

Seasonal climate forecasts multi-model ensembles

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SECLI-FIRM Stakeholder Workshop 15th June

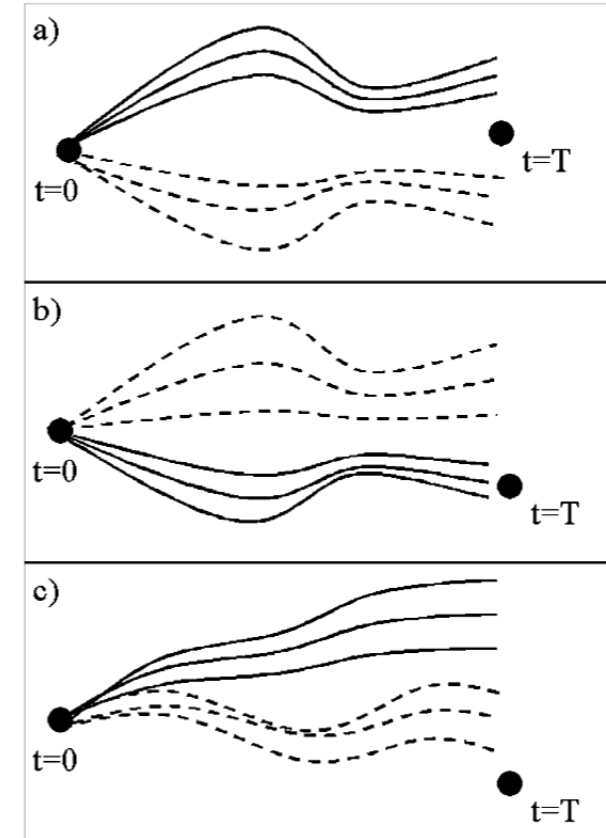
Brief introduction to the concept of Multi Model Ensembles

Results from methods of model selection from SECLI-FIRM

Discussion on the use of and potential advantages and limitations of using a weighted mean when combining models.

Why use more than one skillful model?

- a) The two systems lie above and below the verification leading to improvement from error cancelation
- b) One wrong one right leading to a multi model better/worse than the individually models, respectively.
- c) Both models wrong leading to same conclusion as in b)



Source: R.Hagedorn et al., 2005
<https://doi.org/10.3402/tellusa.v57i3.14657>

Overview of models retrieved for SECLI-FIRM

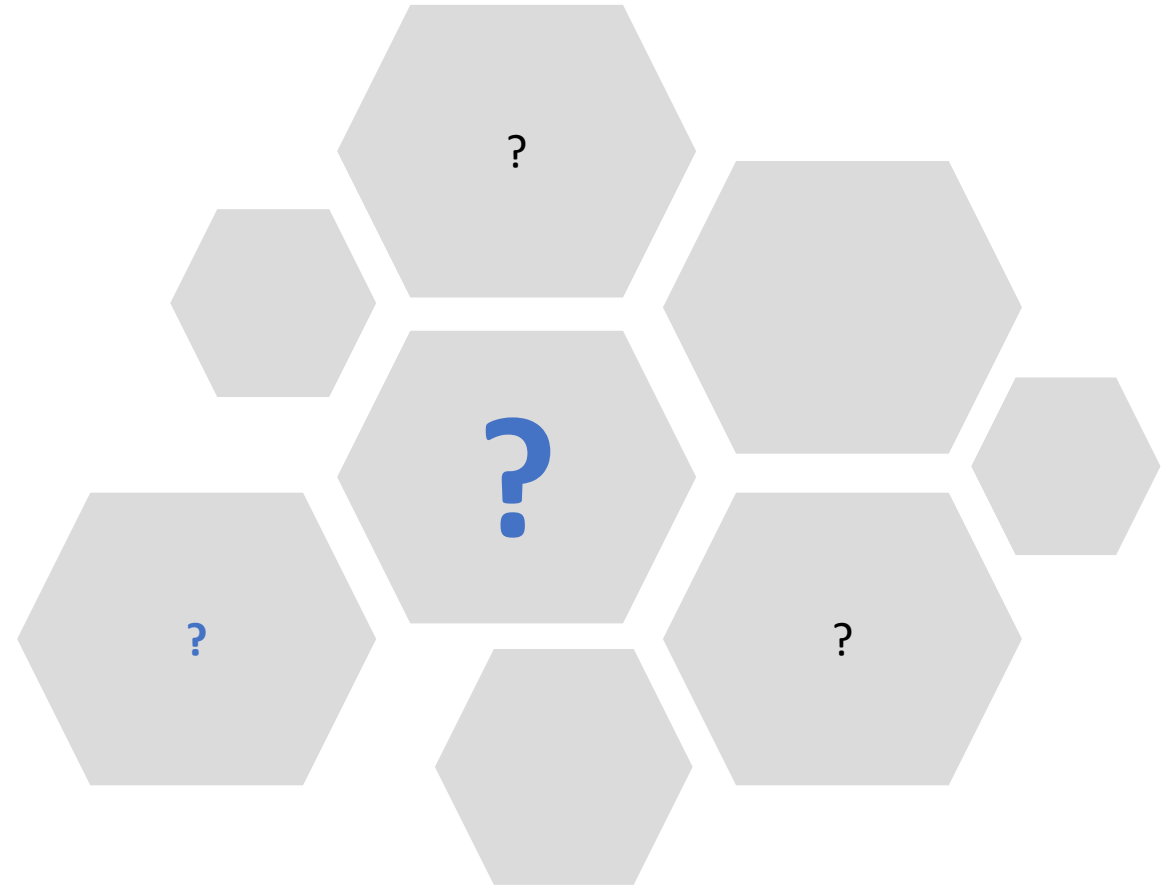
Model	Latest System	Horiz. Res.	Temporal Res.	# Ens. members: hindcast/forecasts	Hindcast Period	Ensemble Generation
ECMWF	5	1° x 1°	Daily/Monthly	25/51	1993-2016	Burst
UKMO	14	1° x 1°	Daily/Monthly	28/60	1993-2016	Lagged
MF	6	1° x 1°	Daily/Monthly	25/51	1993-2016	Mixed
DWD	2	1° x 1°	Daily/Monthly	30/50	1993-2016	Burst
CMCC	3	1° x 1°	Daily/Monthly	40/50	1993-2016	Burst
NASA	2	1° x 1°	Monthly	4/10	1981-2016	Lagged
CCMA	2	1° x 1°	Monthly	10/10	1981-2018	Burst
CCSM4	4	1° x 1°	Daily/Monthly	10/10	1982-2016	Burst
GEMNEMO	1	1° x 1°	Monthly	10/10	1993-2016	Burst
NCEP	2	1° x 1°	Daily/Monthly	28/28	1982-2018	Lagged
GFDL	B1	1° x 1°	Monthly	12/12	1980-2018	Burst
JMA	5	1° x 1°	Daily/Monthly	10/10	1993-2016	Burst

