

# Comparison of irradiation data from different numerical weather models and their combination in multi-model forecasts

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## Structure:

- **Relevance and objectives of this study**
- **Data and method overview**
- **Validation of (multi-)models**
- **Potential of machine learning**
- **Operational Application**

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## Relevance and objectives:

- Radiation forecasts are input for PV production forecast
- Accurate forecasting of PV power is crucial for:
  - Grid integration
  - Electricity trading
  - Energy management systems
  - Smart home management
- Minimizing forecast errors by implementing machine learning methodologies to combine:
  - Different numerical weather models
  - Real time satellite data
  - Cloud motion techniques

## Relevance and objectives:

- **Hypothesis: Mixing different models can significantly reduce forecasting errors**

## Research questions:

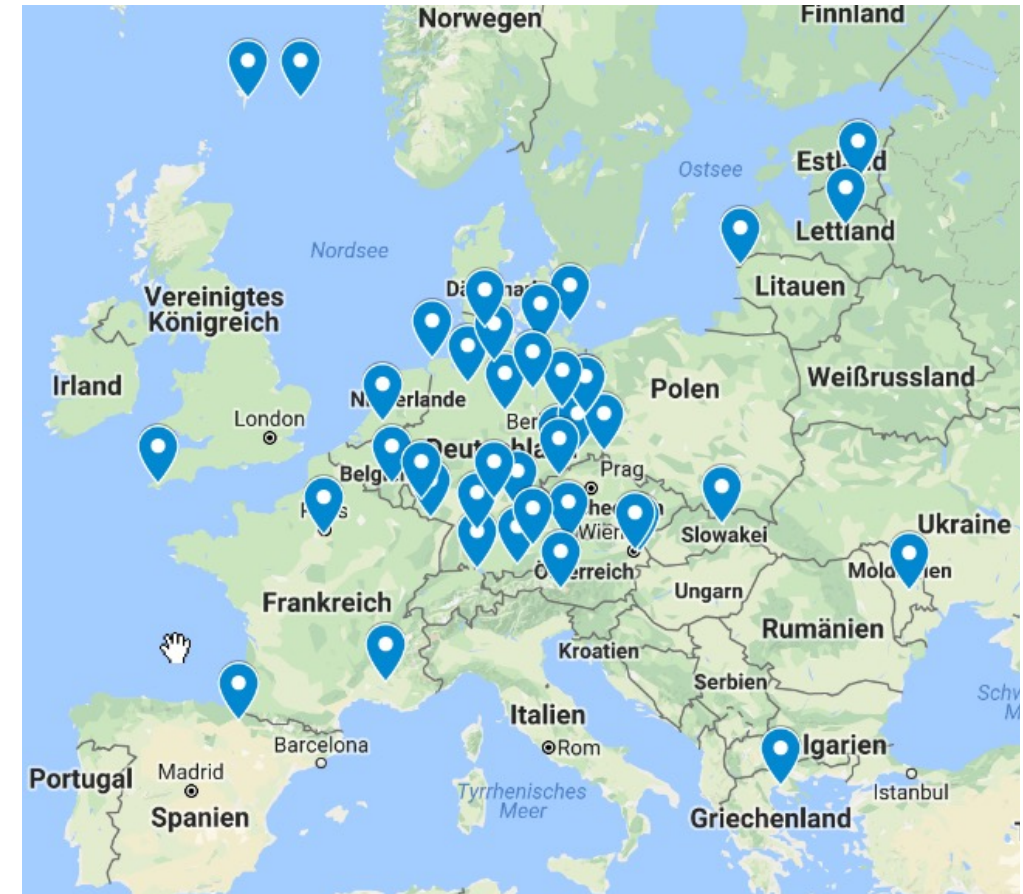
1. Do multi-models with different initialization data achieve lower errors than combinations based on the same data source?
2. Will multi-models with 3-4 models across all sites considers achieve lower errors than multi-models with only two models?

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## Data and method overview:

- Measurement data from three different measuring networks (DWD, BSRN & GAW) for a total of 40 stations
- Simulation data from five different weather models:
  - ECMWF: IFS
  - DWD: ICON-EU
  - NOAA: GFS
  - meteoblue – NEMS & NEMS2



## Data and method overview:

- Comparison based on the common **error values** for 2016 & 2017 (after MESOR 2009)
- Comparison of the individual models
- Comparison of different model combinations (without weighing)
- ECMWF-IFS & meteoblue multimodal as reference (highly accurate)

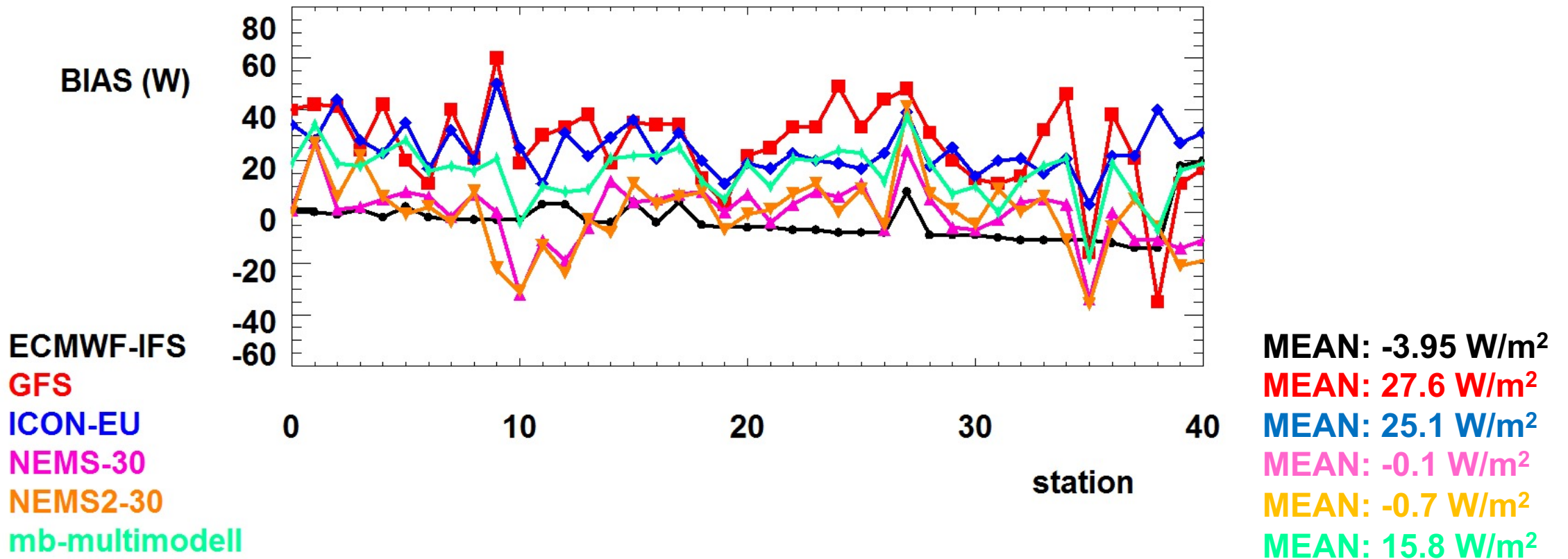
| #  | Wettermodell | Räumliche Auflösung | Anbieter               | Land        | Initialisierung |
|----|--------------|---------------------|------------------------|-------------|-----------------|
| 1. | GFS          | 22km                | NOAA <sup>1</sup>      | USA         | GFS             |
| 2. | NEMS30       | 30km                | meteoblue <sup>1</sup> | Schweiz     | GFS             |
| 3. | NEMS2-30     | 30km                | meteoblue <sup>1</sup> | Schweiz     | ECMWF           |
| 4. | ICON         | 13km                | DWD <sup>2</sup>       | Deutschland | ECMWF           |
| 5. | multimodel   | 3km-30km            | meteoblue <sup>1</sup> | Schweiz     | GFS & ECMWF     |
| 6. | IFS          | 9km                 | ECMWF <sup>2</sup>     | England     | ECMWF           |

