

# Compressing large spatio-temporal model data: saving storage space while preserving scientific integrity

Dorit Hammerling

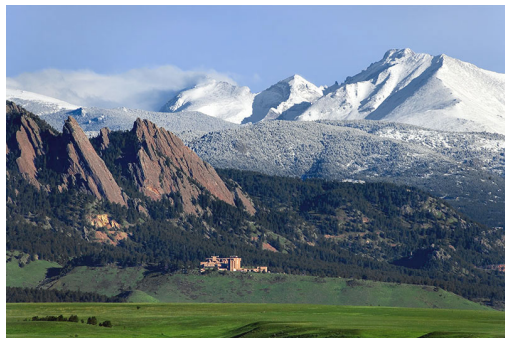
Department of Applied Mathematics and Statistics  
Colorado School of Mines (CSM)

Visiting Appointment: National Center for Atmospheric Research (NCAR)

Joint work with Alexander Pinard (CSM) and Allison Baker (NCAR)  
... and many other contributors

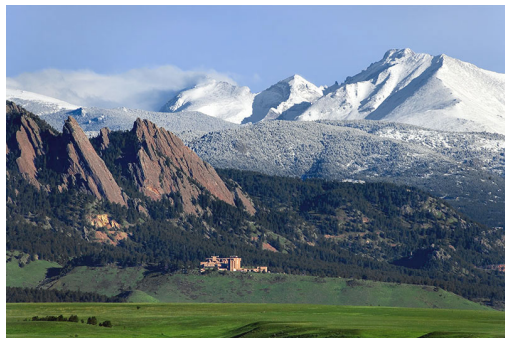
March 12, 2026

# The National Center for Atmospheric Research (NCAR)



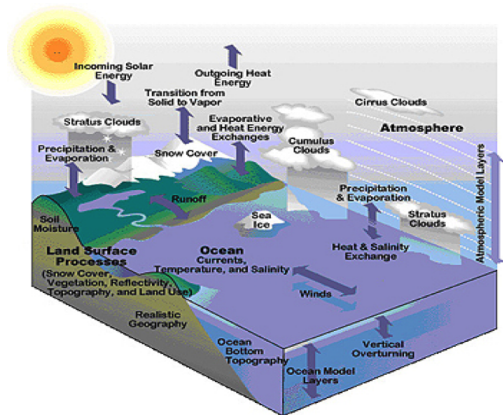
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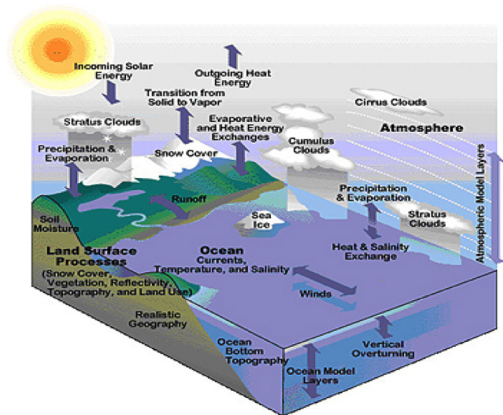
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# NCAR's Community Earth System Model (CESM)



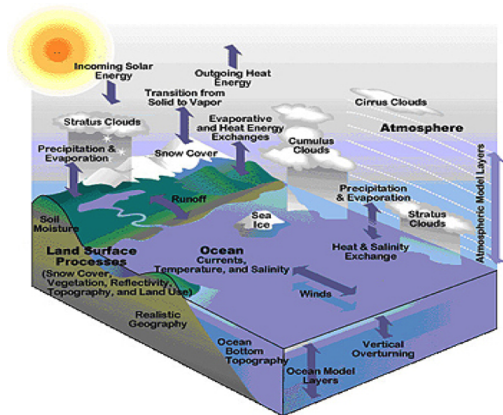
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- complex! Large code base: approx. 2 Millions lines of code
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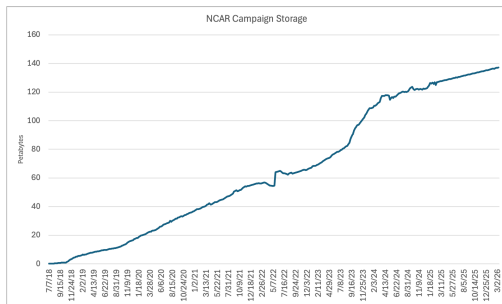
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# Why compress earth system data?

Increasing resolution and computational power lead to more and more data. *And there is no end in sight!*



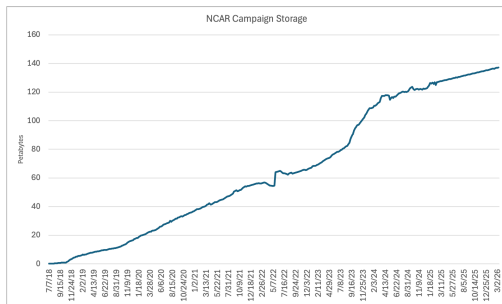
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Data storage is becoming a limiting factor for climate science.