Overview of models retrieved for SECLI-FIRM

12 models

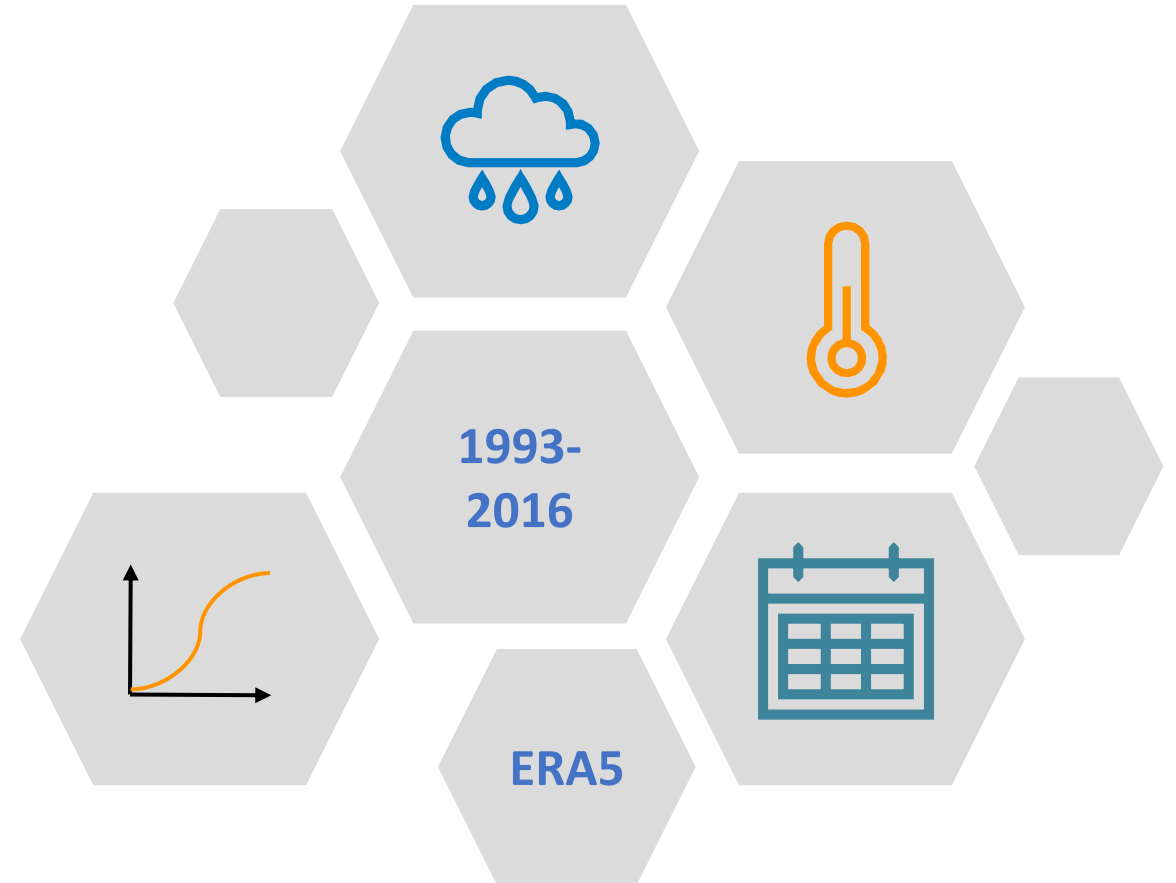
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Can the skill be improved
by obtaining the optimal
combination of models
compared with including
all models?



Method for MME combination

- T_p and T_a for the hindcast period 1993-2016.
- Deterministic, anomaly correlation using mean of ensemble members.
- Probabilistic, brier score for a binary event (colder/warmer...drier/wetter)
- Monthly forecast with 1 month lead.
- ERA5 reanalysis as observational data.





Examples of results for a deterministic forecast:

A monthly forecast with a lead of 1-month of 2m temperature anomalies over the domain of Spain (35,44 ; -10,3) for land only.