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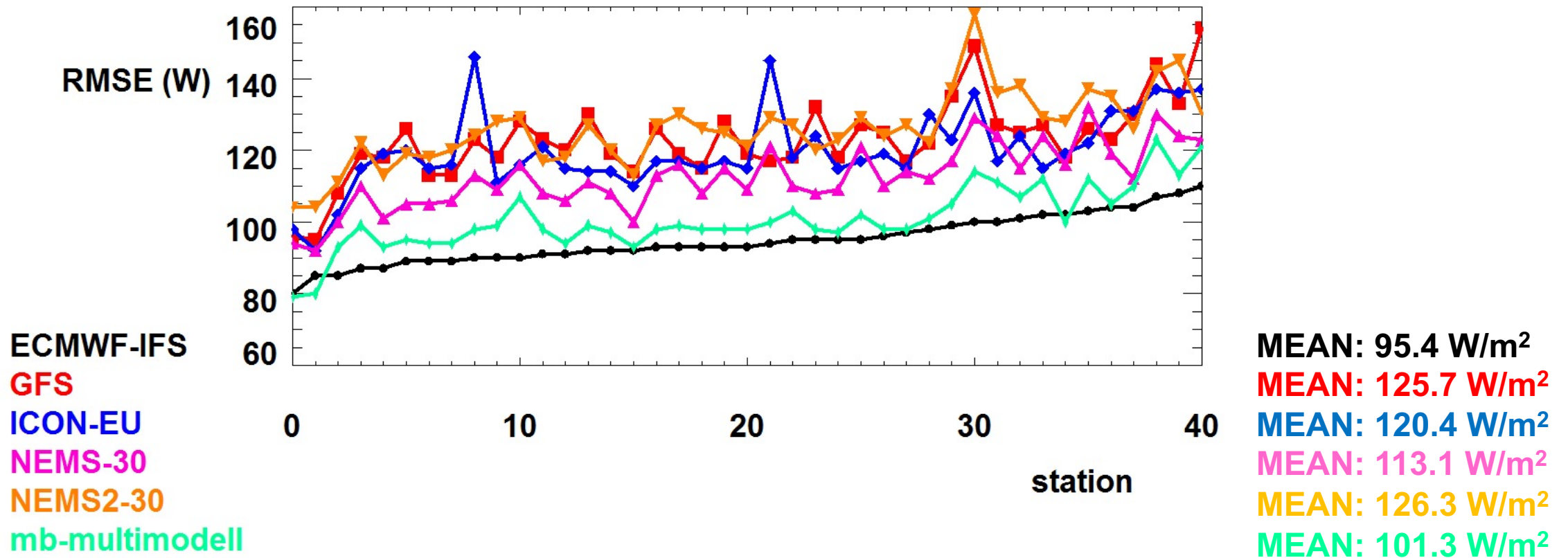
## Validation of single models:

- Comparison of the systematic error (BIAS)



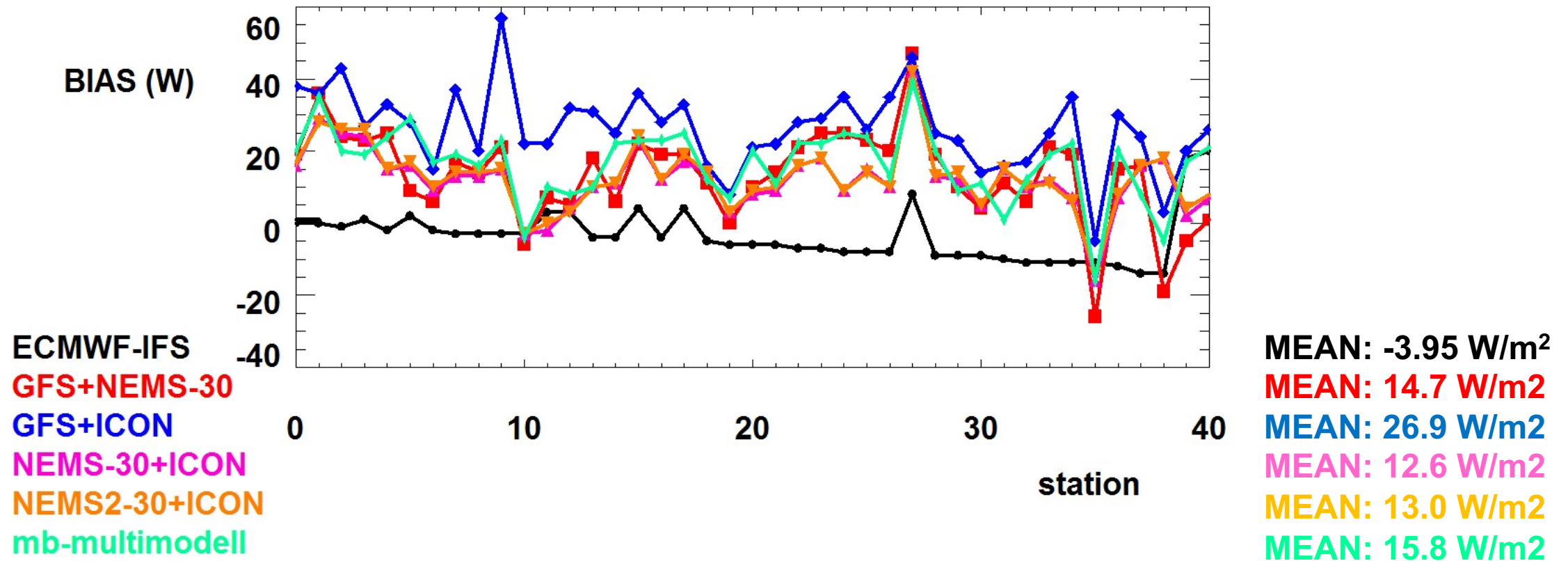
## Validation of single models:

- Comparison of the absolute error (RMSE)



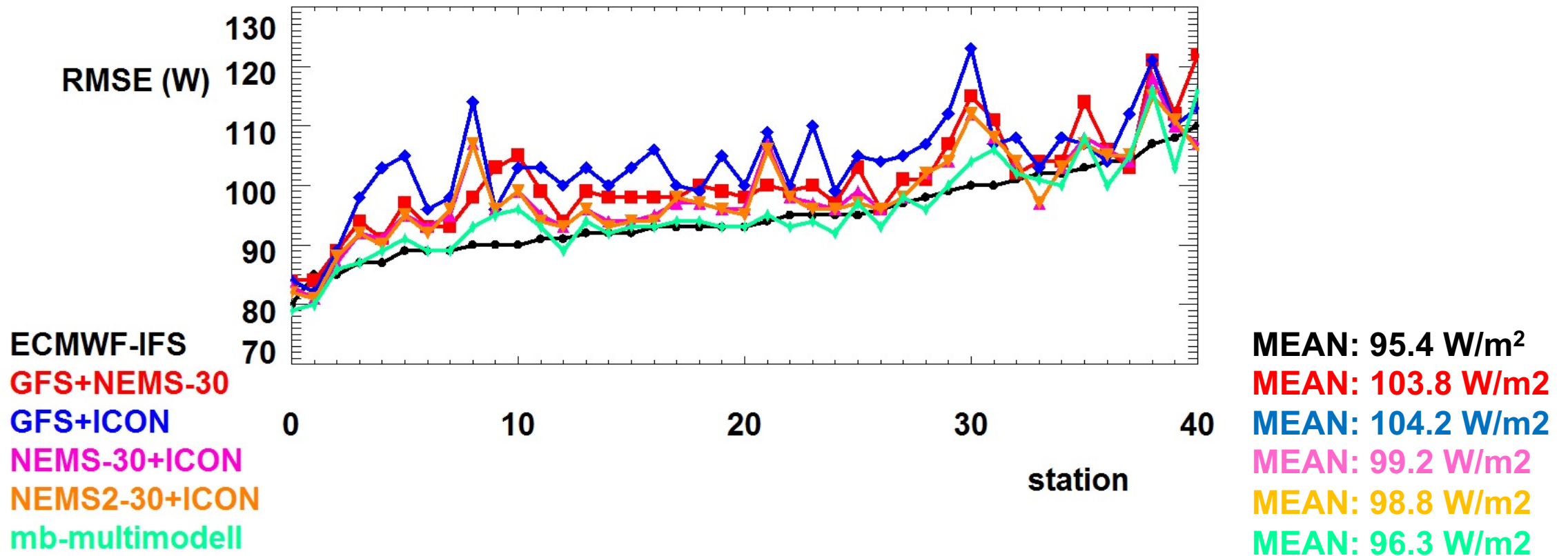
## Validation of various (2) multi-model combinations:

- Comparison of the systematic error (BIAS)



## Validation of various (2) multi-model combinations:

- Comparison of the absolute error (RMSE)