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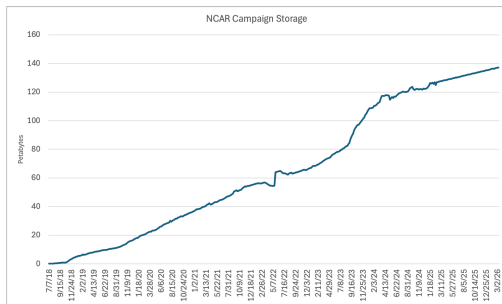
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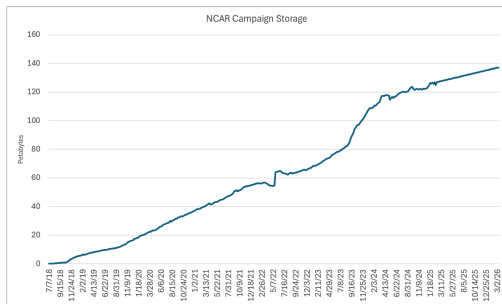


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# Basics of Compression

Compression: representing a set of numbers by a smaller set of numbers

2-step process:

Compression:  $X \Rightarrow C$

Decompression or Reconstruction:  $C \Rightarrow \tilde{X}$

Two categories:

Lossless:  $X = \tilde{X}$

Lossy:  $X \sim \tilde{X}$

Lossless compression generally not efficient for scientific data.

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# Lossless compression rates for scientific data

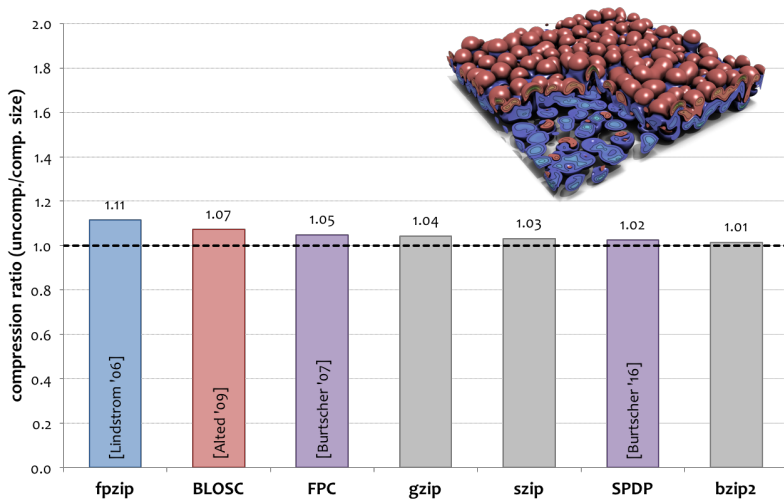


Image and study credit: Peter Lindstrom, Lawrence Livermore National Laboratory

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# What makes scientific data special?

*Hasn't Netflix figured that out yet?*

Scientists do all kinds **all kinds** of analysis with earth science data:

- Extreme values
- Subtle shifts in seasonal cycles
- Changes in gradients
- Energy budgets
- Derived variables
- Derivatives
- ...

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# What has been done at NCAR so far?

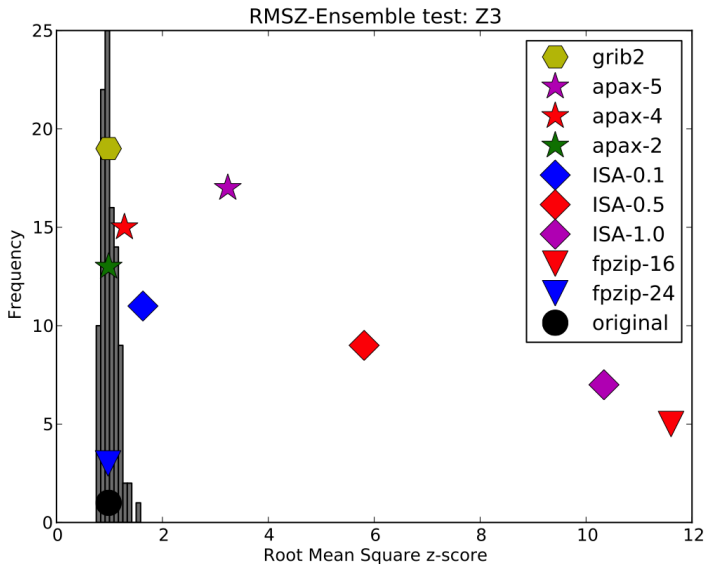
The early days ...

Compression in the context of an ensemble:

*Do the compression-introduced differences exceed **ensemble** variability?*

The pixel-wise differences between the original and reconstructed climate model data are evaluated in the **context of an ensemble** using metrics such as root-mean square z-score, maximum normalized point-wise error, linear regression coefficient to detect biases, etc.

# One metric: Root mean square z-score



## Pepsi challenge

Can climate scientists differentiate compressed and uncompressed data?



## Pepsi challenge data: non-blind tests to dig deeper

Main finding from the blind test: with smart analysis we can identify which data sets were compressed.

Has applying compression changed **relevant** features of the data?

Specifically, did ...

