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Simpler approaches to exploring Climate Projection Uncertainty

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Simple approaches

- Full probabilistic approaches to climate projections are complex, intensive and often computationally expensive endeavours
- We have yet to come to a consensus of the best methodology to be applied, so pragmatic (and often brave) decisions need to be made.
- Simpler approaches can be adopted with existing climate data, that still satisfy the aim of informing climate adaptation that is robust to current uncertainties
- Good current examples of this approach in Australia's Climate Futures and the Netherlands' Climate Projections.



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Example from Australia's Climate Futures program



Australia's Climate Futures

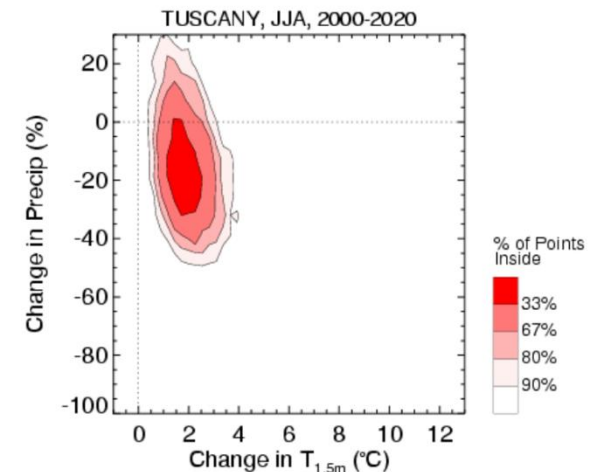
		Annual Surface Temperature (°C)			
		Slightly Warmer < +0.5	Warmer +0.5 to +1.5	Hotter +1.5 to +3.0	Much Hotter > +3.0
Annual Rainfall (%)	Much Wetter > +15.0				
	Wetter +5.0 to +15.0		2 of 30 GCMs +	9 of 30 GCMs 1 of 6 DS +	2 of 30 GCMs +
	Little Change -5.0 to +5.0			12 of 30 GCMs 4 of 6 DS +	3 of 30 GCMs +
	Drier -15.0 to -5.0			2 of 30 GCMs +	
	Much Drier < -15.0				

Source: Australian Climate Futures

Climate Futures uses frequency of GCM projections within different bins, to inform on the spread of future changes.

Individual simulations can then be selected to sample vulnerabilities e.g. A central simulation or a high impact simulation could be chosen from a given bin to drive regional and/or impacts models.

Contrast with the probabilistic approach. Does this provide similar information?



Source: Harris et al, 2013



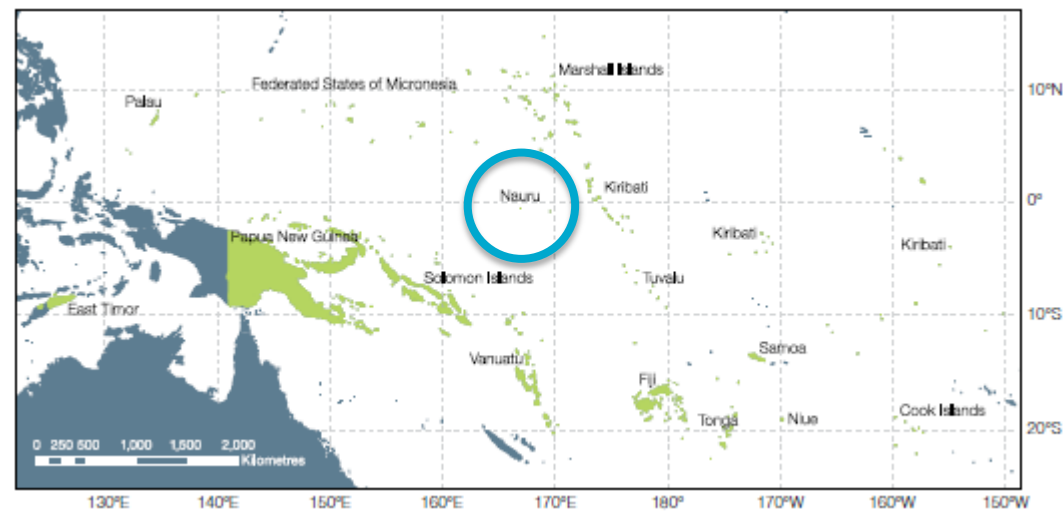
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Example from Pacific Island context

