Wind Turbine Blade Defect Forecasting

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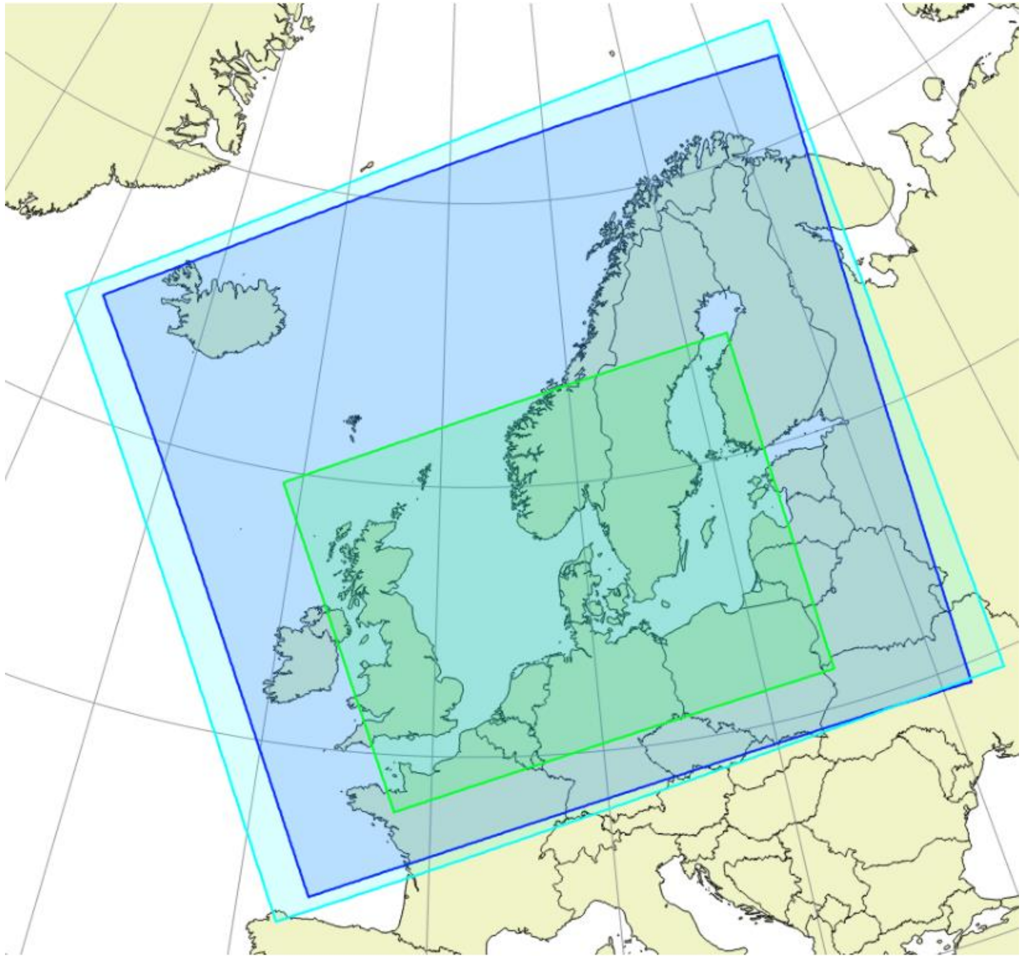
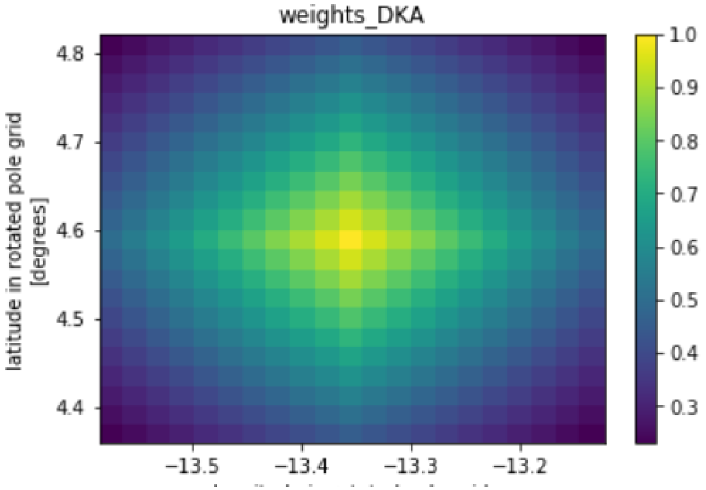
Objectives

