AI-based forecasts – a focus on severe convection

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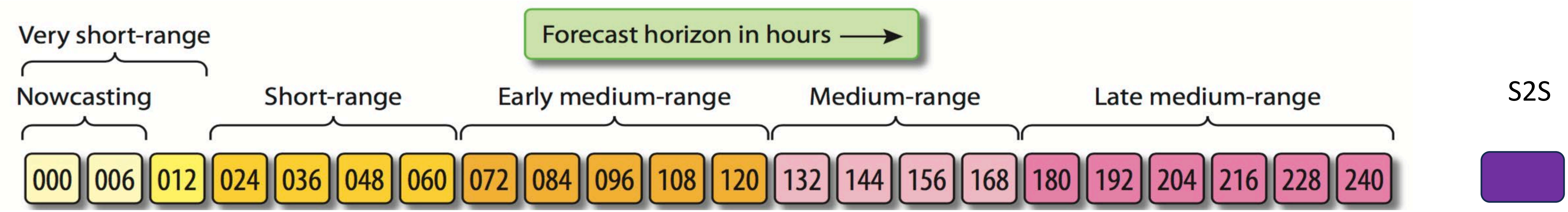
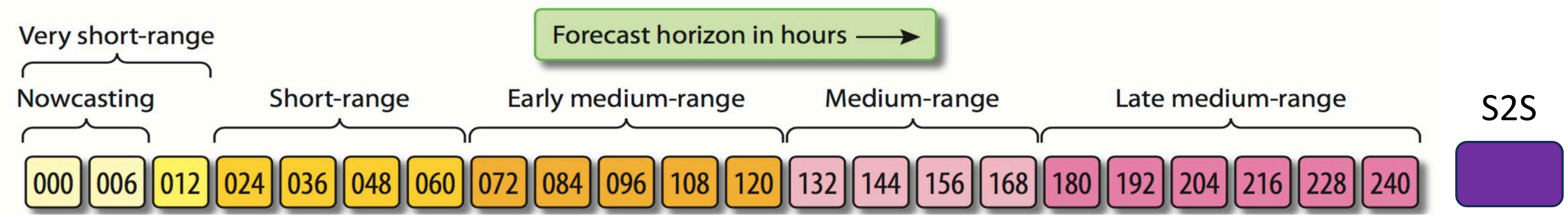
Storyline / discussion points

- Overview AI-based weather forecasting
- Impact-oriented forecasts/impact models
- Convective environments – a formidable challenge for all models?
- Teaching and training

Overview AI-based forecasting systems | lead times

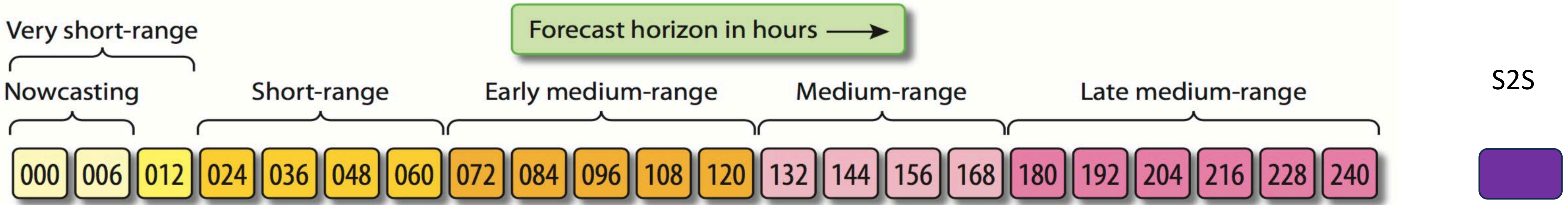


Stull Practical Meteorology



Main forecast targets	thunderstorms, precipitation, solar production	local weather including extremes	weather systems and weather types

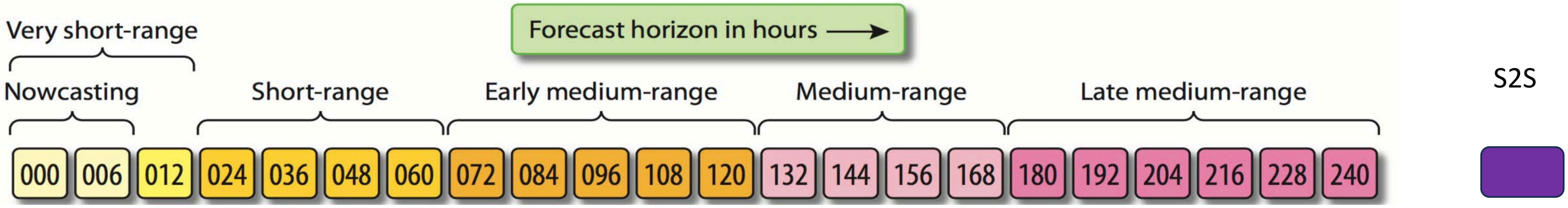
impacts / warnings



Stull Practical Meteorology

Review_McGovern et al.
MetNet-2
Nowcast net
Leinonenetal
…

AIFS (ECMWF)
Graphcast (Google Deep Mind)
FourCastNet (NVIDIA)
Fuxi (Fudan University)
Pangu (Huawei Cloud)
to come NASA/IBM model
…



Stull Practical Meteorology

Review_McGovern et al.
MetNet-2
Nowcast net
Leinonenetal
…

seamless prediction?
flood forecasting

AIFS (ECMWF)
Graphcast (Google Deep Mind)
FourCastNet (NVIDIA)
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Pangu (Huawei Cloud)
to come NASA/IBM model
…

seamless prediction?
droughts, energy

Storyline / discussion points

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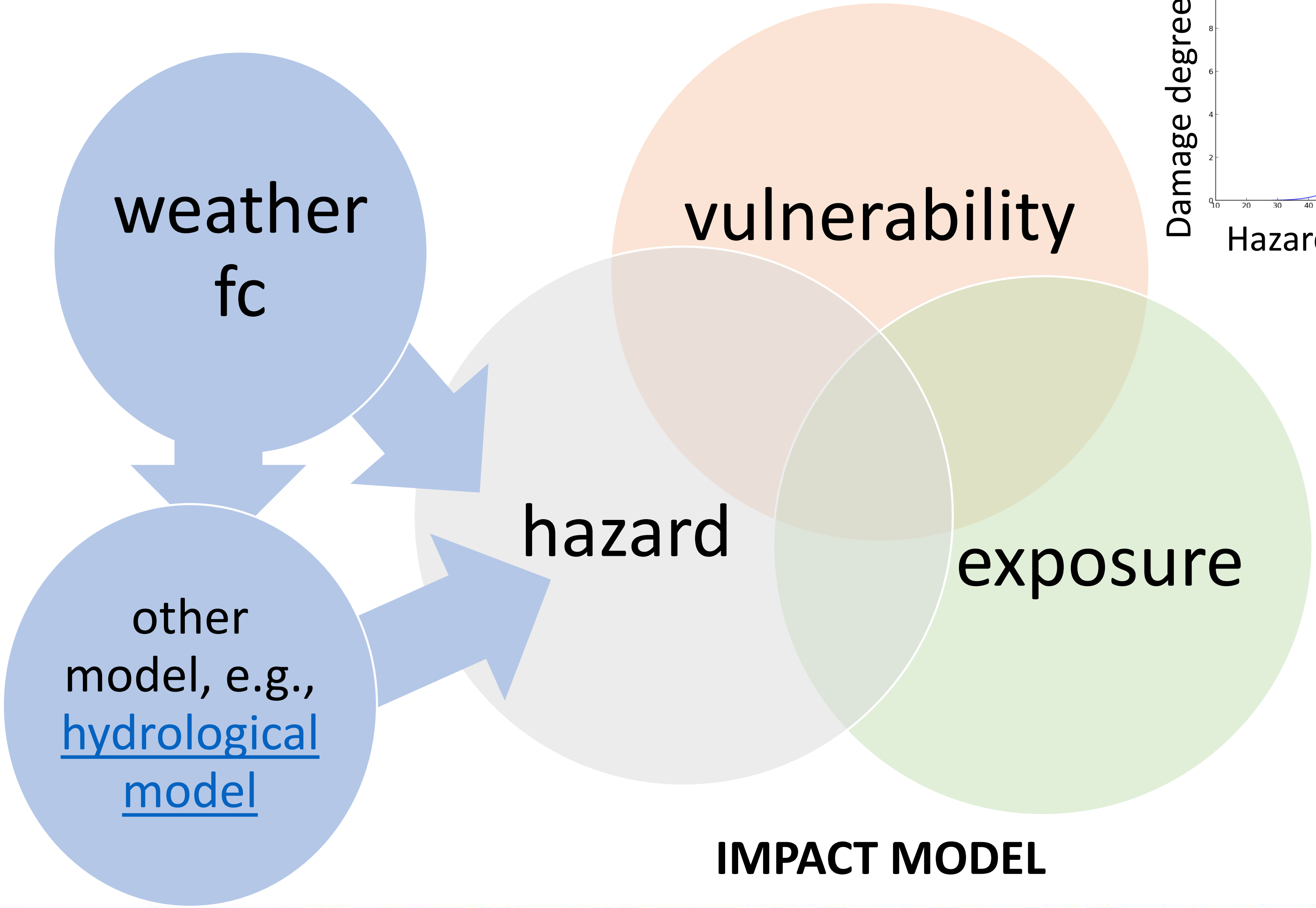
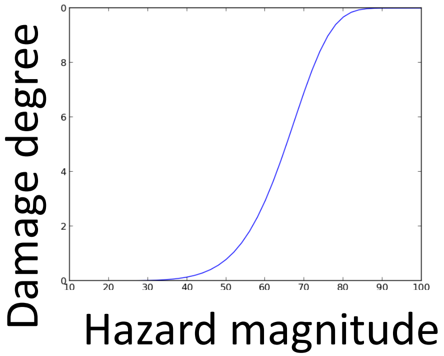
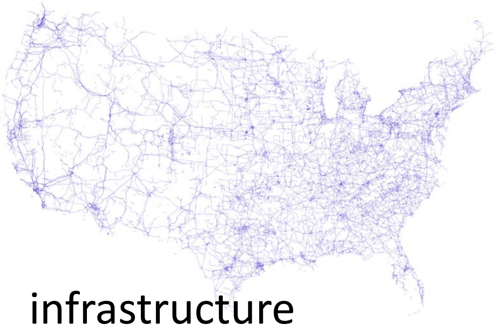
- **Impact-oriented forecasts/impact models**
- Convective environments – a formidable challenge for all models?
- Teaching and training

