


The challenge of rainfall estimation and prediction across scales
LEARNING FROM PATTERNS

Efi Foufoula-Georgiou
University of California, Irvine

Langbein Lecture
2019 AGU

Walter Langbein – the keen observer

Courtesy of Bill Dietrich

Walter Langbein – the theoretician

The Concept of Entropy in Landscape Evolution

1962

By LUNA B. LEOPOLD *and* WALTER B. LANGBEIN

THEORETICAL PAPERS IN THE HYDROLOGIC AND GEOMORPHIC SCIENCES

GEOLOGICAL SURVEY PROFESSIONAL PAPER 500-A

River Meanders—Theory of Minimum Variance

1966

By WALTER B. LANGBEIN *and* LUNA B. LEOPOLD

PHYSIOGRAPHIC AND HYDRAULIC STUDIES OF RIVERS

GEOLOGICAL SURVEY PROFESSIONAL PAPER 422-H

The geometry of a meander is that of a random walk whose most frequent form minimizes the sum of the squares of the changes in direction in each unit length. Changes in direction closely approximately a sine function of channel distance. Depth, velocity, and slope are adjusted so as to decrease the variance of shear and the friction factor in a meander over that in an otherwise comparable straight reach of the same river

UNITED STATES GOVERNMENT PRINTING OFFICE, WASHINGTON : 1966

STEADY STATE IN THE STOCHASTIC THEORY OF LONGITUDINAL RIVER PROFILE DEVELOPMENT

A.E. SCHEIDEGGER and W.B. LANGBEIN

1966

Walter Langbein – the practitioner

Transactions, American Geophysical Union Volume 30, Number 6 December 1949

1949

ANNUAL FLOODS AND THE PARTIAL-DURATION FLOOD SERIES

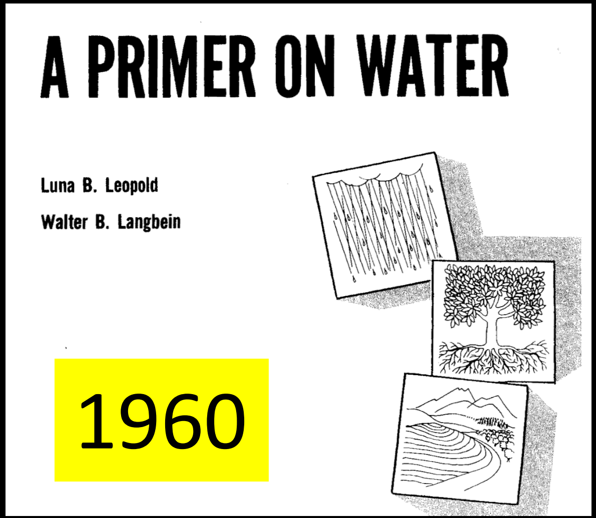
W. B. Langbein

Abstract--Flood data are ordinarily listed either in annual-flood series or in a partial-duration series. If the expectancy of a flood in the duration series ϵ is known, then the probability of that flood being an annual flood is shown to be $e^{-\epsilon}$. From this relationship it is possible to transform recurrence intervals in the partial duration series to those in the annual-flood series. It is shown that for equivalent floods, the recurrence intervals in the partial-duration series are smaller than in the annual-flood series, but that the difference becomes inconsequential for floods greater than about five-year recurrence interval.

$$\operatorname*{Limit}_{n\to\infty}\left[1-\frac{\varepsilon}{n}\right]^n = \exp\left[-\varepsilon\right]$$

Transform recurrence intervals in the partial duration series to those in the max annual flood series

Walter Langbein – the science communicator



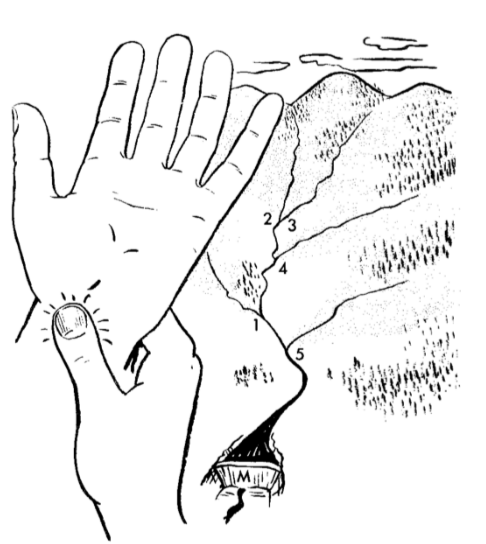


FIGURE 16—*Tributaries in a natural river basin.*

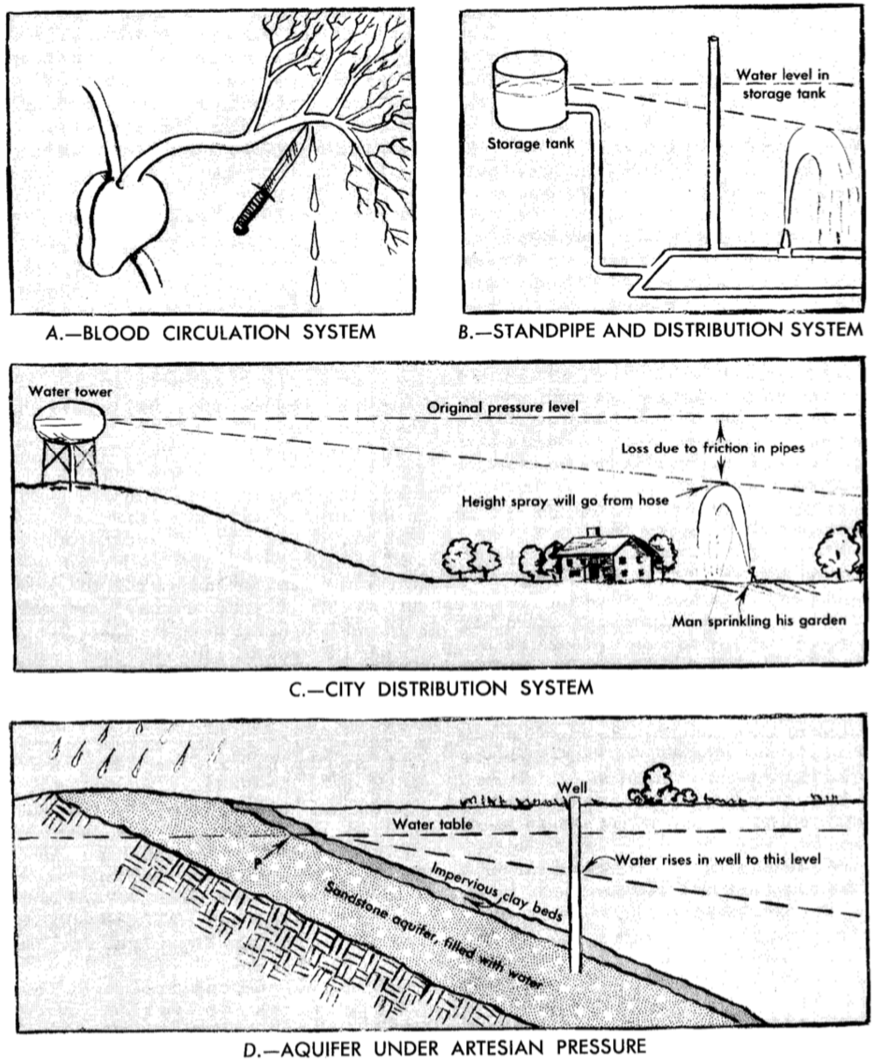


FIGURE 6 —*Examples of fluids under pressure.*

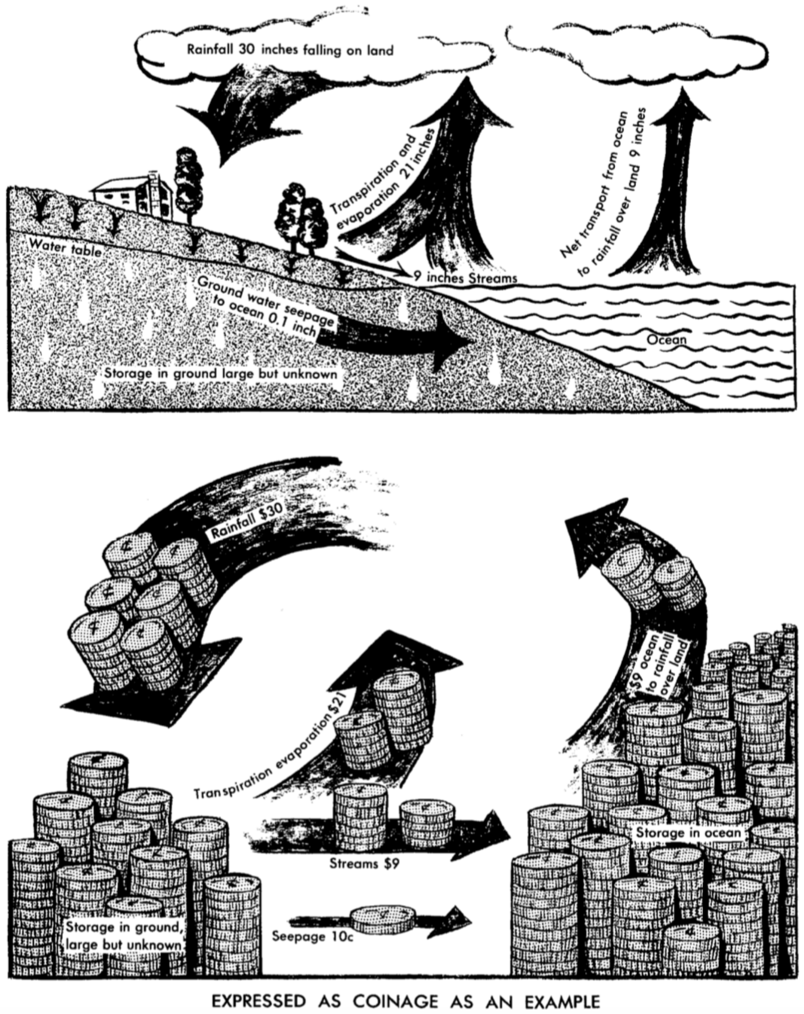


FIGURE 13 —*Water budget over the continental United States.*

Walter Langbein – the visionary

USGS Water Program

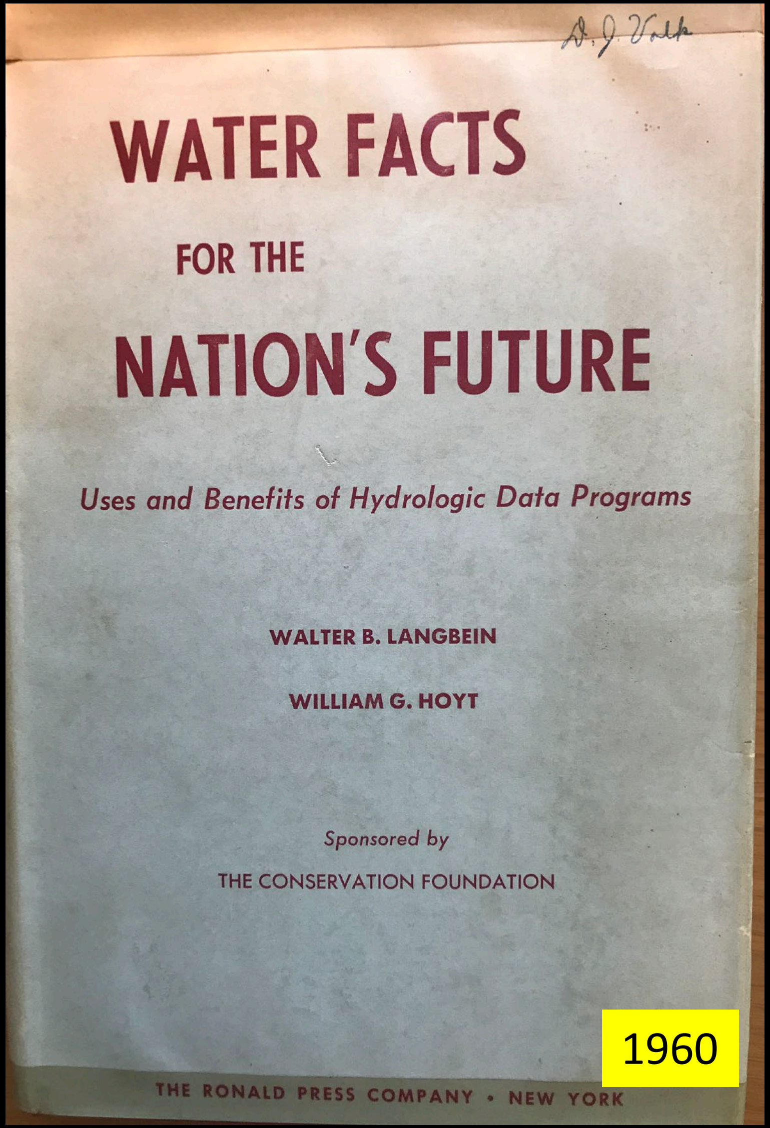
National network of hydrologic data

Flood Insurance Program

Intern. Hydrologic Decade (1965-1974; UNESCO)

Intern. Association for Hydrologic Sciences (IAHS)

World Meteorological Organization (WMO)



1960

Walter Langbein – the visionary

USGS Water Program

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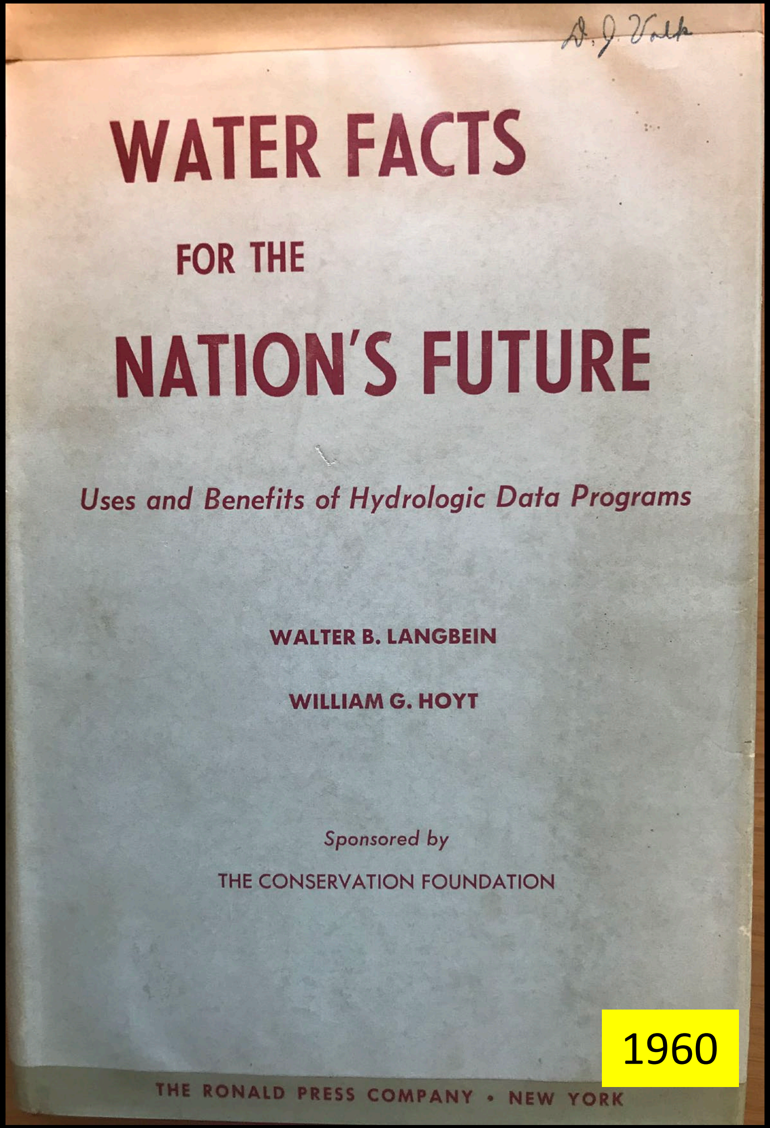
World Meteorological Organization (WMO)

… "Science is built up with facts, as a house is with stones. But a collection of facts is no more a science that a heap of stones is a house"
– HENRY POINCARE

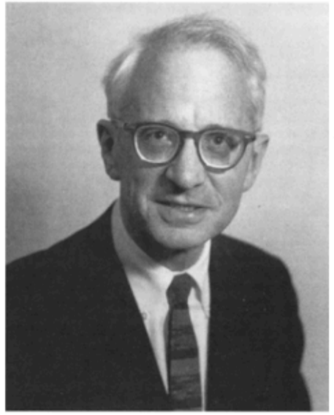


1960

VHP Scope

Virtual Hydrologists Project (VHP)

Walter B. Langbein (1907–1982)



Walter Langbein was dedicated to science that benefited the public good and was known as a versatile and talented hydrologist. Born in New Jersey in 1907, he obtained his civil engineering degree in 1931 from Cooper Union while attending night classes and working for a construction company. In 1935, he joined the U.S. Geological Survey (USGS) in Albany, but within a year he was transferred to the national headquarters, where he served as a research engineer and senior scientist for the rest of his life.

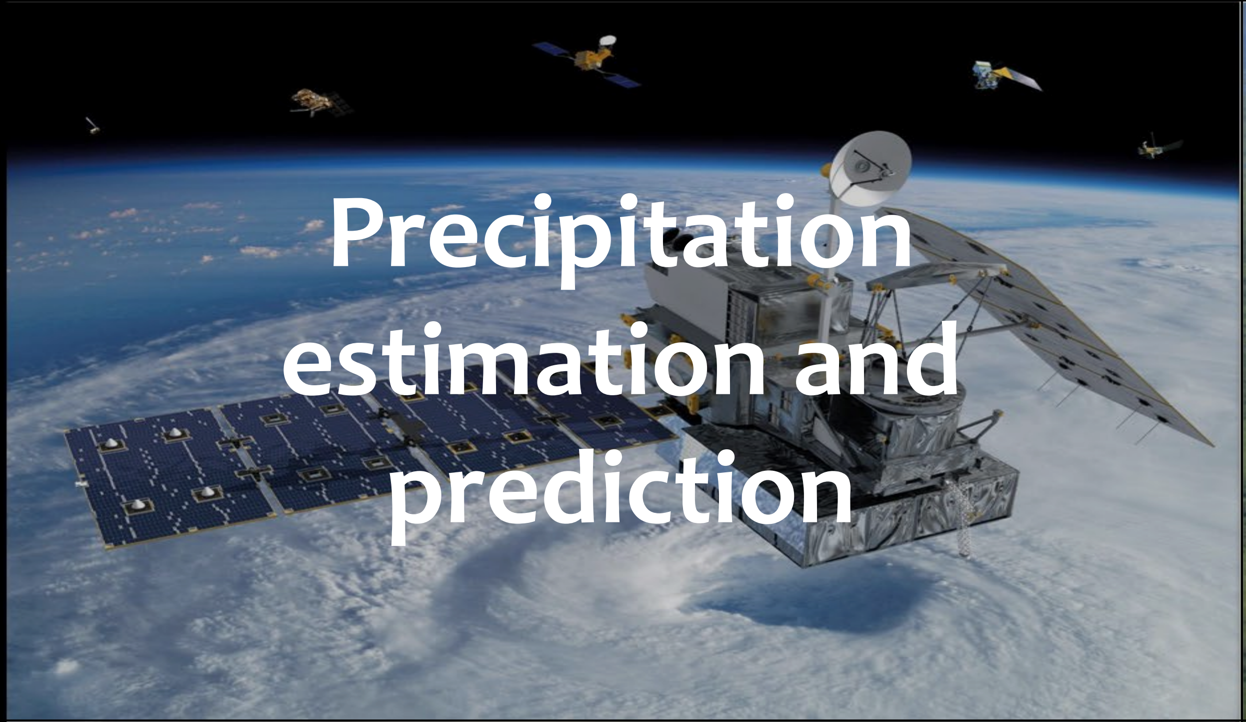
Langbein's contributions to the field of hydrology are extensive. His 1955 book, *Floods*, with W. G. Hoyt, was instrumental in the development of the National Flood Insurance Program. He developed methods in flood hydrology and the application of statistical methods to the analysis of hydrologic data. He studied evaporation from water bodies, varying from small stock ponds on the Navajo Reservation to Lake Mead. He studied infiltration in stream channels and its effect on flood wave passage. As early as 1944, Langbein was interested in the use of hydrologic data for the estimation of climate change. With Luna Leopold, he worked to establish a national program in water resources research, which led to the development of the Office of Water Resources Research within USGS. Langbein was instrumental in founding the International Hydrologic Decade (1965–1974), and his participation in the decade focused attention on the determination of the worth of hydrologic data for water resources development. The theory of scientific network design for water data networks evolved from his work.

Walter Langbein was awarded the William Bowie and Robert E. Horton Medals from the American Geophysical Union, the J. C. Stevens Award of the American Society of Civil Engineers, the Distinguished Service Award of the Department of the Interior, and the Warren Prize of the National Academy of Sciences. He and Professor Korzun of the Soviet Union were named corecipients of the International Prize in Hydrology, awarded by the International Association of Hydrologic Sciences.

Langbein once remarked that one's professional career is a race against obsolescence. As noted by others, any hydrologist would claim that Walter B. Langbein clearly won the race.

https://connect.agu.org/hydrology/about/vhp-scope/walterlangbein





Precipitation
estimation and
prediction

Tributary and
distributary Networks

Meandering
and braided rivers

Human dominated
landscapes

Driving scientific questions

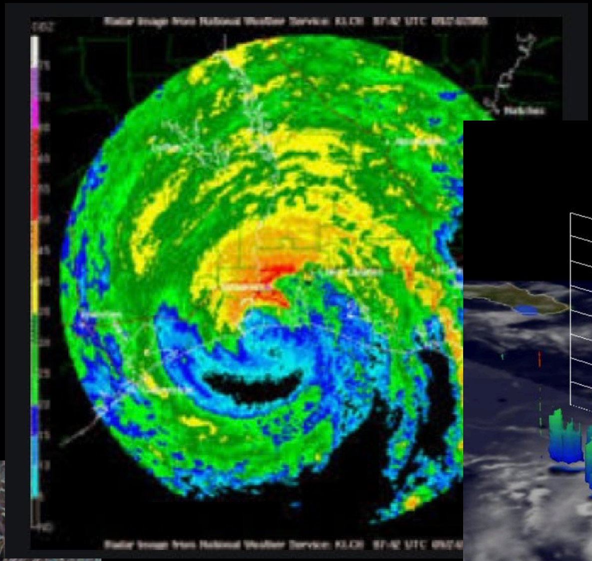
1. How do physics organize **precipitation** systems across spatio-temporal scales?

2. How can this organization be used to improve **estimation, modeling and prediction** at local to global scales?

3. How can we gain mechanistic **process** understanding from **landscape patterns** and form?

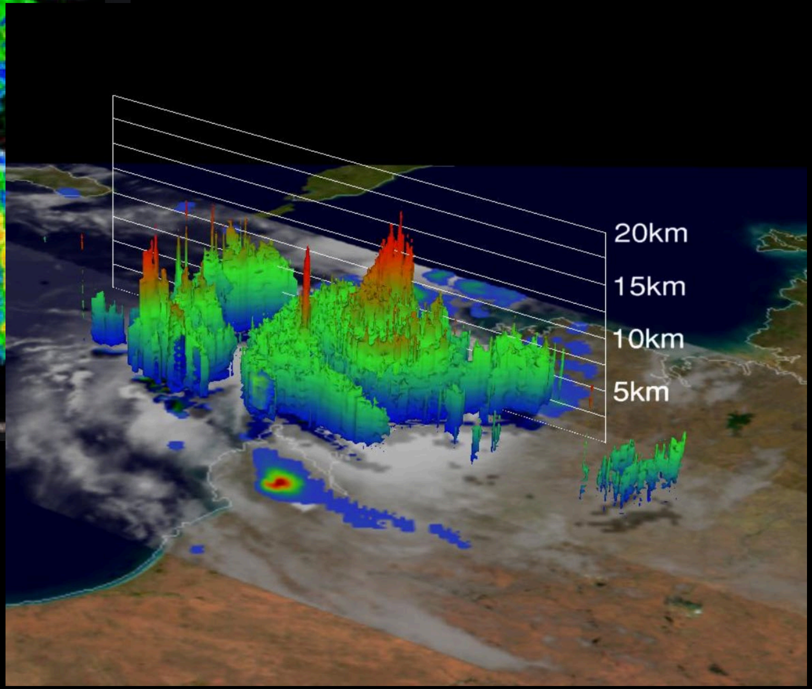
4. How do **perturbations** propagate through a complex ecohydrological system determining its vulnerability to change?

