

---

# Optimized significant wave height forecasts and their benefit on the prediction of possible working times

---

Offshore Wind R&D Conference 2015

14. October 2015

Bremerhaven, Germany

Thomas Kanefendt, Arne Wessel, Britta Mey



# Fraunhofer

## IWES

---

---

# Overview

- Motivation
  - Why improving significant wave height forecasts?
- Methods
  - How to improve the forecasts?
- Data
  - On which information is the work based?
- Results
  - Any improvements for the workability at sea?
- Conclusion
  - What is worth to remember?
- Acknowledgements
  - Where does the money come from?



---

# Motivation

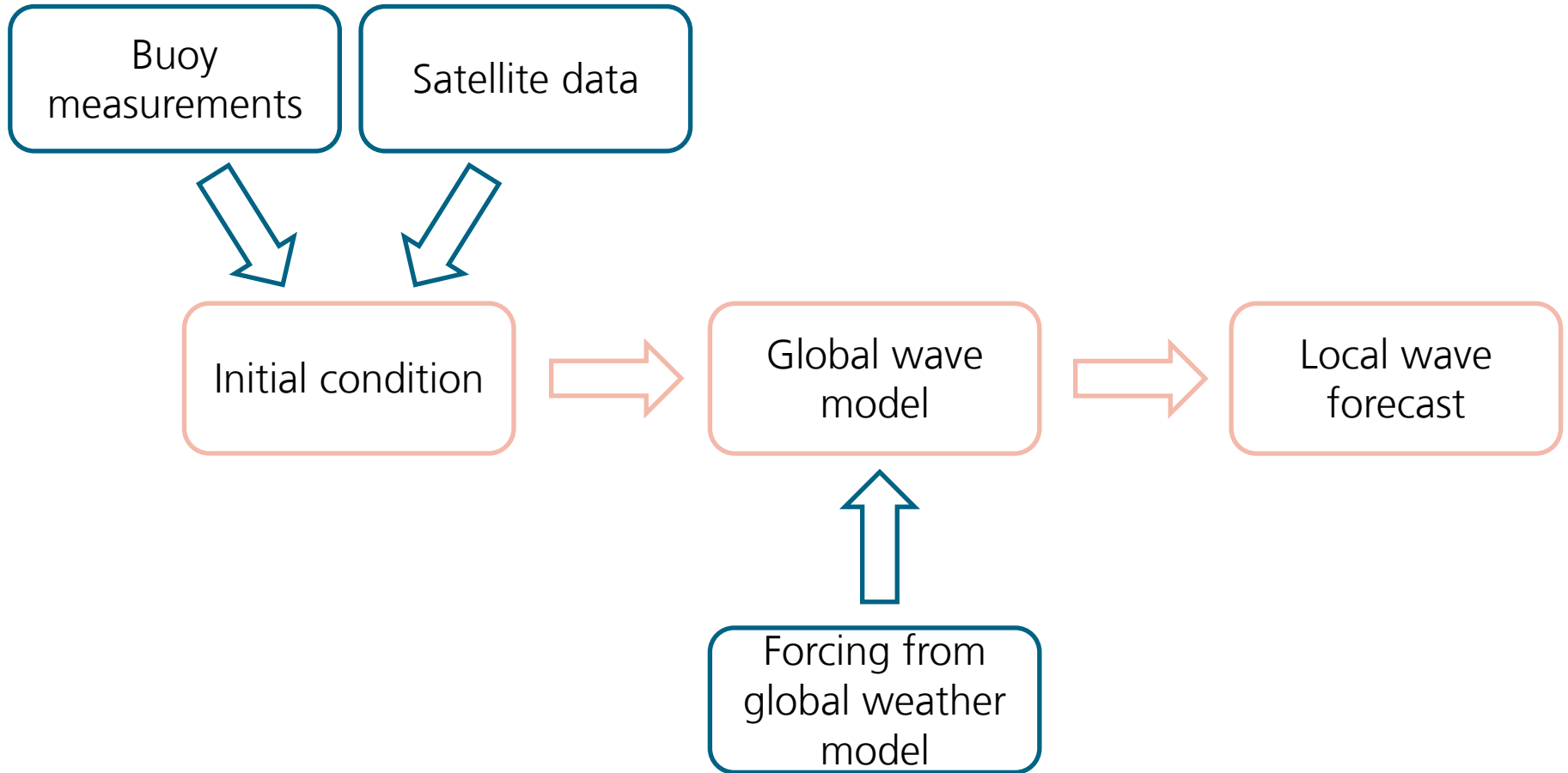
---

## More precise forecasts

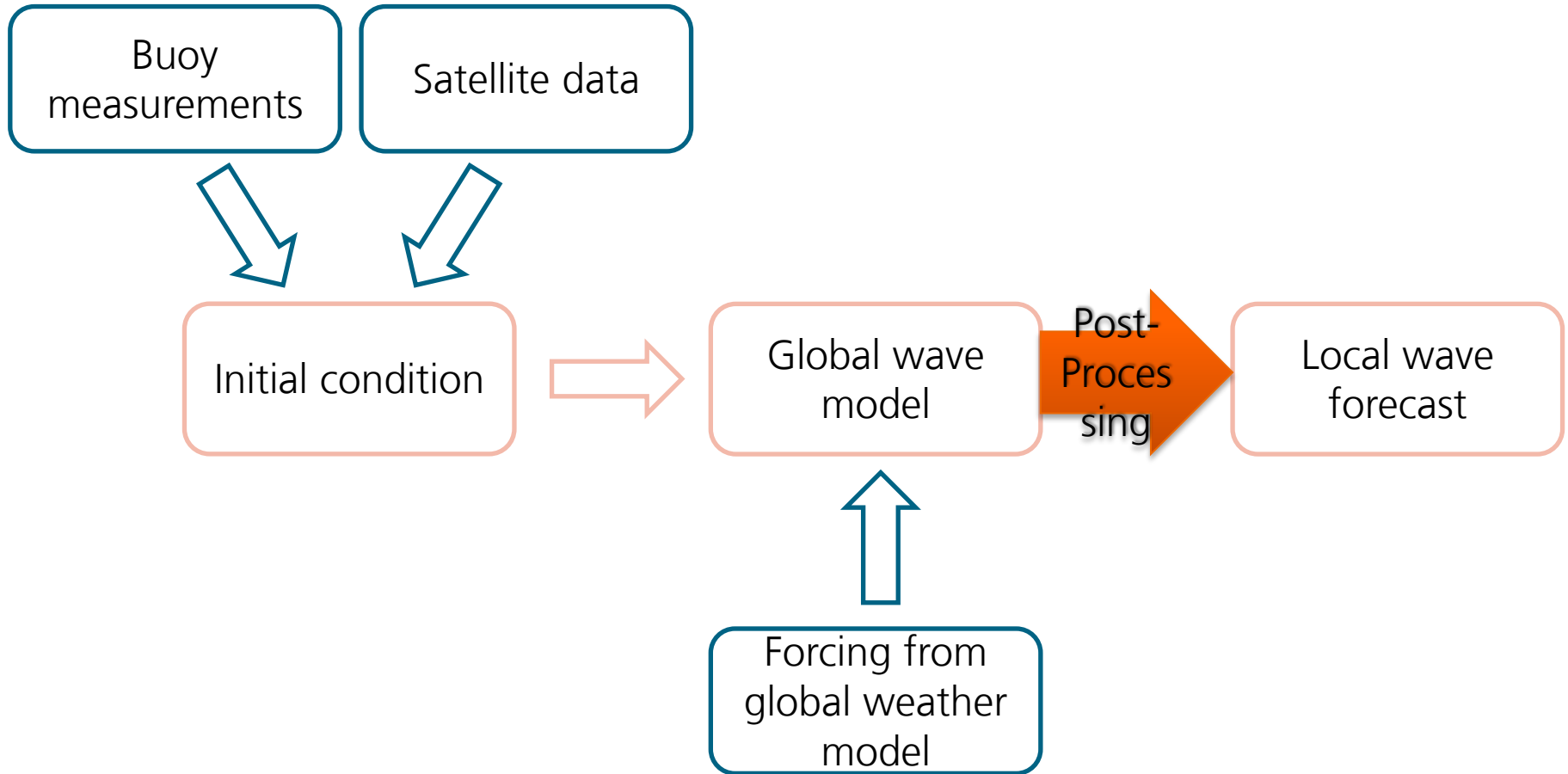
- miss less often possible working times
  - overall project is finished in a shorter time
- predict the threshold values better
  - less operations have to be stopped

