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Adaptive Lossy Compression of Environmental Data

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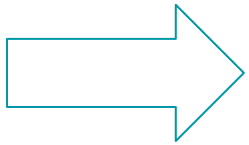
What is the result?

It is possible to improve lossy compression for **certain** time series data by only gradually increasing file size.



Application in climate research for compression of environmental indices.

Agenda

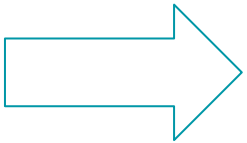
Importance of compression for climate research

Introduction and description of proposed method

Application on environmental indices used in climate research

Importance of compression

- Environmental data is 4D (longitude, latitude, altitude, time)
- Weather v climate simulations
- Current European ReAnalysis (ERA5) dataset needs 2.26 TiB p.a. and variable



Generate a compression method specific for environmental data

But how?

Compression 101

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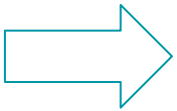
$$\pi = 3 \text{ v } \pi = \frac{C}{d}$$

- Lossy v lossless
- Distinguish between information and data
  - Understand the relationship within the data
  - Eliminate data without information
  - Compression works best with redundant data
- Temporal and spatial information can help to predict the behaviour variables.



Environmental indices

Environmental indices

- Temporal information of observations for forecasting weather phenomena (like precipitation or monsoon season)
  - ENSO34, NAO, QBO30, QBO50, …
- These indices can to be saved and used by the compression algorithm to gain information about the data

What are success criteria?

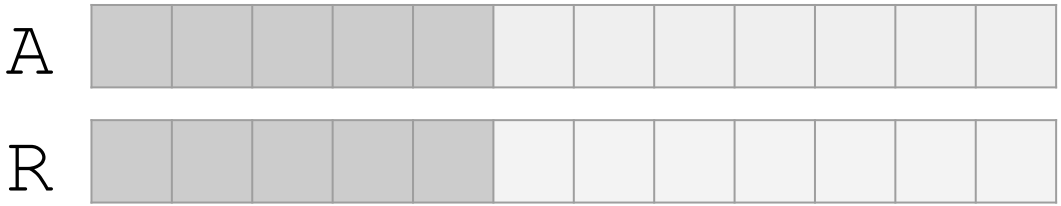
- **Compression ratio**
  - Filesize (after) / Filesize (before)
- Memory usage
- Compression/Decompression time

Additional criteria in case of lossy compression:

- **Quality of reconstructed data (community specific)**

Quality criteria for compressed indices

- A lossy compression algorithm is considered successful, if the correlation between the **original time series A** and the **reconstructed time series R** is 1.

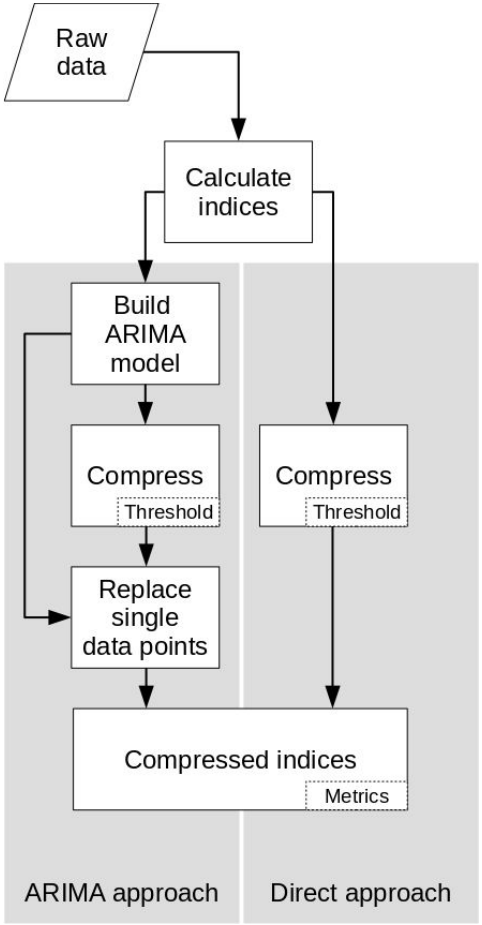


$$Corr_{s,e}(A,R) = 1.0$$

Direct & proposed approach

Direct approach
Compression using zfp (which allows lossy compression by gradually lowering precision).

ARIMA approach
From us proposed approach.



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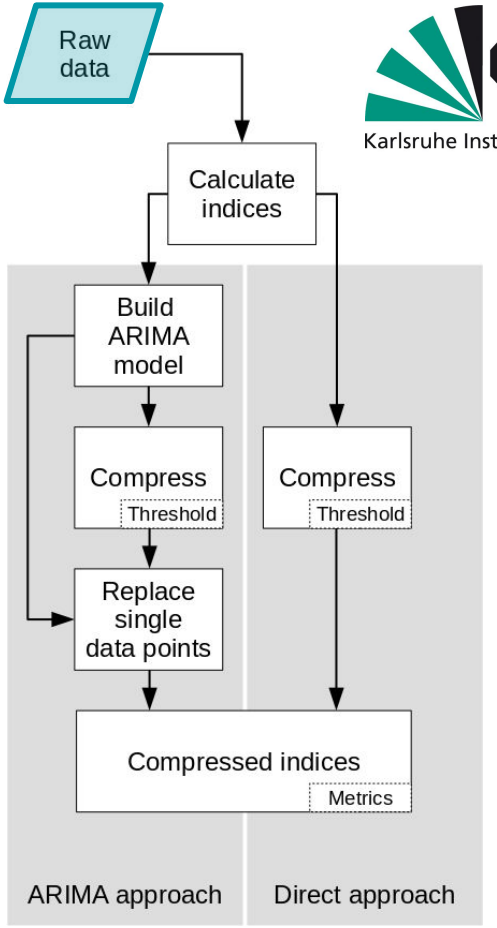
Raw data

128 x 64	horizontal grid
6	vertical level
1979 - 2013	temporal (10h timesteps)

daily monthly



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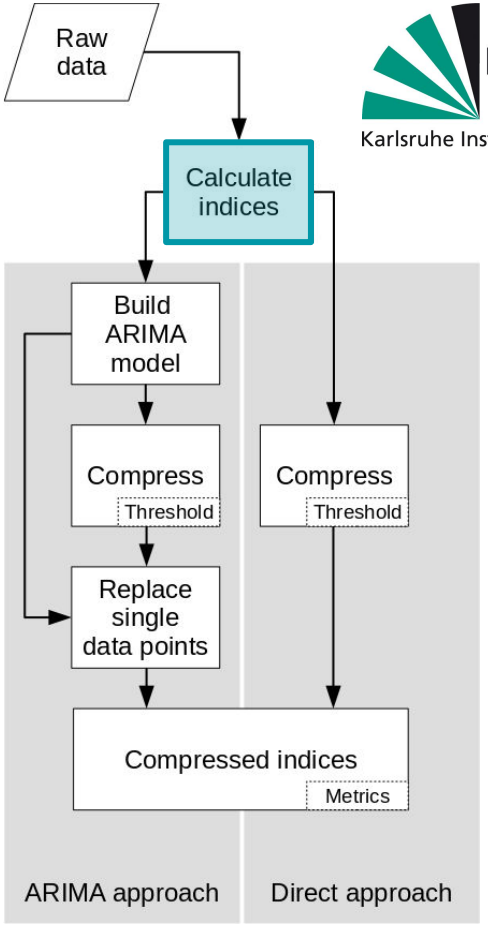
Calculate indices