Our data: multi-sensor observations

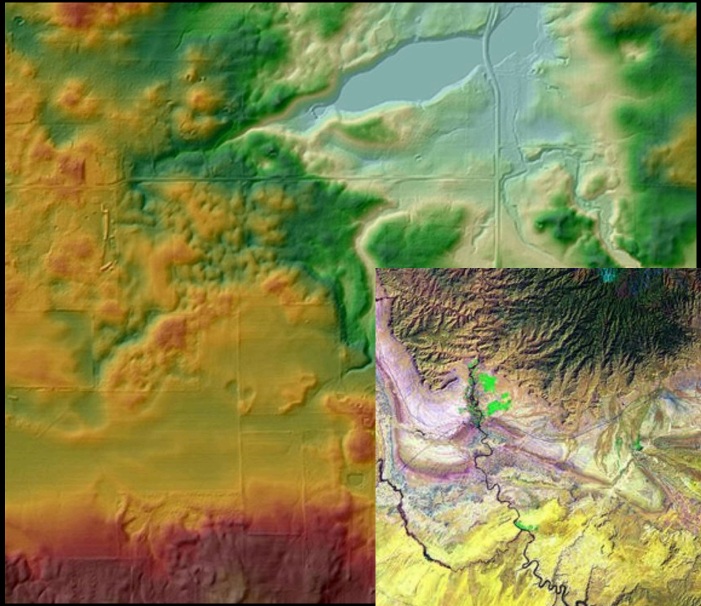


NEXRAD

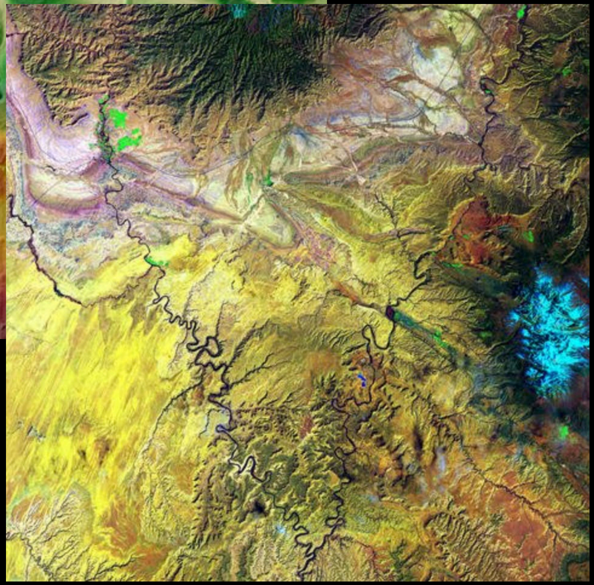
Rainguage



TRMM/GPM

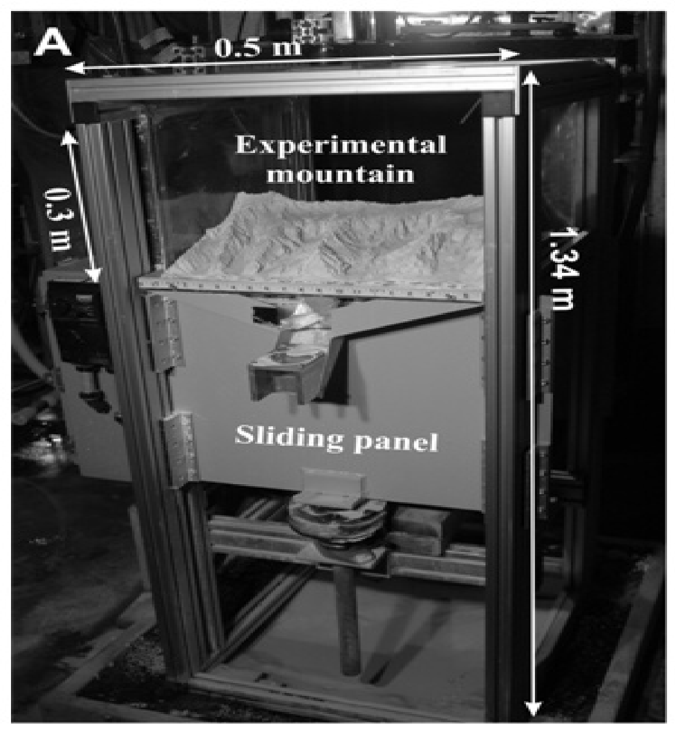


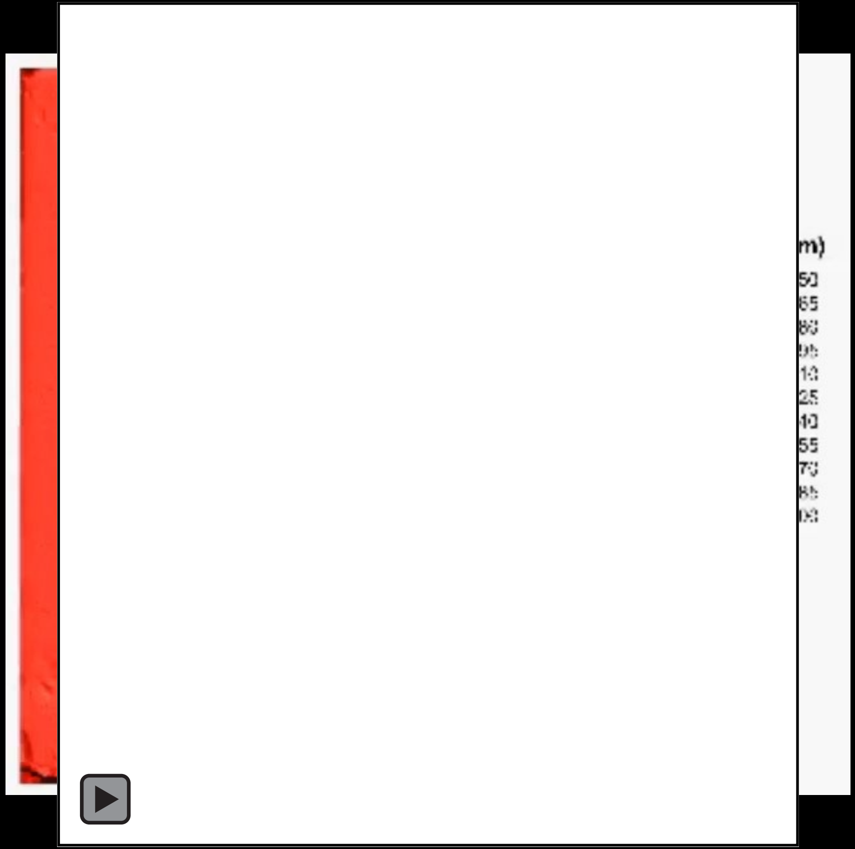
LIDAR



LANDSAT

Our data: Lab experiments



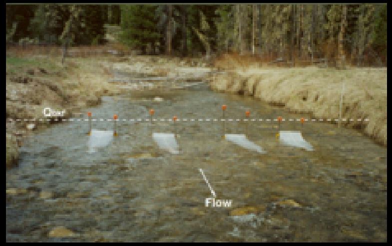


St. Anthony Falls Laboratory, Univ. of Minnesota

Arvind Singh, Vamsi Ganti, Victor Sapozhnikov

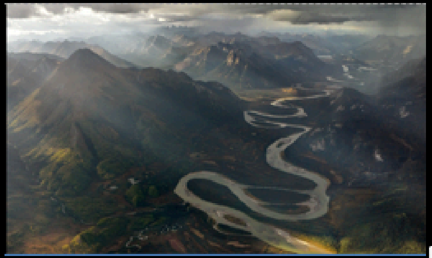
Across processes & scales

Pebble scale



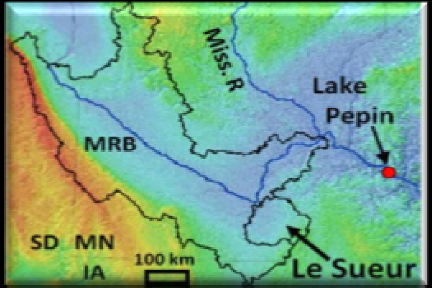
- Stochastic transport
- Semi-mech to bed load
- Bridging theory and exp

Plot scale / single river scale



- Meander bends
- Cutoff effects
- Residence/travel time
- Hillslope transport

Watershed scale

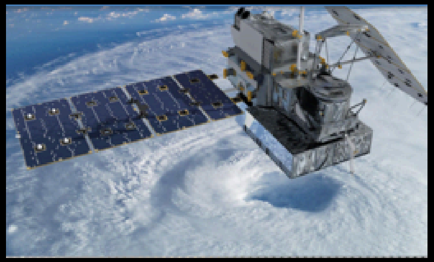


- Landscape evolution
- Cascade of hydrology to ecology/water quality
- Wetlands for water quality

Continental scale

- River deltas
  - Topology/Dynamics
  - Process from form
  - Optimality Principle
  - Vulnerability

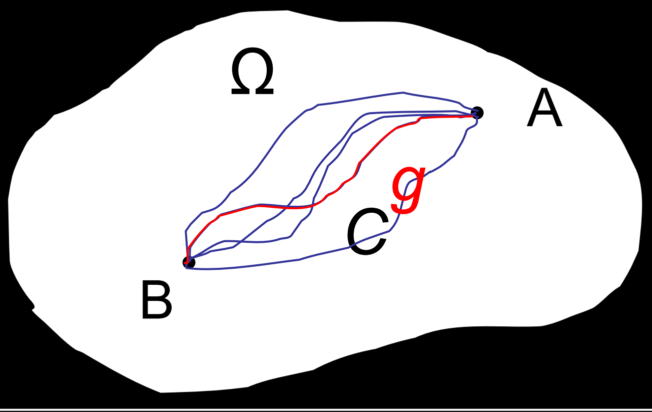
Global scale



- Precipitation retrieval
- Trends in extremes
- Large scale dynamics to local precipitation

From raw data to quantitative patterns …

***Ω*: Surface described by the regularized LIDAR data through nonlinear filtering.**



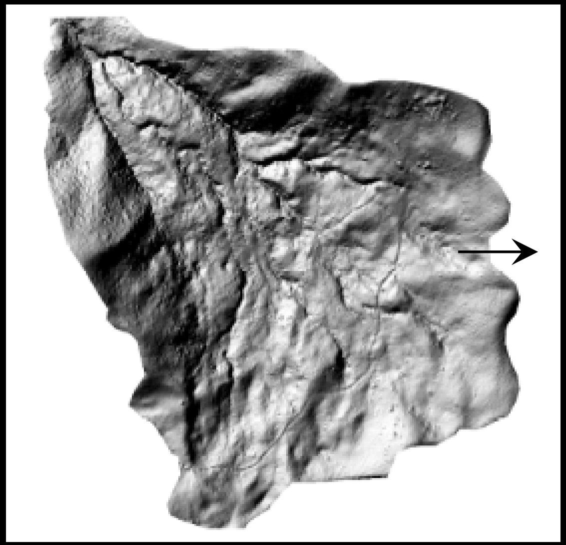
Cost function *ψ:* cost of traveling on the curve C.

Geodesic curve curve with minimal cost, among all possible curved connecting the two point *a* and *b*

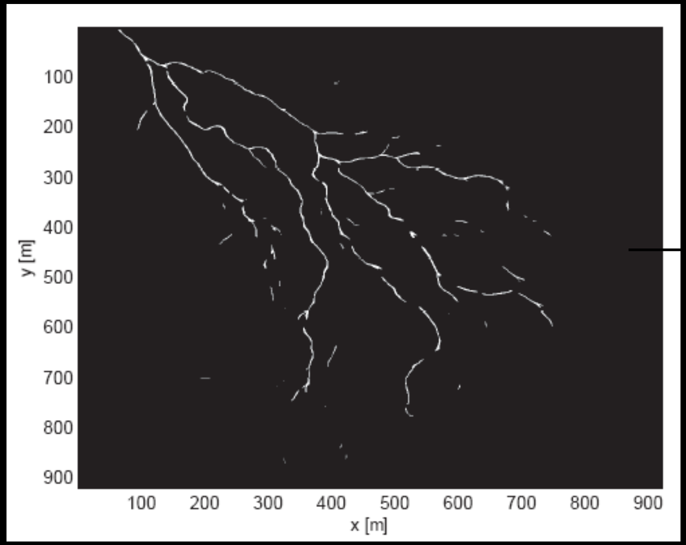
$$g(a,b) := \arg\left(\min_{C\in\Omega}\int_a^b \psi(s)\,ds\right)$$

Geomorphologically Inspired image Processing

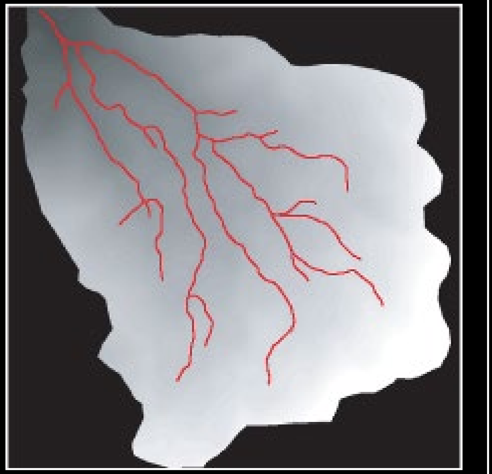
Example of river network extraction on Skunk Creek, South Fork Eel River basin, CA



Original data



Likely channelized pixels

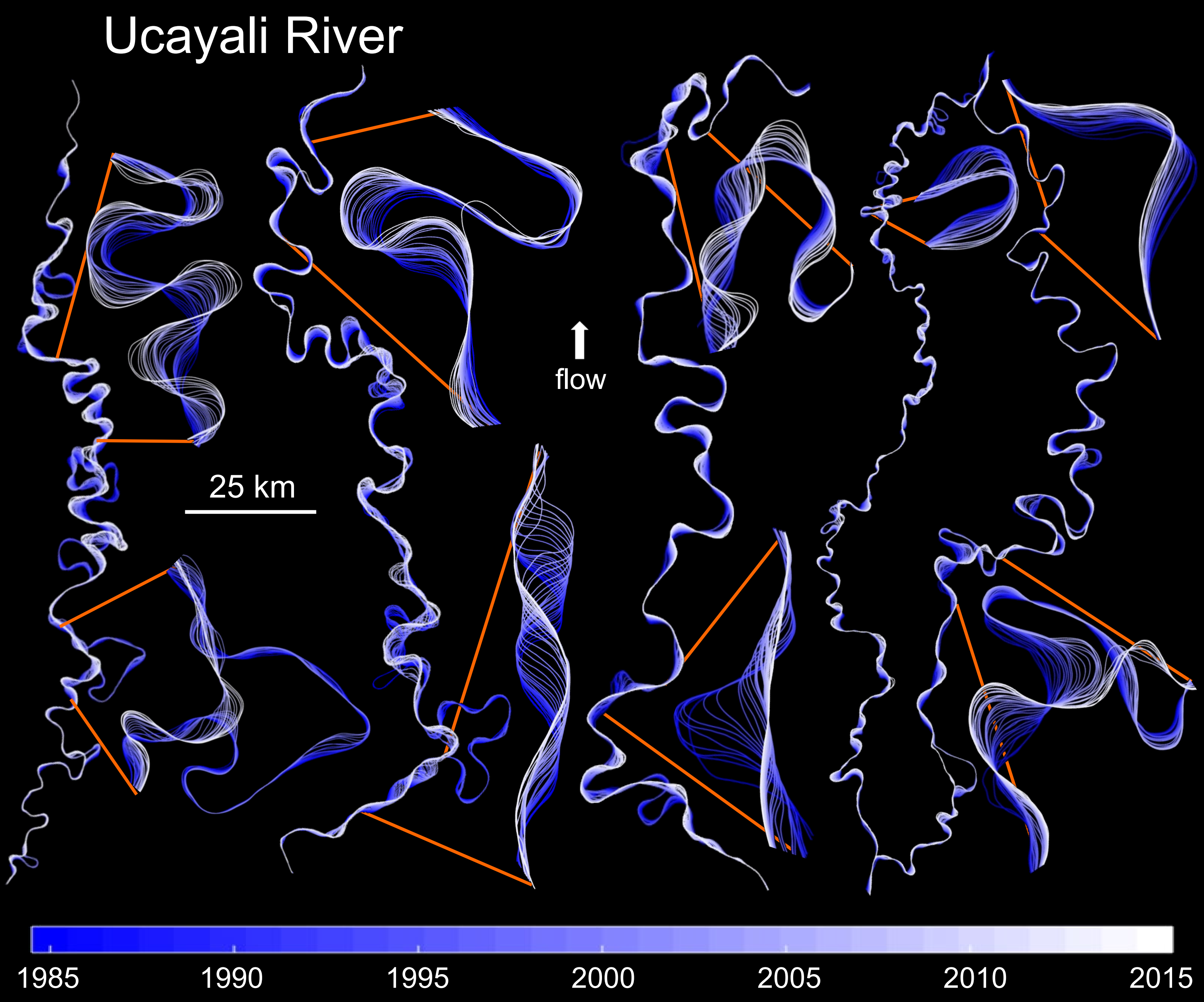


Extracted channels through geodesics

GeoNet Toolbox

Paola Passalacqua's Group

Passalacqua et al. 2010, 2012



Mining Landsat archives

to **resolve bend scale river dynamics**

RivMAP Toolbox

Jon Schwenk's group

Schwenk et al., 2015, 2016a,b, 2017

ne life of a meander bend…

Does the shape of an oxbow lake rry the signature of its forming namics?

Does process nonlinearity express elf on the static planform geometry?

How far upstream and downstream cutoff perturbations propagate?

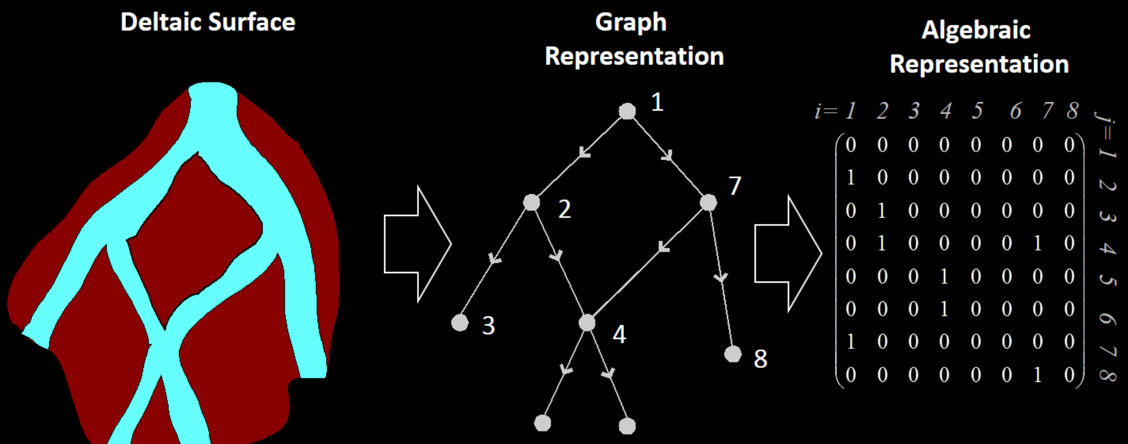
Schwenk et al., 2015, 2016a,b, 2017

The complexity of river deltas…

-- What physical processes are recorded in delta channel network topology?

-- Can a quantitative framework for delta classification be built based on suitable metrics?

-- Is there an optimality principle behind the self-organization of deltas?



Entropy and optimality in river deltas

Alejandro Tejedor[a], Anthony Longjas[a], Douglas A. Edmonds[b,c], Ilya Zaliapin[d], Tryphon T. Georgiou[e], Andrea Rinaldo[f,g,1], and Efi Foufoula-Georgiou[a,1]

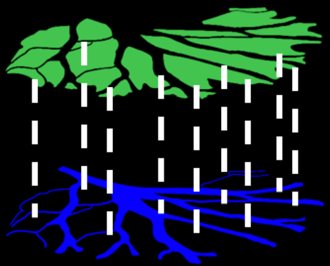
PNAS

Tejedor et al., 2015a,b, 2016, 2017a,b, 2018

The complexity of river deltas…

Coupled processes

Multi-layer Networks

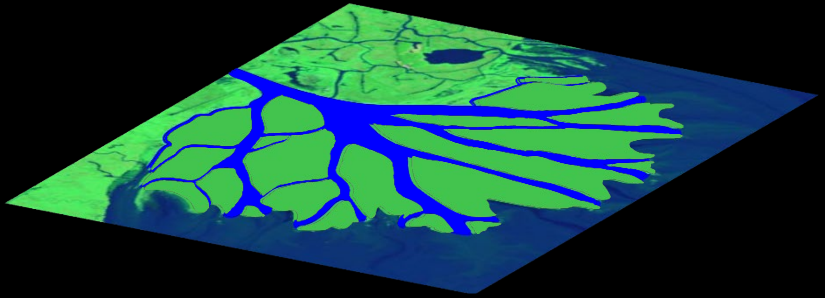


$$\mathscr{A} = \begin{pmatrix} A^C & I \\ I & A^I \end{pmatrix}$$

Supra-Adjacency Matrix

$$\mathscr{L} = \begin{pmatrix} D_C L^C + D_X I & -D_X I \\ -D_X I & D_I L^I + D_X I \end{pmatrix}$$

Supra-Laplacian Matrix



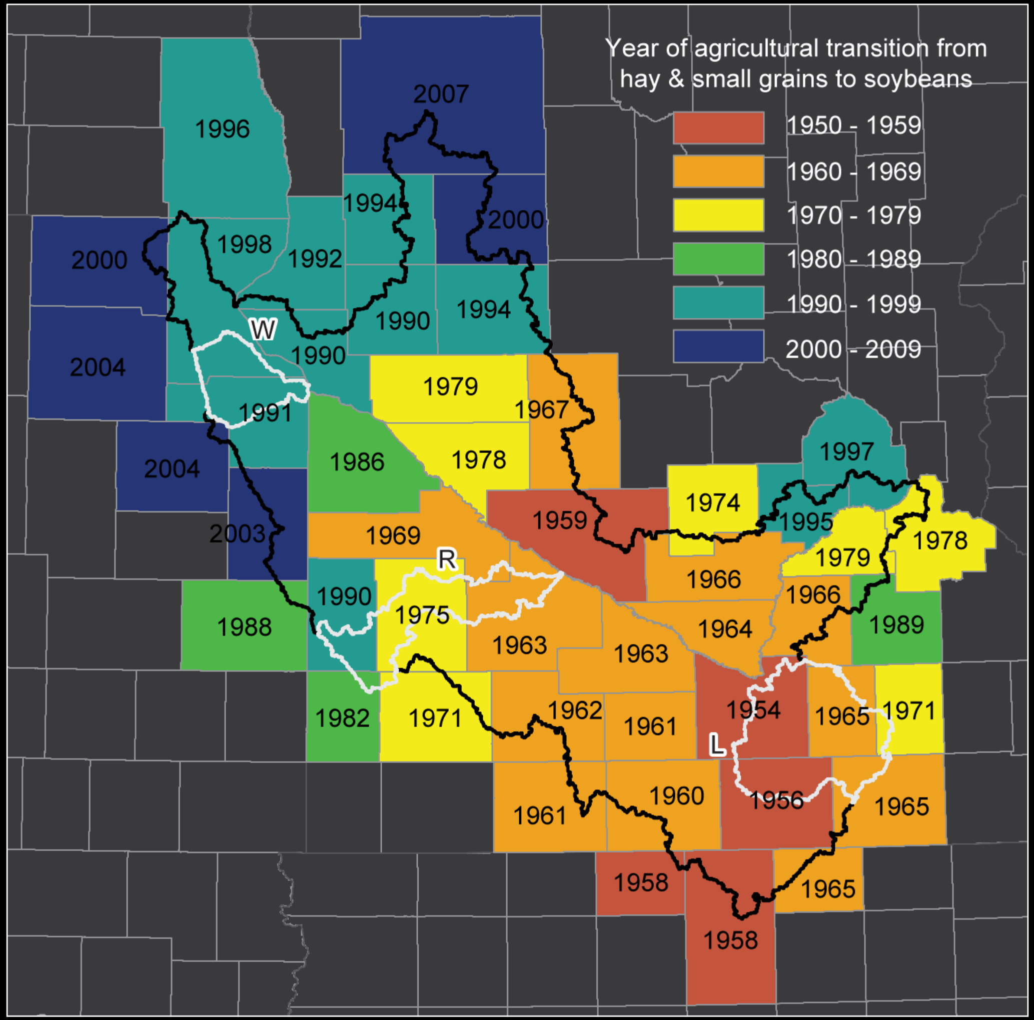
Tejedor et al., 2015a,b, 2016, 2017a,b, 2018

Intensively managed landscapes

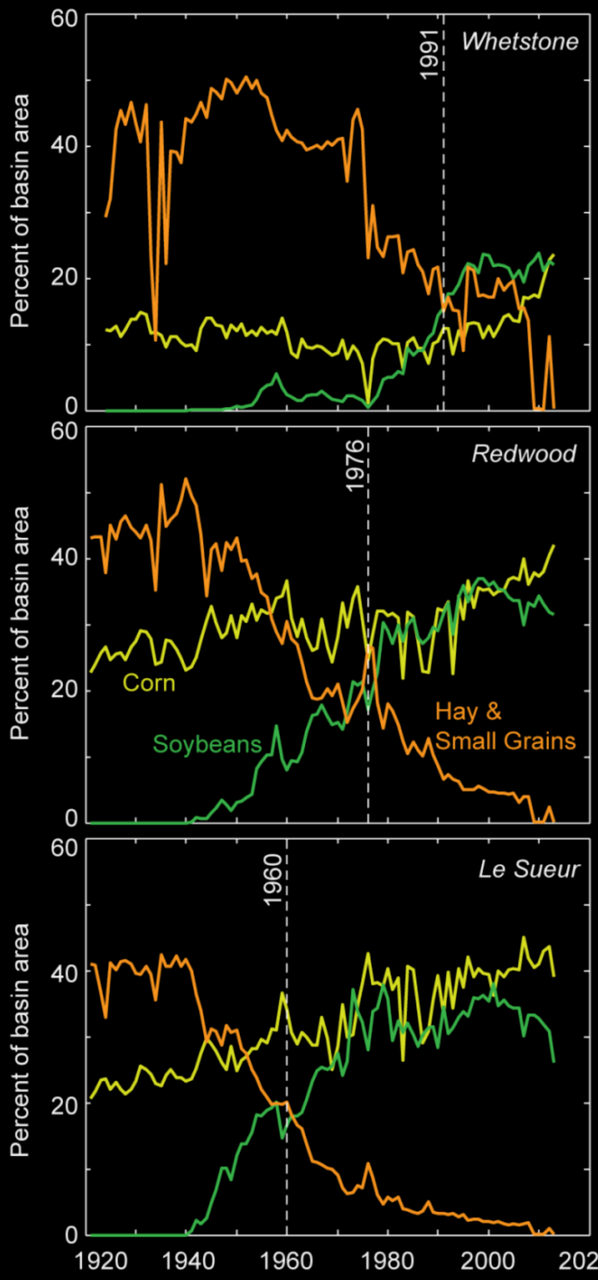
Transition from hay and small grains to soybeans changed the eco-hydrology of the system

(Photo: S. Levine, B. Call, P. Belmont)

w/ Belmont, Hansen, Grant, Wilcock, Finlay



Foufoula-Georgiou et al., 2015, WRR



Czuba et al., 2014, 2015, 2017

Today's focus:

RAINFALL

1. Global estimation from space
2. Seasonal prediction

Walter Langbein – the visionary

"… Precipitation stations are more numerous where people live … than where precipitation is more variable and therefore most important to record."