Direct Model Projections

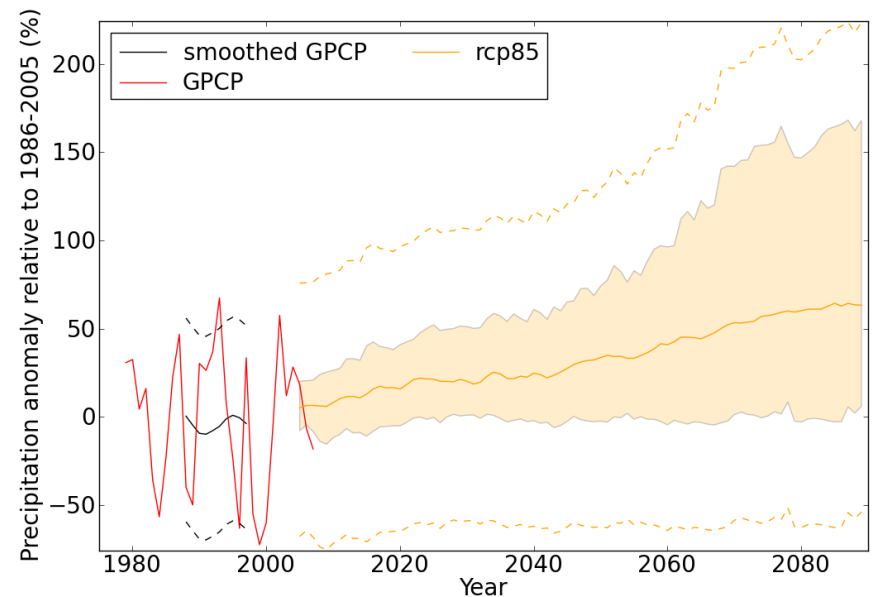
PACCSAP Country Report Update

Annual mean rainfall change 2090: **6% to 168% (RCP8.5) with low confidence.**

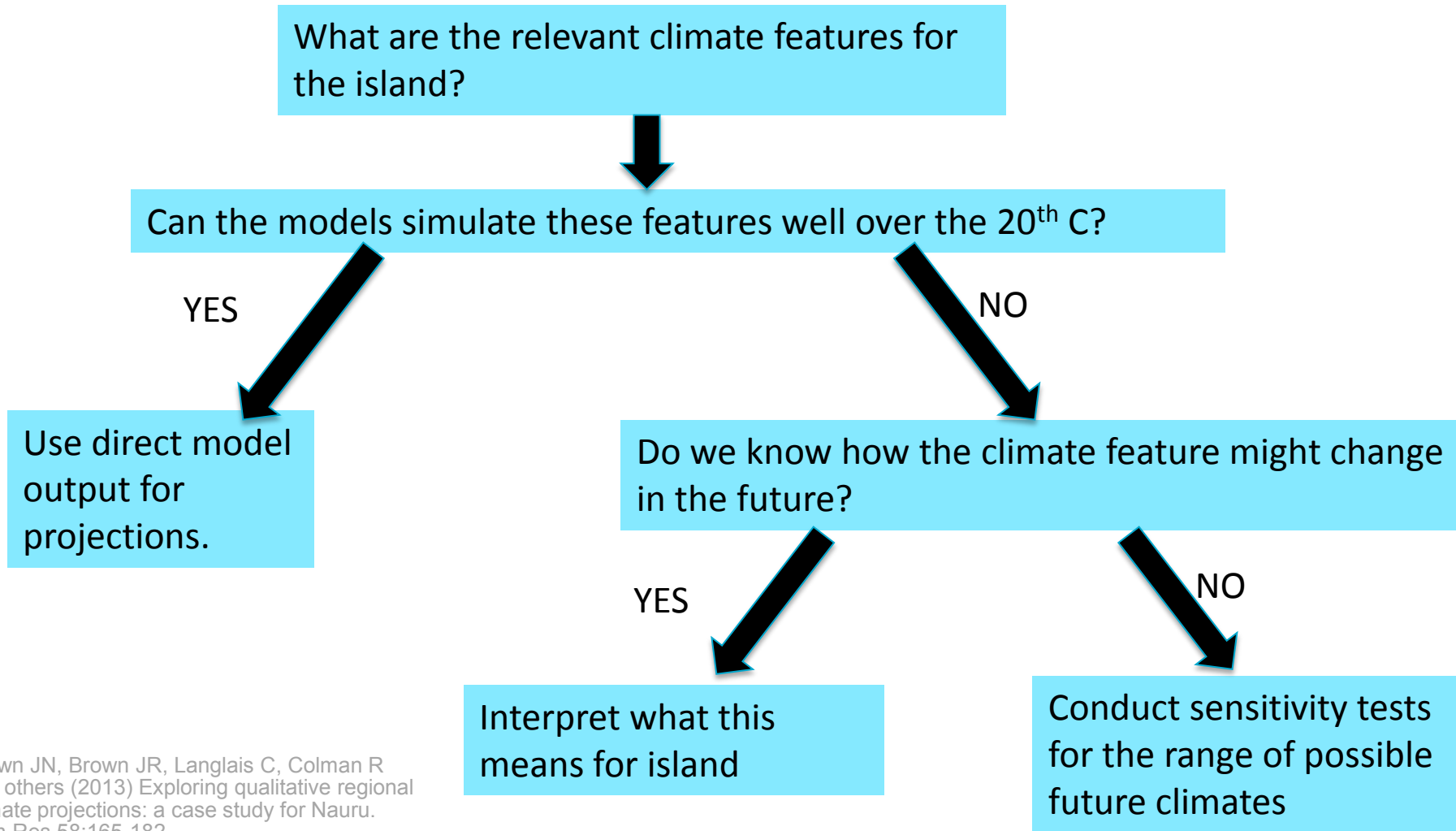


- Doesn't reflect the breadth of understanding we do actually have.
- Some aspects we do have higher confidence in.
- Doesn't indicate where the big unknowns are that need further research

c) Mean Annual Precipitation



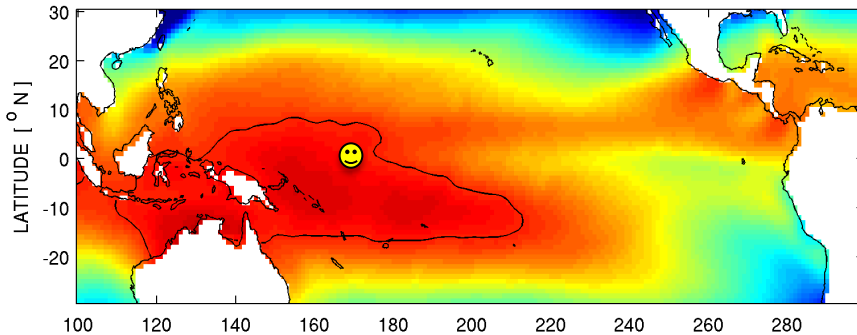
How can we make a robust climate projection?



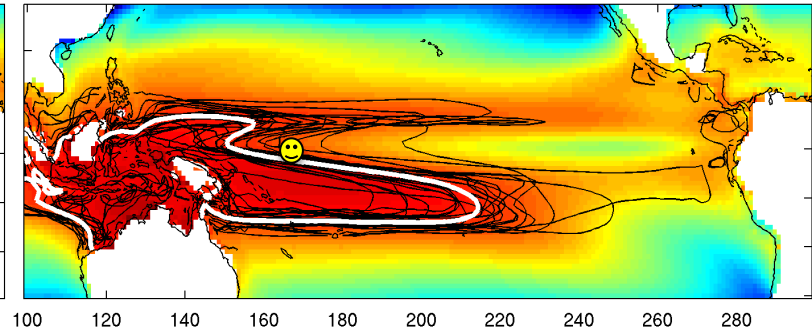
Brown JN, Brown JR, Langlais C, Colman R and others (2013) Exploring qualitative regional climate projections: a case study for Nauru. *Clim Res* 58:165-182

Why projections are difficult at Nauru.

