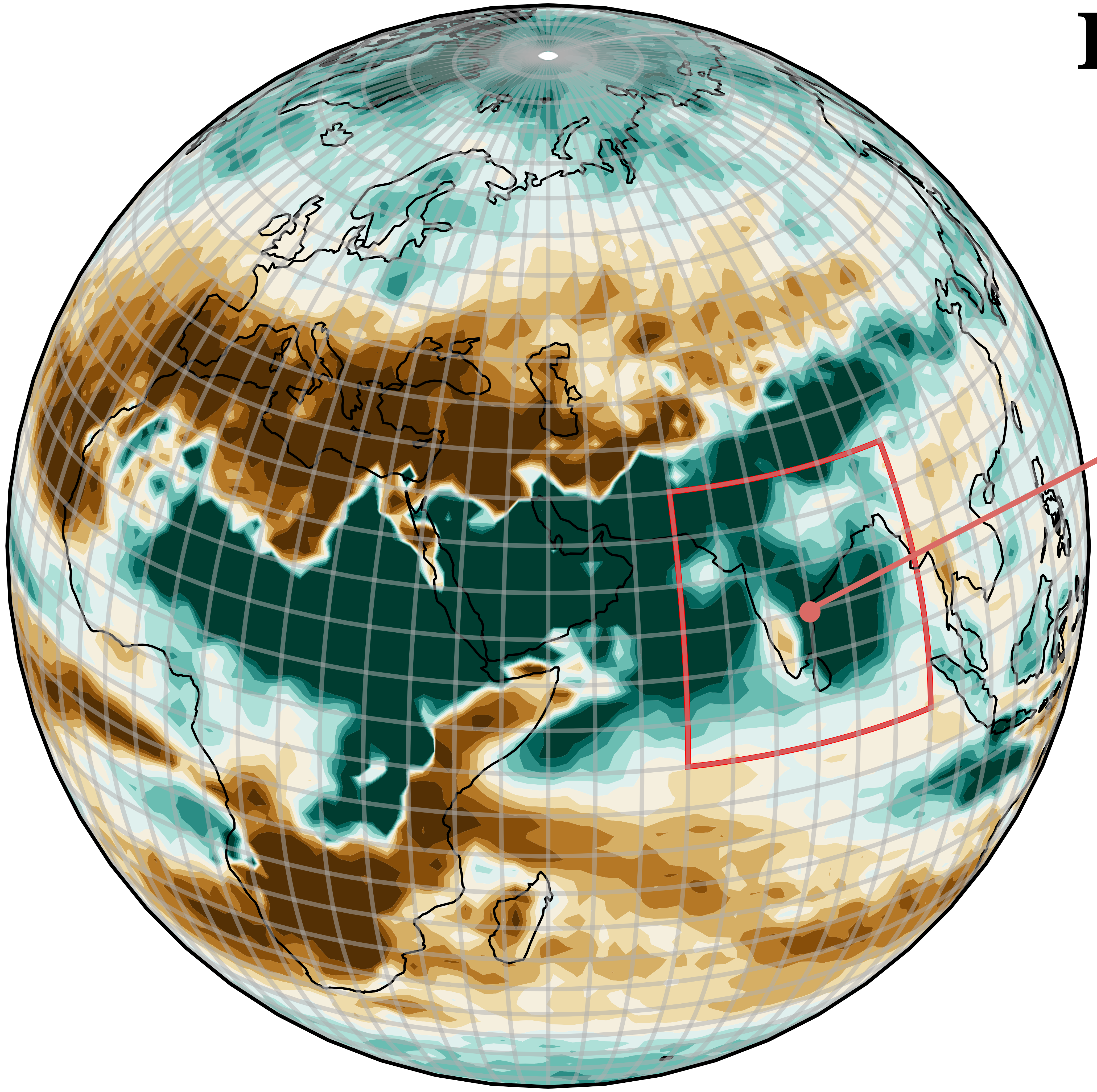
CNRM-CM6-1-HR



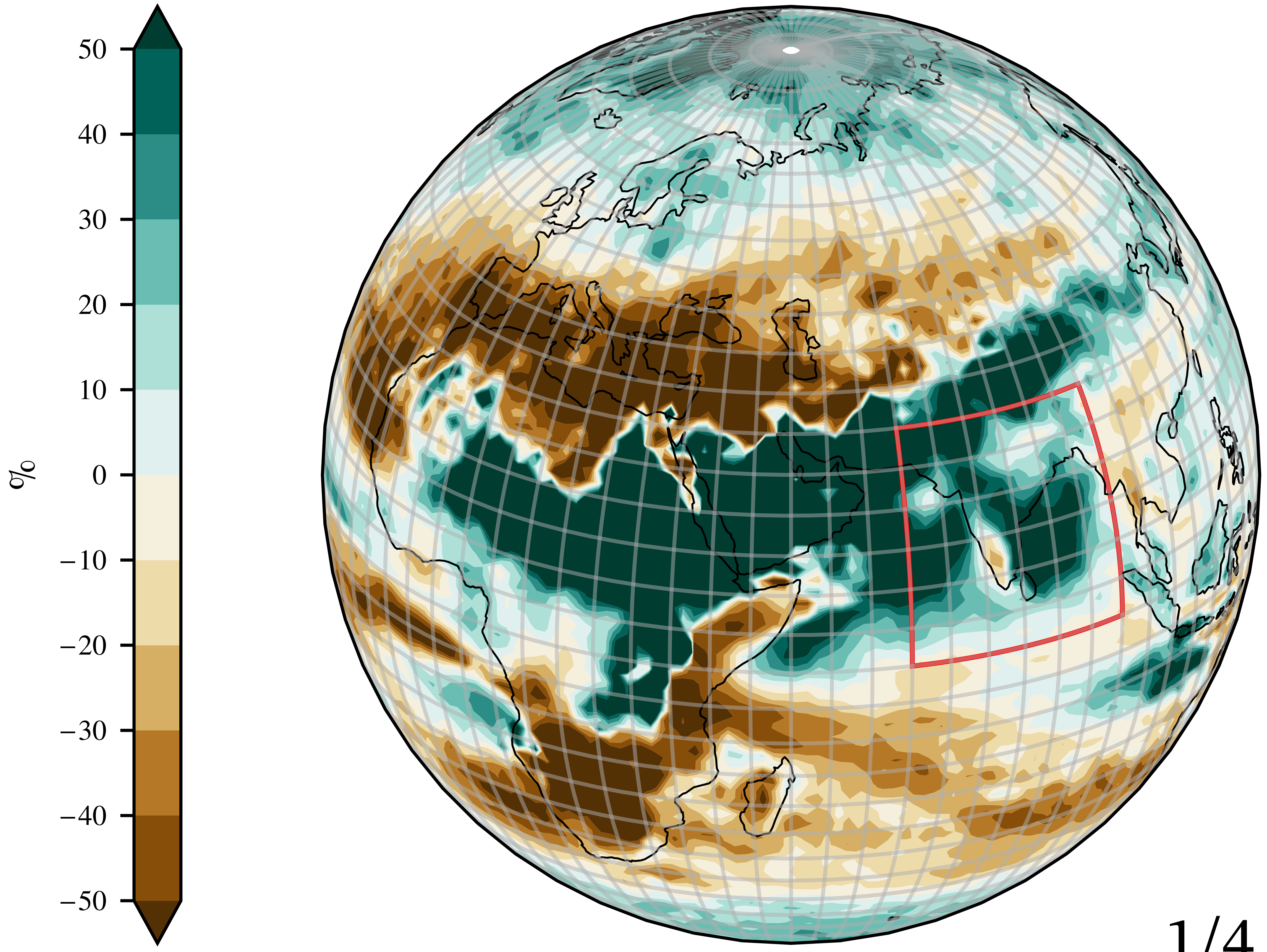
Improving regional climate projections via observational constraints : An *original method* applied on Indian Summer Monsoon

George Whittle, Hervé Douville (CNRM) & Pascal Terray (IPSL-LOCEAN)

AMA 2026

1. Framing the problem

Future JJAS precipitation relative change
2081-2100 against 1995-2014 (SSP5-8.5)
CNRM-CM6-1-HR



1/4

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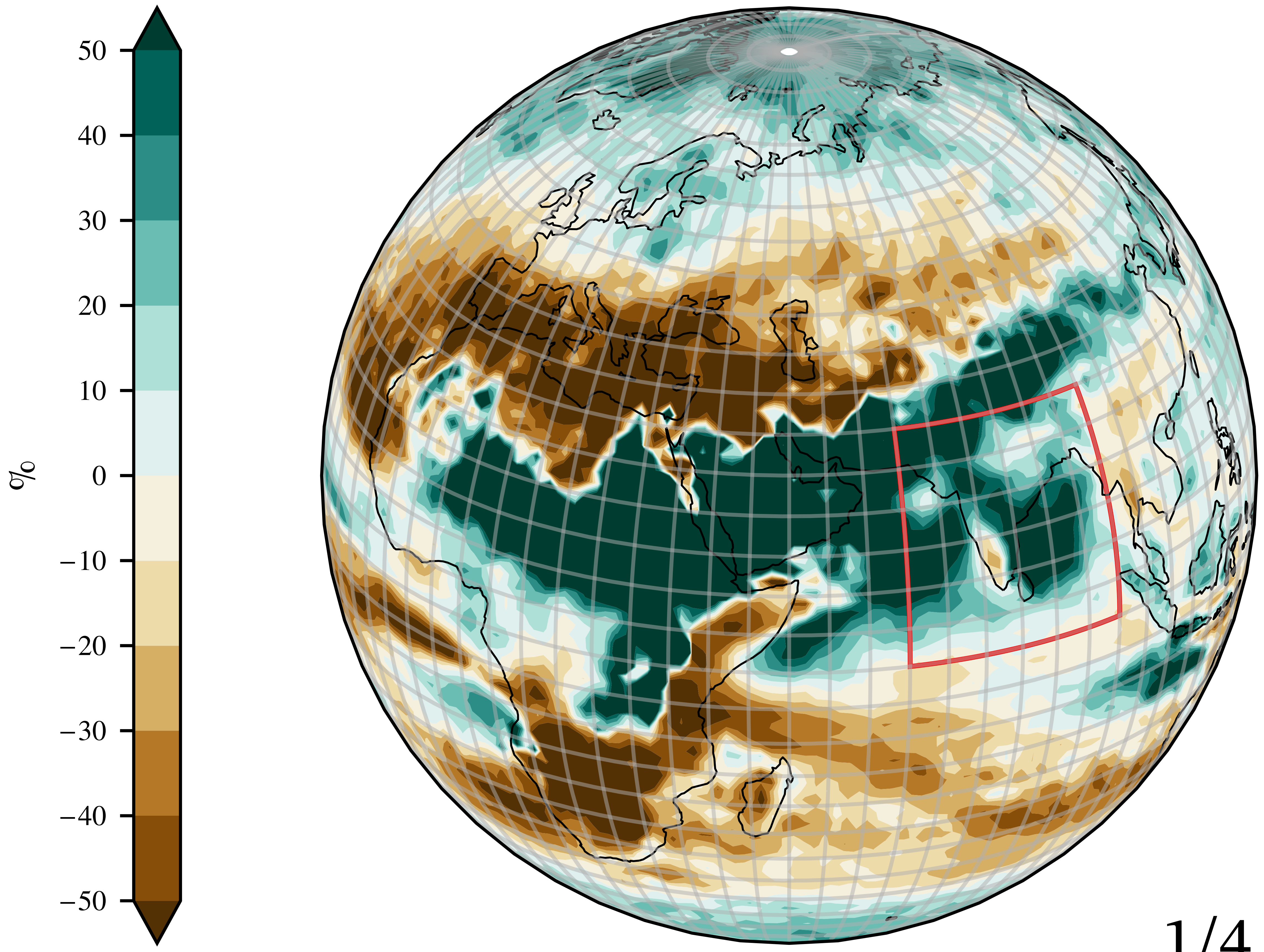

1/4

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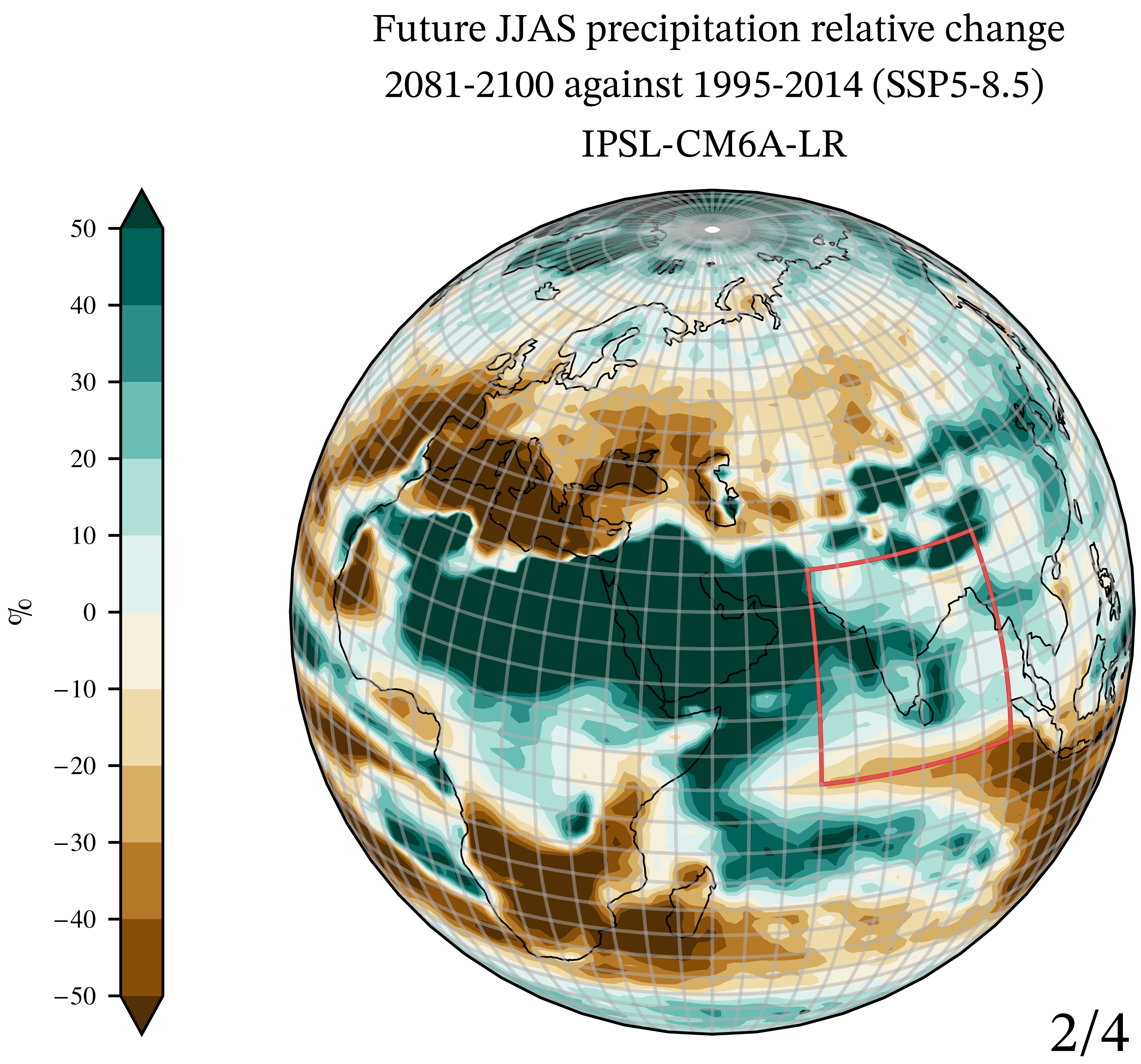

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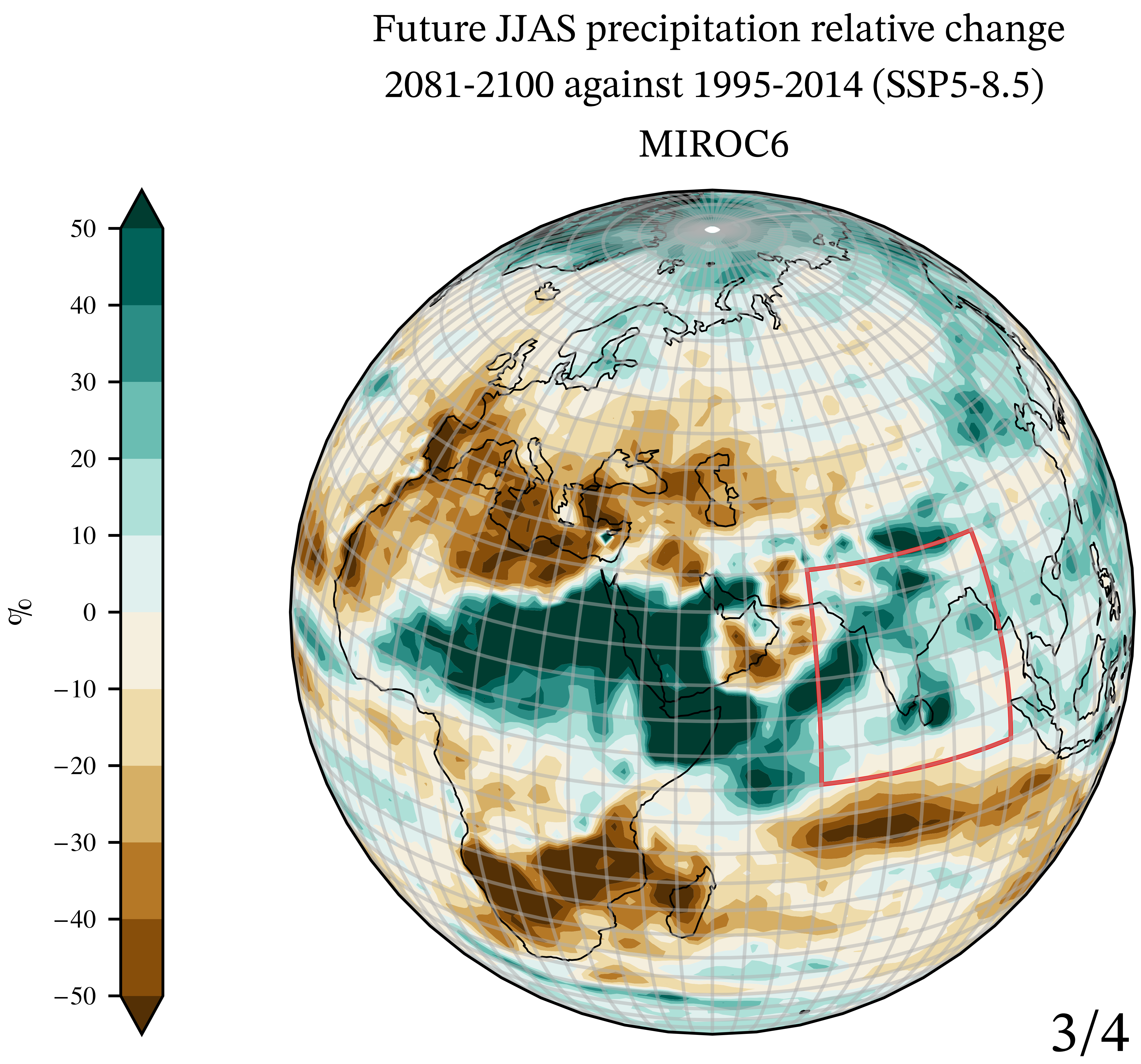

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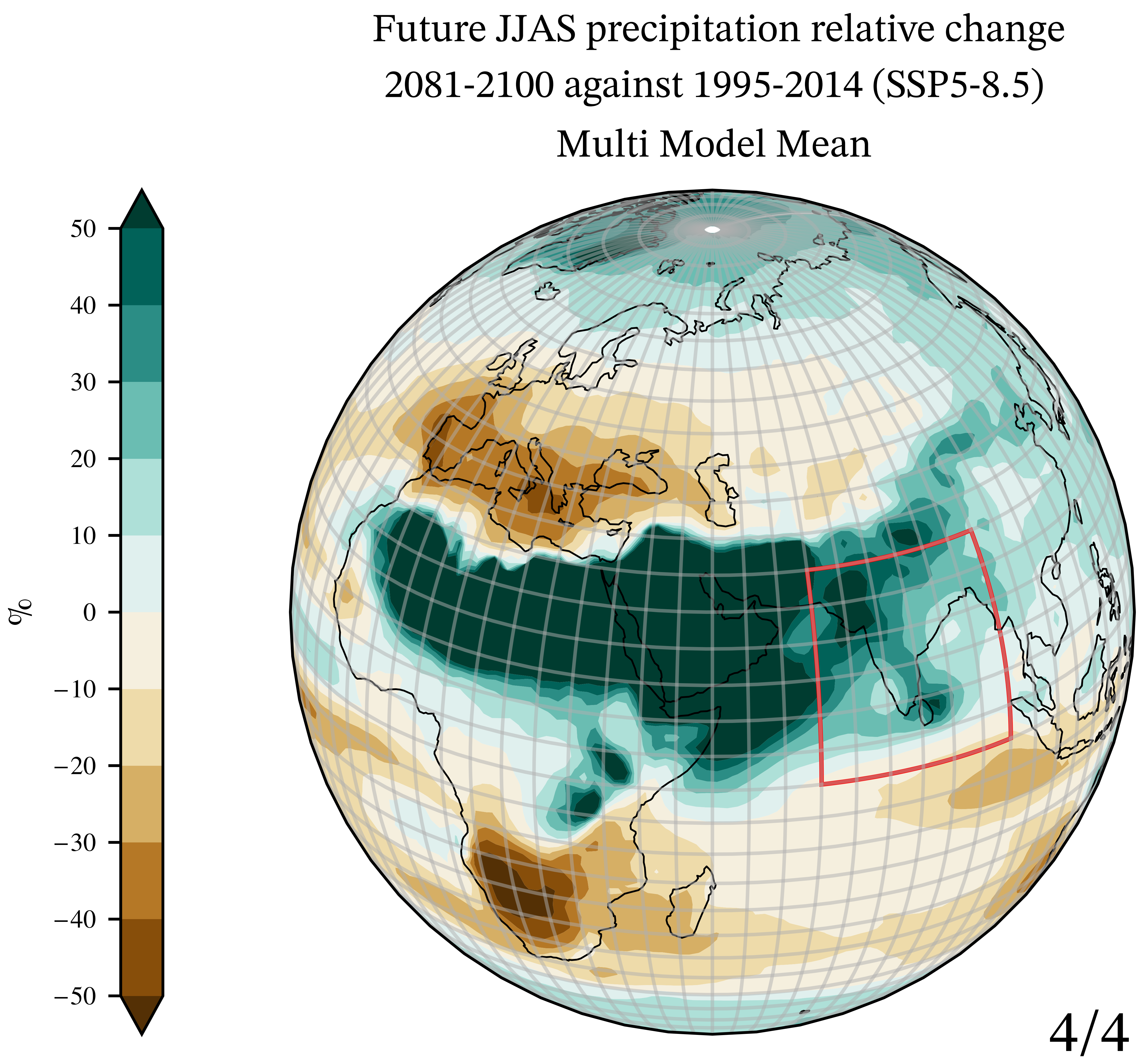

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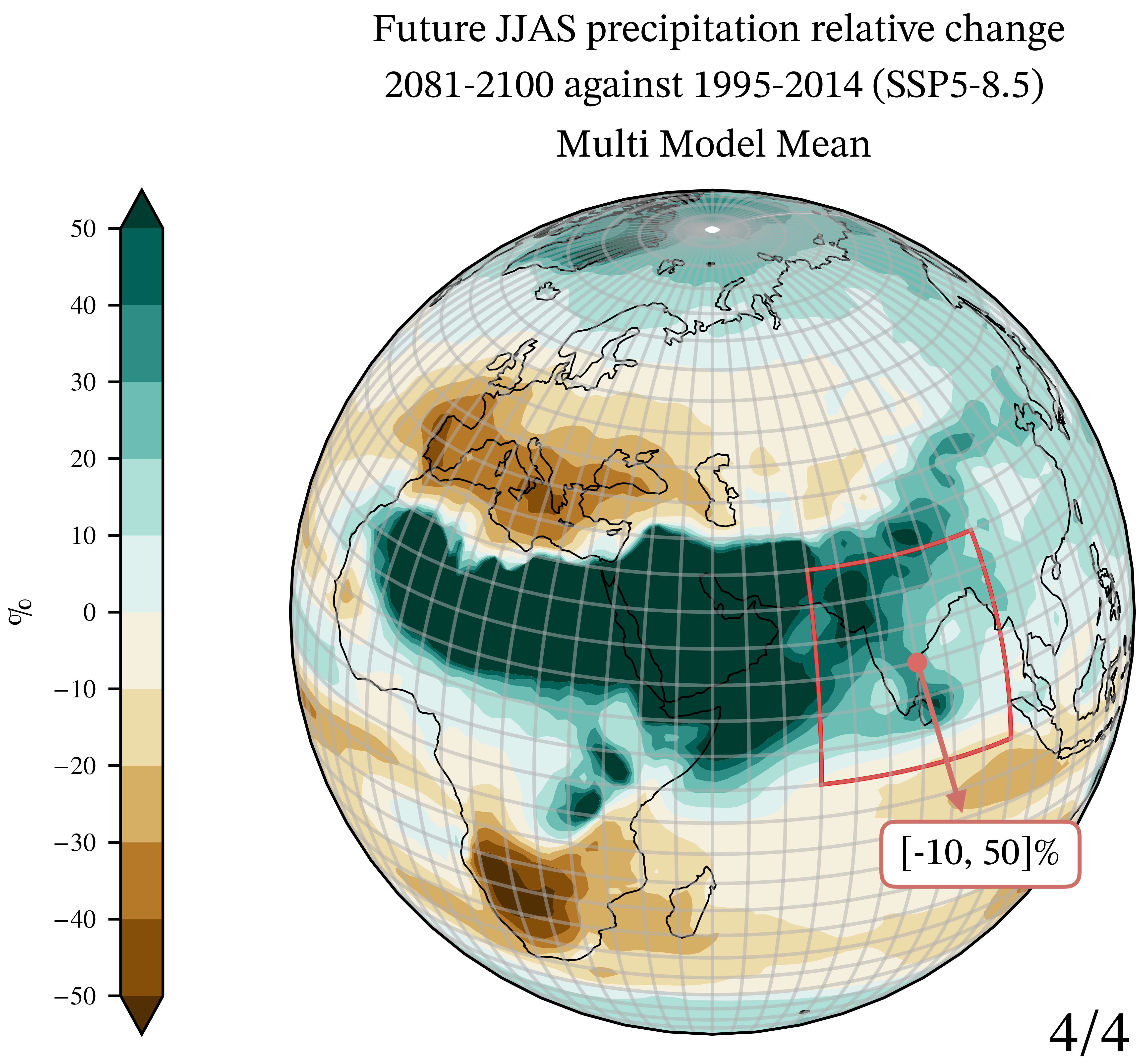