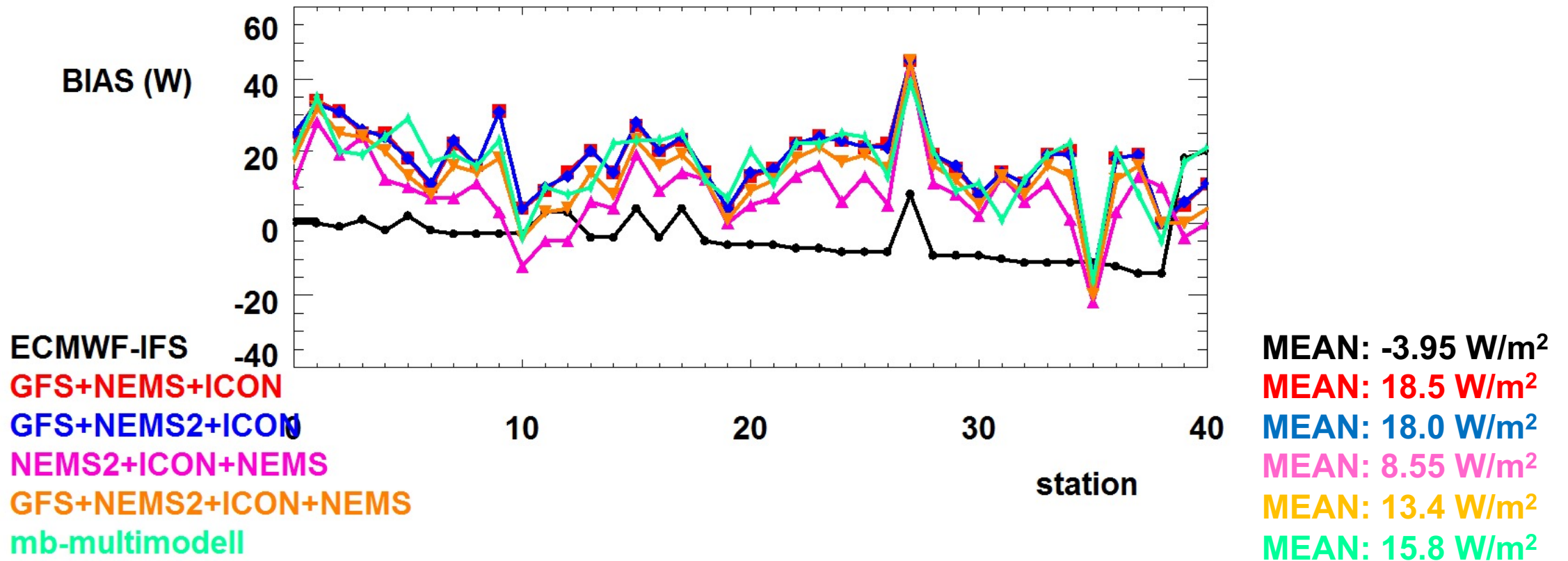


## Results:

- GFS + NEMS is better than ICON + GFS.
  - NEMS + ICON performs best, regardless of whether NEMS or NEMS2, **or both**, are used.
- > The source of initialization data is not crucial.**
- A simple average of two models significantly reduces the error compared to the single models.
  - Multimodelling with high BIAS models is less effective

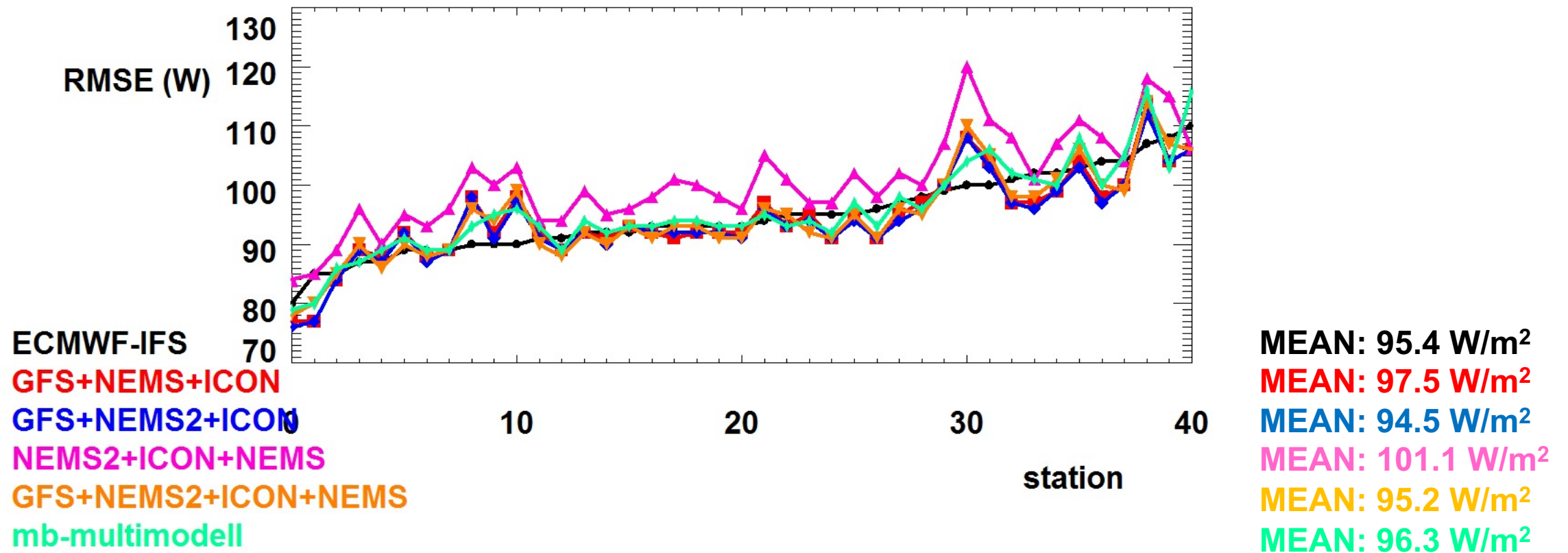
# Validation of various multi-model combinations:

- Comparison of the systematic error (BIAS)



## Validation of various multi-model combinations:

- Comparison of the absolute error (RMSE)



## Conclusion:

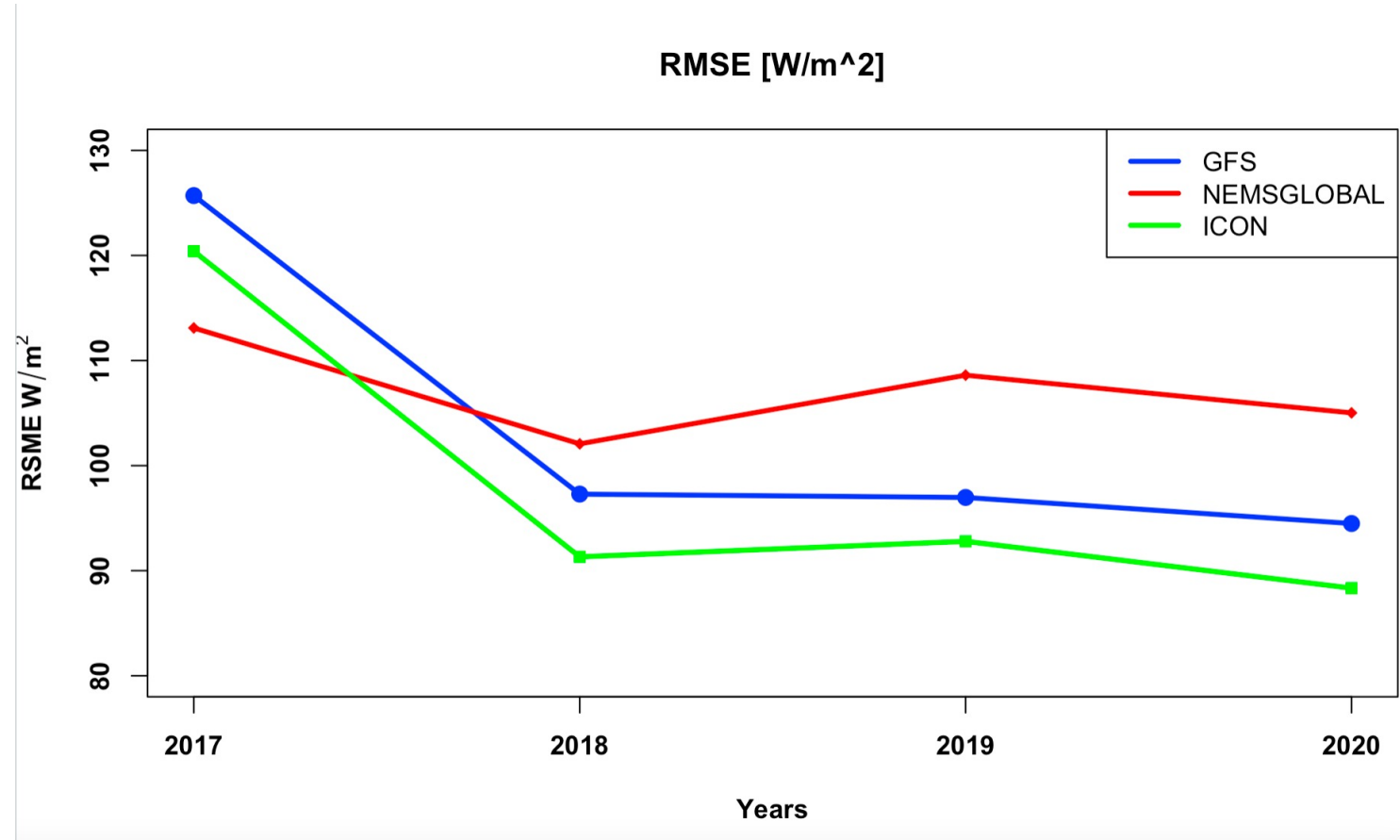
- **Multimodelling significantly reduces the forecast errors for radiation**
- **Different cloud schemes within the model are important, not the initialization**
- **Multi-model combinations of 3 or 4 models (25-30%) perform better than combinations of 2 models (20.25%)**

