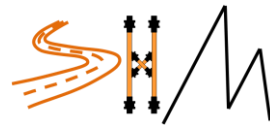


A Hybrid Approach for Prediction of Long-Term Behavior in Concrete Structures

Mauricio Pereira

Branko Glisic



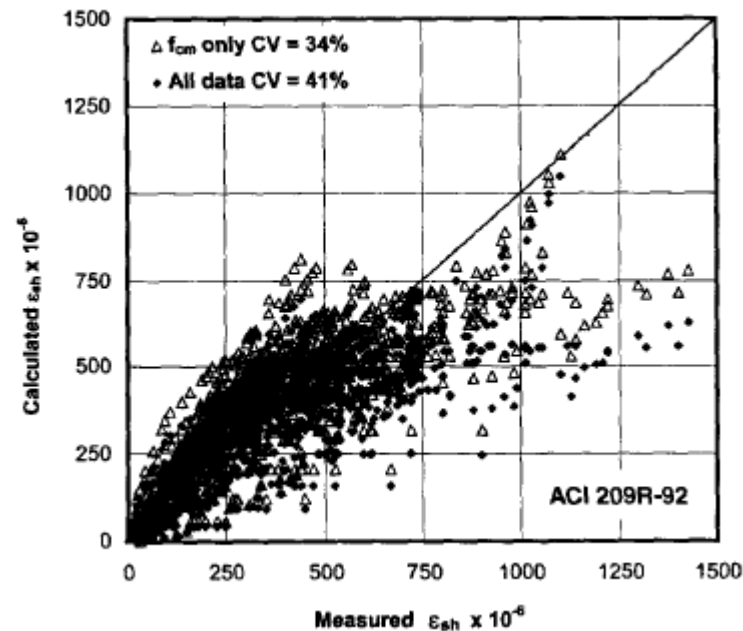
Structural Health Monitoring Lab



- Create innovative methods to predict the long-term behavior of concrete structures
 - Analytical and/or numerical modeling
 - Machine learning (ML)
 - Data Analytics
 - Structural health monitoring (SHM)

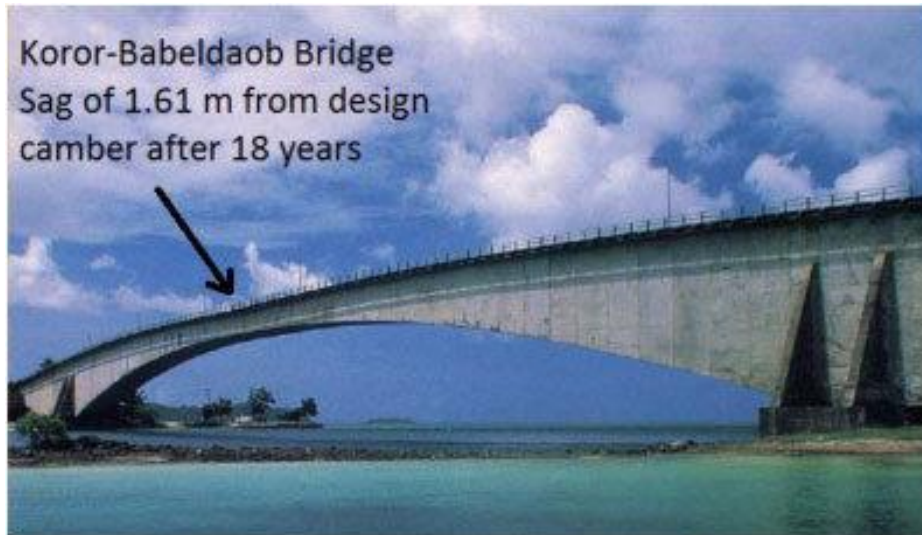
Motivation

- Concrete structures are ubiquitous in our society
- Lifespans can range multiple decades and may need to be extended
- Long-term time-dependent behavior of concrete is complex to model
 - Creep and shrinkage are stochastic, depend on temperature, humidity, loading
 - Lack of long-term in-situ data



Motivation

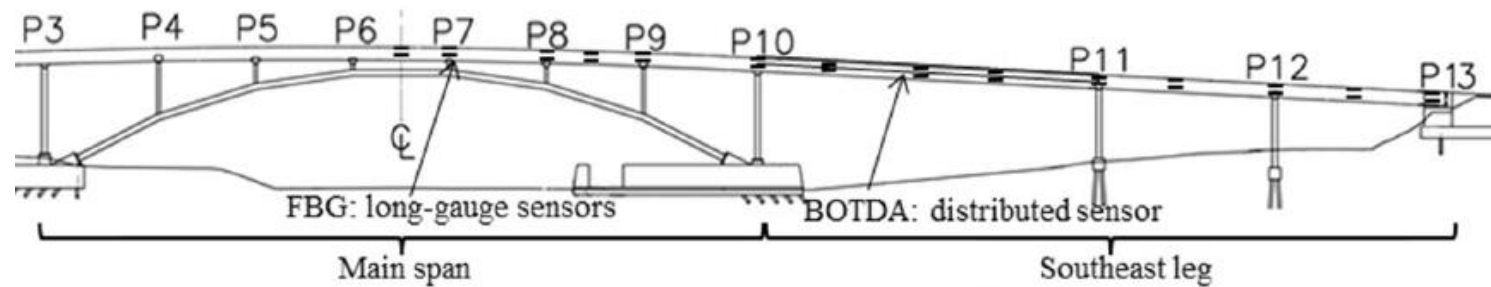
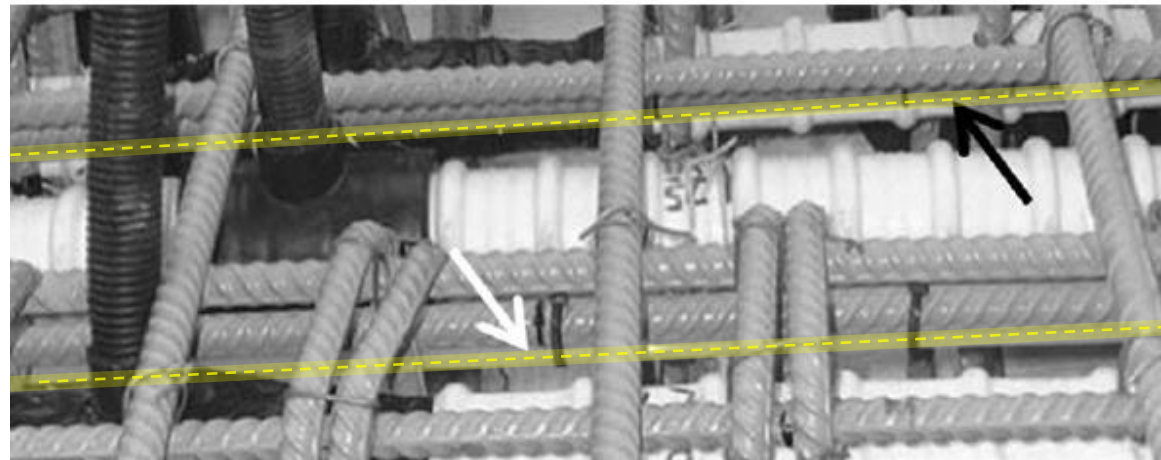
- Poor prediction can lead to limited serviceable life
- Accurate prediction enables the detection of unexpected behavior
 - Degradation processes, changes in boundary conditions, sensor malfunction, etc.