... *the extremes change?*

... *the causal relationship between variables change?*

... *derived variables change?*

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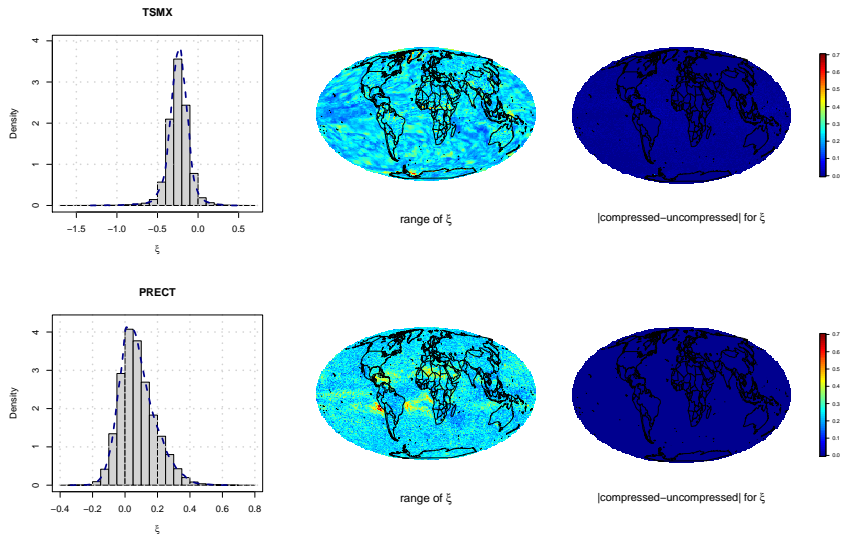
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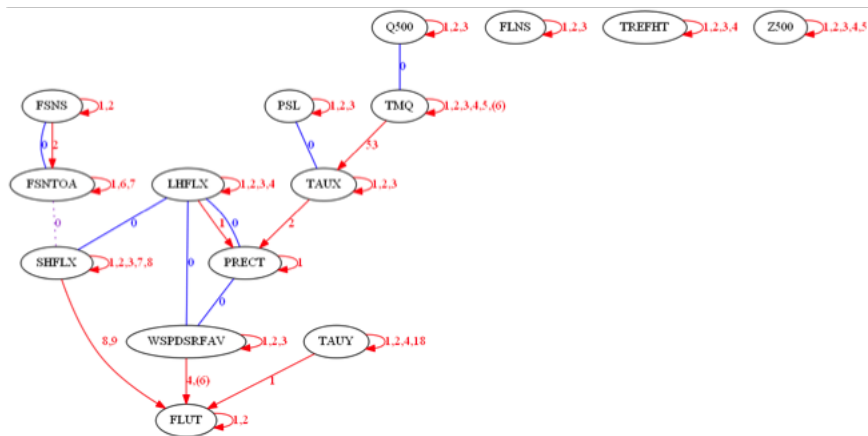
... *derived variables change?*

...

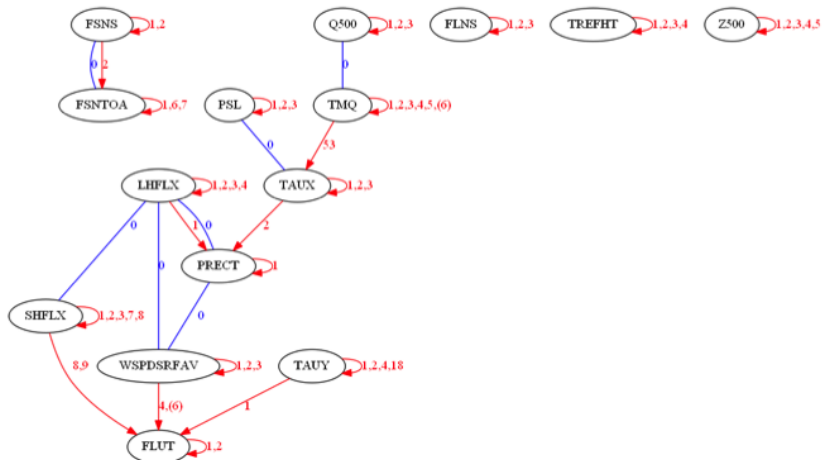
# Are the extreme values affected?



# Causal Discovery for original data

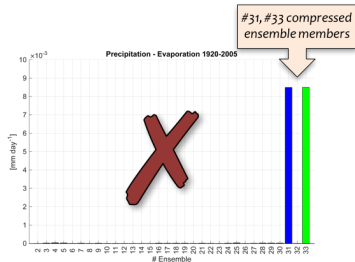
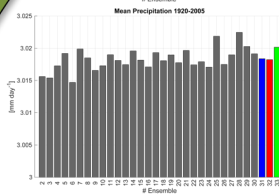
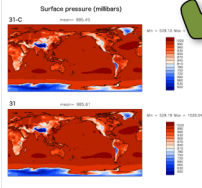
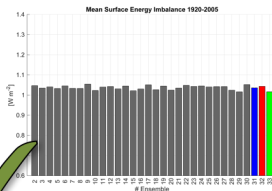
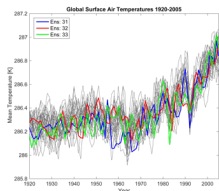


# Causal Discovery for reconstructed data



Causal relationships are for the most part not affected.

# Not all is rosy: Derived variables



Small biases in compressors can cause problems if systematic.

