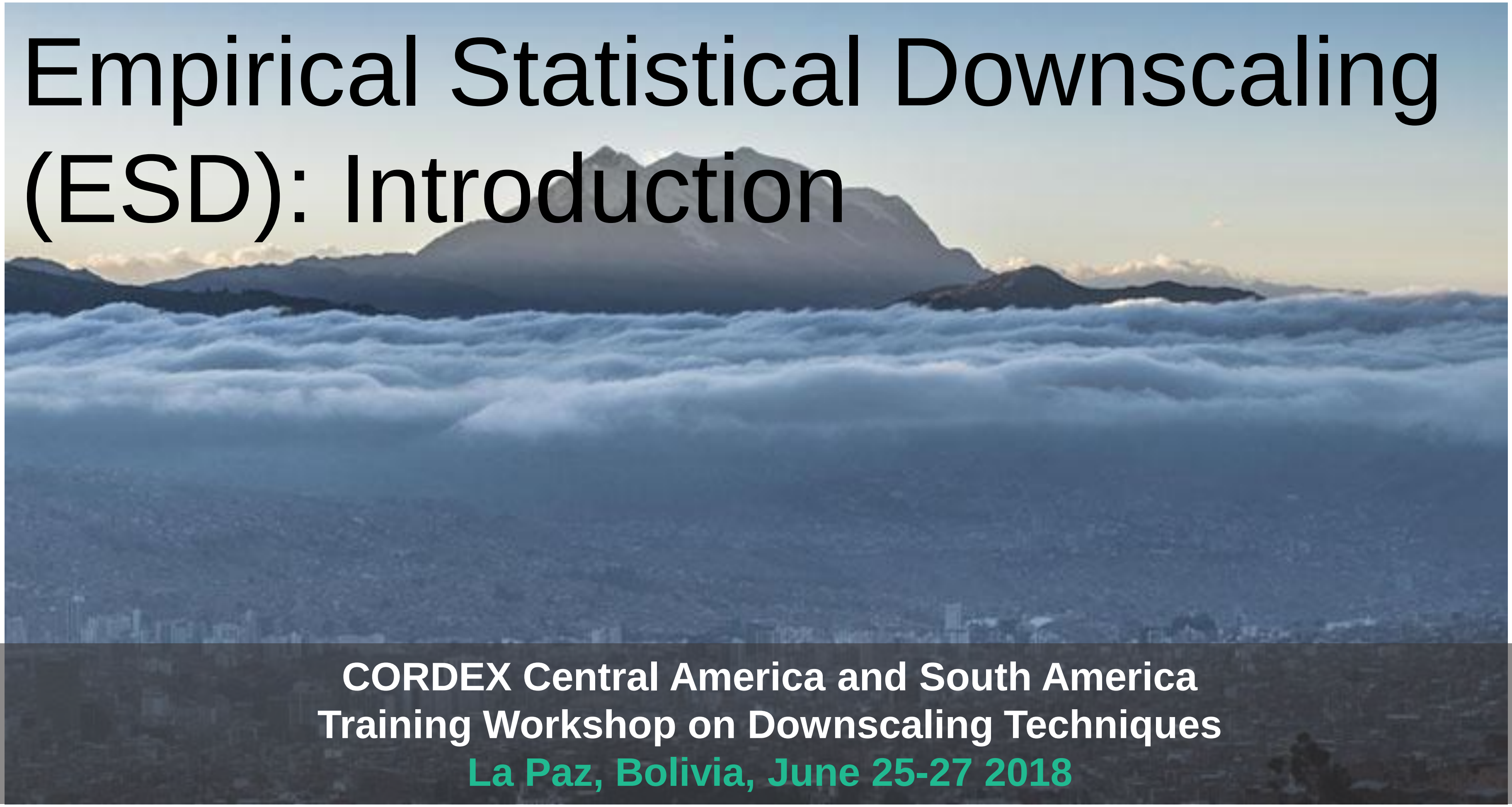
Empirical Statistical Downscaling (ESD): Introduction



CORDEX Central America and South America
Training Workshop on Downscaling Techniques
La Paz, Bolivia, June 25-27 2018

Why Downscaling?