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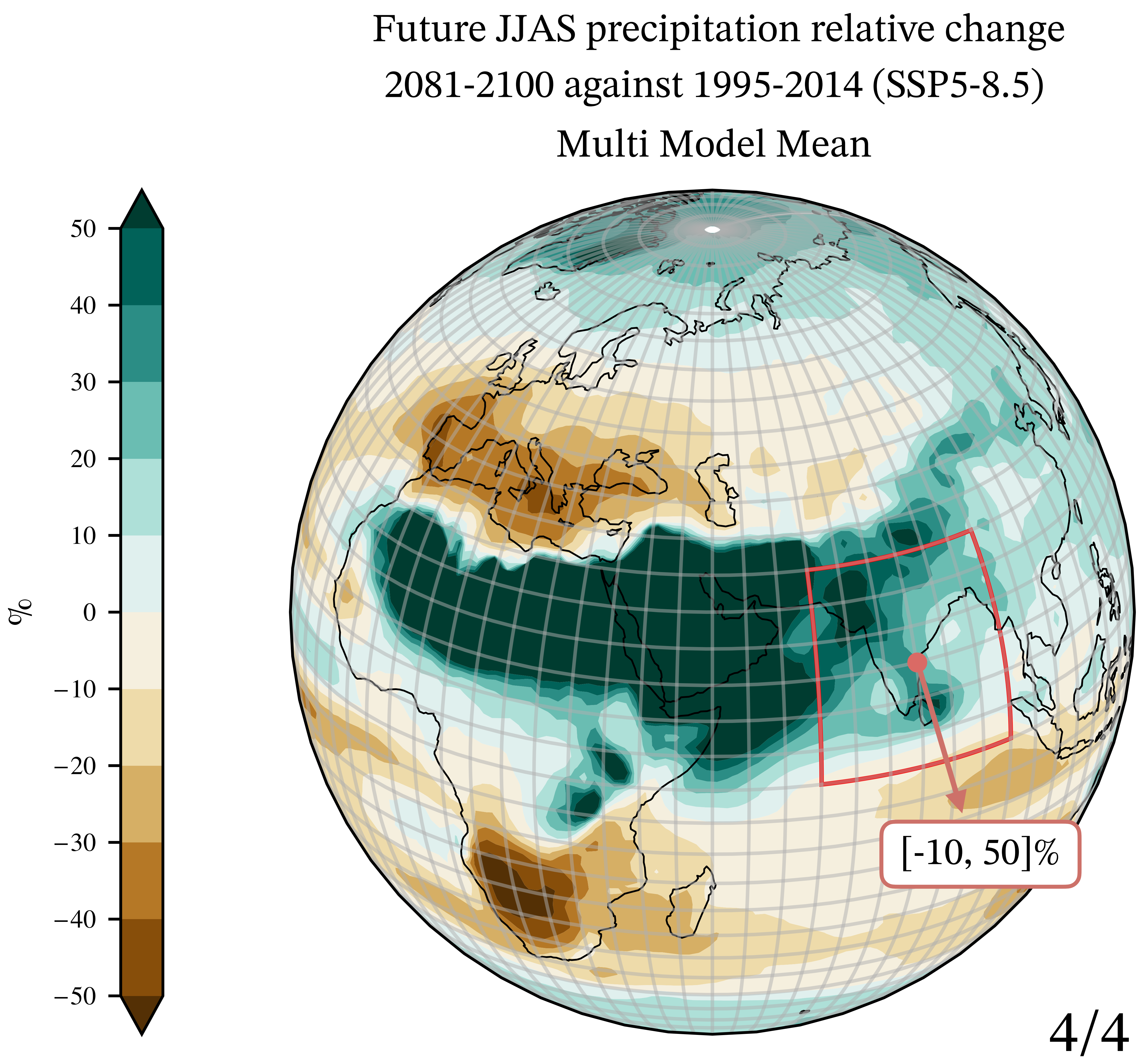

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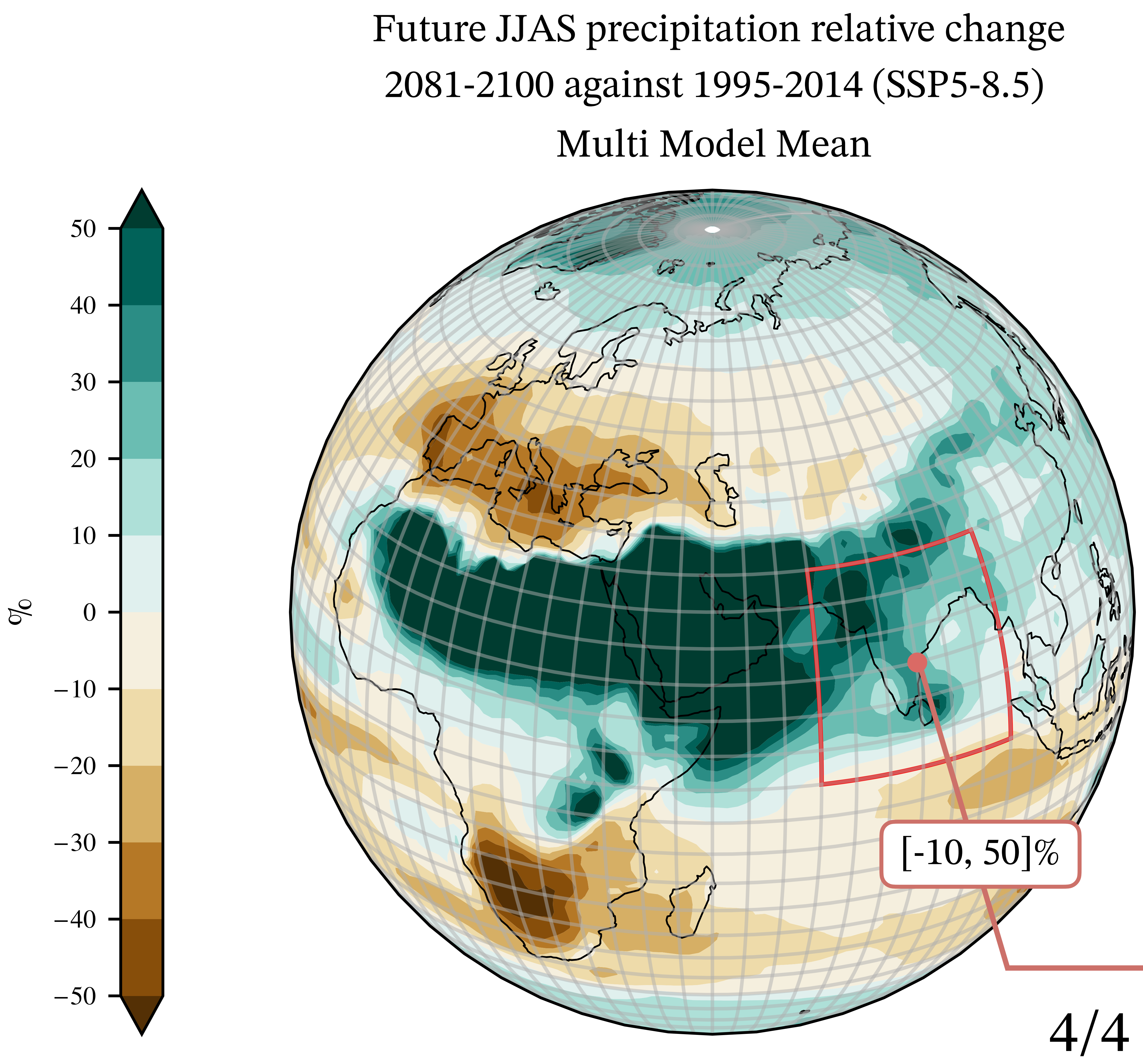

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- Major difficulty for production of a robust and reliable regional climate information *(Hall, 2014, Xie et al., 2015)*
- The goal of the PhD is to **reduce inter model spread of precipitation projections**
- Focus on Southern Asia region to study Indian Summer (JJAS) precipitations

What is a *good* climate model ?

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Traditional model evaluation

nature climate change
PERSPECTIVE
https://doi.org/10.1038/s41558-019-0436-6

Progressing emergent constraints on future climate change

Alex Hall[1*], Peter Cox[2], Chris Huntingford[3] and Stephen Klein[4]

> *[Traditional model evaluation] has been unkindly, but perhaps not inaccurately, compared to a 'beauty contest'. While traditional evaluation may make sense as a basic first step in certifying that an ESM is in fact an ESM, its utility in identifying those that produce trustworthy simulations of future climate is unclear. Conversely, an ESM regarded as less attractive in a 'beauty contest' could be dismissed, yet it may contain more accurate and useful estimates of some key attribute of future change.*

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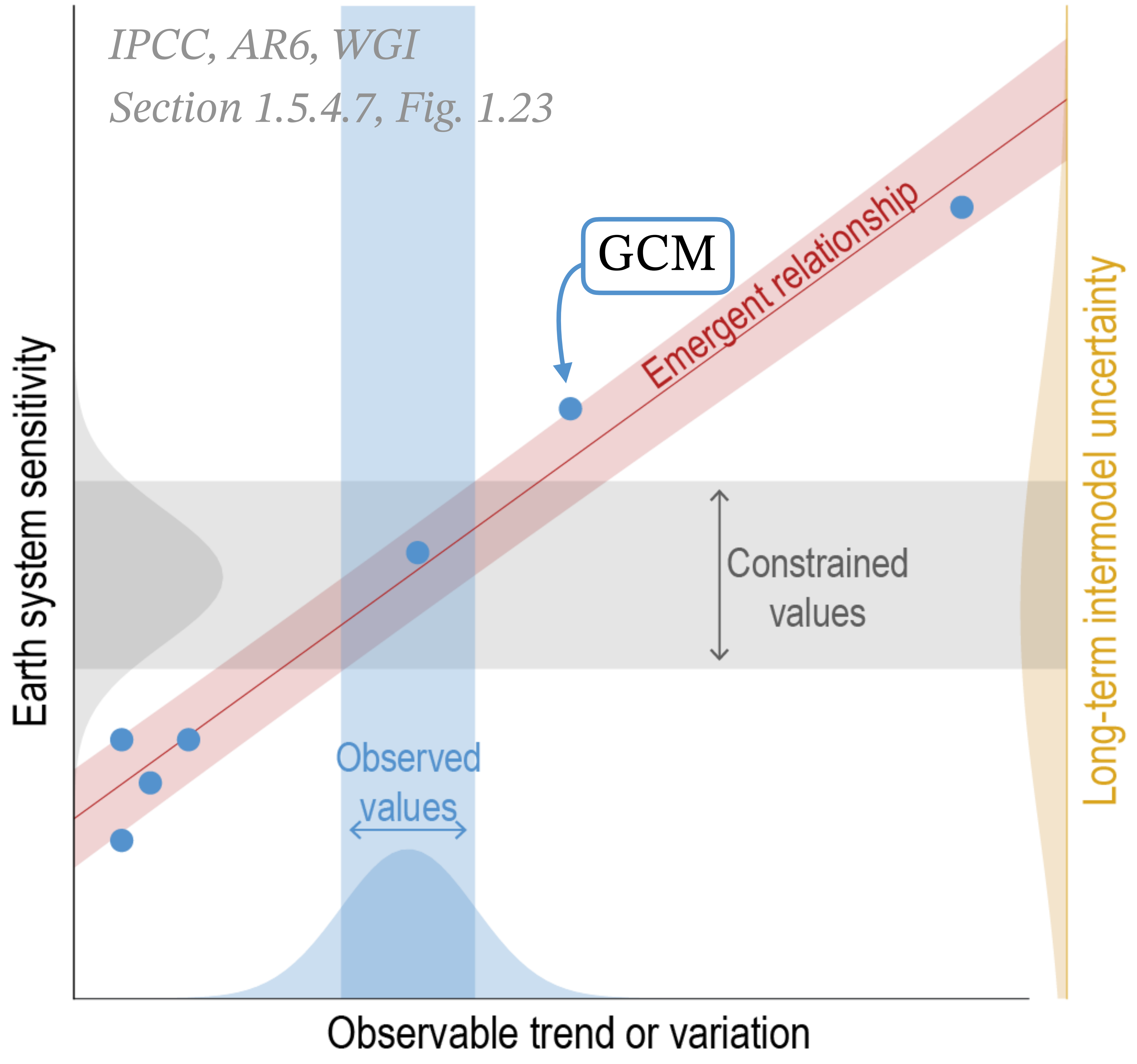
Emergent constraint



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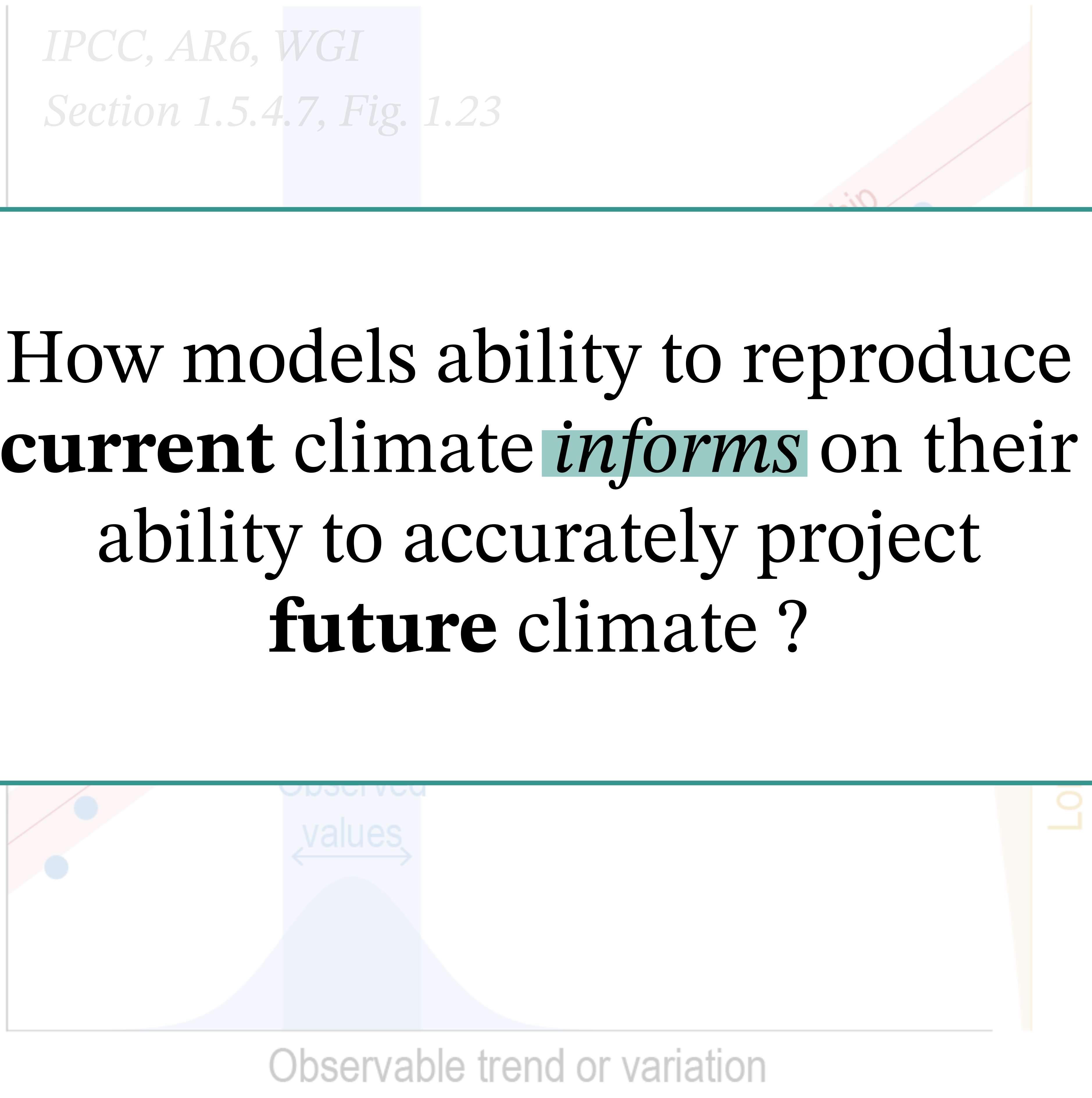

How models ability to reproduce **current** climate *informs* on their ability to accurately project **future** climate ?

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How to reduce inter-model spread in projection of precipitation change over India ?

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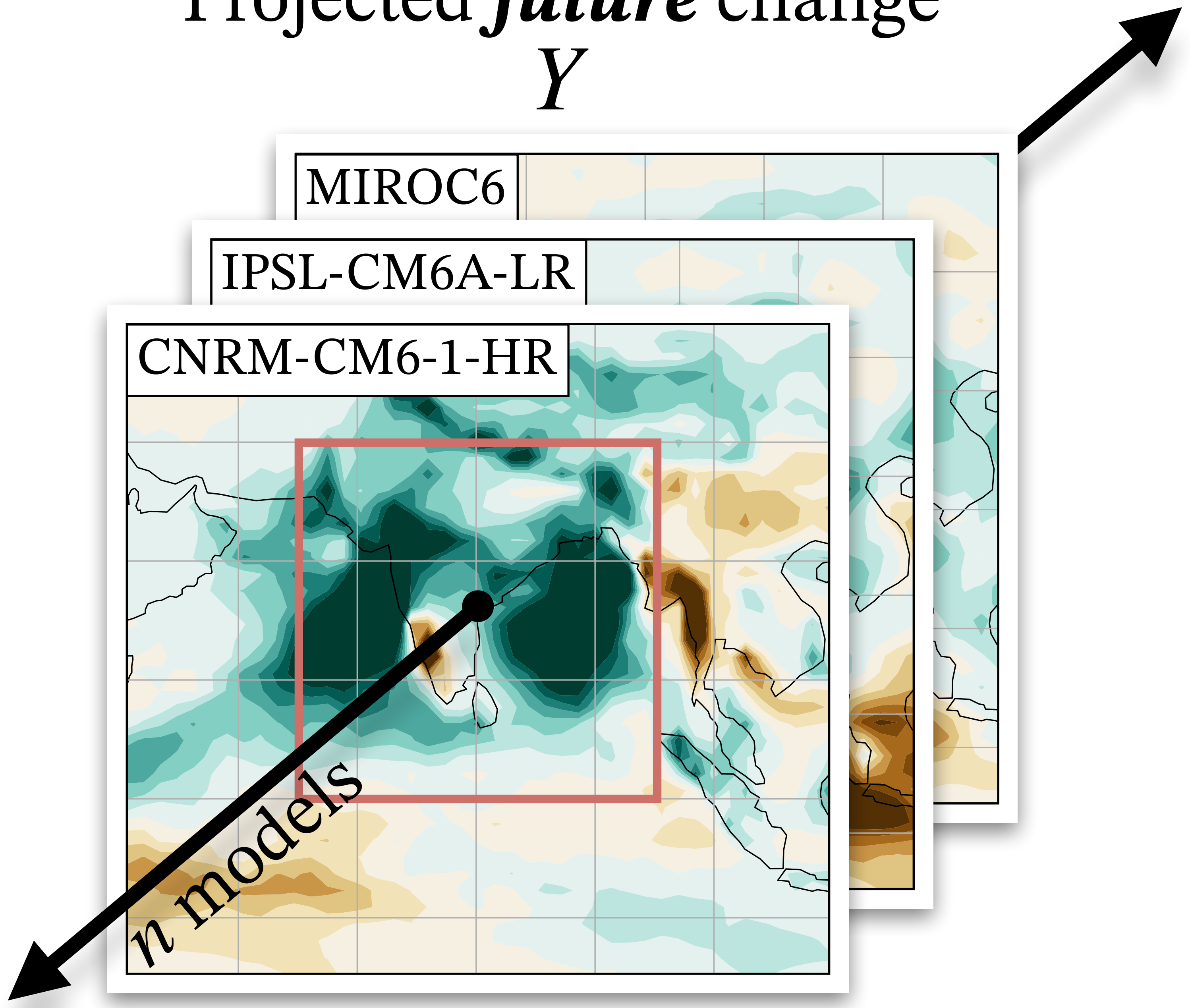
Projected ***future*** change
Y



Mean change between
2081-2100 and 1995-2014

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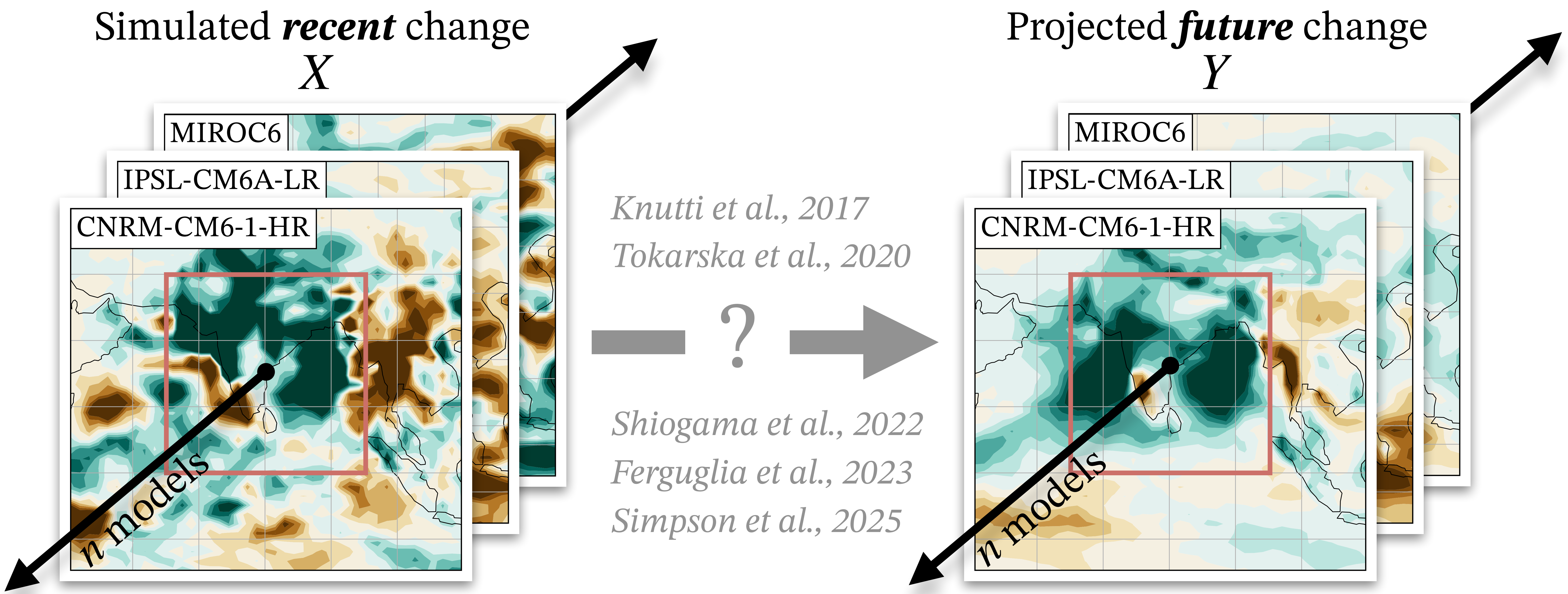