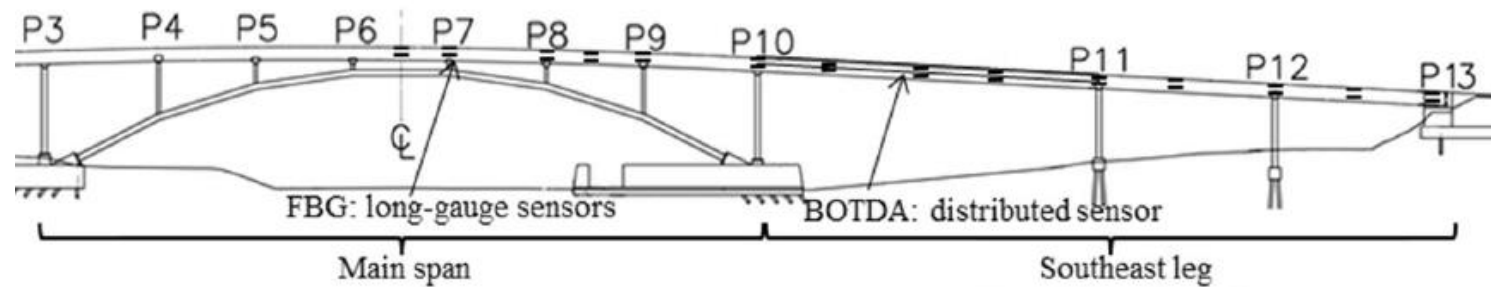
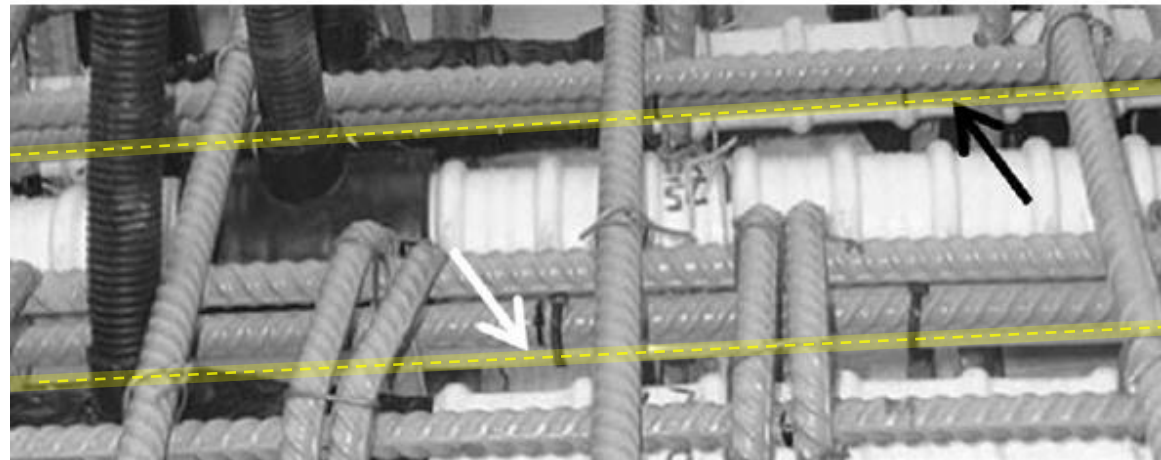
R. Wendner, Mija H. Hubler & Z.P. Bažant (2013)