 reduce the costs of offshore wind energy

# Introduction on Wave Forecasts



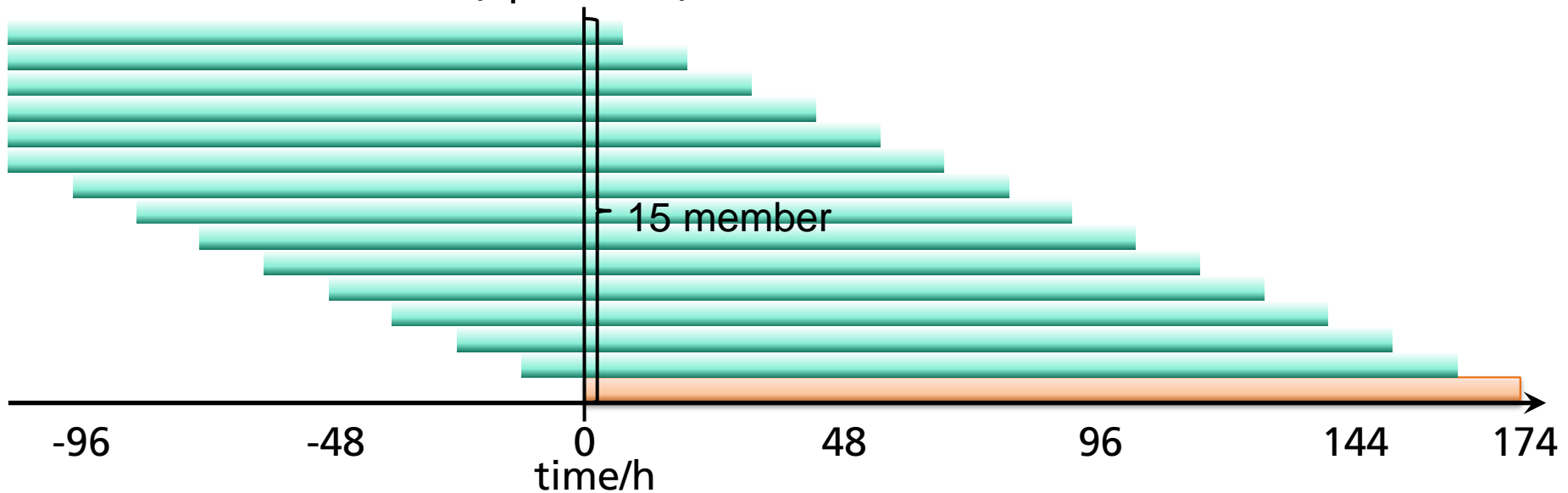
# Introduction on Wave Forecasts



# Methods – time-lagged Ensemble (TLE)

## basics

- old forecasts have valuable information
- forecasts of only one model
  - updated every 12 hours, forecast lead time 174 hours
  - max. 15 member (up to +6 h)