Sea Surface Temperature
Observations

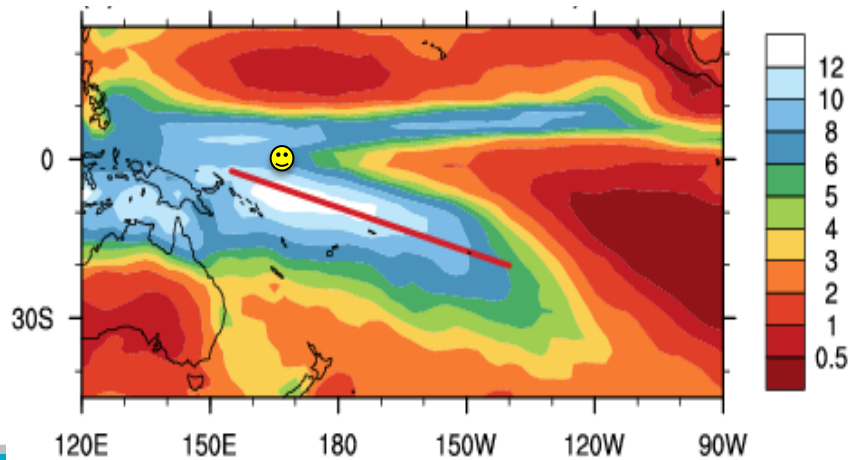


Models

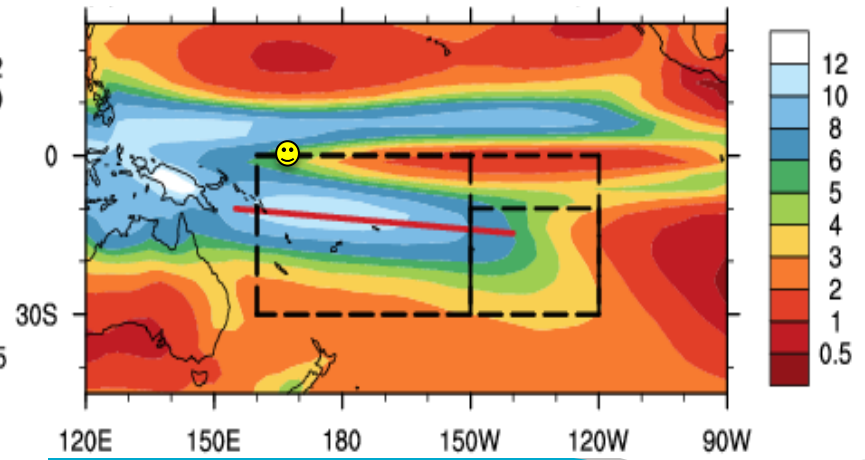


Rainfall

Observations

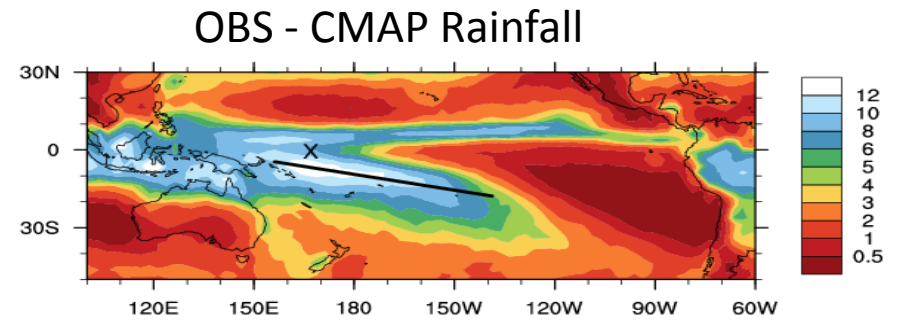


Models

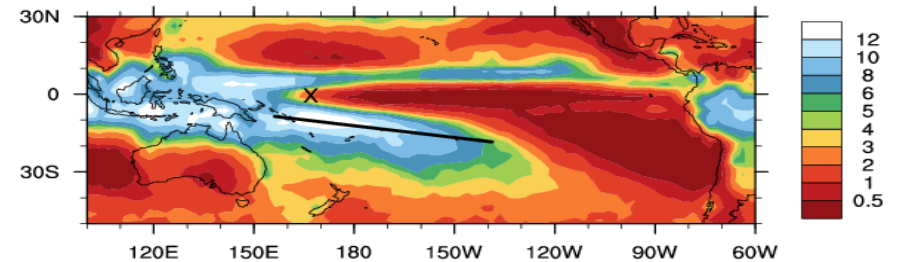


What are the relevant climate features?

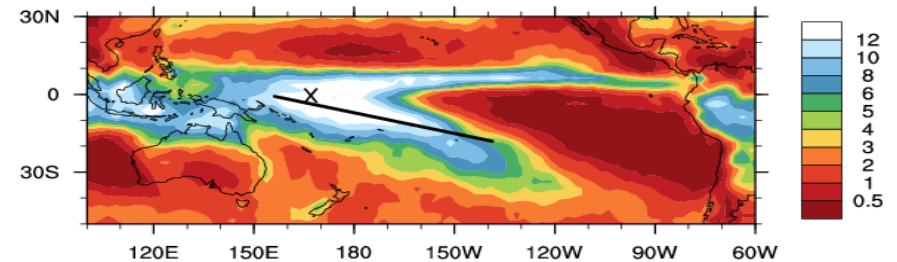
Annual Mean Rainfall



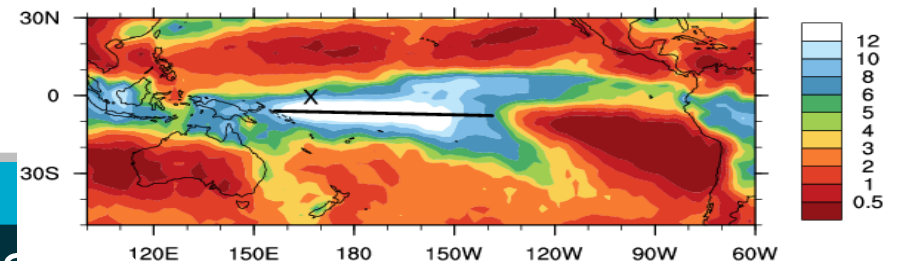
La Nina (dry conditions)



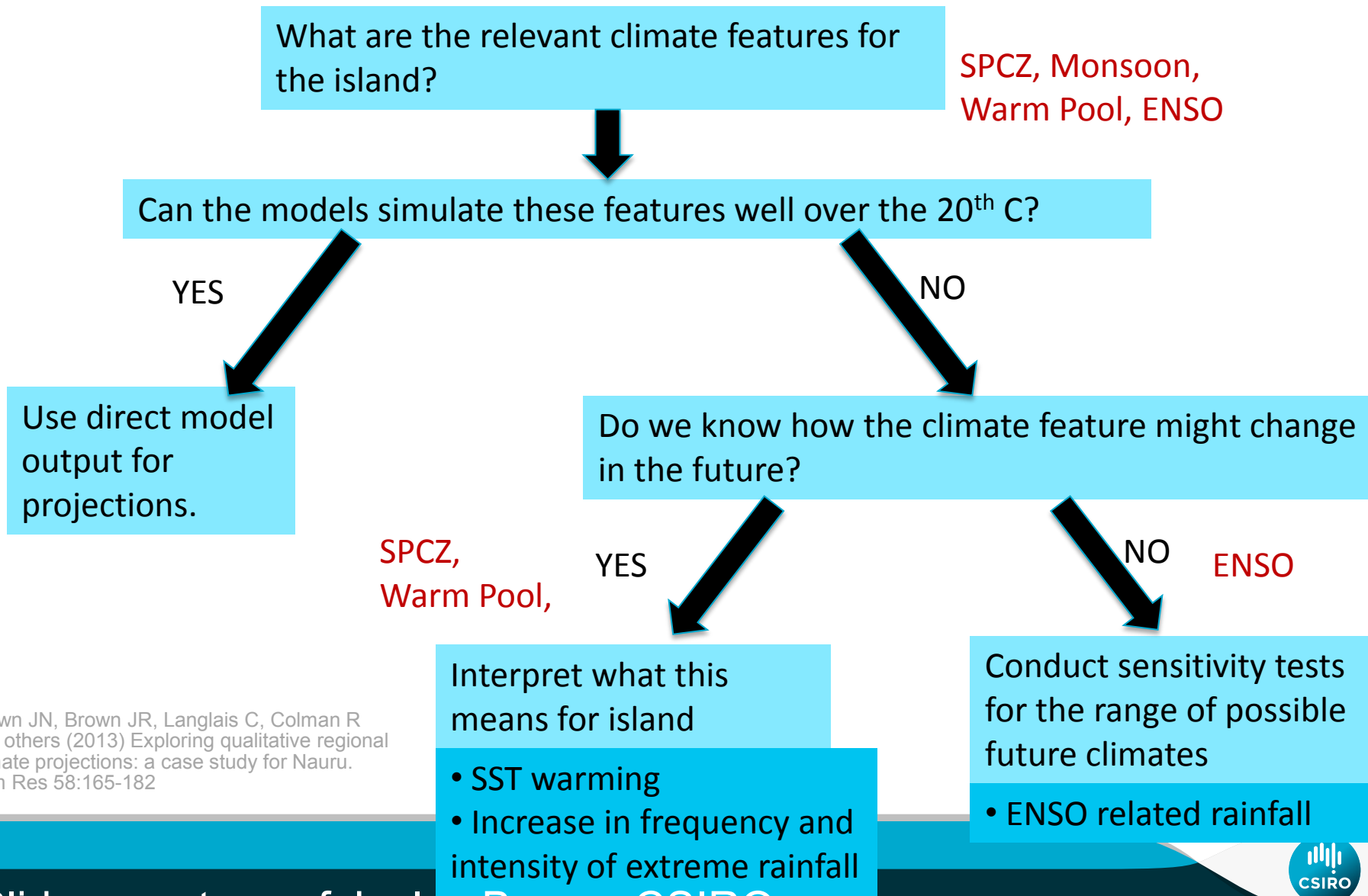
El Nino (wet conditions)



Extreme El Nino (not so wet condntions)



How can we make a robust climate projection?