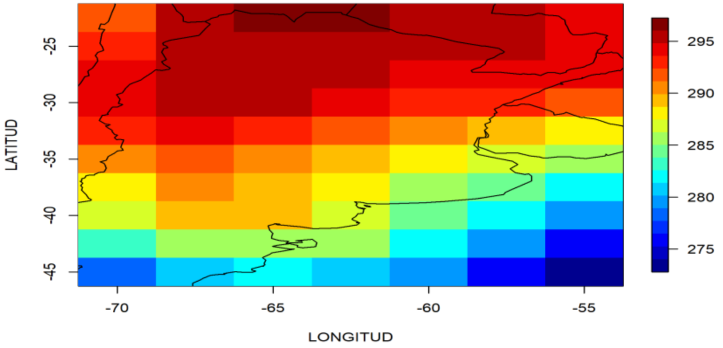
GCMs	• Global Climate Models (GCMs) are designed to describe large-scale climate characteristics and the potential evolution of the future climate
Global Climate	• The global climate is to a great extent the response to the differential solar forcing, the earth rotation, and the large-scale structure of the earth's surface (land–sea distribution, topography).
Regional Climate	• The regional climates, on the other hand, are the response of the global climate to regional details.

Zorita & Von Storch, 1999

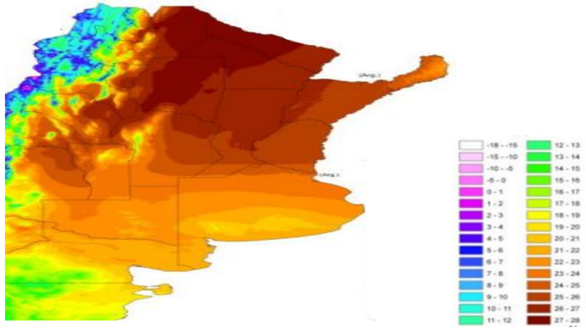
Why Downscaling?

Daily Mean Temperature

GCM output



Observations



Therefore, it seems reasonable that GCMs are able to simulate the global climate adequately even though the regional climates are not skillfully simulated.

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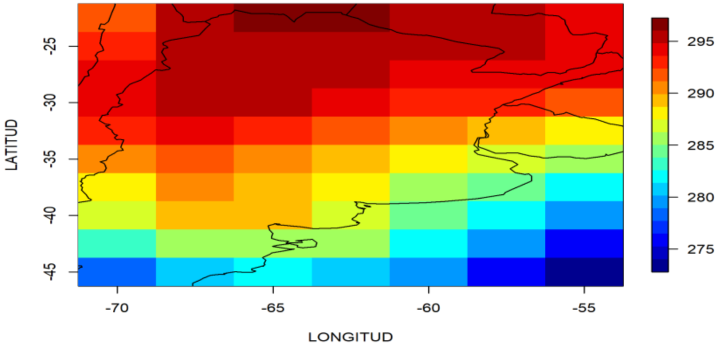

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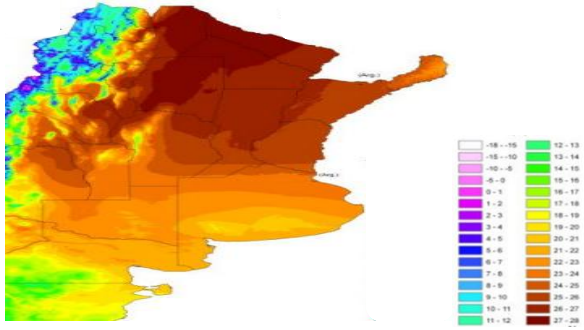