# Artifacts in derivative computations (velocity divergence)

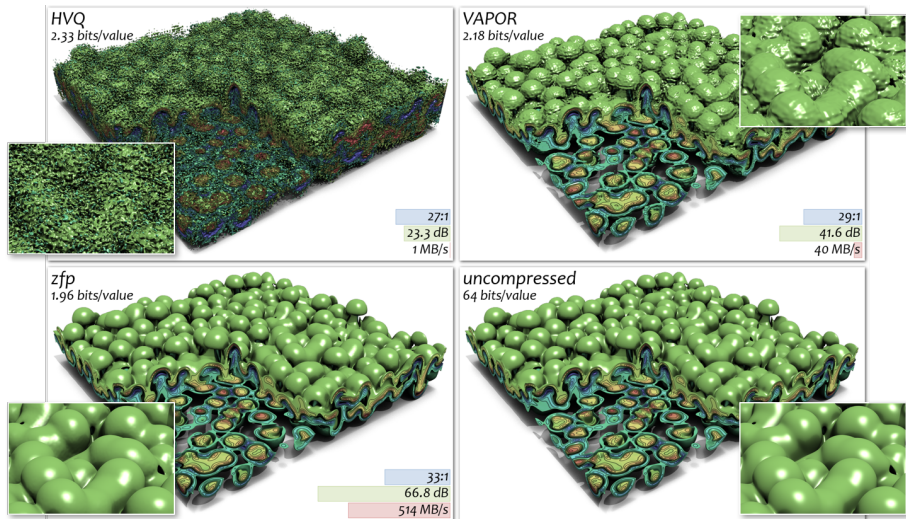


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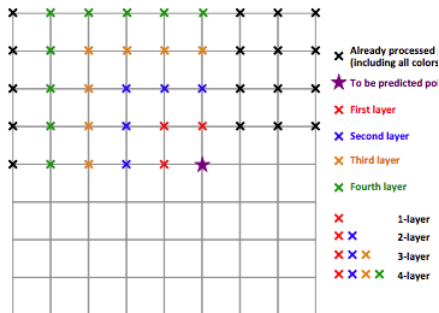
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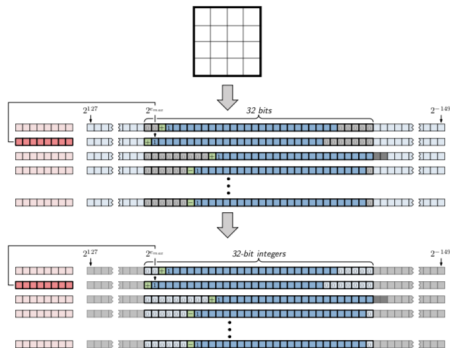
*We want to be **REALLY** careful and look at many things!*

# Two Leading Compression Algorithms for Numerical Data

## sz (Argonne)

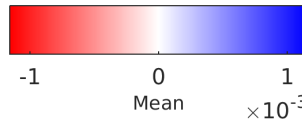
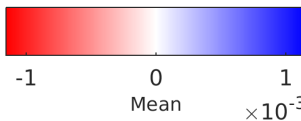
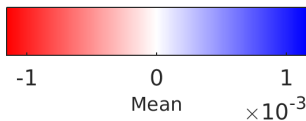
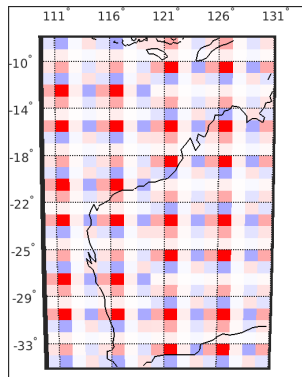
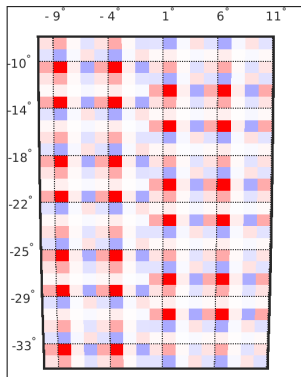
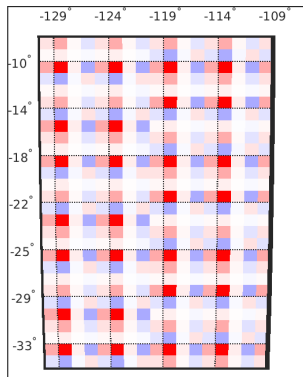


## zfp (LLNL)

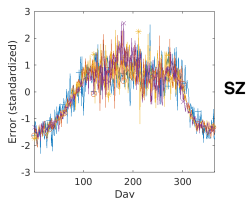
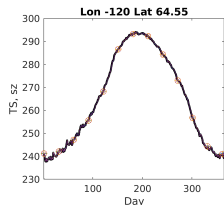
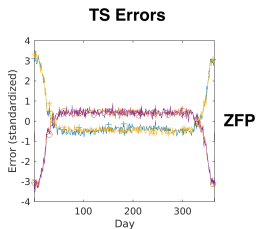
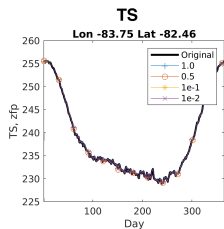


It helps to know how the algorithms work - collaboration is key!

# Zoomed in Mean Errors in TS (zfp)



# Seasonal Cycles in TS and TS Errors



- Absolute bias in seasonal cycle is small
- ZFP: sign of bias depends on the tolerance level
- SZ: seasonal cycle is slightly enhanced

# LDCPy: Large Data Comparison for Python

Large Data Comparison for Python (ldcpy) facilitates data analysis and visual comparison of massive datasets. In particular, the analysis tools are intended to mimic those done in the field of climate science.