Impact models| the classical approach



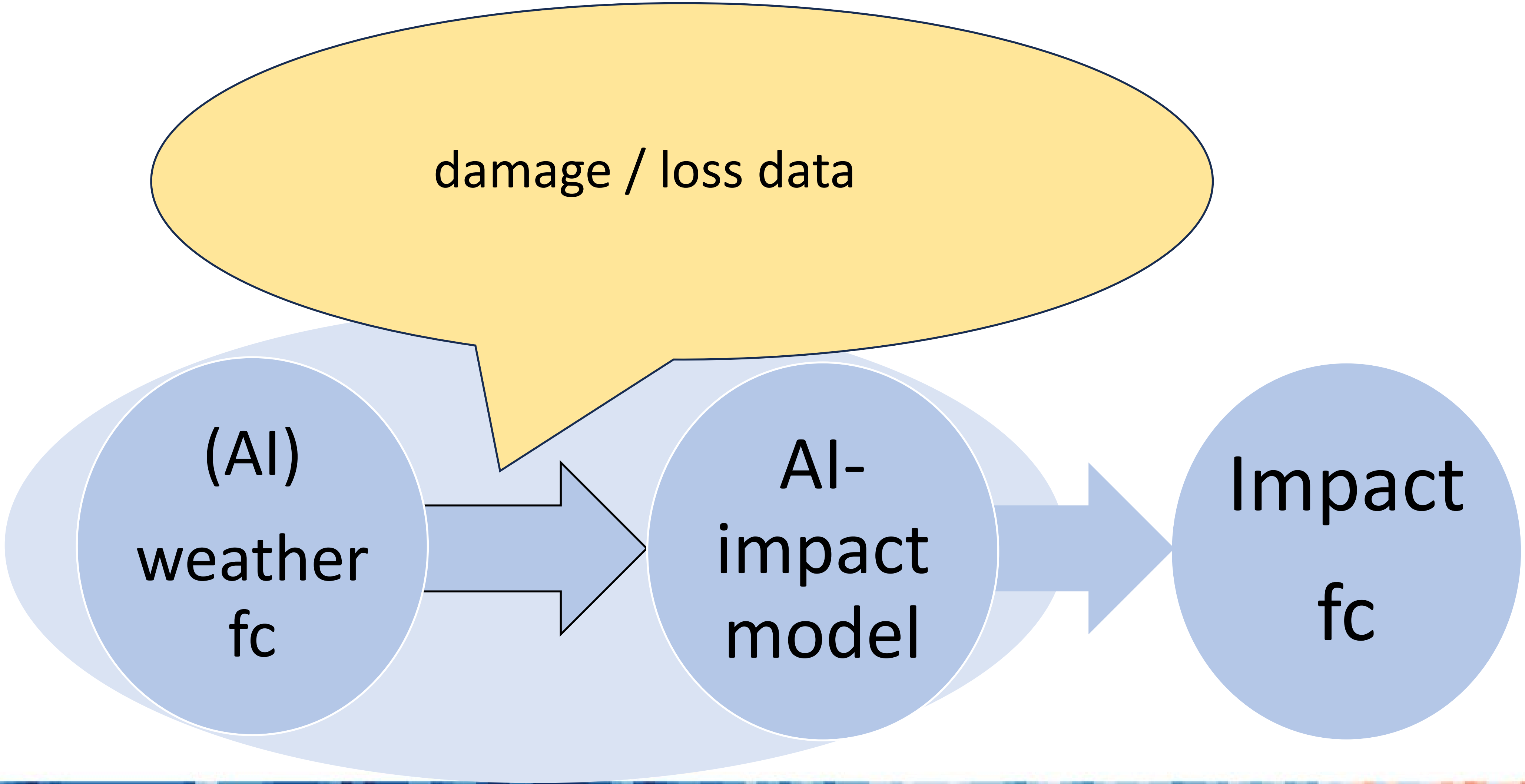


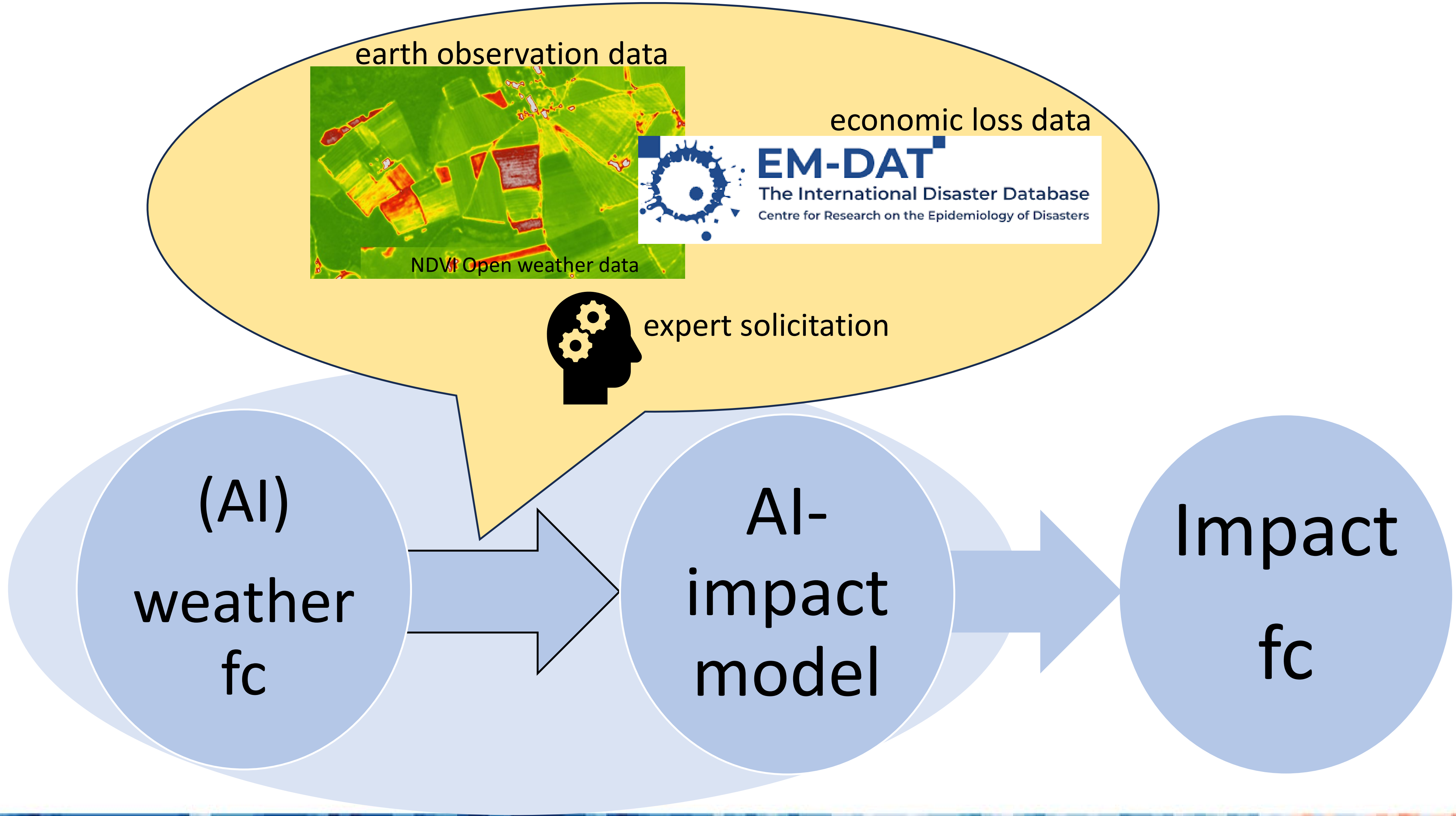
IMPACT MODEL

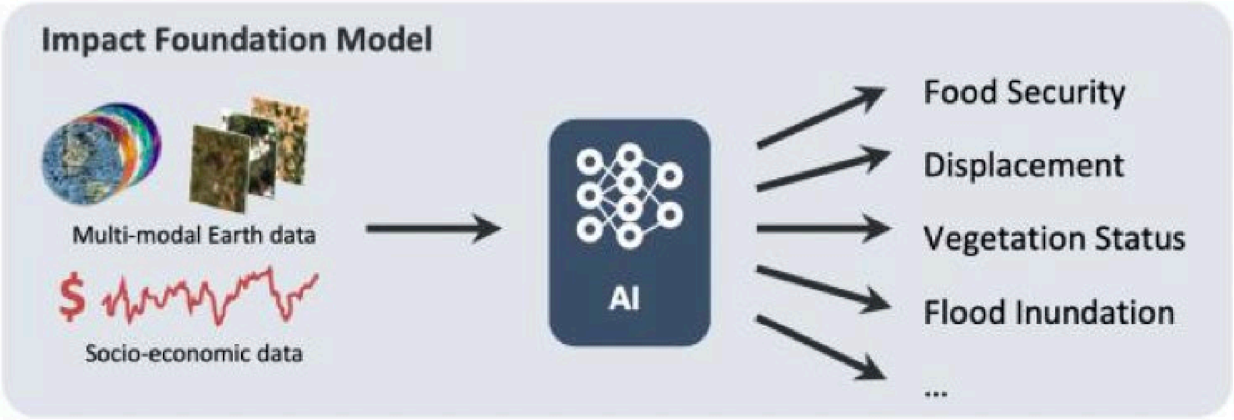


infrastructure
Washington Post

Impact / risk models | the future approach?




earth observation data
NDVI Open weather data
economic loss data
EM-DAT
The International Disaster Database
Centre for Research on the Epidemiology of Disasters
expert solicitation
(AI) weather fc
AI-impact model
Impact fc



[Reichstein et al. preprint]

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Global Insured Losses From Severe Convective Storms Hit New High of $60B: Swiss Re

December 7, 2023

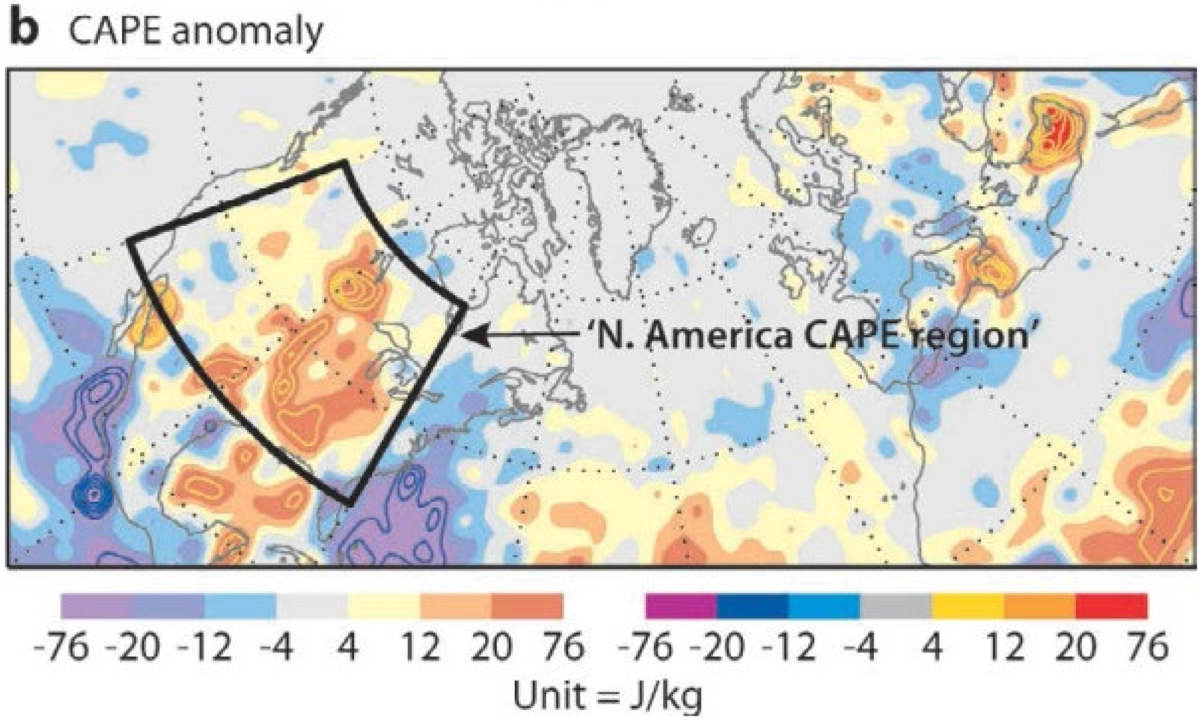
https://www.insurancejournal.com/news/international/2023/12/07/751177.htm

Worldwide Severe Convective Storms in 2022

Event Name	Date	Region	Economic Losses (USD mn)
—	March 14–17	Asia	105
—	April 11–15	Asia	130
—	April 23–25	Asia	120
—	May 16–June 1	Asia	0.2
North China Storms	June 10–14	Asia	300
North China Storms	June 19–23	Asia	180
—	July 25–28	Asia	630
—	Aug. 1–31	Asia	500
Emmelinde	May 20	Europe	630
Finja	May 22–25	Europe	470

https://beinsure.com/statistics/worldwide-severe-convective-storm/

Severe convection| Forecast busts over Europe



Rodwell et al. 2013 BAMS

- Convection over North America, i.e. **an area of high CAPE** is associated with forecast busts over Europe
- A flow situtation with reduced predictability
- Strong influence of initial condition uncertainties on the forecast

Severe convection | Ingredient wind shear

Current AI-based models cannot resolve convection explicitly, we therefore focus on the ingredients of convective environments.