## Structure:

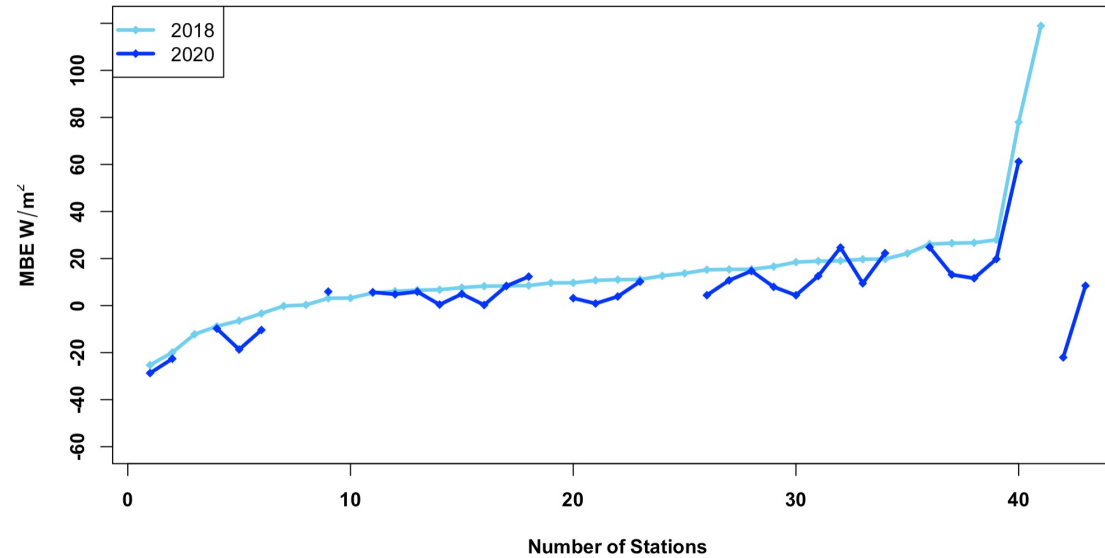
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# Weather models are evolving

- Raw models are steadily improved
- Validation of raw models from 2017-2020 show a **slight decrease** of solar radiation forecast errors



MEAN: 13.44 W/m<sup>2</sup>  
MEAN: 6.04 W/m<sup>2</sup>

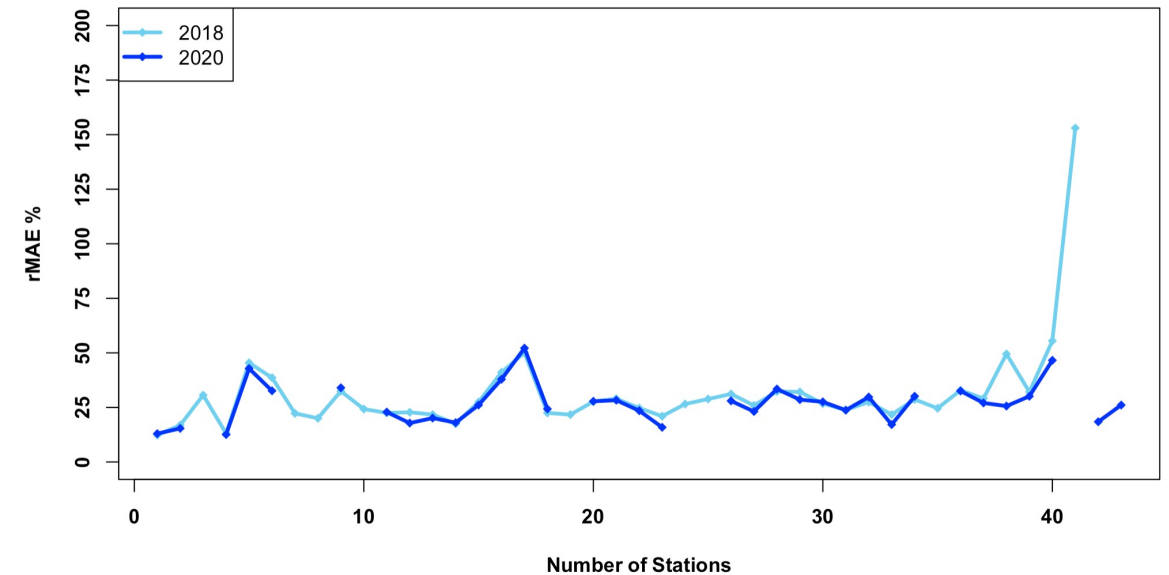
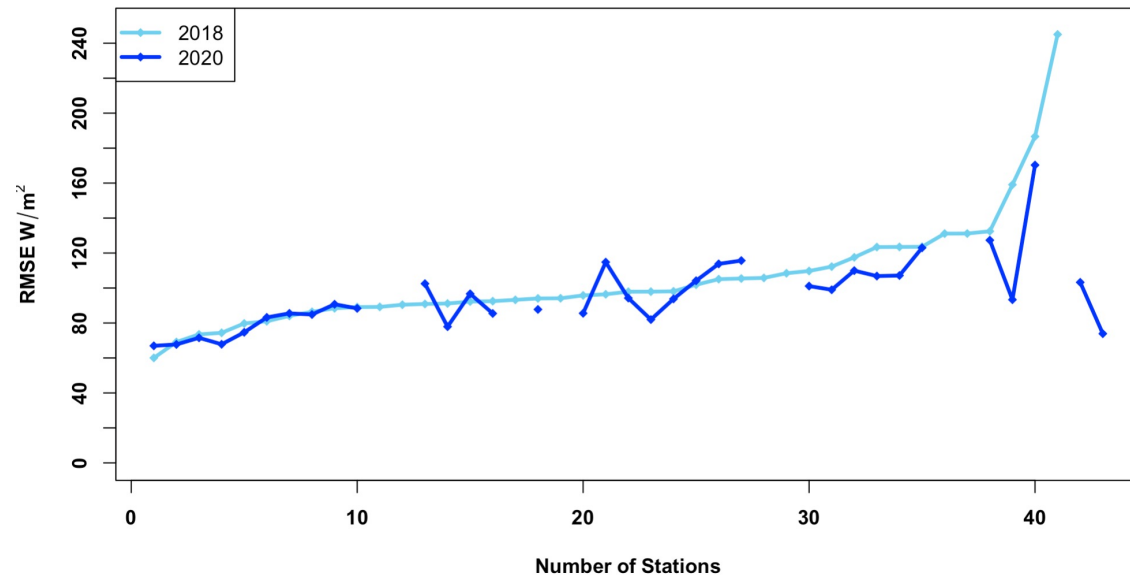