Brown JN, Brown JR, Langlais C, Colman R and others (2013) Exploring qualitative regional climate projections: a case study for Nauru. *Clim Res* 58:165-182

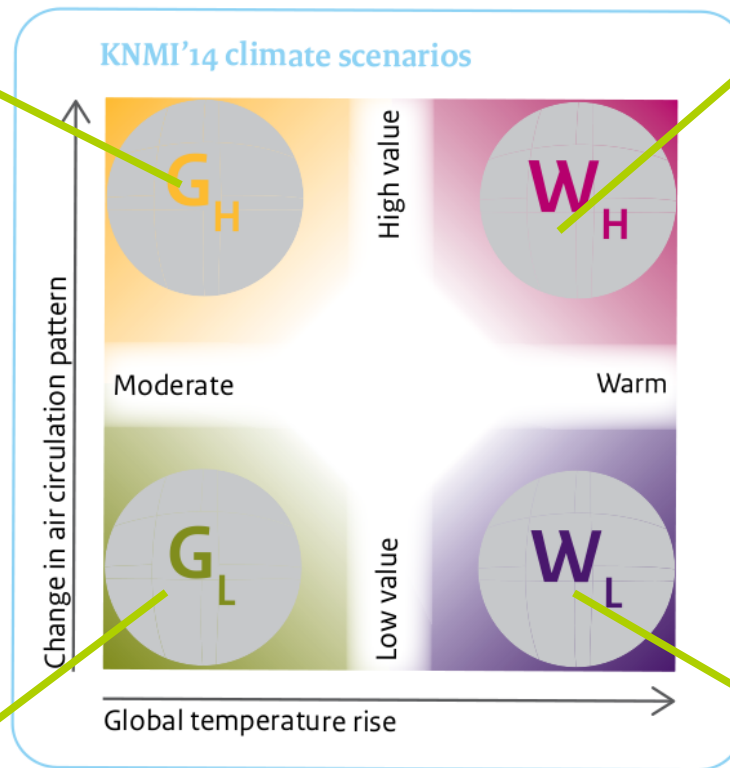


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Netherlands Climate Projections

Netherlands Climate Projections: Selecting Narratives

Central estimate of projected T change + strong circulation change



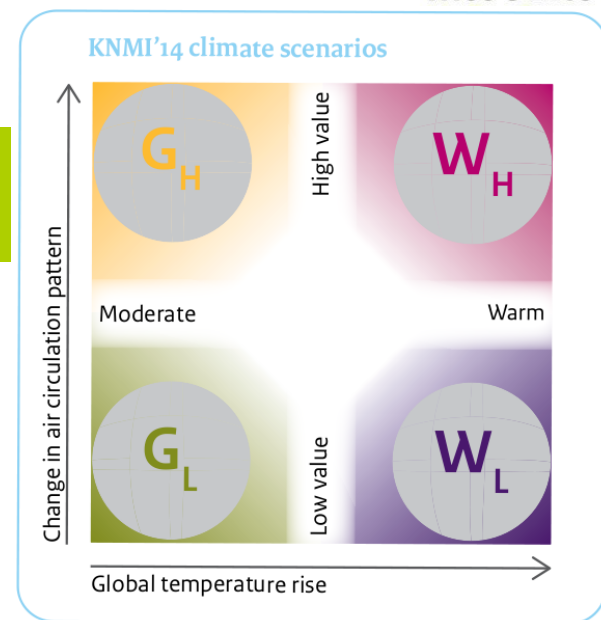
High end estimate of projected T change + strong circulation change

Central estimate of projected T change

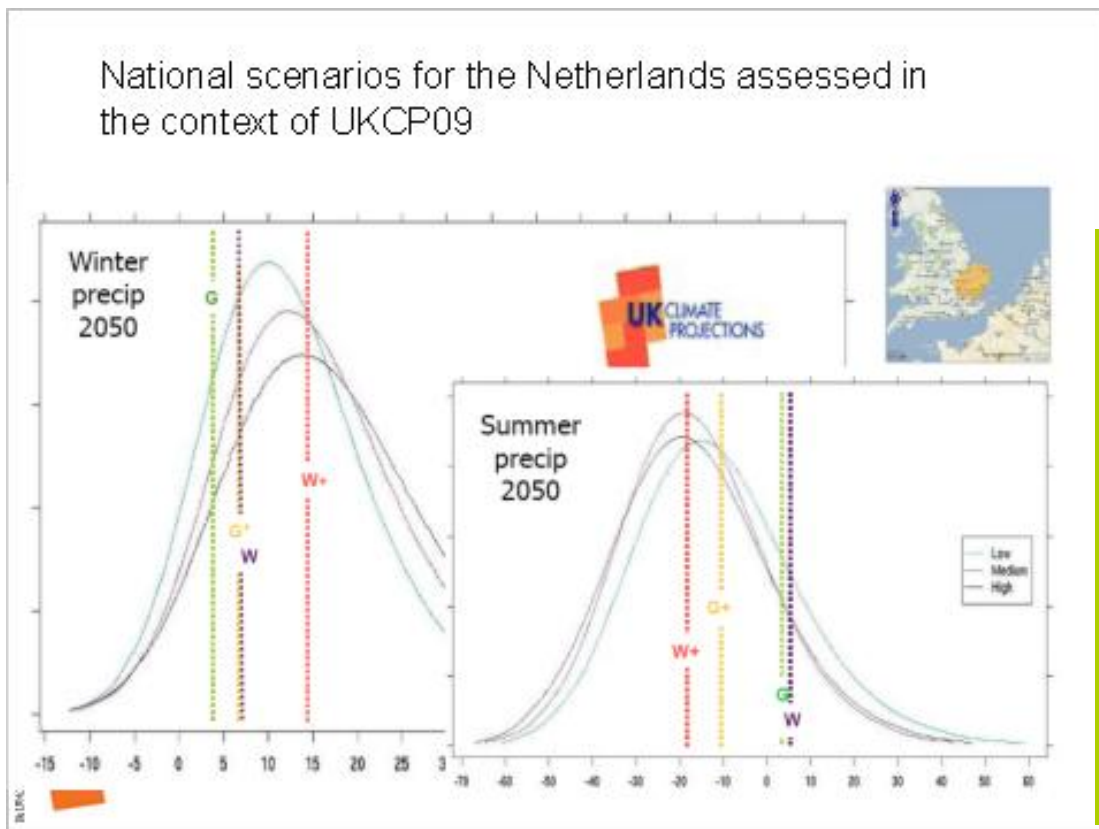
High end estimate of projected T change

UKCP09 compared to Netherlands national climate projections

Four scenarios sampling uncertainty in Netherlands national climate projections



National scenarios for the Netherlands assessed in the context of UKCP09



The Dutch 4 narrative scenarios have been compared with UKCP by applying the Dutch approach to East Anglia in the UK.