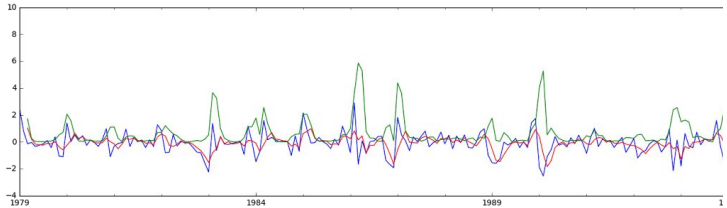
Index	Var	Lat [N]	Lon [E]	Alt [hPa]
ENSO34	T	[-5;5]	[190;240]	surface
QBO*x*	u	[-5;5]	[0;360]	*indicated by x*
NAO	p	Lisbon and Reykjavík		surface

T = temperature, u = westerly wind, p = pressure

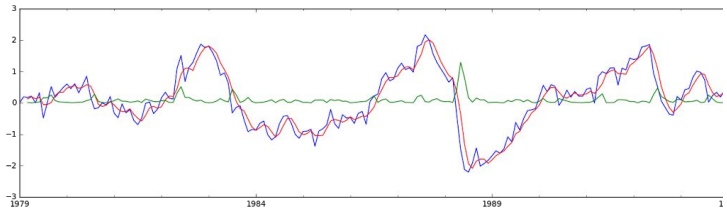


Calculate indices

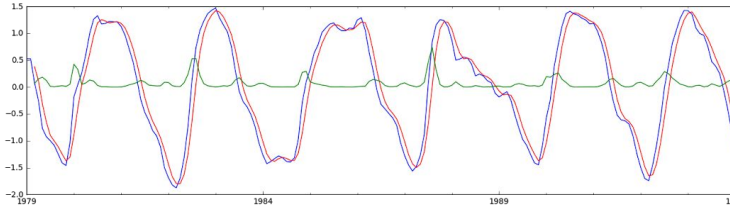
- Stationary time series
  - No trend
  - Variance is time independent



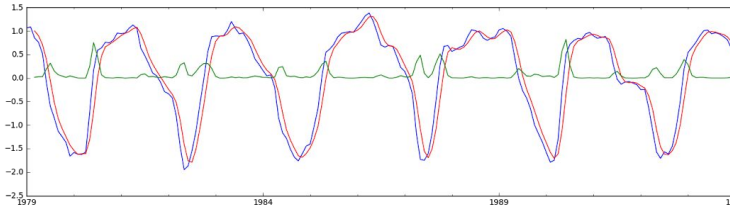
NAO



ENSO34



QBO30



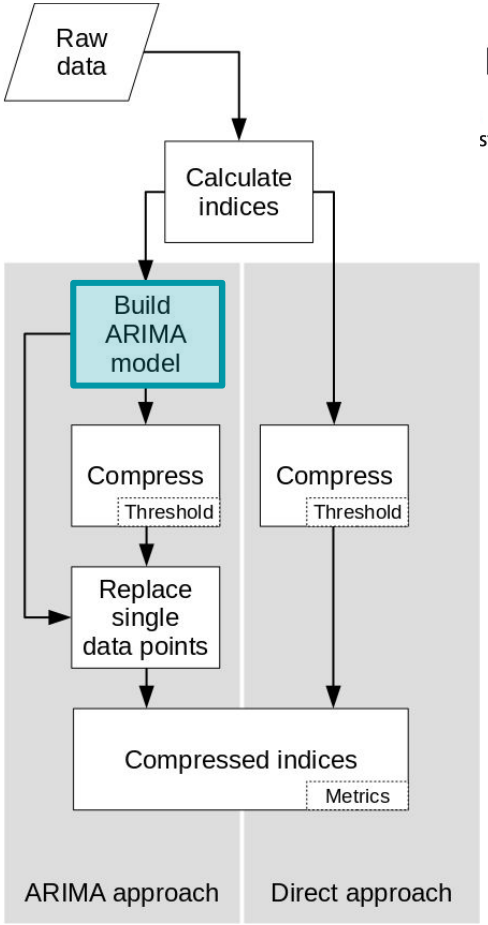
QBO50

Build an Auto Regressive Integrated Moving Average model

Model the relationship of a data point x with its preceding values and predict future values.

Auto Regressive:
Regression on previous values.

Moving Average:
Regression on previous errors.



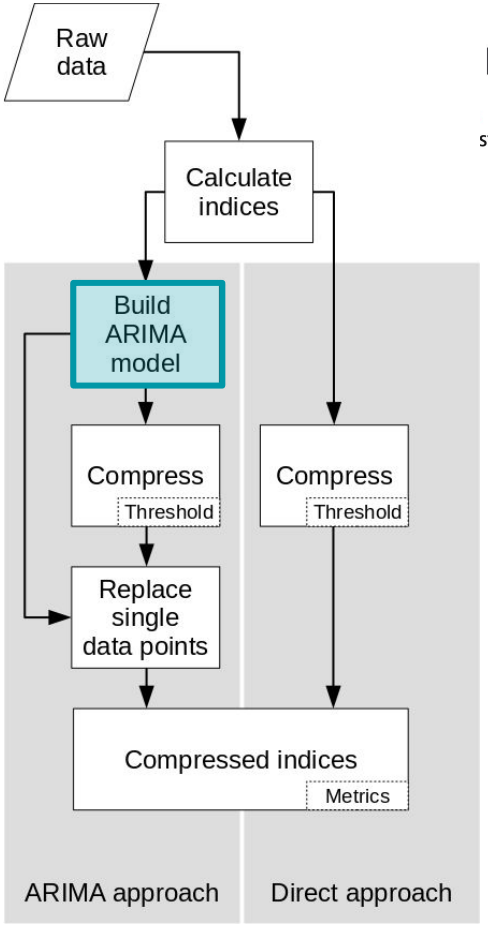
Build an Auto Regressive Integrated Moving Average model

Notation used for the ARIMA model:

$$ARIMA(p, d, q)(P, D, Q)_s$$

p = autoregressive order
d = differential order
q = moving average order
s = seasonal period