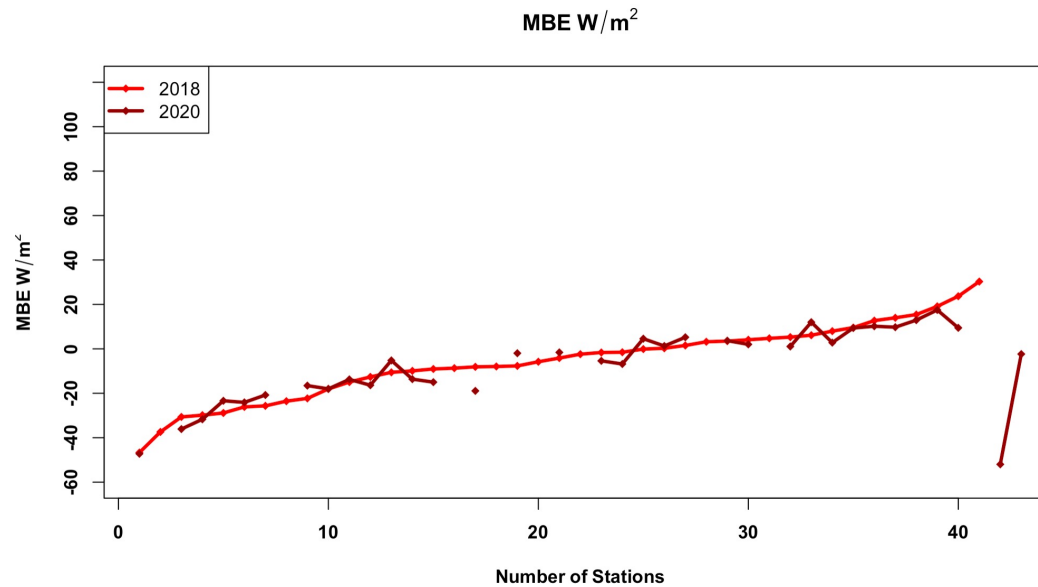
MEAN: 105.41 W/m<sup>2</sup>  
MEAN: 95.61 W/m<sup>2</sup>

RMSE W/m<sup>2</sup>

rMAE %

MEAN: 31.40 %  
MEAN: 26.85 %





MEAN:  $-5.68 W/m^2$

MEAN:  $-7.91 W/m^2$

MEAN:  $111.60 W/m^2$

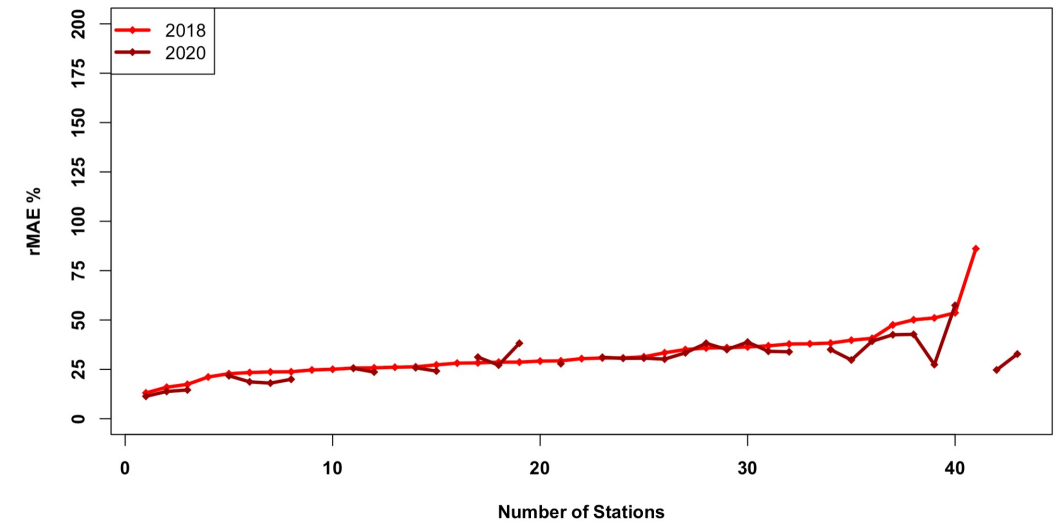
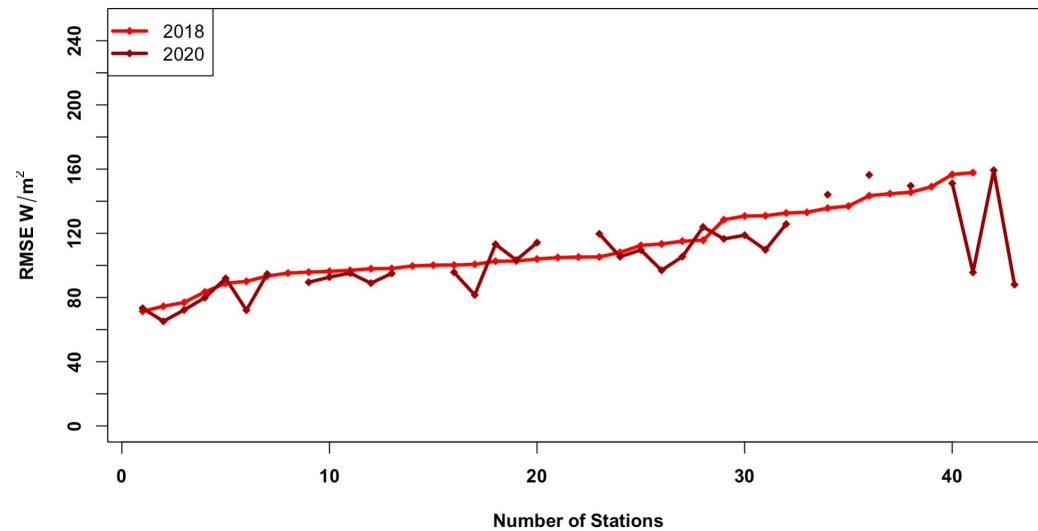
MEAN:  $105.73 W/m^2$