Spain land only

Numer of models in best combi: 5

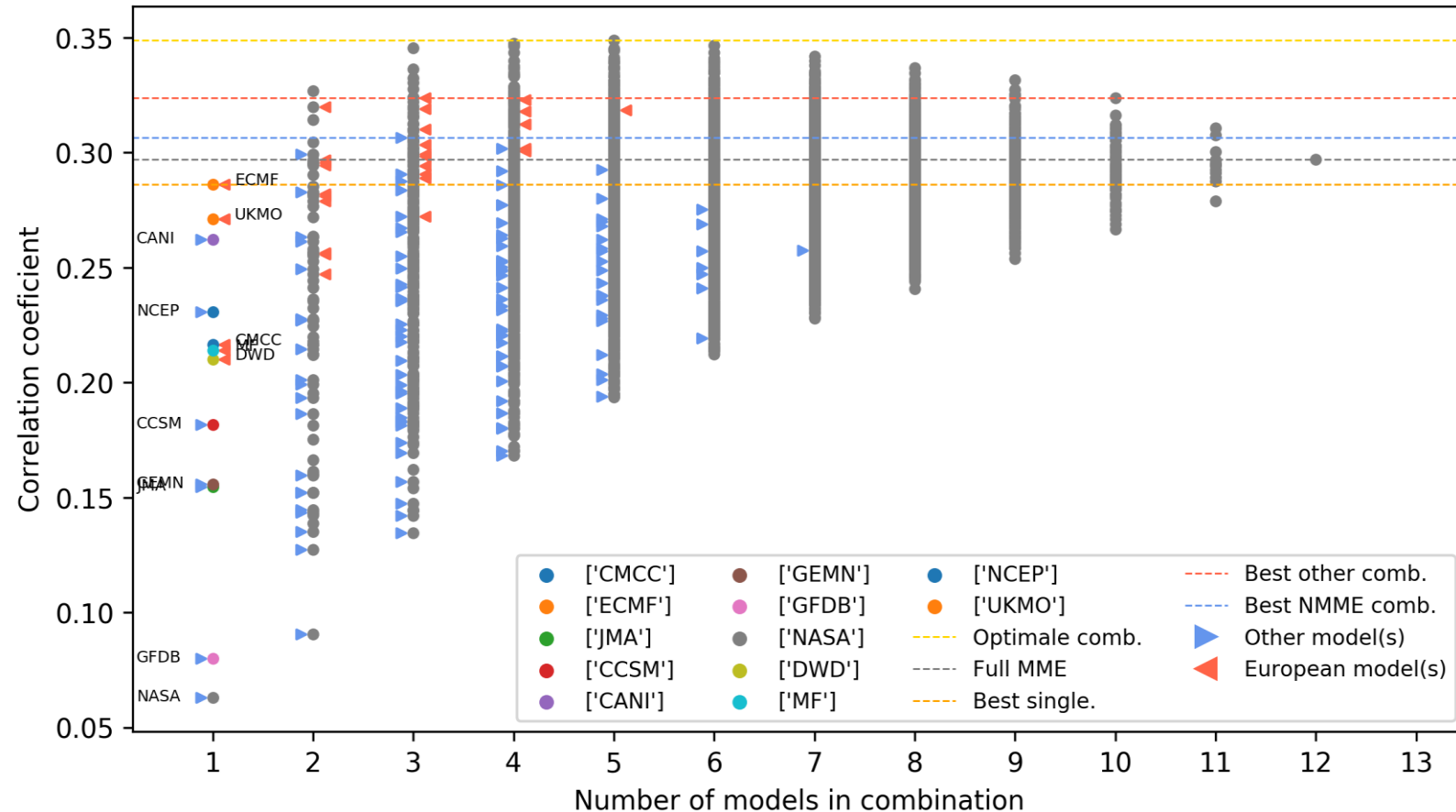
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Best other models comb.: ['CCSM' 'CANI' 'NCEP'] with $r = 0.306$