# Data

type	name	period	time resolution	spatial resolution
wave model forecast	GSM	10/2005-05/2012	3 h up to +174 h	0.75° x 0.75°
	GWAM	03/2012-01/2013	1 h up to +174 h	0.25° x 0.25°
wave model analysis	GSM	03/2008-05/2012	00, 12 UTC	0.75° x 0.75°
	GWAM	03/2012-01/2013	00, 12 UTC	0.25° x 0.25°
measurements	FINO1	10/2005-12/2012	10 min	--
	FINO3	01/2009-12/2012	10 min	--

# Results

mean absolute error of significant wave height in m

location: FINO1

period: 03/2012-12/2012

method	target	best MAE	worst MAE	MAE GWAM
mean	--	43.38 cm (3 member)	46.44 cm	46.69 cm
multilinear regression	FINO1	40.60 cm (9 member)	41.08 cm	46.69 cm
multilinear regression	GSM analysis	39.57 cm (10 member)	39.94 cm	46.69 cm
ANN	FINO1	40.31 cm (8 member)	41.50 cm	46.69 cm

 all TLEs beat direct model output (DMO)!



# Results

## weather window

- accuracy

- $$\frac{\text{hits} + \text{correct negatives}}{\text{total}}$$

- hit rate

- $$\frac{\text{hits}}{\text{hits} + \text{misses}}$$

- false alarm rate

- $$\frac{\text{false alarms}}{\text{false alarms} + \text{correct negatives}}$$

		observed	
		yes	no
predicted	yes	hits	false alarms
	no	misses	correct negatives

# Results

## weather window

### ■ definition of event

- duration: 10 h
- max. sign. wave height: 1.5 m

### ■ test case

- location: FINO1
- period: 03/2012-12/2012
- forecast horizons: 24-164 h

method	target	accuracy	hit rate	false alarm rate
GWAM (DMO)	--	76.67 %	77.76 %	24.13 %
mean	--	76.95 %	<b>79.25 %</b>	24.73 %
multilinear regression	FINO1	<b>78.37 %</b>	78.27 %	<b>21.56 %</b>

---

# Quantile forecast method

---

- Statistic method
  - Errors of the past are projected to the future
  - Error distribution determined empirically
- Take error dependencies into account
  - Dependency from forecast horizon
  - Dependency from the forecasted significant wave height