Linear trend between 1979 and 2024

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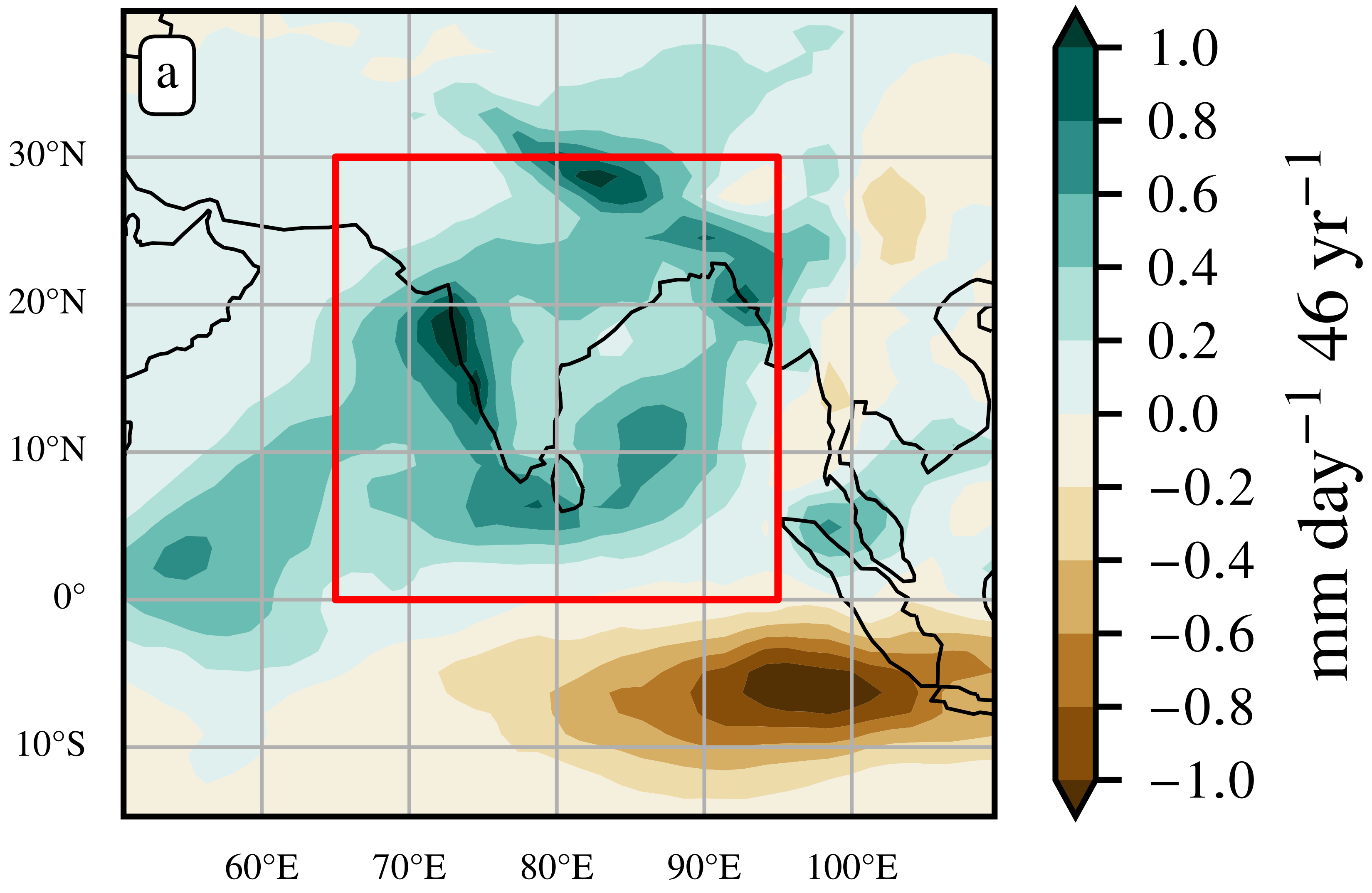
Inter-model **mean**

Simulated ***recent*** change
μ_X



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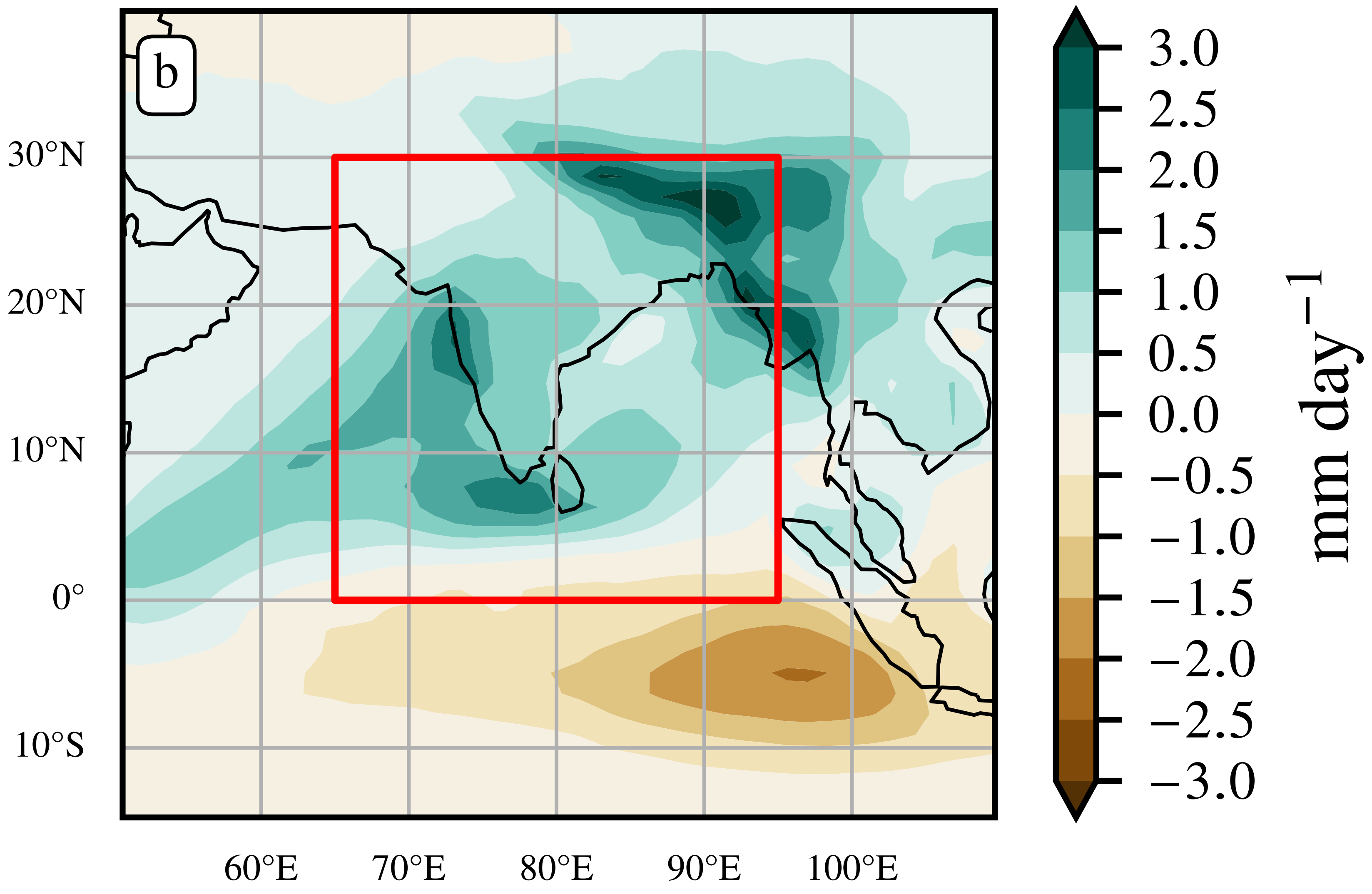

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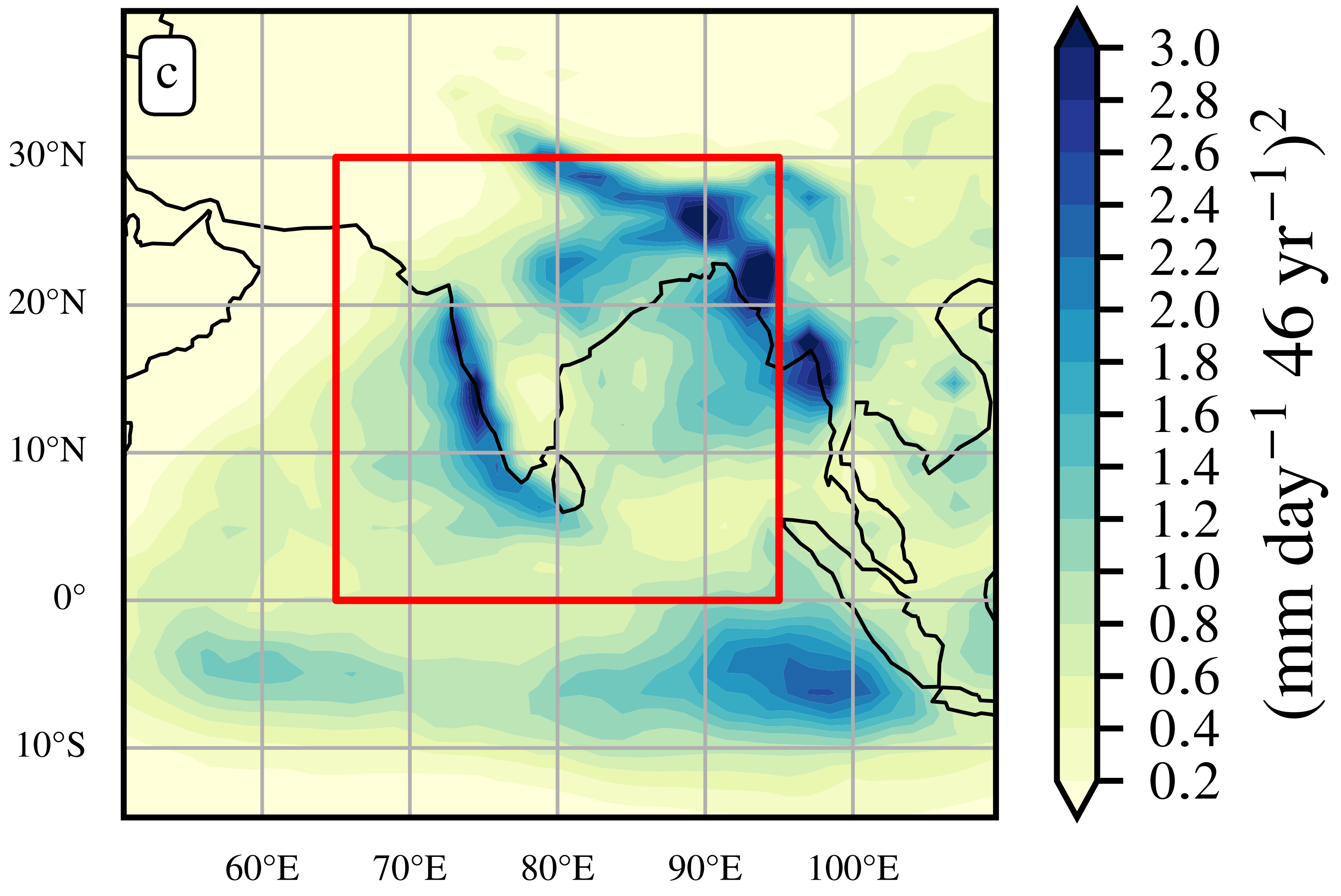
Inter-model **variance**

Simulated ***recent*** change

σ_X^2



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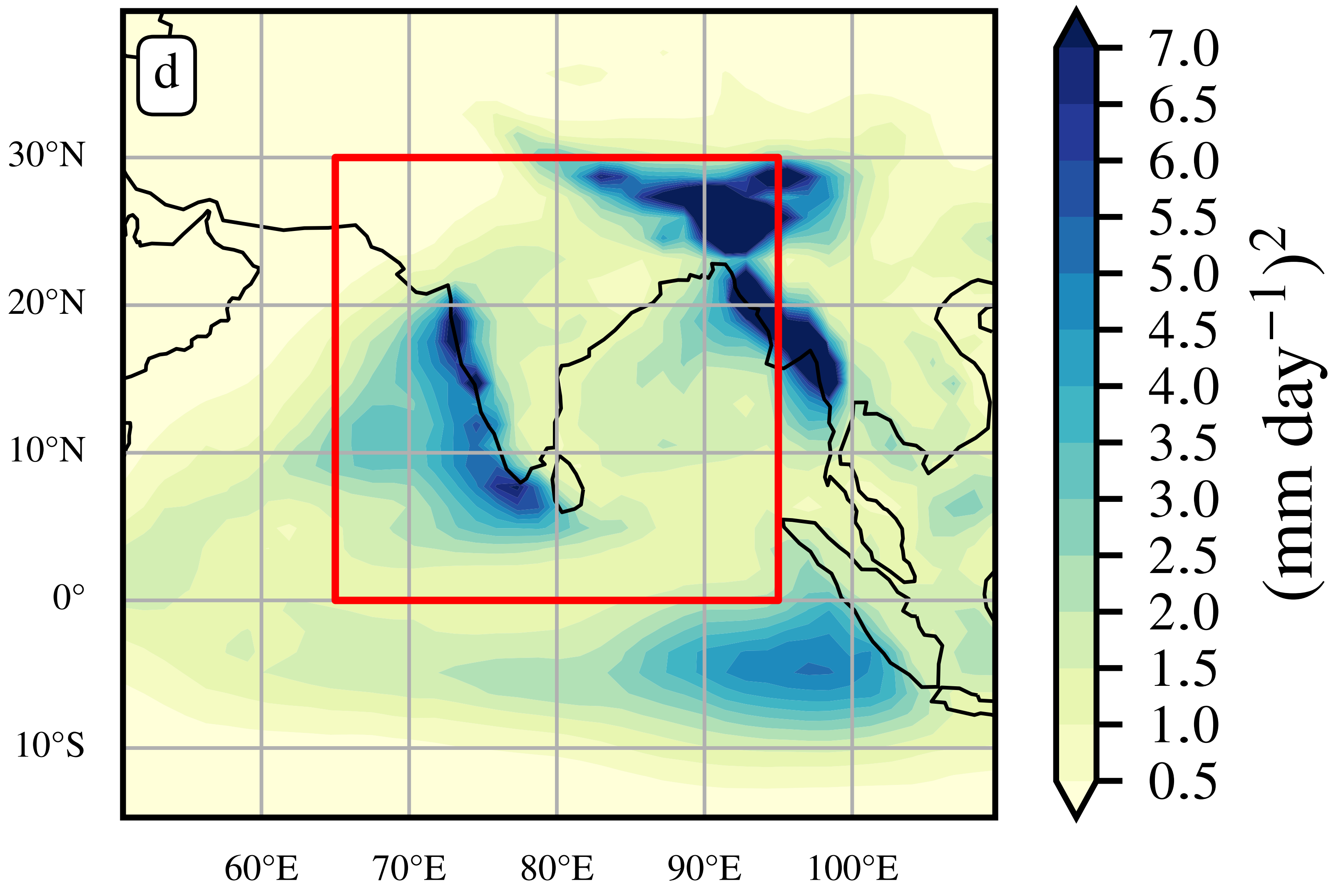
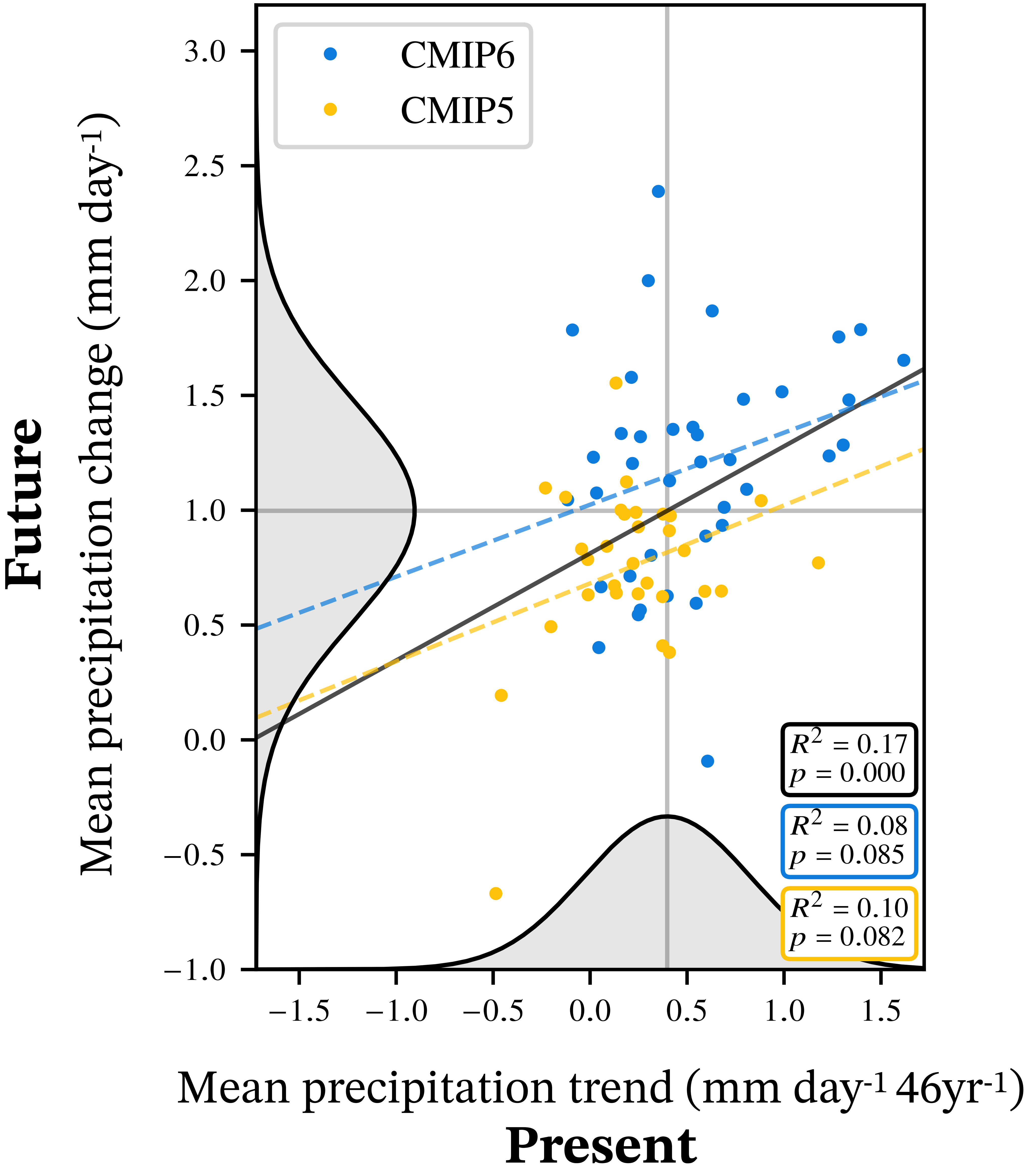
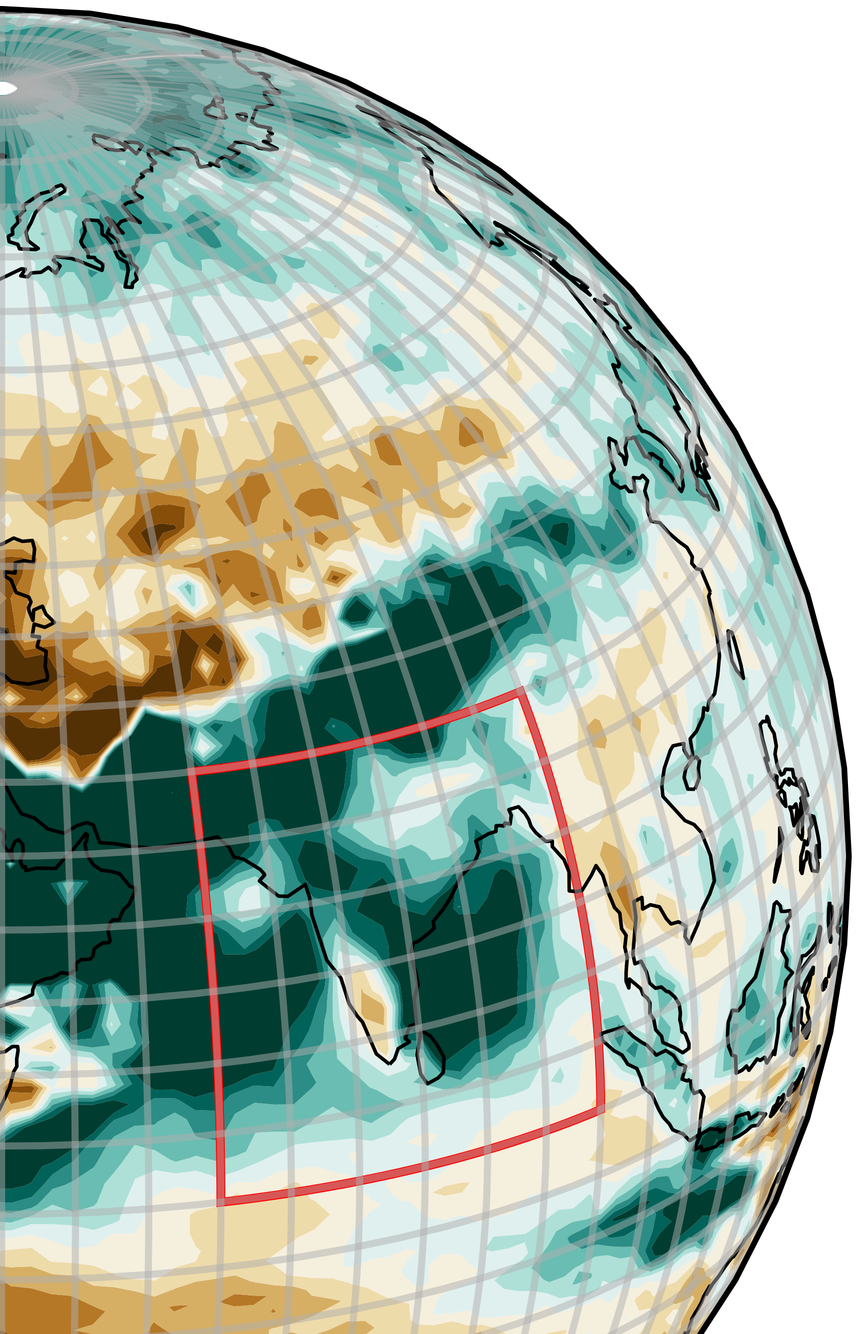


Mean change between 2081-2100 and 1995-2014

2. Traditional Emergent Constraint





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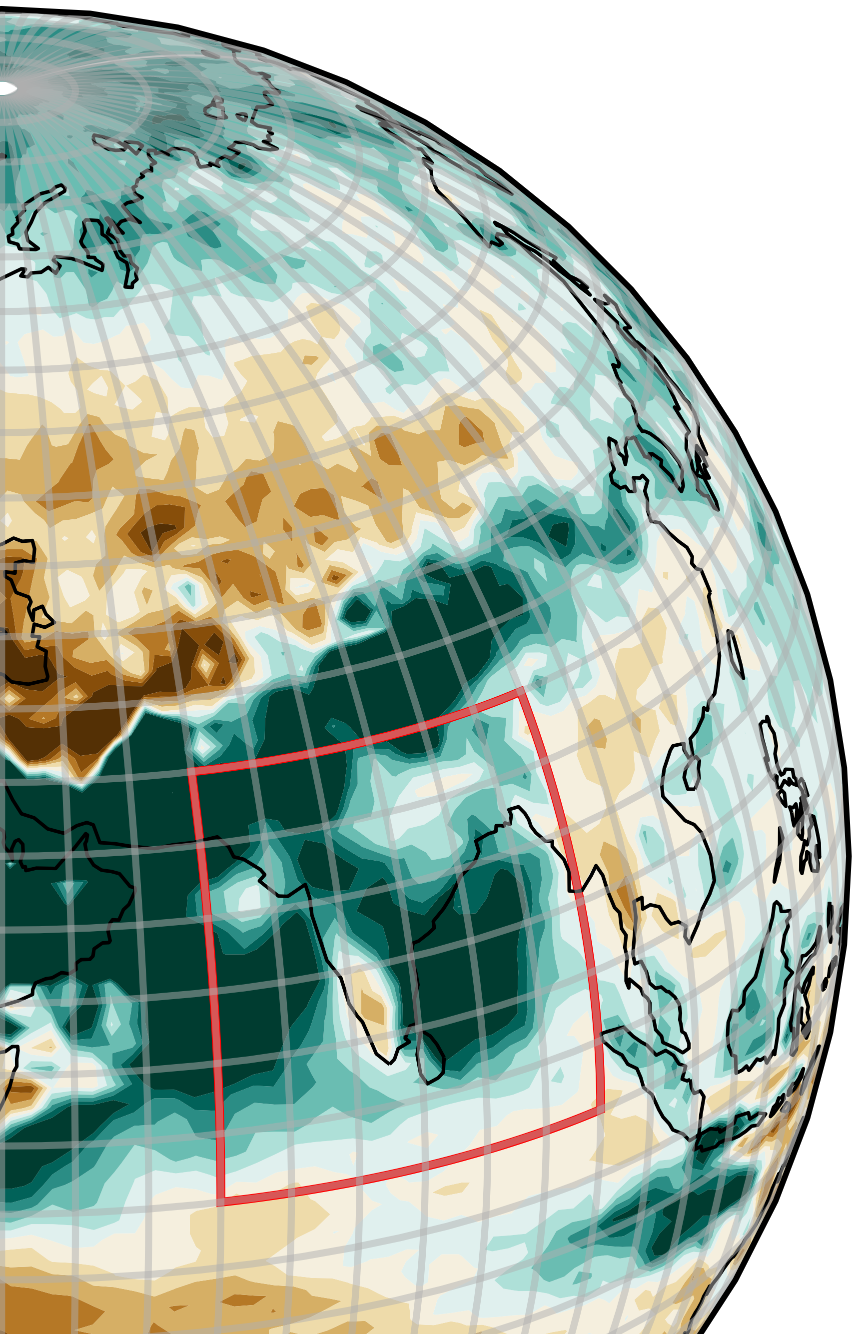