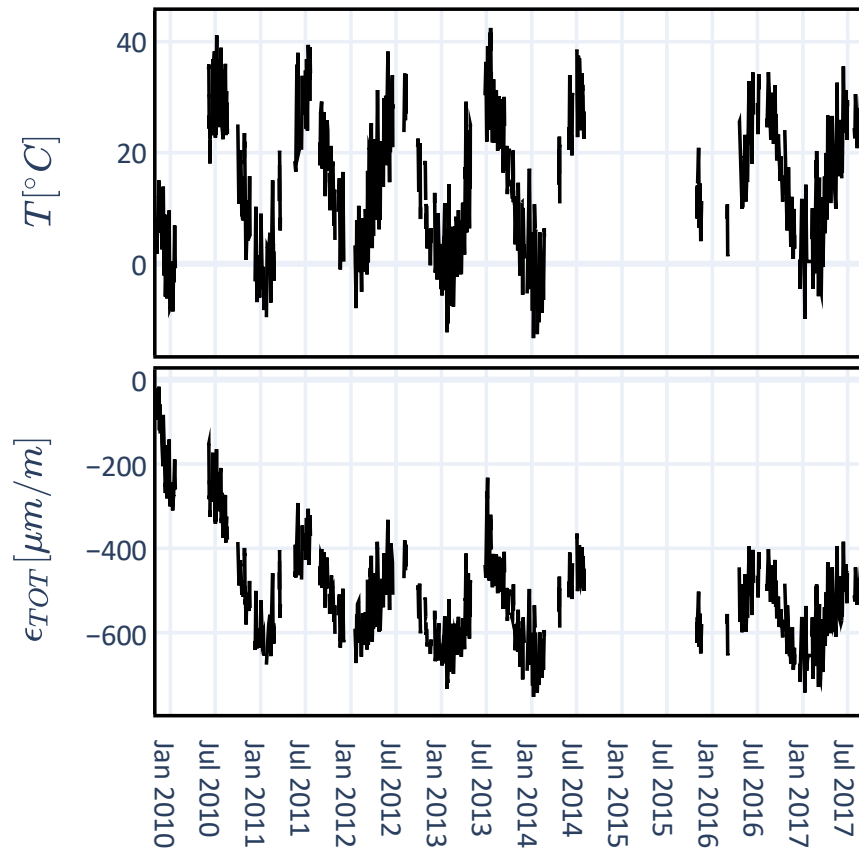
1.1 Streicker Bridge



1.1 Streicker Bridge



1.2 Strain Measurement Modeling



$$\epsilon_{TOT}^t = \epsilon_T^t + \epsilon_e^t + \epsilon_R^t$$

$$\epsilon_T^t = \alpha \cdot \Delta T^t$$

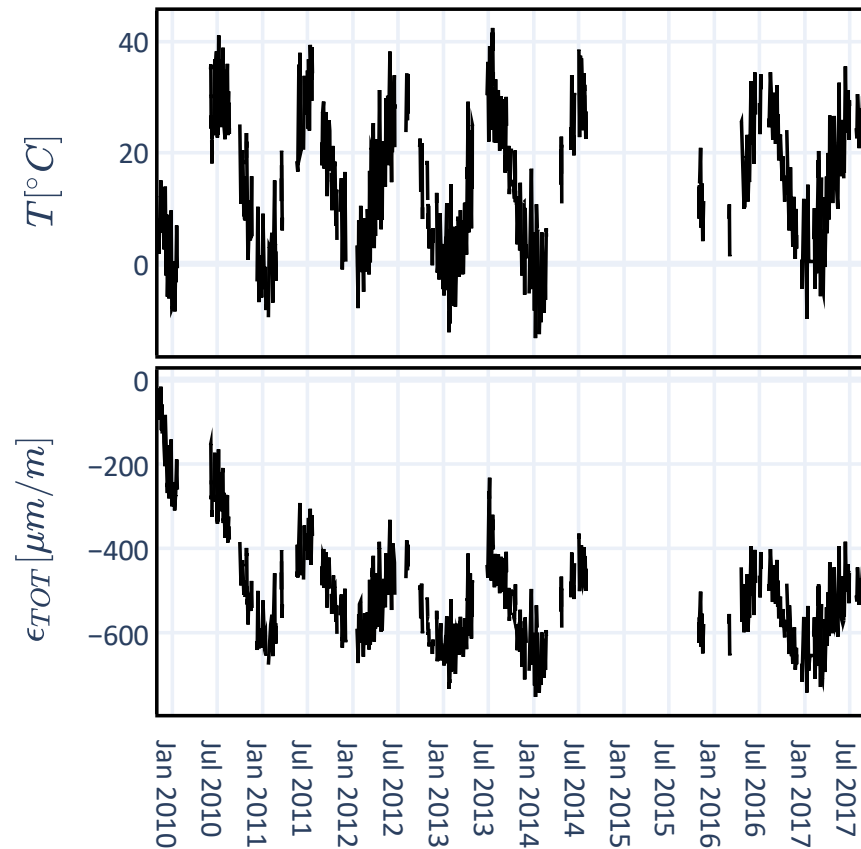
$$\epsilon_e^t = \epsilon_{e,P}^t + \epsilon_{e,T}^t$$

$$\epsilon_{e,T}^t = \epsilon_{e,T}(\Delta T^{t,\tau}) = \epsilon_{e,T}^{t,\tau}$$

$$\epsilon_{TD}^{t,\tau} = \alpha \cdot \Delta T^t + \epsilon_{e,T}^{t,\tau}$$

$$\epsilon_{TOT}^{t,\tau} = \epsilon_{TD}^{t,\tau} + \epsilon_{e,P}^t + \epsilon_R^t$$

1.2 Strain Measurement Modeling



$$\epsilon_{TOT}^{t,\tau} = \epsilon_{TD}^{t,\tau} + \epsilon_{e,P}^t + \epsilon_R^t$$

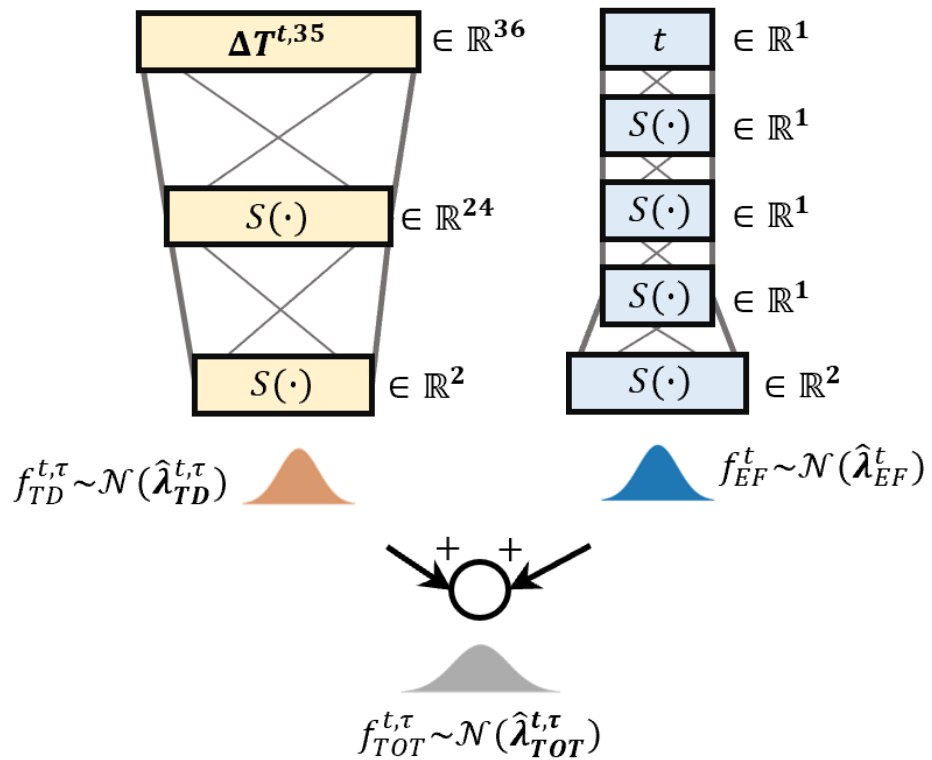
$$\delta \epsilon_{TOT}^{t,\tau} = \epsilon_{TD}^{t,\tau} + \delta \epsilon_{e,P}^t + \delta \epsilon_R^t$$

$$\delta \epsilon_{TOT}^{t,\tau} = \epsilon_{TD}^{t,\tau} + \delta (\epsilon_{e,P}^t + \epsilon_R^t)$$

$$\delta \epsilon_{TOT}^{t,\tau} = \epsilon_{TD}^{t,\tau} + \delta \left((1 - \chi^t) \epsilon_R^t + \epsilon'_{e,P} \left(\frac{\chi^t}{\chi'} \right) \right)$$

$$\delta \epsilon_{TOT}^{t,\tau} = \epsilon_{TD}^{t,\tau} + \epsilon_{EF}^t$$

2.1 PNN: Architecture



$$\varepsilon_{TOT}^{t,\tau} = \varepsilon_{TD}^{t,\tau} + \varepsilon_{e,P}^t + \varepsilon_R^t$$