Whilst they sample some of the underlying uncertainty, the PDFs suggest that the ranges maybe a conservative estimate.

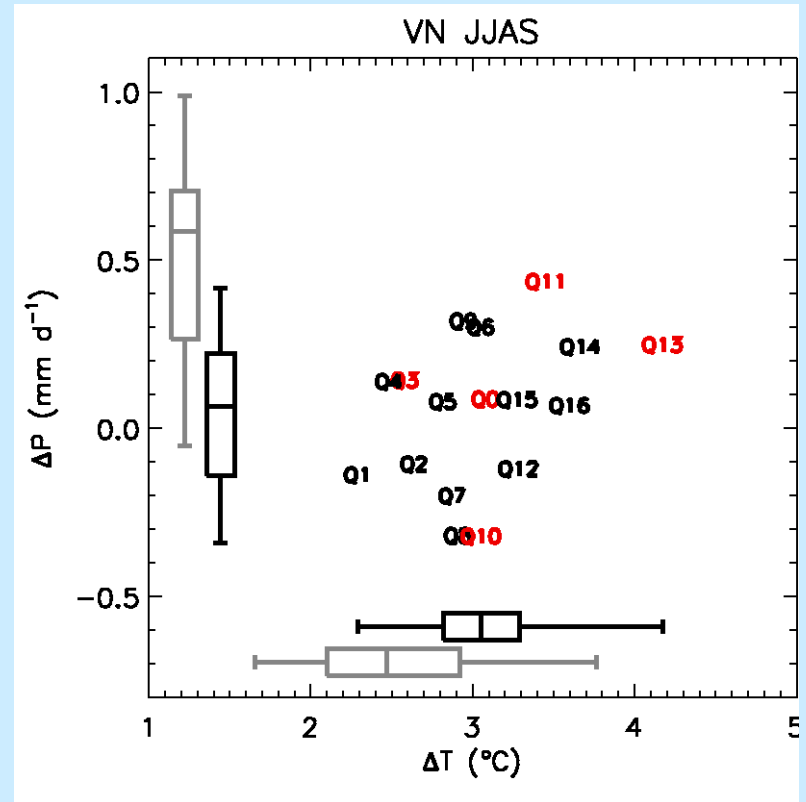


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Selecting from CMIP ensembles to sample plausible future changes

Developing criteria for sub-selection

- 1. Ensure that the sub-set is representative of *range* of future changes
- 2. Should we/can we also make use of information about *how realistic* the different GCMs are to eliminate some models?



Example from *McSweeney et al. 2012* –

Sub-selection from 17 member perturbed physics ensemble for Vietnam

Should information about model performance be used in sub-selection?

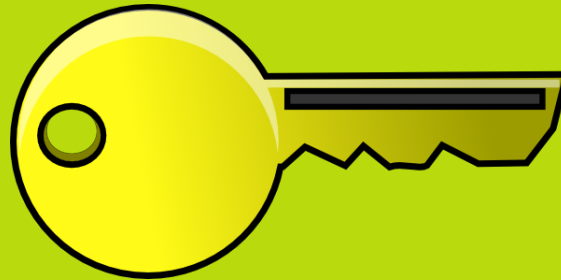


- ‘Horses for courses’ – all models have something wrong!
- Infinite number of potential metrics/thresholds
- Circular reasoning – models calibrated with the same data that they are evaluated against (i.e. tuning leads to convergence)
- Encourages ‘climate model beauty contests’

But...

- At the **regional** scale, it can be easier to identify models that are clearly worse than others
- We often **have** to sub-select (when downscaling or driving impacts models from all simulations is not an option)
- Including a ‘worst’ model in a sub-set gives it a higher relative weight (i.e. is 1/5 rather than 1/30)

Should information about model performance be used in sub-selection?



Can we link aspects of poor performance directly to a model's ability to simulate plausible future climates??
(See guidance by Knutti et al, 2010)

- We often **have** to sub-select (when downscaling or driving impacts models from all simulations is not an option)
- Including a 'worst' model in a sub-set gives it a higher relative weight (i.e. is 1/5 rather than 1/30)



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Examples of using model skill in sub-selecting projections

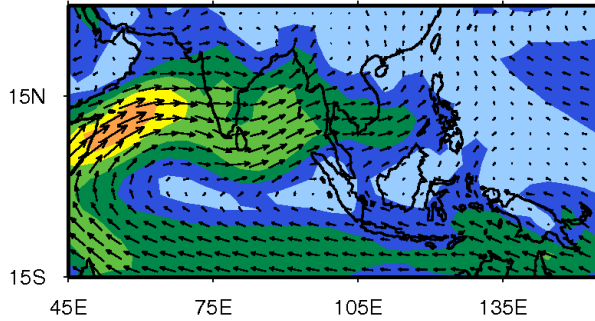
McSweeney, 2014 decision-making framework for elimination

		Model Projections	
		Outlier	Other models predict similar outcomes too.
Model Performance	Significant shortcoming clearly linked to confidence in its projections ('Implausible')	Exclude ✘	Exclude ✘
	Significant shortcomings not clearly linked to confidence in its projections. ('Biases/Significant Biases')	Include ✔	Exclude ✘
	Model performance is satisfactory ('Satisfactory')	Include ✔	Include ✔

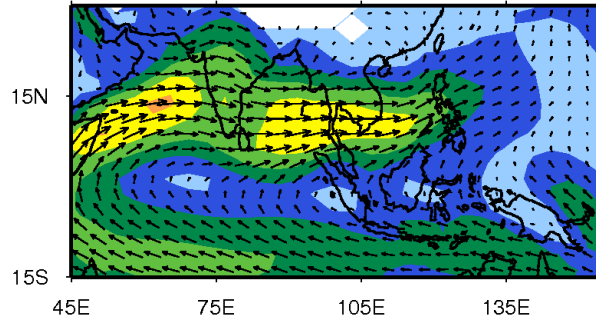


Examples: JJAS Monsoon Circulation ('implausible')