P, D, Q = appropriate seasonal order



Build an Auto Regressive Integrated Moving Average model

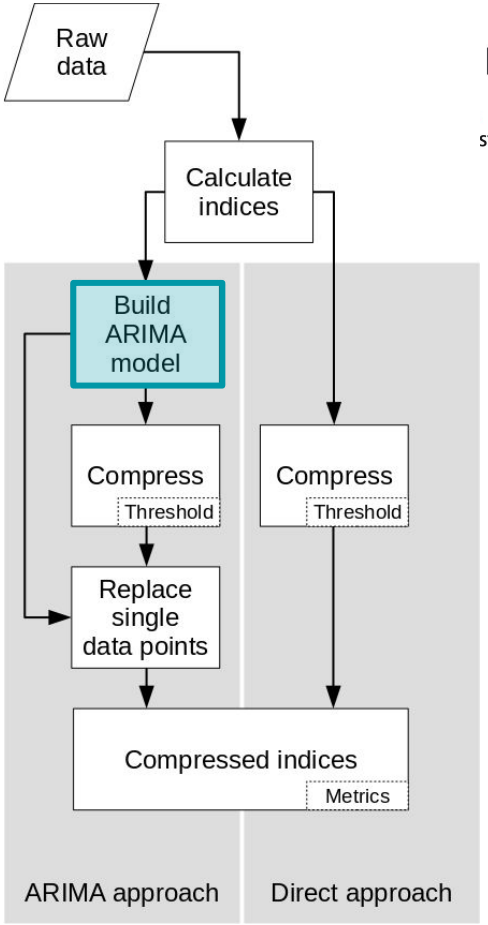
Notation used for the ARIMA model:

$$ARIMA(p, d, q)(P, D, Q)_s$$

The ARIMA model produces a prediction x' for the time series x which has an error of e.

$$x_i = x'_i + \epsilon_i$$

The time series x can be fully reproduced if the parameter of the ARIMA model and e are known.

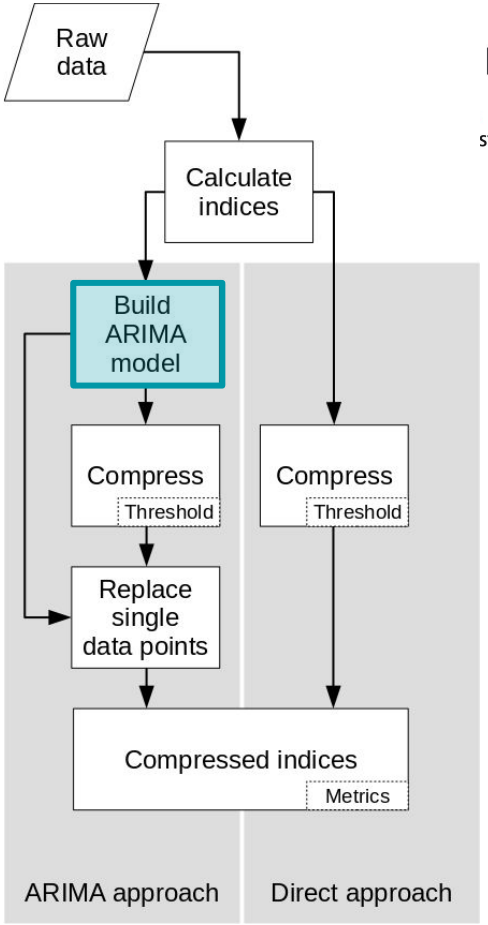


Build an Auto Regressive Integrated Moving Average model

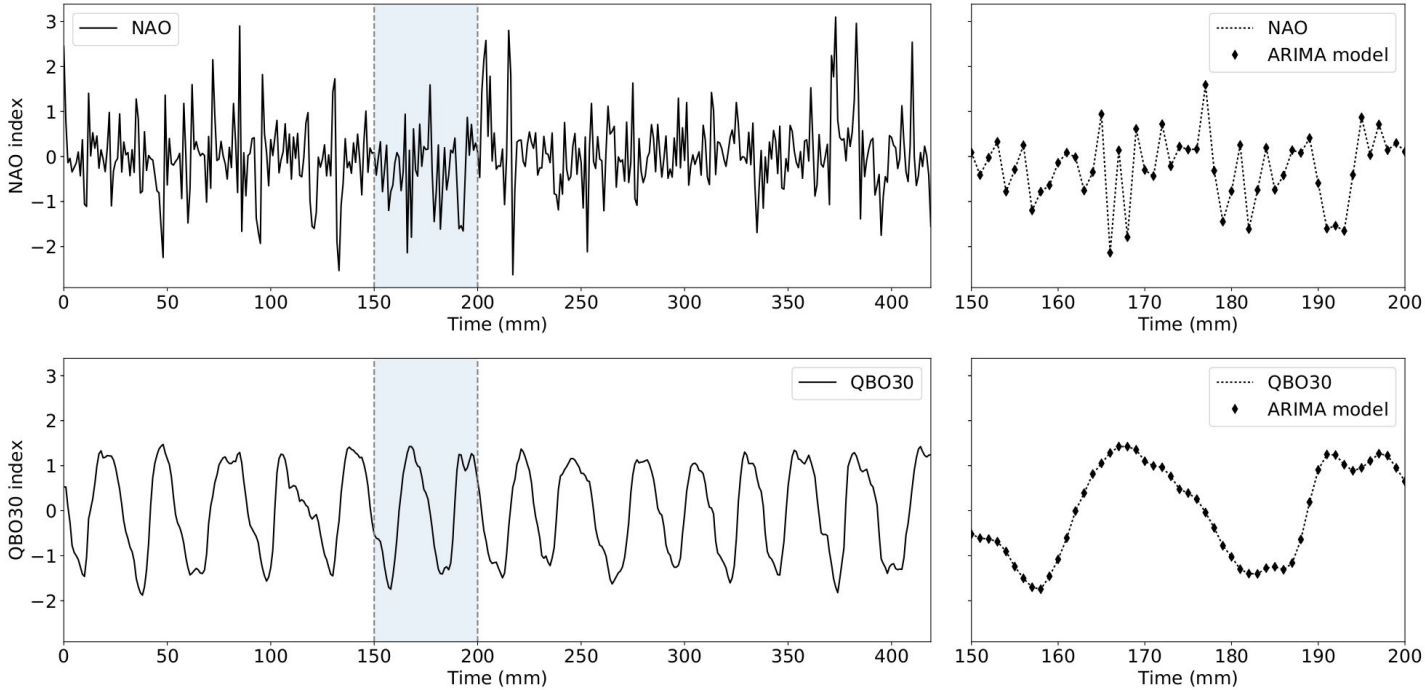
ARIMA(p, 0, q)(0, 0, 0)0

$$x_i = x'_i + \epsilon_i$$

$$x'_i = \sum_{k=1}^{p} ar_k \cdot x_{i-k} + \sum_{j=1}^{q} ma_j \cdot x_{i-j}$$



How good is the reconstruction of the ARIMA model?