Severe convection | Ingredient wind shear

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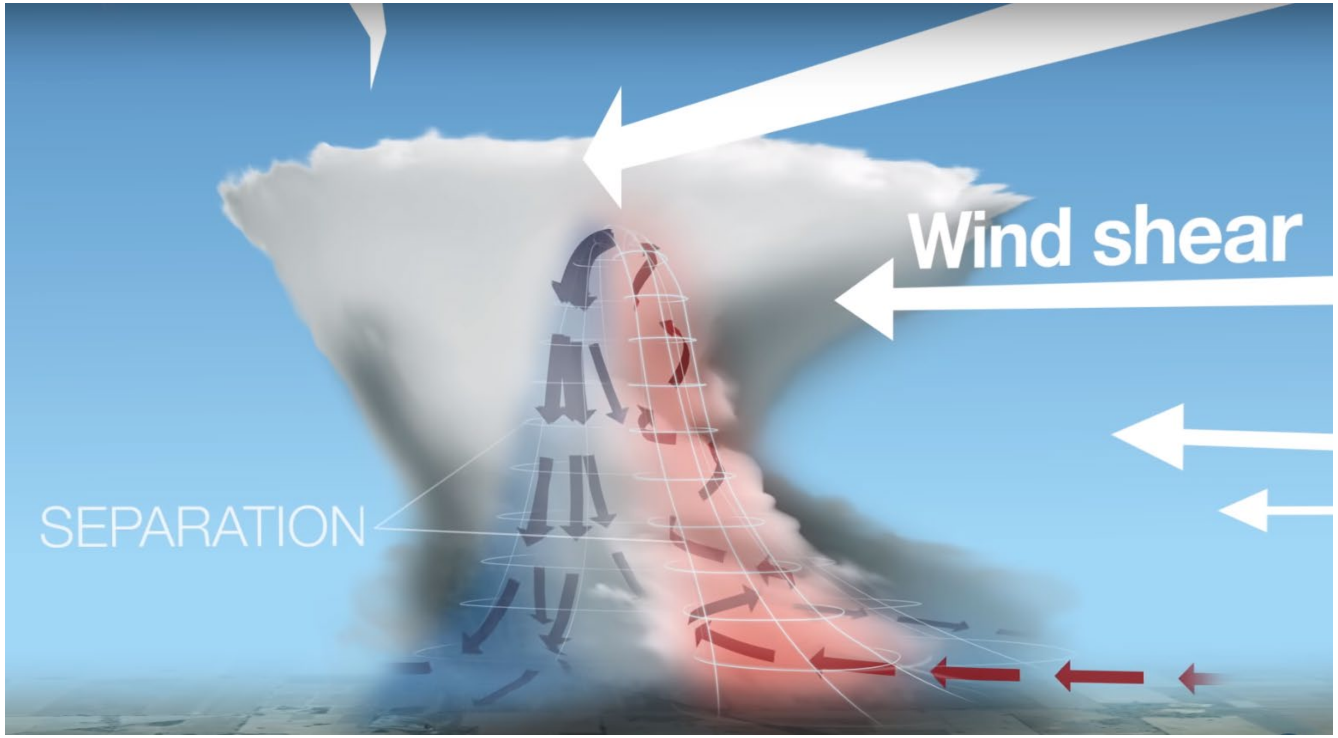
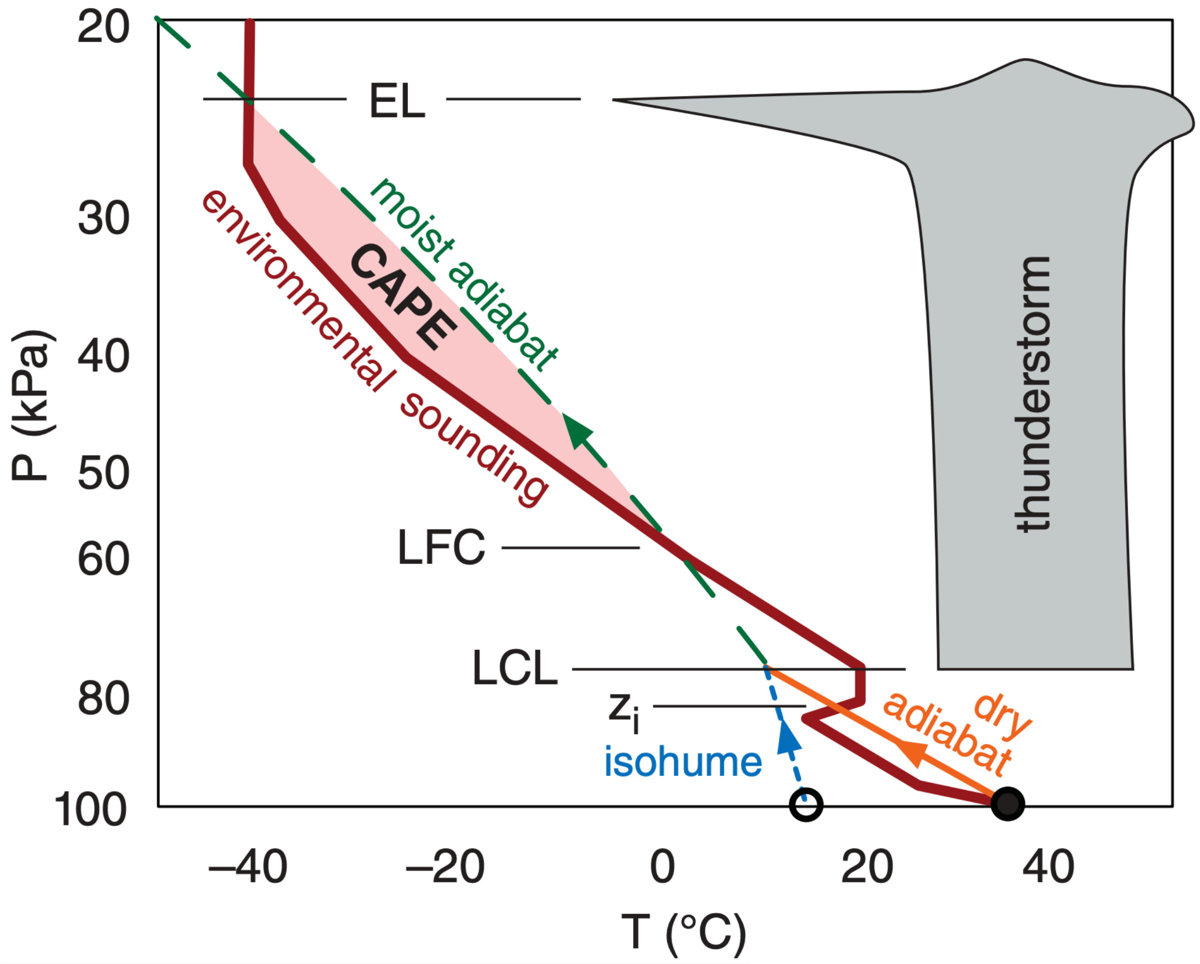


BOM

Wind shear:
Change of wind (speed and direction) with height

Severe convection | Ingredient stability

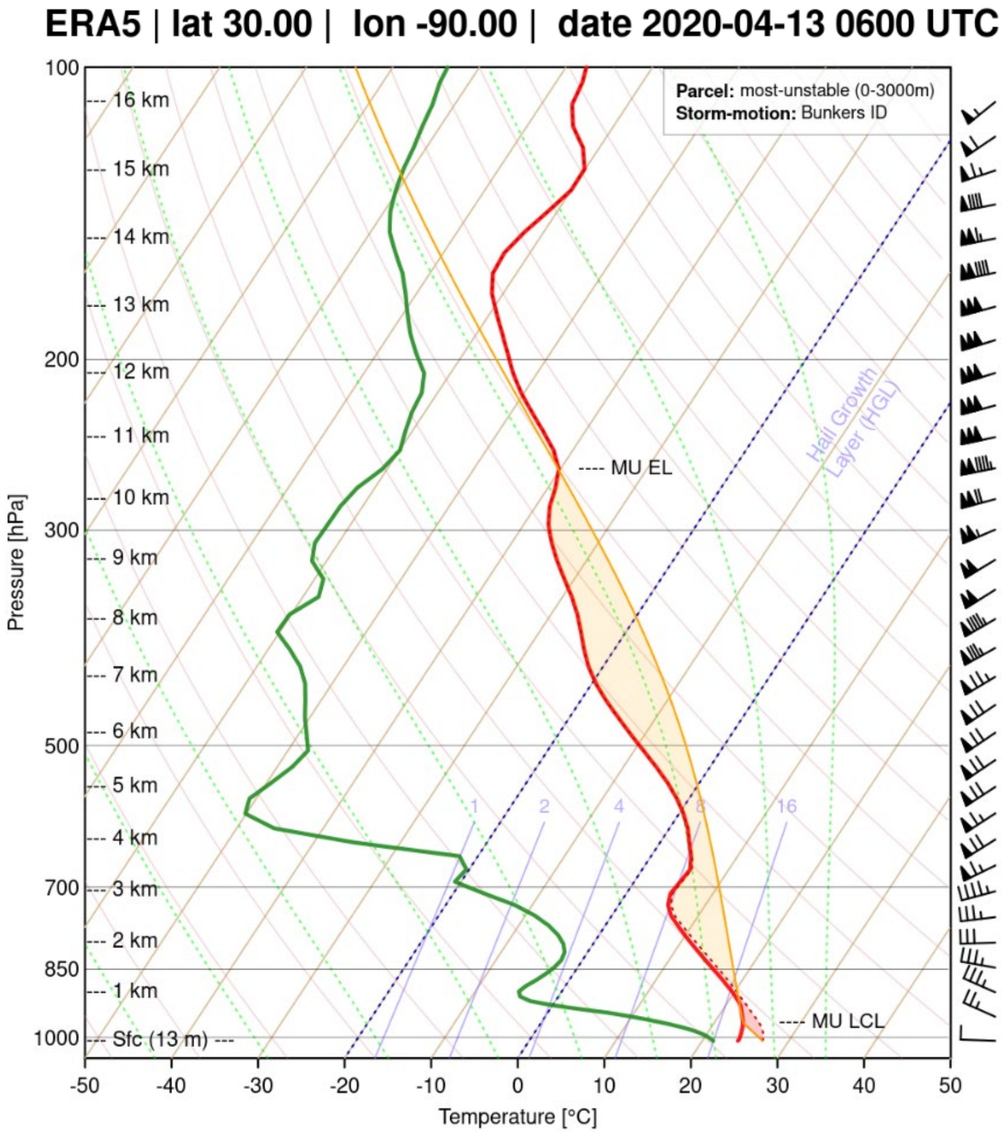


- CAPE = convective available potential energy
- A measure for the energy that can fuel the ascent of an air parcel and hence severe thunderstorms
- Vertical integral
- CAPE combines information on moisture and temperature

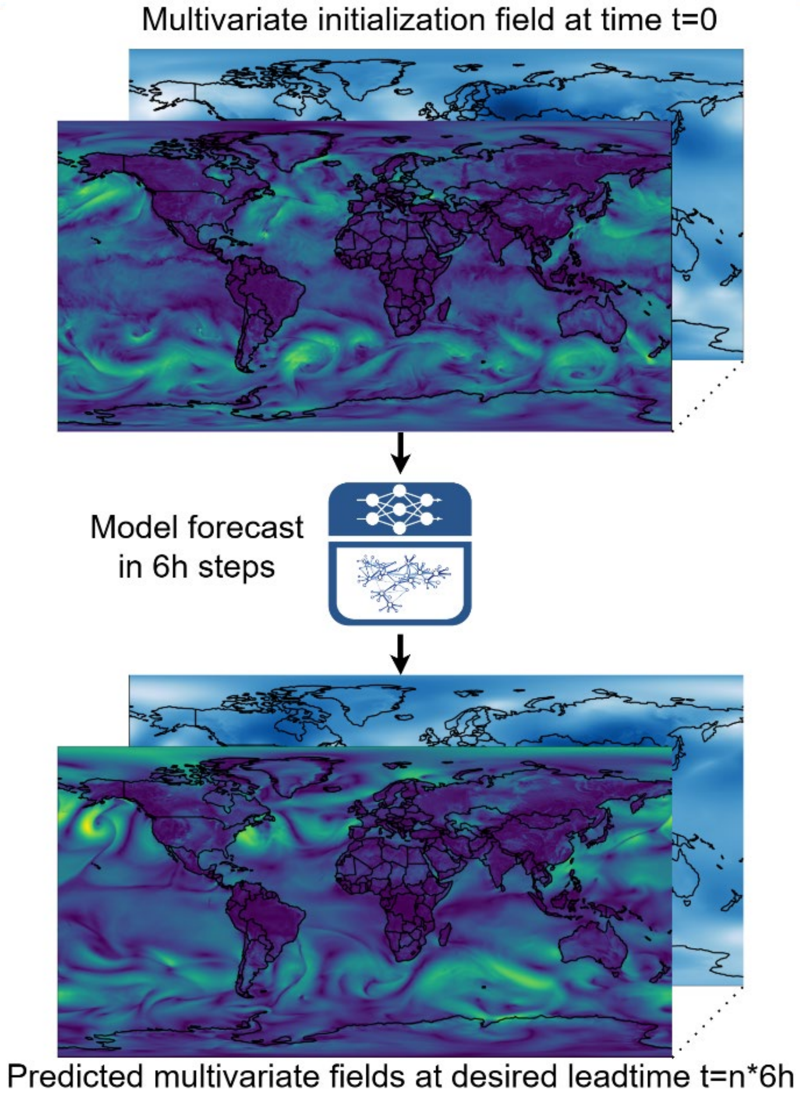
Stull, Practical Meteorology Thunderstorm Fundamentals

- Challenging forecast task
  - Severe convection requires instability and shear
  - Co-location of thermodynamic and dynamic accuracy
  - Accuracy of vertical profile