Best single model: ['ECMF'] with $r = 0.286$

All models with $r = 0.297$





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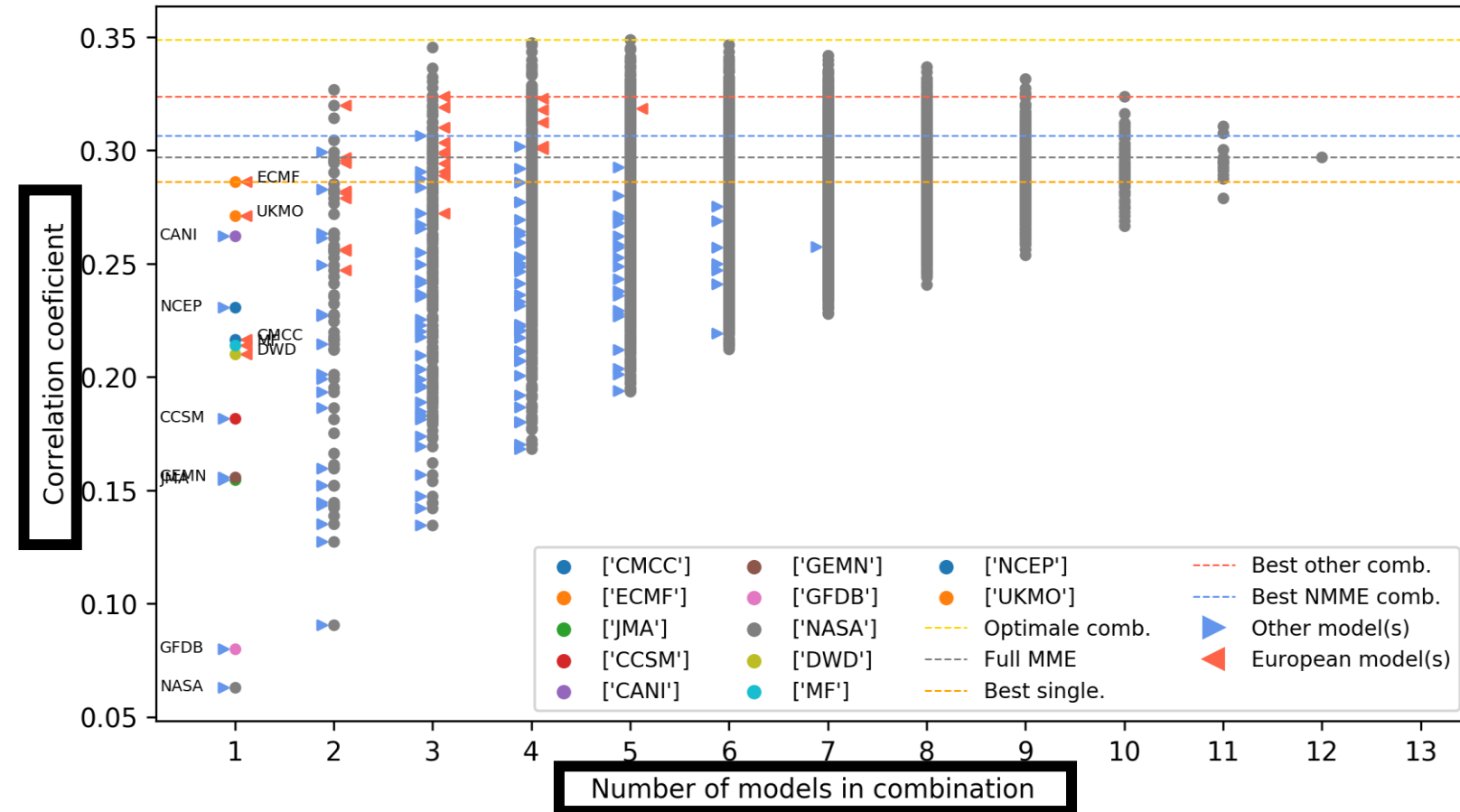
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