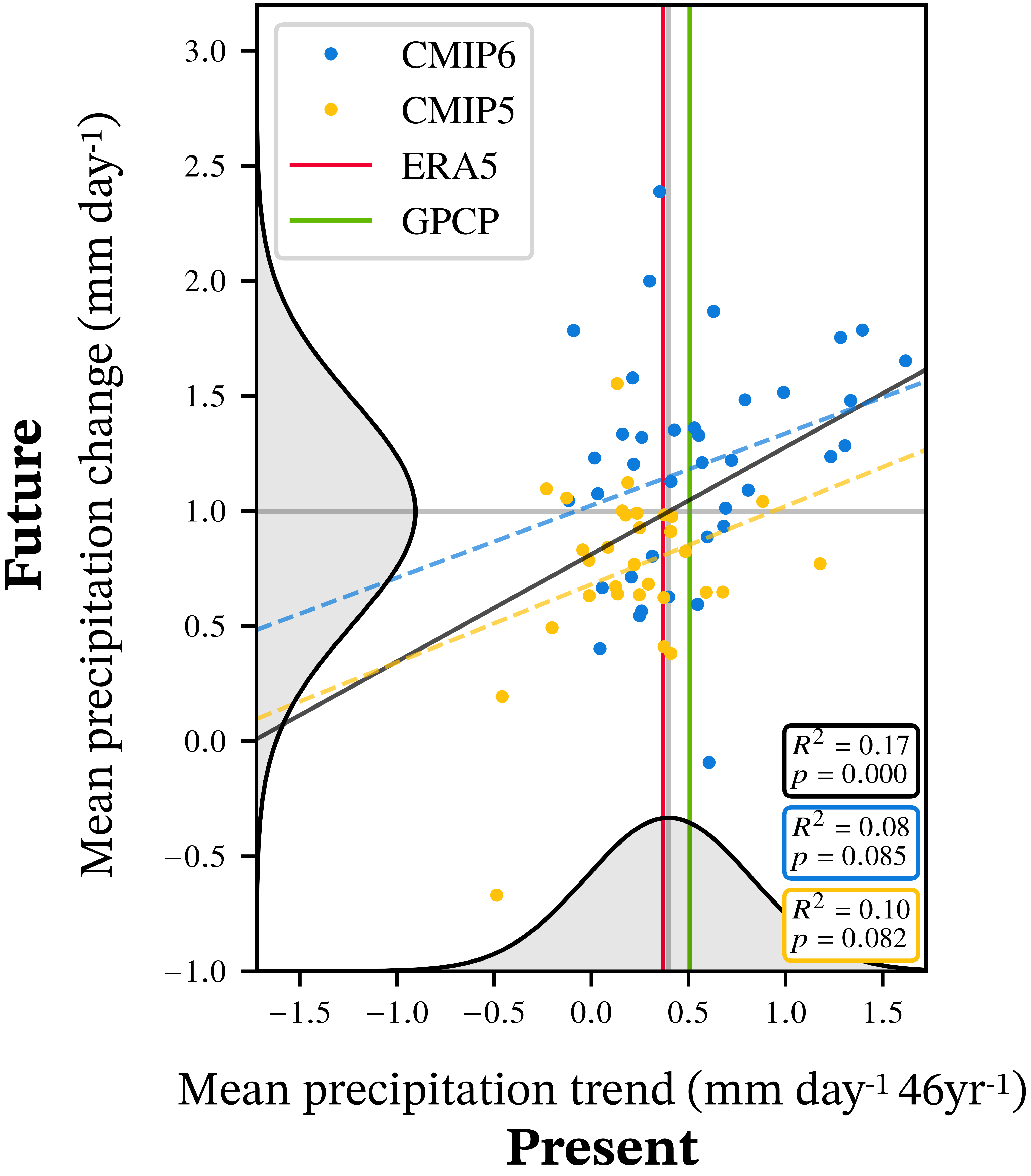

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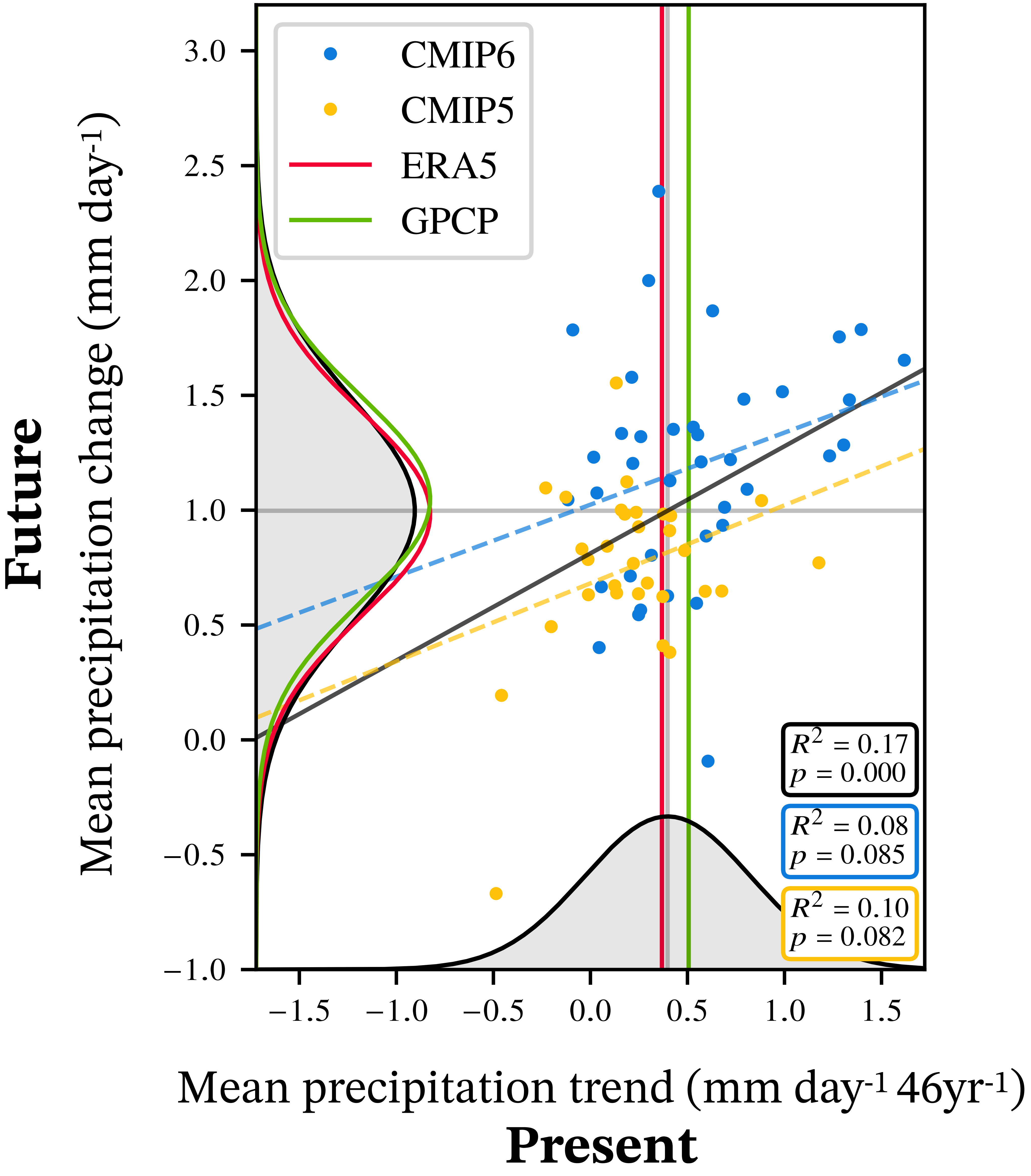
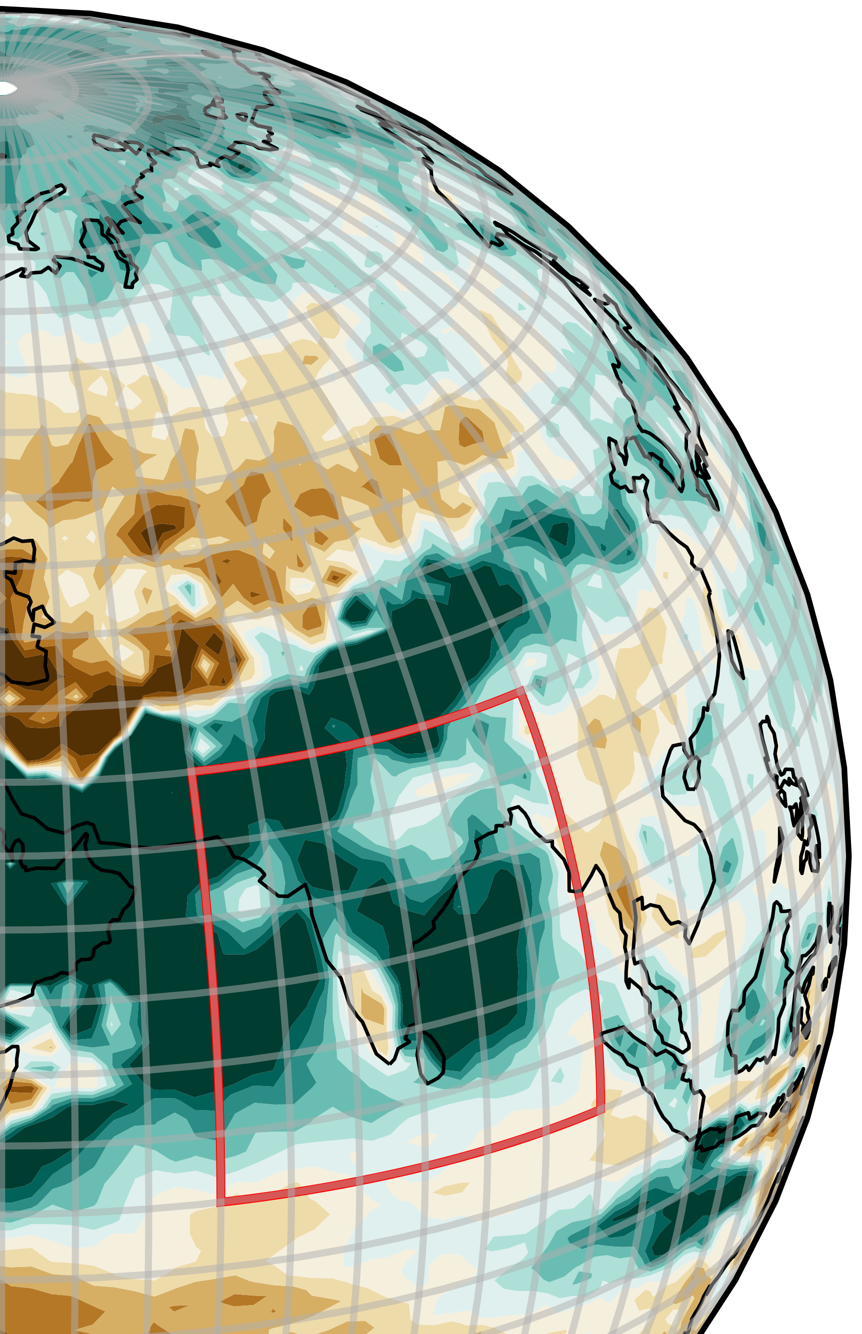
Uncertainty reduction: **17%**





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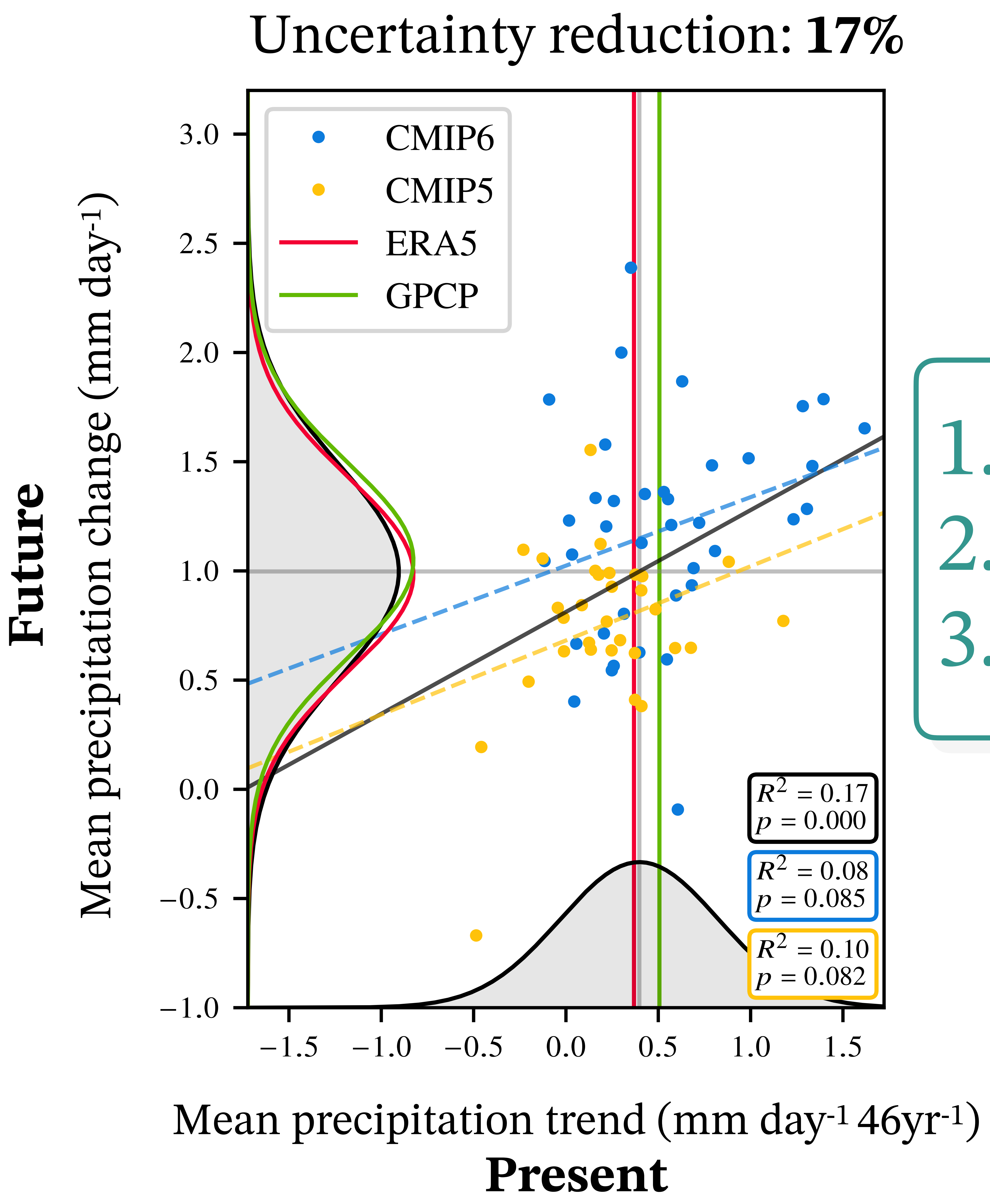

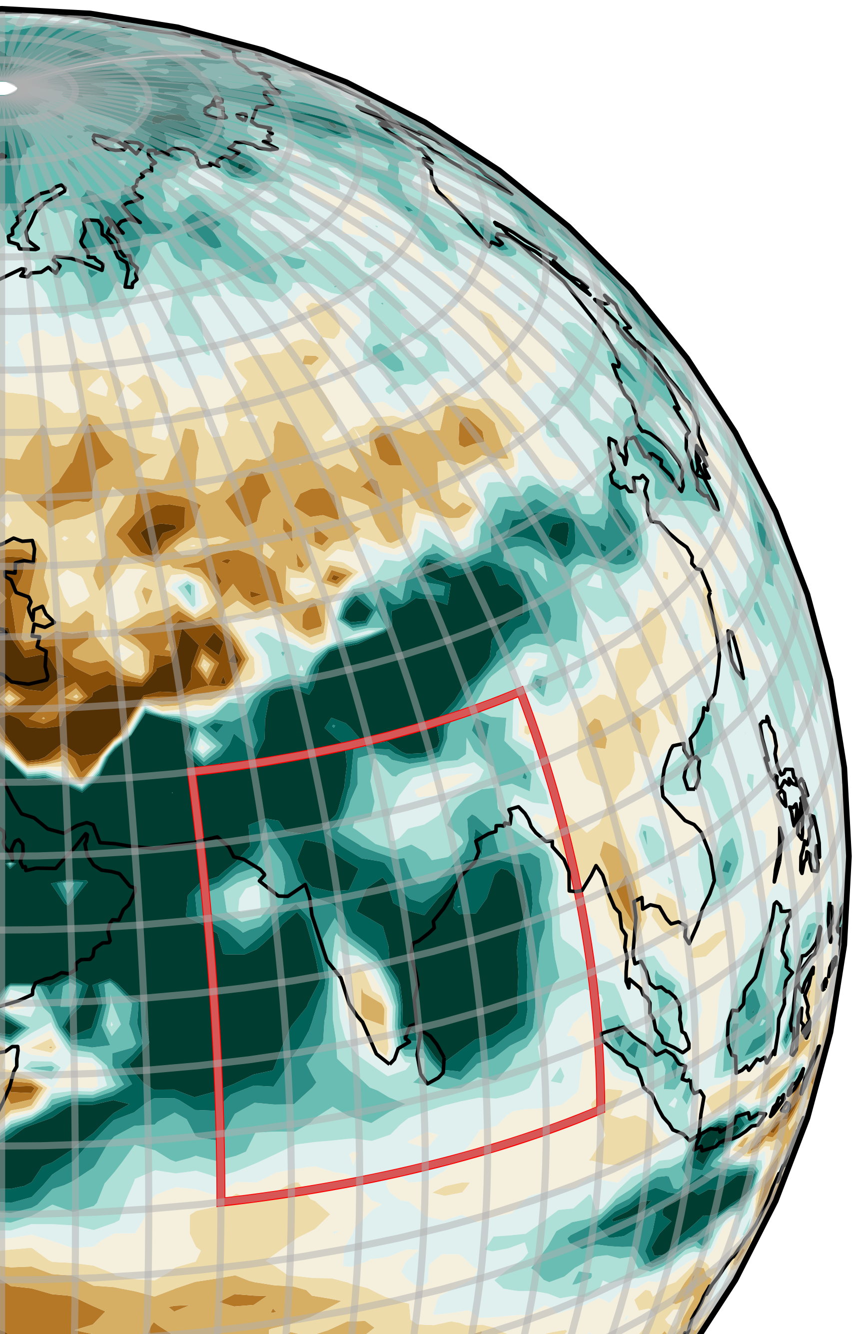

1. Poor uncertainty reduction
2. Lost the spatial information
3. Constrained the *mean* only

3. Inter-model Maximum Covariance Analysis (MCA) constraint

- MCA (PCA’s older brother !) looks for maximum covariance between two fields *(Bretherton et al., 1992)*

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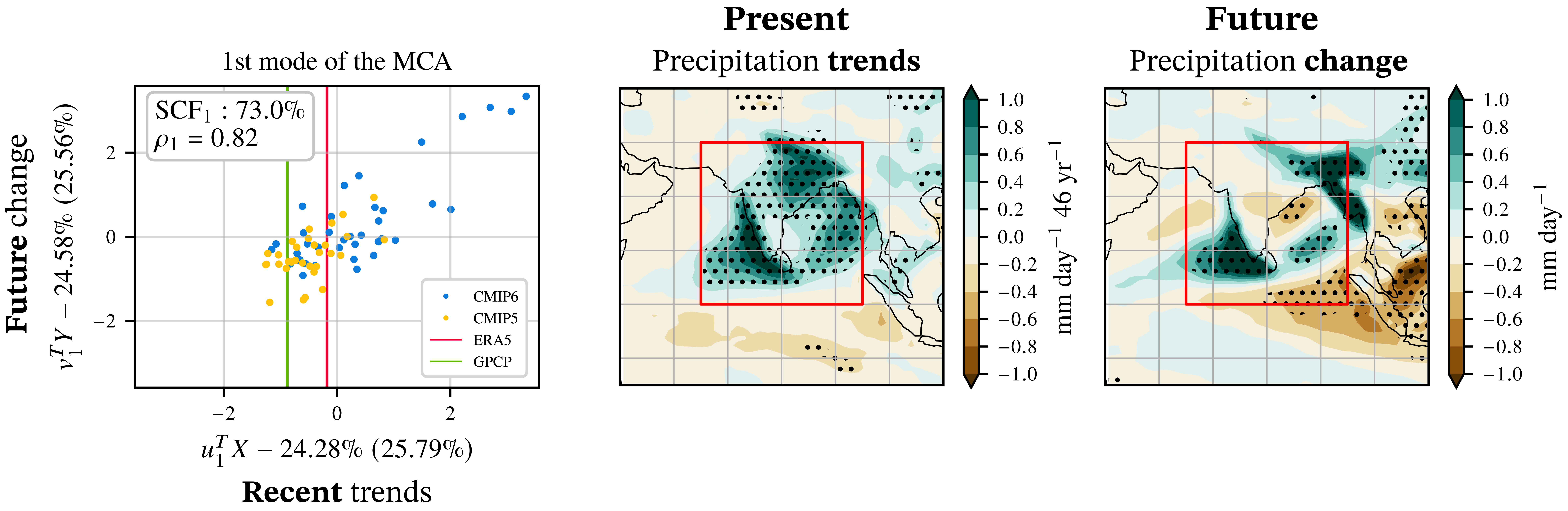