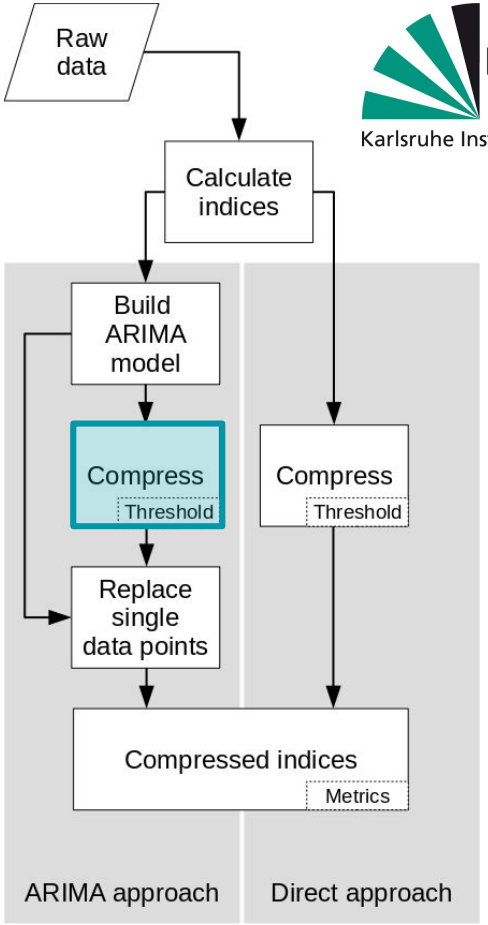


Build an Auto Regressive Integrated Moving Average model

Timeline	ARIMA Model			
	Monthly		Daily	
	Model	RMSD	Model	RMSD
ENSO34	ARIMA(3,0,2)(1,0,0)$_{12}$	5.067e-8	ARIMA(5,2,4)(0,0,0)$_{0}$	4.686e-4
NAO	ARIMA(1,0,0)(1,0,0)$_{12}$	8.195e-9	ARIMA(2,0,2)(0,0,0)$_{0}$	1.440e-7
QBO30	ARIMA(2,0,3)(1,0,0)$_{12}$	1.0877e-7	ARIMA(5,0,4)(0,0,0)$_{0}$	1.084e-7
QBO50	ARIMA(1,1,1)(1,0,1)$_{12}$	2.909e-6	ARIMA(5,0,4)(0,0,0)$_{0}$	4.488e-8

Different compression methods

- Experiment 1:
  Lossless compression
- Experiment 2:
  Lossy compression with threshold
- Experiment 3:
  Lossy compression with replacement



Exp. 1:
Lossless compression

	Compression ratio			
	Monthly		Daily	
	ARIMA	Direct	ARIMA	Direct
ENSO34	1.043	1.024	1.036	1.009
NAO	1.043	1.033	1.033	1.026
QBO30	1.038	1.005	1.032	0.961
QBO50	1.045	1.014	1.033	0.969

Exp. 2:
Lossy compression with threshold τ = 1e-5

	Compression ratio			
	Monthly		Daily	
	ARIMA	Direct	ARIMA	Direct
ENSO34	.386	.371	.658	.322
NAO	.386	.386	.377	.370
QBO30	.381	.357	.376	.273
QBO50	.668	.362	.377	.281

Exp. 2:
Lossy compression with threshold τ = 1e-5

	Compression Ratio			
	Monthly		Daily	
	ARIMA	Direct	ARIMA	Direct
ENSO34	.386	.371	.658	.322
NAO	.386	.386	.377	.370
QBO30	.381	.357	.376	.273
QBO50	.668	.362	.377	.281

Exp. 3:
Lossy compression (w/ replacement)

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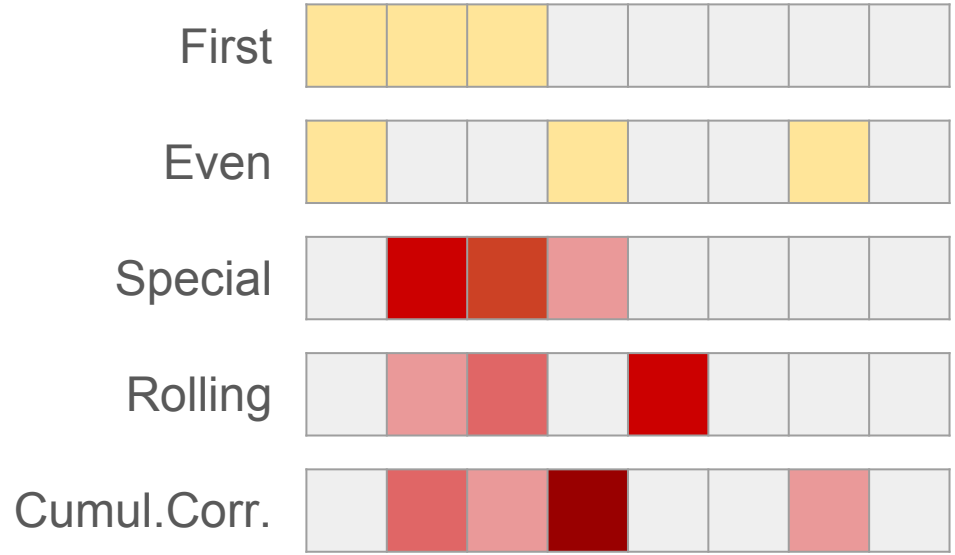
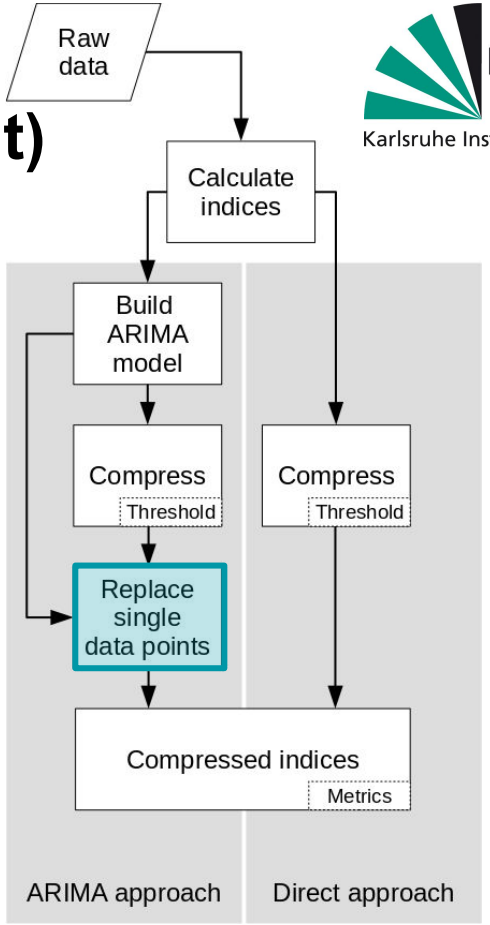
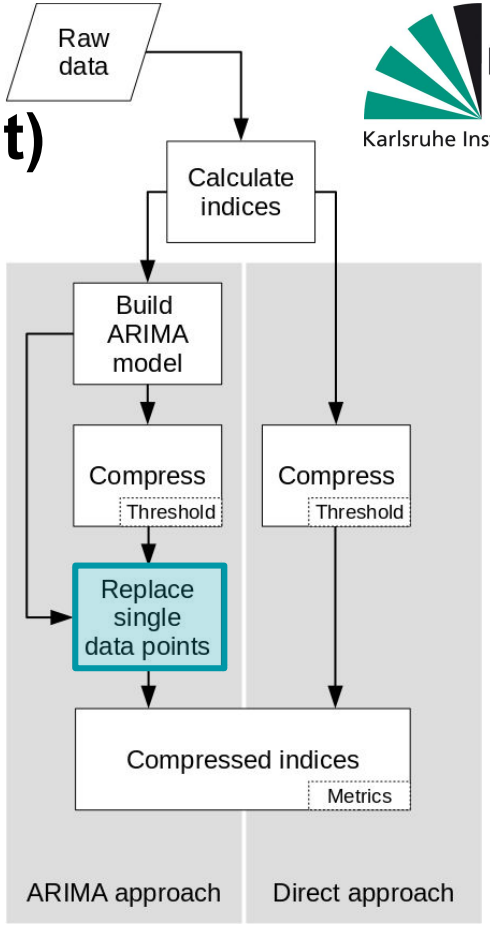
Methods for finding data points to be replaced:





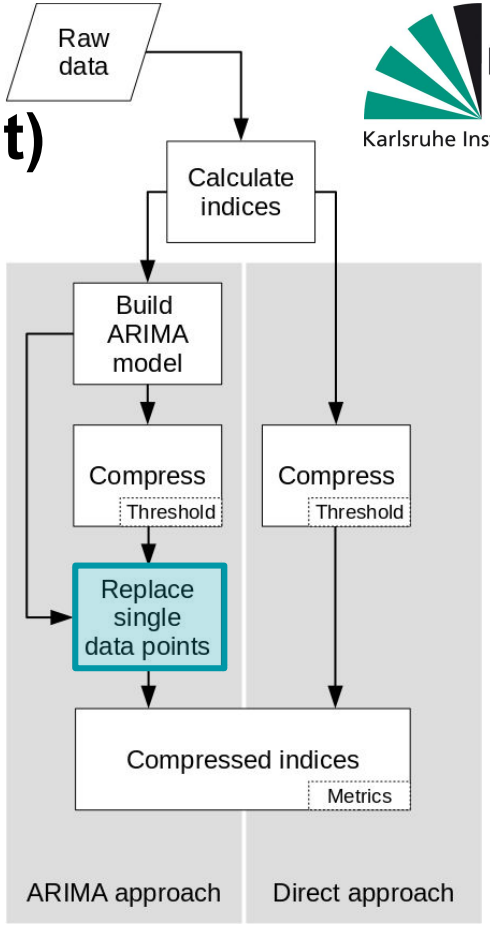
Exp. 3:
Lossy compression (w/ replacement)

- Special
  - Calculate $Corr_{1,i}$
  - Sort from low to high
  - Replace values contributing to lowest $Corr_{1,n}$
- Rollling
  - Calculate windowed $Corr_{j\text{-}bs,j}$
  - Sort from low to high
  - Replace values contributing to lowest $Corr_{1,n}$



Exp. 3:
Lossy compression (w/ replacement)

- Cumul.Corr.
  - Calculate $Corr_{1,i}$
  - Identify datum with biggest drop
  - Replace values contributing to identified datum



Exp. 3: Lossy compression (w/ replacement)

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	Correlation Coefficient (Monthly, 10%, Method: Special)				
	zfp02	**zfp03**	**zfp04**	**zfp05**	**zfp06**
NAO	.354	.725	.924	.979	.994
+1 Bit					
+2 Bit					
+3 Bit					
QBO30	.139	.482	.635	.972	.986
+1 Bit					
+2 Bit					
+3 Bit					

Exp. 3: Lossy compression (w/ replacement)