- Note: CAPE is derived from pressure levels in all models and ERA-5



Taszarek et al., 2017; rawinsonde.com

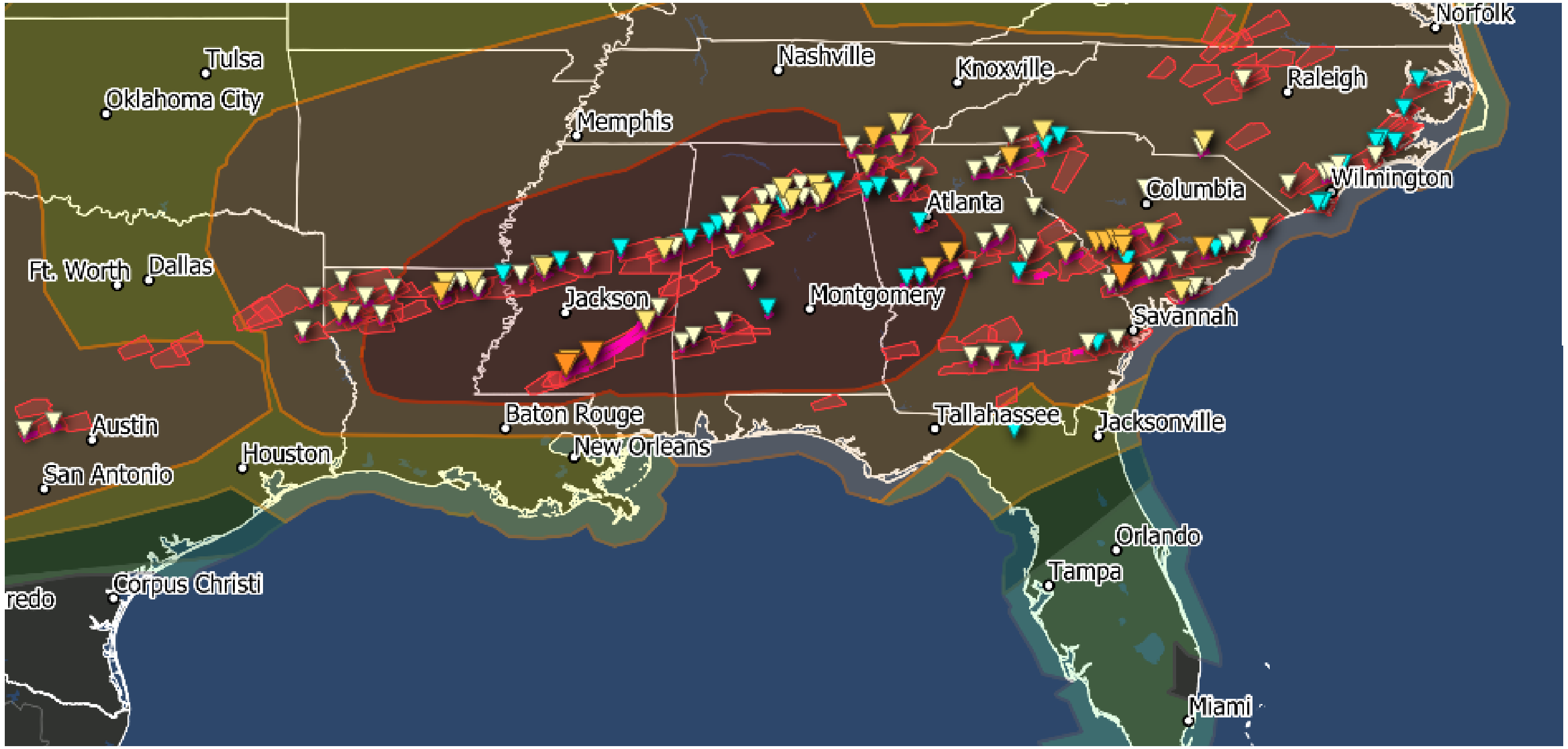


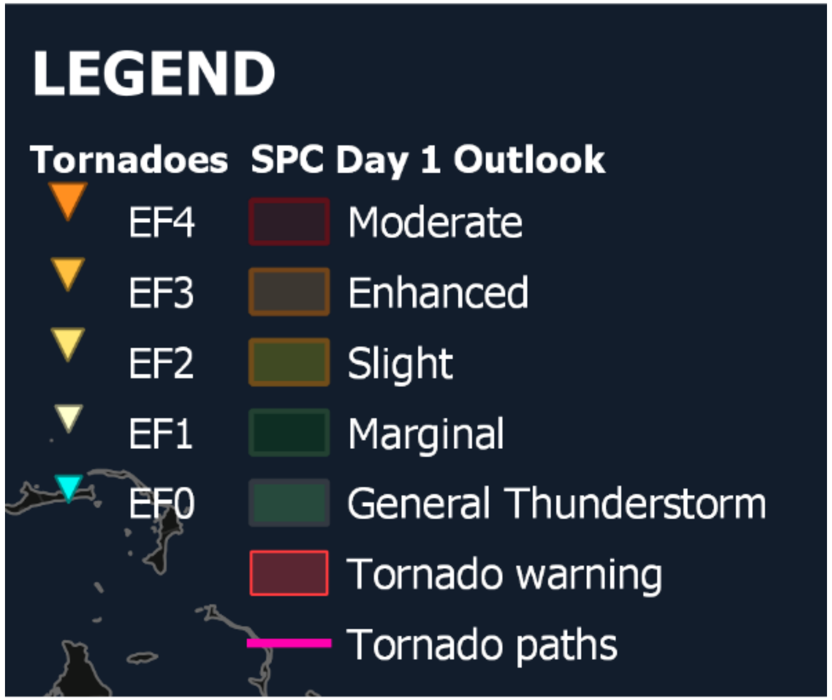
Data	Type
Pangu-weather	Transformer model
Graphcast	Graph neural net
Fourcastnet	Spherical fourier neural operators
IFS	Numerical weather prediction model
ERA-5	Reanalysis

Bi et al., 2023; Lam et al., 2023; Bonev et al., 2023; Rasp et al. 2023; Image credit: Louis Poulain-Auzeau

Case study | Tornado outbreak April 12/13 2020

- Convective outbreak at leading edge of a trough
- Warnings issued 4 days prior by Storm Prediction Center
- 141 tornadoes in 10 states, 38 fatalities



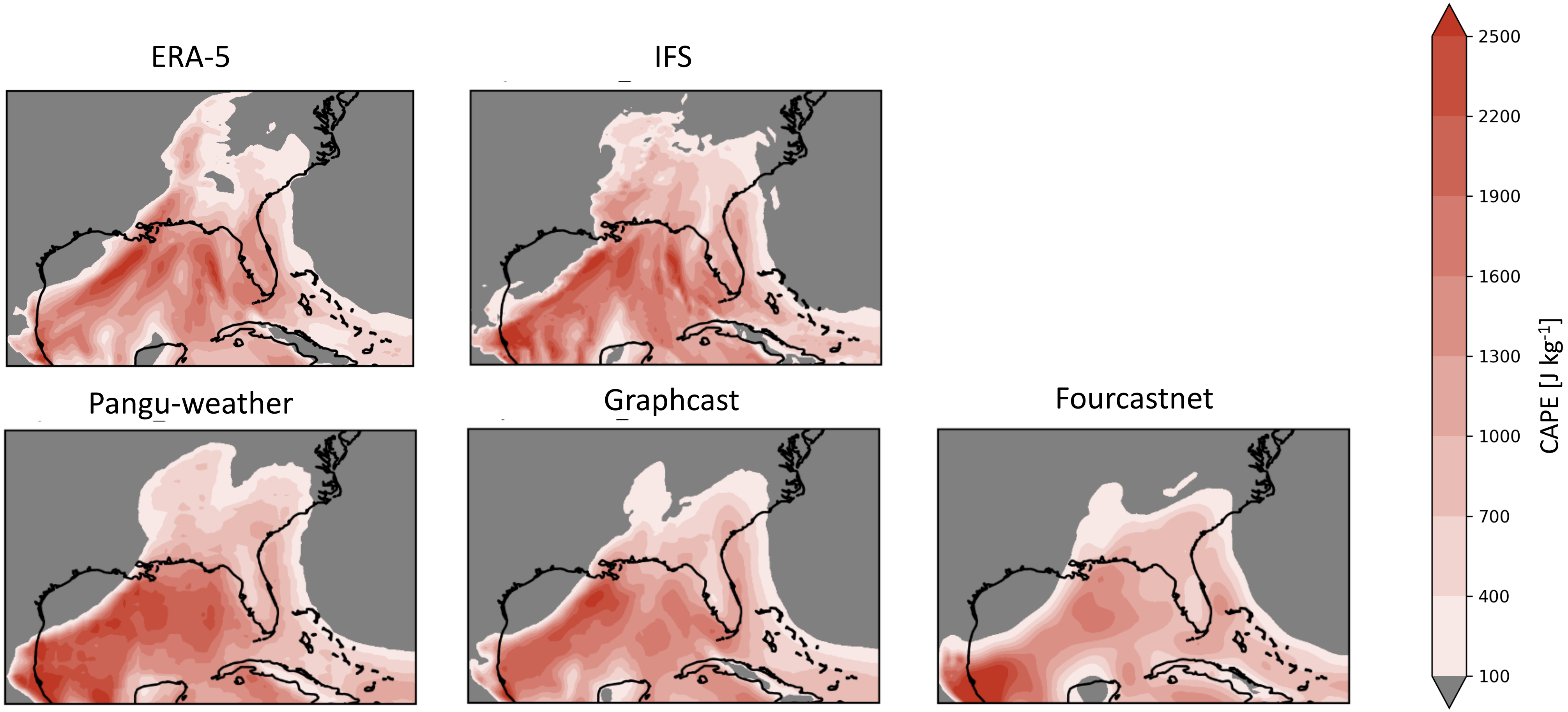


Storm Prediction Center, 2020

CAPE @ 6 UTC 13 April 2020 | 42 hours lead-time

Image credit: Monika Feldmann

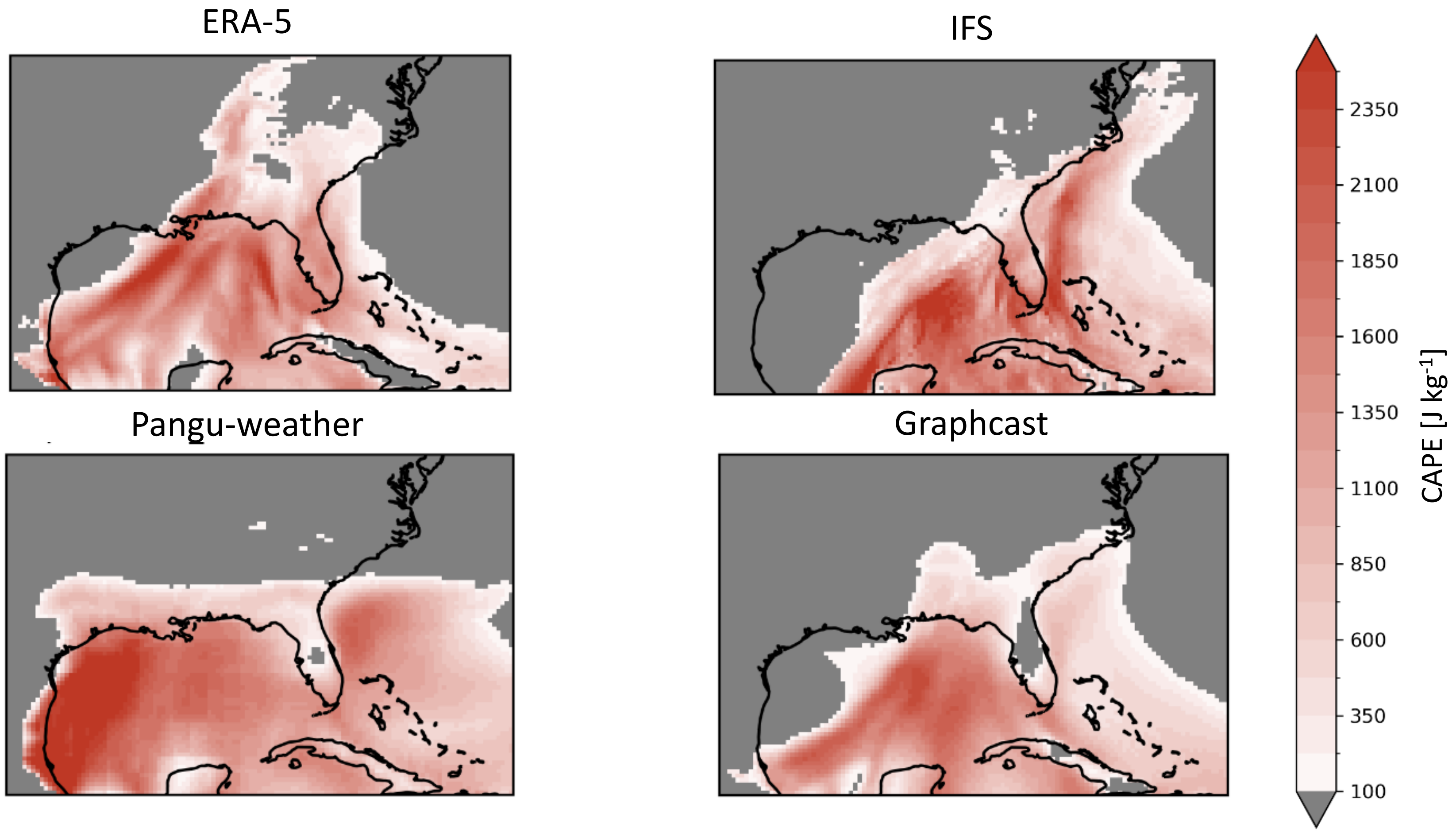
CAPE @ 6 UTC 13 April 2020 | 42 hours lead-time