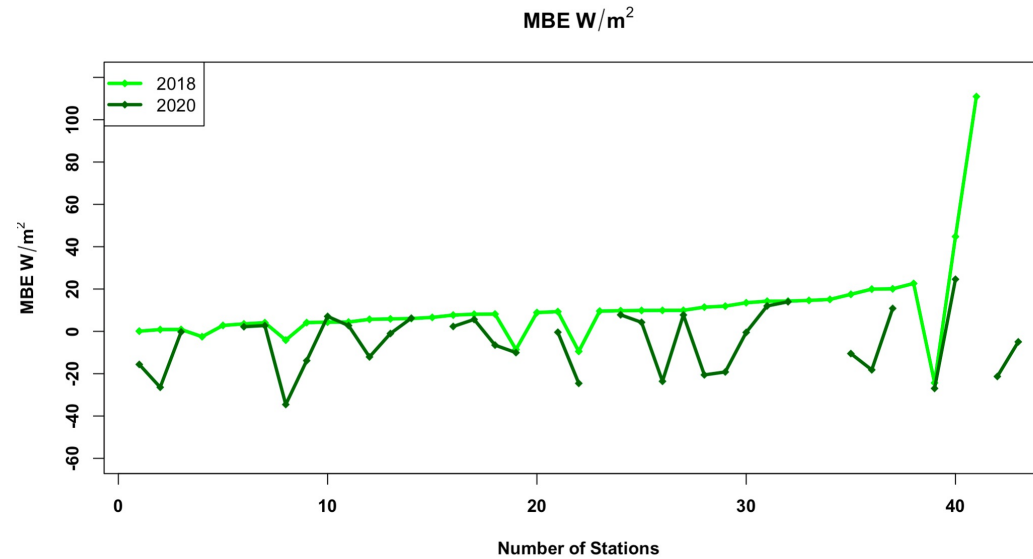
RMSE  $W/m^2$

rMAE %

MEAN: 30.73%

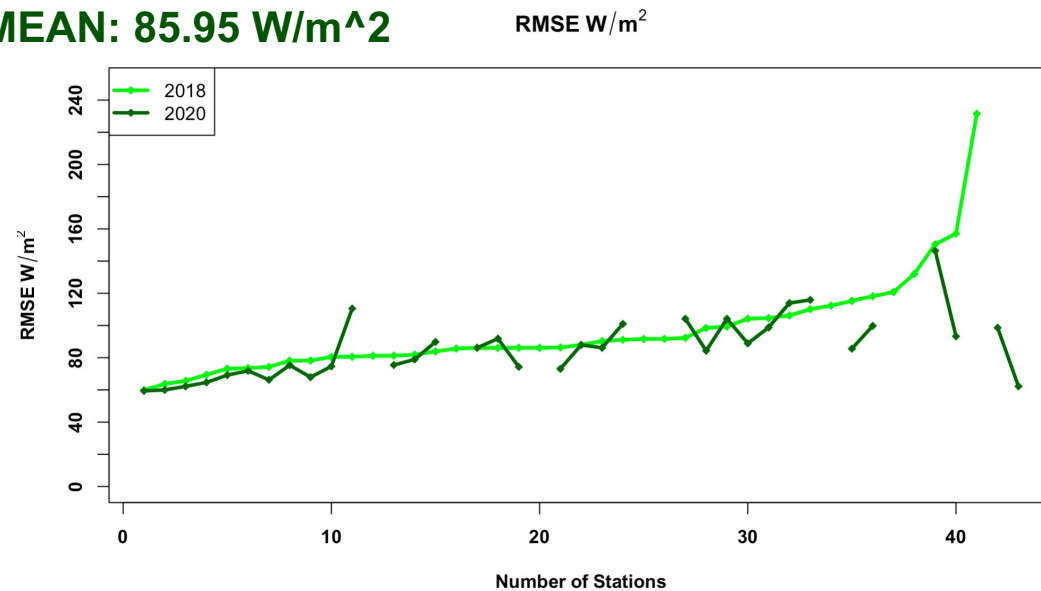
MEAN: 27.73 %



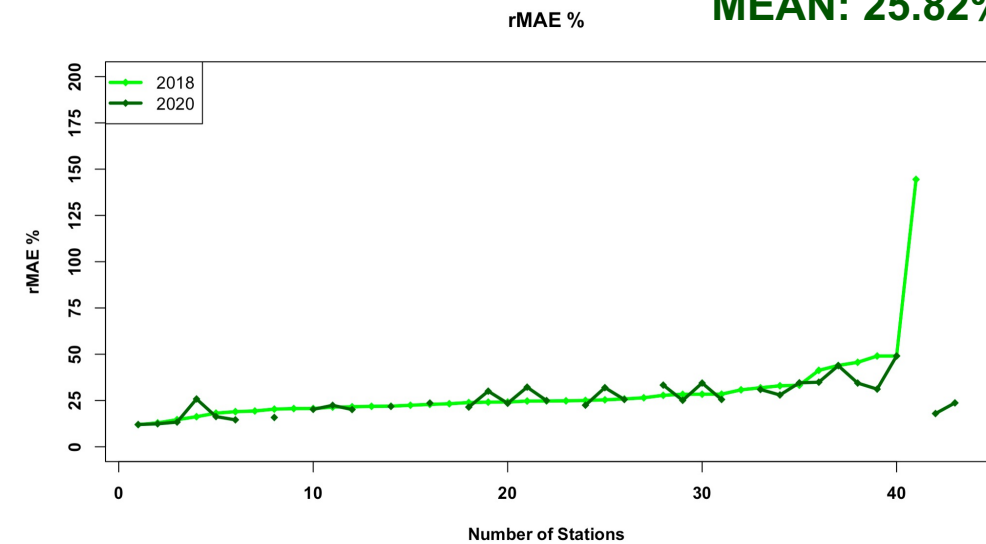


MEAN: 10.31  $W/m^2$   
MEAN: -5.32  $W/m^2$

MEAN: 96.28  $W/m^2$   
MEAN: 85.95  $W/m^2$



MEAN: 29.12%  
MEAN: 25.82%



# Weather models are evolving

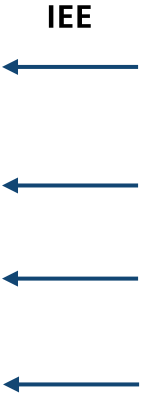
- New global models were released e.g. GEM15 of the Canadian weather service
- High resolution models for Central Europe were released (e.g. ICON-D2, AROME2)
- Different models have different time horizons, regional coverage
- Satellite data is required for real time corrections
- Different **weighting** for seasonal and regional accuracy

➡ machine learning is required for automatization



|          |
|----------|
| GEM15    |
| 389m asl |
| NEMS2-30 |
| 500m asl |
| NEMS12   |
| 336m asl |
| NMM12    |
| 363m asl |
| ICON13   |
| 307m asl |