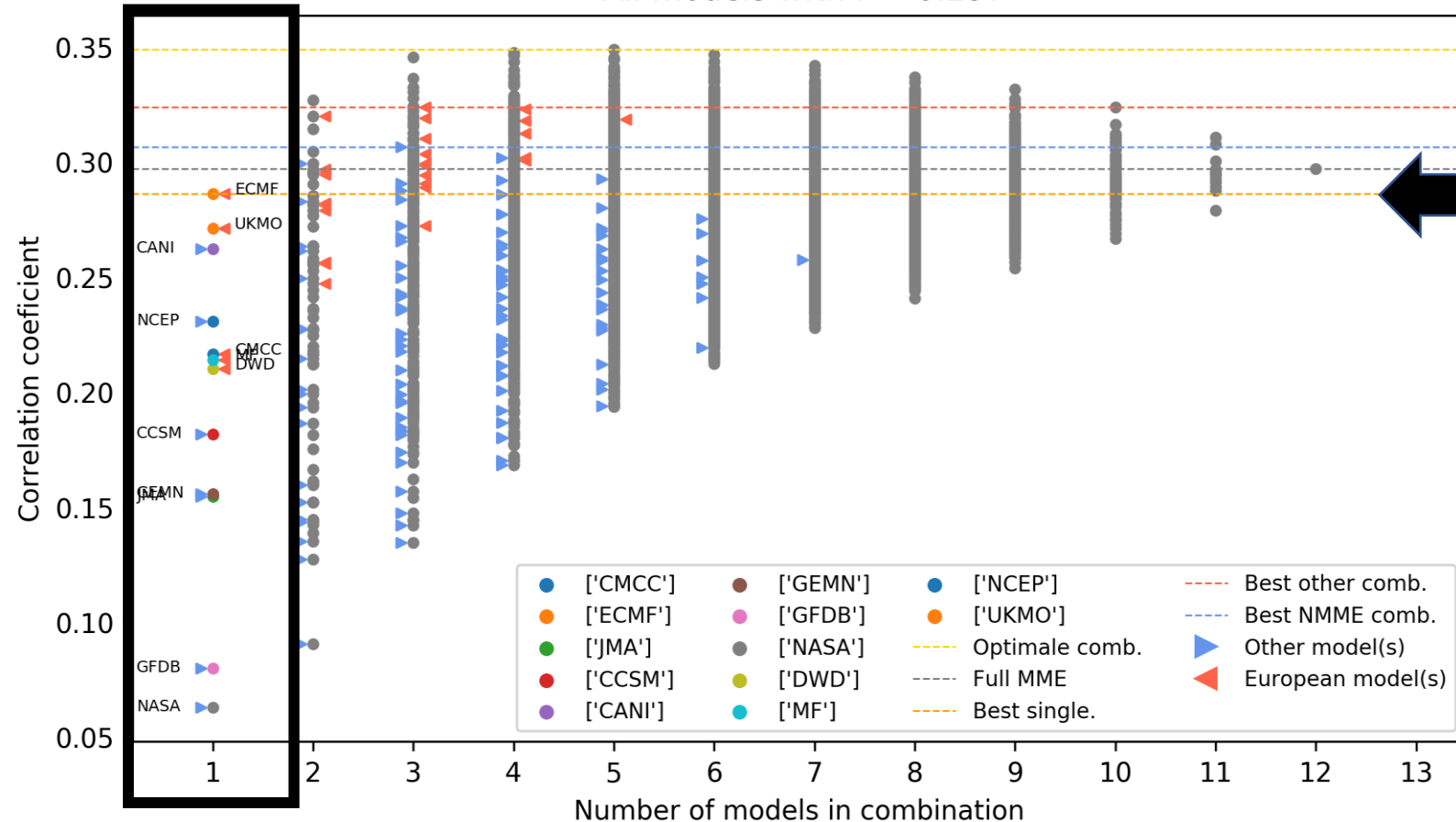
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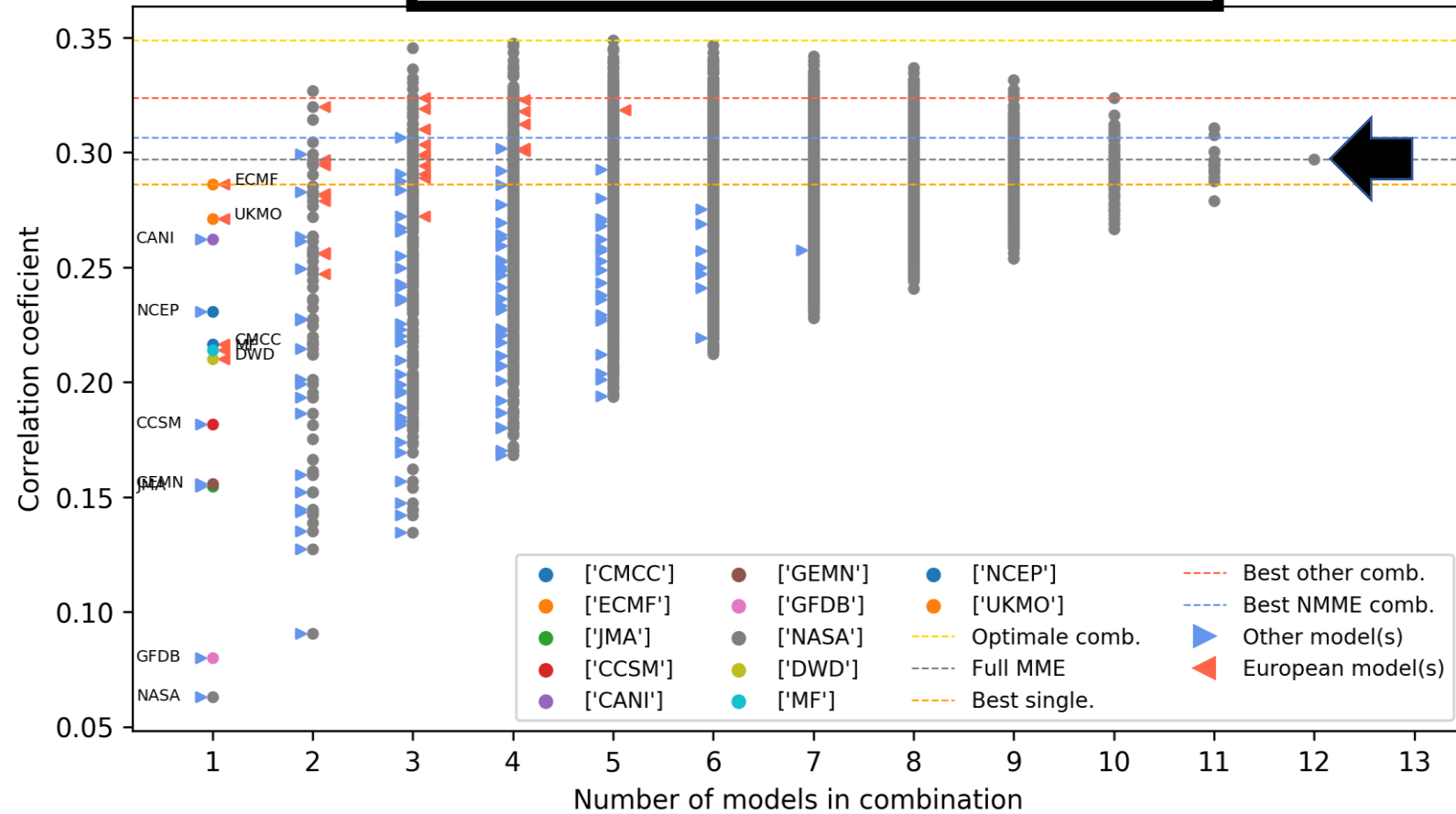
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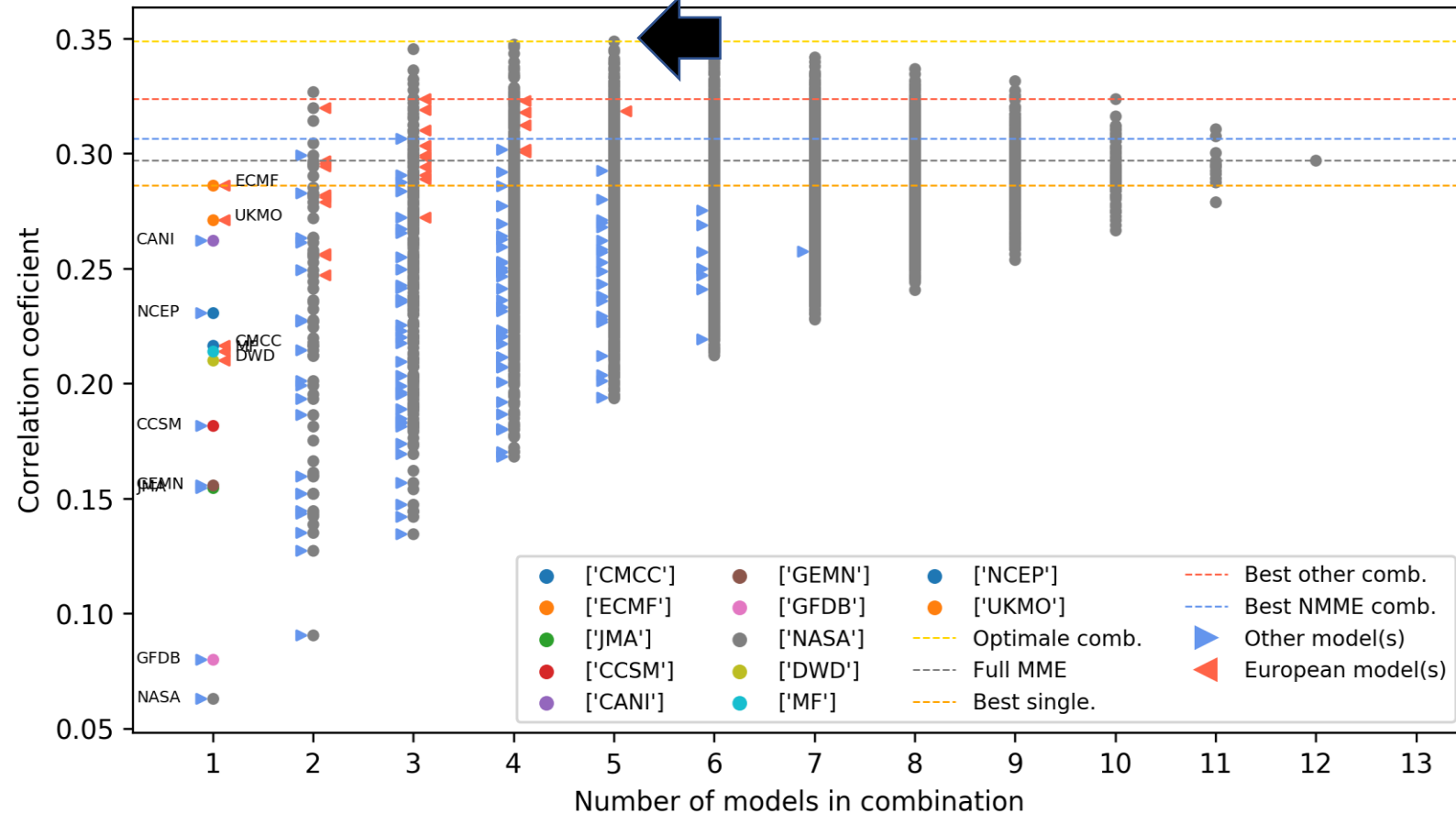