- Github Repository: [//github.com/NCAR/ldcpy](https://github.com/NCAR/ldcpy)



## Large Data Comparison for Python

ldcpy is a utility for gathering and plotting metrics from NetCDF or Zarr files using the Pangeo stack. It also contains a number of statistical and visual tools for gathering metrics and comparing Earth System Model data files.

**AUTHORS:** Alex Pinard, Allison Baker, Dorit Hammerling

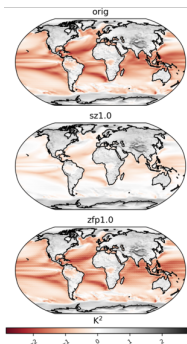
**COPYRIGHT:** 2020 University Corporation for Atmospheric Research

**LICENSE:** Apache 2.0

- Documentation: <http://ldcpy.readthedocs.io/en/dev>

# LDCPy: Large Data Comparison for Python cont.

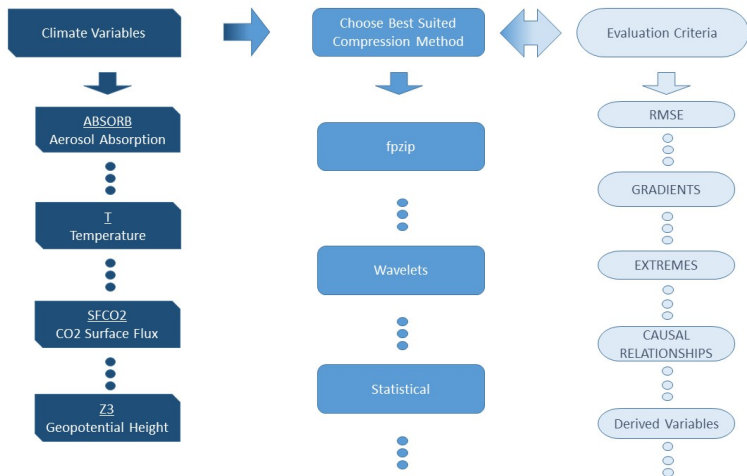
- Versatile comparisons for spatio-temporal data
- Suitability for a wide range of data volumes (single time slice to many years)
- Easy interaction through Jupyter Notebooks
- Supports NetCDF and object store data formats



Key word	Description
cw_con_var	East-West Contrast Variance
ns_con_var	North-South Contrast Variance
mean	mean
std	standard deviation
variance	variance
prob_positive	probability that a point is positive
prob_negative	probability that a point is negative
odds_positive	odds that a point is positive
mean_abs	mean of abs. errors
mean_squared	mean of the squared errors
rms	square root of the mean-squared error
sum	sum of the values
sum_squared	sum of the squared values
quantile	quantile of the data
lag1	deseasonalized lag-1 correlation at each point
standardized_mean	The deseasonalized mean values
ann_harmonic_ratio	The ratio of the annual harmonic frequency value to the 50 frequencies surrounding the annual frequency
pooled_var_ratio	The ratio of the variance at each point to the global pooled variance
zscore	z-score of a point under the null hypothesis that the mean is zero
ssim_value	Structural Similarity Index
ks_p_value	P-value for two-sample KS test
spatial_rel_error	percentage of grid points whose relative error exceeds a (1e-4) threshold
pearson	Pearson correlation coefficient: measures the linear correlation between variables

- Extensible: continually adding new features (and taking requests)!

# Automation: finding the best method for each variable



*The variables differ a lot, necessary to use specific compression settings.*

## For each variable, pass quantifiable metrics:

Overall Goal: determine a relationship between the suite of derived quantities and statistics (LDCPy!) and a few quantifiable metrics such that we can use thresholds to determine optimal compression levels.

- Pearson correlation coefficient test ✓
- Kolmogorov-Smirnov test ✓
- Spatial relative error test ✓
- Data Structural Similarity Index test (newly developed by us!) ✓

Optimal method is what passes the metrics at the highest compression ratio.

*Currently done by brute force checking each compressor at various settings.*

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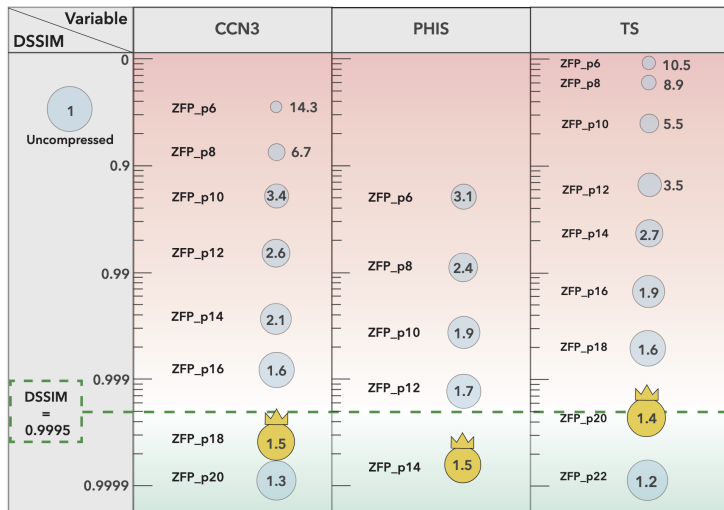
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# Optimal compression levels via brute force checking