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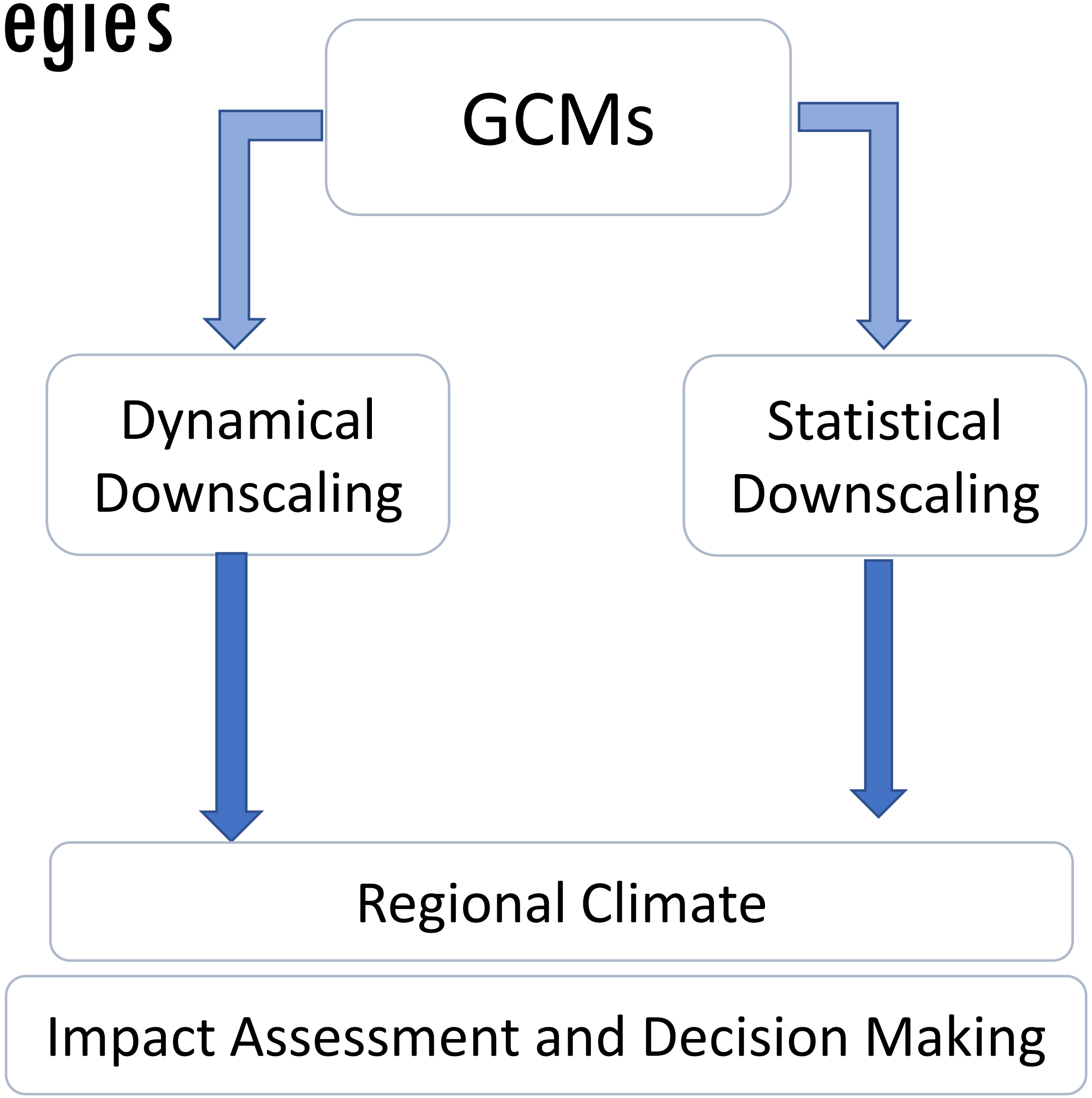
DOWNSCALING

Relates the large-scale information provided by GCMs to the regional-scale climate information needed to assess impacts and decision-making.