| GFS22    |
| 407m asl |
| NEMS30   |
| 500m asl |

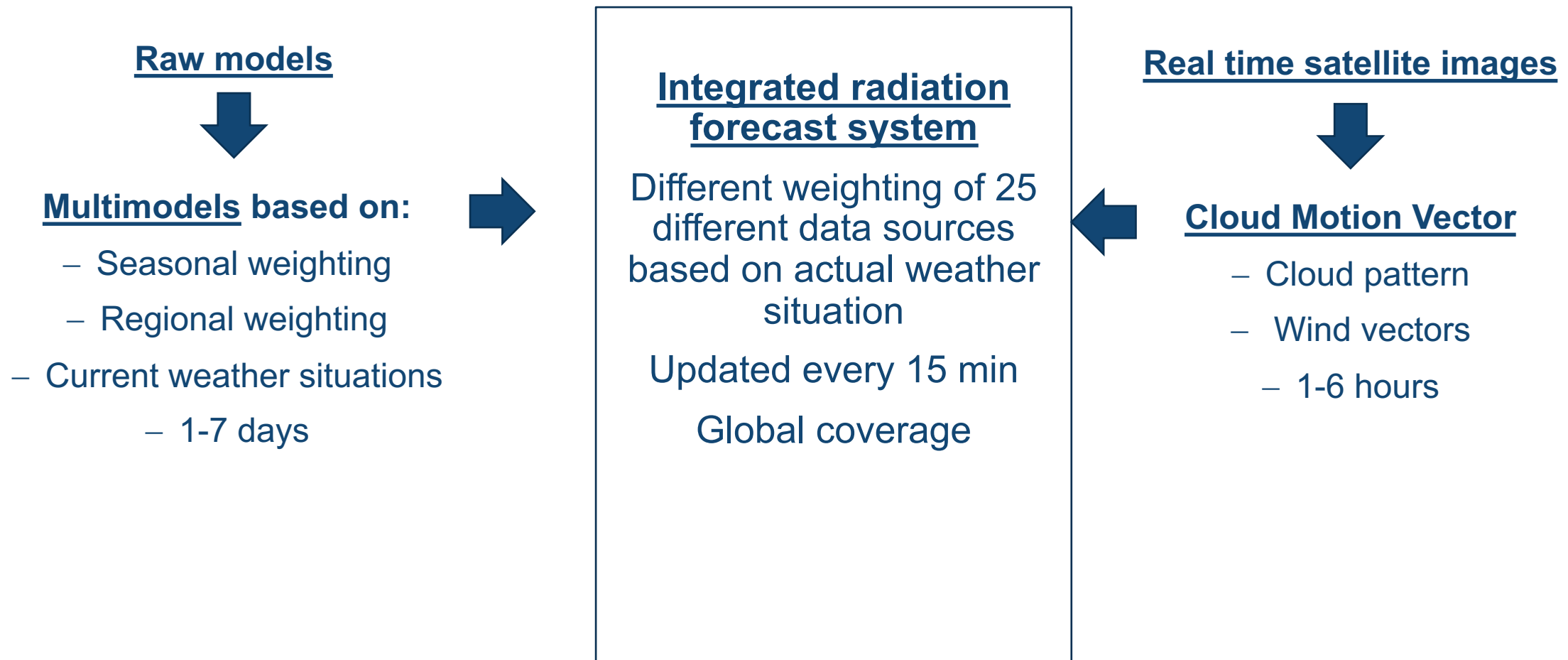
|          |
|----------|
| AROME2   |
| 290m asl |
| HIRLAM7  |
| 323m asl |
| HARMN-5  |
| 322m asl |
| ICON-D2  |
| 281m asl |
| NEMS4    |
| 284m asl |
| NMM4     |
| 315m asl |
| ARPEGE11 |
| 287m asl |
| ARPEGE40 |
| 235m asl |
| ICON7    |
| 259m asl |
| UKMO-17  |
| 347m asl |
| NEMS2-12 |
| 336m asl |



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# Integrated radiation forecast with machine learning methods



## Take home message

- **Forecasting is crucial for efficient PV system operation**
- **Combining multiple models reduces forecast errors significantly**
- **Different models have different temporal and regional availability**
- **Machine learning algorithms enable automated combination of multiple models with real time satellite data**
- **Operational system is steadily improved, with data availability**