The presence of high CAPE air is captured by all models, differences in the structure

Image credit: Monika Feldmann

CAPE @ 6 UTC 13 April 2020 | 174 hours lead-time



The presence of high CAPE air is captured by all models, differences in the structure

Image credit: Monika Feldmann

CAPE @ 6 UTC 13 April 2020 | 174 hours lead-time

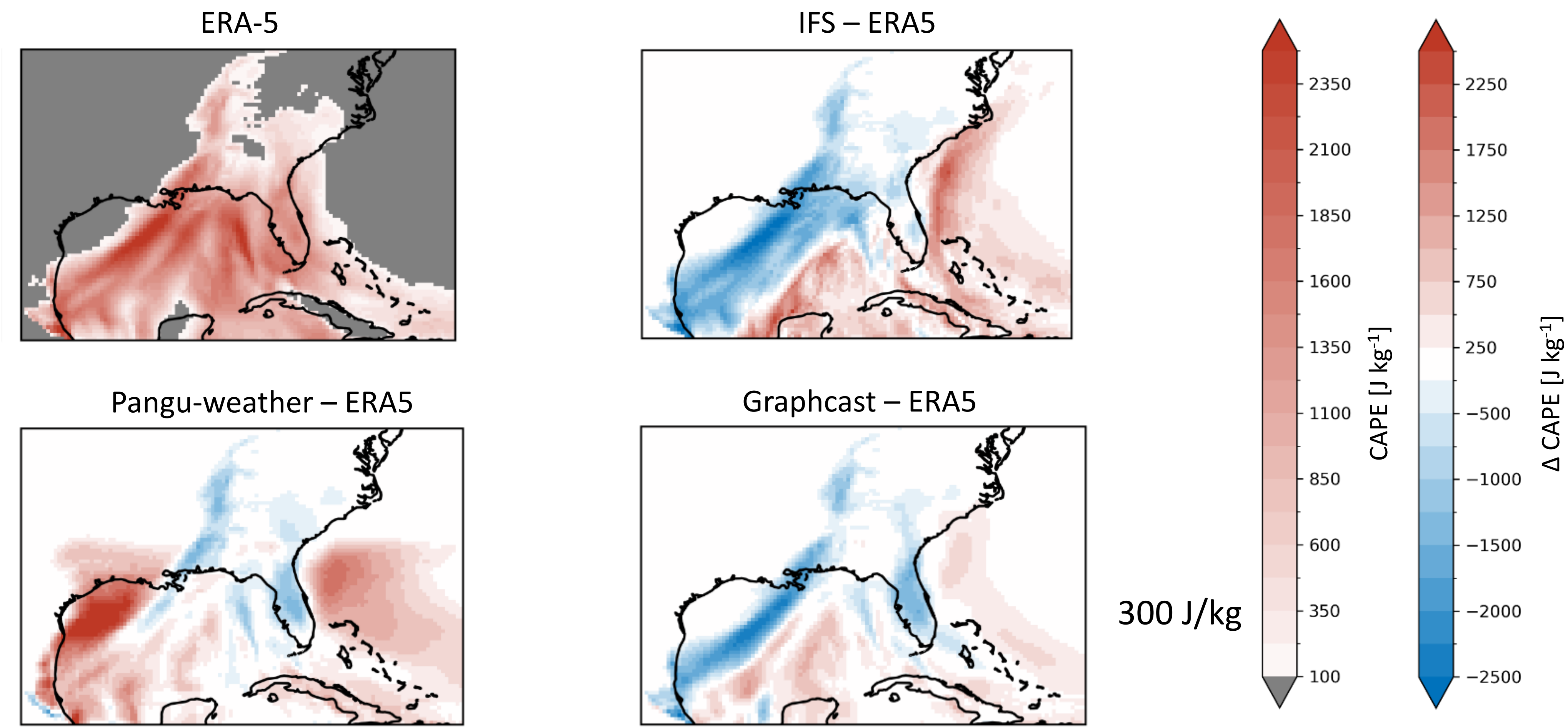
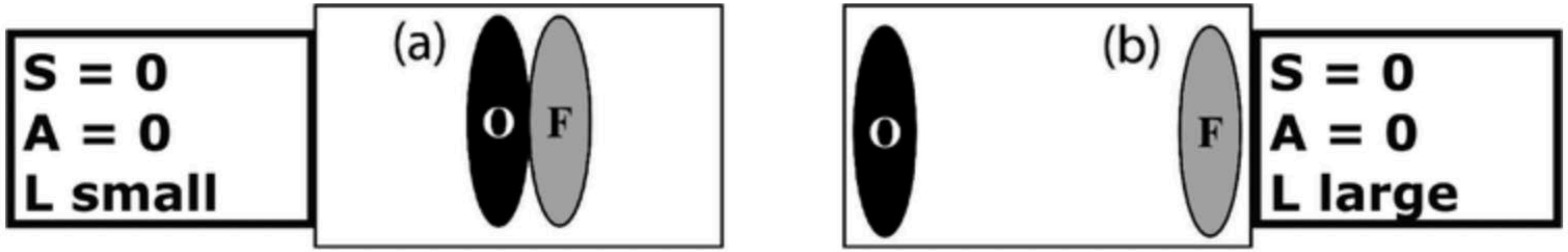


Image credit: Monika Feldmann

Object-based forecast verfication | SAL and FSS

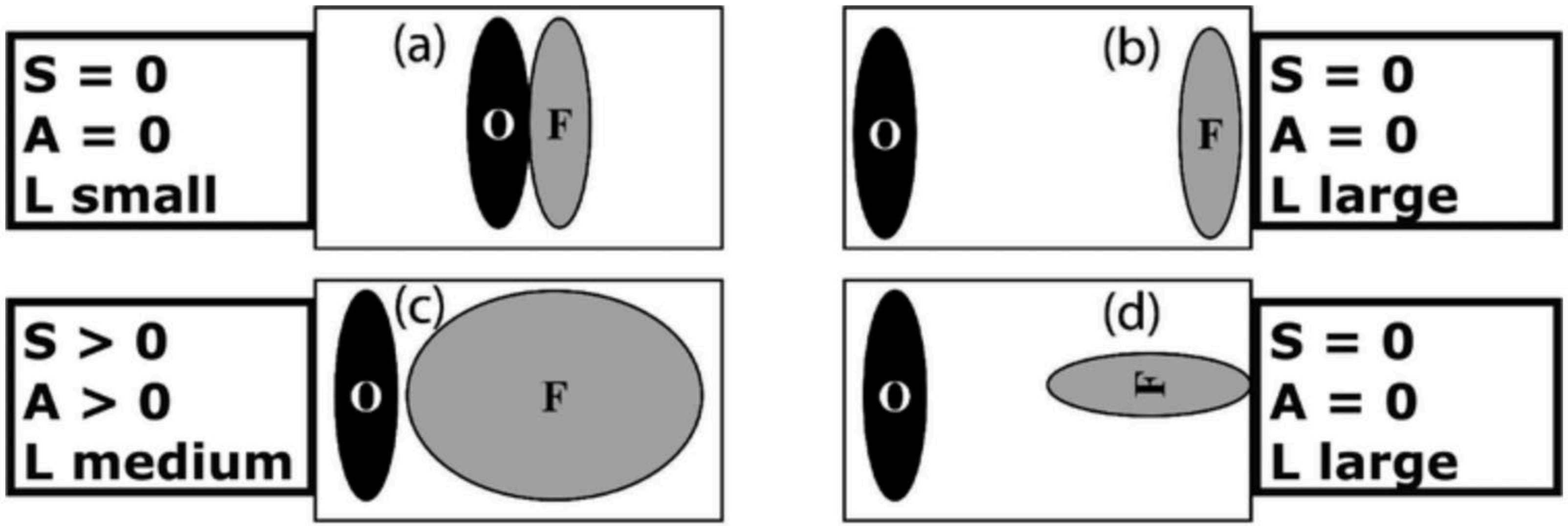
SAL = Structure (S) Amplitude (A) Location (L)