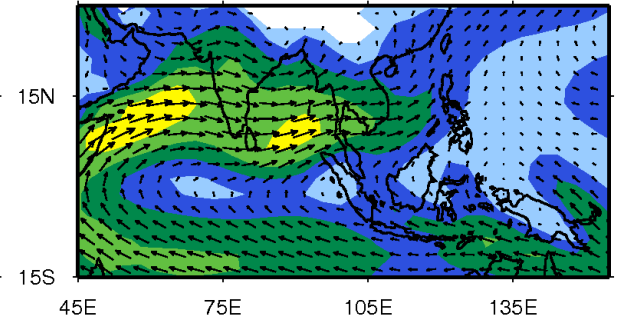
Observed: ERA40 1979-98 JJAS



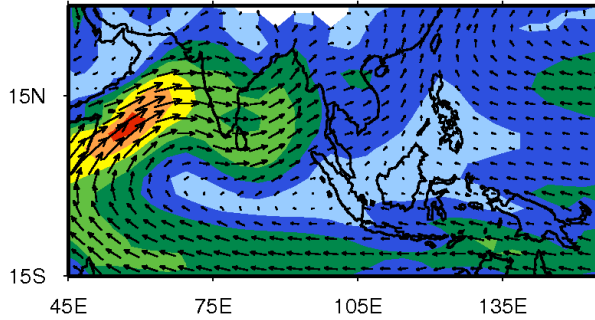
HadGEM2-ES: 1961-90 *



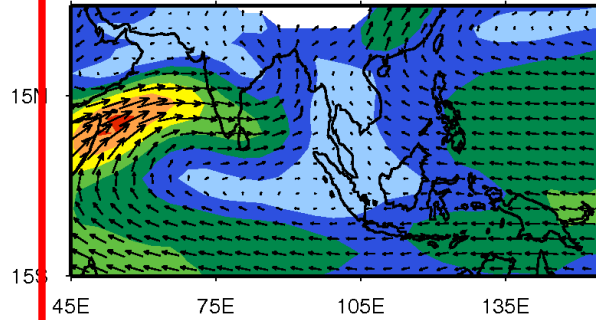
ACCESS1-0: 1961-90 *



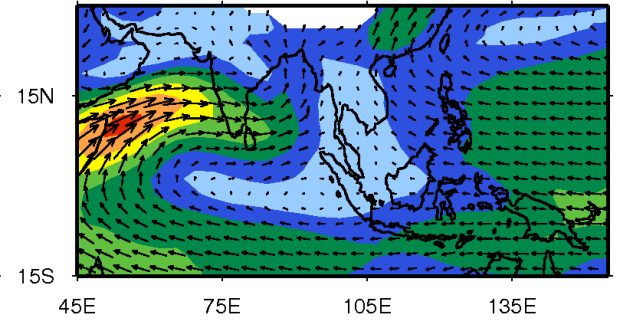
MIROC5: 1961-90 *



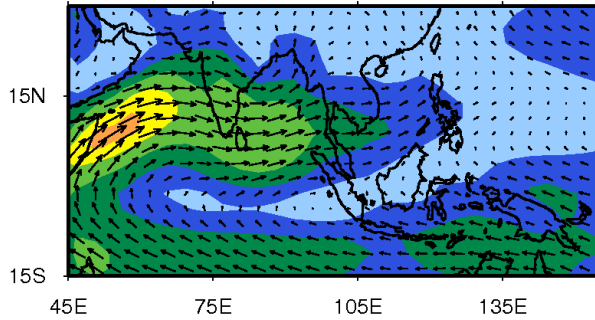
MIROC-ESM: 1961-90 *



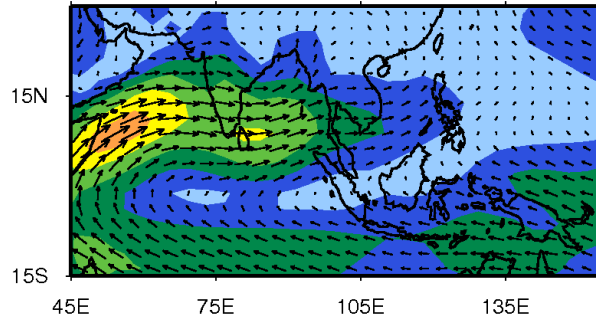
MIROC-ESM-CHEM: 1961-90 *



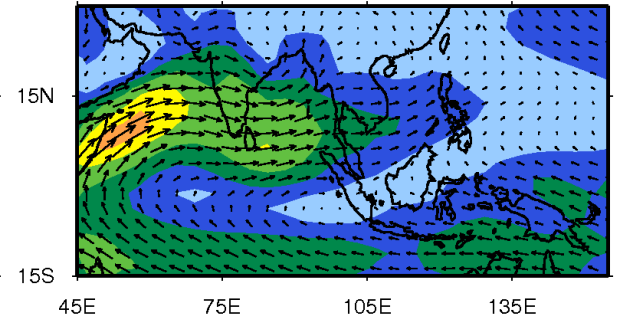
MPI-ESM-LR: 1961-90 *



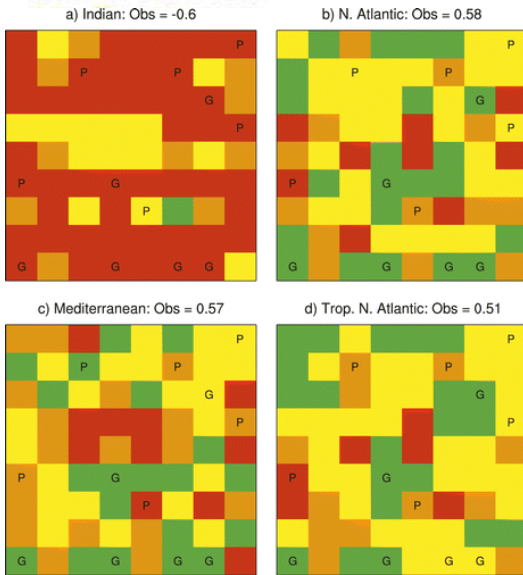
MPI-ESM-MR: 1961-90 *



MPI-ESM-P: 1961-90



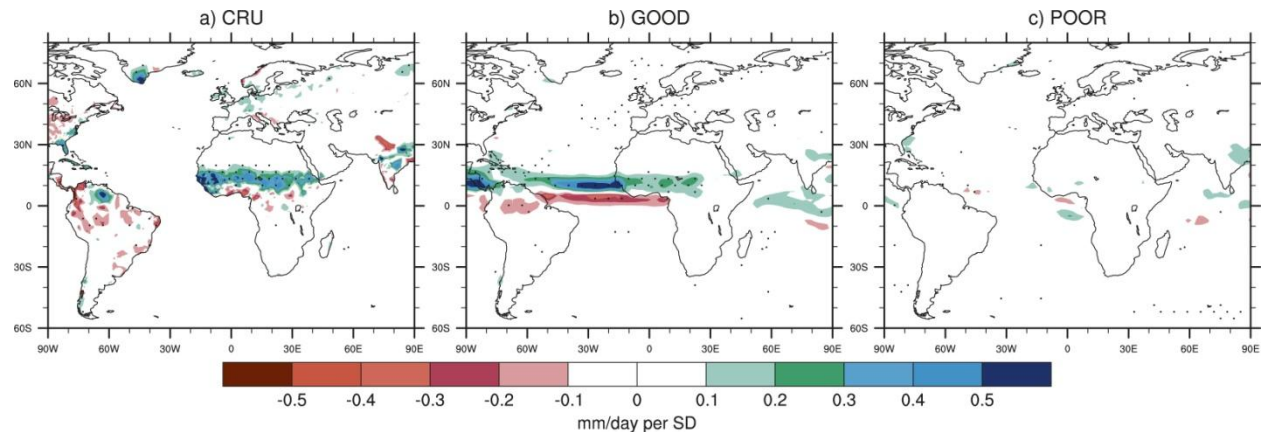
Examples: West African Sahel Rainfall processes (what is 'implausible'?)



Simulated relationships between Sahel rainfall and ocean temperature changes are first assessed in CMIP5 simulations.