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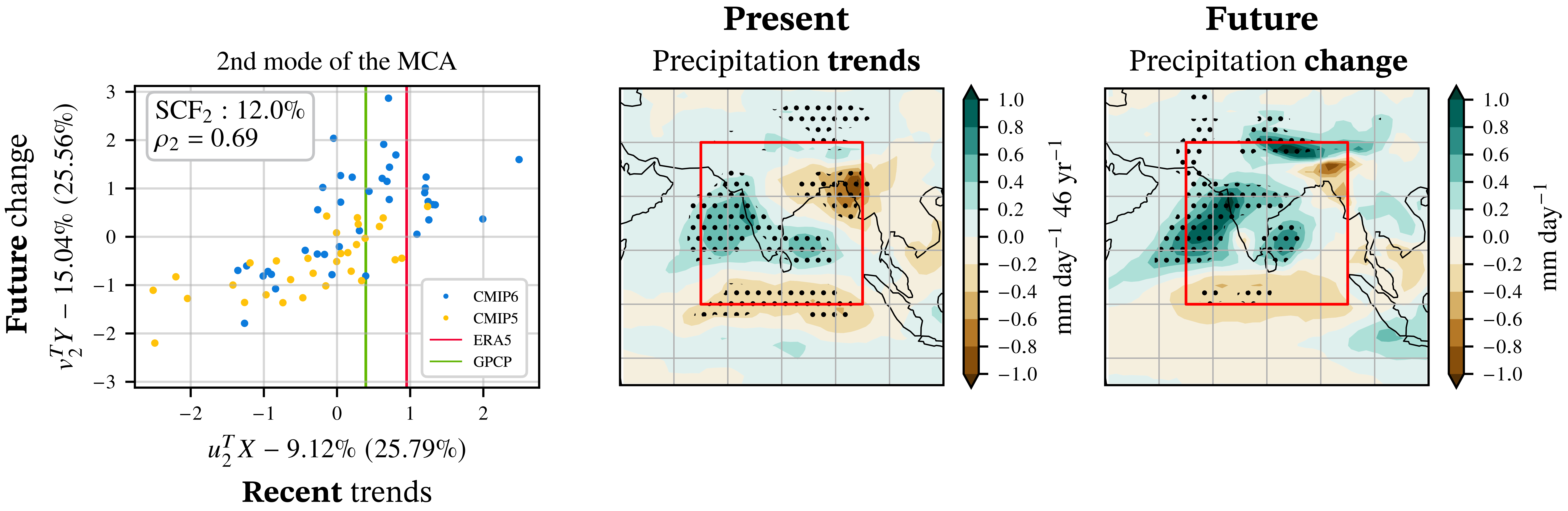
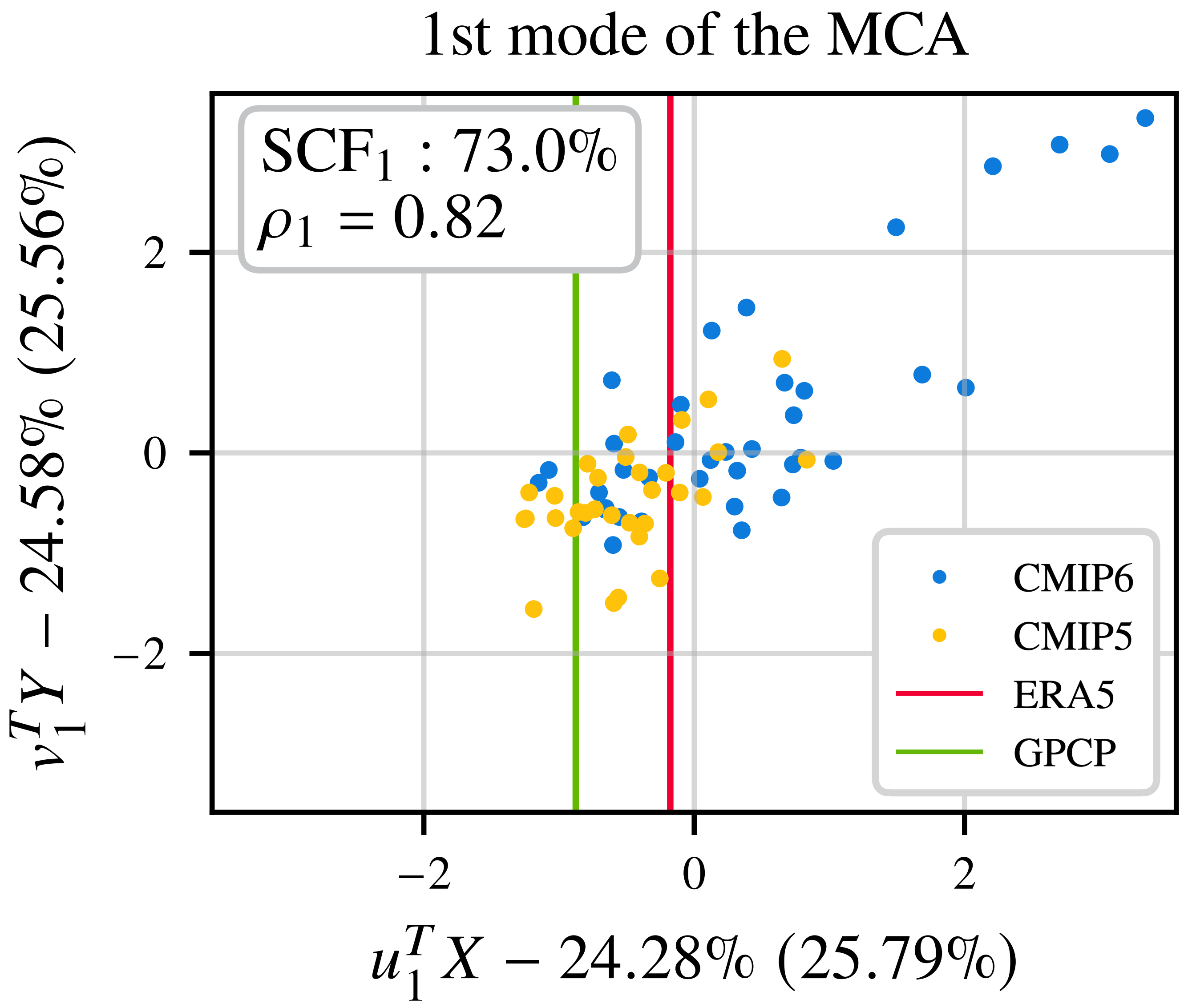


3. Inter-model Maximum Covariance Analysis (MCA) constraint

$\hat{Y}^{(m)}(X)$

Each mode contains a present-future nexus



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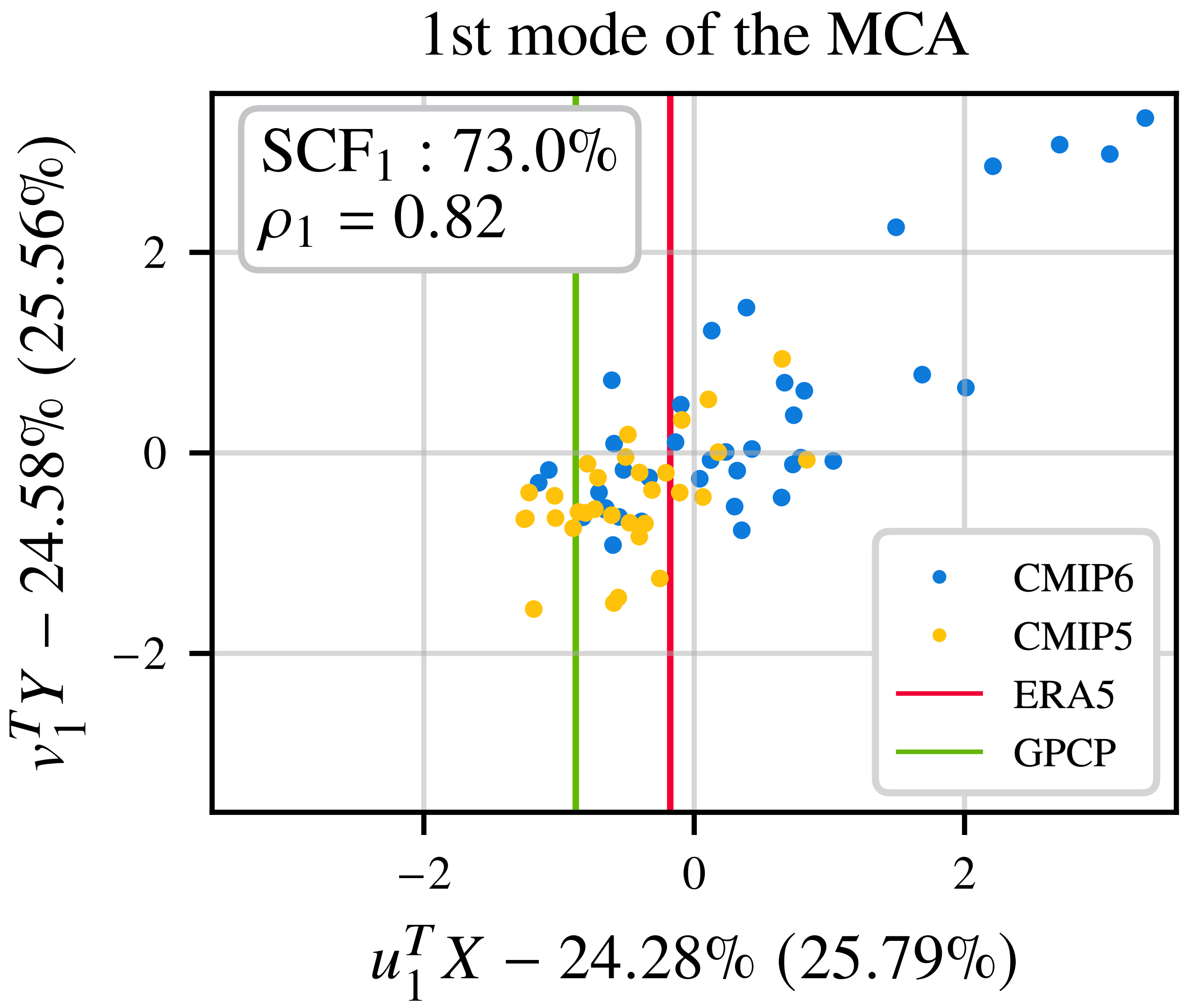
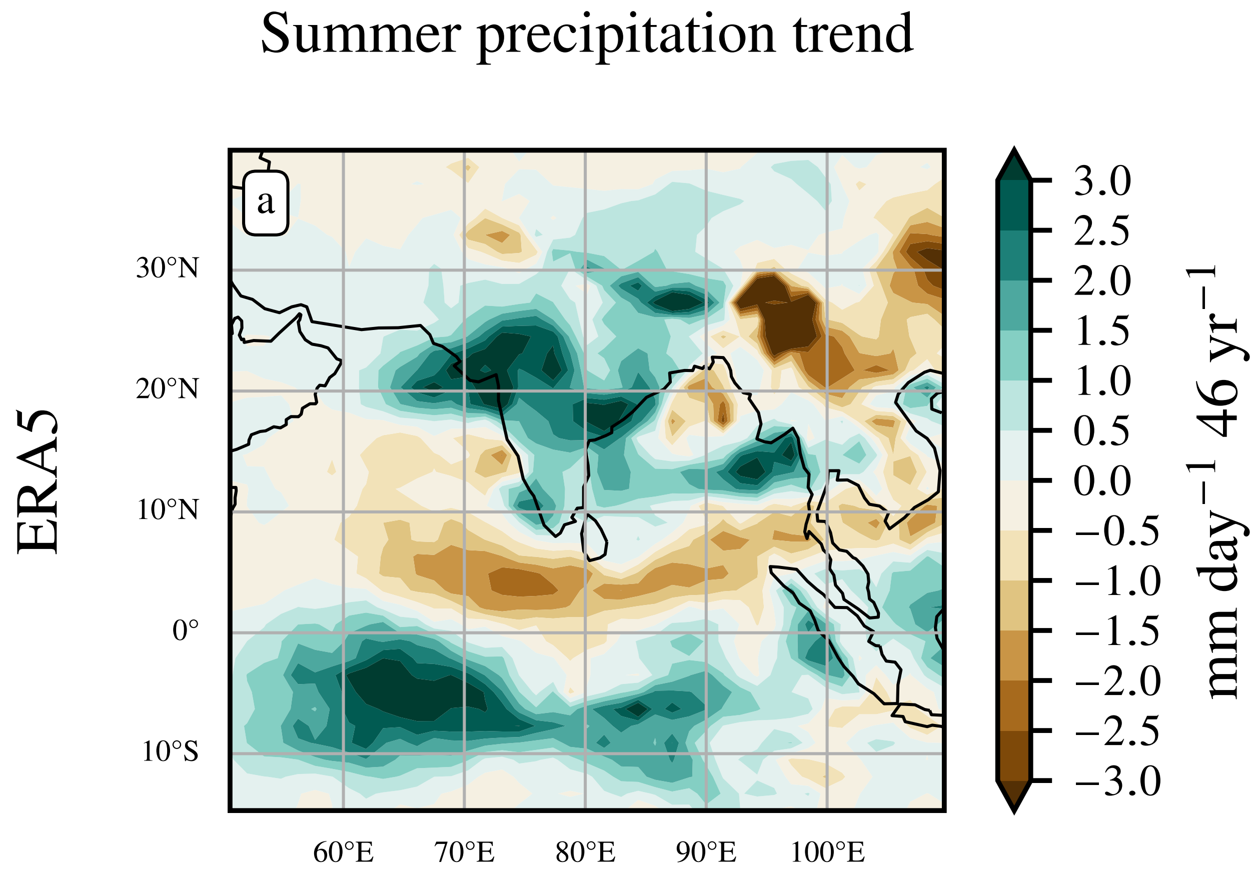


X_o

Combine with observations (ERA5, GPCP)



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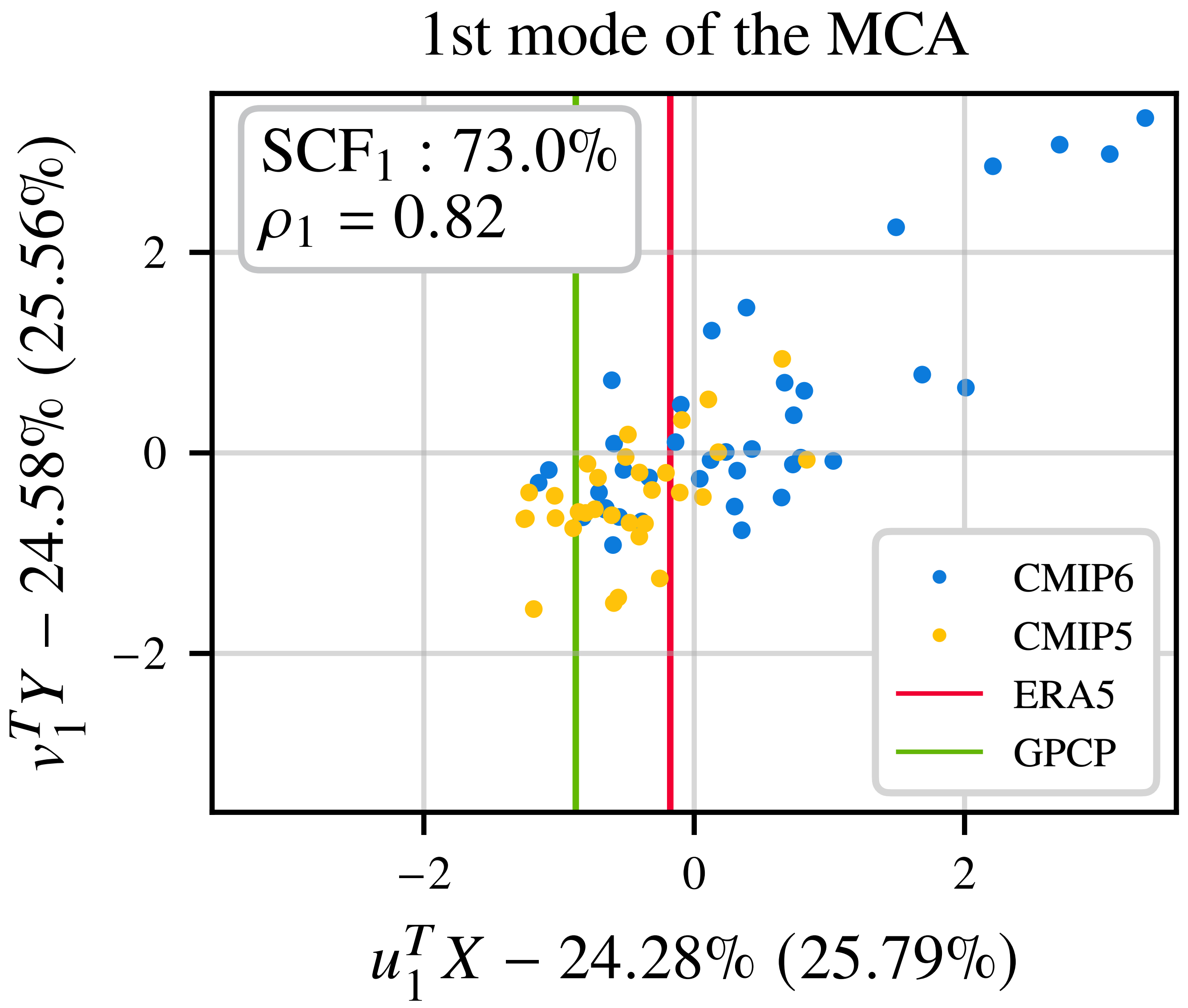

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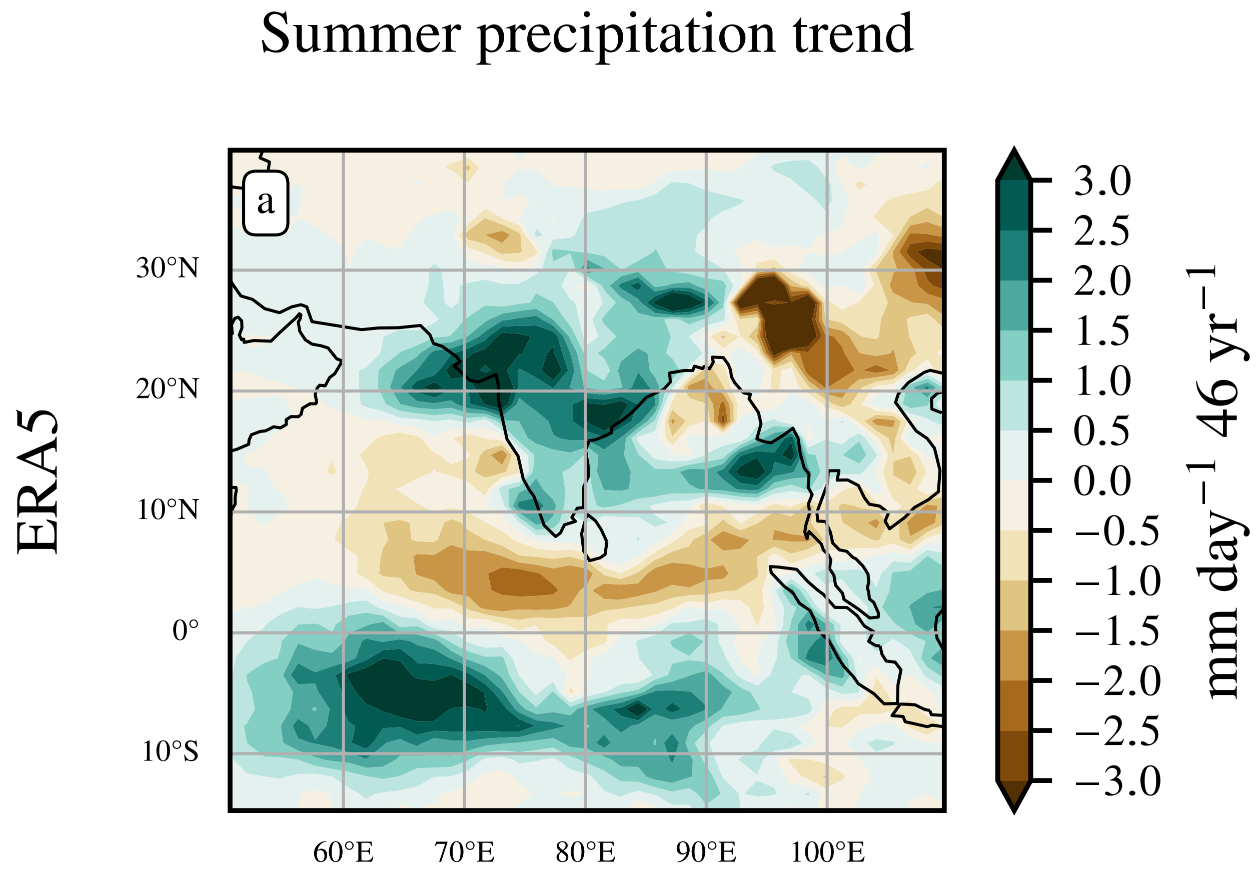


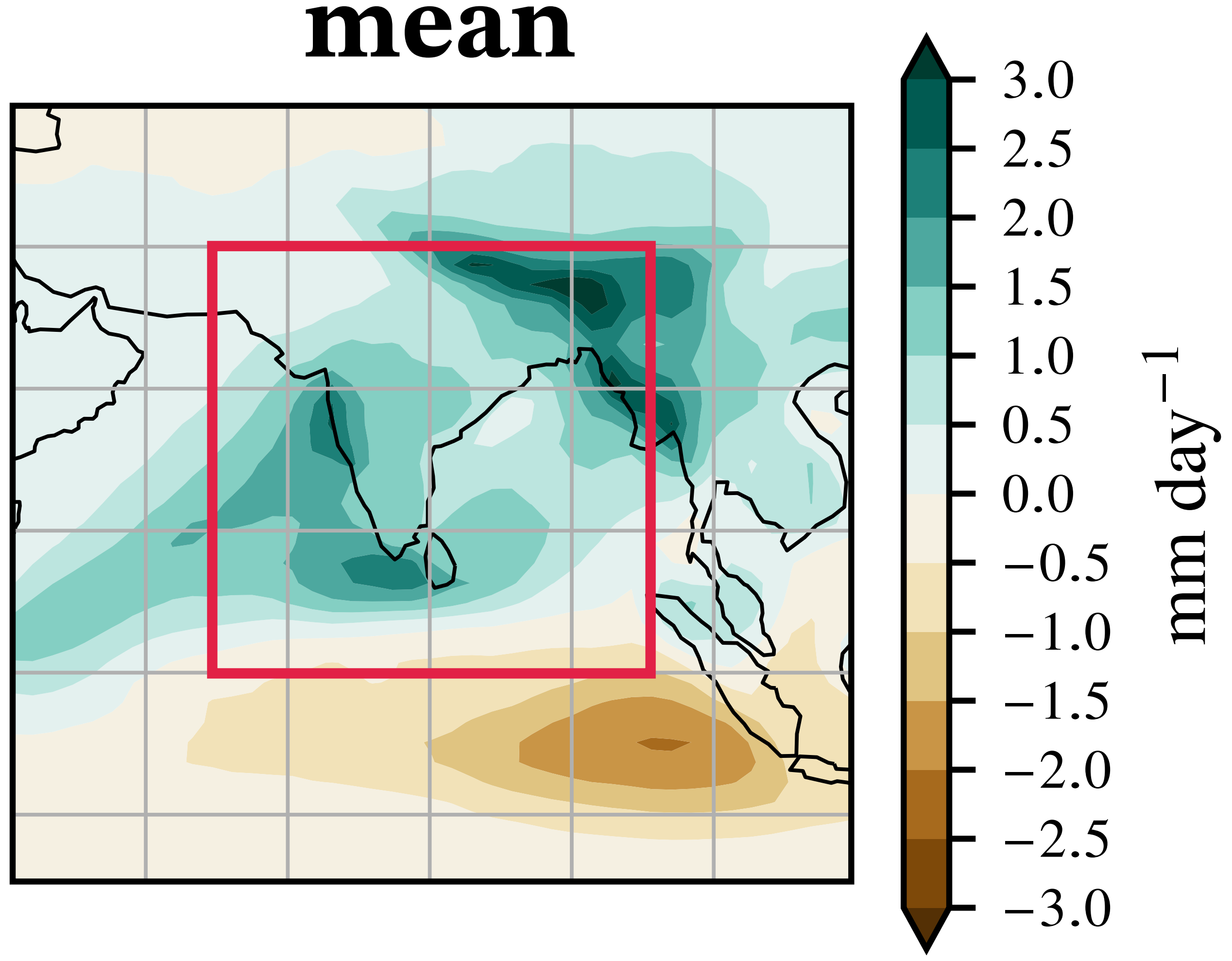
$Y^{(m)} \mid X_o$

Constrained distribution of future change

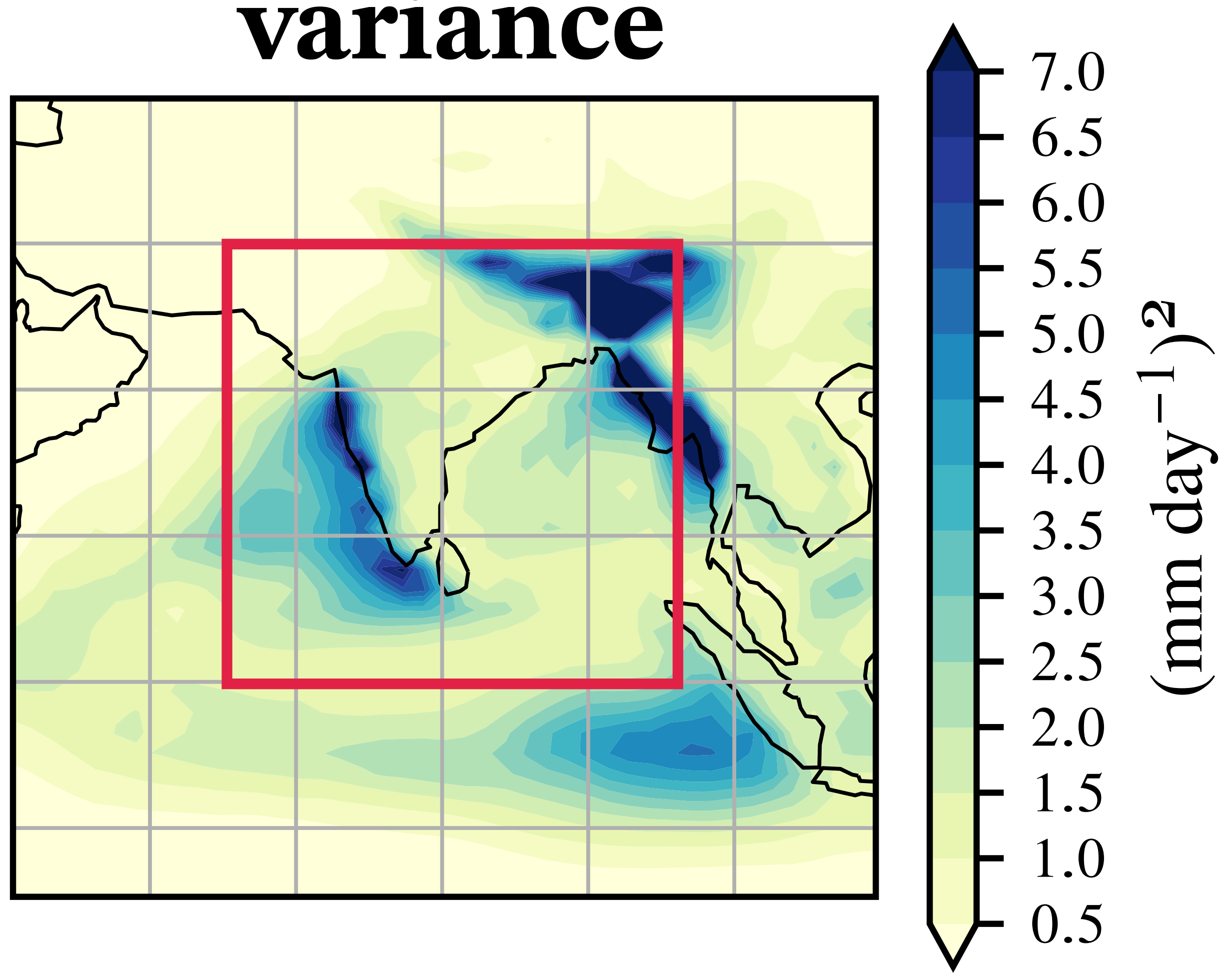
3. Inter-model Maximum Covariance Analysis (MCA) constraint