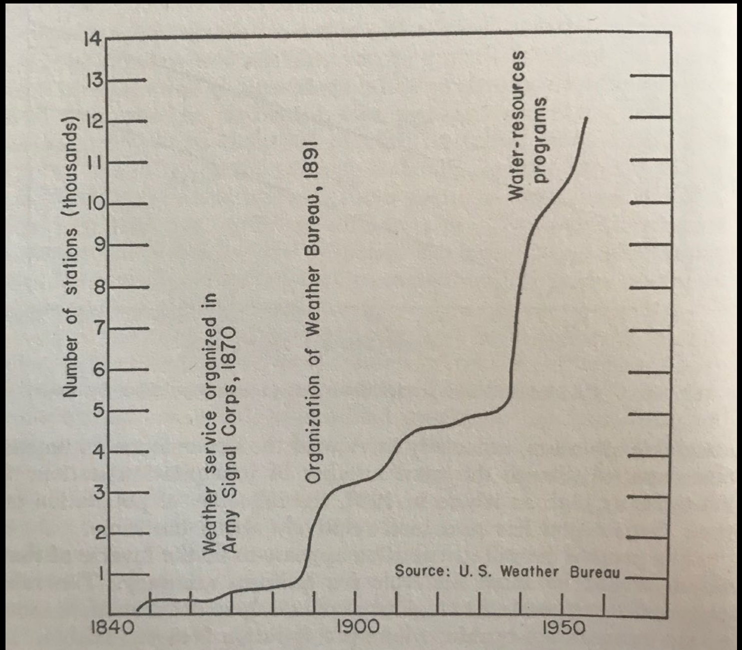
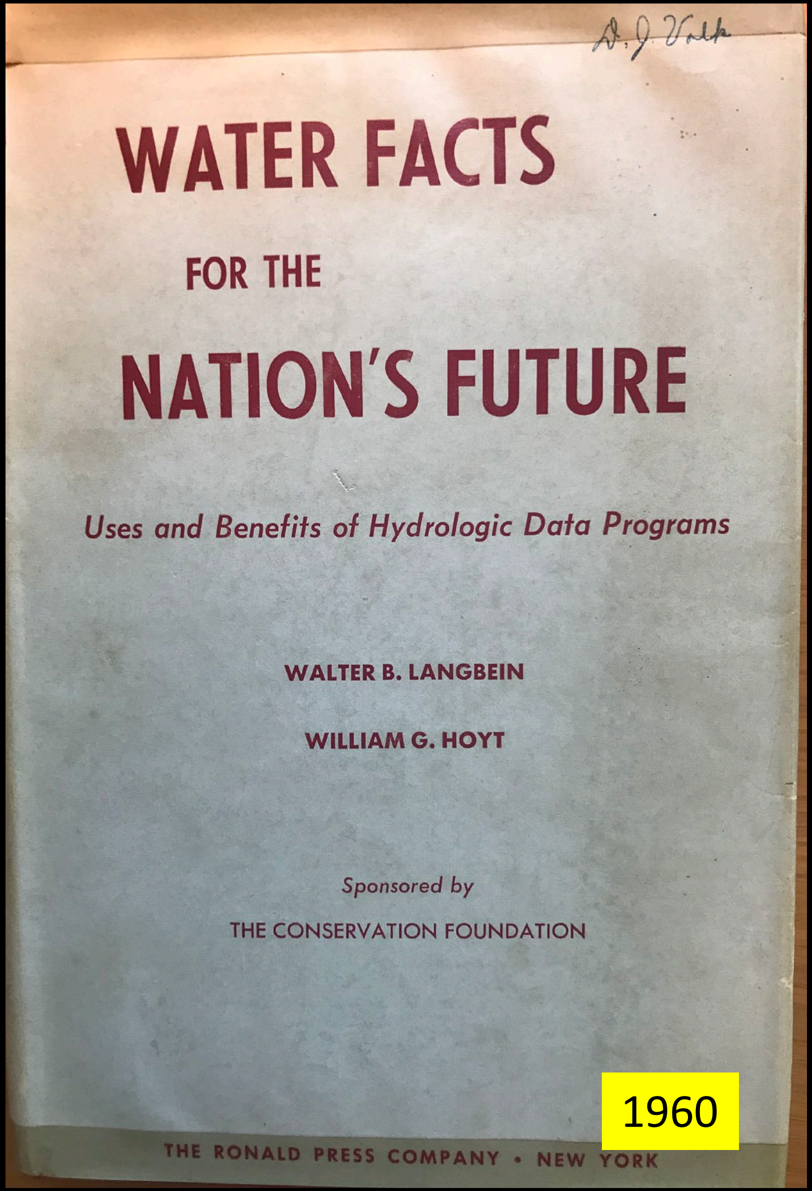


FIGURE 6. Growth of precipitation network in the United States since 1840.

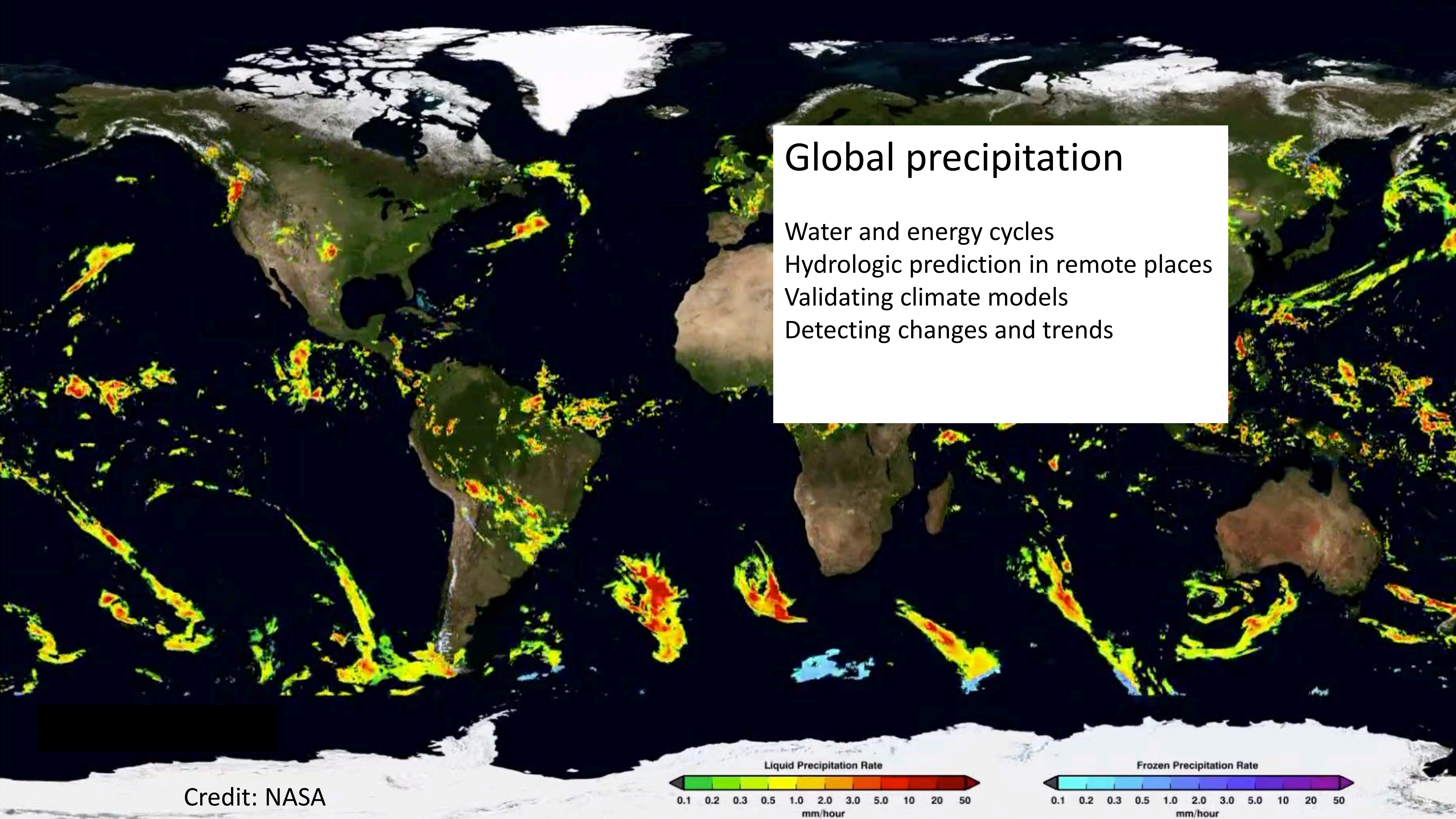


1960

How much of the Earth's surface is covered by raingages?

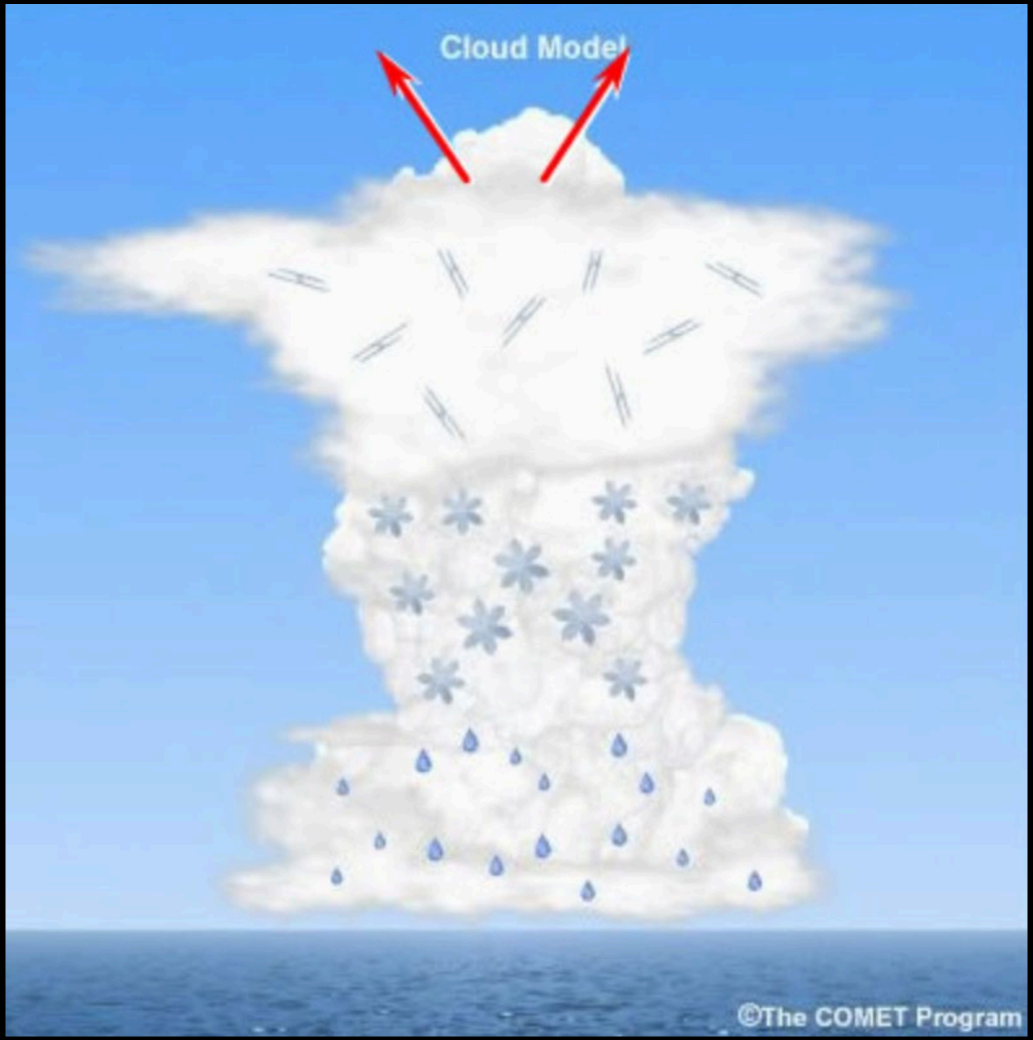
Global precipitation

Water and energy cycles
Hydrologic prediction in remote places
Validating climate models
Detecting changes and trends



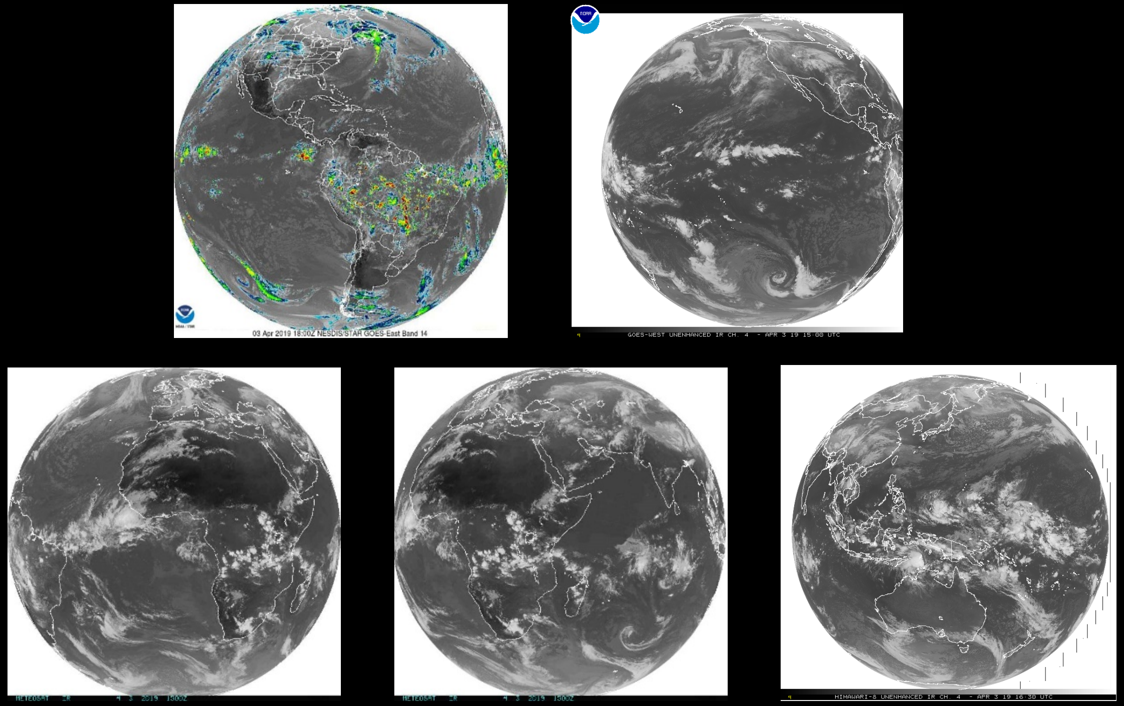
Credit: NASA

How do we observe precipitation from space?



The GEO-IR constellation

(NOAA-NESDIS, EUMETSAT, JMA)

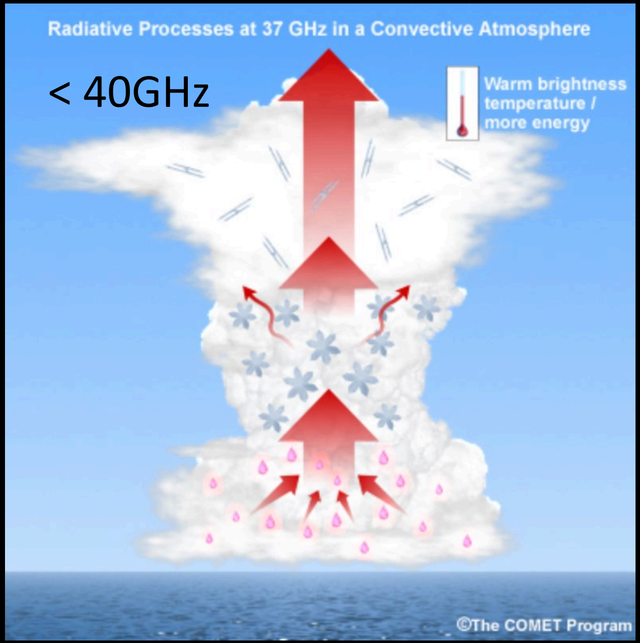


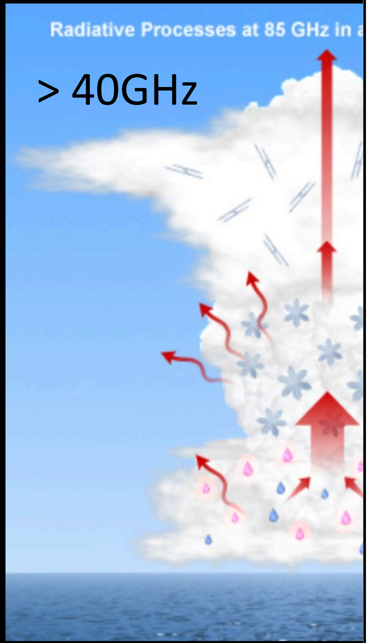
- **5** IR imagers for a quasi-global coverage

One observation every 15-30 mis

How do we observe precipitation from space?

The LEO-GPM constellation



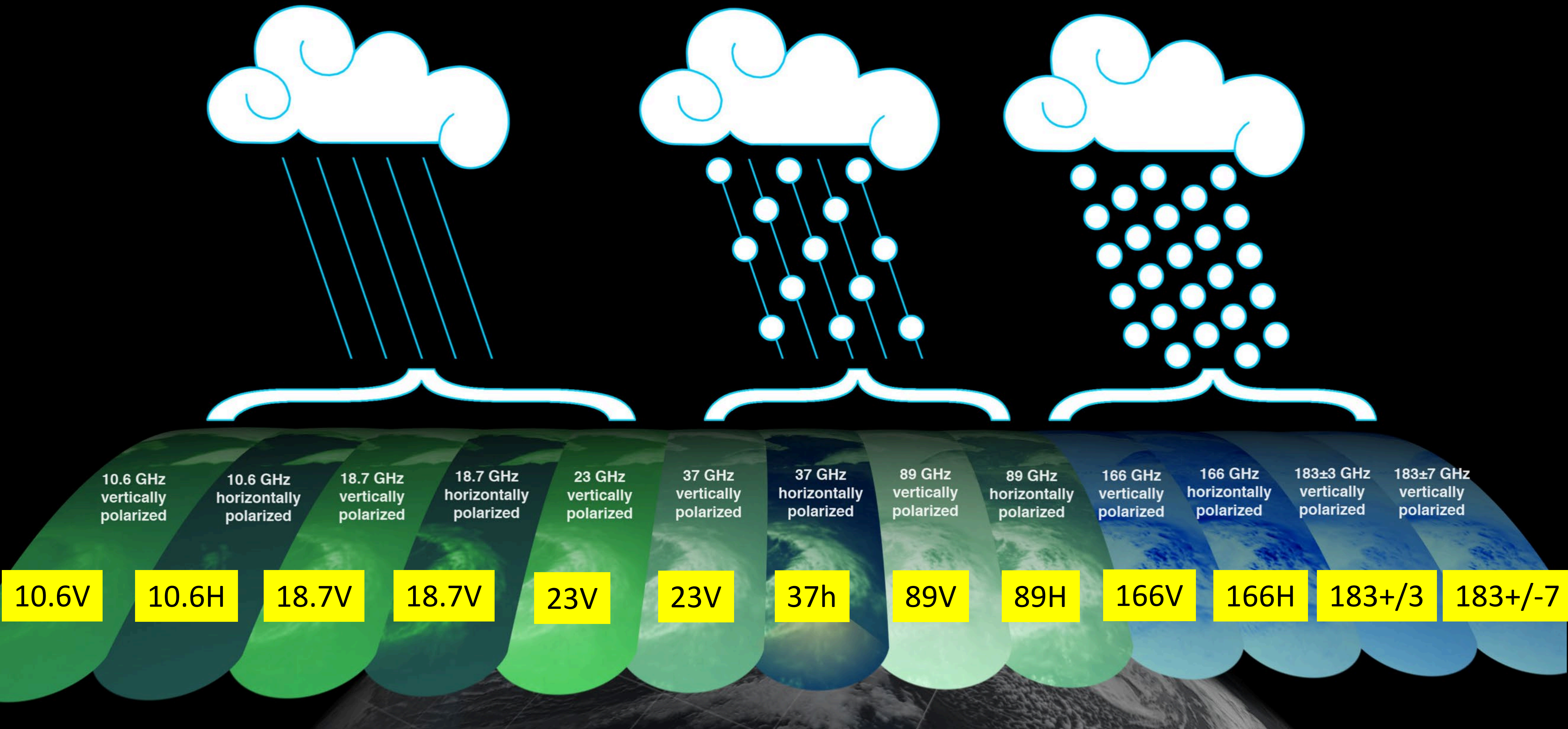


- **5** conical-scan MW imagers
- **8** cross-track MW sounders
- **1** Dual-frequency Precipitation Rad