2 groups are identified that either do well ("Good") or poorly ("Poor") at reproducing the observed Atlantic correlations with rainfall shifts

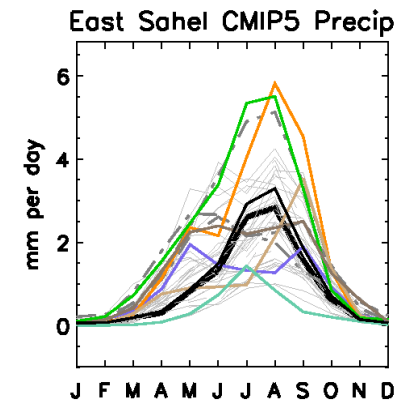
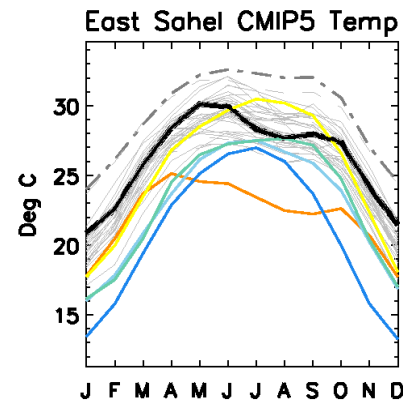
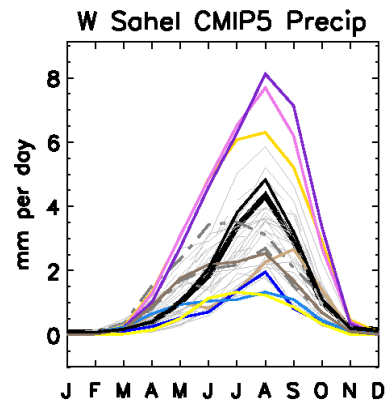
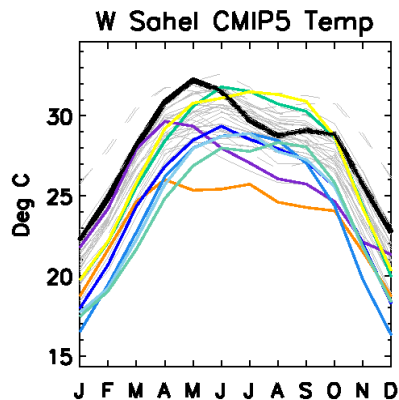
The "Poor" simulations are unable to capture observed changes.



Other examples of poor realism (‘biases’/’significant biases’)

Evidence that models are not representing key processes properly but perhaps not strong enough evidence to rule them out completely?

- e.g. errors in surface variables



McSweeney 2014, sub-selection

Evaluation of large-scale behaviour

Europe:

Circulation

- 850hpa winds
- Storm tracks (Rob Lee, Reading University)

Annual cycles of temperature and rainfall

Africa:

Circulation

850hpa winds – West African Monsoon

SSTs as important driver of rainfall

Annual cycles of temperature and rainfall

Teleconnections (Rowell, 2012)

South East Asia:

Circulation

-Summer and Winter Monsoon flow, 850hpa winds

Annual cycles of temperature and rainfall

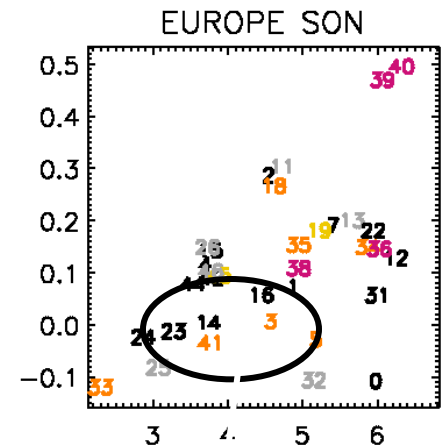
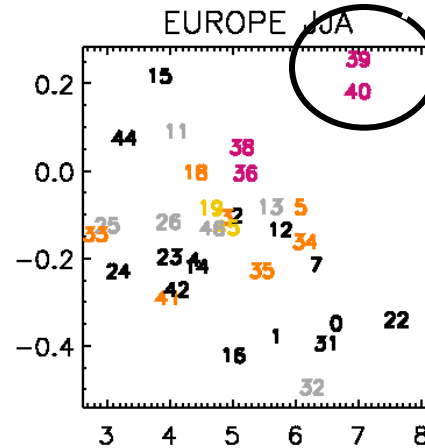
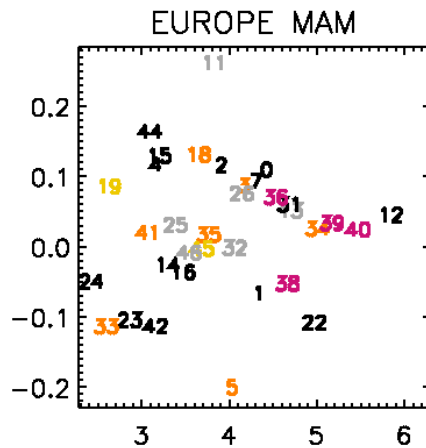
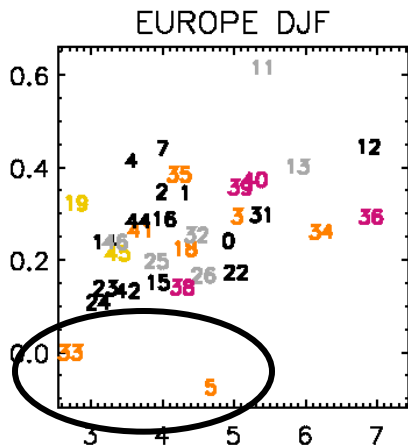
Other aspects of Monsoon behaviour

- indices describing variability, using results from Sperber et al, 2012

3. Applying sub-selection

Complete decision-making matrix

These models are outliers, but we have strong evidence that their projections are **'implausible'** so we eliminate.