- Establish a comprehensive environmental parameter database for Europe
- Identify relationships between blade degradation and environmental conditions
- Develop a blade defect forecasting tool for blade defect prediction based on environmental parameters

Weather time series as inputs



- 3 DMI HARMONIE model domains
  - – DKA = green
  - – NEA = blue
  - – SKA = cyan
- Precipitation provided as surface data
- Wind speed, direction and turbulent kinetic energy given as model level data



Damage progression as outputs

Expected Defect progression from original defect							
Voids				Chipping		Peeling	Erosion
Chipping		Peeling	Erosion	Erosion	Peeling	Erosion	
Erosion	Peeling	Erosion			Erosion		
	Erosion						

- Blade defects are detected by visual inspection

- Damage encoding

$$\Delta\text{damage} = (\text{defect}_{t+1} - \text{defect}_t) + 2 \cdot (\text{severity}_{t+1} - \text{severity}_t)$$

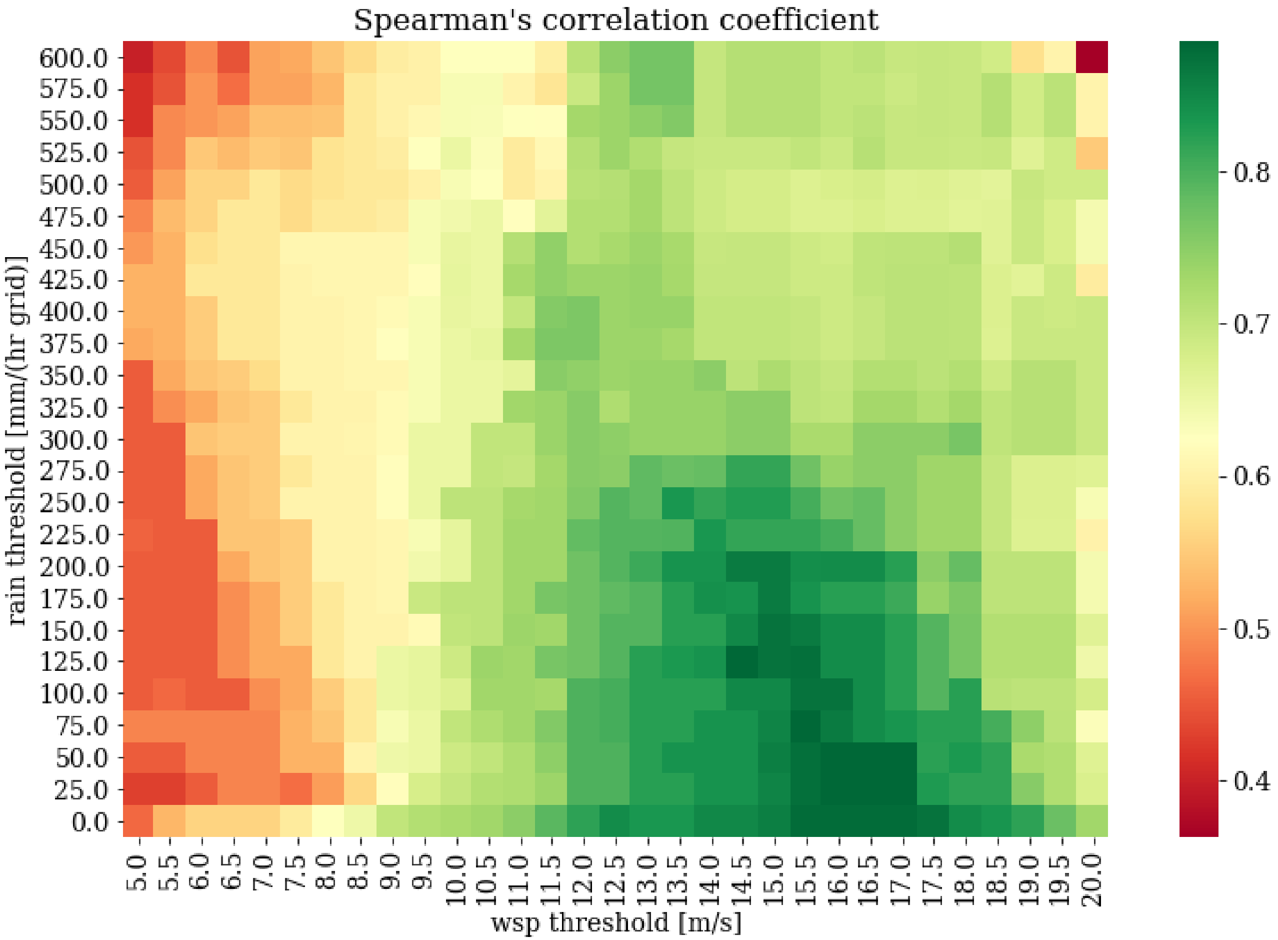
- Needs to be decoded back to human-interpretable values, e.g., probability of severity increase