CR = Compression Ratio

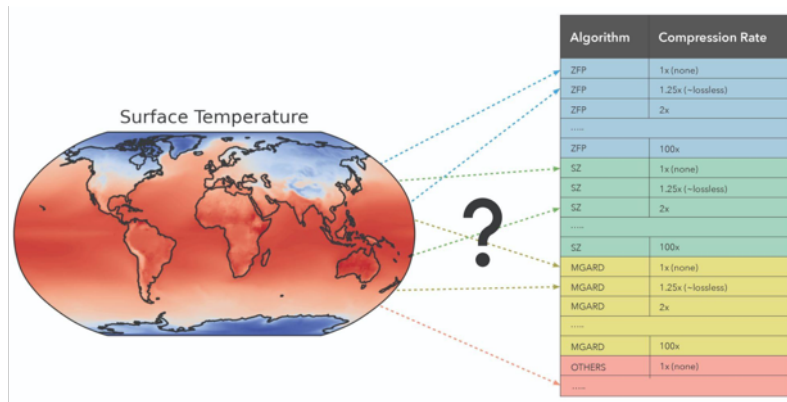


Optimal compression level



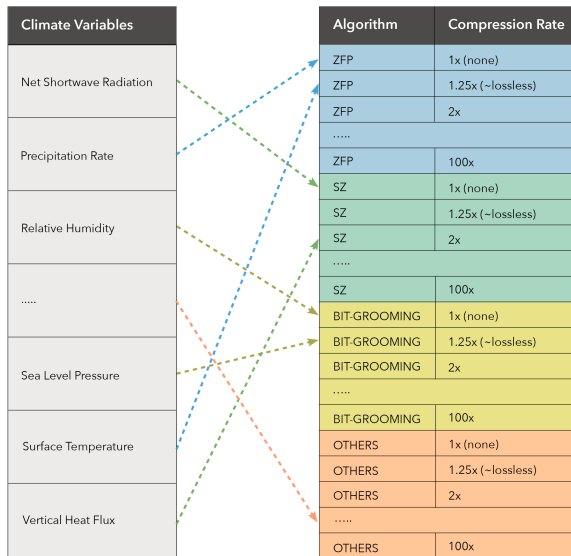
Non-optimal compression level

# Vision for automated compressor selection



*Can we find features in the data that predict the optimal compression settings?*

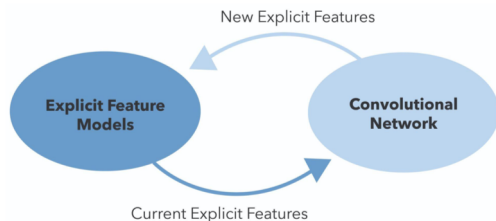
# Towards automating compressor selection ...



- *Can we find **\*generic\*** features that predict the optimal compression settings?*
- *There are hundreds of variables*

# Large scale study to find optimal compressor settings

- 183 climate variables (127 training, 28 validation, 28 test): variables in each group are chosen to be qualitatively different from one another to assess generalization
- 1000s of time slices
- 27 compressor settings: supervised classification problem
- Benchmarking statistical models using explicit features (e.g. max gradients, smoothness measures) of the data and convolutional neural network (potentially discovering new relevant features)



# Modeling Approach

This supervised learning approach requires:

- Labeled data
  - Label the data using the brute-force technique spanning multiple decades. The data consists of 192x288 latitude-longitude time slices of daily output CESM Large Ensemble data.
- Criteria for determining optimal compression
  - DSSIM, Pearson-correlation coefficient, Kolmogorov-Smirnov p-value
- Compressors
  - ZFP, a transform-based method with fixed precision parameters  $p$ .
- Models to train
  - Explicit Feature (and Importance), Implicit Feature

# We tried a lot of things . . .

## Classification models using explicit features:

- Classification Models: Random Forest, Boosting, Neural Network, K-nearest neighbors, Support Vector Machines, Linear Discriminant Analysis, Quadratic Discriminant Analysis, Aggregate Models
- Features: Mean, Variance, North-South Contrast Variance, East-West First Differences, Number of Zeros, Range (unstandardized), Median, Probability of Positive Value, Ratio of high and low frequencies in signal, . . .
  - *None of the features separates the classes well by itself.*

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# Final Models in Publication

## Random Forest

- Maximum tree depth:10,  
N trees:100,  
Min leaf samples:5
- Gradient, Smoothness,  
Information Features

## Convolutional Neural Network

- Two 3x3 convolutional layers  
with 32 filters and 3x3 max  
pooling layers after each  
convolutional layer
- Two-layer feed-forward  
network