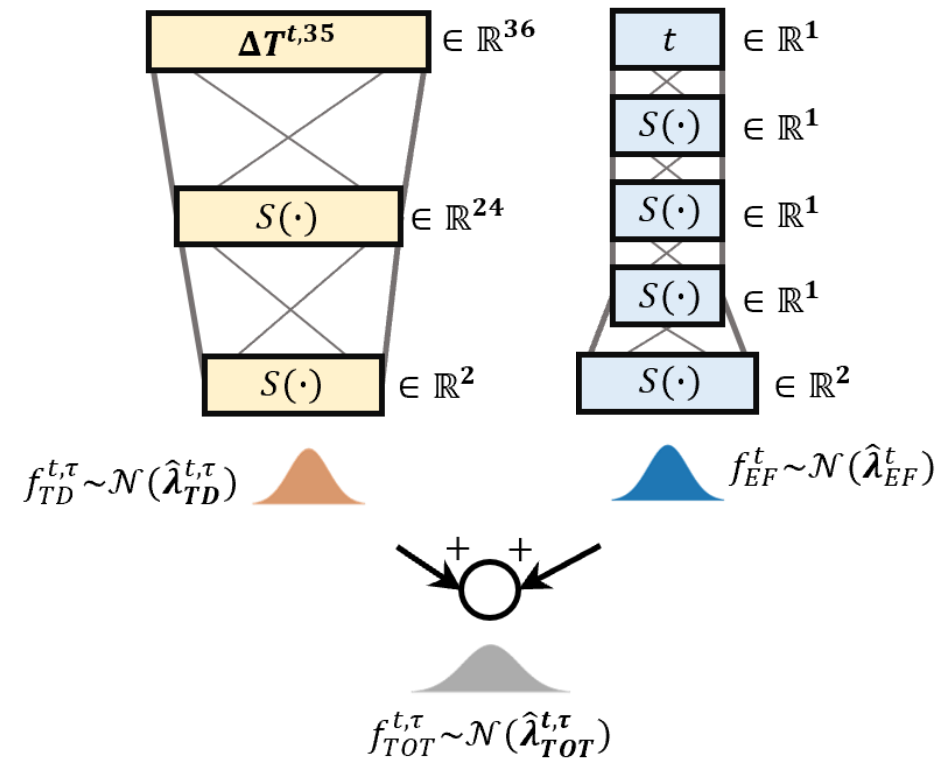
$$\delta \varepsilon_{TOT}^{t,\tau} = \varepsilon_{TD}^{t,\tau} + \delta \varepsilon_{e,P}^t + \delta \varepsilon_R^t$$

$$\delta \varepsilon_{TOT}^{t,\tau} = \varepsilon_{TD}^{t,\tau} + \delta(\varepsilon_{e,P}^t + \varepsilon_R^t)$$

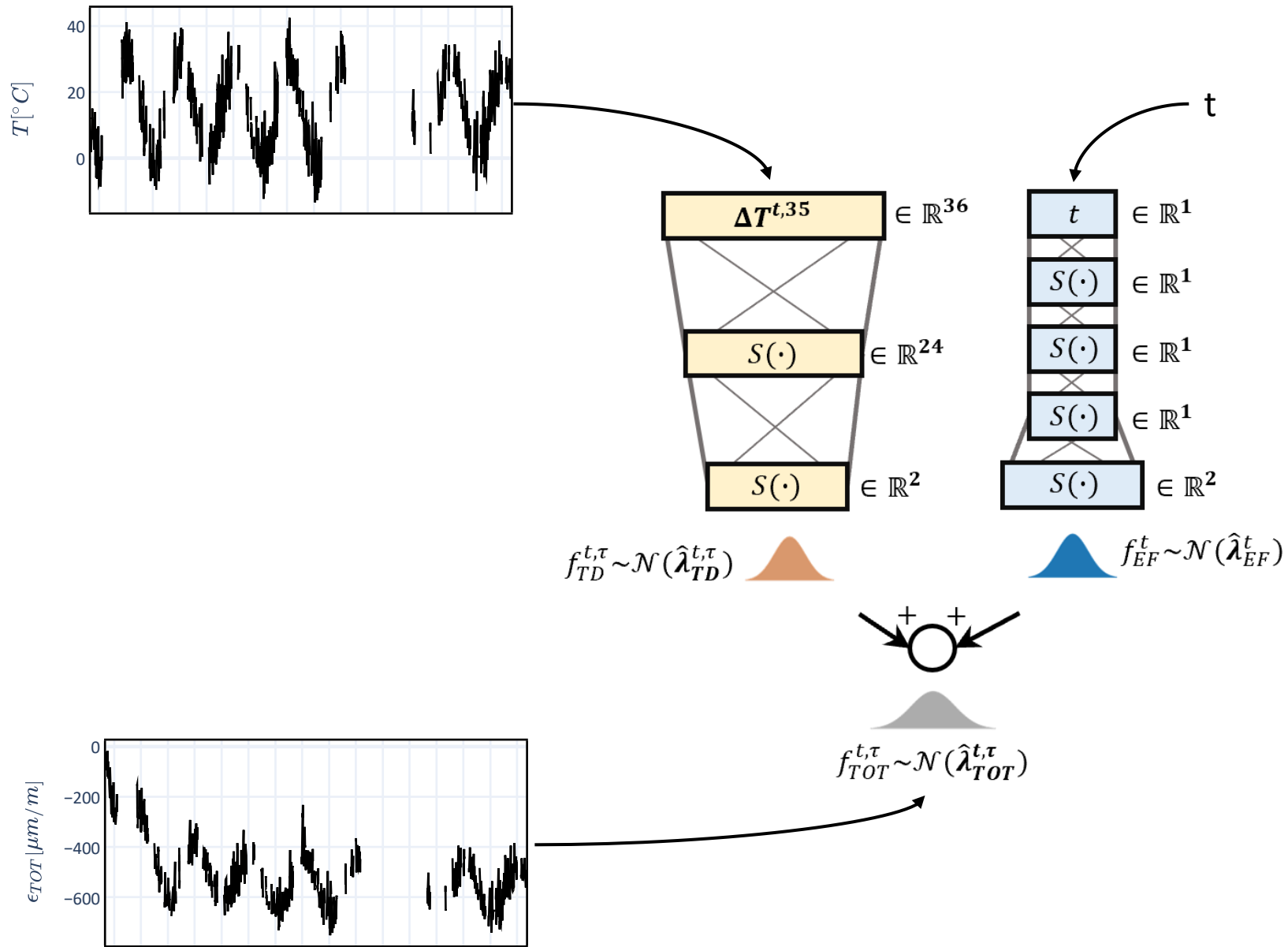
$$\delta \varepsilon_{TOT}^{t,\tau} = \varepsilon_{TD}^{t,\tau} + \delta \left((1 - \chi^t) \varepsilon_R^t + \varepsilon'_{e,P} \left(\frac{\chi^t}{\chi'} \right) \right)$$

$$\delta \varepsilon_{TOT}^{t,\tau} = \varepsilon_{TD}^{t,\tau} + \varepsilon_{EF}^t$$