Downscaling Strategies



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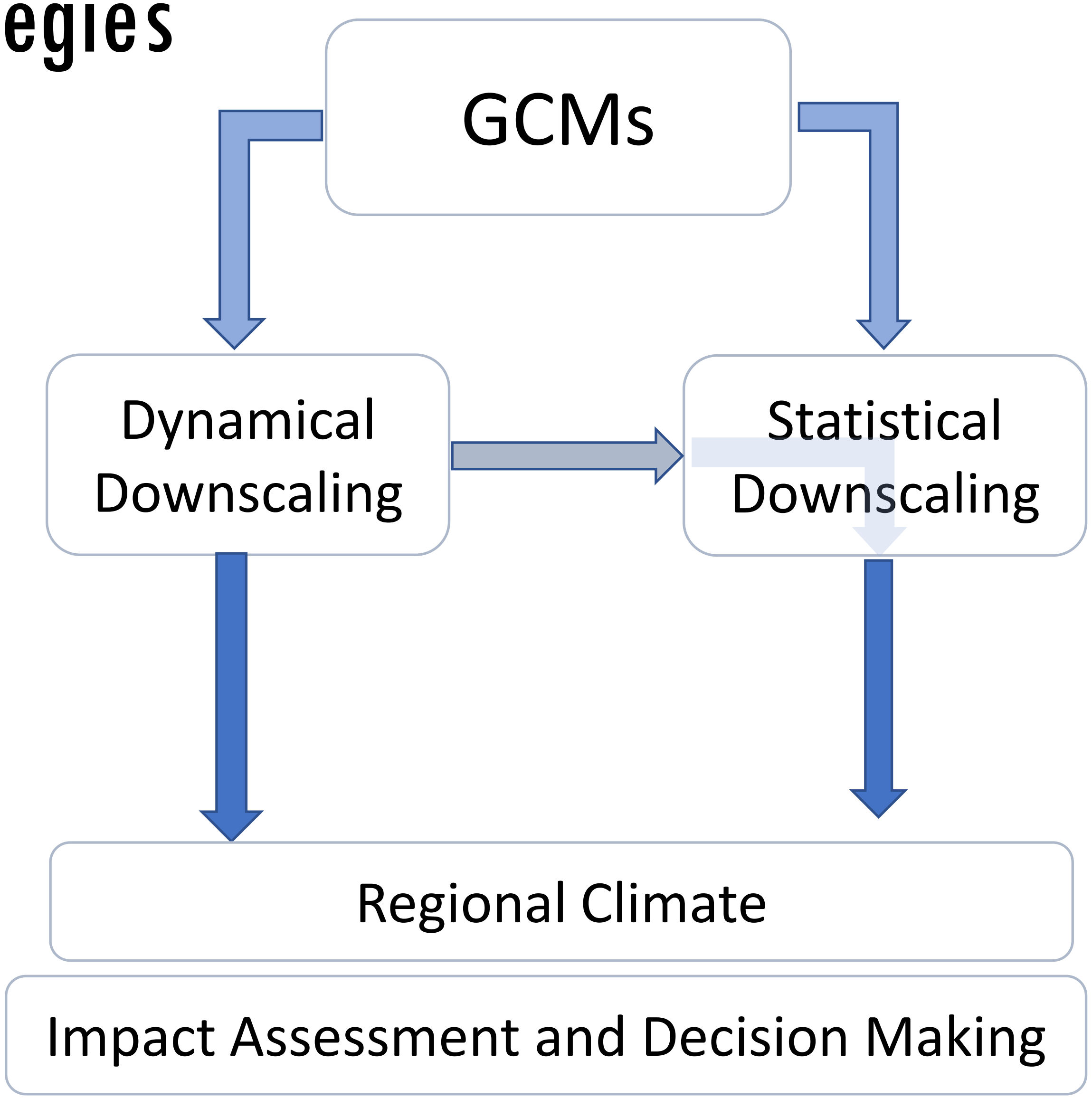
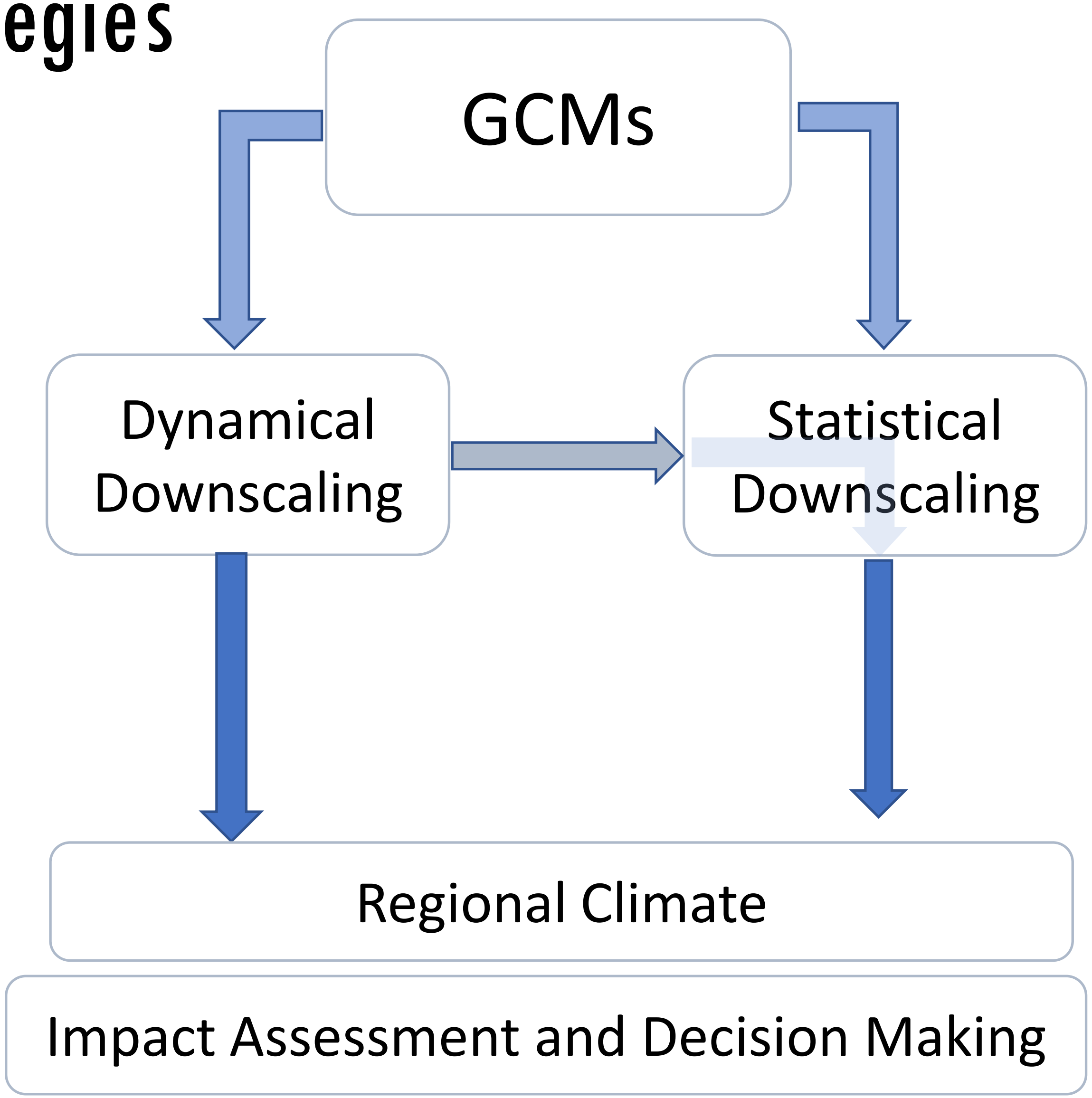