Future change

Inter-model **mean**



Inter-model **variance**



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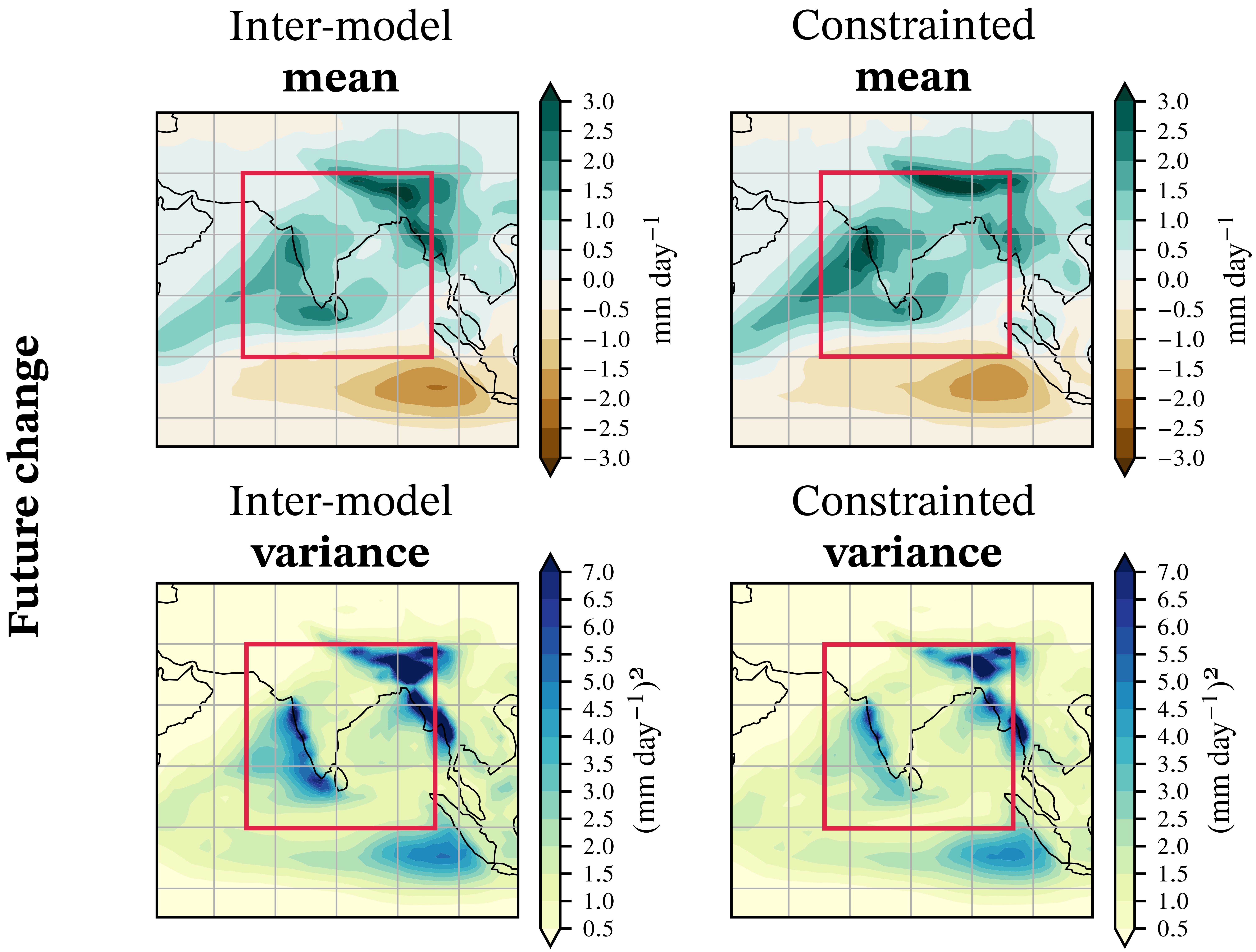

Using 2 modes
ERA5

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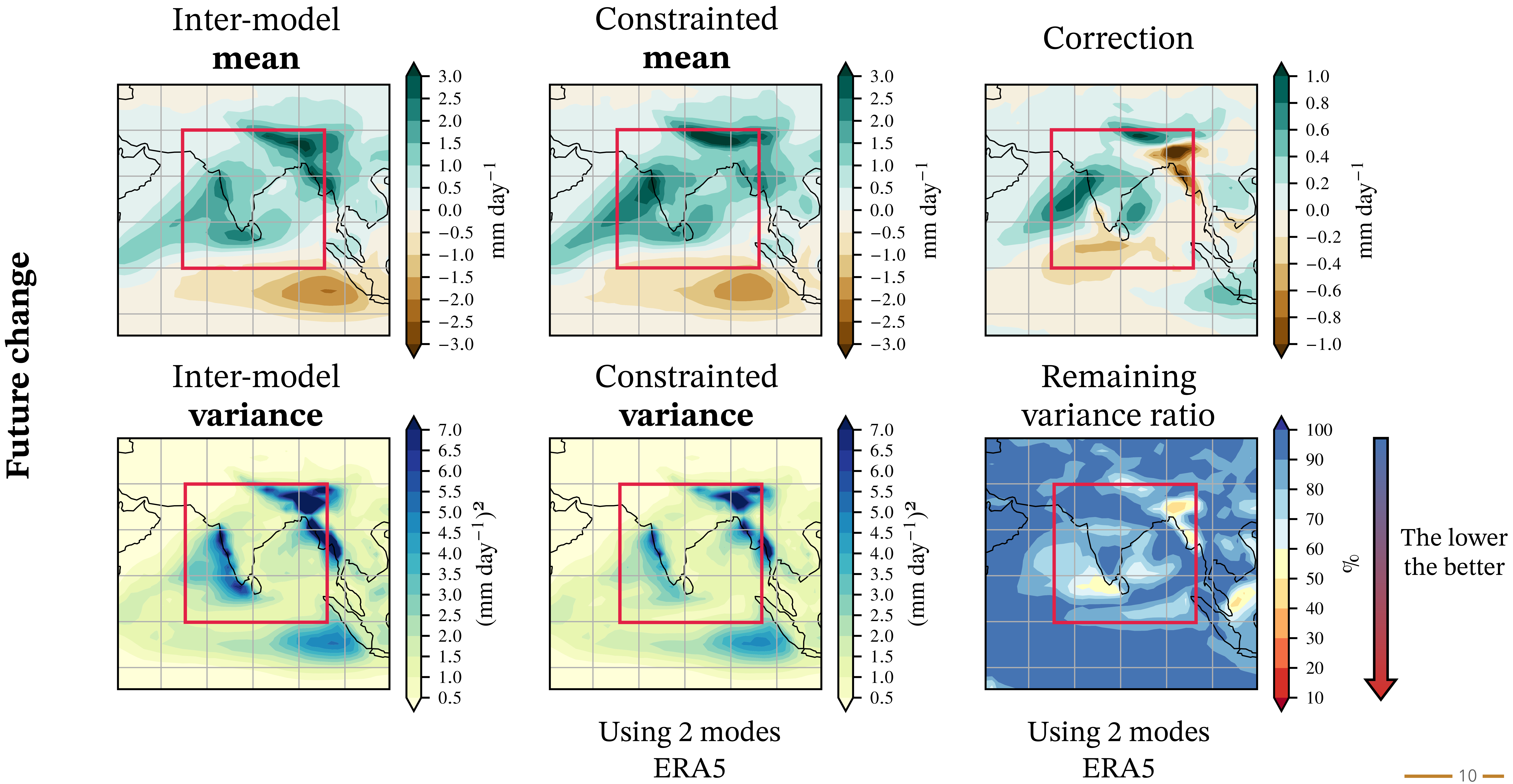

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Perfect model validation

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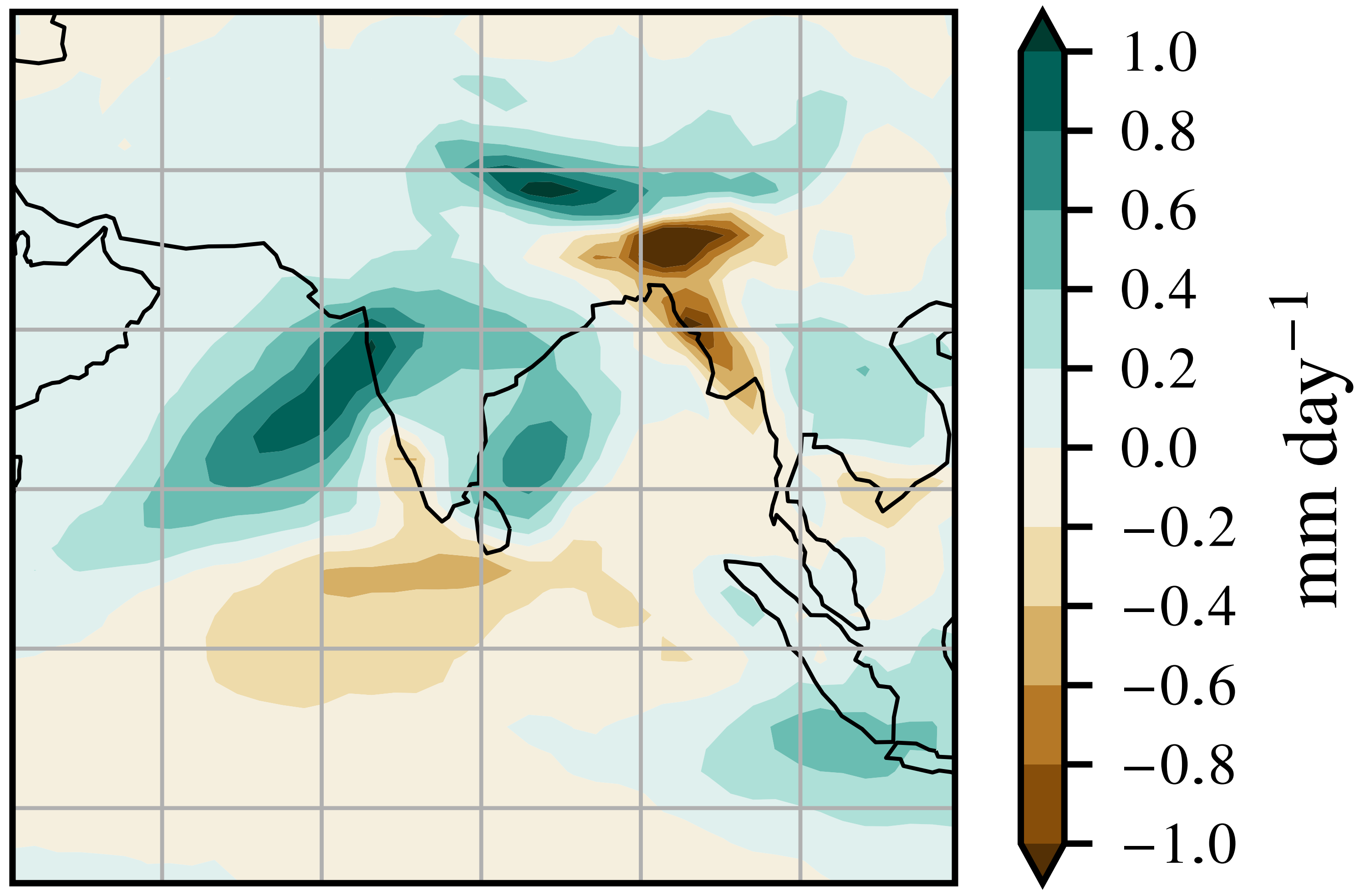
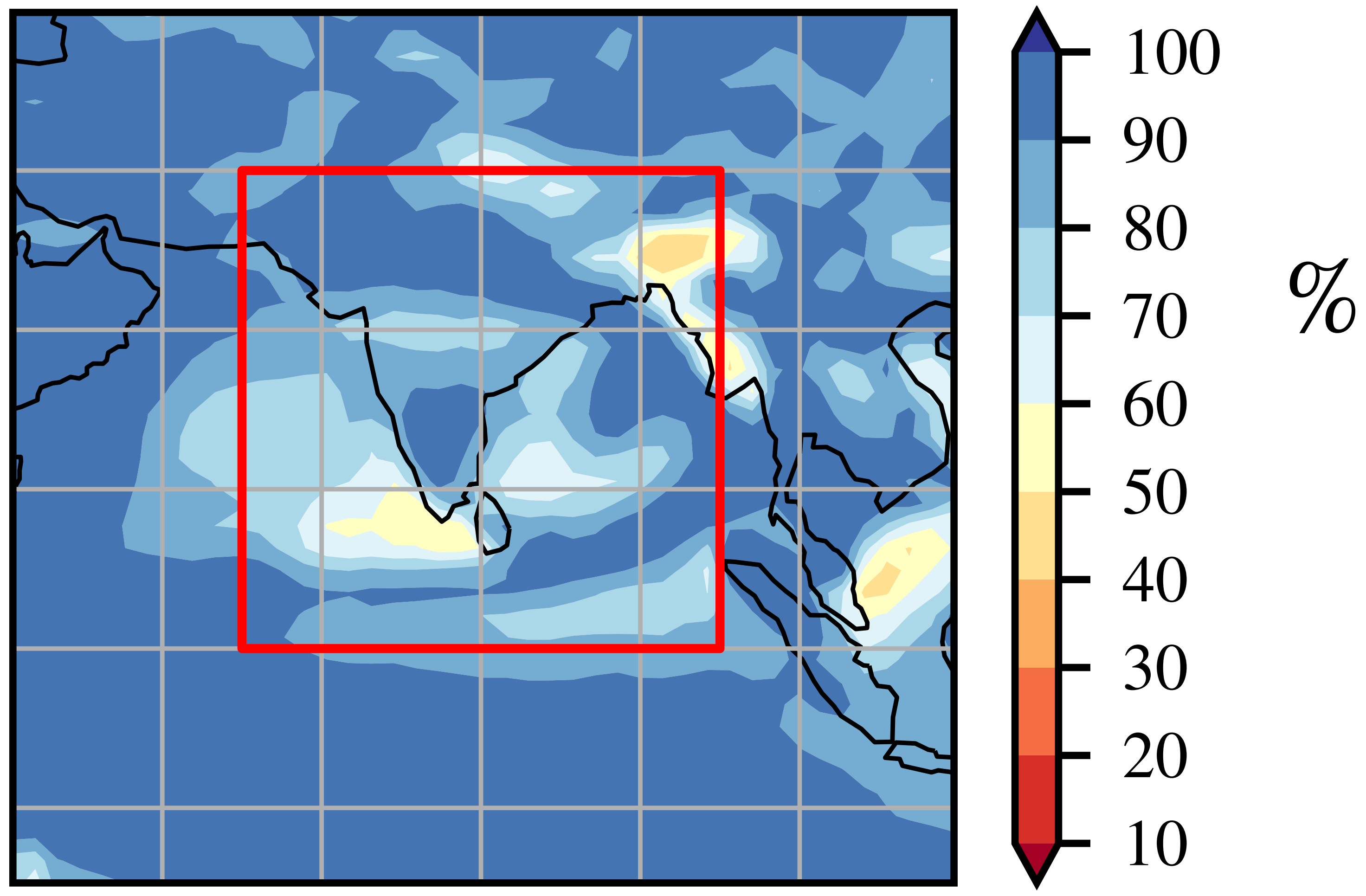
2 modes

5. Conclusion

- Projections of future precipitation change face important model uncertainties





Using 2 modes
ERA5

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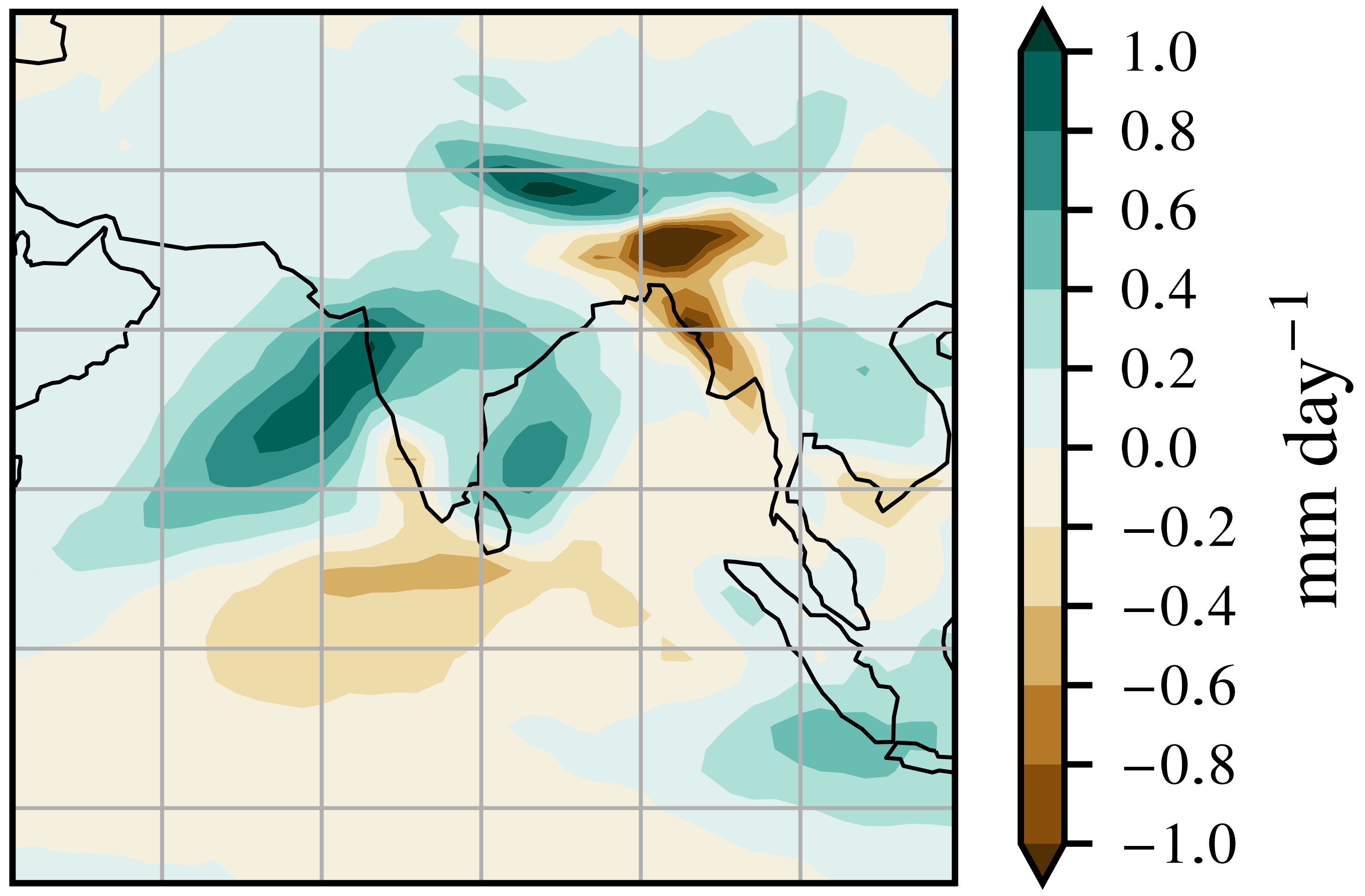
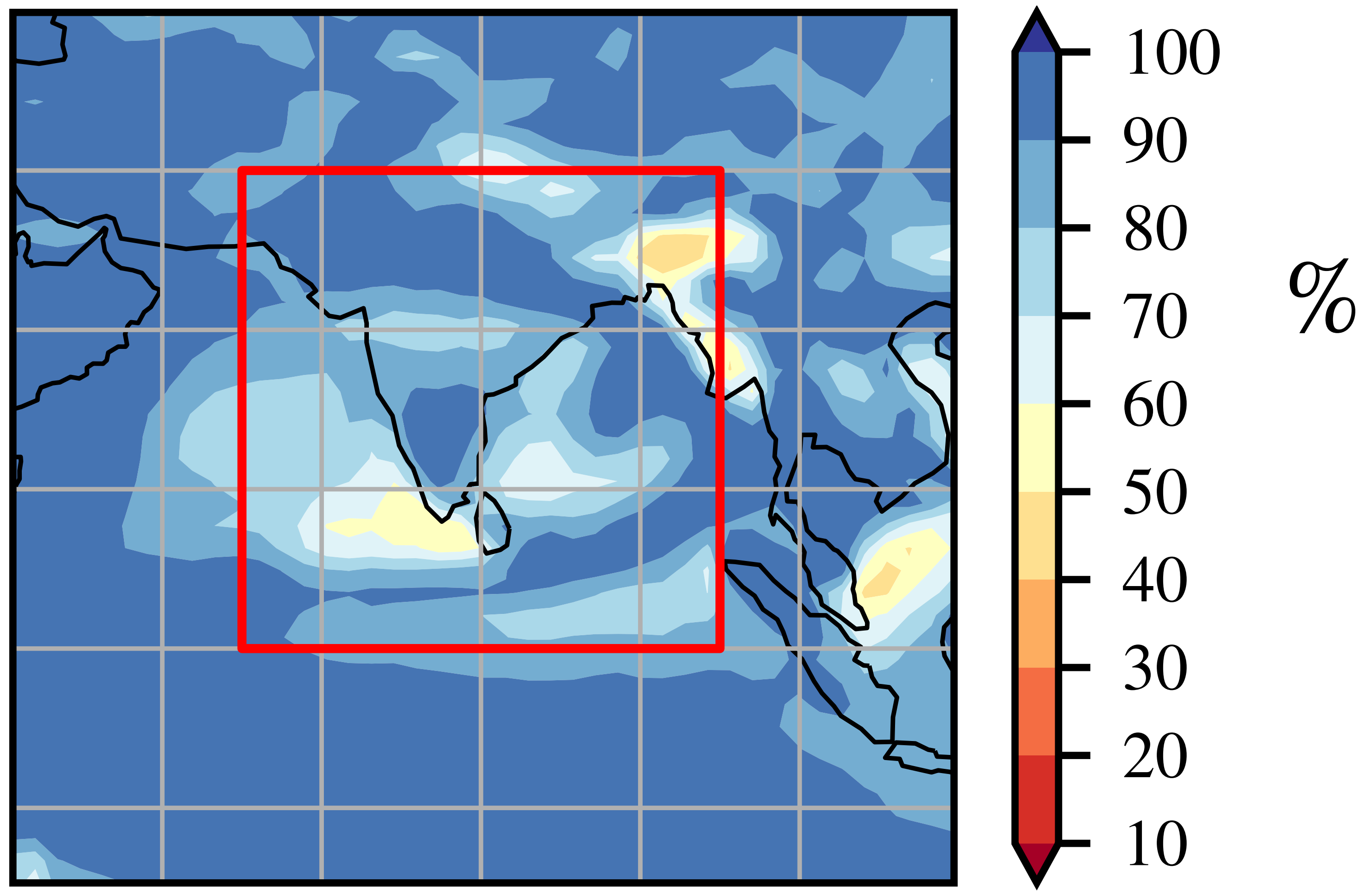