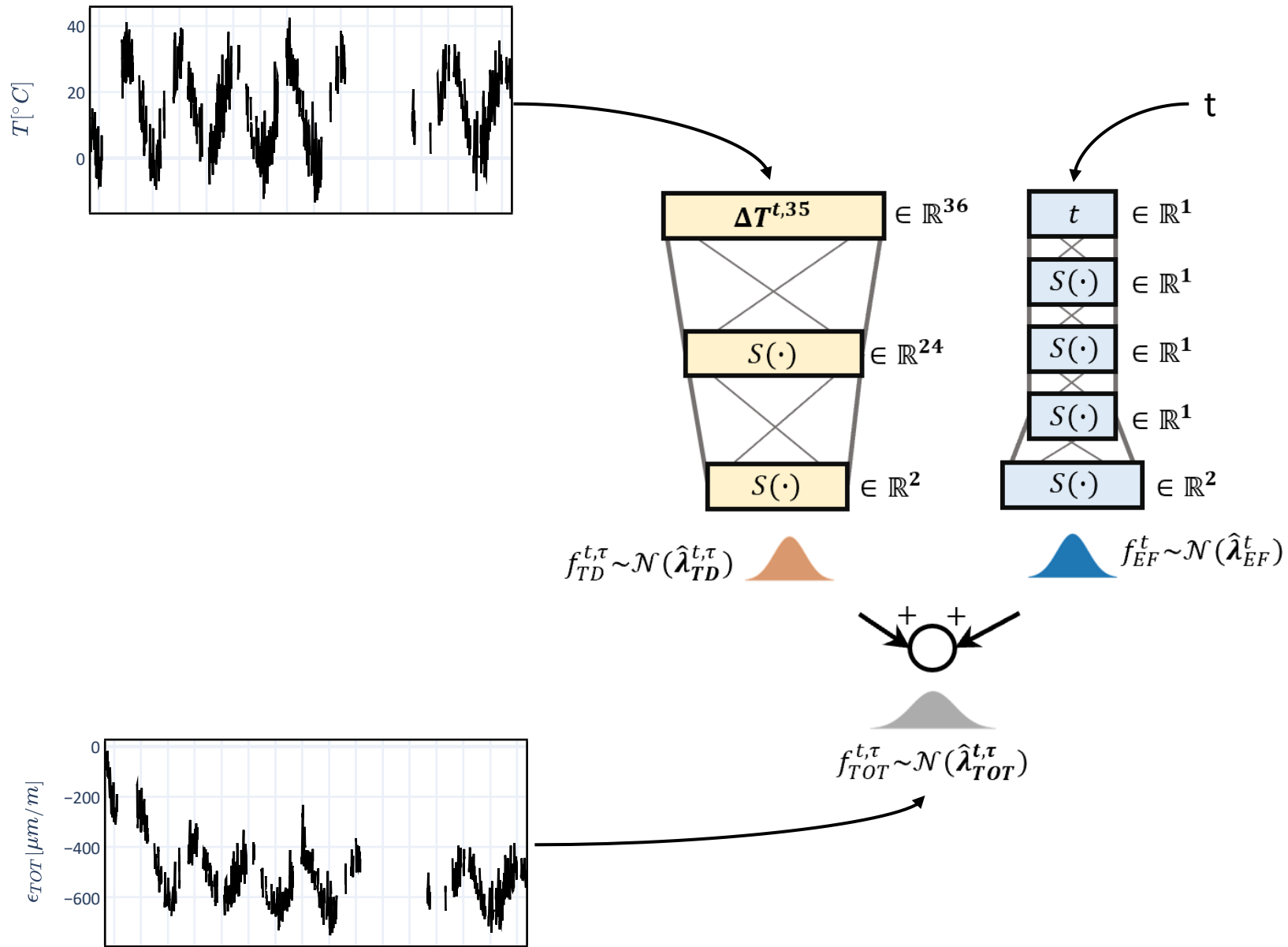
2.1 PNN: Architecture



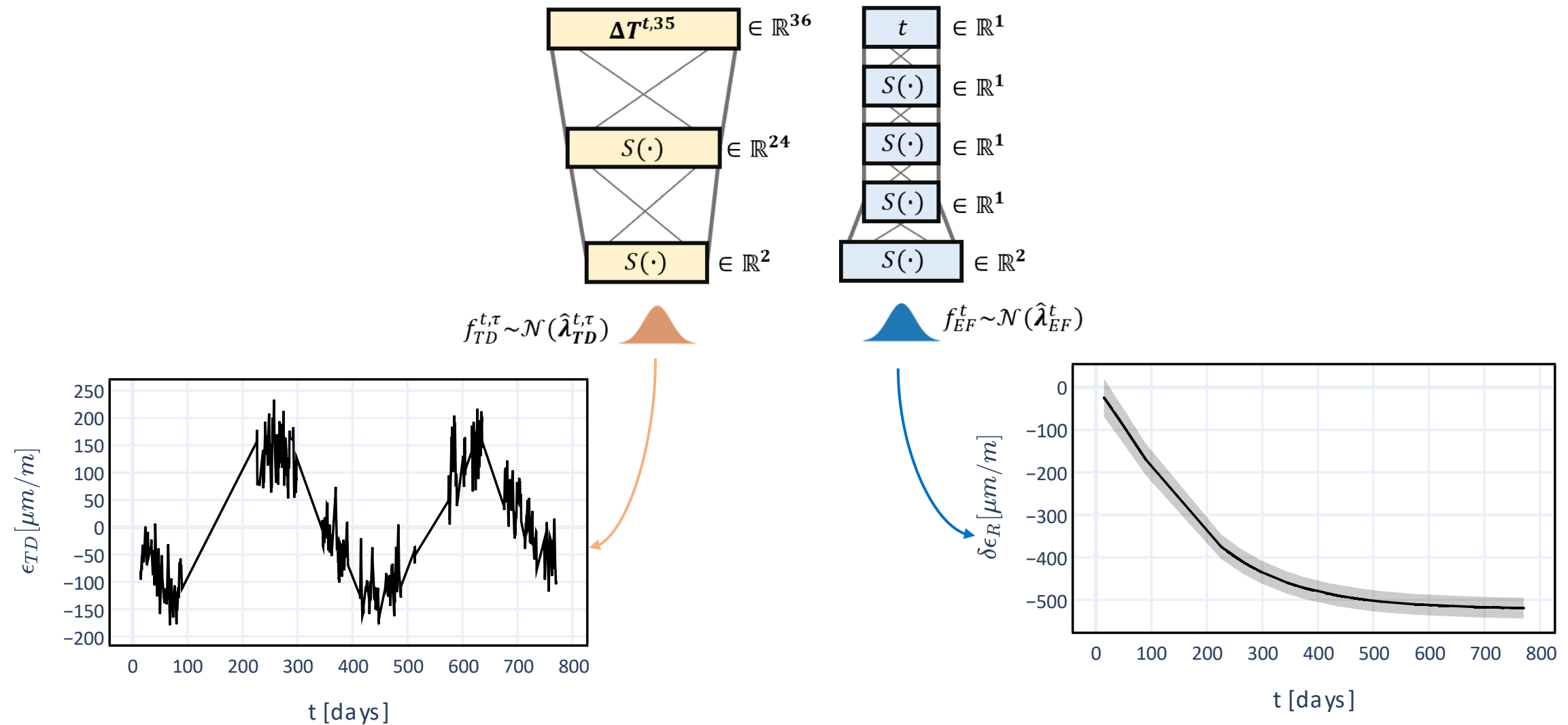
2.1 PNN: Architecture



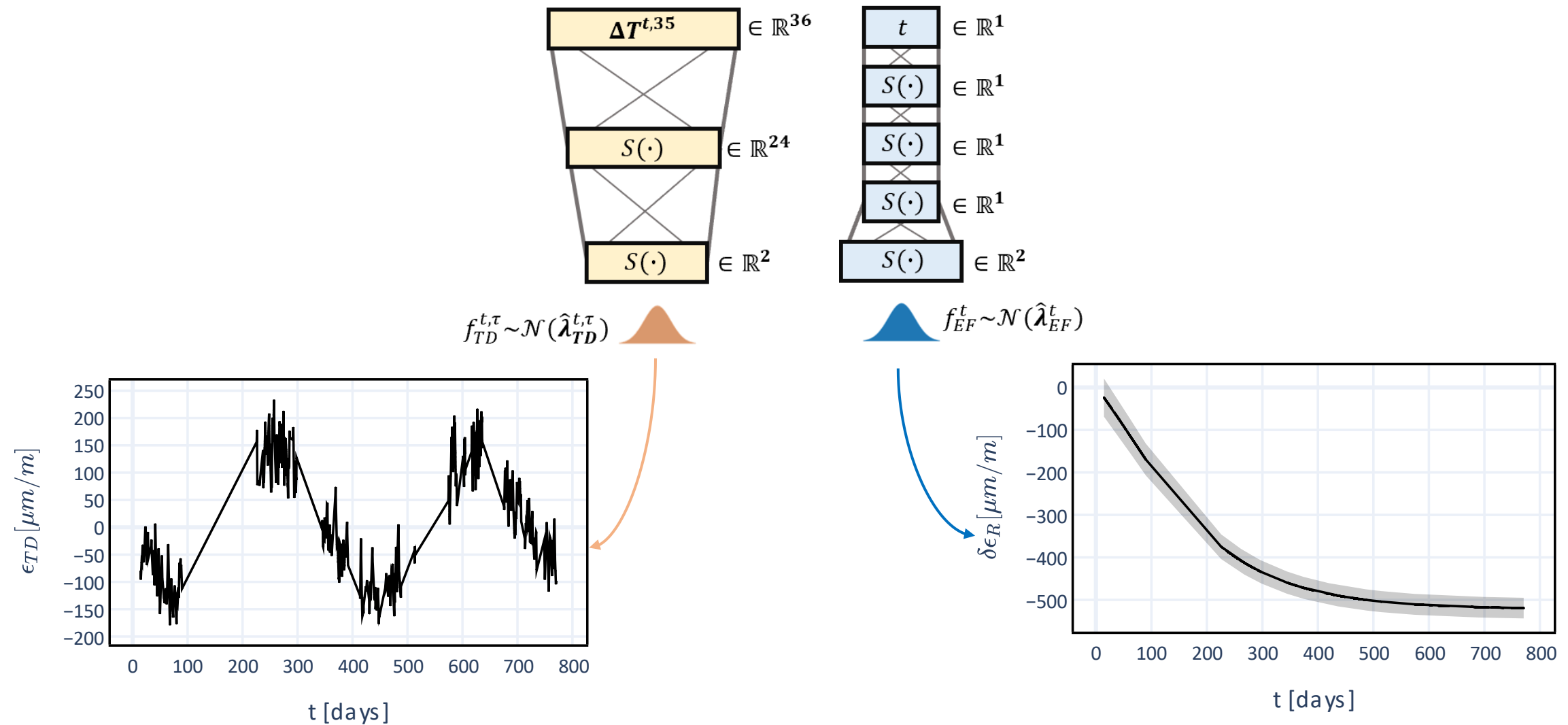
2.1 PNN: Architecture



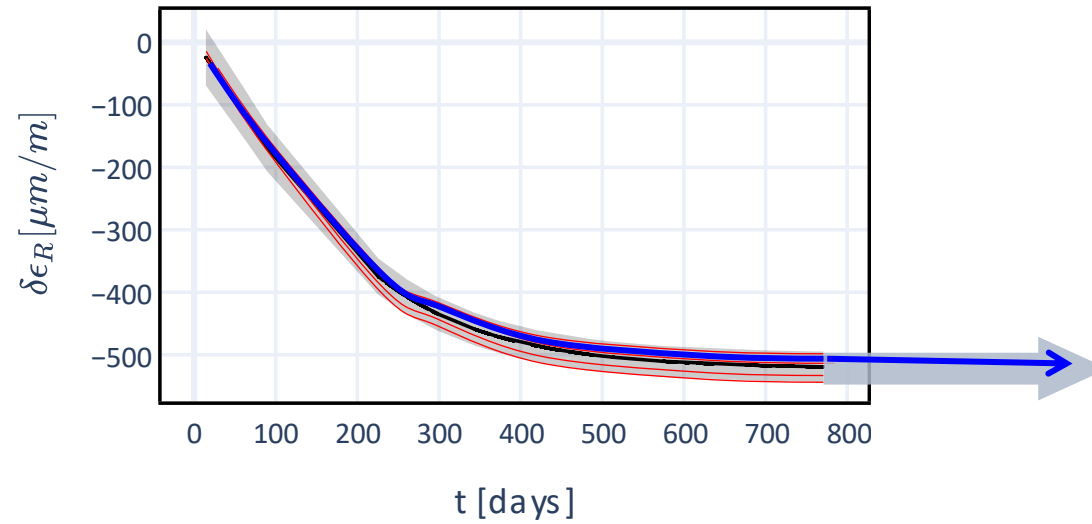