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	Correlation Coefficient (Monthly, 10%, Method: Special)				
	zfp02	**zfp03**	**zfp04**	**zfp05**	**zfp06**
NAO	.354	.725	.924	.979	.994
+1 Bit	.624	.864	.959	.987	.997
+2 Bit	.692	.870	.964	.989	.997
+3 Bit	.705	.878	.965	.989	.997
QBO30	.139	.482	.635	.972	.986
+1 Bit	.050	.575	.935	.968	.996
+2 Bit	.082	.615	.940	.973	.993
+3 Bit	.084	.607	.944	.987	.996

Exp. 3: Lossy compression (w/ replacement)

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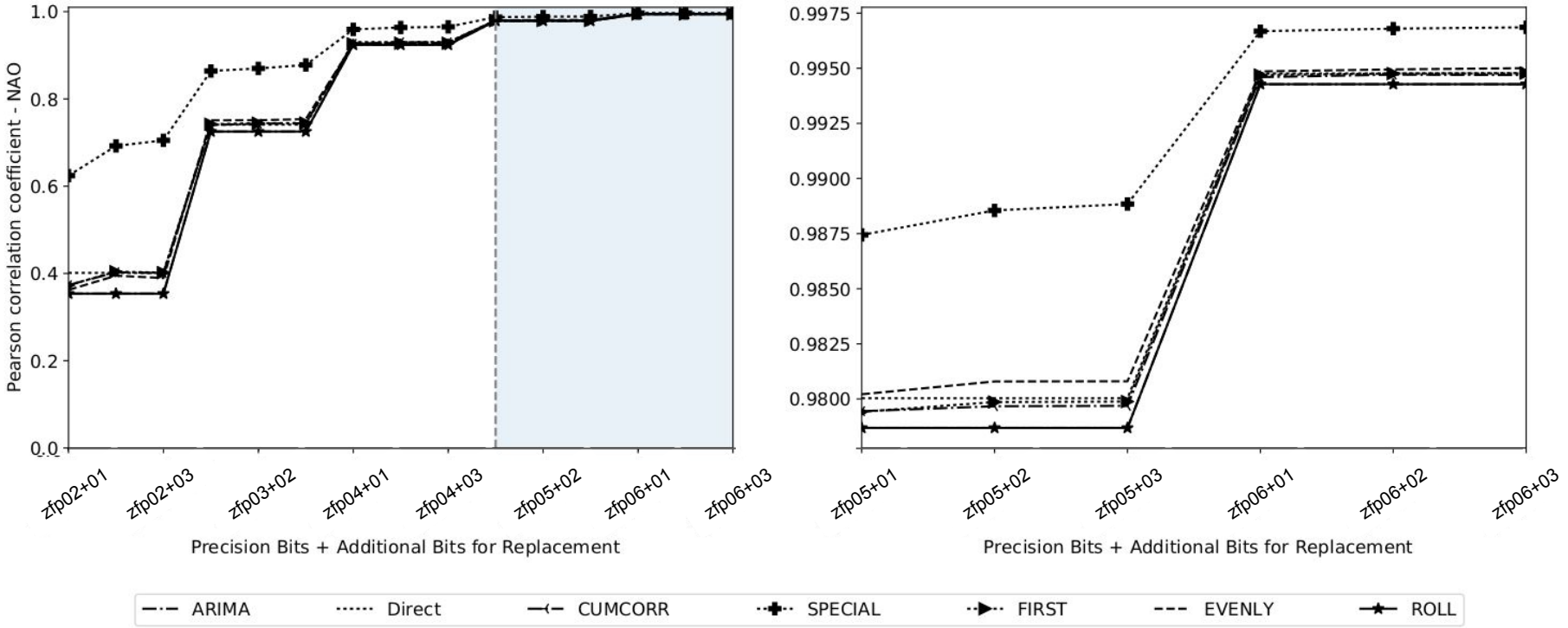
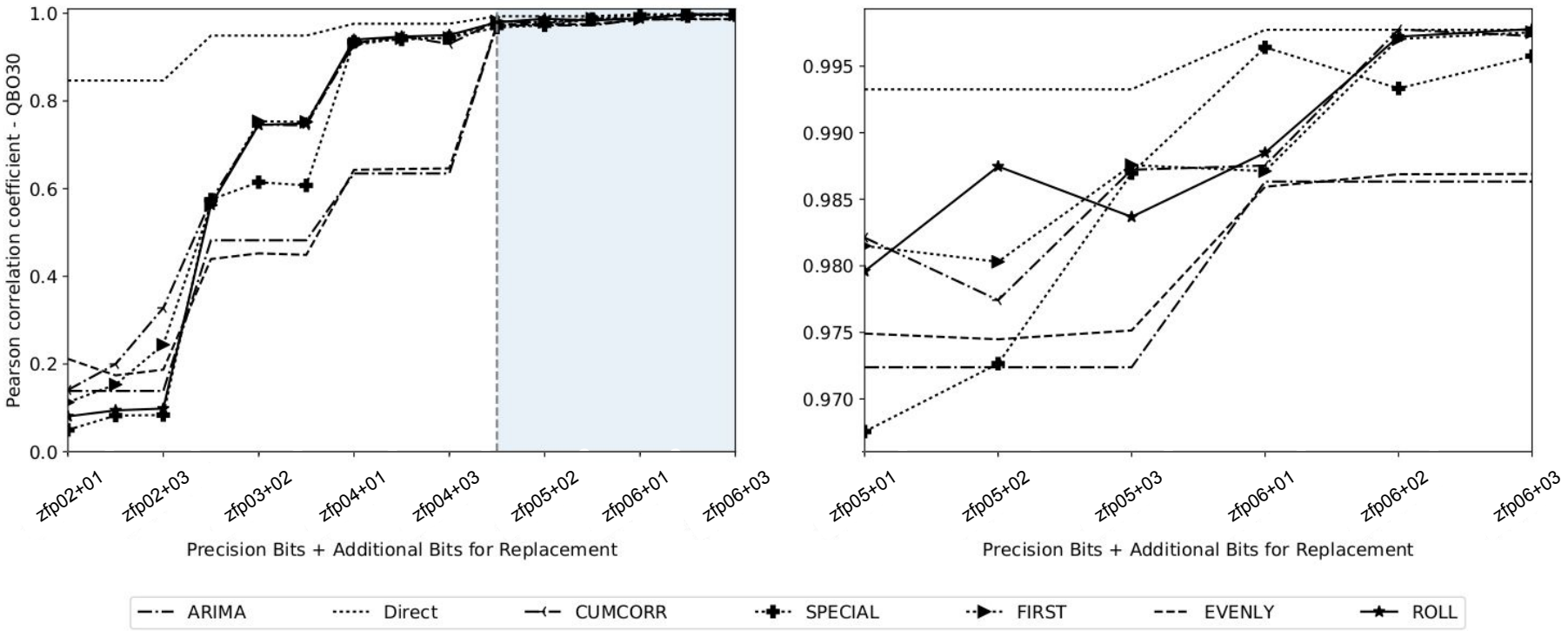
	Correlation Coefficient (Monthly, 10%, Method: Special)				
	zfp02	**zfp03**	**zfp04**	**zfp05**	**zfp06**
NAO	.354	.725 ~15%	.924	.979	.994
+1 Bit	.624 ~25%	.864	.959	.987	.997
+2 Bit	.692	.870	.964	.989	.997
+3 Bit	.705	.878	.965	.989	.997
QBO30	.139 -10%	.482	.635 ~30%	.972 -0.4%	.986
+1 Bit	.050	.575 ~10%	.935	.968	.996 -0.3%
+2 Bit	.082	.615 -1%	.940	.973	.993
+3 Bit	.084	.607	.944	.987	.996