One observation every 2-4 hrs

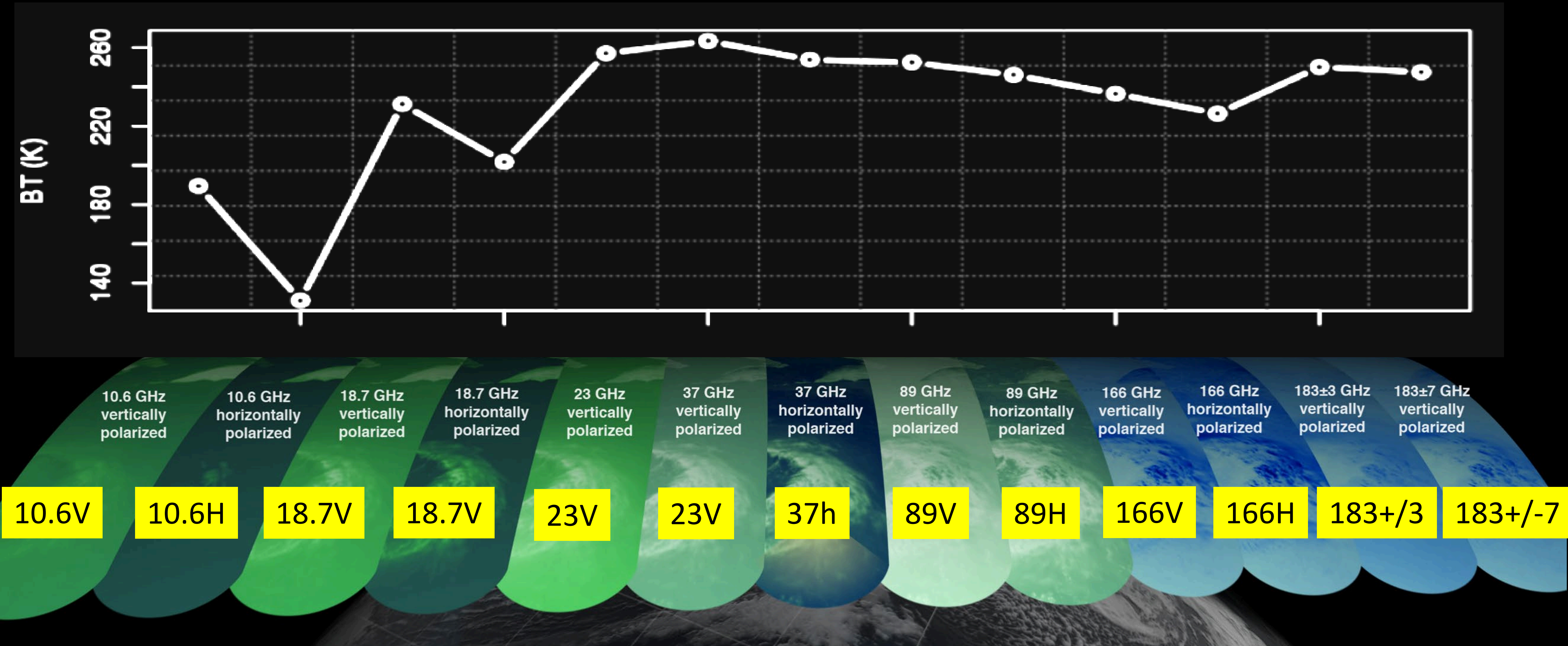
Credit: NASA

Multispectral microwave signature

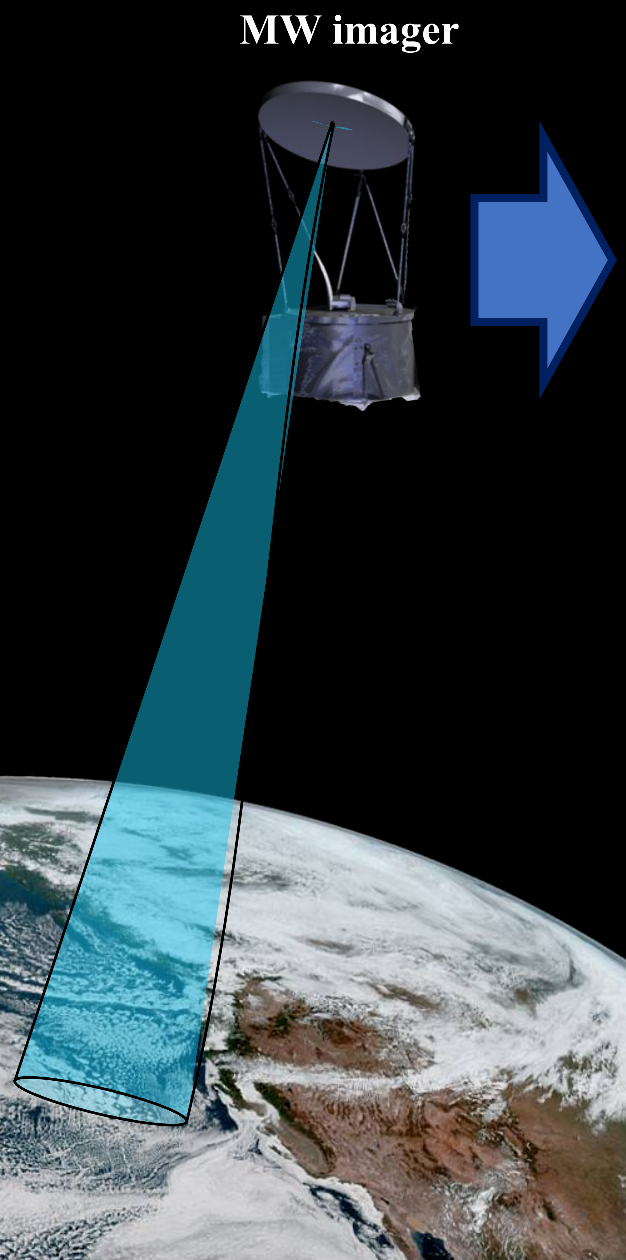


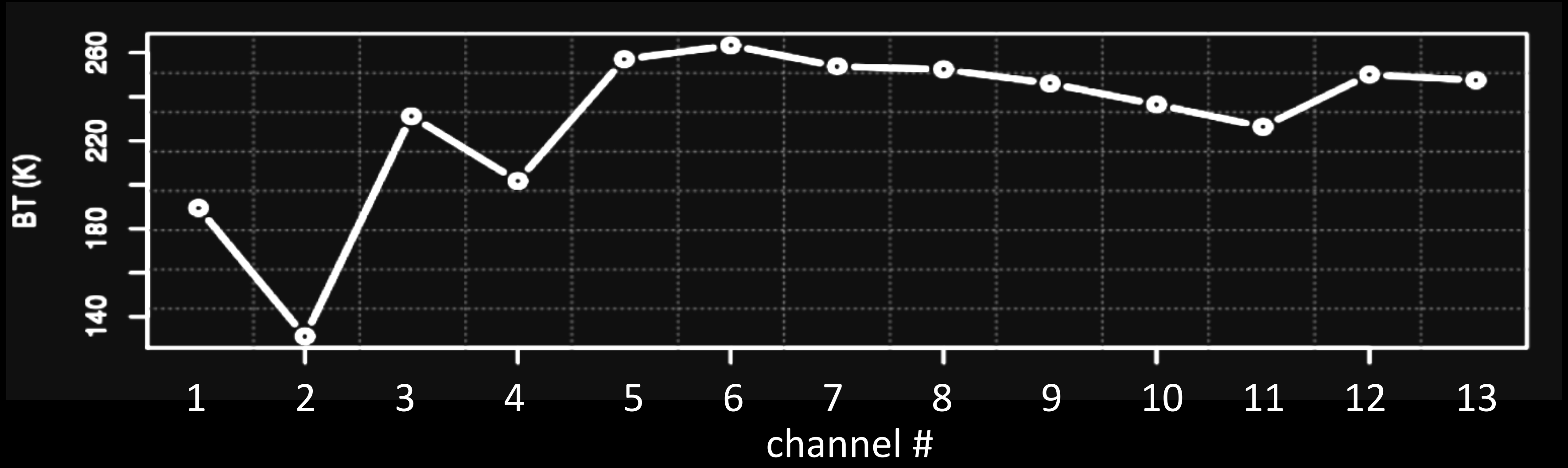
Multispectral microwave signature

Brightness Temperature (TB)



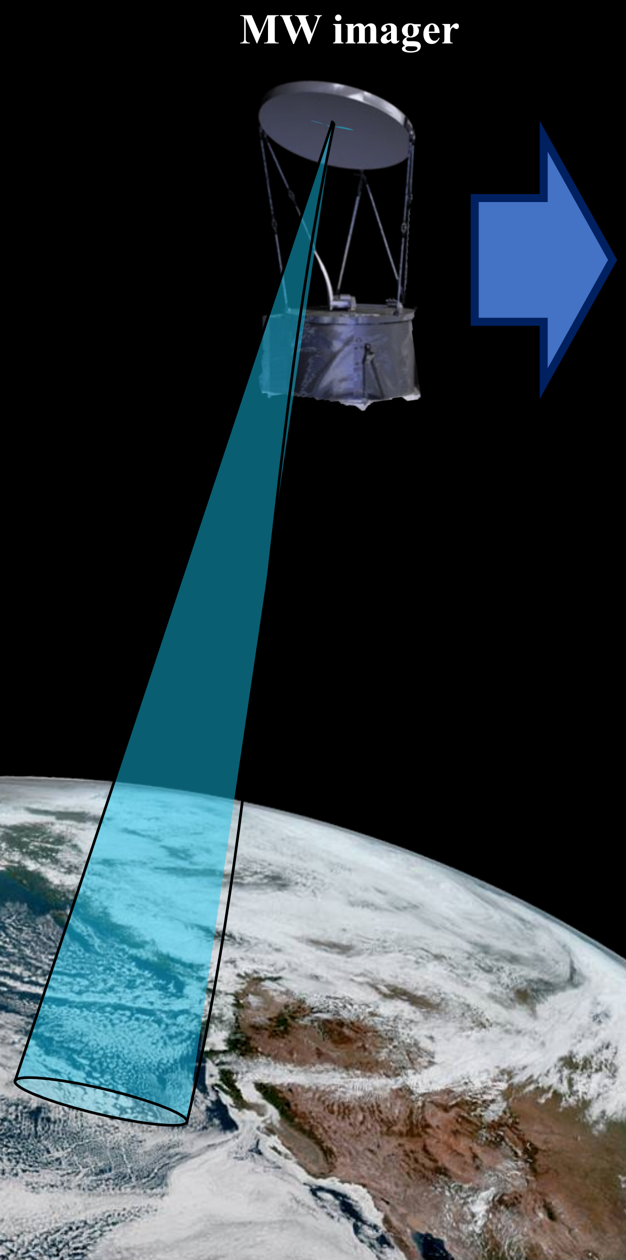
Retrieval is an Inverse Problem

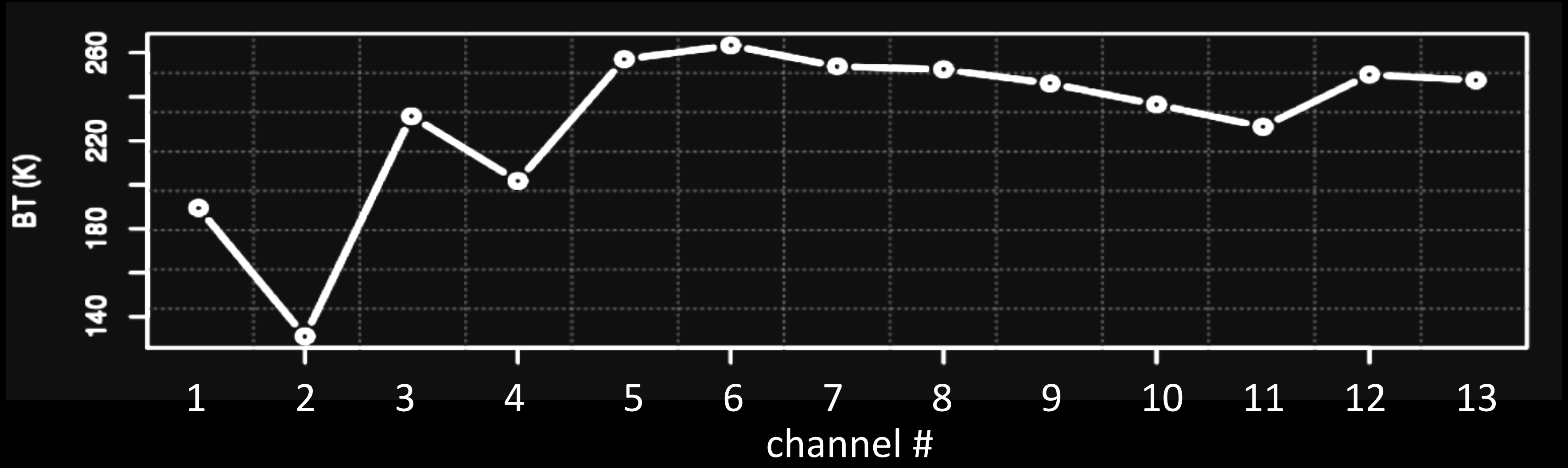




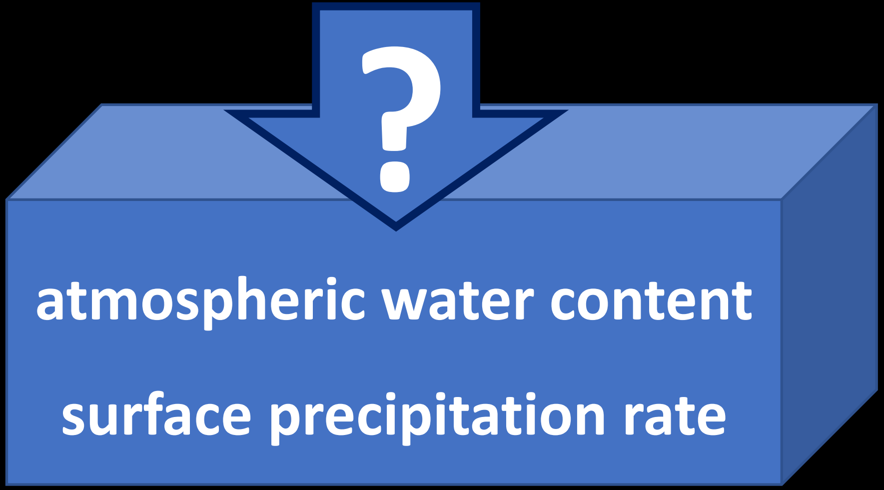
Radiometric signature at the top of the atmosphere

Retrieval is an Inverse Problem





Radiometric signature at the top of the atmosphere

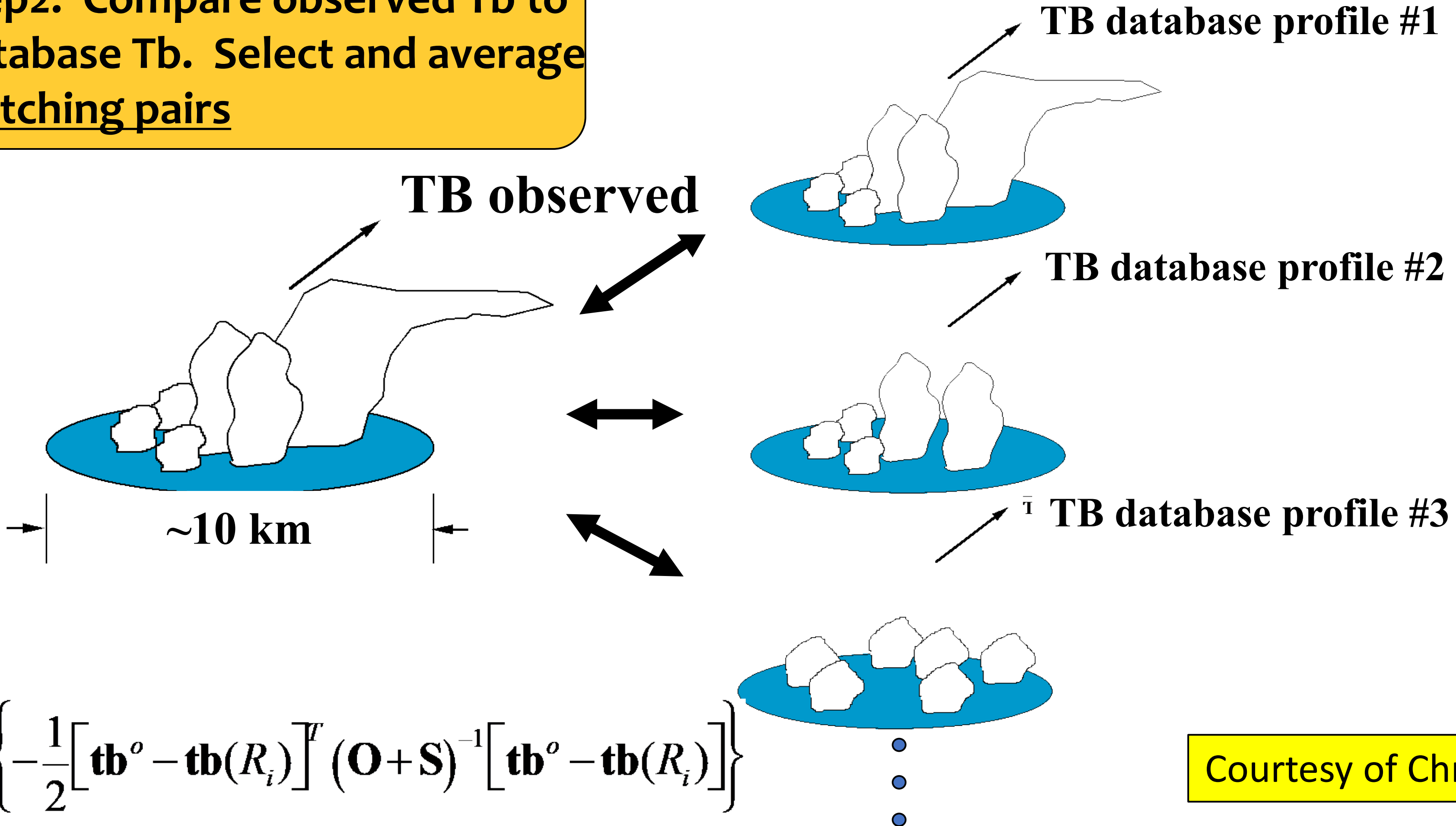


GPM core satellite

The NASA GPM radiometer algorithm: GPROF

Step 1: Use GPM Satellite to derive set of "Observed" profiles that <u>define an a-priori database</u> of possible rain structures.

Step2: Compare observed Tb to Database Tb. Select and average <u>matching pairs</u>



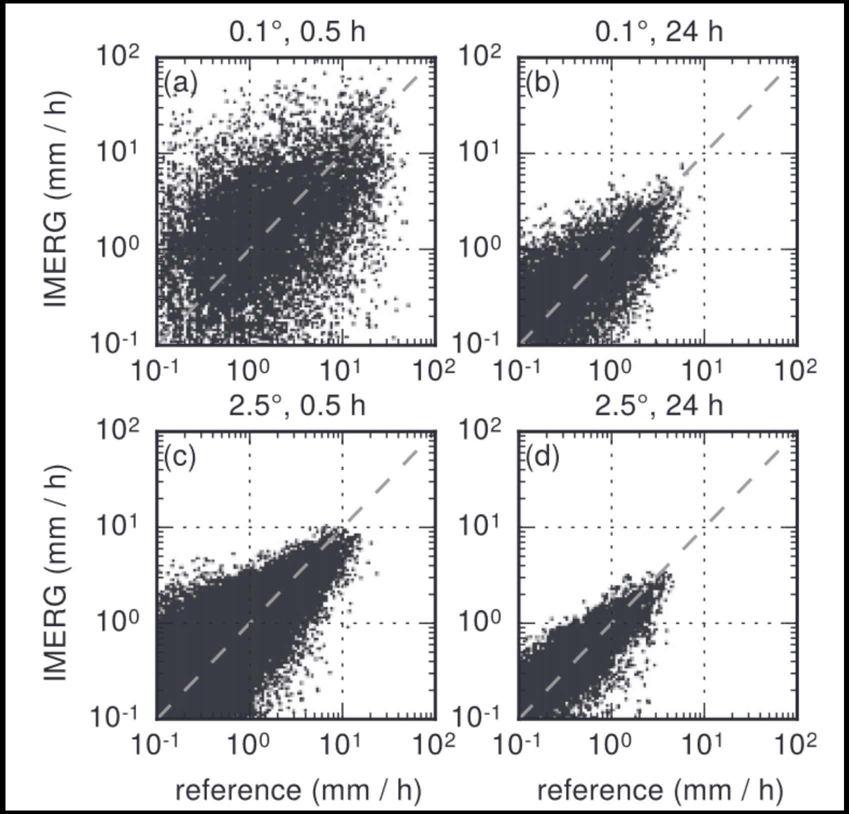
$$J_i = \exp\left\{ -\frac{1}{2}\left[\mathbf{tb}^o - \mathbf{tb}(R_i)\right]^T (\mathbf{O}+\mathbf{S})^{-1}\left[\mathbf{tb}^o - \mathbf{tb}(R_i)\right] \right\}$$

Courtesy of Chris Kummerow

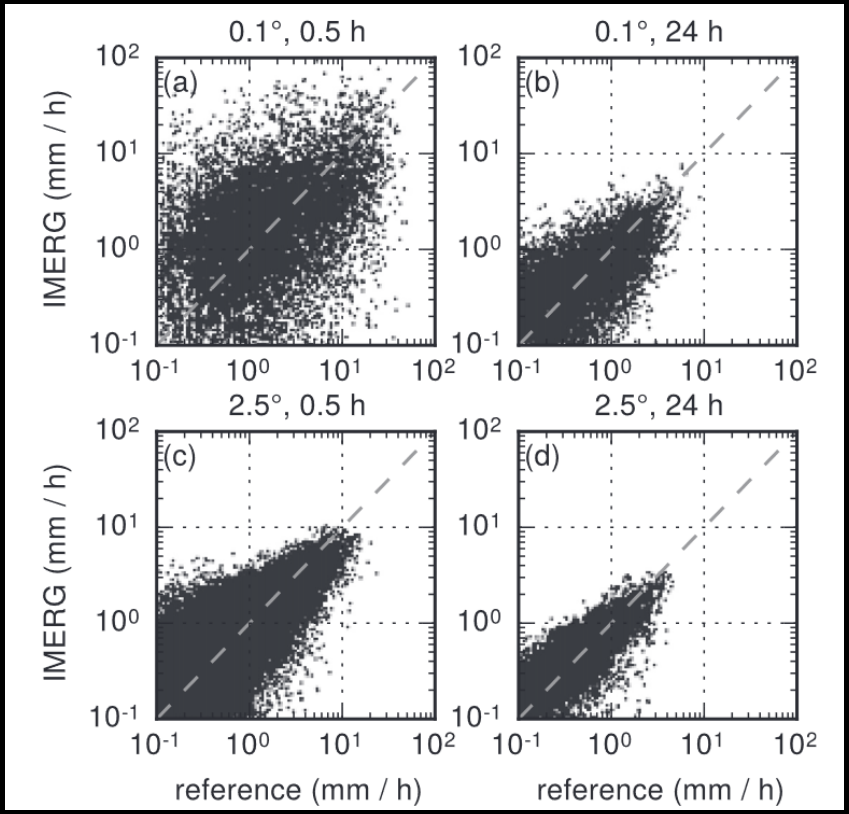
How accurate are these retrievals globally?