FSS = Fractions skill score



Forecast F
Observation O

Wernli et al. 2008



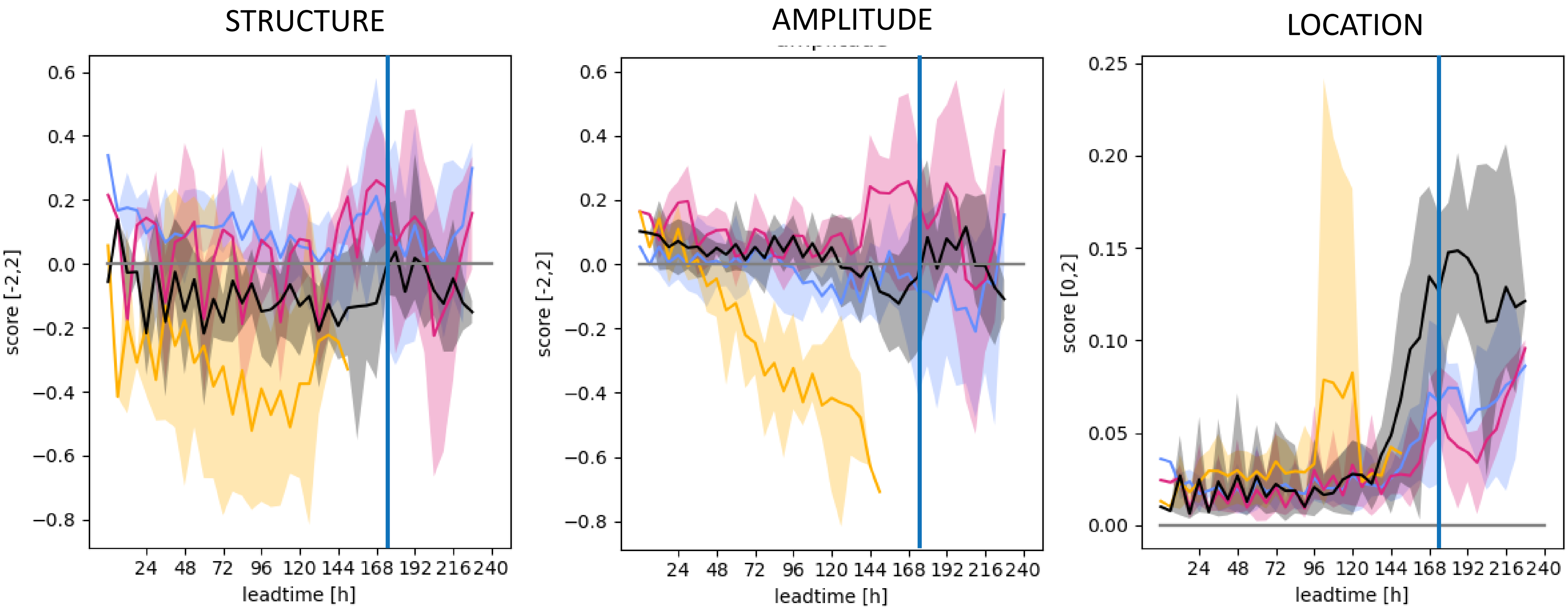
Forecast F
Observation O

best forecast if S,A,L = 0

Wernli et al. 2008

Object-based forecast verfication| SAL CAPE >300J/kg

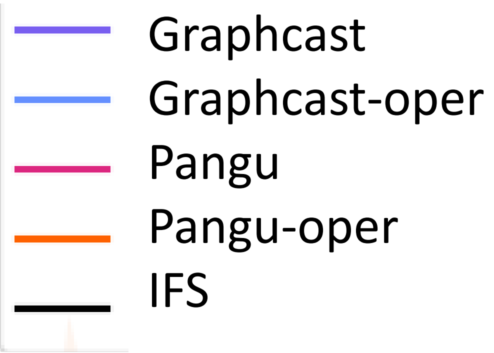
Graphcast
Pangu-weather
Fourcastnet
IFS



8 time steps for verification → colored band

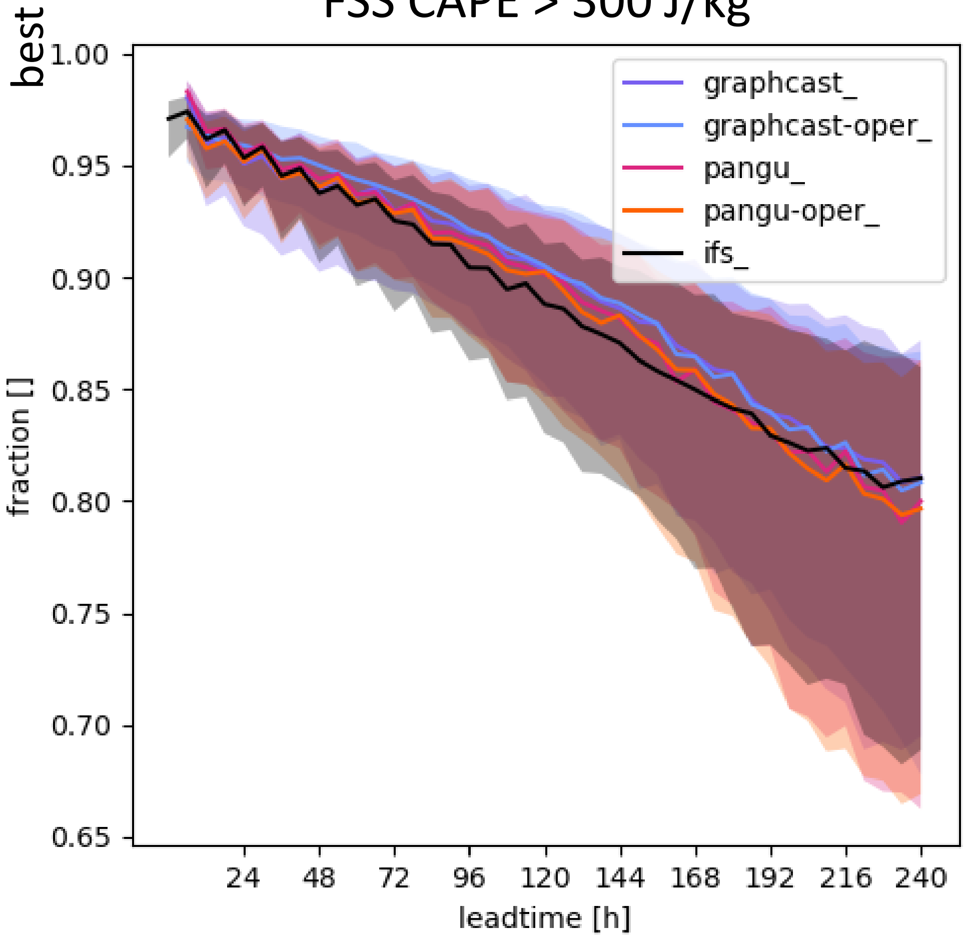
Image credit: Monika Feldmann

Seasonal performance | CAPE fractions skill-score



- Domain USA, March-September 2020
- All models have comparable scores for lead times up to 240 hours

FSS CAPE > 300 J/kg



FSS CAPE > 1000 J/kg

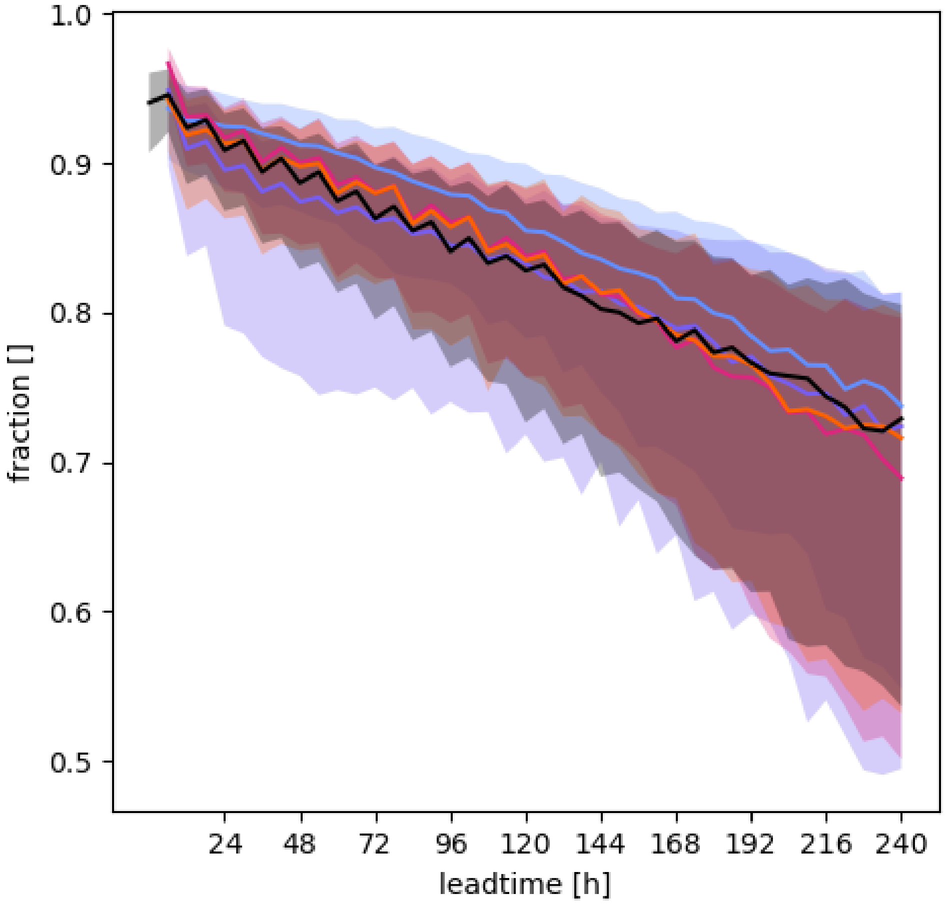
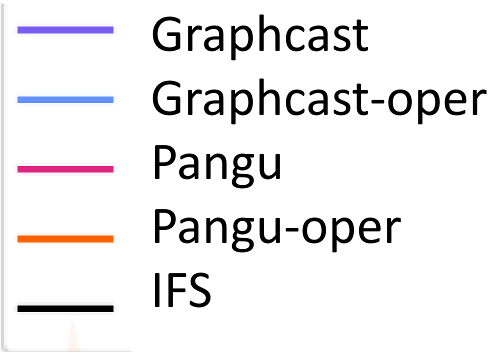
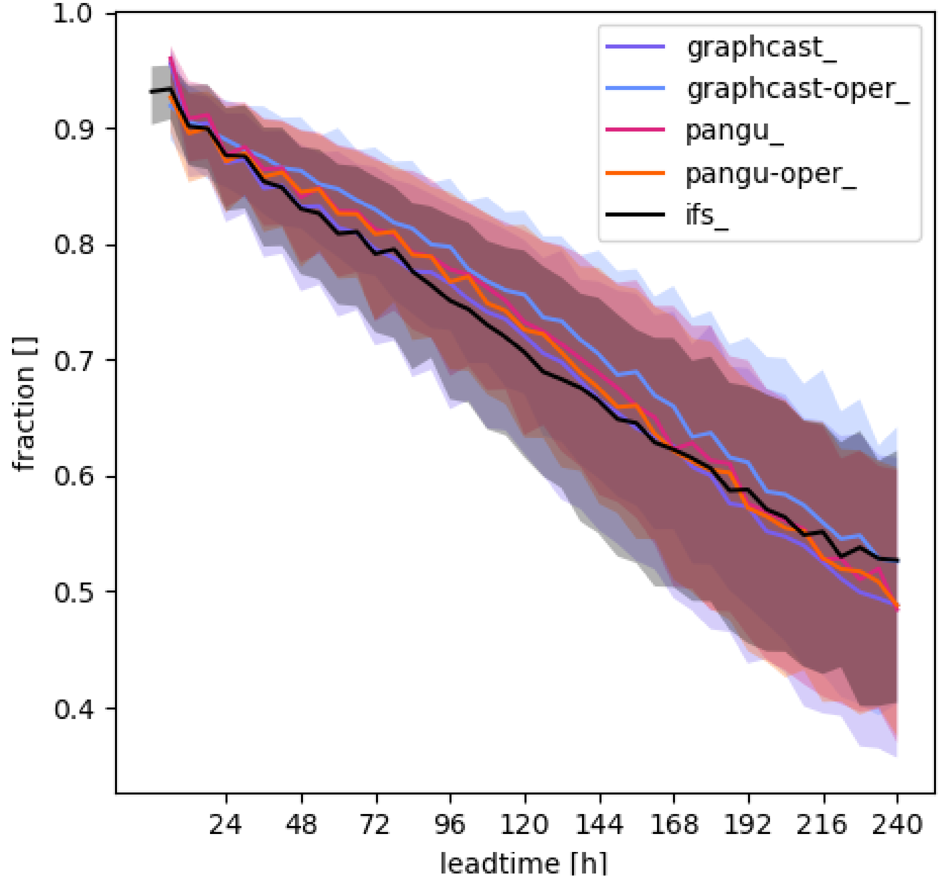


Image credit: Monika Feldmann

Seasonal performance | CAPE X shear



FSS CAPE x shear > 300 m2/s2



FSS CAPE x shear > 500 m2/s2

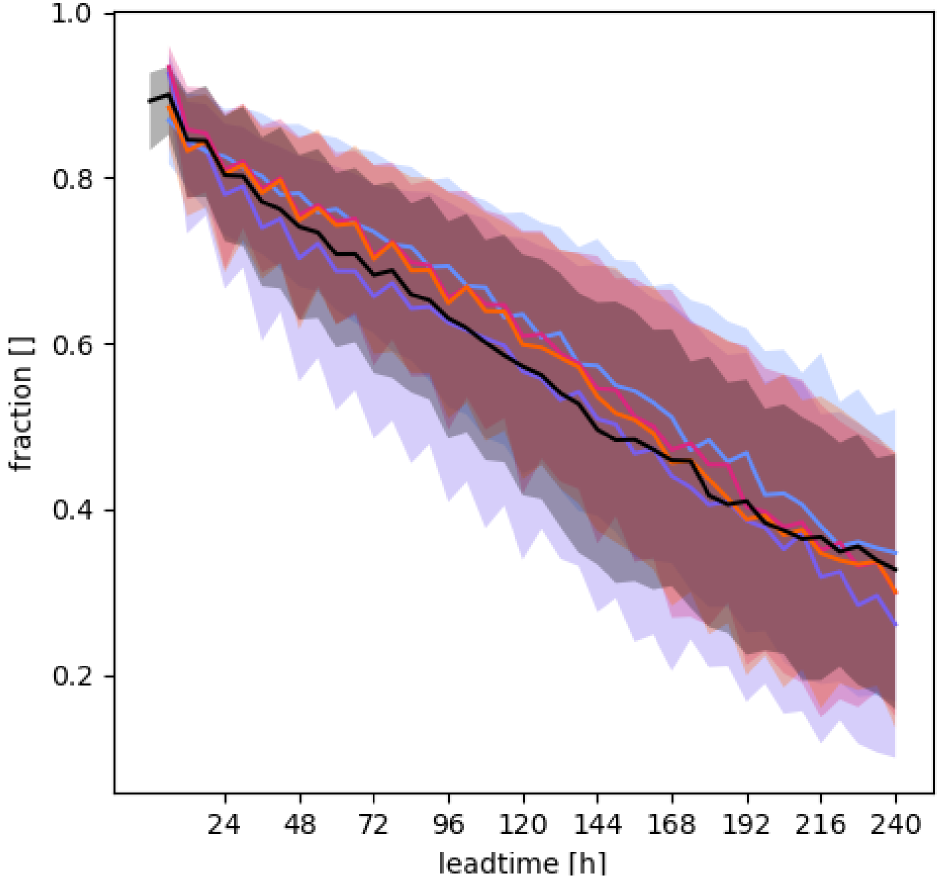


Image credit: Monika Feldmann

Adding more models | ECMWF operational implementation

- Recent event: 2-3 April 2024, tornado outbreak USA

Data		Type
AIFS		Graph neural net
FuXi		Transformer cascade
Pangu-weather		Transformer model
Graphcast		Graph neural net
Fourcastnet		Spherical fourier neural operators
IFS		Numerical weather prediction model