Exp. 3: Lossy compression (w/ replacement)
NAO



Exp. 3: Lossy compression (w/ replacement)
QBO30



Exp. 3: Lossy compression (w/ replacement) over time series NAO

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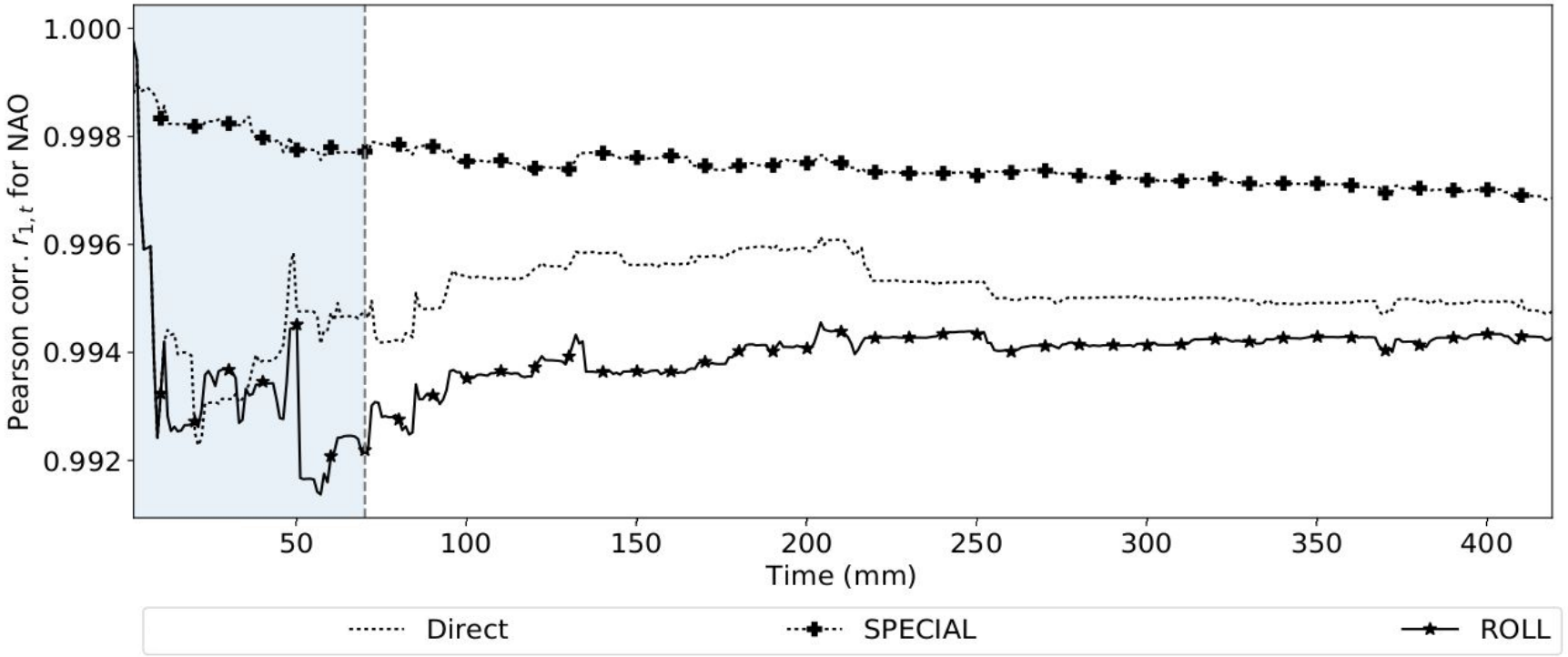
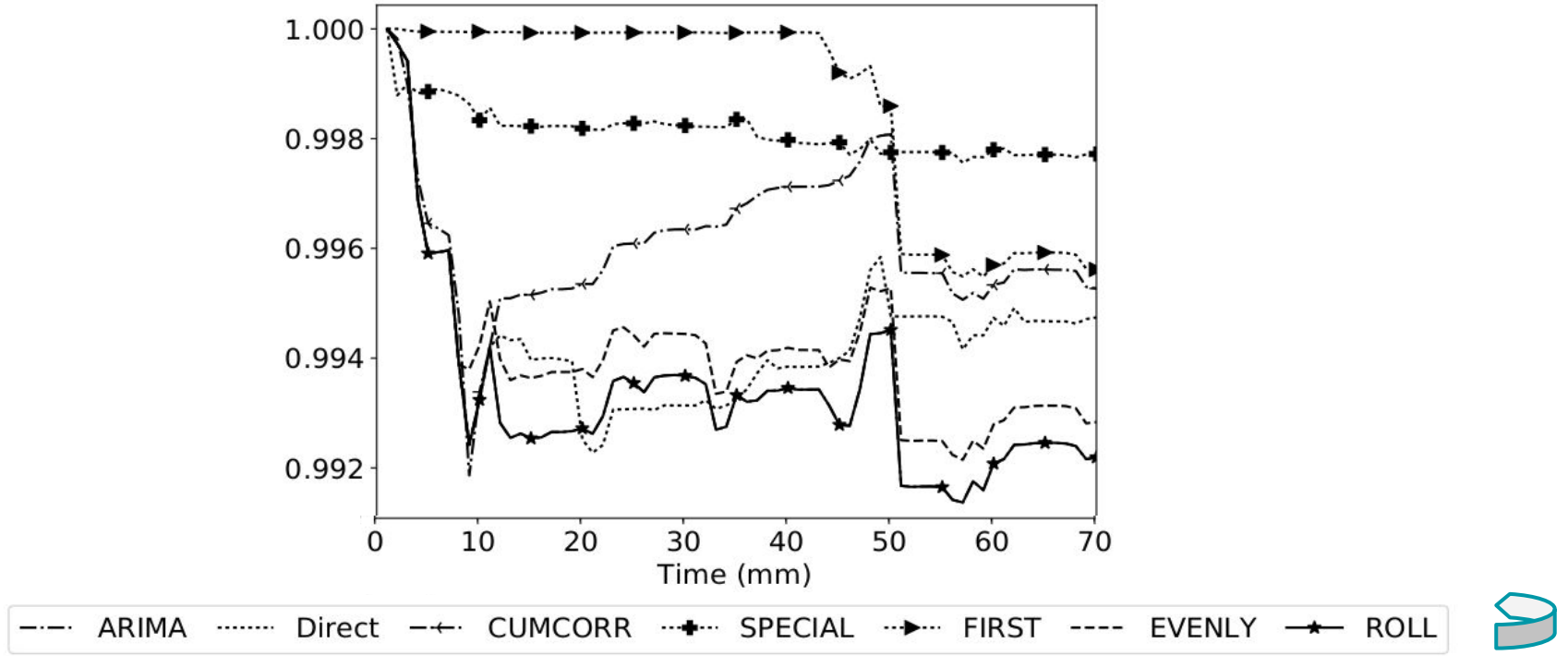
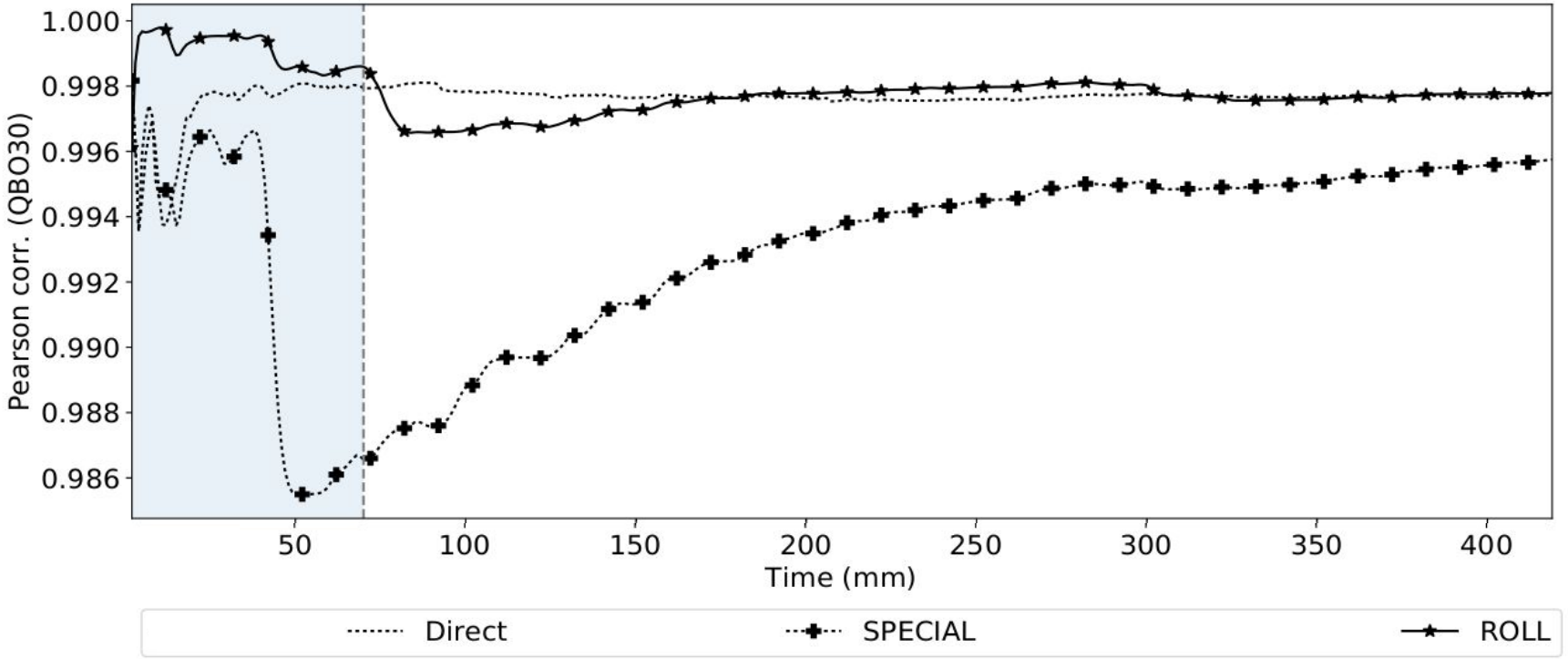