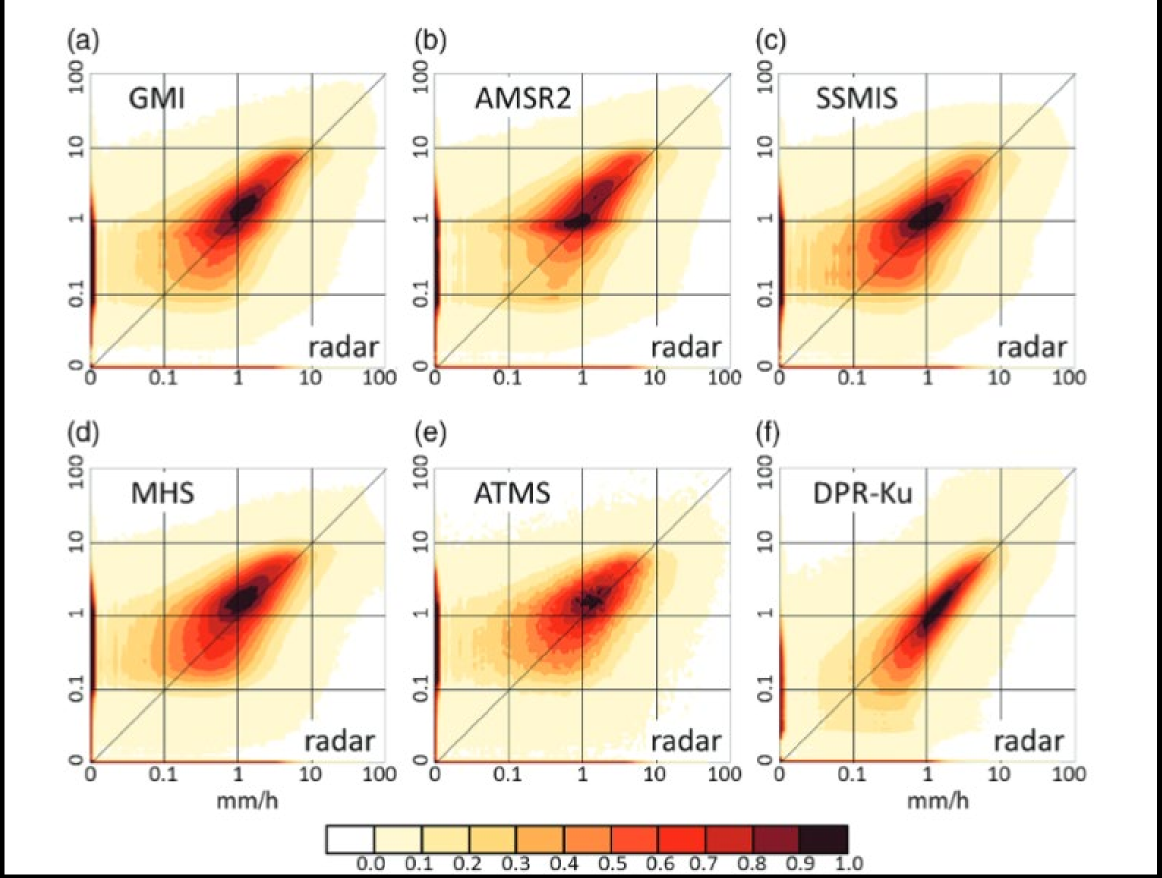
https://pmm.nasa.gov/extreme-weather

THE CLASSICAL APPROACH IN COMPARING/VALIDATING RETRIEVALS

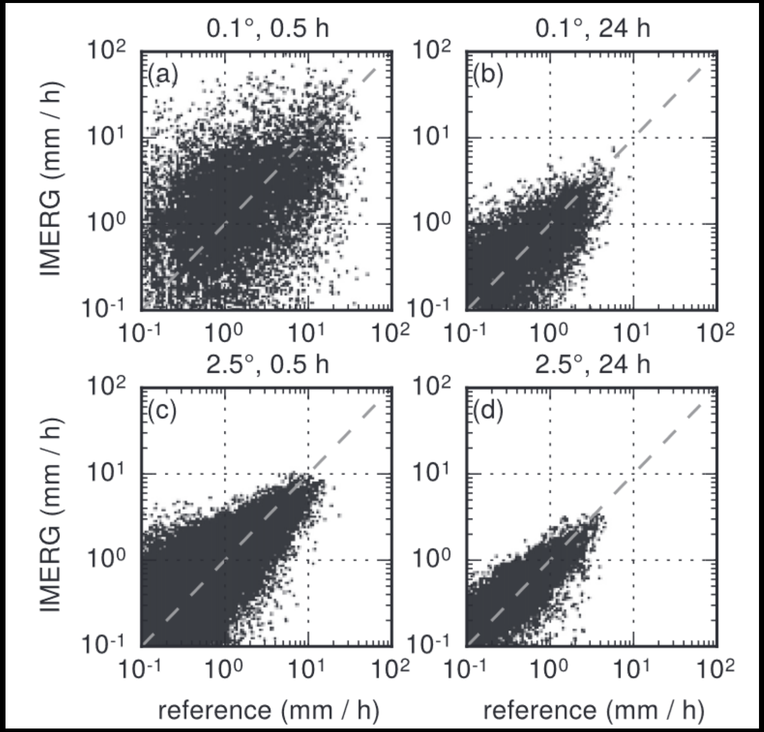


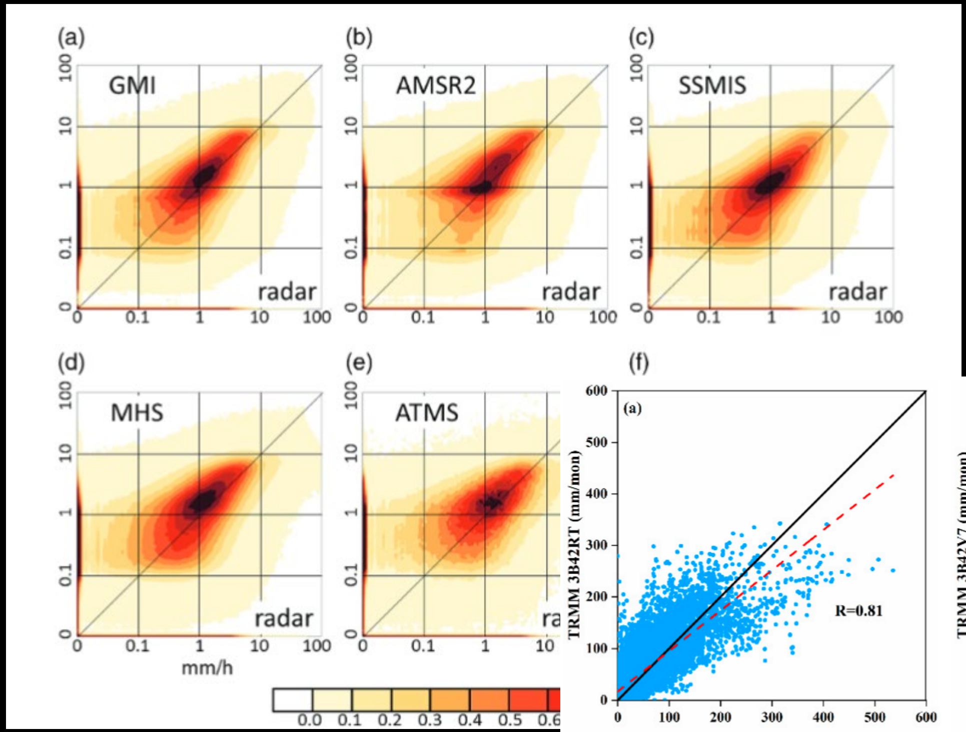
THE CLASSICAL APPROACH IN COMPARING/VALIDATING RETRIEVALS

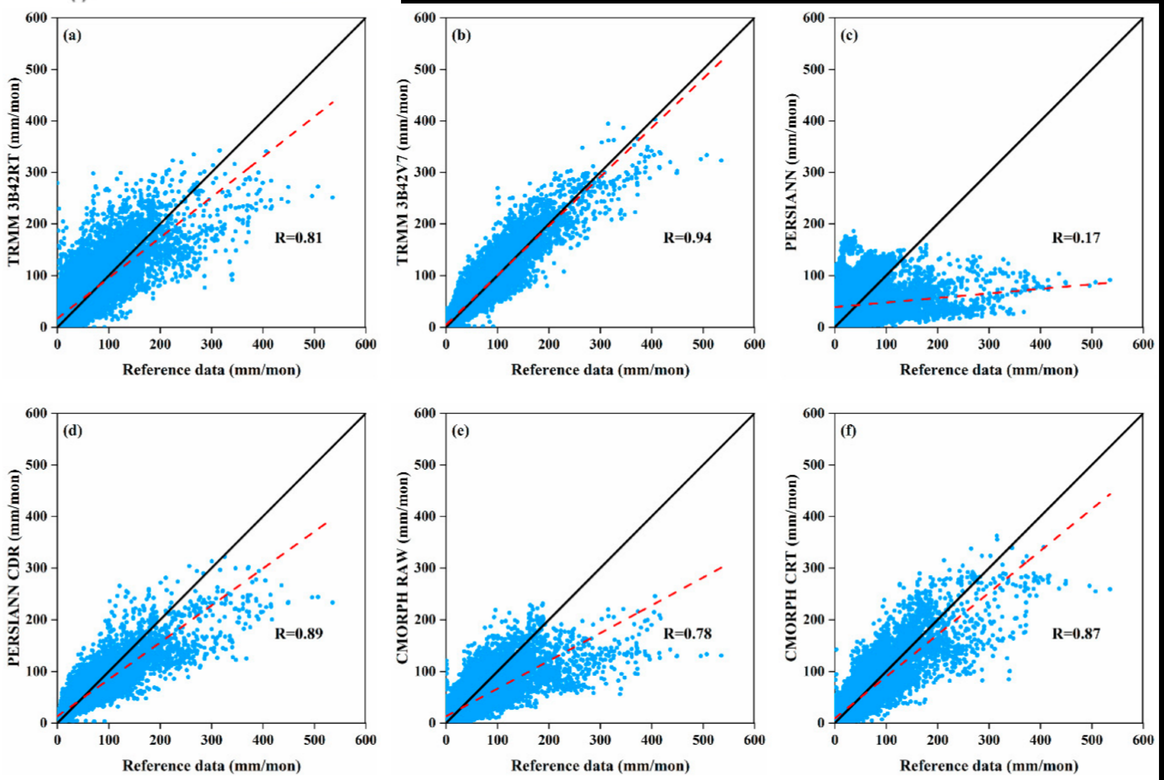




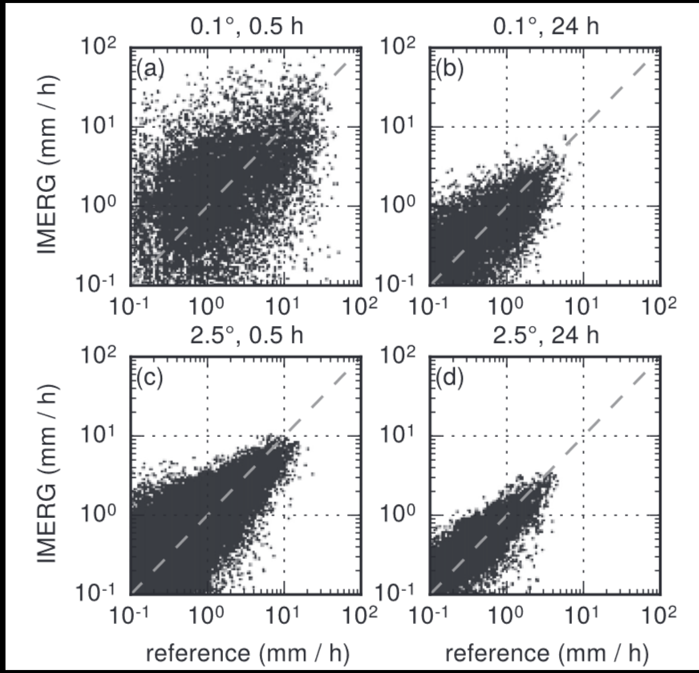
THE CLASSICAL APPROACH IN COMPARING/VALIDATING RETRIEVALS

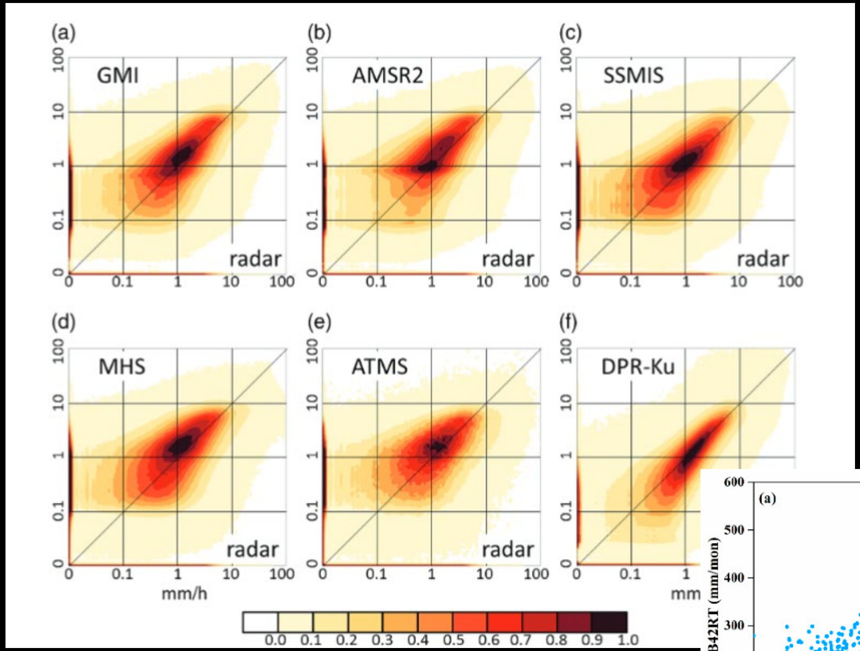


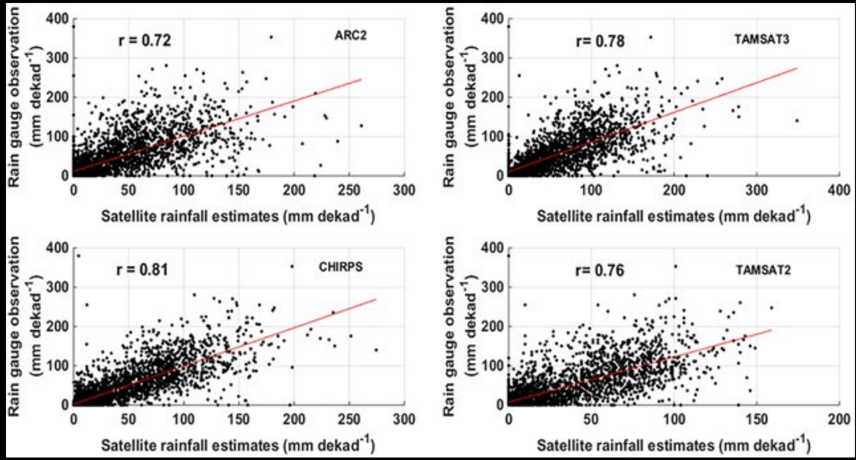


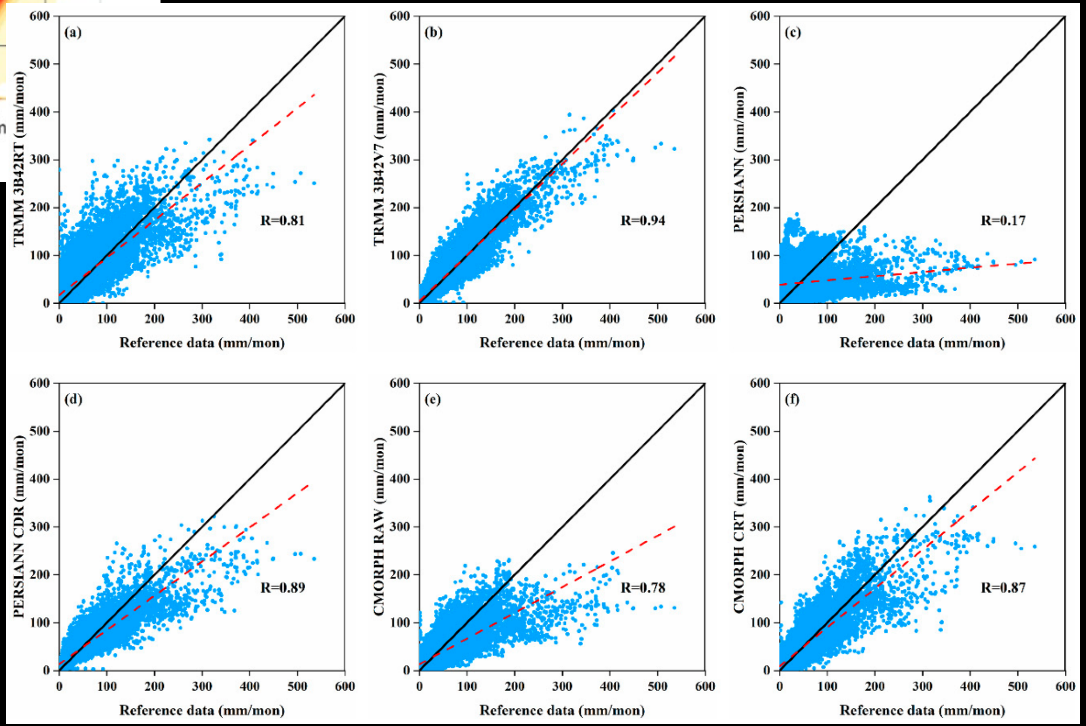


THE CLASSICAL APPROACH IN COMPARING/VALIDATING RETRIEVALS









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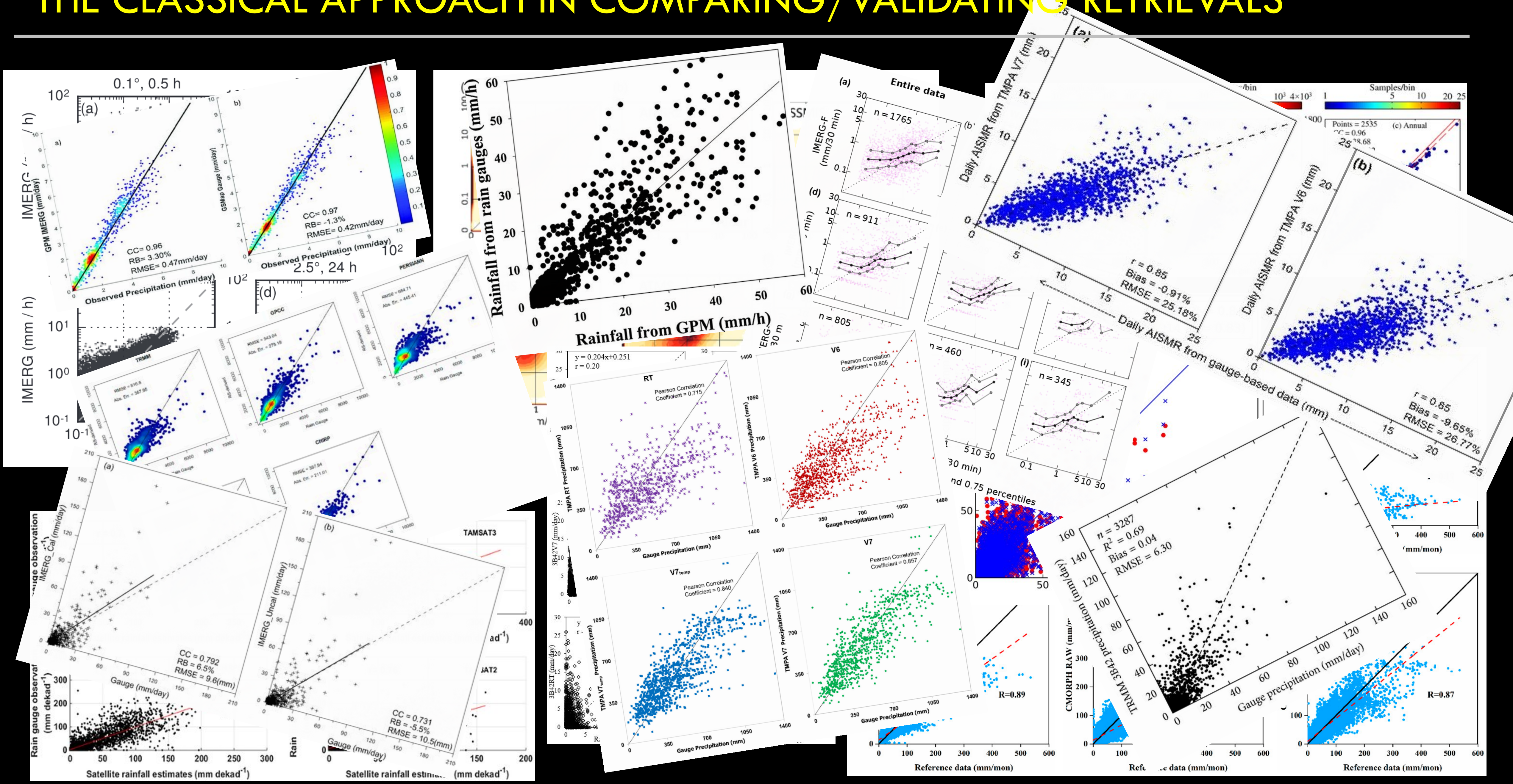

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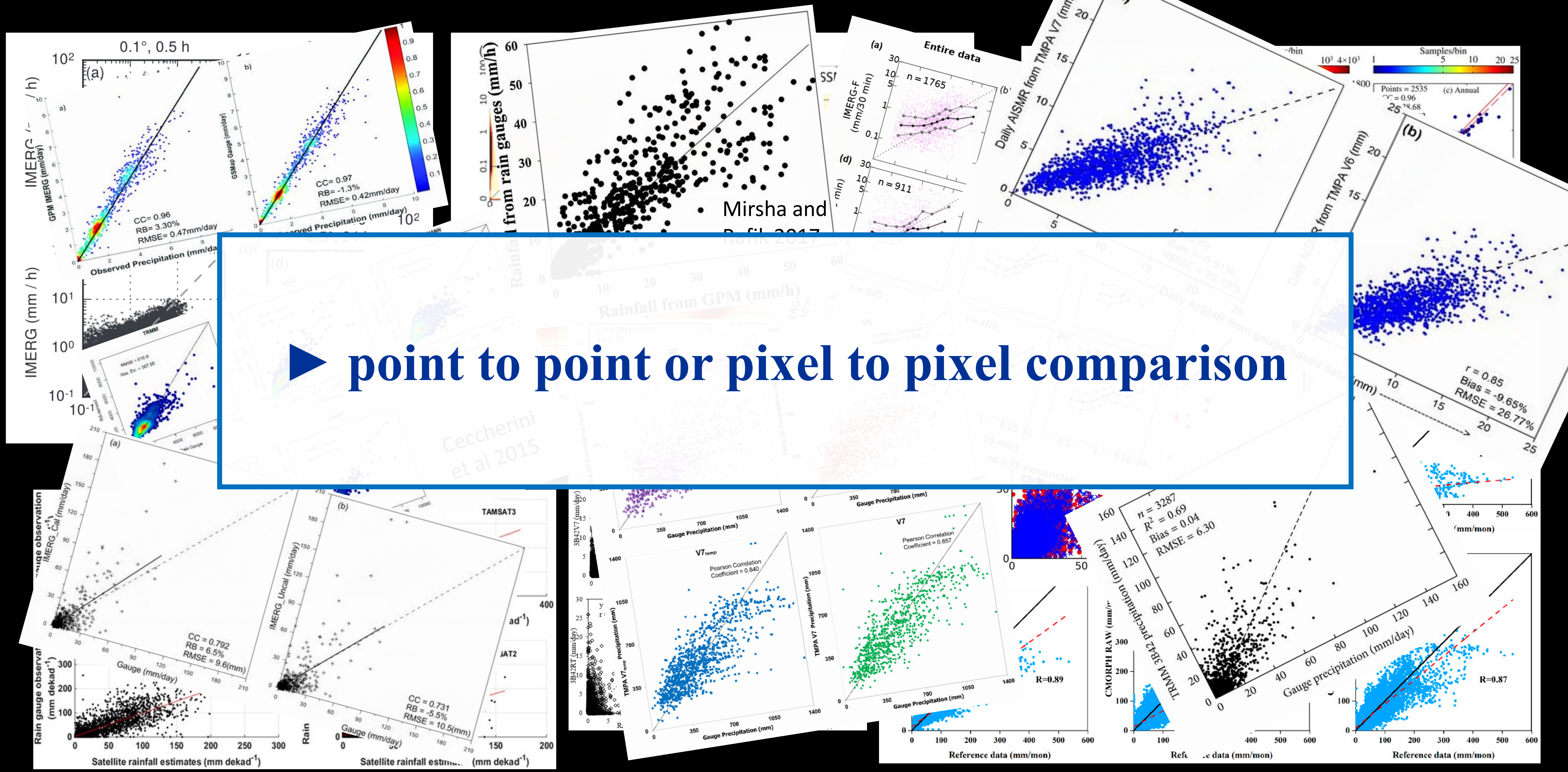
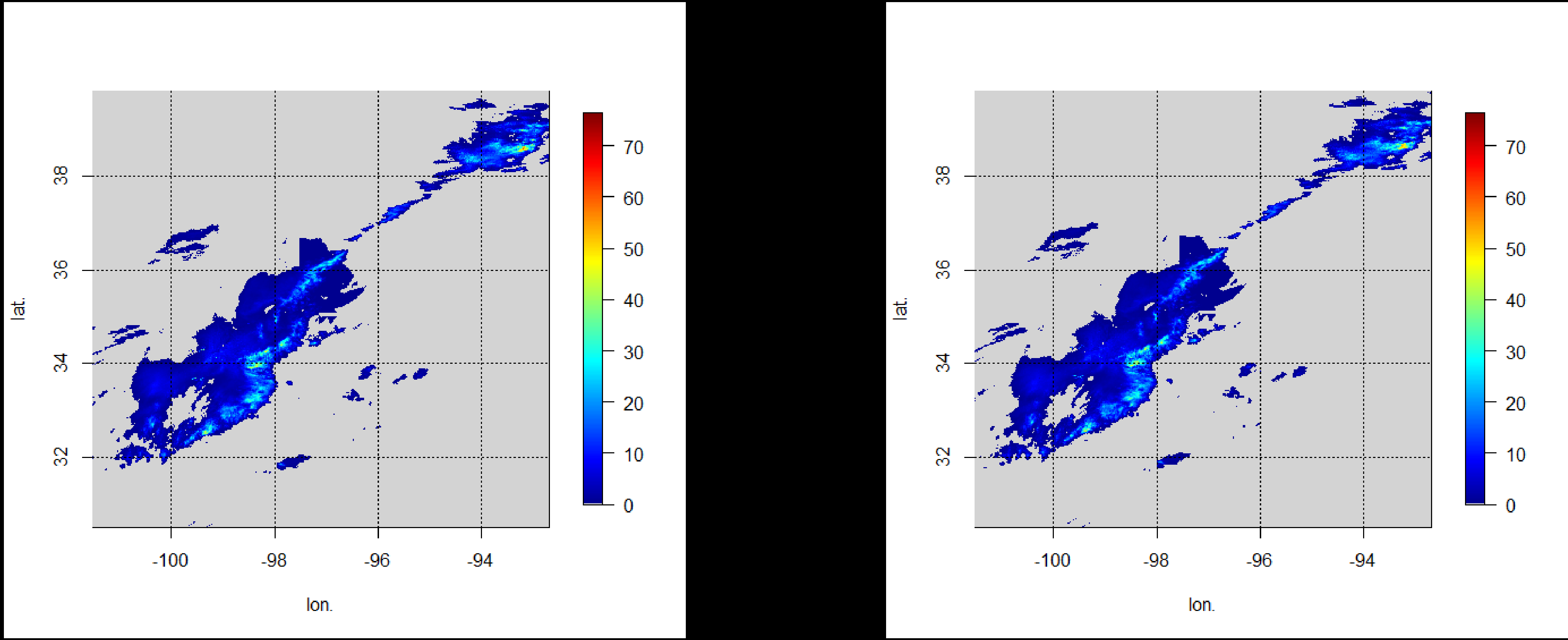