2.2 PNN: Strain decomposition



2.2 PNN: Strain decomposition



2.3 PNN: Code model functions

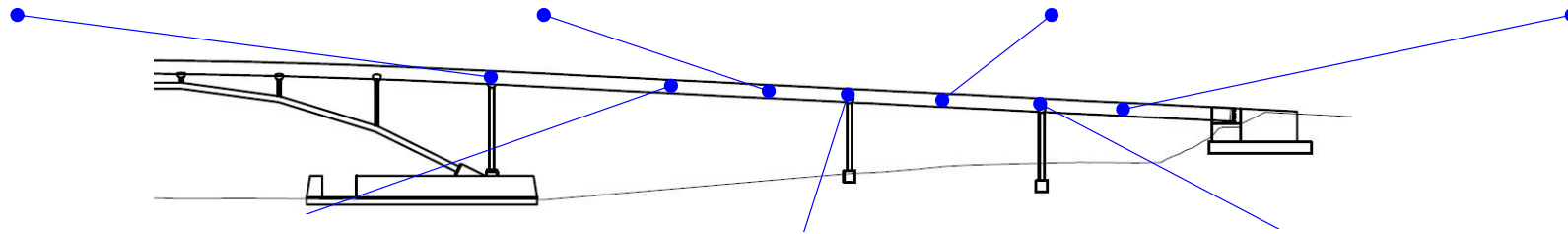


$$\epsilon_{E+T}^t = a \cdot \left(1 - e^{-\frac{t-t'}{b}}\right) + c \cdot \left(\tanh \sqrt{\frac{t-t_0}{d}}\right)$$