Remaining variance ratio



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ERA5

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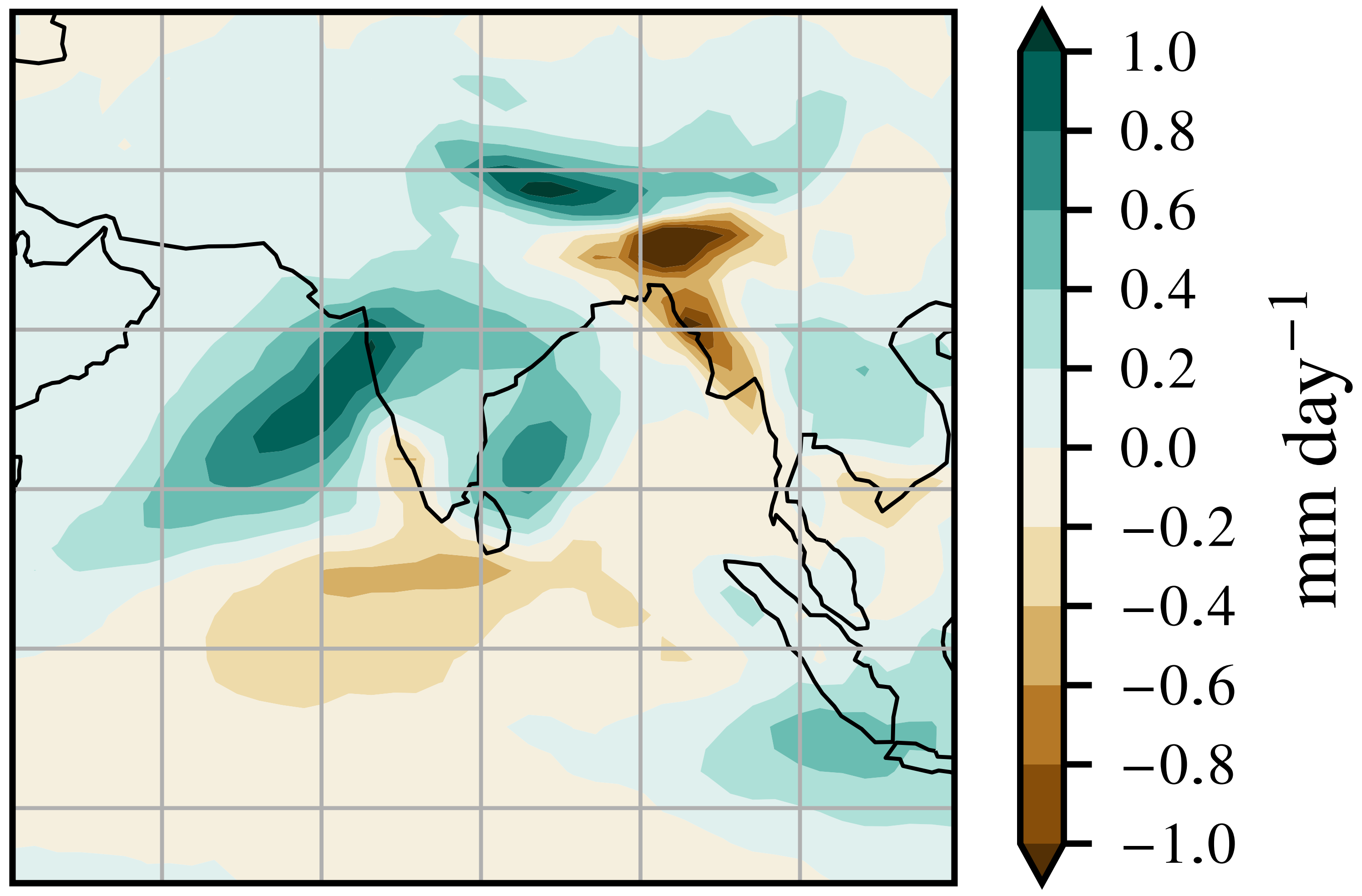

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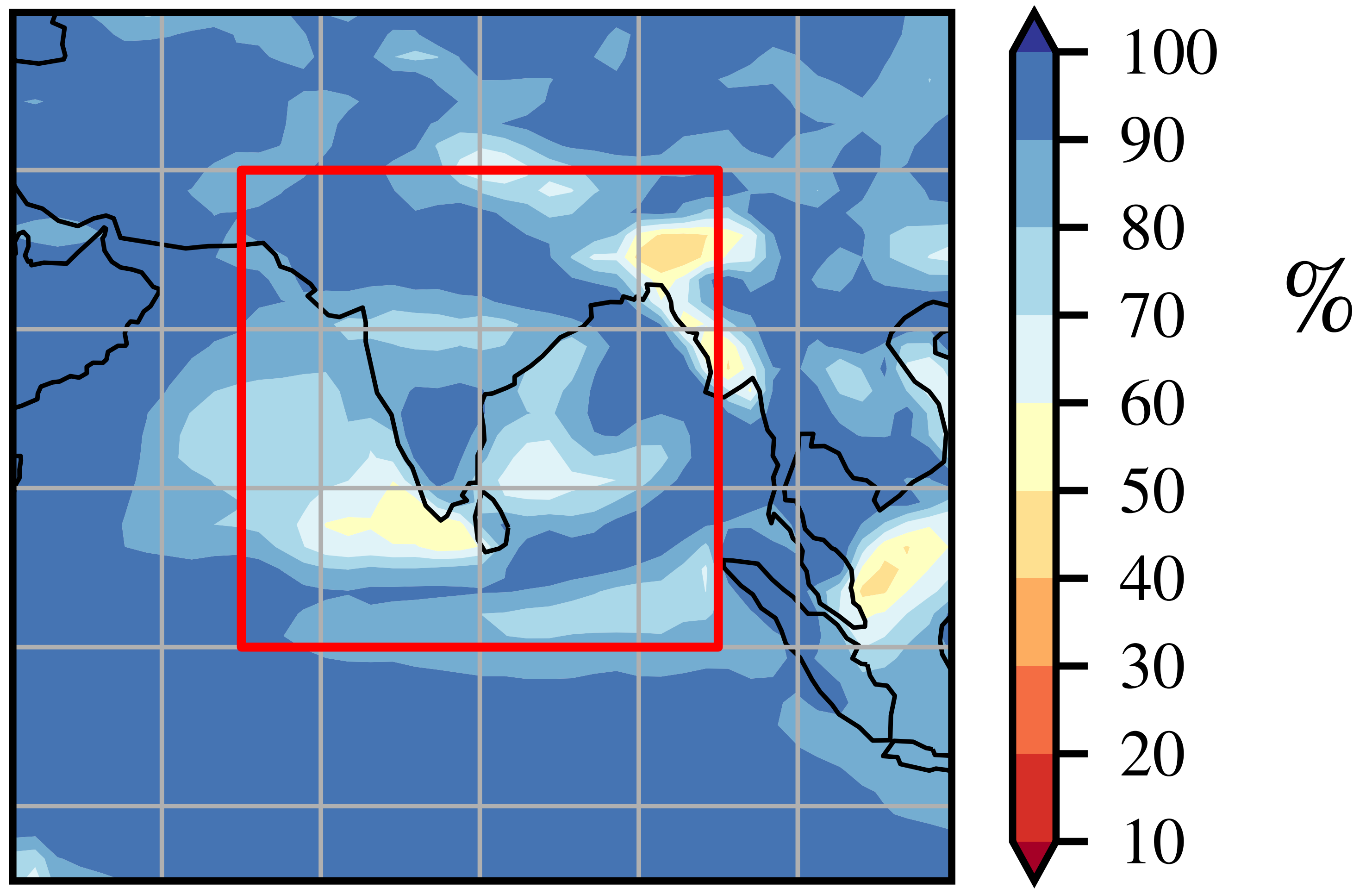

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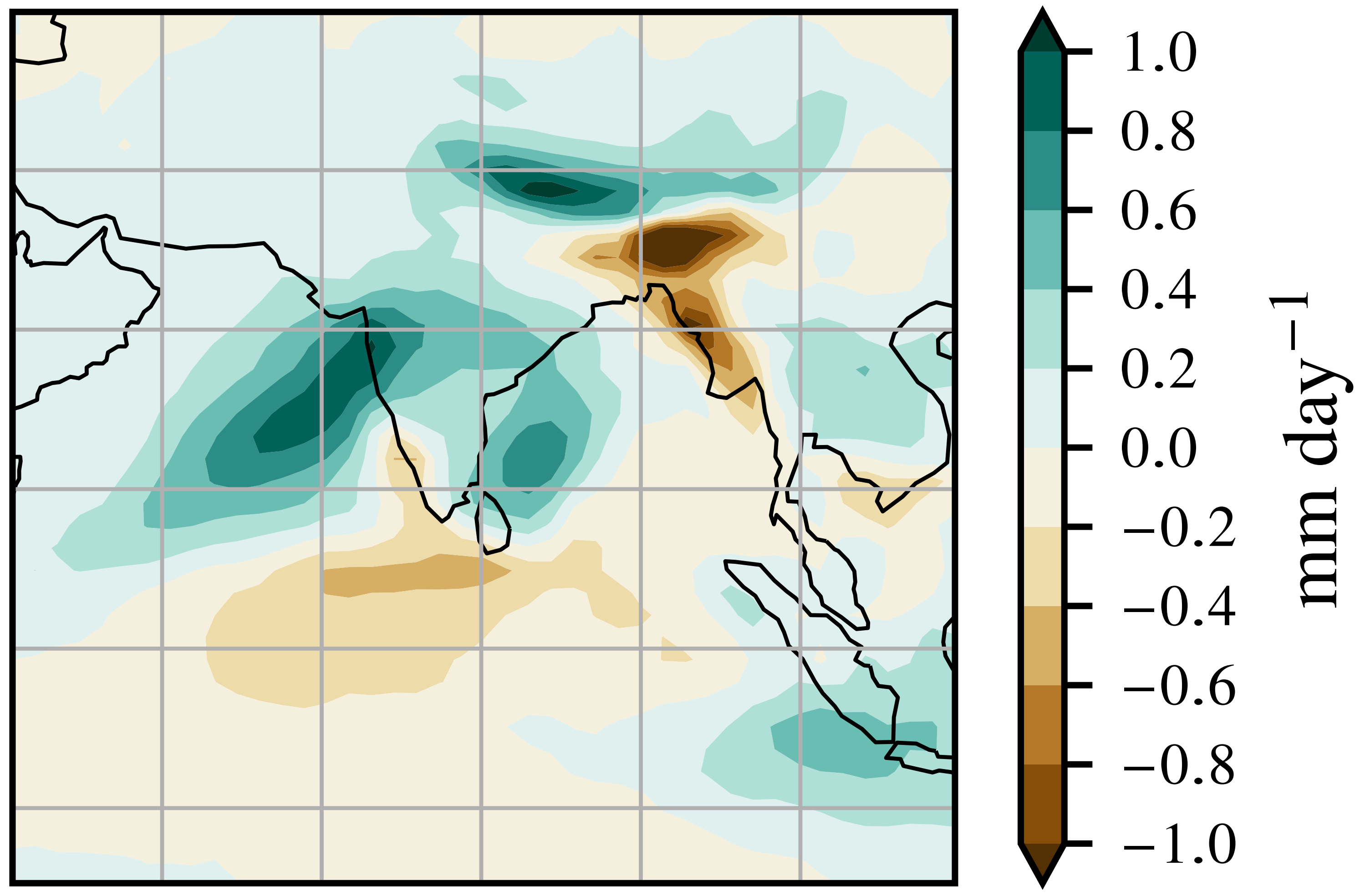

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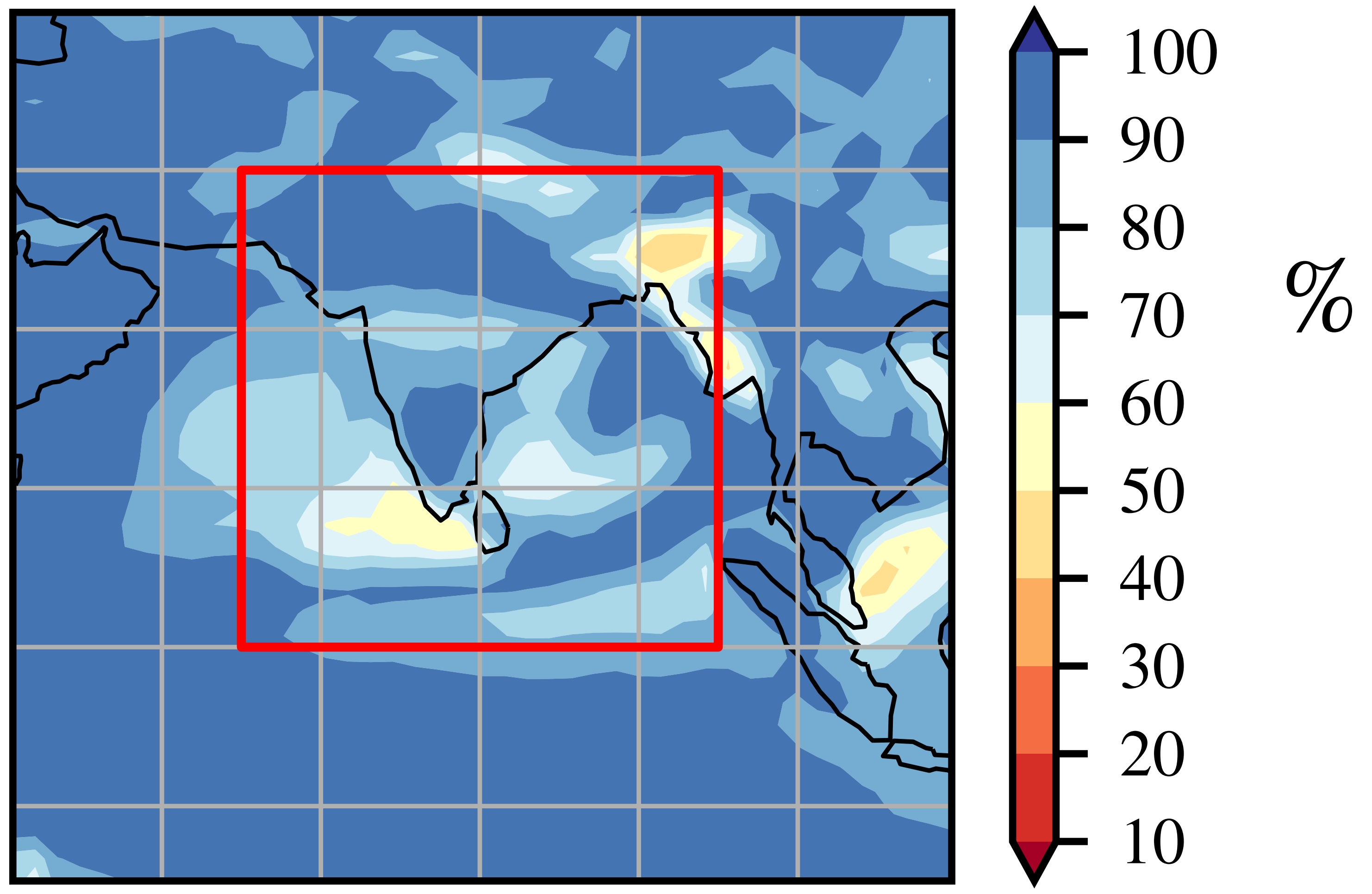

Using 2 modes
ERA5

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Observational constraints on global climate projections:
An original method applied to changes in Indian summer monsoon rainfall

George Whittle,[a, b] Hervé Douville,[a] Pascal Terray,[b]

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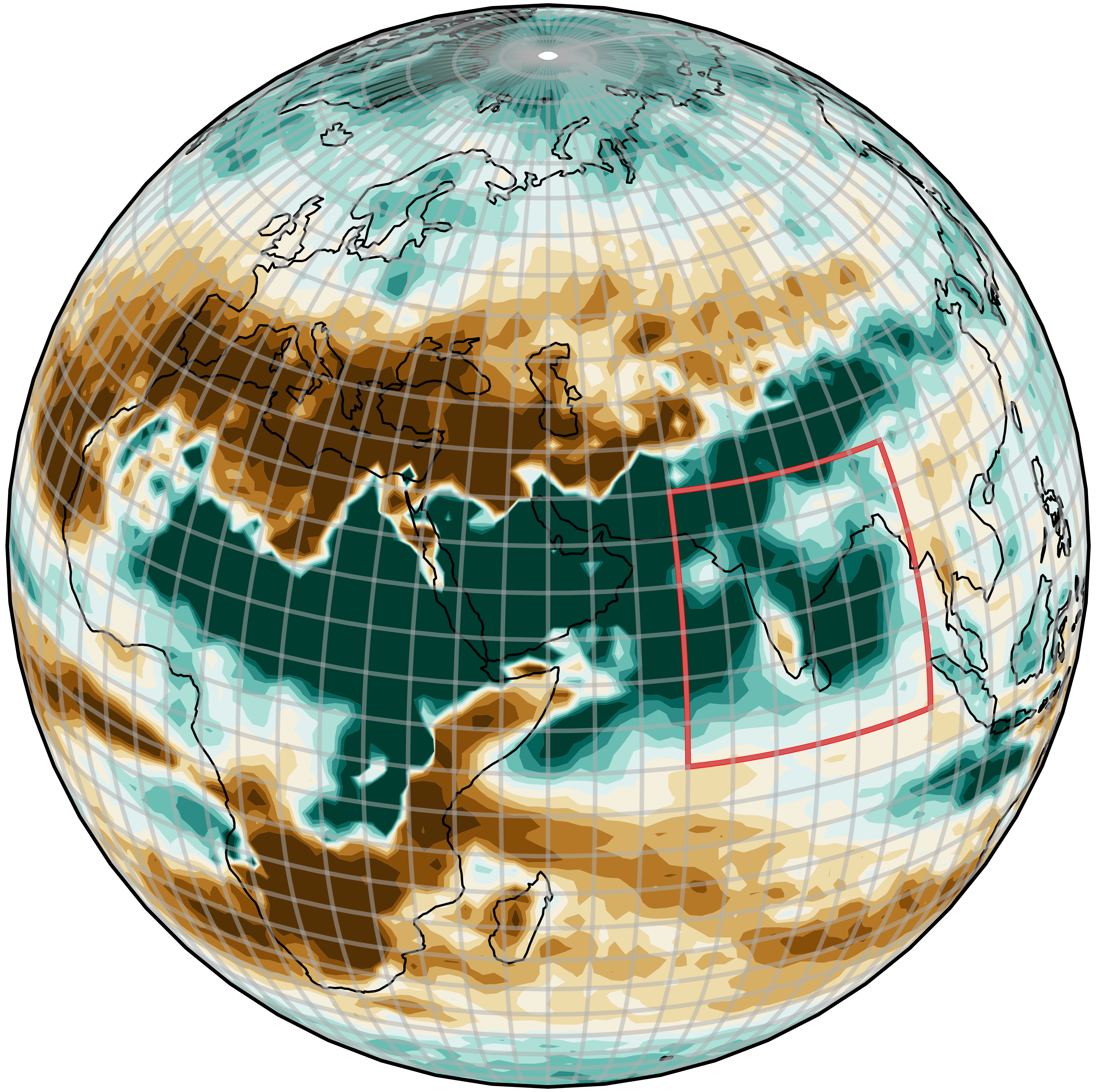
ABSTRACT: The lack of consensus in global projections of regional precipitation changes represents a major obstacle for the design of adaptation policies. This persistent spread is mainly arising from modeling uncertainty, i.e. from our limited knowledge in but also plural representation of complex mechanisms in current global climate models. Regardless of further model developments, here we propose an original statistical method in order to make the best use of available projections. Focusing on the Indian Summer Monsoon Rainfall (IMSR), a regional phenomenon of importance for the livelihood of billions of people, we perform Maximum Covariance Analysis (MCA) to relate the inter-model spread in future precipitation changes to the simulation of recent precipitation linear trends - i.e. looking for a present-future nexus in model representation of precipitation. Observations (ERA5, GPCP) are then used to account for model errors and thus build a revised multi-model ensemble. The robustness of our method is assessed using an out-of-sample validation approach,

CNRM-CM6-1-HR

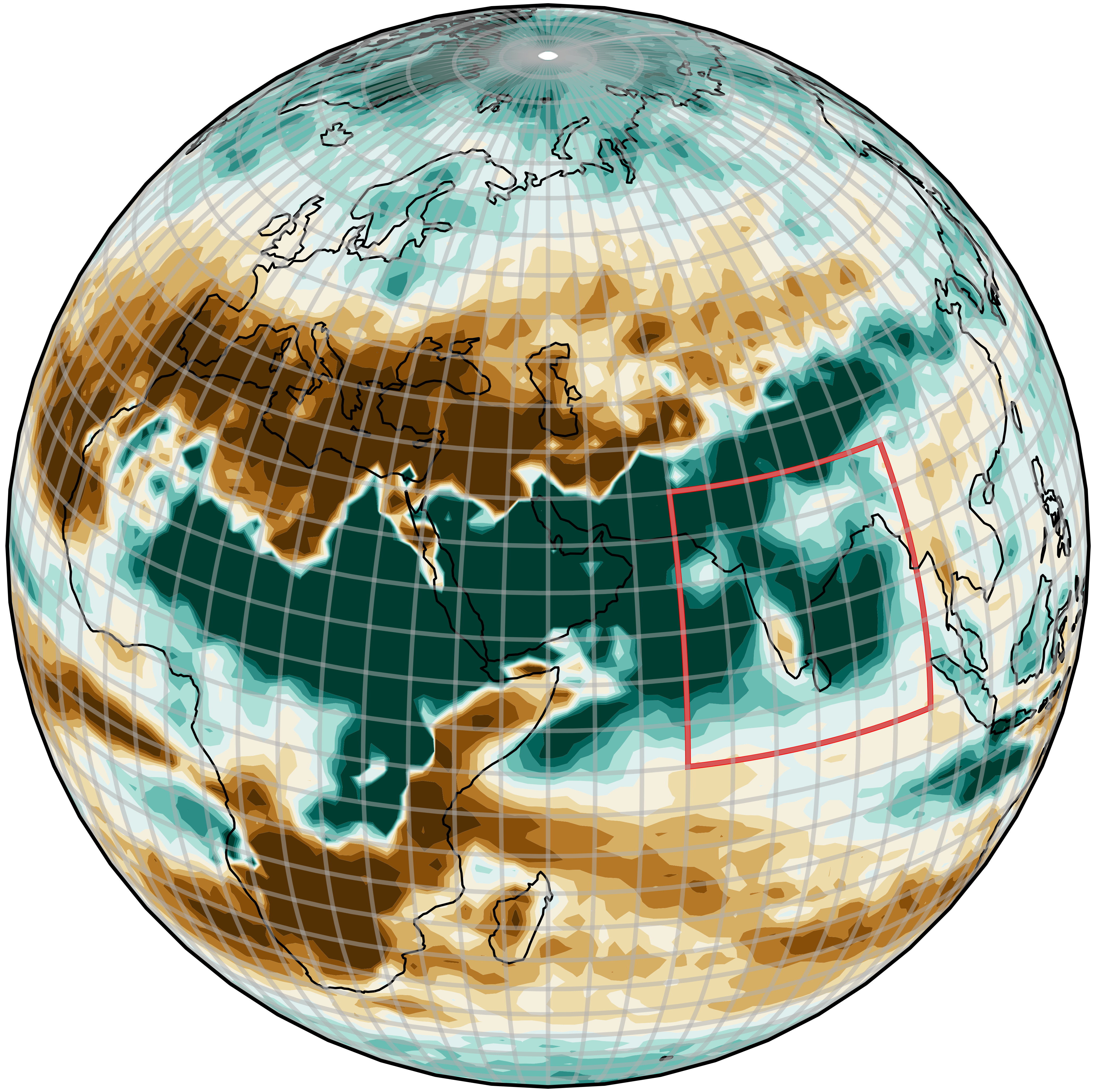


Thank you !
Any questions ?