► **point to point or pixel to pixel comparison**

THE CLASSICAL APPROACH IN COMPARING/VALIDATING RETRIEVALS

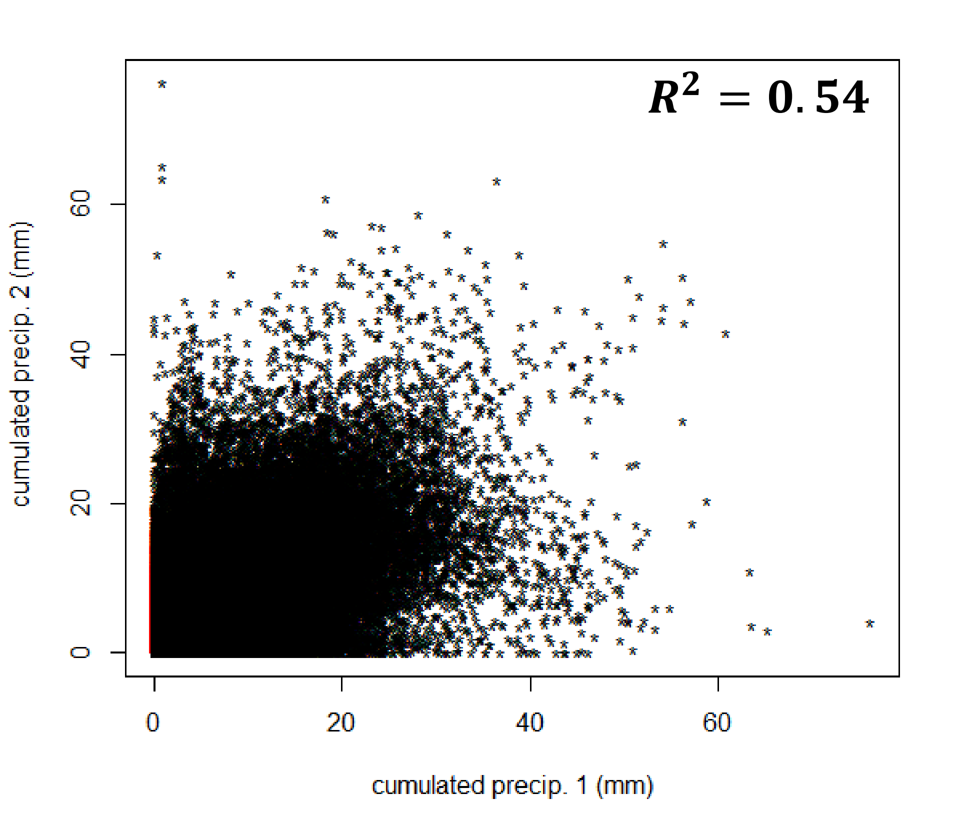
How different are these two fields?



MRMS hourly at 1 km shifted by 7 km

THE CLASSICAL APPROACH IN COMPARING/VALIDATING RETRIEVALS

How different are these two fields?



=> Quite different at the pixel level!

Effective Resolution (ER)

"The finest scale at which retrievals accurately reproduce the <u>local</u> spatial variability of a reference product"

Global multiscale evaluation of satellite passive microwave retrieval of precipitation during the TRMM and GPM eras: effective resolution and regional diagnostics for future algorithm development

Clement Guilloteau[1,*], Efi Foufoula-Georgiou[1], *and* Christian D. Kummerow[2]

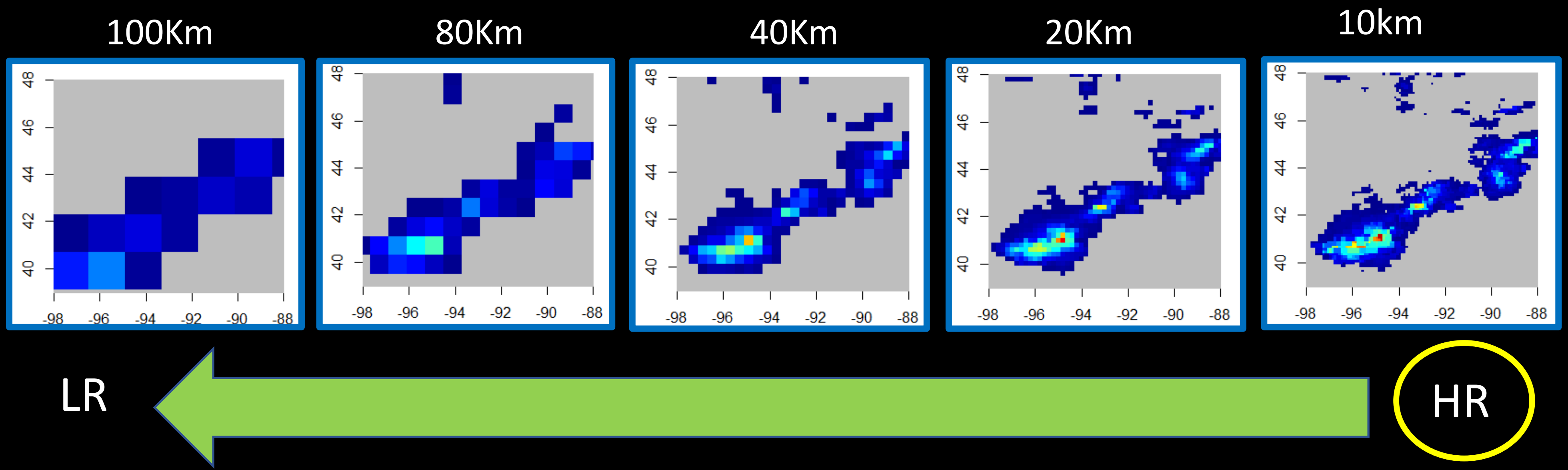
[1] *Department of Civil and Environmental Engineering, University of California, Irvine*

[2] *Department of Atmospheric Science, Colorado State University, Fort Collins*

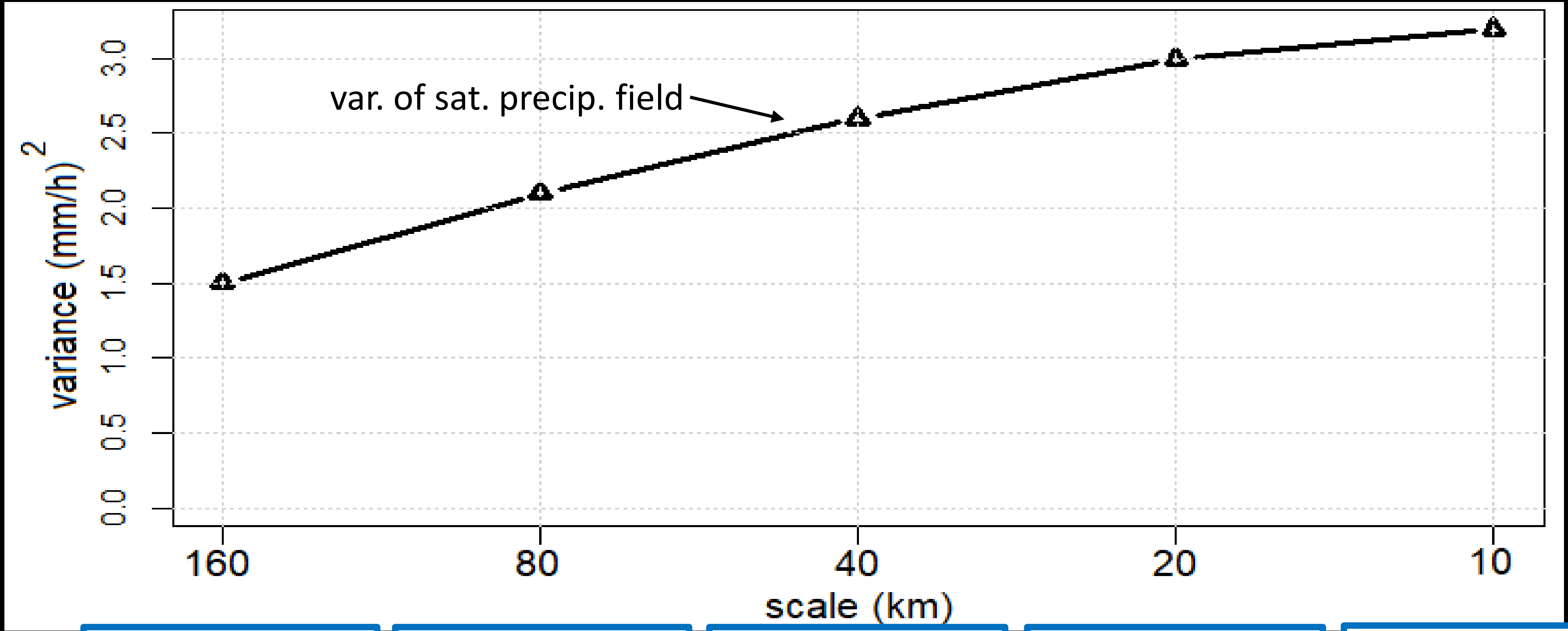
Guilloteau et al., *JHM*, 2017; *JTech* 2018

Variance as a function of the scale

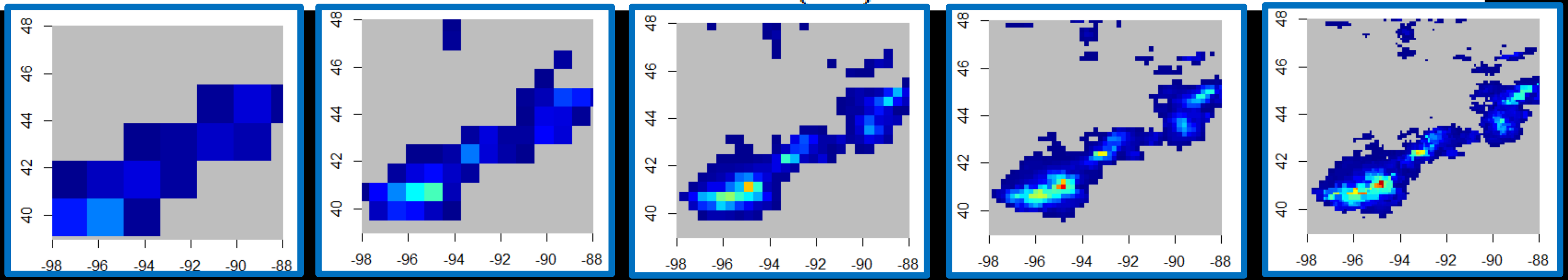
satellite precipitation field



Variance as a function of the scale



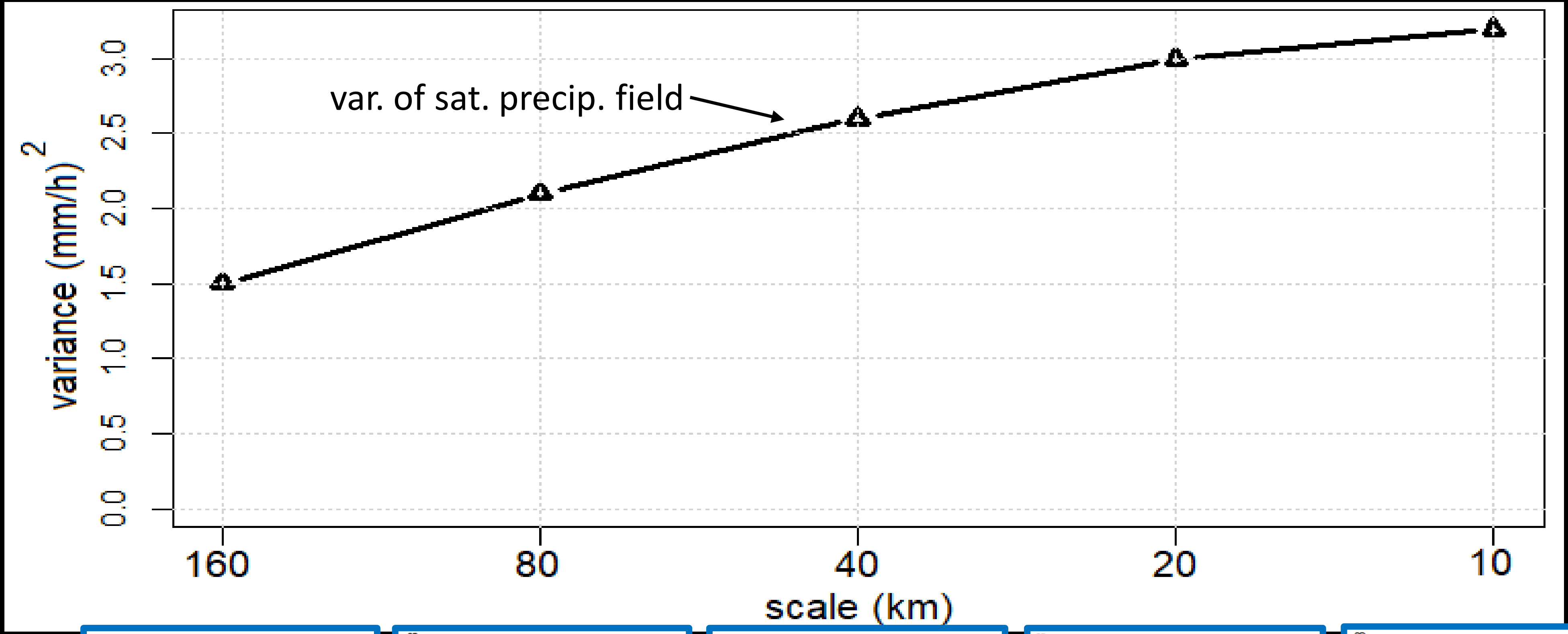
satellite precipitation field



LR

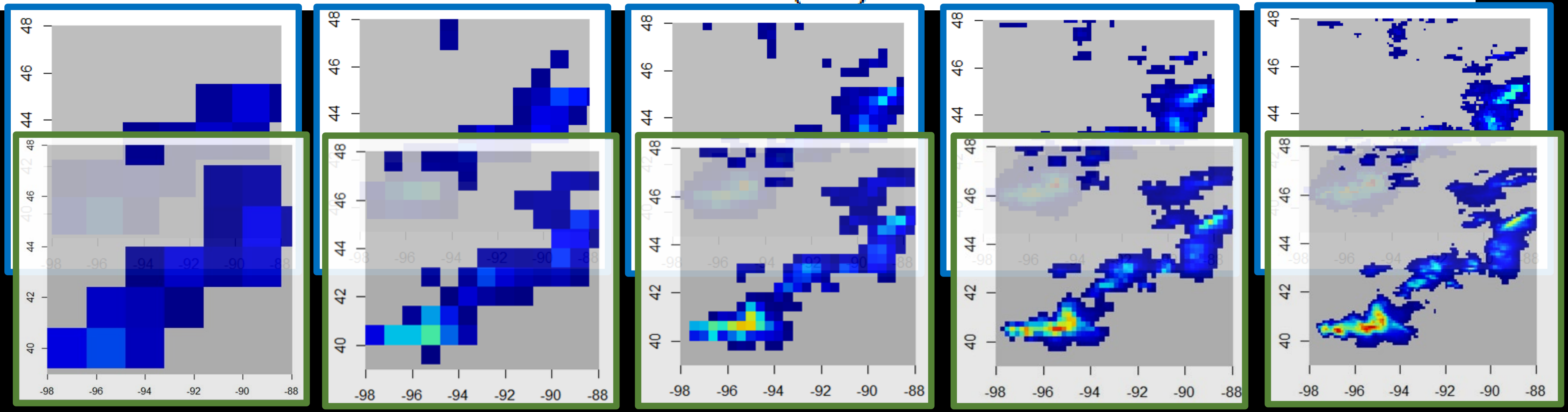
HR

Variance as a function of the scale

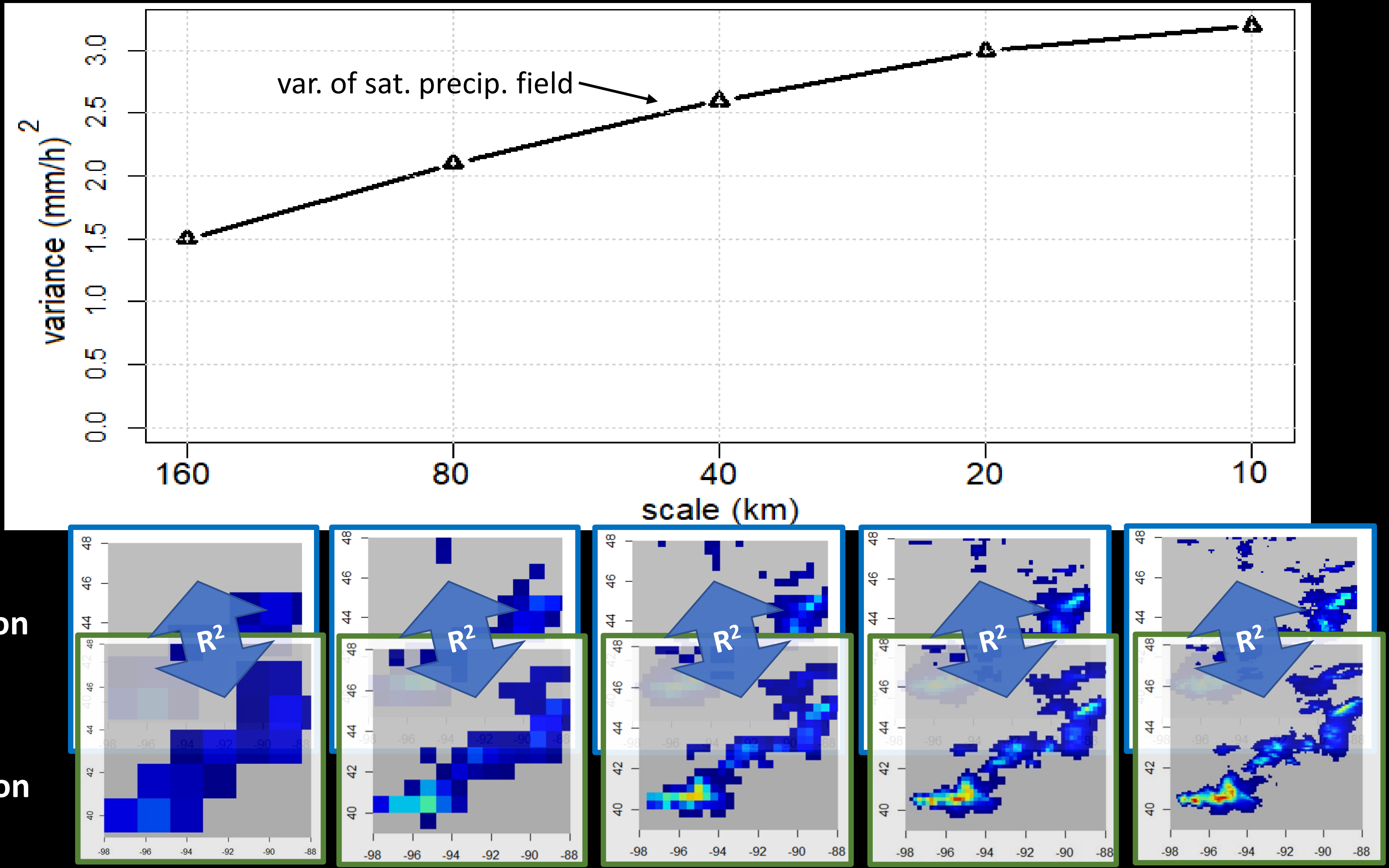


satellite precipitation field

radar precipitation field



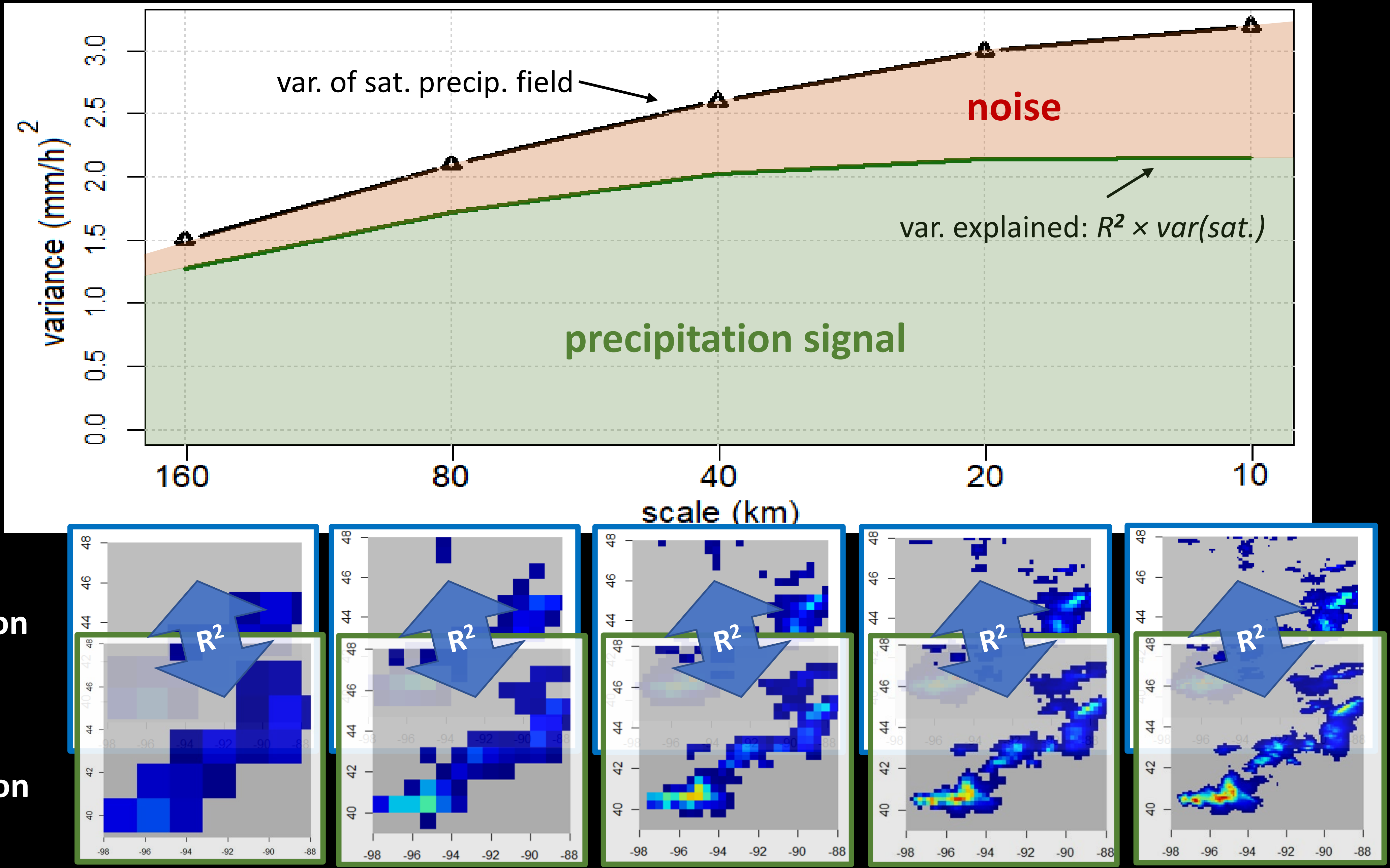
Variance as a function of the scale



satellite precipitation field

radar precipitation field

Precipitation signal or noise?