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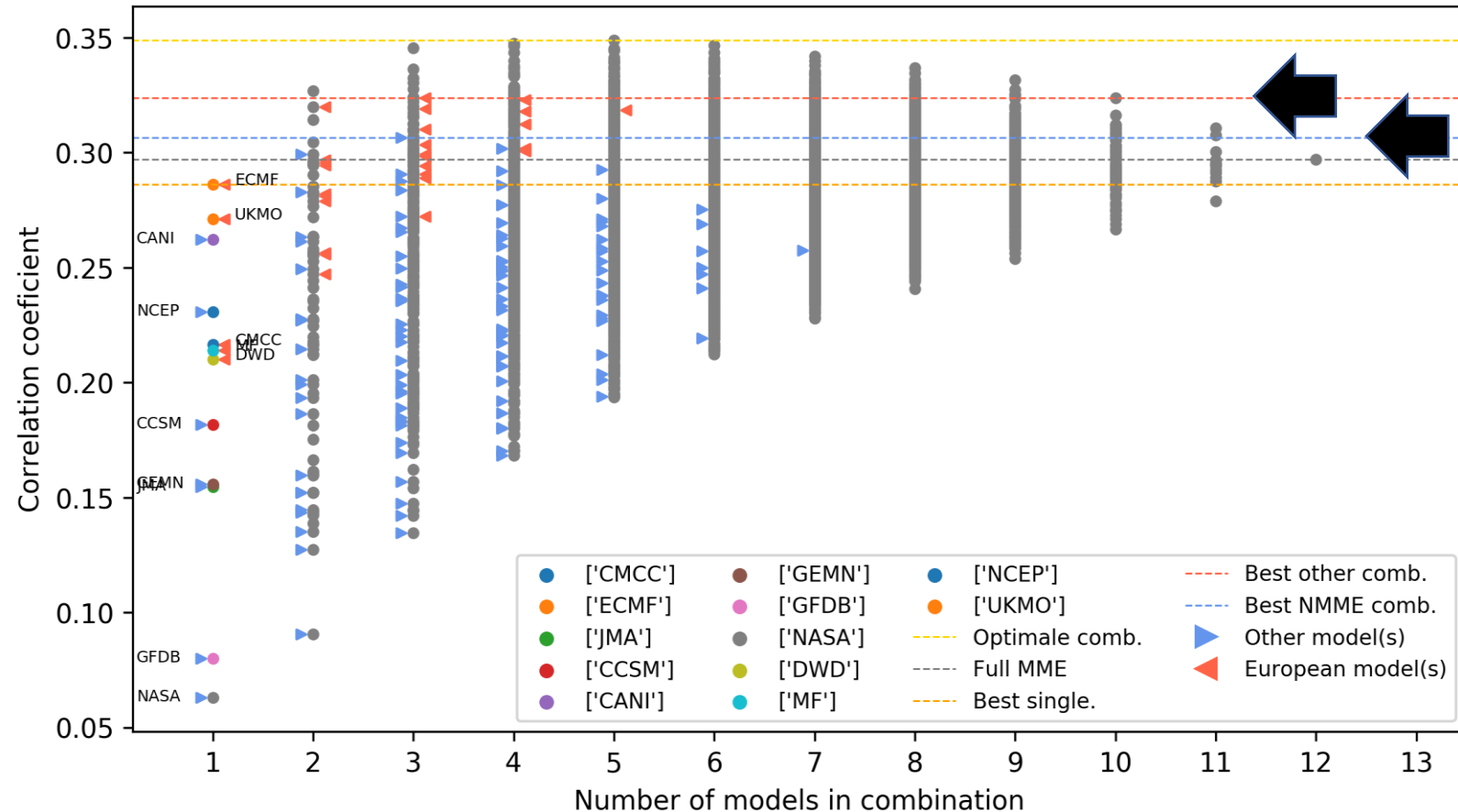
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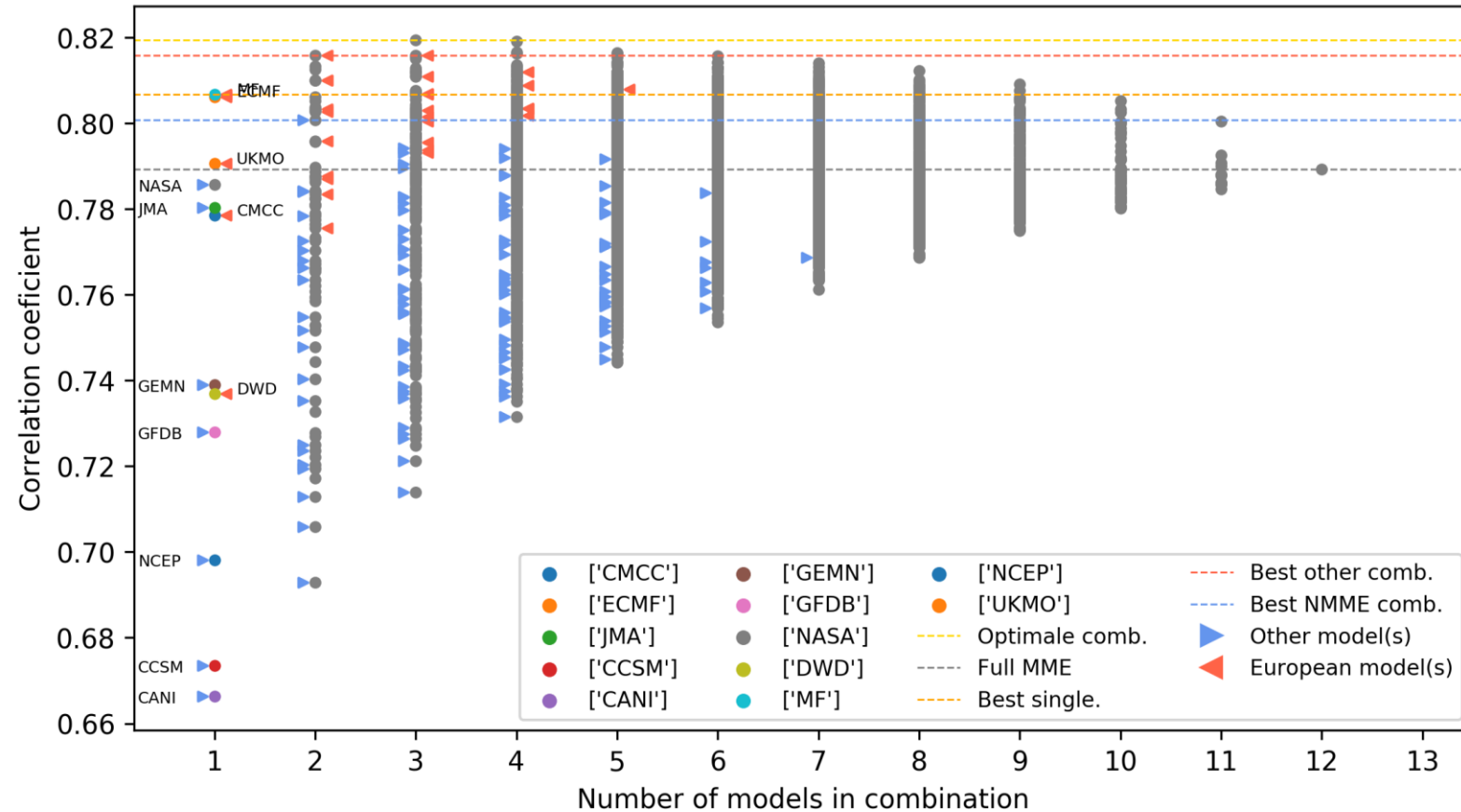