Downscaling Strategies

Based on regional climate models (RCMs) : simulate regional climate processes using GCM fields as boundary conditions.



Based on empirical-statistical relationships between large-scale atmospheric variables provided by GCMs/RCMs and local variables.

Advantages and Disadvantages

Advantages

ESD

- Station-scale climate information from GCM-scale output.
- Cheap, computationally undemanding and readily transferable.
- Can be applied to a large ensembles of climate scenarios that permit risk/uncertainty analyses.
- Applicable to “exotic” predictands (such as air quality)

RCM

- 10-50 km resolution climate information from GCM-scale output.
- Respond in physically consistent ways to different external forcings.
- Resolve atmospheric processes such as orographic precipitation.
- Consistency with GCM.

Wilby & Fowler, 2010

Advantages and Disadvantages

Disadvantages

ESD

- Dependent on the realism of GCM boundary forcing.
- Choice of domain size and location affects results.
- Requires high quality data for model calibration.
- Predictor-predictand relationships are often non-stationary.

RCM

- Dependent on the realism of GCM boundary forcing.
- Choice of domain size and location affects results.
- Require significant computing resources.
- Ensembles of climate scenarios seldom produced.

Wilby & Fowler, 2010

Advantages and Disadvantages

Disadvantages

ESD

- Choice of predictor variables affects results.
- Choice of empirical transfer scheme affects results.
- Low-frequency climate variability problematic.
- Always applied offline, therefore results do not feed back into the host GCM.

RCM

- Initial boundary conditions affect results.
- Choice of cloud/convection scheme affects results.
- Not readily transferred to new regions or domains.
- Typically applied offline, therefore results do not always feed back into the host GCM.

Wilby & Fowler, 2010

Note that ..

All downscaling strategies use GCM output as input. Therefore downscaling is fully dependent on the skill of the GCM.

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Downscaling relationships should remain valid under future climates.

All downscaling is heavily dependent on adequate observational data:

- For ESD data are needed to develop the downscaling relationships.
- For RCM observational data are used to develop the model's parameterizations.
- In all cases, observations are required to evaluate method performance.

Comparative Studies on Downscaling Strategies

Comparative studies between RCM and ESD simulations suggest that both approaches show comparable skills to represent regional climate characteristics, adding value to GCM simulations.

ESD methods have been widely validated and compared for local climate modelling in different regions across the globe identifying their strengths and weaknesses in each case.

Different international initiatives have also contributed to the intercomparison of methods, such as the STARDEX project (Statistical and Regional dynamical Downscaling of Extremes for European regions) or VALUE: COST Action (Validating and Integrating Downscaling Methods for Climate Change Research).

Comparative Studies on Downscaling Strategies

In spite of this, in the CAM and SAM regions the ESD potential to simulate regional climate characteristics has not been explored as thoroughly or systematically as in other parts of the world.

In addition, coordinated studies between RCM and ESD simulations exploring their strengths and weaknesses have not been performed exhaustively in the CAM and SAM regions.

These are some of the reasons of why we are here …

ESD Methods

There is a variety of ESD methods that can be explored. These methods can be classified according to different criteria, depending on their approach, implementation and application.

ESD Techniques

ESD methods can be classified according the type of the Statistical Technique

Transfer Functions
Based on linear or nonlinear regression models

Analogs and Weather Typing

Weather Generators

Wilby et al., 2004; Wilby & Fowler, 2010

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These techniques can be combined!

Wilby et al., 2004; Wilby & Fowler, 2010

ESD Techniques

ESD methods can also be classified into

Generative Methods
Based on mathematical models (e.g. regression, parametric q-q map)

Non-Generative Methods
Based on an algorithm (e.g. analogs, empirical q-q map)

Gutierrez et al. 2013

ESD Approaches

Perfect Prognosis (PP)

Calibration: links between *observed* large-scale predictors (e.g. ERA Interim Reanalyses) and *observed* local-scale predictands (e.g. rain gauge precipitation) are established.

Model Output Statistics (MOS)

Calibration: statistical relationships between predictors and predictands is calibrated using *simulated predictors* (eg precipitation output from a GCM/RCM and *observed predictands* (e.g. rain gauge precipitation).