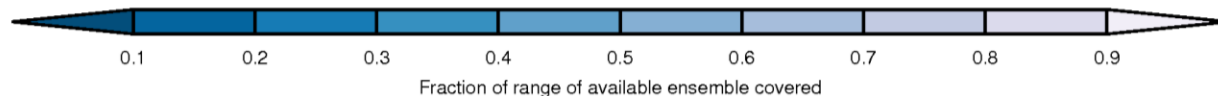
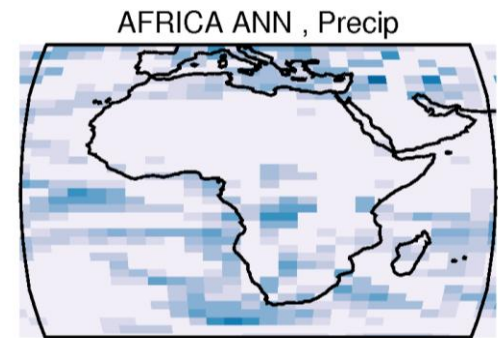
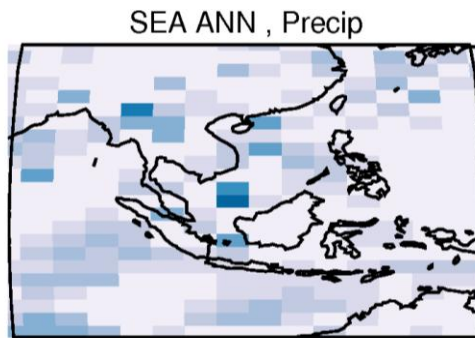
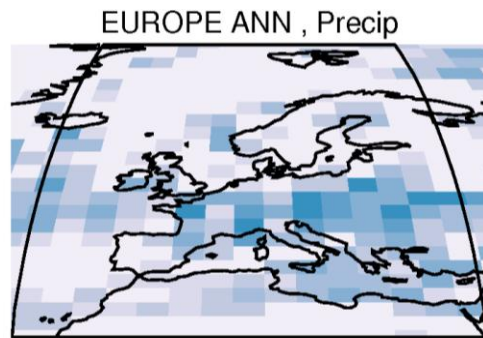
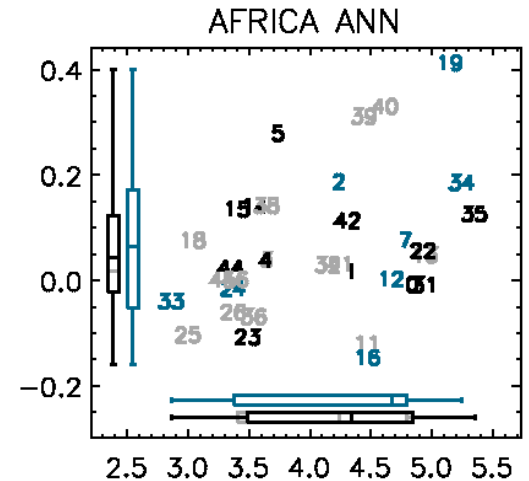
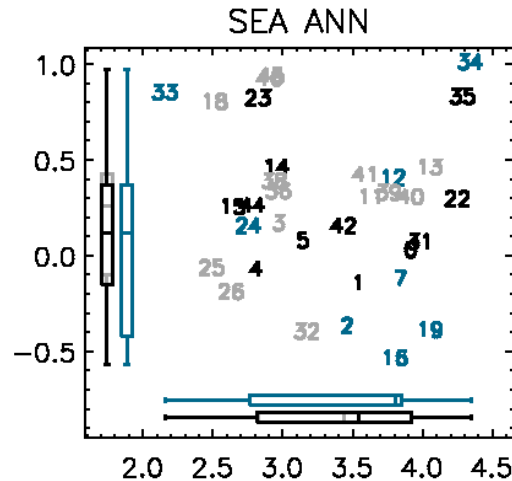
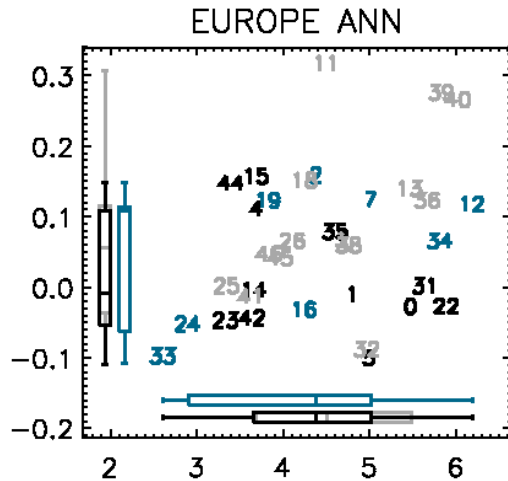


These models are deemed to have **'significant biases'**, but as they are outliers, we include. However, may warrant further investigation.

Other model with **'biases/significant biases'** are not outliers, so we can exclude them without affecting the range of projections.

3. Applying sub-selection

Select from remaining models to span range (8/16)



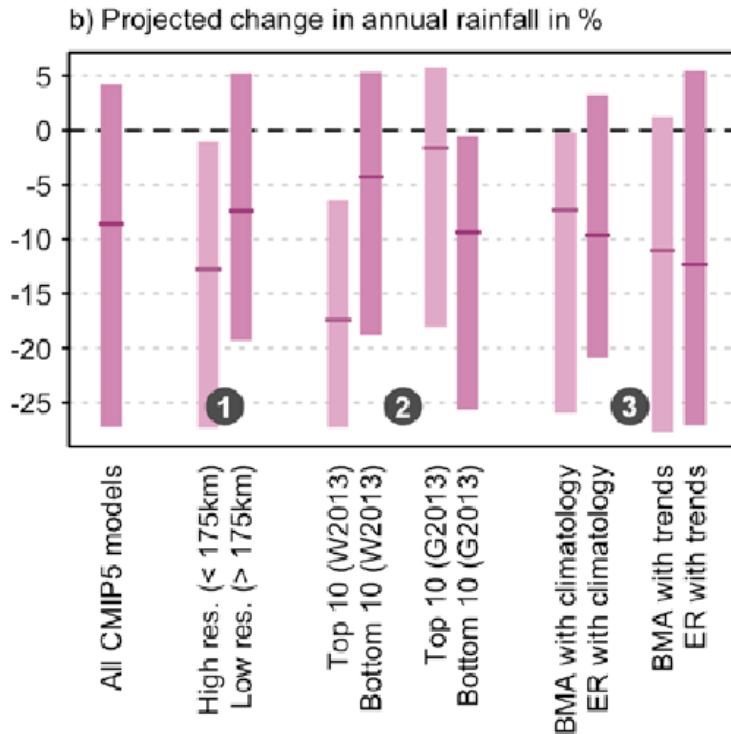
Summary of McSweeney, 2014 method

Strategic sub-selection approaches can be useful when in order to represent GCM uncertainty in regional projections a meaningful way (examples given on downscaling from CMIP5) McSweeney. 2014 approach makes use of available information about model performance in the regions of interest to ‘avoid’ poorer models whilst maximizing the range of future projections included across seasons, variables and regions

Where baseline is clearly too unrealistic for a model to give plausible projections we can eliminate with confidence.

Where realism is poor, but not clearly linked to ability to give realistic projections, whether we include or exclude depends on position in ensemble (i.e. is it an outlier?)

Caution: Multiple lines of evidence may not always agree.



10 models that best represent the average rainfall, surface temperature and mean sea level pressure in Australia (Watterson et al. 2013a) indicate stronger drying for southern Australia, whereas the 10 models that best represent important modes of circulation variability in the southern hemisphere (Grainger et al. 2013, 2014) indicate less drying

Source: CLIMATE CHANGE IN AUSTRALIA, Chapter 6

Summary

- The two McSweeney et al, papers represent a good introduction to applying this simpler approaches.
- Both Australian and Dutch Climate Projections selected climate projections from climate simulations considered “good” based on evaluation against observed climate.
- Requires knowledge and expertise in understanding the key processes (that are linked to projected future changes) in particular countries and regions.
- These National Climate Projections represents simpler, non-probabilistic approaches that do address current needs to inform climate decisions so that they are robust to some of the current uncertainties in climate projections.

Questions and discussion

Key References:

KNMI (2014): KNMI'14: Climate Change scenarios for the 21st Century – A Netherlands perspective; by Bart van den Hurk, et al. Scientific Report WR2014-01, KNMI, De Bilt, The Netherlands. www.climatescenarios.nl

Australian Climate Futures <http://www.climatechangeinaustralia.gov.au/en/>

Brown JN, Brown JR, Langlais C, Colman R and others (2013) Exploring qualitative regional climate projections: a case study for Nauru. *Clim Res* 58:165-182

McSweeney, C. F., Jones, R. G., Lee, R. W., & Rowell, D. P. (2014). Selecting CMIP5 GCMs for downscaling over multiple regions. *Climate Dynamics*, 44(11-12), 3237-3260.

McSweeney, CF, RG Jones, and BBB Booth, 2012: Selecting Ensemble Members to Provide Regional Climate Change Information. *Journal of Climate*, 25, 7100-7121.

Martin, E. R., Thorncroft, C., & Booth, B. B. (2014). The multidecadal Atlantic SST—Sahel rainfall teleconnection in CMIP5 simulations. *Journal of Climate*, 27(2), 784-806.