Examples of results for a deterministic forecast:

A monthly forecast with a lead of 1-month of 2m temperature anomalies over the domain of Colombia (0,10N ; -80,-70) for land only.

Colombia land only

Numer of models in best combi: 3
 Best combination: ['ECMF' 'NASA' 'MF'] with $r = 0.82$
 Best European comb.: ['ECMF' 'MF'] with $r = 0.816$
 Best other models comb.: ['JMA' 'NASA'] with $r = 0.801$
 Best single model: ['MF'] with $r = 0.807$
 All models with $r = 0.789$





Numer of models in best combi: 5

Best combination: ['CANI' 'GFDB' 'DWD' 'MF' 'UKMO'] with $r = 0.42$

Best European comb.: ['ECMF' 'DWD' 'MF' 'UKMO'] with $r = 0.398$

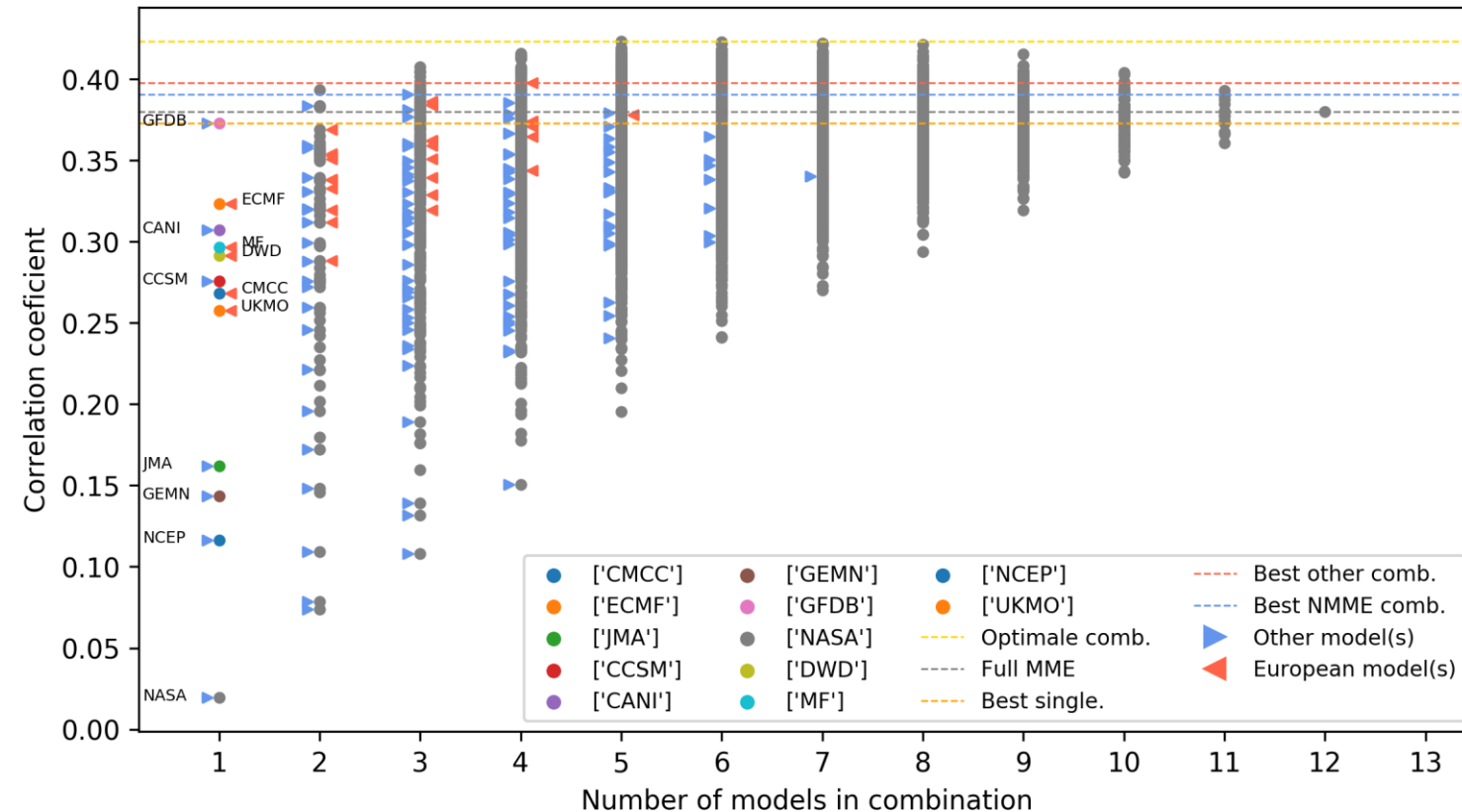
Best other models comb.: ['CANI' 'GEMN' 'GFDB'] with $r = 0.391$