SAL score CAPE >300 J kg-1

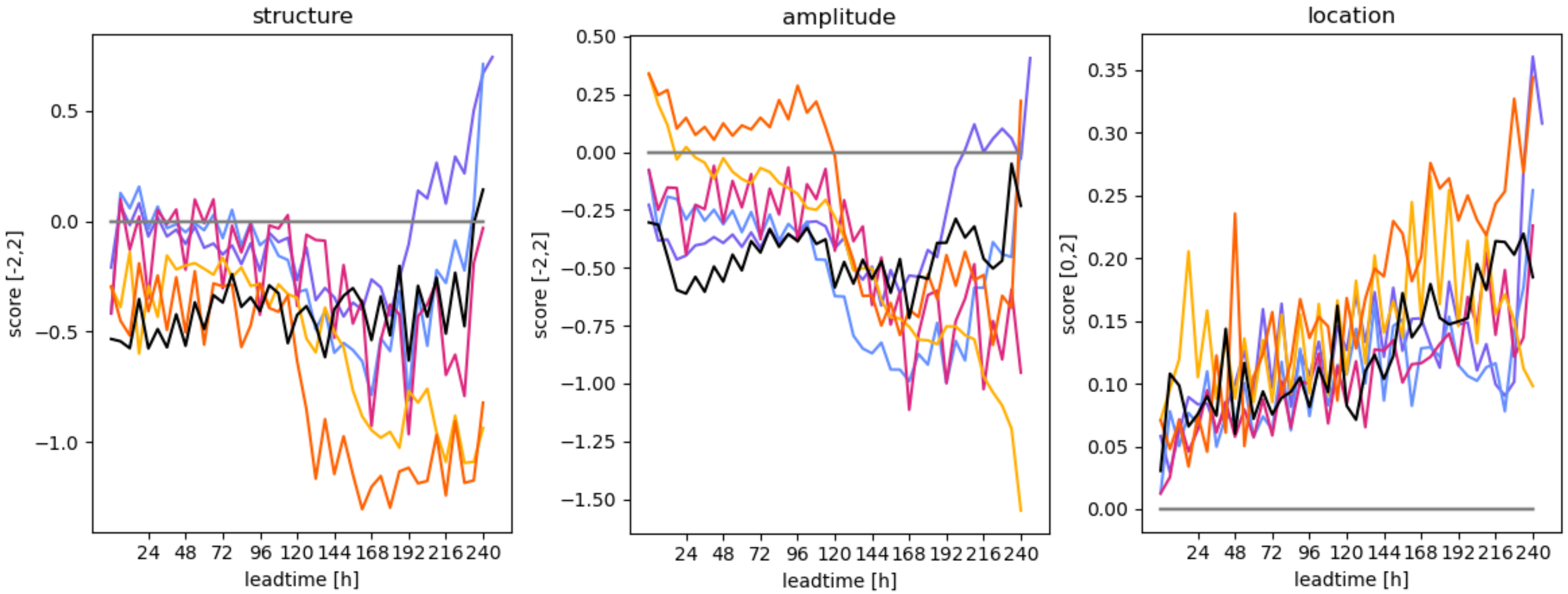


Image credit: Monika Feldmann

ECMWF AIFS Blog, 2024; Chen et al., 2023

The role of moisture | Q vs. RH

- CAPE derived from T and Q
- Nonlinear conversion of RH(T,p) to Q
- Sensitive to errors in RH, T and p
- Skill of Q derived from RH worse than direct prediction

Data	Type	Moisture
AIFS	Graph neural net	Q
Pangu-weather	Transformer model	Q
Graphcast	Graph neural net	Q
Fourcastnet	Spherical fourier neural operators	RH
FuXi	Transformer cascade	RH

Conclusion convective env. evaluation

- AI models capable of producing realistic CAPE values
  - Co-location of high CAPE and shear
  - Nonlinear combination of CAPE and shear
- Models with Q appear to perform better than models with RH
- Models with Q can outperform IFS

Next steps

- Expansion to other convective hotspots
- Need for more reference data in all models → hindcast archive

- How can the next generation of meteorology students be trained best?
  - Process understanding vs. AI knowledge?

- How to ensure training and access outside of Europe?


ECMWF
esa
-lab

Conclusion and Outlook

- AI models capable of producing realistic CAPE values
  - Co-location of high CAPE and shear
  - Nonlinear combination of CAPE and shear
- Models in group 1 appear to perform better than group 2
- Models in group 1 partially outperform IFS

Next steps

- Case studies in other convective hotspots
- Regional seasonal analyses of 2020

Perspective: evaluation of extreme events

- Need for more reference data in all models → hindcast archive

Data	Type	Differences
AIFS	Graph neural net	Q
Pangu-weather	Transformer model	3D cube, Q
Graphcast	Graph neural net	3D cube, Q
Fourcastnet	Spherical fourier neural operators	2D channels, RH
FuXi	Transformer cascade	2D channels, RH

Sources

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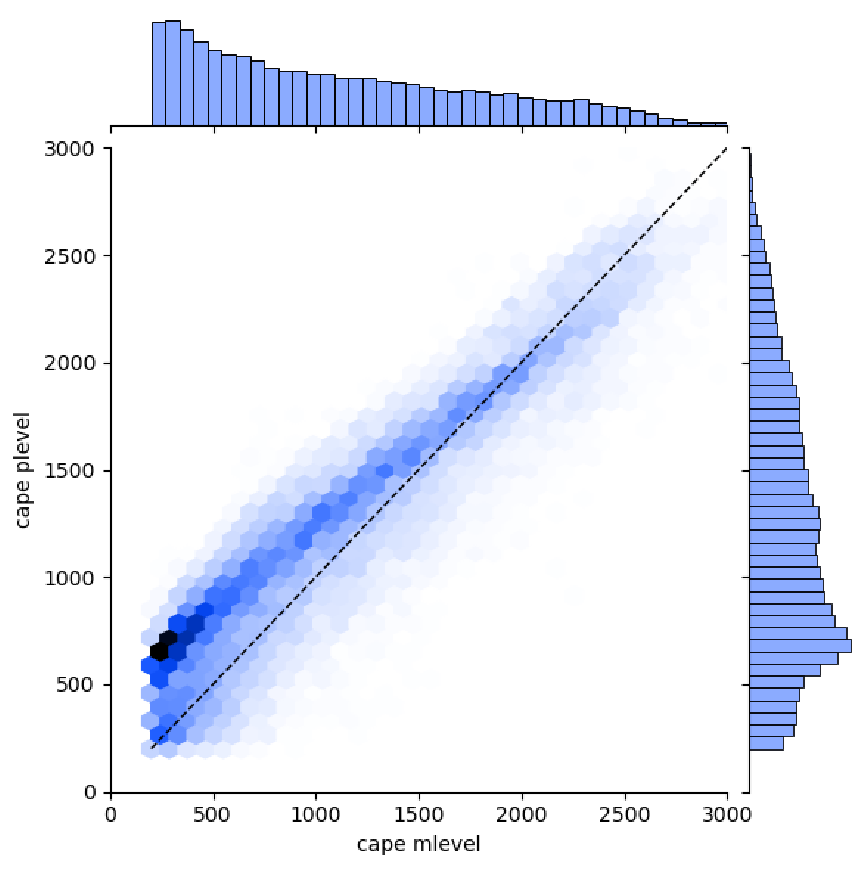
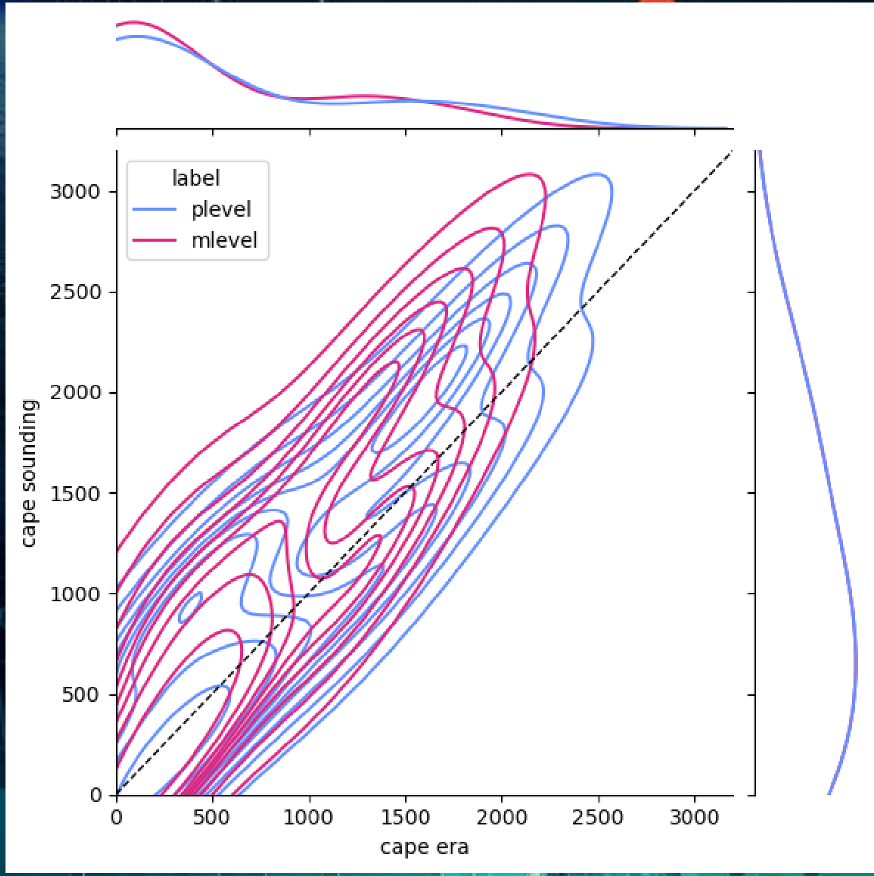
- Tom Beucler et al. ,Climate-invariant machine learning.Sci. Adv.10, eadj7250(2024). DOI:10.1126/sciadv.adj7250

Observations vs. reanalysis

- Reduced number of vertical levels impacts CAPE computation
- Overestimation of low values
- Underestimation of extremes
- Comparison with observed soundings shows underestimation by reanalysis





CAPE scores 2 - 3 April 2024?