George Whittle, Hervé Douville (CNRM) & Pascal Terray (IPSL-LOCEAN)

AMA 2026

CNRM-CM6-1-HR



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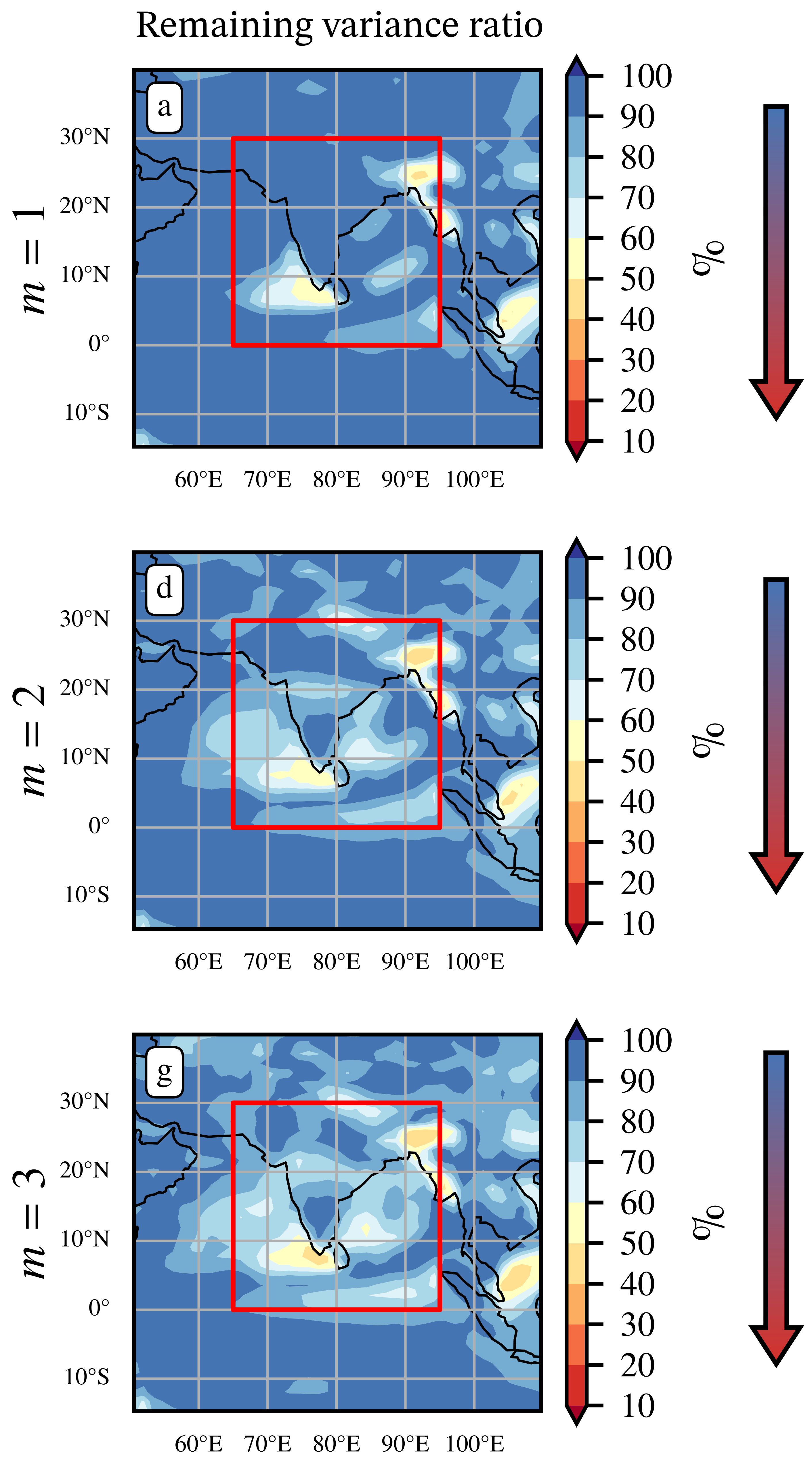
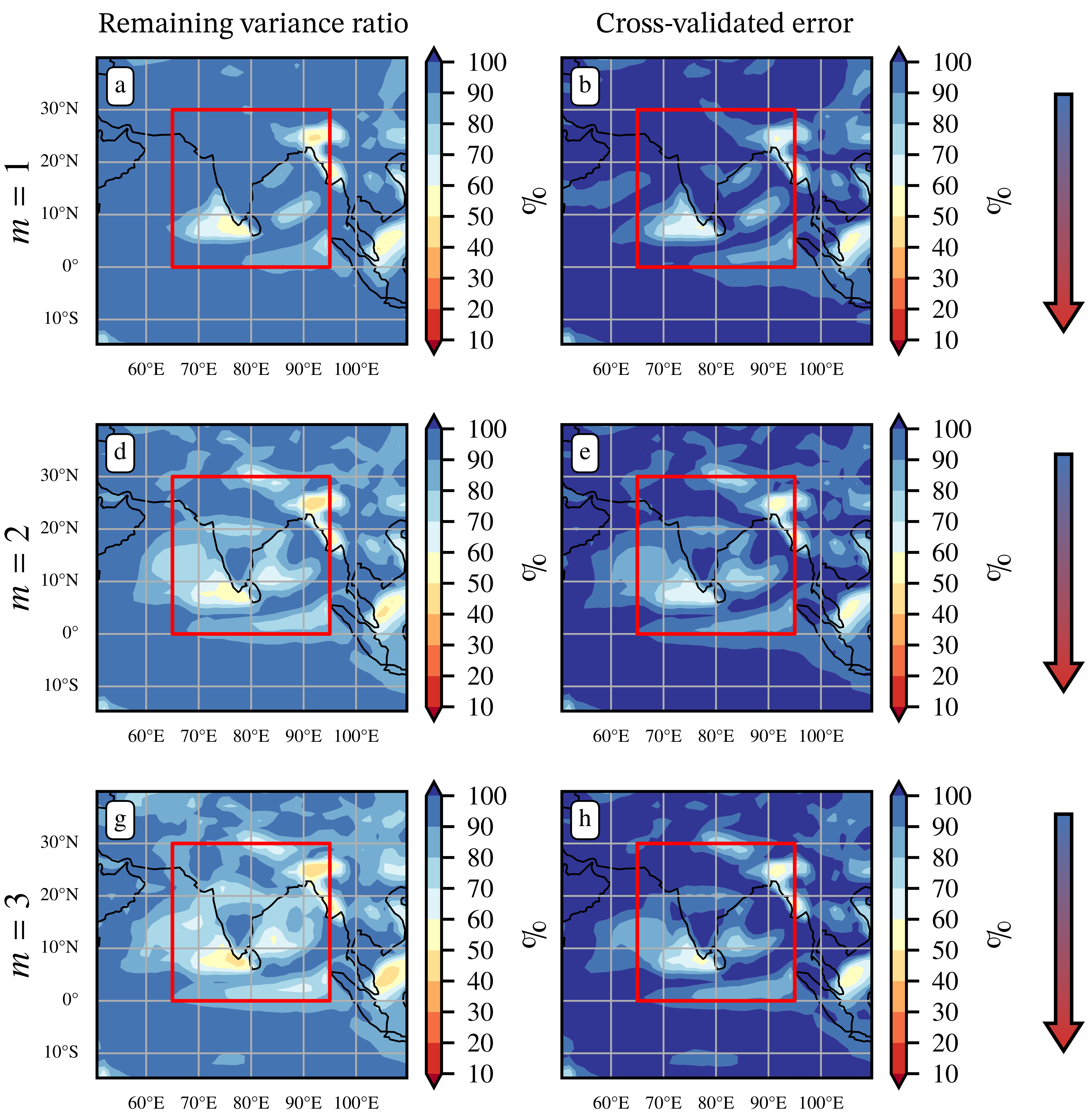
Appendix



Remaining variance ratio
a
d
g
m = 1
m = 2
m = 3
30°N
20°N
10°N
0°
10°S
60°E
70°E
80°E
90°E
100°E
100
90
80
70
60
50
40
30
20
10
%

Appendix



Remaining variance ratio
Cross-validated error
a
b
d
e
g
h
m = 1
m = 2
m = 3
30°N
20°N
10°N
0°
10°S
60°E 70°E 80°E 90°E 100°E
100
90
80
70
60
50
40
30
20
10
%

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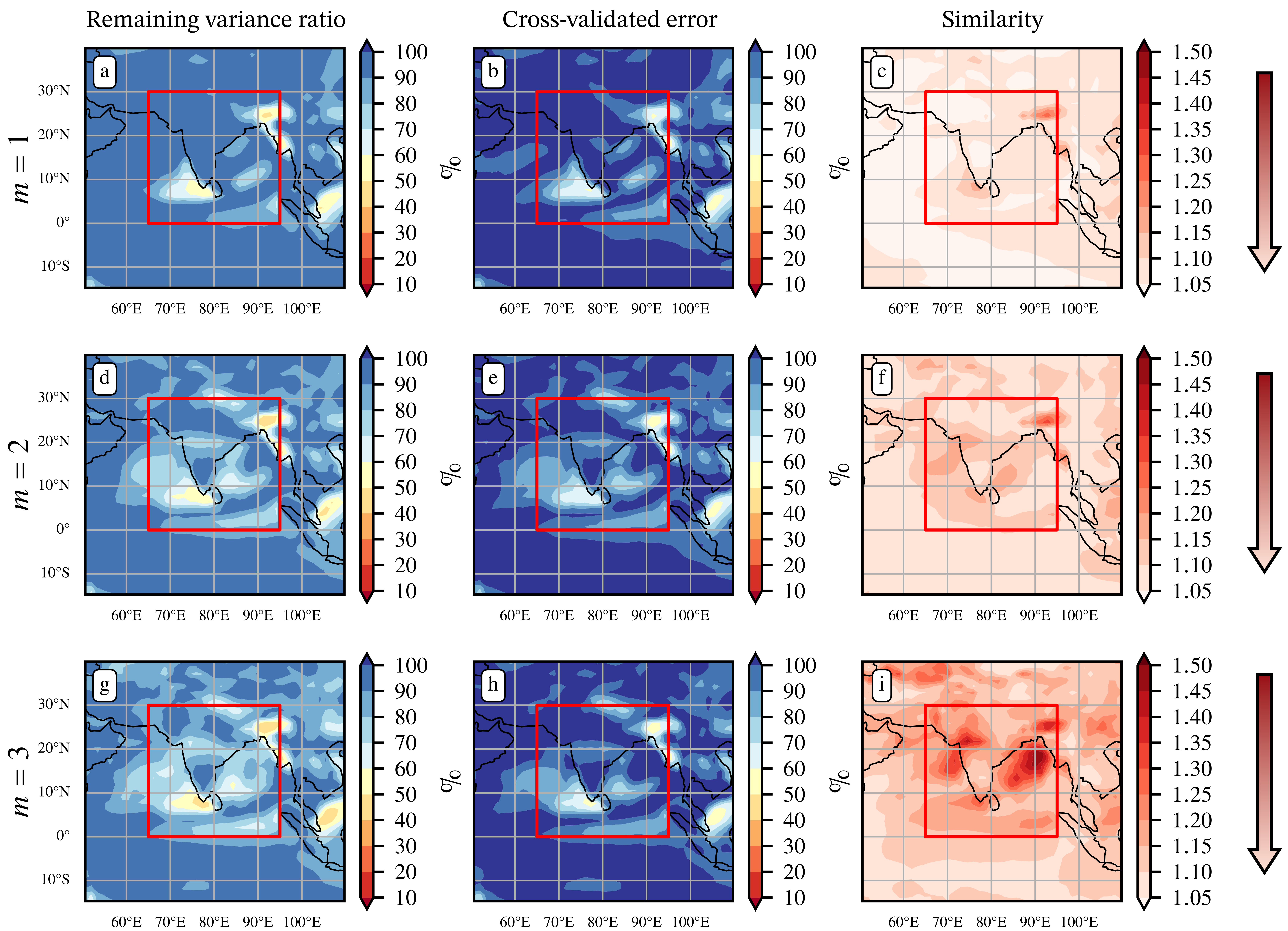
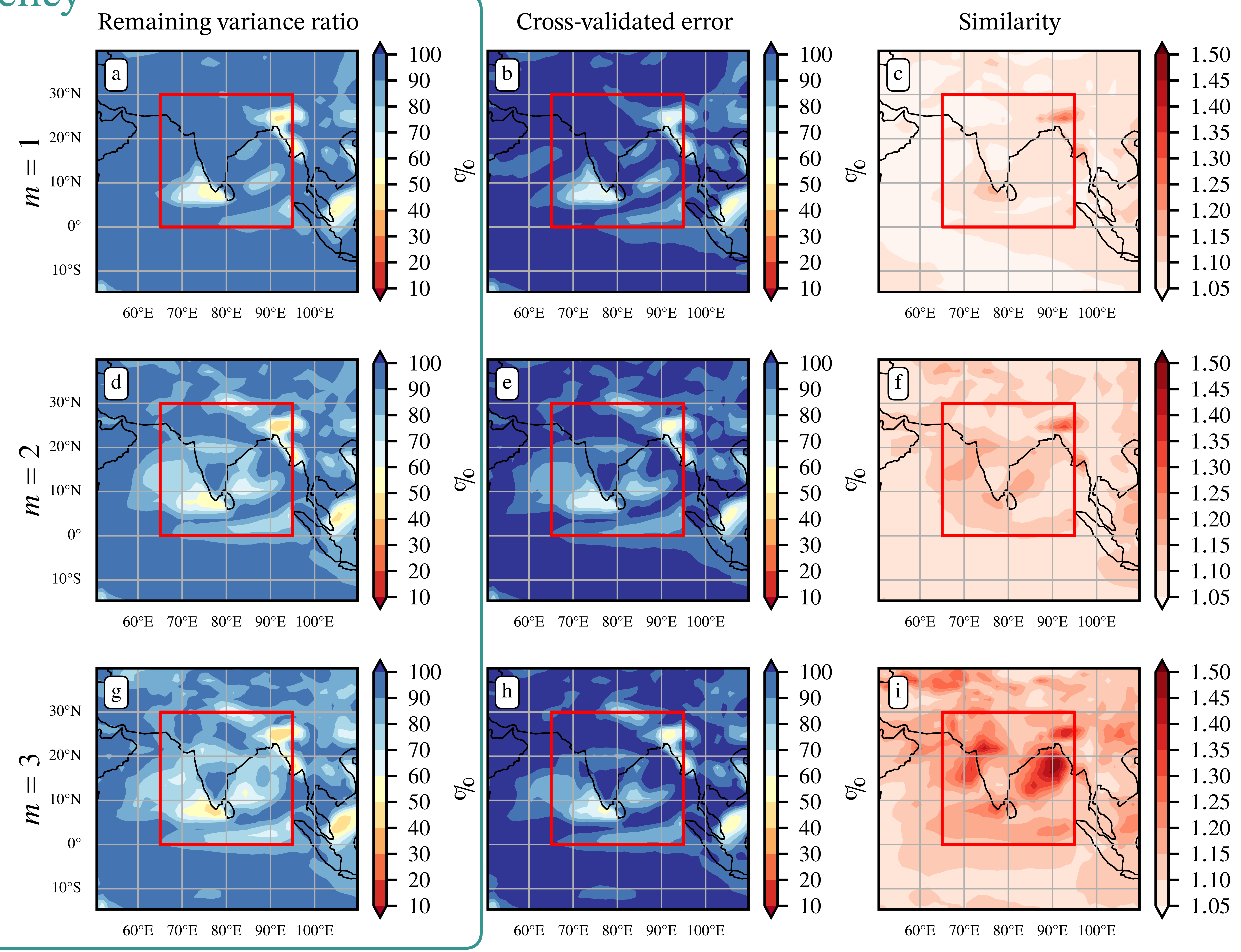


Remaining variance ratio
Cross-validated error
Similarity
m = 1
m = 2
m = 3
a
b
c
d
e
f
g
h
i
%
30°N
20°N
10°N
0°
10°S
60°E 70°E 80°E 90°E 100°E
100 90 80 70 60 50 40 30 20 10
1.50 1.45 1.40 1.35 1.30 1.25 1.20 1.15 1.10 1.05

Efficiency


Remaining variance ratio
Cross-validated error
Similarity
a
b
c
d
e
f
g
h
i
m = 1
m = 2
m = 3
30°N
20°N
10°N
0°
10°S
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%
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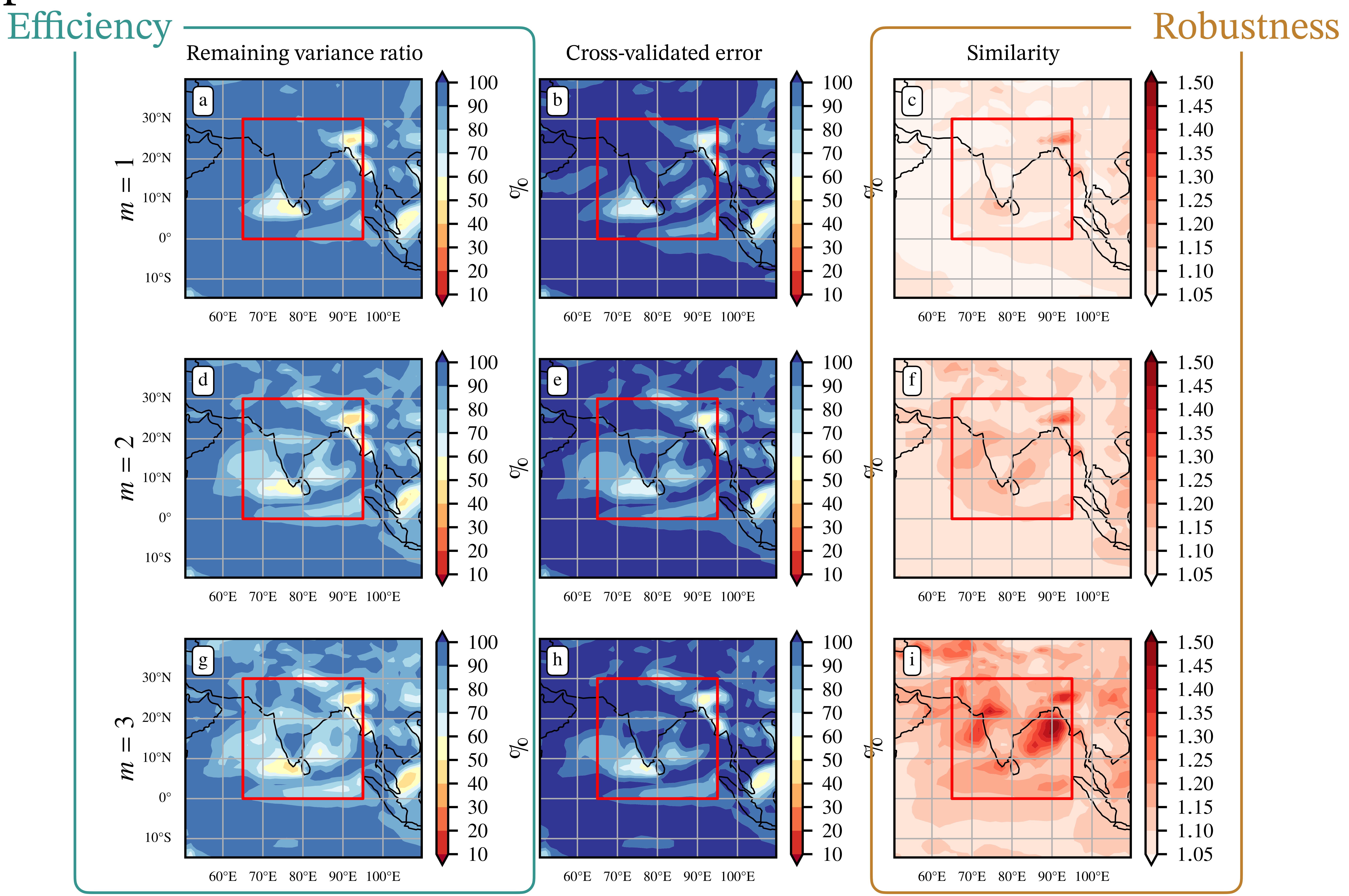
Efficiency
Robustness
Remaining variance ratio
Cross-validated error
Similarity
m = 1
m = 2
m = 3
a
b
c
d
e
f
g
h
i
30°N
20°N
10°N
0°
10°S
60°E 70°E 80°E 90°E 100°E
%
100 90 80 70 60 50 40 30 20 10
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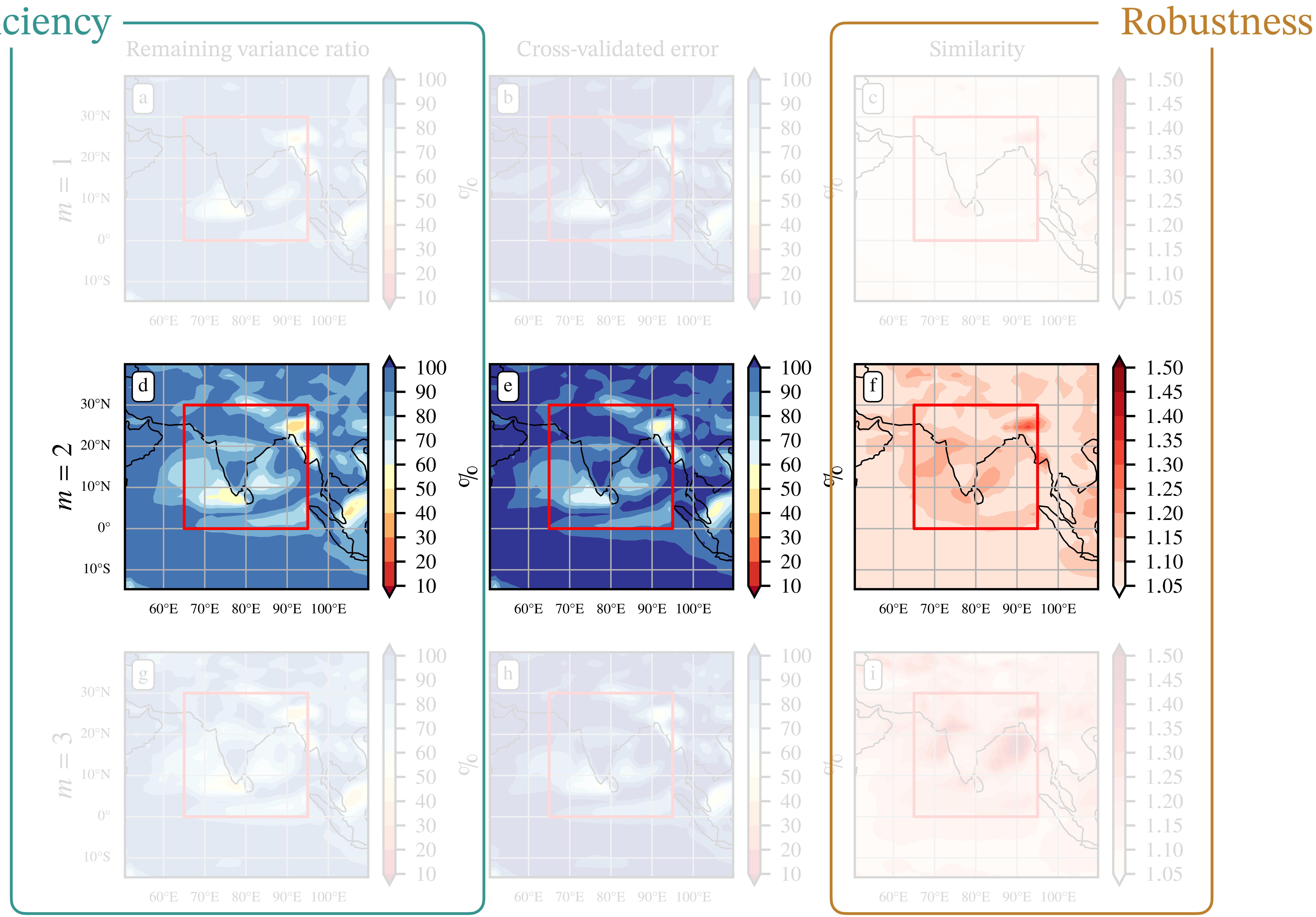
Efficiency
Robustness
Remaining variance ratio
Cross-validated error
Similarity
a
b
c
d
e
f
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h
i
m = 1
m = 2
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10°S
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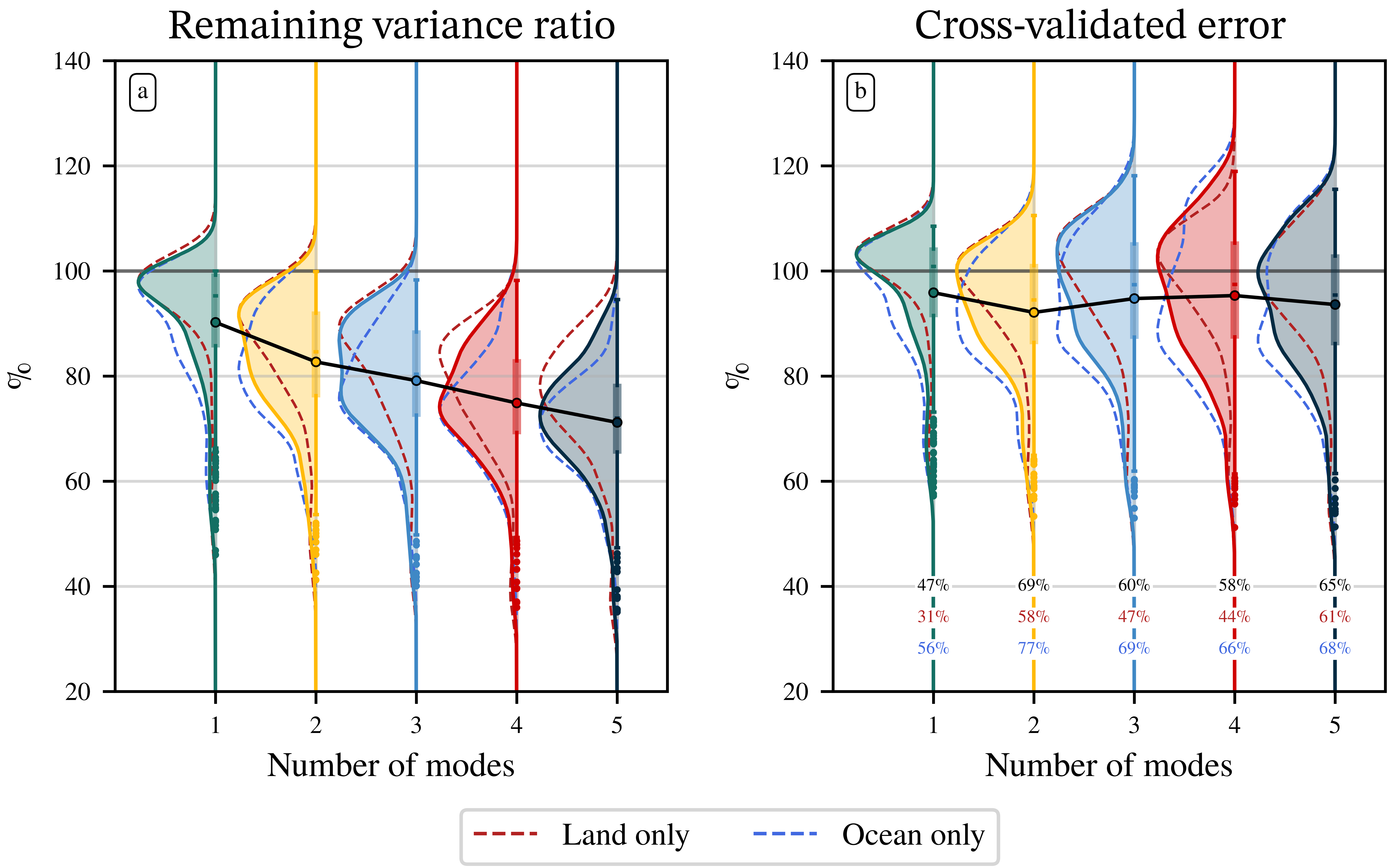

Remaining variance ratio
Cross-validated error
a
b
140
120
100
80
60
40
20
%
1
2
3
4
5
Number of modes
47%
31%
56%
69%
58%
77%
60%
47%
69%
58%
44%
66%
65%
61%
68%
Land only
Ocean only