Best single model: ['GFDB'] with $r = 0.373$

All models with $r = 0.38$

Examples of results for a deterministic forecast:

A monthly forecast with a lead of 1-month of Total precipitation over the domain of interest for CS5 in Colombia (2,3N ; 78,77W) for land only.

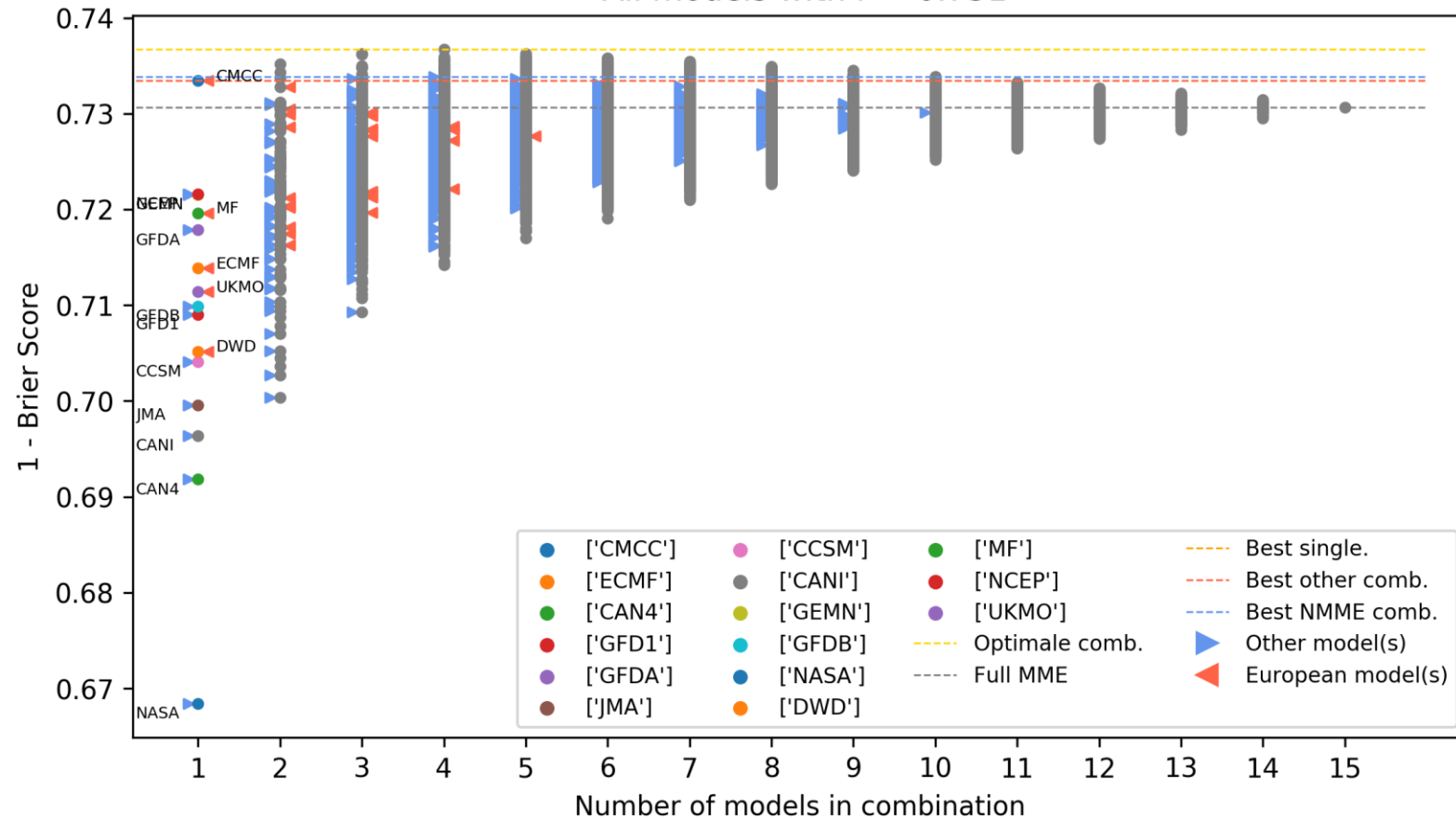




Examples of results for a probabilistic forecast:

A monthly forecast with a lead of 1-month of 2m temperature anomalies over the domain of Mediterranean (30,50 ; -10,50) for land only.

Binary weighting model combinations, Correlation coefficient (r) with ERA5
 Variable: ta season: All months domain: mask
 Numer of models in best combi: 4
 Best combination: ['CMCC' 'GFDA' 'GEMN' 'NCEP'] with $r = 0.74$
 Best European comb.: ['CMCC'] with $r = 0.733$
 Best other models comb.: ['GFD1' 'GFDA' 'GEMN' 'NCEP'] with $r = 0.734$
 Best single model: ['CMCC'] with $r = 0.733$
 All models with $r = 0.731$



Summary

- Often best combination is involving more than one model.
- Best combination often does not include all models.
- Often best combination involves a "mix" of independent models.
- All models are useful as the best combination depends on: variable, season, domain..

Questions and Discussion



Questions and Discussion

Is there a strong argument for favouring a simple mean versus a weighted approach when combining multi-models?

Is there a clear advantage in adopting an adaptive choice of models depending on variable, region, season as opposed to a 'global' choice?