satellite precipitation field

radar precipitation field

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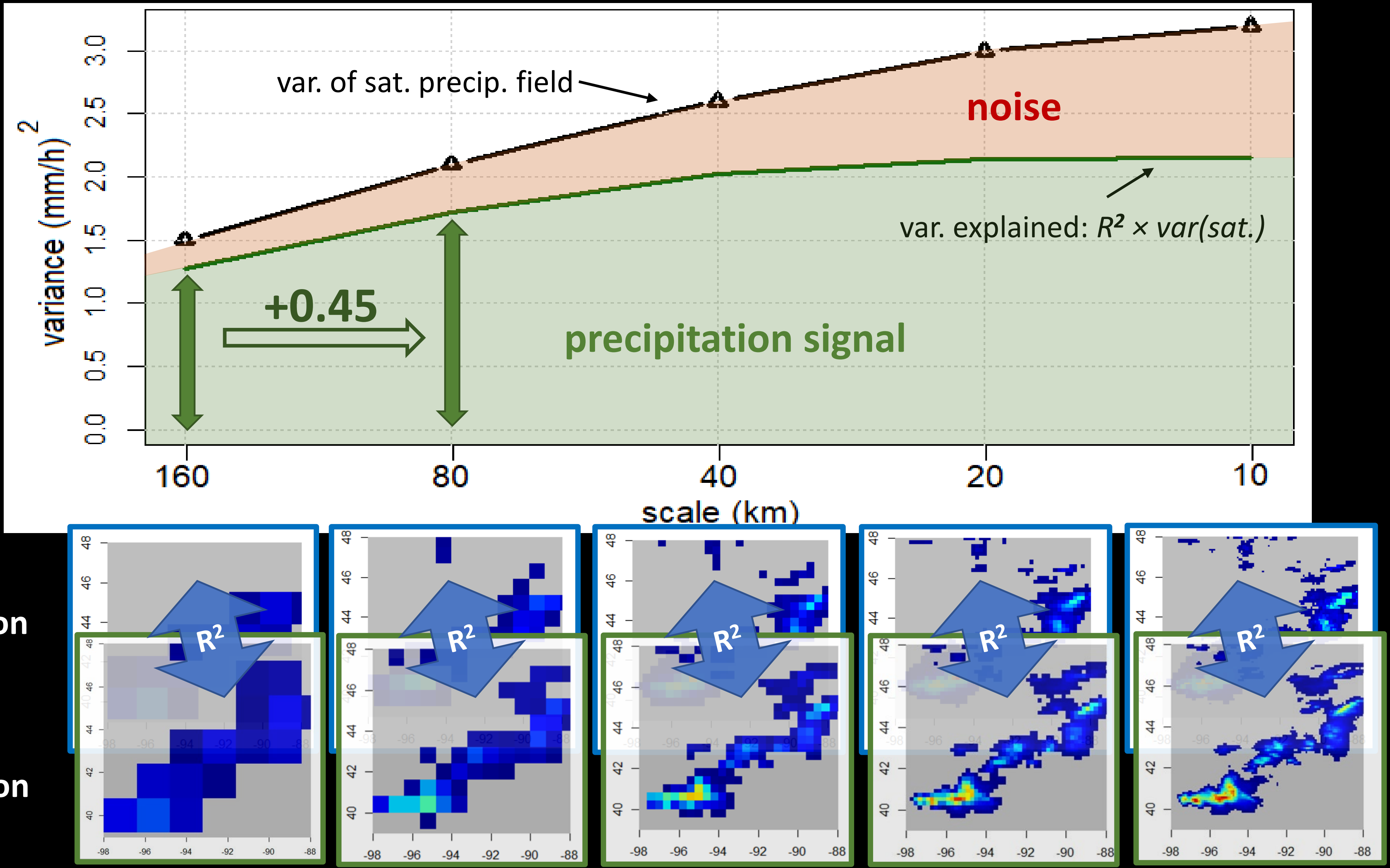

satellite precipitation field

radar precipitation field

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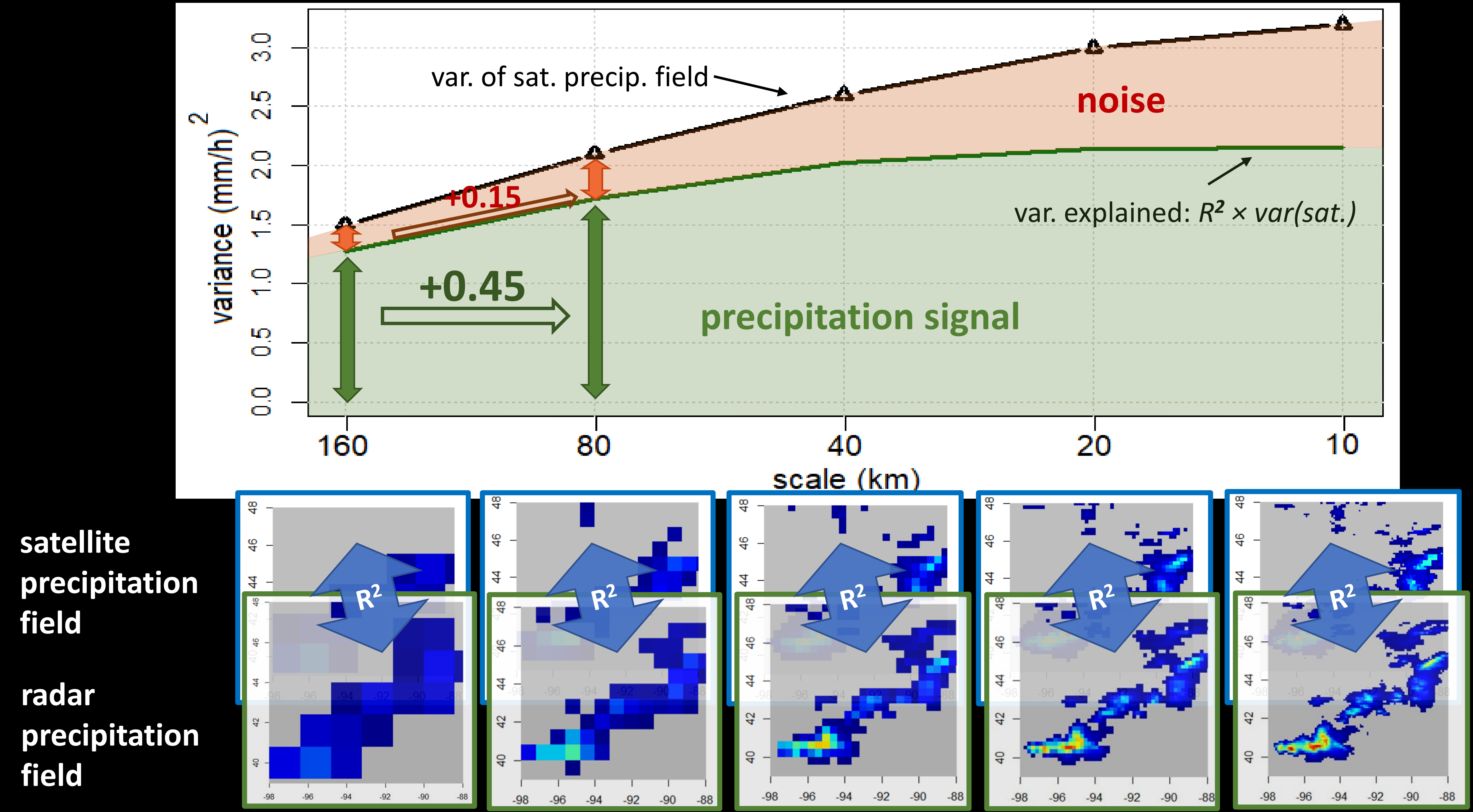

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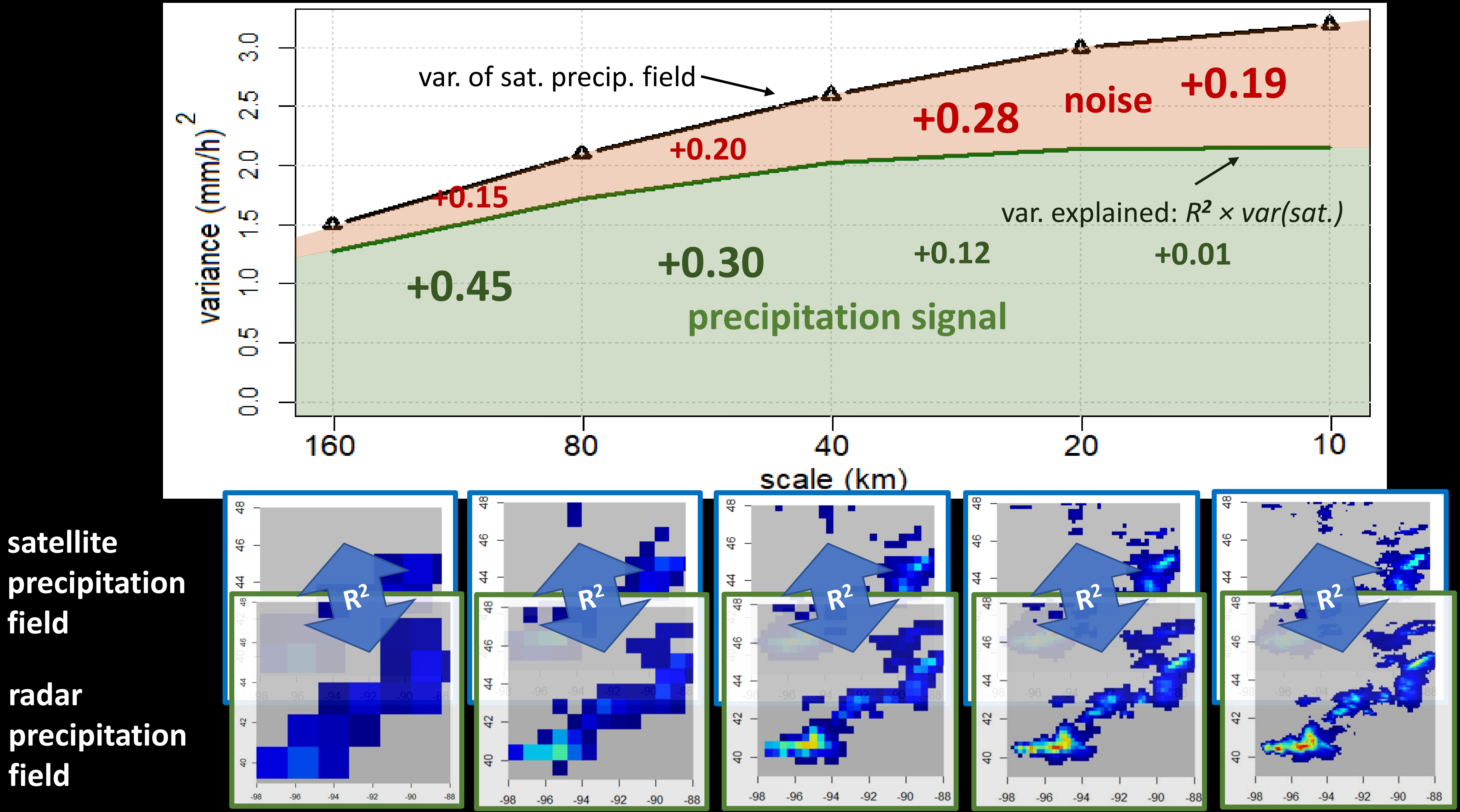
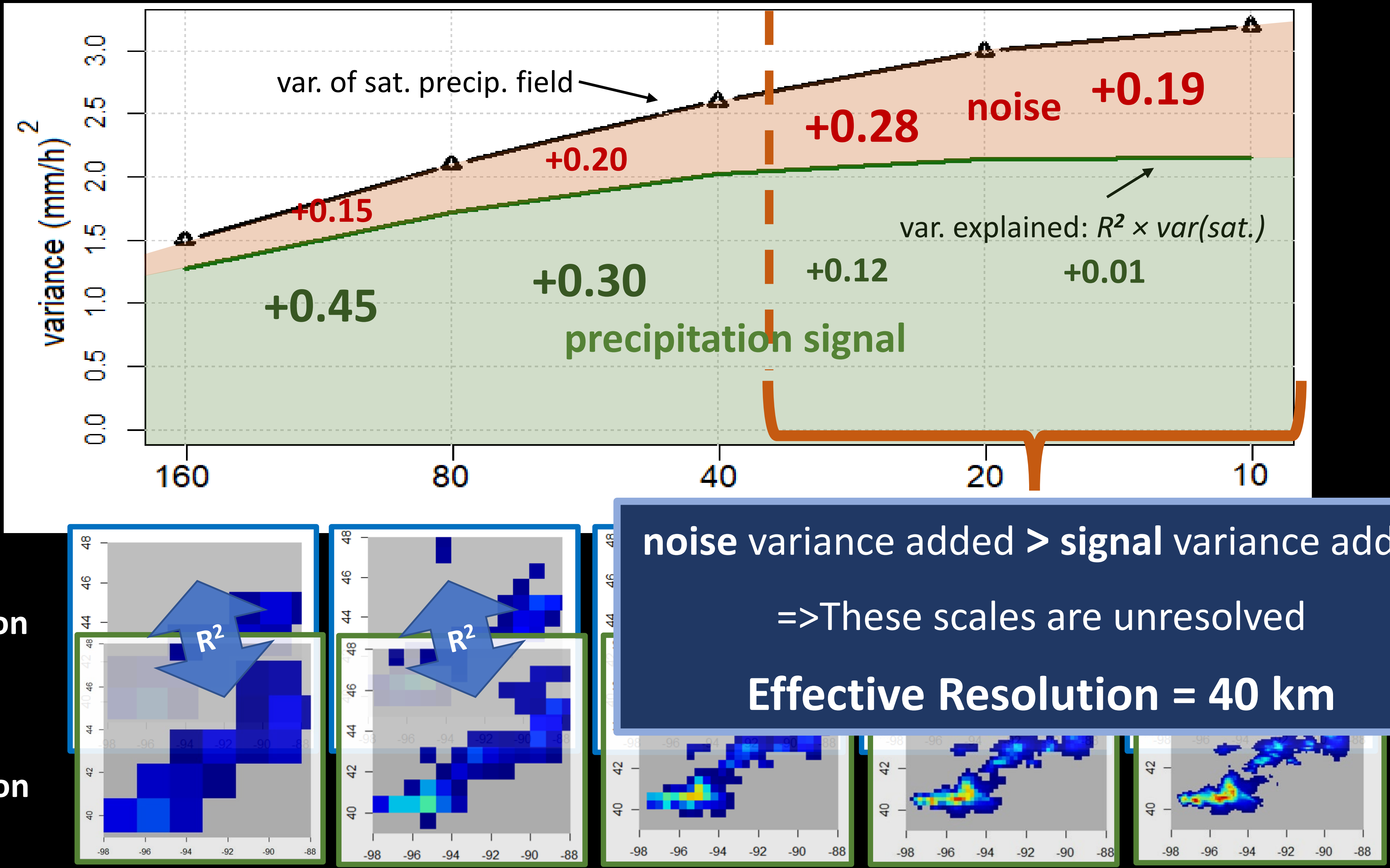


Precipitation signal or noise?



satellite precipitation field

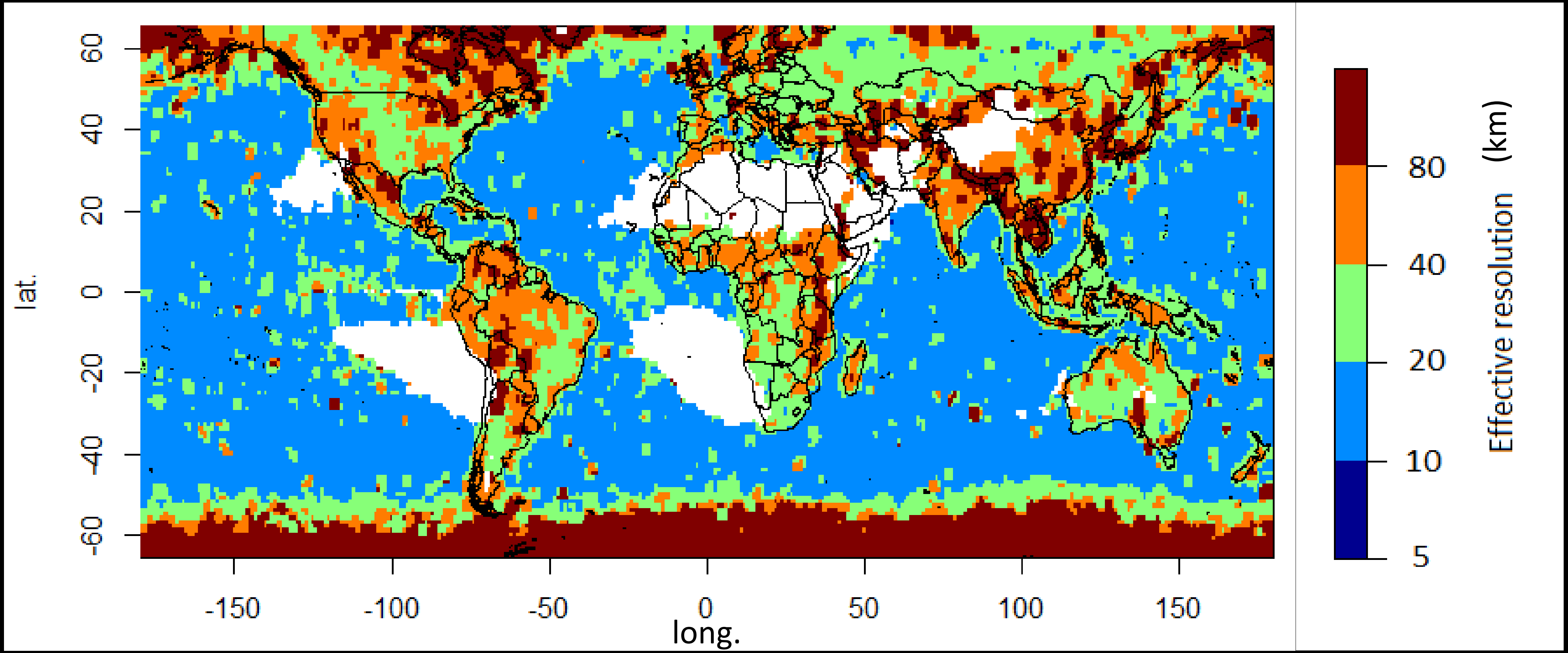
radar precipitation field

noise variance added **> signal** variance added

=>These scales are unresolved

Effective Resolution = 40 km

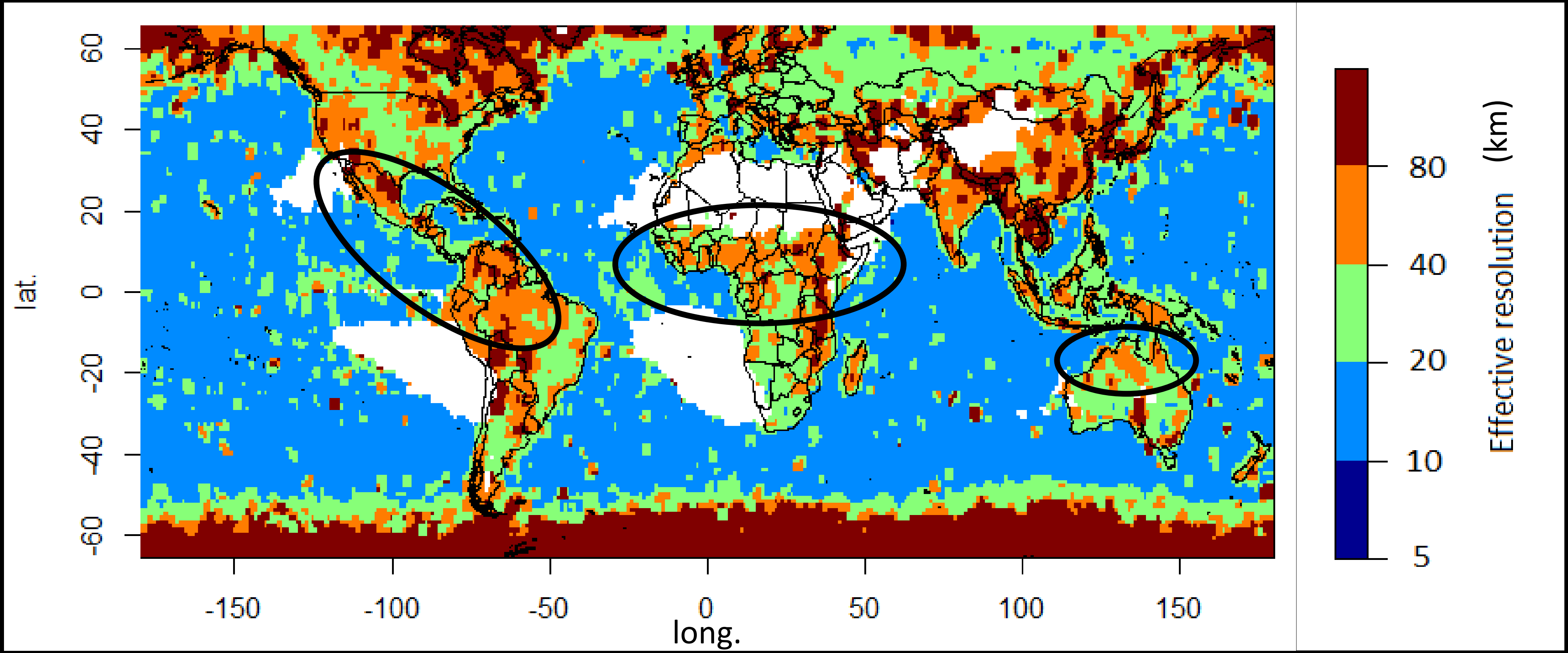
Effective Resolution of GPROF GMI vs. KuPR



- 16,500 GPM orbits: March 2014 to February 2017
- Local values computed from all observations in 3°×3° boxes.