Type	Defect	Severity
Voids	1	1
Voids	1	2
Voids	1	3
Chipping	2	1
Chipping	2	2
Chipping	2	3
Peeling	3	1
Peeling	3	2
Peeling	3	3
Erosion	4	1
Erosion	4	2
Erosion	4	3
Erosion	4	4
Erosion	4	5

Input data given as sequences

2013	2014	2015	2016	2017	2018	2019	2020	D0 [-]	seq len [mo]	ΔD [-]
WF1										
								0	72	2
WF2										
								0	60	20
								0	72	30
								20	12	8
WF3										
								0	48	3
WF4										
								0	36	2
								0	72	2
								2	36	1
WF5										
								0	60	20
								0	72	45
								0	84	28
								21	12	2
								21	24	6
								25	12	4

Representing weather in stratified format



- Correlation between damage progression and number of hours above threshold
- High correlation for high wind speeds in combination with rain
- Mesoscale weather model does not consider wake effects, blockage, etc.

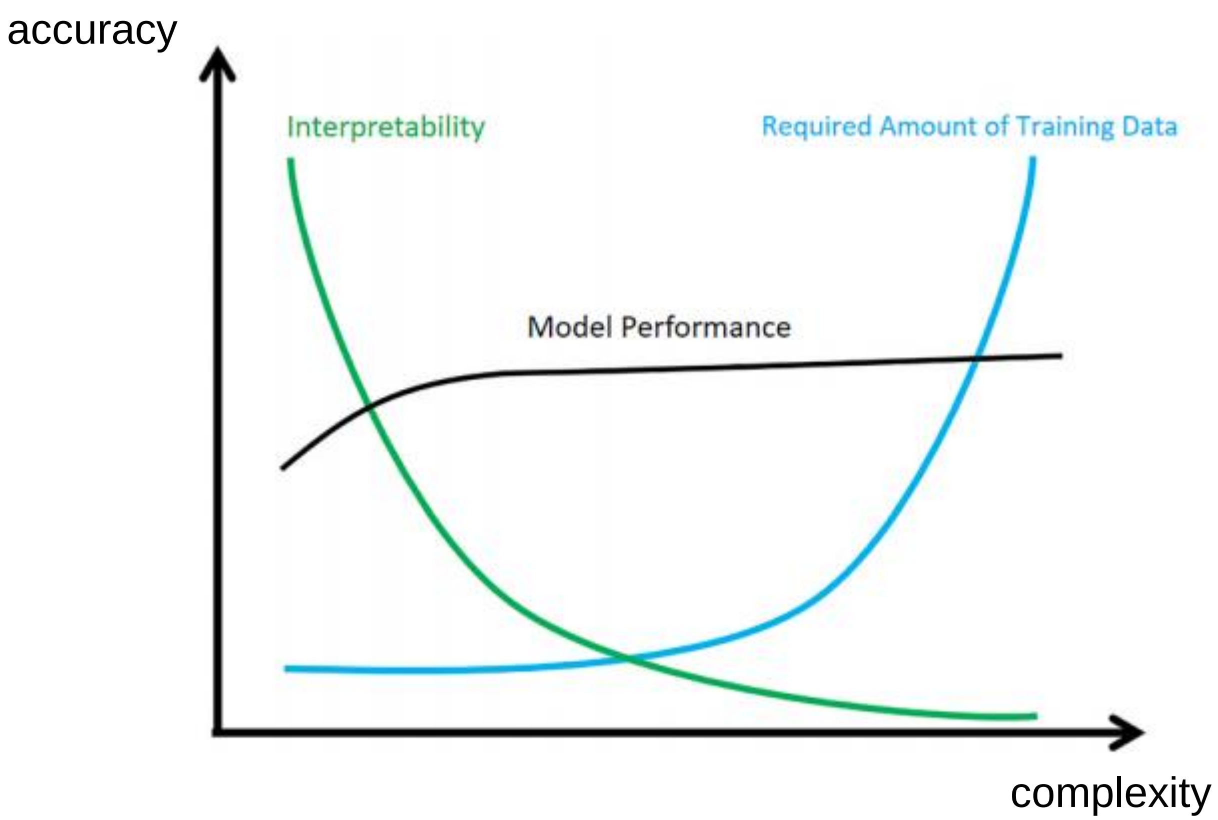
Model evaluation

- Exhaustive cross-validation using leave-*p*-out

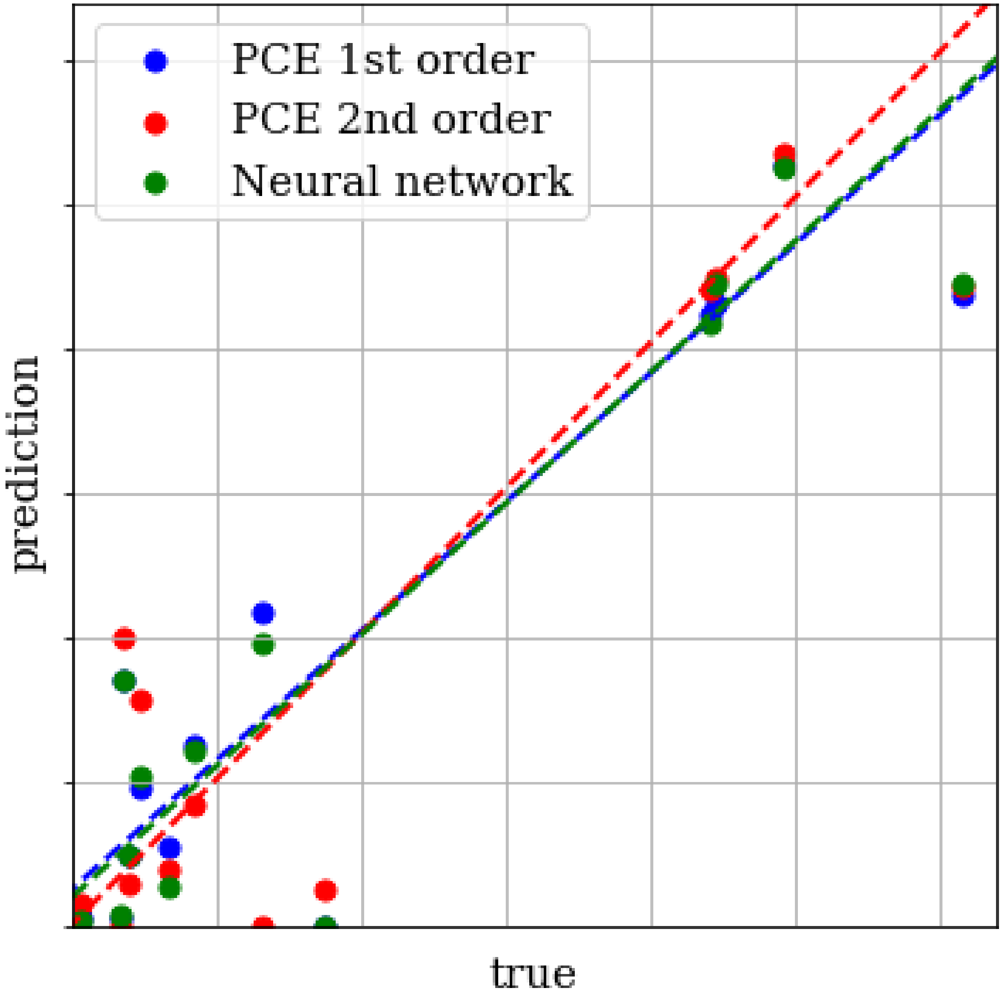
  1. Choose number of samples p to leave out for validation
  2. Train N models based on the number of unique combinations
  3. Calculate concatenated score for the model type/architecture
  4. ”Sanity checks” to verify physicality. Evaluated based on the expected value and standard deviation of the outputs from the N models
  5. Overall model assessment is based on results from 3. and 4.