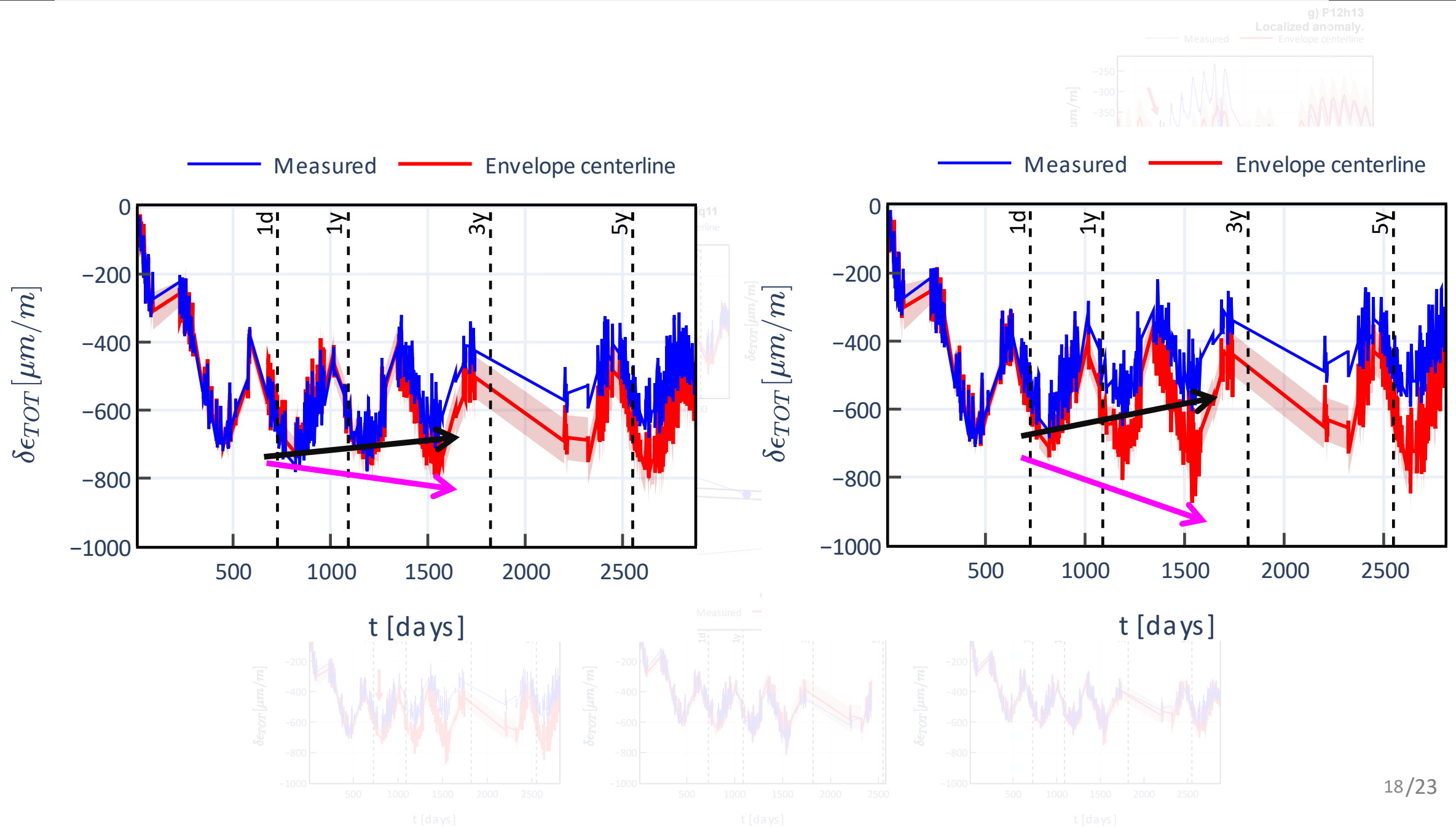
3. Results: Multiple models

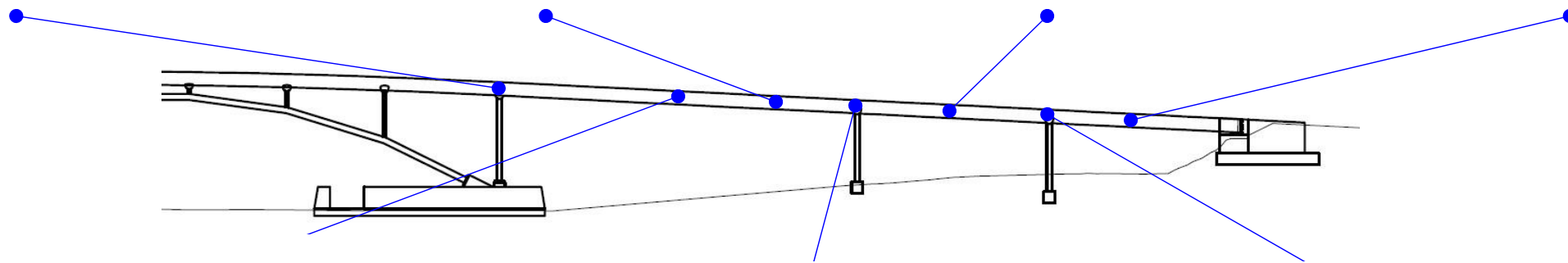
— E+T — ACI — CEB — B4 — Measured

3. Results: Prediction envelope



3. Results: Prediction envelope

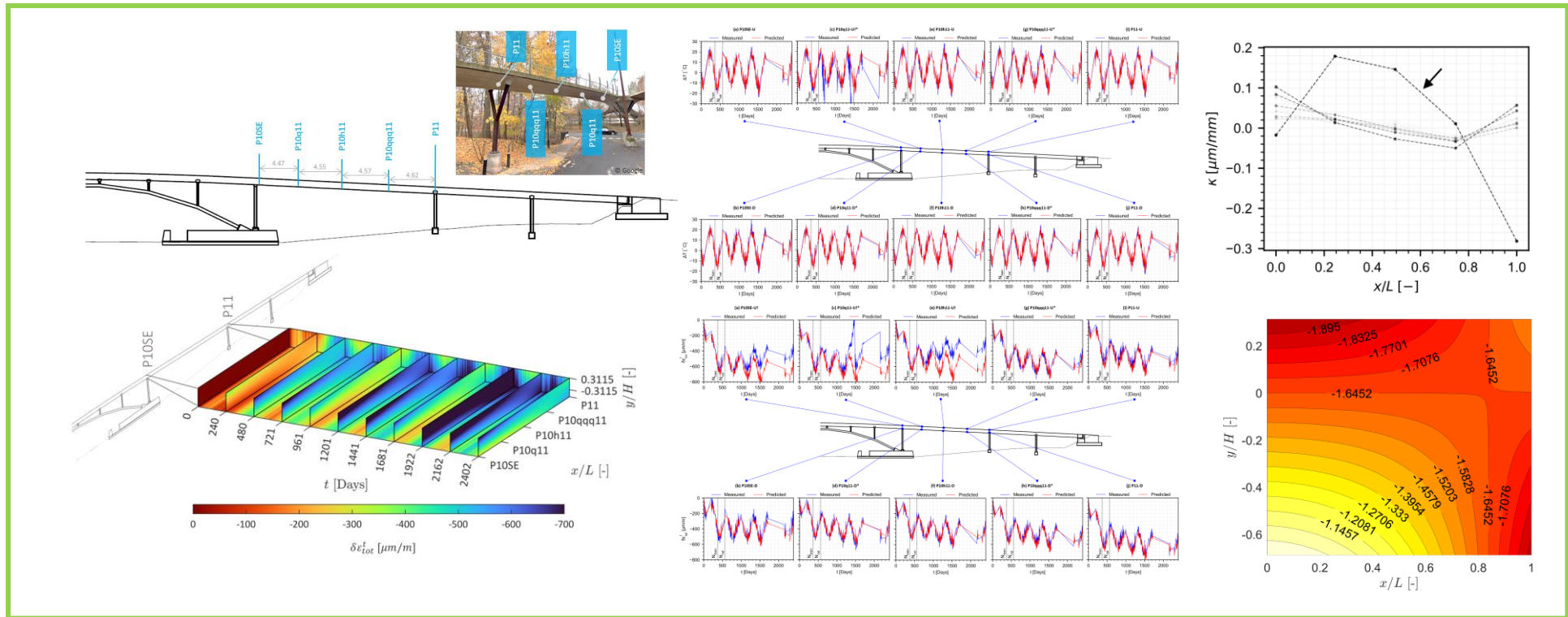
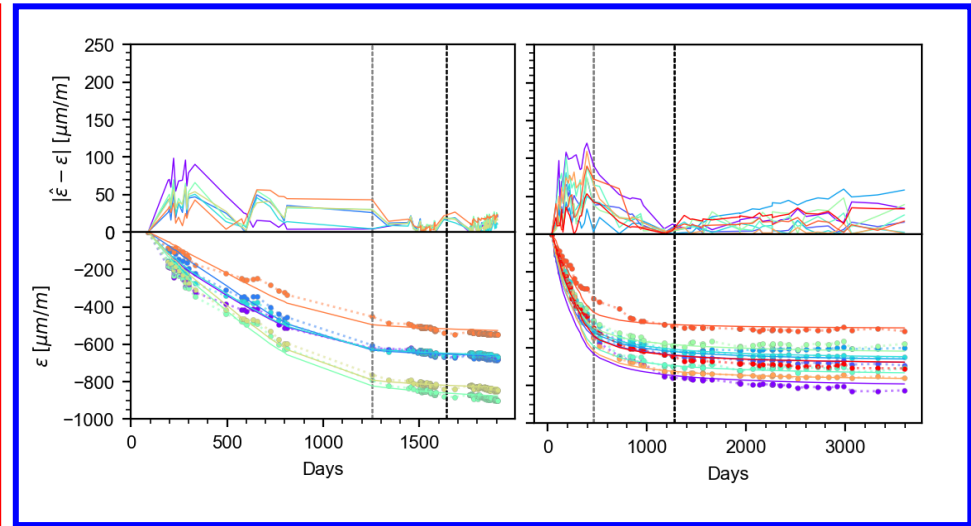
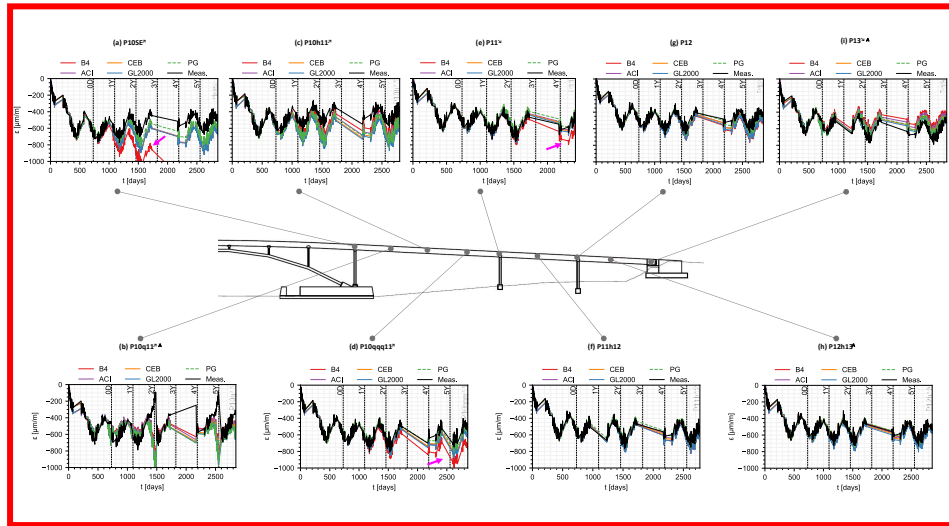




4. Conclusions

- By combining
 - SHM
 - Probabilistic ML
 - Strain modeling
 - Domain specific functions
- We can:
 - Motivate the machine-learning model architecture
 - Decompose the total strain into temperature and time-dependent components
 - Predict structural response envelopes multiple-years ahead
 - Detect both sudden and gradual anomalies

5. Ongoing work



Acknowledgements

- NSF Grant CMMI-2038761
- Princeton University
- Vivek Kumar, Hiba Abdel-Jaber

Thank you!
Questions? :D