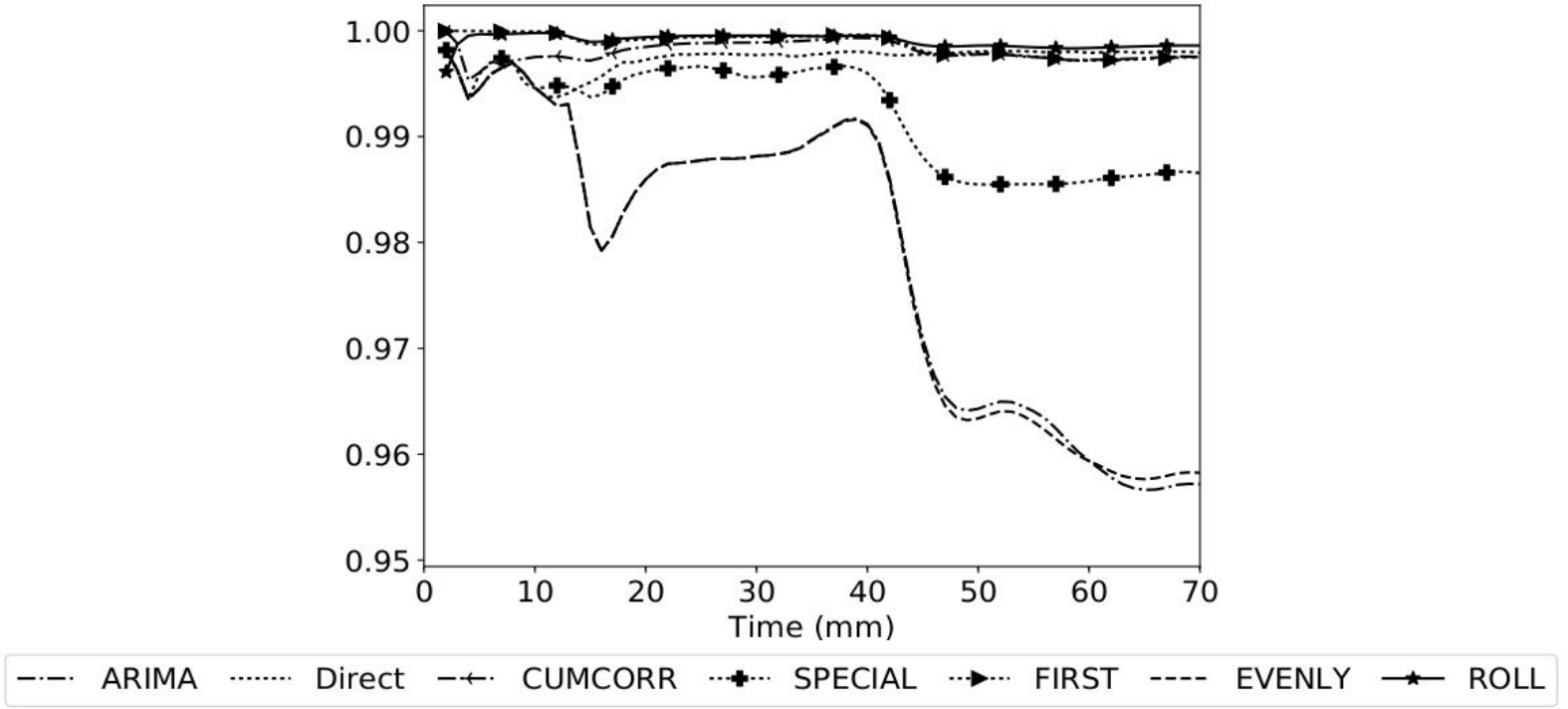
Exp. 3: Lossy compression (w/ replacement) over time series NAO



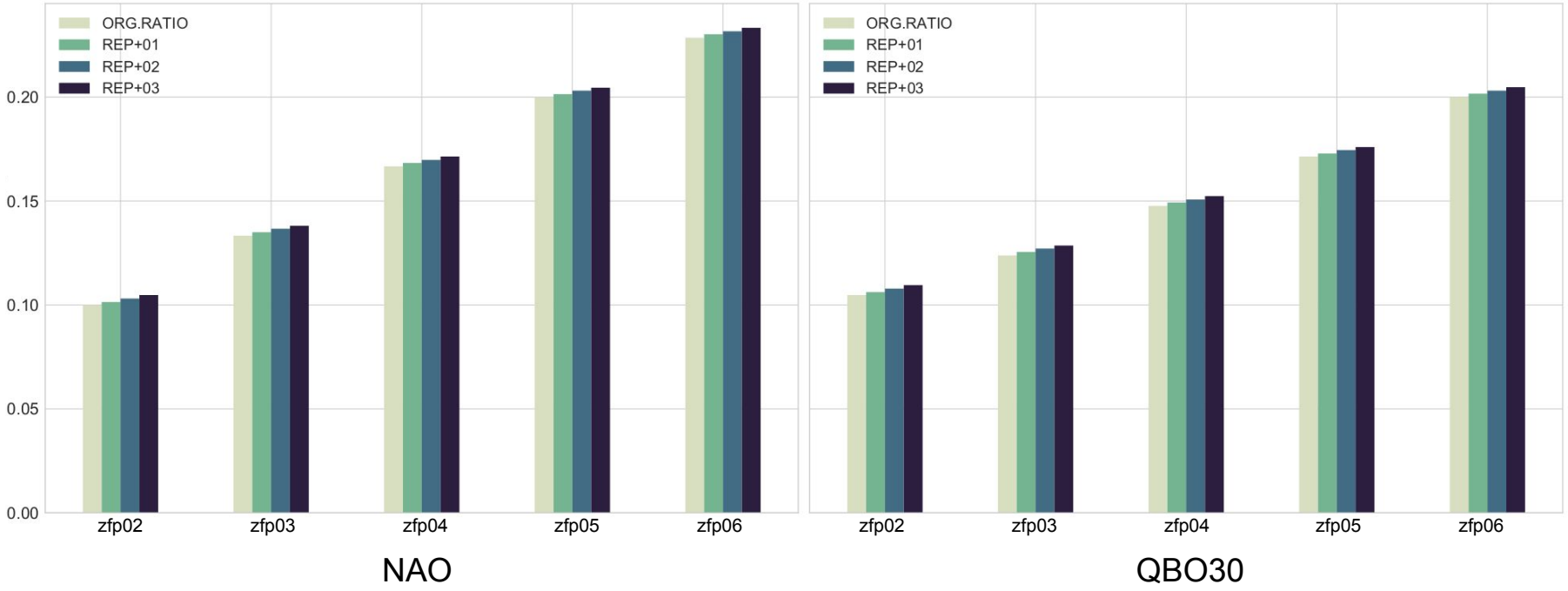
Exp. 3: Lossy compression (w/ replacement) over time series QBO30



Exp. 3: Lossy compression (w/ replacement) over time series QBO30



Exp. 3: Lossy compression (w/ replacement) compression ratio



Conclusion and further analysis

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- It is **possible to improve quality** of the reconstructed data by replacing several data points with slightly higher precision.
- ARIMA models using a **differentiation step** have difficulties and performed worse than other models.
- Time series expressed with **small auto-regressive and moving-average** order can be improved significantly.

- Further analysis will focus on why certain time series (like QBO30) **do not show the same improvement** like NAO and why there is **loss in quality** using higher precision data.
- It is a **complementary method** to the direct approach and will not replace it *yet*.

One more thing...

- Data and Code available (GPL-v3)
  - github.com/ucyo/adaptive-lossy-compression
- Contact
  - Cayoglu@kit.edu

- Thanks to Peter Braesicke, Tobias Kerzenmacher, Jörg Meyer and Achim Streit