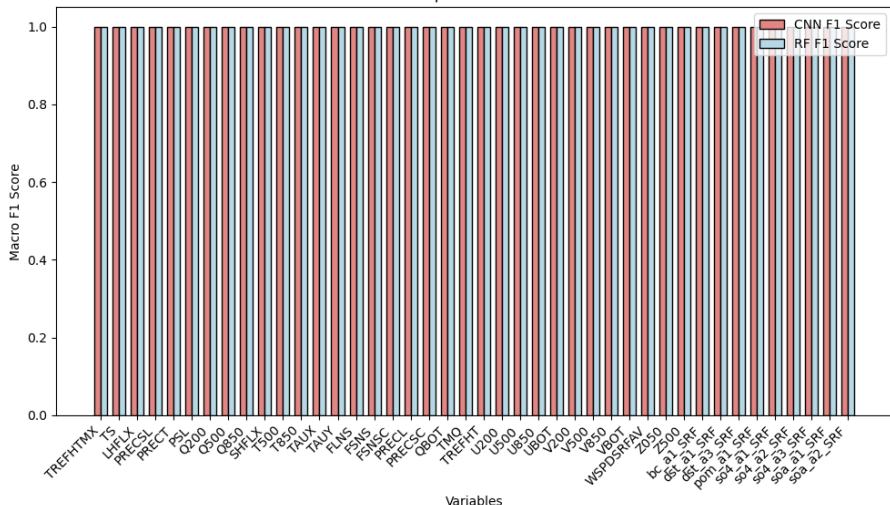
Category	Feature
Gradients	East-West first differences mean
	East-West first differences maximum
	North-South first differences mean
	North-South first differences maximum
Smoothness	Mean east-west Contrast Variance
	Mean north-south Contrast Variance
	Magnitude range over entire dataset
Information Content	Average dataset entropy
	Bitwise real information content

# Aggressive vs conservative compression

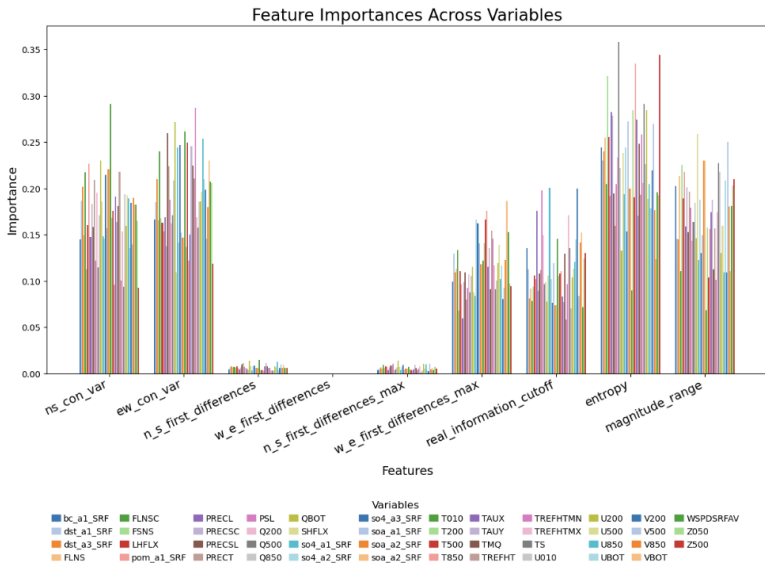
Variable	Aggressive					Conservative				
	zfp_p_8	zfp_p_10	zfp_p_12	zfp_p_14	zfp_p_16	zfp_p_18	zfp_p_20	zfp_p_22	zfp_p_24	Lossless
bc_a1_SRF	0	236	1,363	1	0	0	0	0	0	0
dst_a1_SRF	0	1,447	152	1	0	0	0	0	0	0
dst_a3_SRF	0	1,507	93	0	0	0	0	0	0	0
FLNS	0	1,482	118	0	0	0	0	0	0	0
FLNSC	0	1,546	54	0	0	0	0	0	0	0
LHFLX	0	933	667	0	0	0	0	0	0	0
pom_a1_SRF	0	312	1,288	68	0	0	0	0	0	0
PRECL	0	0	1,532	68	0	0	0	0	0	0
PRECS	0	1,201	357	42	0	0	0	0	0	0
PRECSL	0	860	637	103	0	0	0	0	0	0
PRECT	0	1	1,590	9	0	0	0	0	0	0
PSL	0	0	0	0	0	0	1,600	0	0	0
Q200	0	0	215	1,385	0	0	0	0	0	0
Q500	0	0	1,600	0	0	0	0	0	0	0
Q850	0	0	1,600	0	0	0	0	0	0	0
QBOT	0	0	1,585	15	0	0	0	0	0	0
SHFLX	0	88	1,512	0	0	0	0	0	0	0
so4_a1_SRF	0	0	1,504	96	0	0	0	0	0	0
so4_a2_SRF	0	0	1,128	472	0	0	0	0	0	0
so4_a3_SRF	0	0	1,582	18	0	0	0	0	0	0
soa_a1_SRF	0	740	860	0	0	0	0	0	0	0
soa_a2_SRF	0	389	1,192	19	0	0	0	0	0	0
TAUX	0	775	825	0	0	0	0	0	0	0
TAUY	0	948	652	0	0	0	0	0	0	0
T010	0	0	0	0	0	36	1,560	4	0	0
T500	0	0	0	0	0	1,594	6	0	0	0
T850	0	0	0	0	0	1,482	118	0	0	0
TMQ	0	0	1,597	3	0	0	0	0	0	0
TREFHT	0	0	0	0	0	1,568	32	0	0	0
TREFHTMN	0	0	0	0	0	1,477	123	0	0	0
TREFHTMX	0	0	0	0	0	1,599	1	0	0	0
TS	0	0	0	0	0	1,572	28	0	0	0