# Quantile forecast results – weather window

## ■ Definition of event

- duration: 10 h
- max. sign. Wave height: 1,5 m
- Forecast horizon: 24-164 h

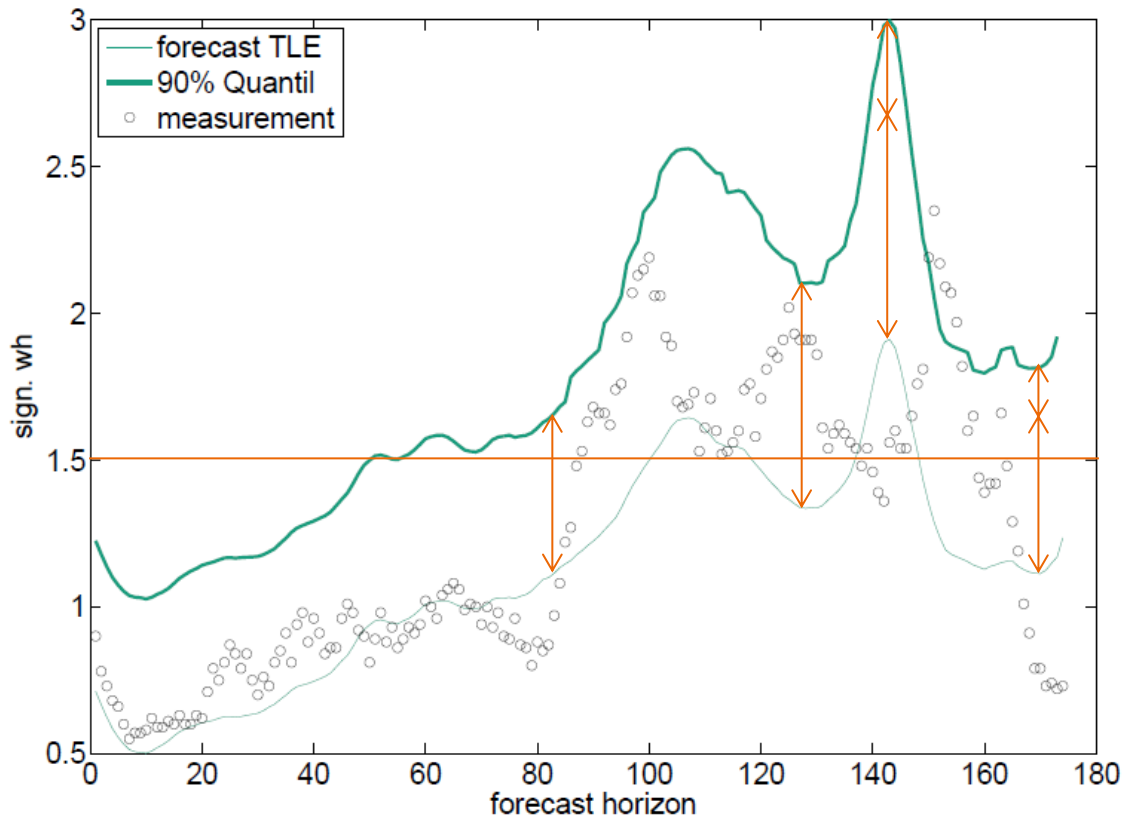
		observed	
		Yes	No
forecasted	Yes	A	B
	No	C	D

## ■ Result

Loca-tion	forecast	accuracy	Hit rate	False alarm rate
		$(A+D) / n$	$A / (A+C)$	$B / (B+D)$
FINO1	GWAM	76,68 %	77,74 %	24,08 %
	TLE (1 Jahr)	<b>78,00 %</b>	<b>80,47 %</b>	23,80 %
	TLE 90%-Quantil	67,48 %	23,84 %	<b>0,73 %</b>

# Quantile forecast

## example time series



- 11.04.2012 13 UTC – 18.04.2012 18 UTC
- 90%-quantile has different distances to TLE depending on
  - forecast horizon
  - forecasted sign. wave height
- 90%-quantile more often exceeds threshold of 1.5 m

---

# Conclusions

---

- good improvements of the sign. wave height achieved
  - in terms of MAE
  - with respect to the workability at offshore wind farms
- best method depends on
  - error to be reduced
    - MAE
    - accuracy and false alarm rate
    - hit rate
  - location (not shown)
- quantile forecasts help making decisions

# Acknowledgements

The work presented has been funded by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety in the project “Wetterabhängigkeit und Prognoseverfahren für den Bau und Betrieb von Offshore Windparks” (BMU FKZ: 0325409).

Supported by:



based on a decision of the Parliament  
of the Federal Republic of Germany

project partners:



---

# Thank you for your attention!



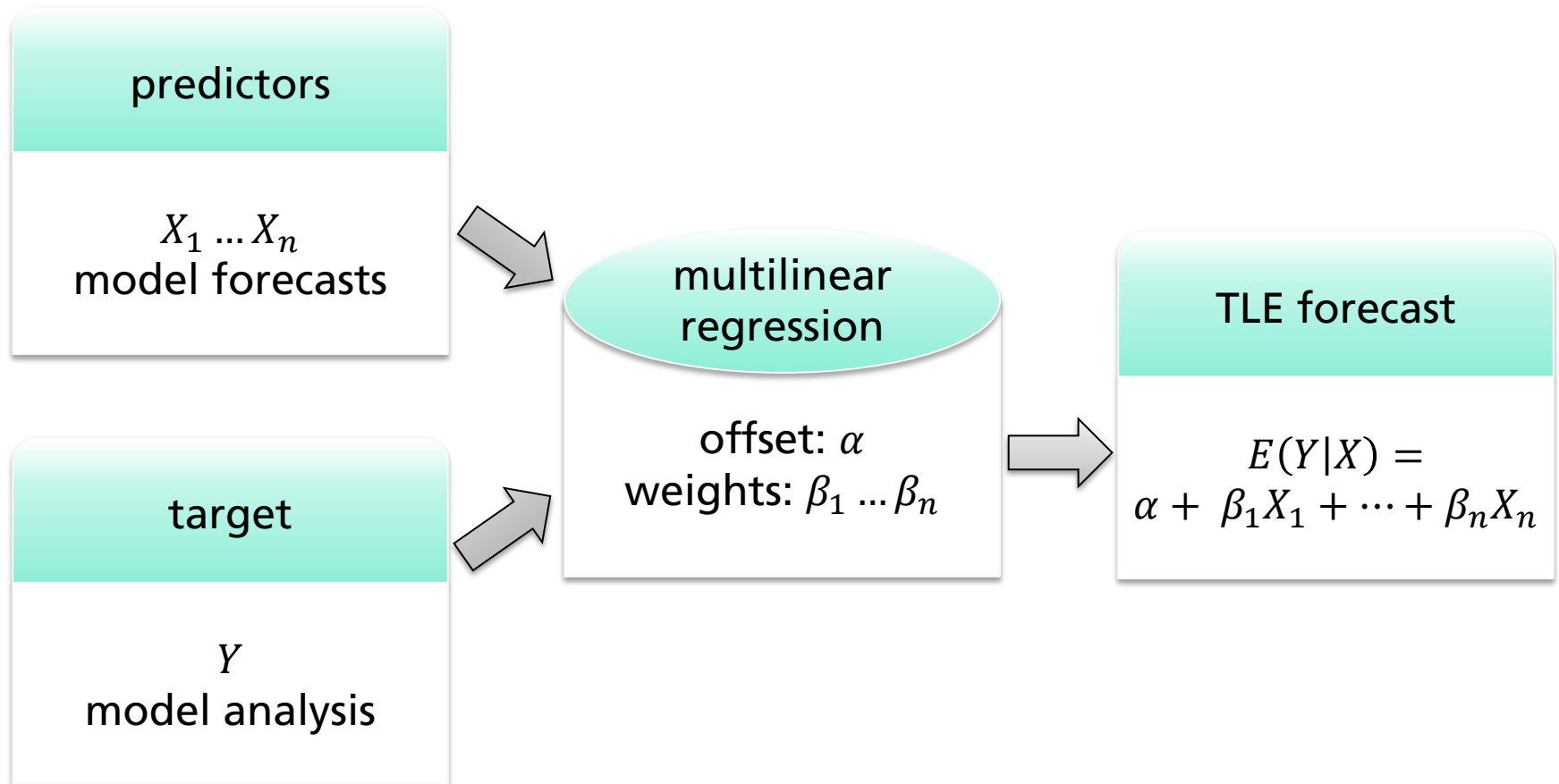
---

Dipl.-Met. Thomas Kanefendt  
Königstor 59 | 34119 Kassel/Germany  
+49 561 7294-474  
[thomas.kanefendt@iwes.fraunhofer.de](mailto:thomas.kanefendt@iwes.fraunhofer.de)