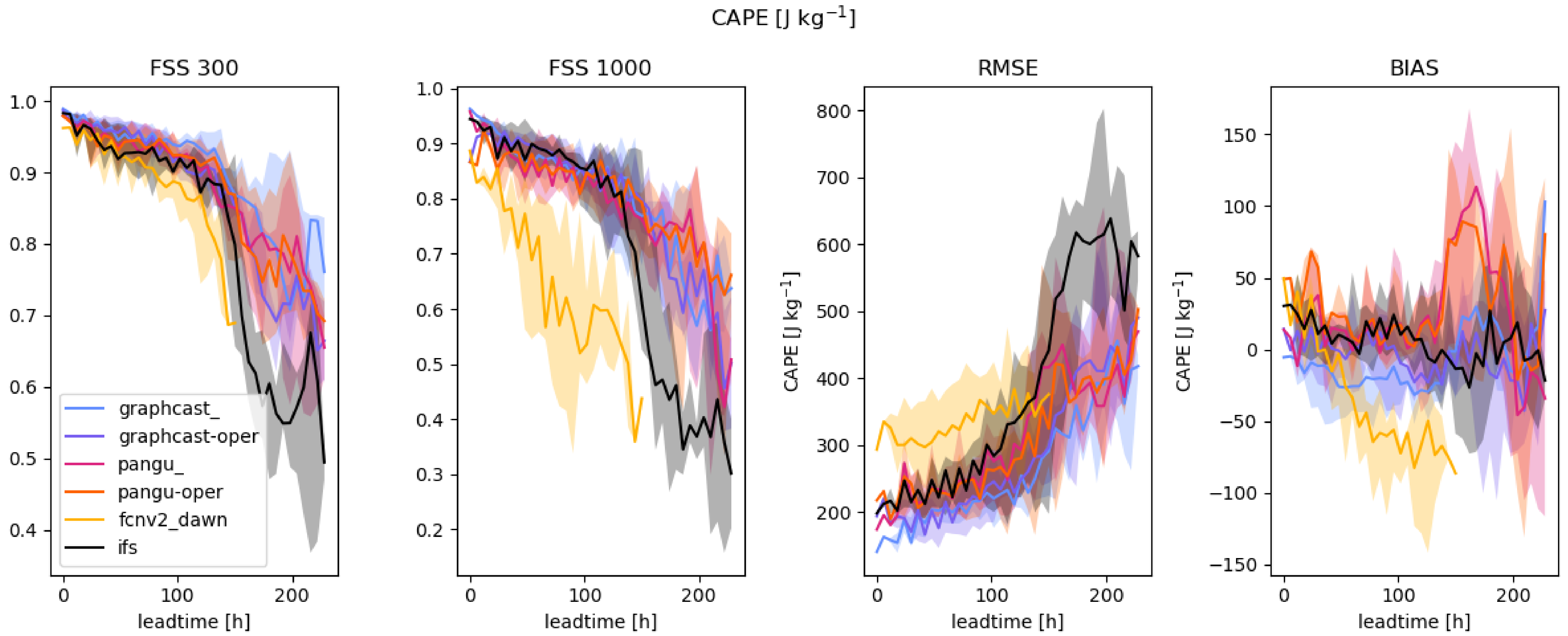
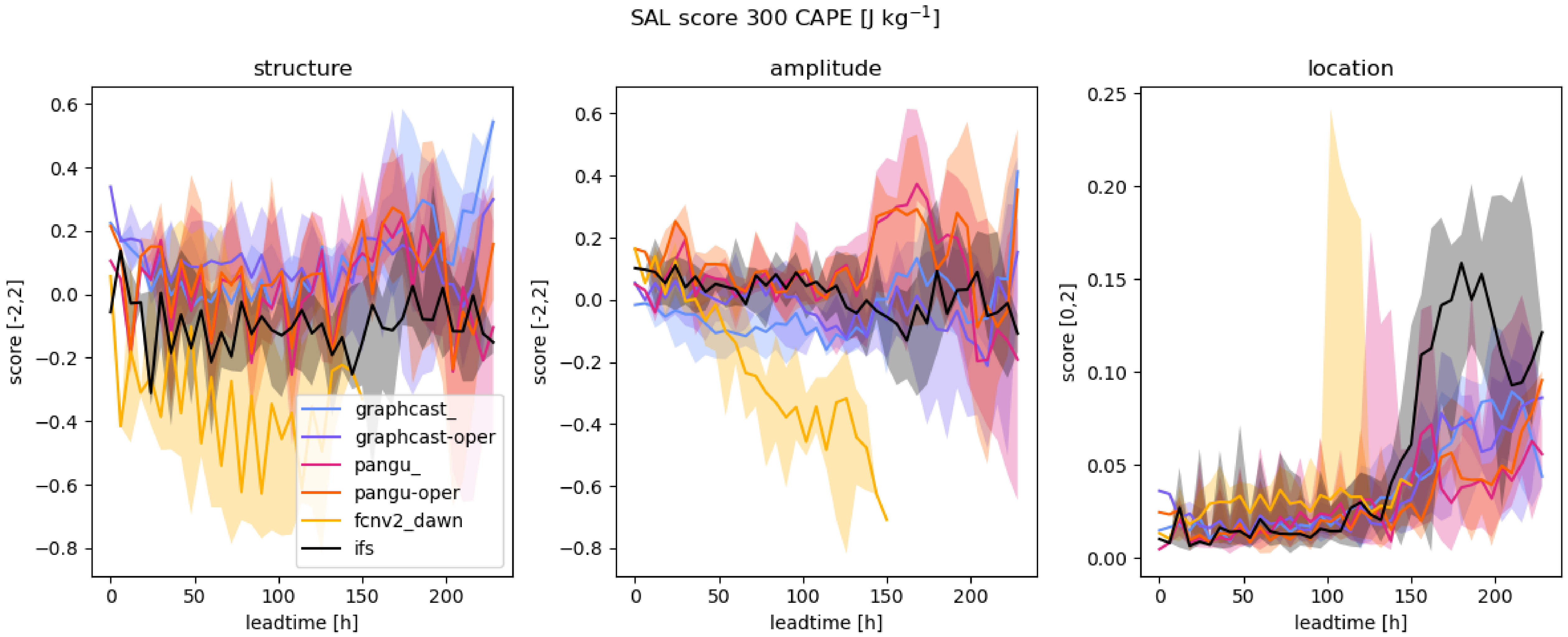
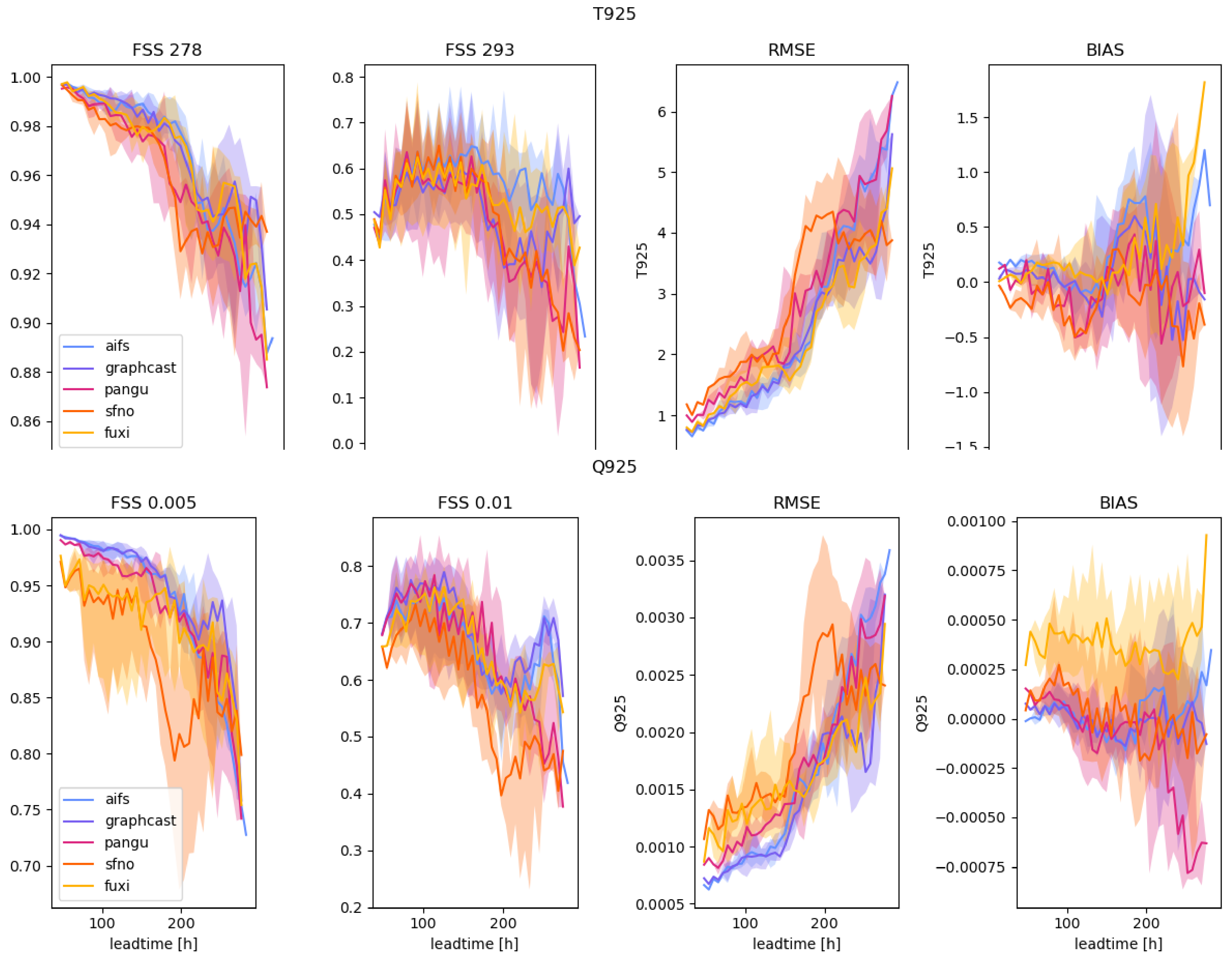


Image credit: Monika Feldmann



SAL score 300 CAPE [J kg−1]
structure
amplitude
location
score [-2,2]
score [0,2]
leadtime [h]
graphcast_
graphcast-oper
pangu_
pangu-oper
fcnv2_dawn
ifs

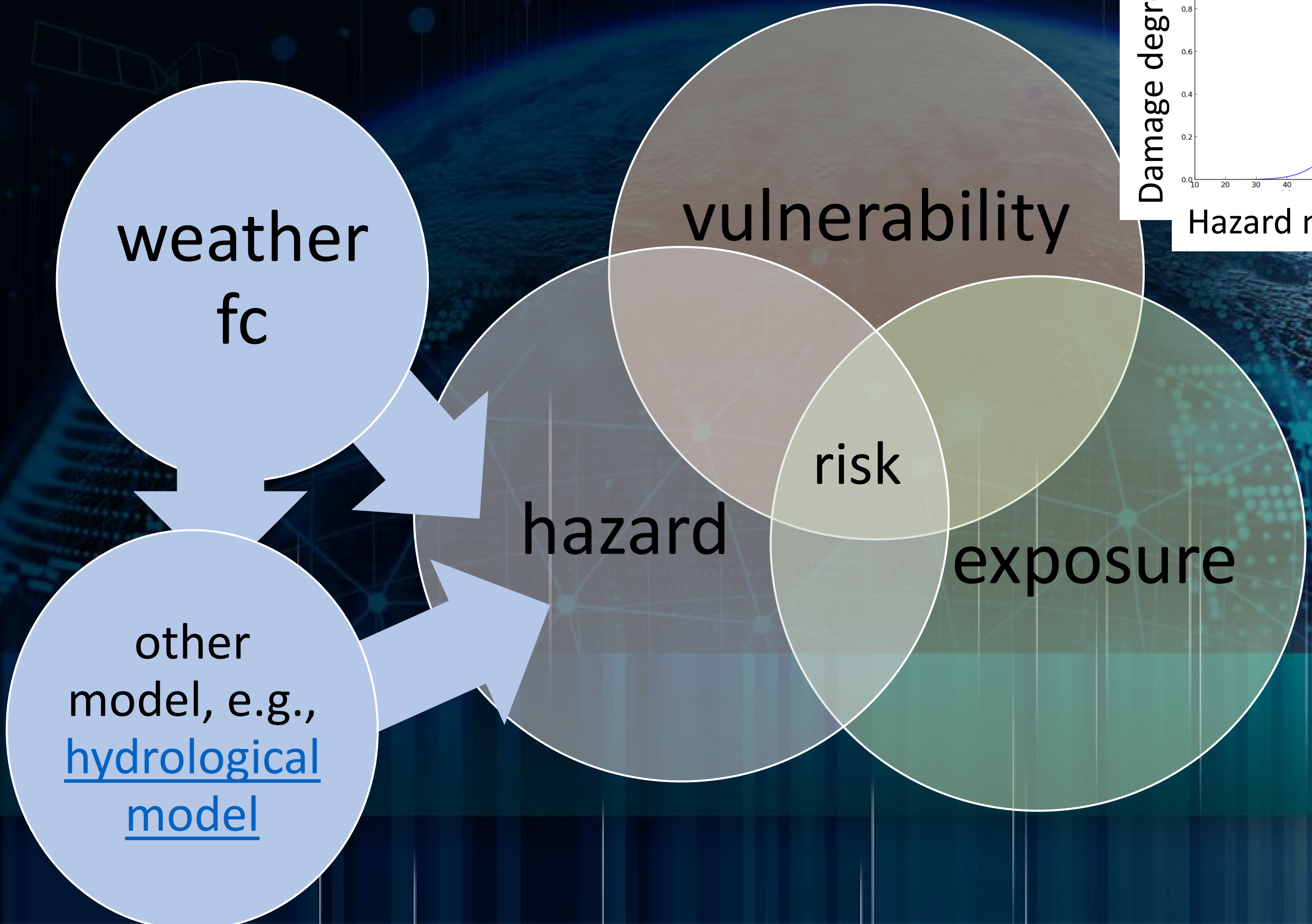
ECMWF

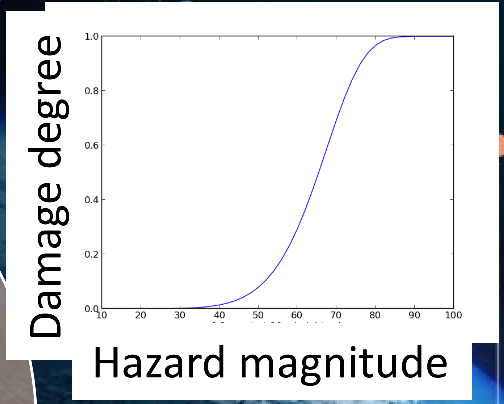

T925
FSS 278
FSS 293
RMSE
BIAS
T925
aifs
graphcast
pangu
sfno
fuxi
Q925
FSS 0.005
FSS 0.01
RMSE
BIAS
Q925
leadtime [h]

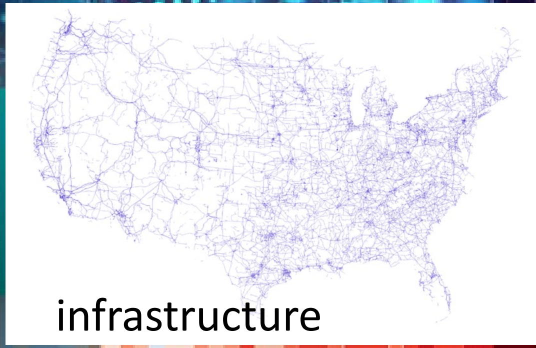
Wish list | Access to more cases

- Results are highly preliminary because they are based only on two cases → need for more cases
- Ideal world: Forecasts started from operational analyses with all AI models for the period starting in 2020

Impact / risk models | the classical approach







Washington Post