# Aggressive vs conservative classification works throughout

Macro F1 Score Comparison for CNN and RF Models



# How informative are chosen Random Forest features?

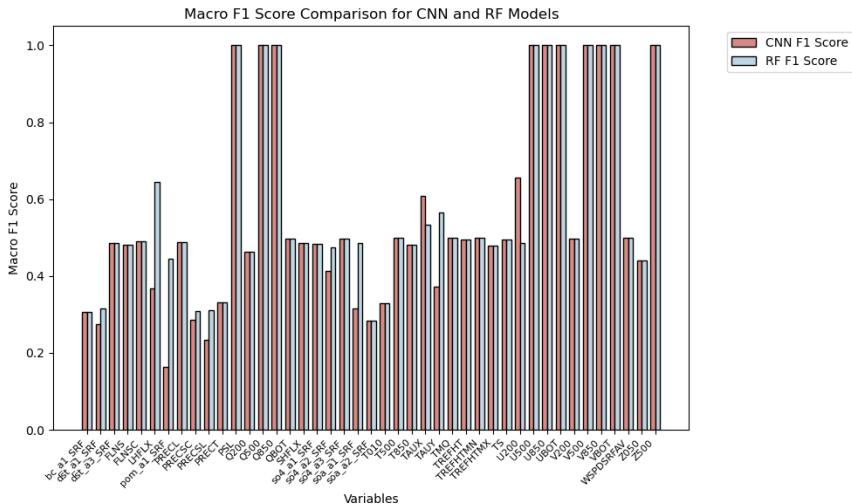


# Refining the predictions for individual climate variables

Is it possible to predict the precise class of a time slice if trained on other time slices of the same climate variable?

Variable	Aggressive					Conservative				Lossless
	zfp.p.8	zfp.p.10	zfp.p.12	zfp.p.14	zfp.p.16	zfp.p.18	zfp.p.20	zfp.p.22	zfp.p.24	
bc.a1.SRF	0	236	1,363	1	0	0	0	0	0	0
dst.a1.SRF	0	1,447	152	1	0	0	0	0	0	0
dst.a3.SRF	0	1,507	93	0	0	0	0	0	0	0
FLNS	0	1,482	118	0	0	0	0	0	0	0
FLNSC	0	1,546	54	0	0	0	0	0	0	0
LHFLX	0	933	667	0	0	0	0	0	0	0
pom.a1.SRF	0	312	1,288	68	0	0	0	0	0	0
PRECL	0	0	1,532	68	0	0	0	0	0	0
PRECS	0	1,201	357	42	0	0	0	0	0	0
PRECSL	0	860	637	103	0	0	0	0	0	0
PRECT	0	1	1,590	9	0	0	0	0	0	0
PSL	0	0	0	0	0	0	1,600	0	0	0
Q200	0	0	215	1,385	0	0	0	0	0	0
Q500	0	0	1,600	0	0	0	0	0	0	0
Q850	0	0	1,600	0	0	0	0	0	0	0
QBOT	0	0	1,585	15	0	0	0	0	0	0
SHFLX	0	88	1,512	0	0	0	0	0	0	0
so4.a1.SRF	0	0	1,504	96	0	0	0	0	0	0
so4.a2.SRF	0	0	1,128	472	0	0	0	0	0	0
so4.a3.SRF	0	0	1,582	18	0	0	0	0	0	0
soa.a1.SRF	0	740	860	0	0	0	0	0	0	0
soa.a2.SRF	0	389	1,192	19	0	0	0	0	0	0
TAUX	0	775	825	0	0	0	0	0	0	0
TAUY	0	948	652	0	0	0	0	0	0	0
T010	0	0	0	0	0	36	1,560	4	0	0
T500	0	0	0	0	0	1,594	6	0	0	0
T850	0	0	0	0	0	1,482	118	0	0	0
TMQ	0	0	1,597	3	0	0	0	0	0	0
TREFHT	0	0	0	0	0	1,568	32	0	0	0
TREFHTMN	0	0	0	0	0	1,477	123	0	0	0
TREFHTMX	0	0	0	0	0	1,599	1	0	0	0
TS	0	0	0	0	0	1,572	28	0	0	0

# Only works for some variables ...

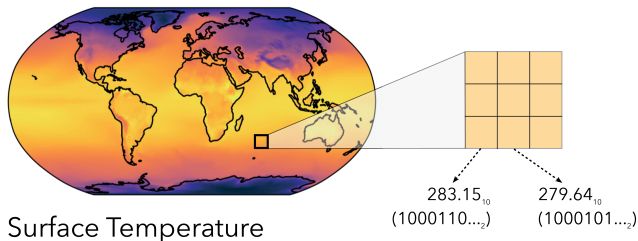


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# Ongoing work and thanks!

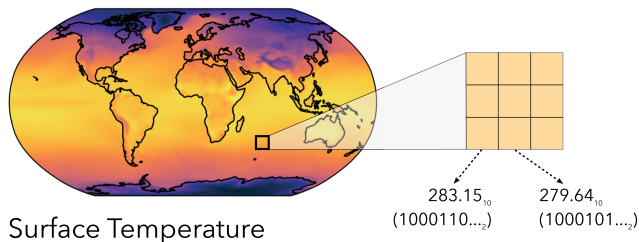
- Real Information Content: spatial correlation in bit planes



- Thanks! Any questions: [hammerling@mines.edu](mailto:hammerling@mines.edu)

# Ongoing work and thanks!

- Real Information Content: spatial correlation in bit planes



- Thanks! Any questions: [hammerling@mines.edu](mailto:hammerling@mines.edu)