Modelling

- Baseline model
  - Mean value as basis
- Polynomial chaos expansion
  - 1^{st}, 2^{nd} and 3^{rd} order
- Neural networks
  - Shallow feedforward
  - Few neurons

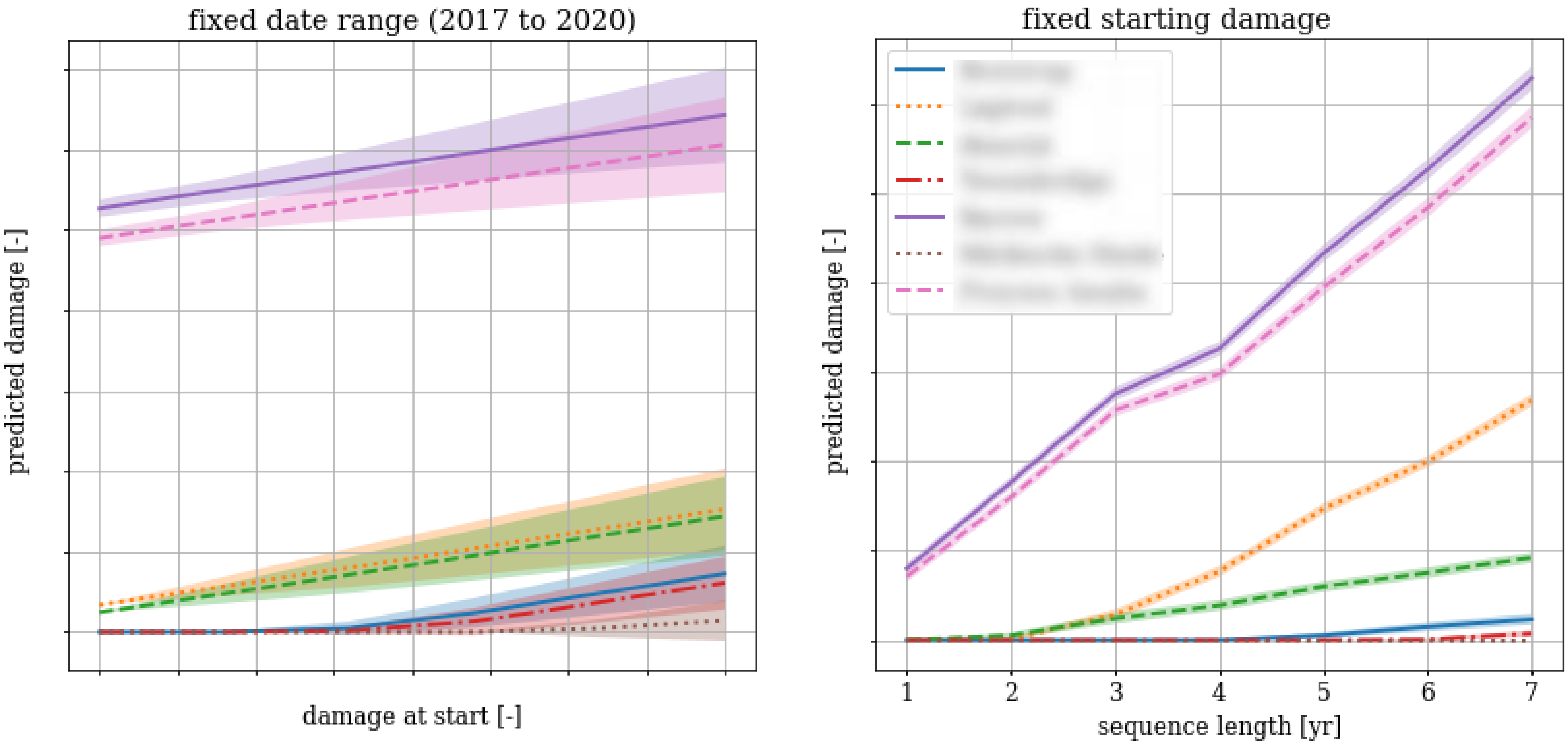


Results



Model	*ME*	*MAE*	*MAPE*	R^2
PCA 1st	5.1	298.1	60.6	0.93
PCA 2nd	14.4	389.1	92.3	0.90
NN	-3.2	308.8	68.6	0.93

Results


fixed date range (2017 to 2020)
predicted damage [-]
damage at start [-]
fixed starting damage
predicted damage [-]
1
2
3
4
5
6
7
sequence length [yr]

Limitations

- Number of samples limits the complexity
- Initial state of the blades and unknown repairs
- Variation in blade type and coating
- Temporal/spatial resolution of weather data
- Missing meteorological inputs; droplet size

Preliminary conclusions

- Data-driven methodology for quantifying and predicting damage progression based on blade inspections and weather data

- High correlation between damage progression and number of rain/high wind events

- For the current number of samples, simple models are to be preferred over complex models

Questions