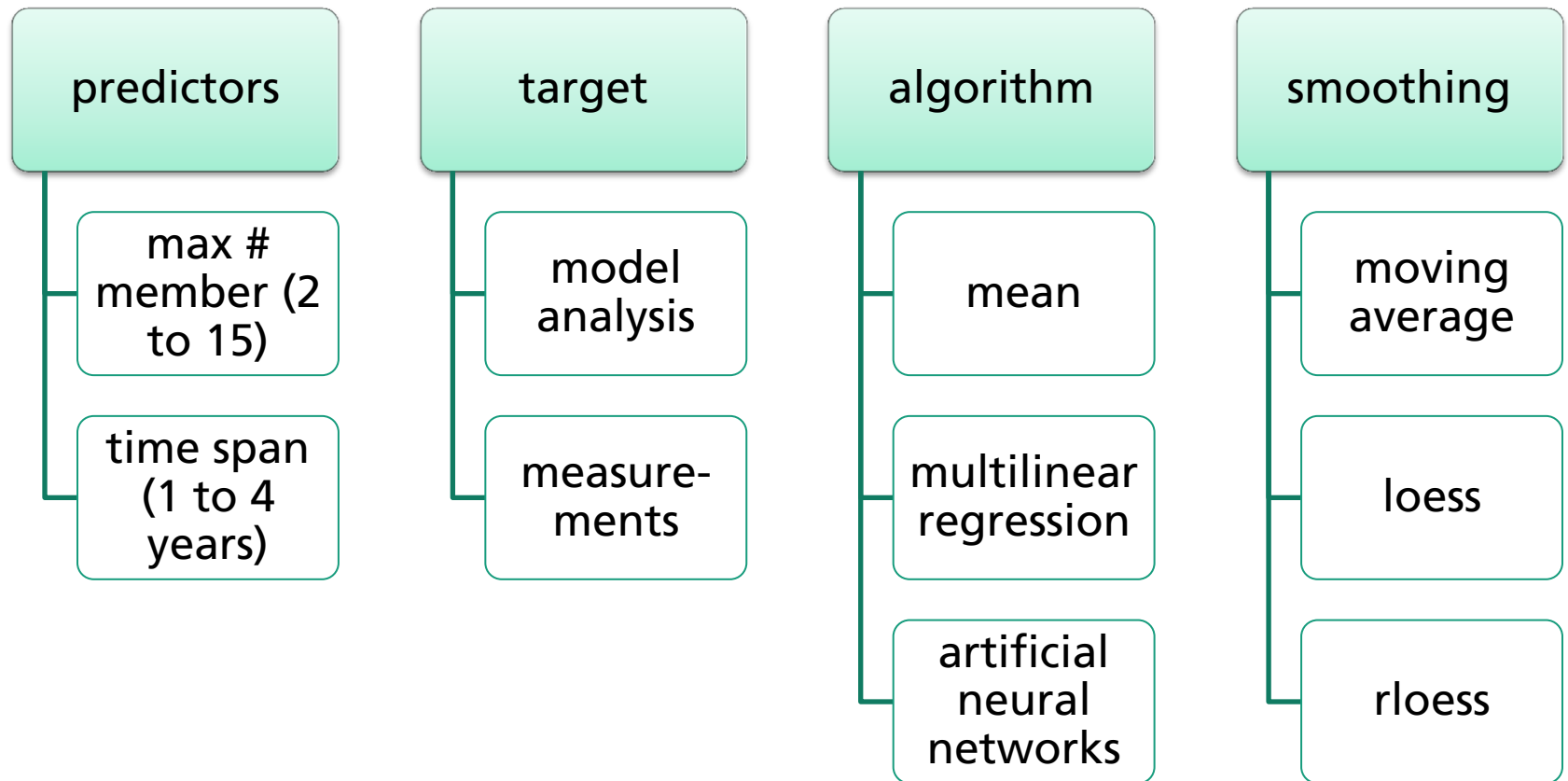
# Methods – time-lagged Ensemble (TLE)

## multilinear regression



# Methods – time-lagged Ensemble (TLE)

## examined variations



# Methods – time-lagged Ensemble (TLE)

## artificial neural networks (ANN)

### ■ Advantages of ANN

- allow for non-linear relationships
- hidden dependencies could be caught

### ■ Experimental Setup

- same inputs and targets as for multilinear regression
- 1 hidden layer
- 2 or 3 neurons in the hidden layer