Maraun et al 2010

ESD Approaches

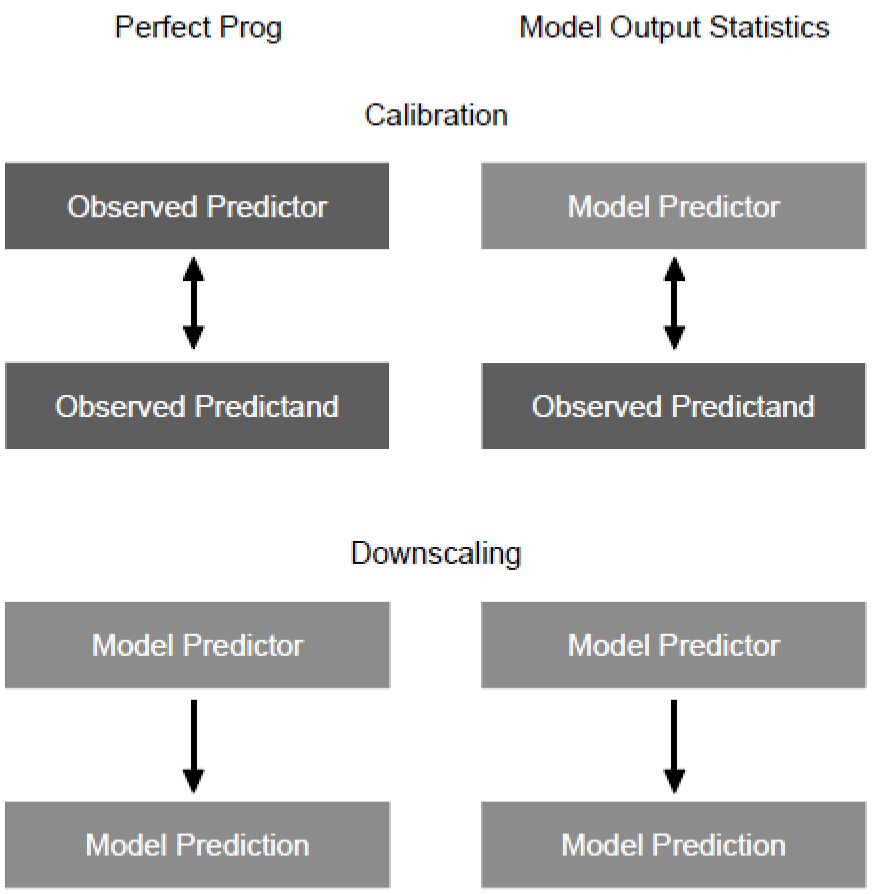

Figure 10.1 Perfect prognosis vs. model output statistics. The top shows the origin of predictor and predictand data during calibration, the bottom the same for the actual downscaling.

Maraun, D.,Widmann, M. 2018

Assumptions and caveats

Perfect Prognosis (PP)

- GCMs accurately (realistically and bias free) simulate the predictor ("perfect").
- The statistical relationship between the predictor and predictand does not change over time, that is, it should be temporally stable (Stationarity assumption).
- The predictor should carry the climate change signal.
- There is a strong relationship between the predictor and predictand: the predictors should account for a major part of the variability in the predictands (Informative predictors).

MOS

- Predictors need to be credibly simulated (realistic apart from correctable biases).
- In a climate change context, changes of the predictors have to be credibly simulated.
- Predictors need to be representative of the target variable, i.e., they have to represent the same spatial scale and location.
- The transfer function needs to have a suitable structure, which is applicable under changed climate conditions.

Maraun, D.,Widmann, M. 2018

Summarizing

Table 1: Conceptual diagram of the classification framework for statistical downscaling methods according to the different statistical techniques (Tech.) and approaches (Appro.), indicating also the deterministic or stochastic nature of the techniques and the time-series (event wise) or distributional character of the calibration. Some popular techniques typically used in some of the cases are indicated for illustrative purposes.

Appro. \ **Tech.**		**Generative**		**non-Generative**	
		Deterministic	Stochastic	Deterministic	Stochastic
PP	Eventwise	Regression, Neural Nets.	GLMs	Analogs, weather types	Analog resampling
	Distribution	Regression on PDF parameters			
MOS	Eventwise	Regression, Neural Nets.	GLMs	Analogs	Analog resampling
	Distribution	Bias correction, parametric q-q map	Nonhomogeneous HMM	q-q map	

3.3

Gutierrez et al. 2013

In this training workshop we will work on …

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3.3

Today
Maria Laura

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3.3

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Wednesday
Kyo

3.3

Gutierrez et al. 2013

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