Guilloteau et al., JHM, 2017

Effective Resolution of GPROF GMI vs. KuPR



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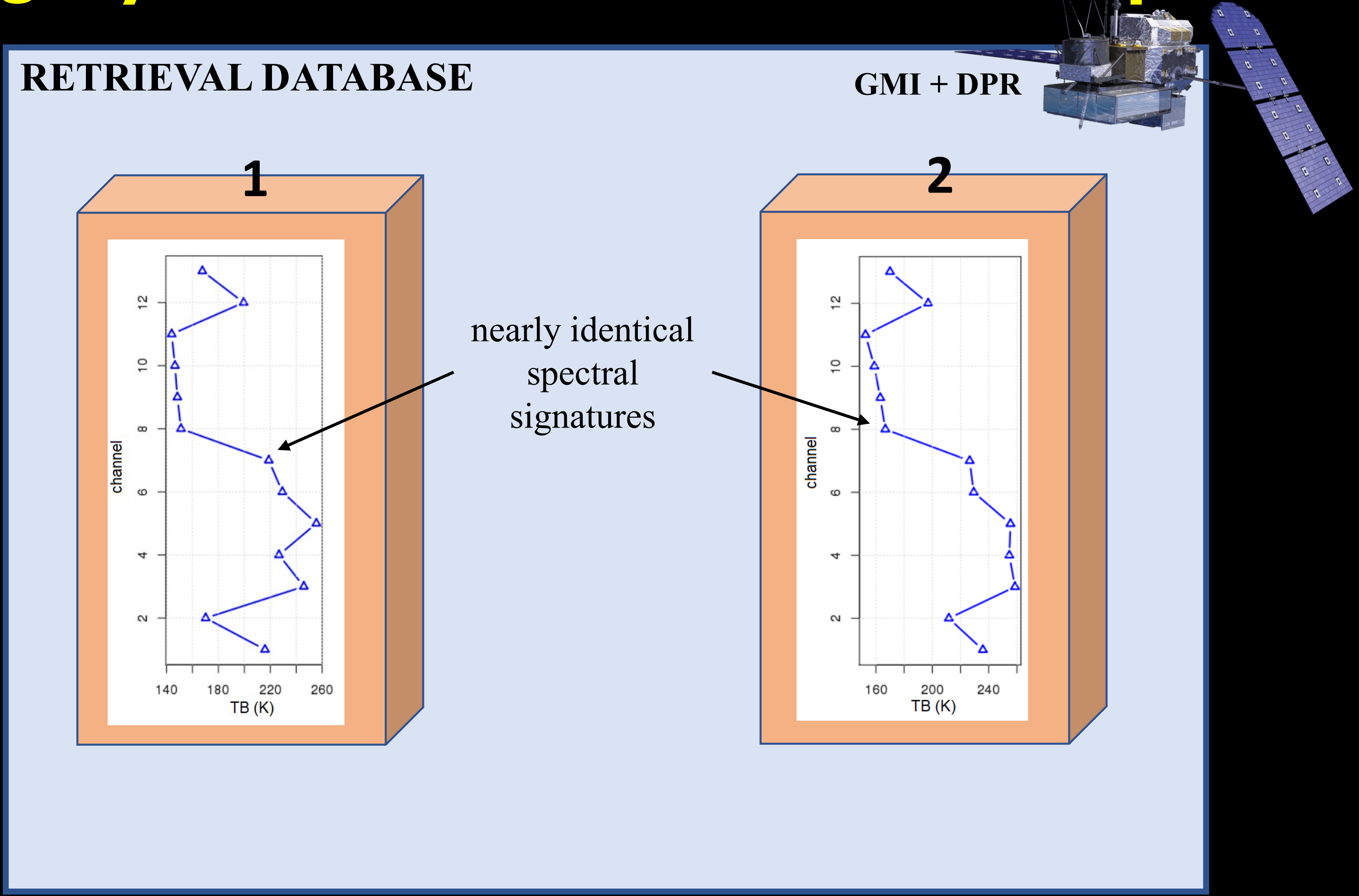
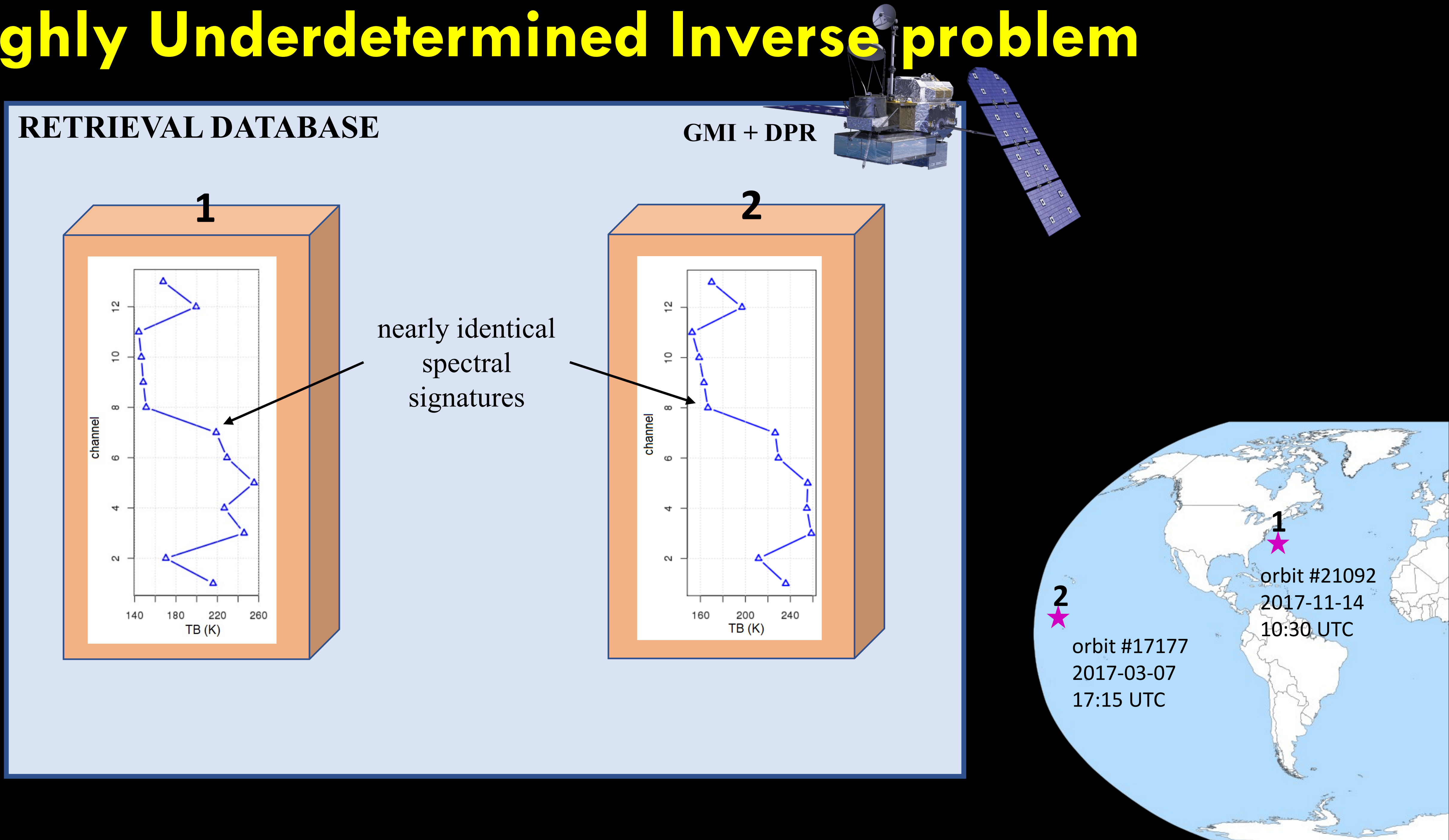
Guilloteau et al., JHM, 2017

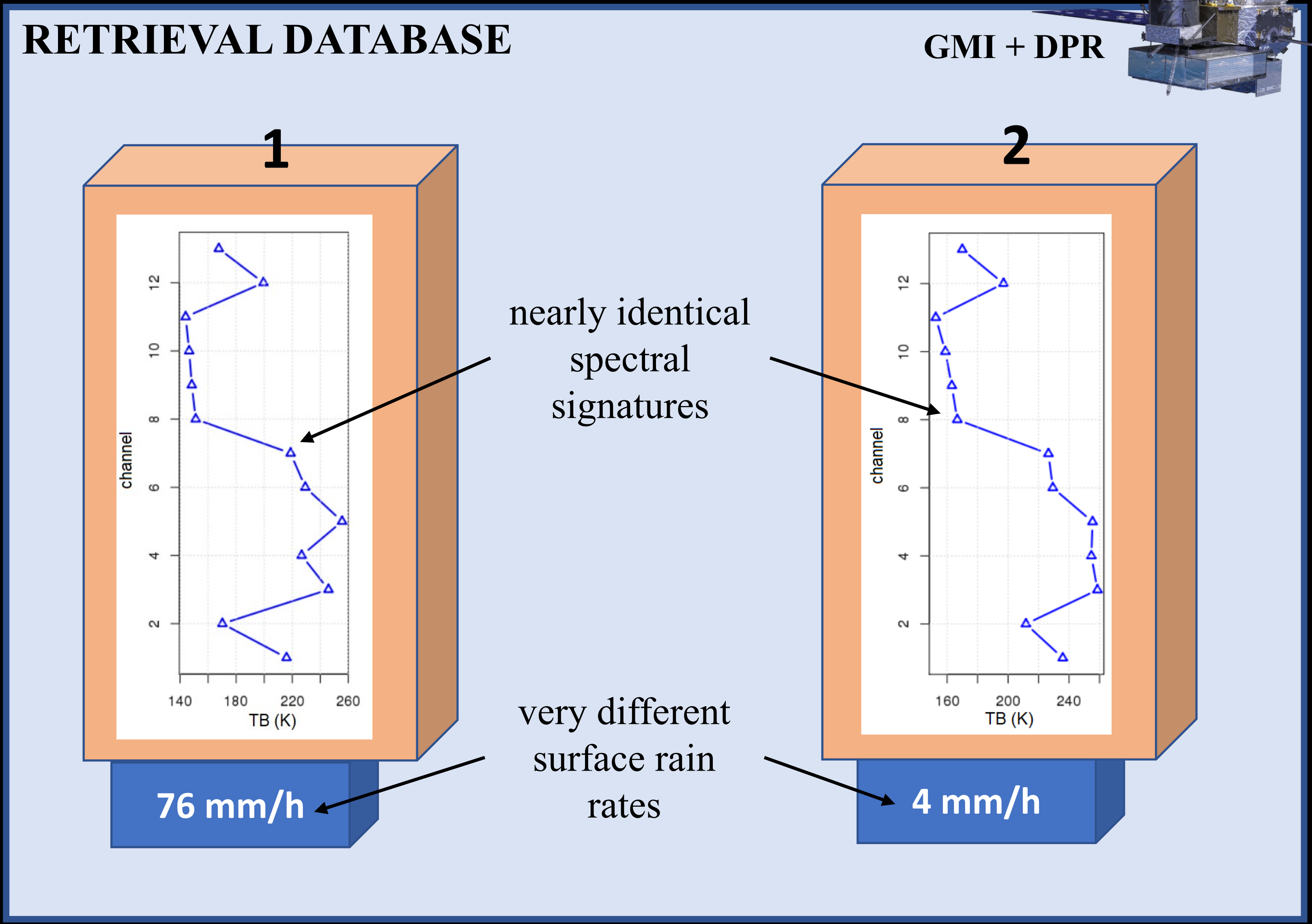
Highly Underdetermined Inverse problem

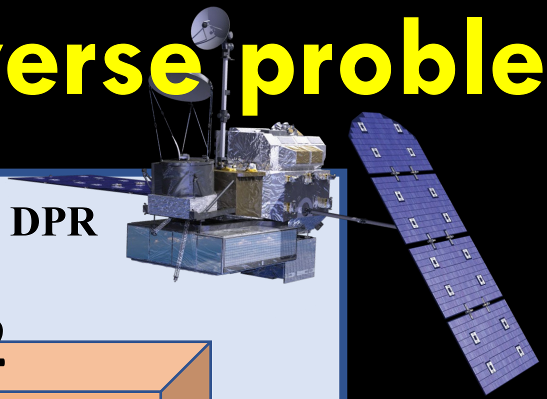


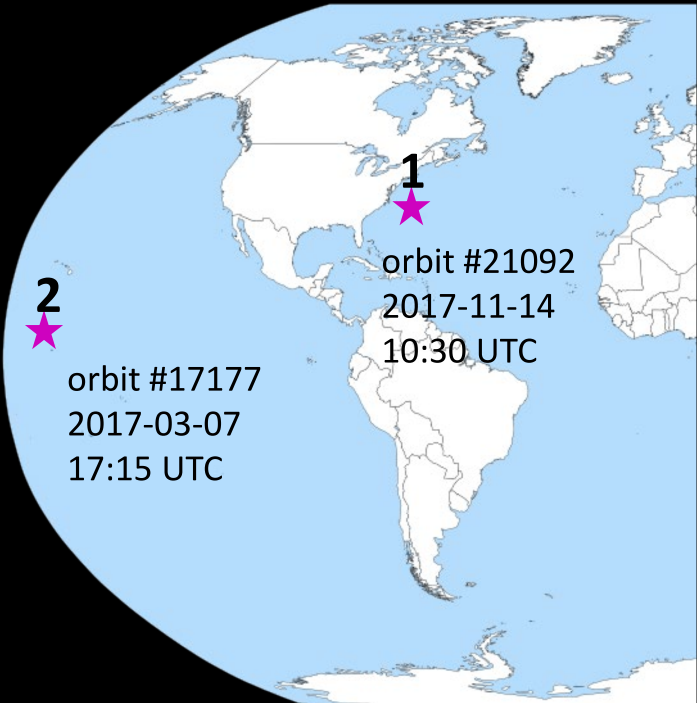
Highly Underdetermined Inverse problem



Highly Underdetermined Inverse problem

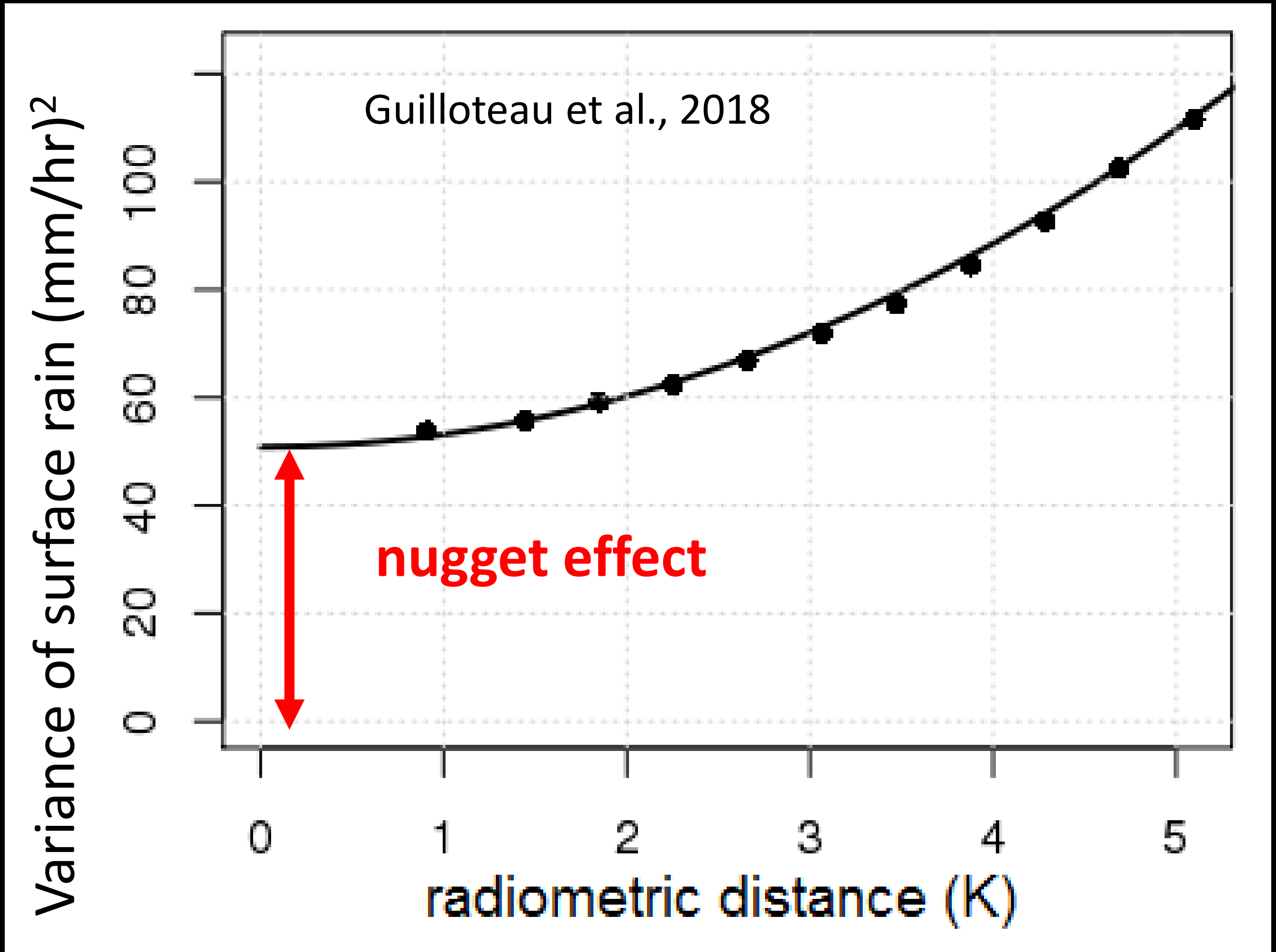






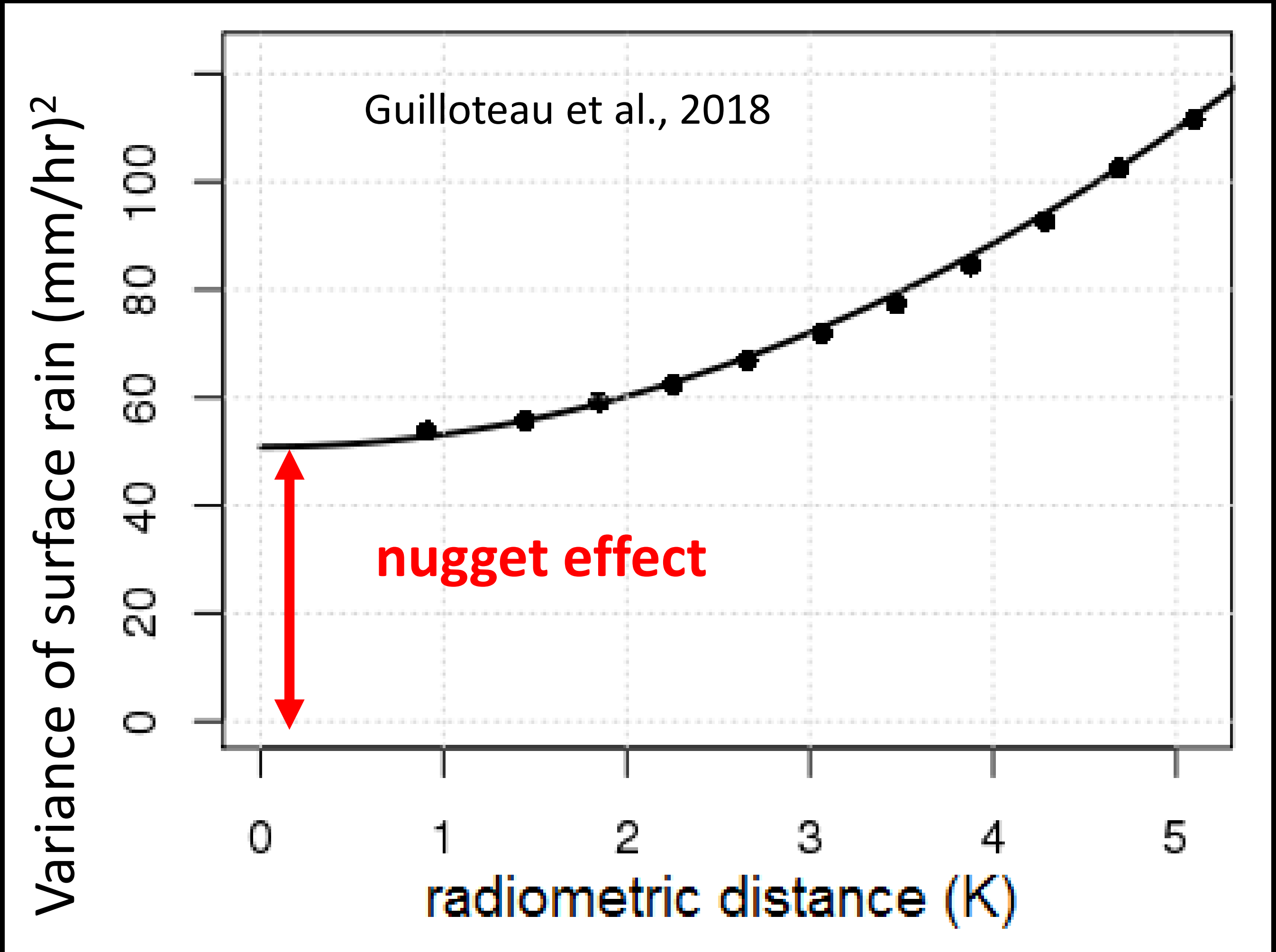
Highly Underdetermined Inverse problem

4,000 neighbors in TB space



Highly Underdetermined Inverse problem

4,000 neighbors in TB space



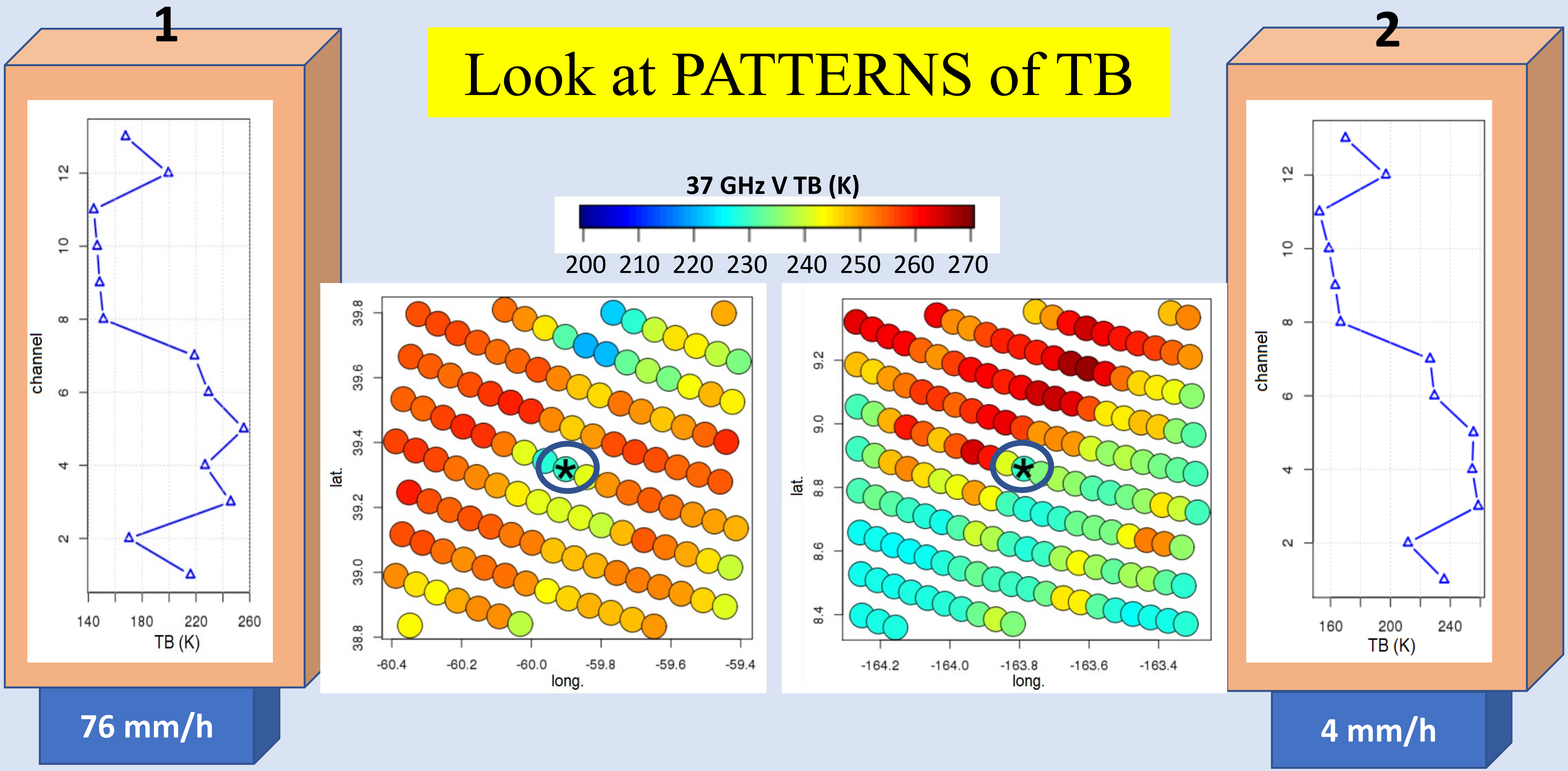
1) Increasing the size of the data base will not help

2) Improved inversion algorithms (KNN Bayesian, L1-L2, etc.) limited improvement in retrieval accuracy/extremes

e.g., Ebtehaj et al., 2015, 2016 (L1-L2)

We propose to look beyond the pixel …

RETRIEVAL DATABASE



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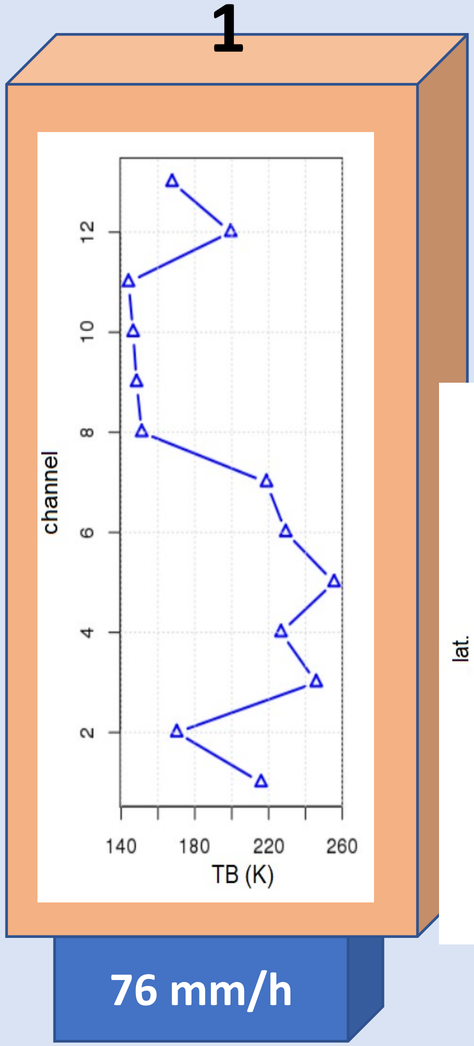
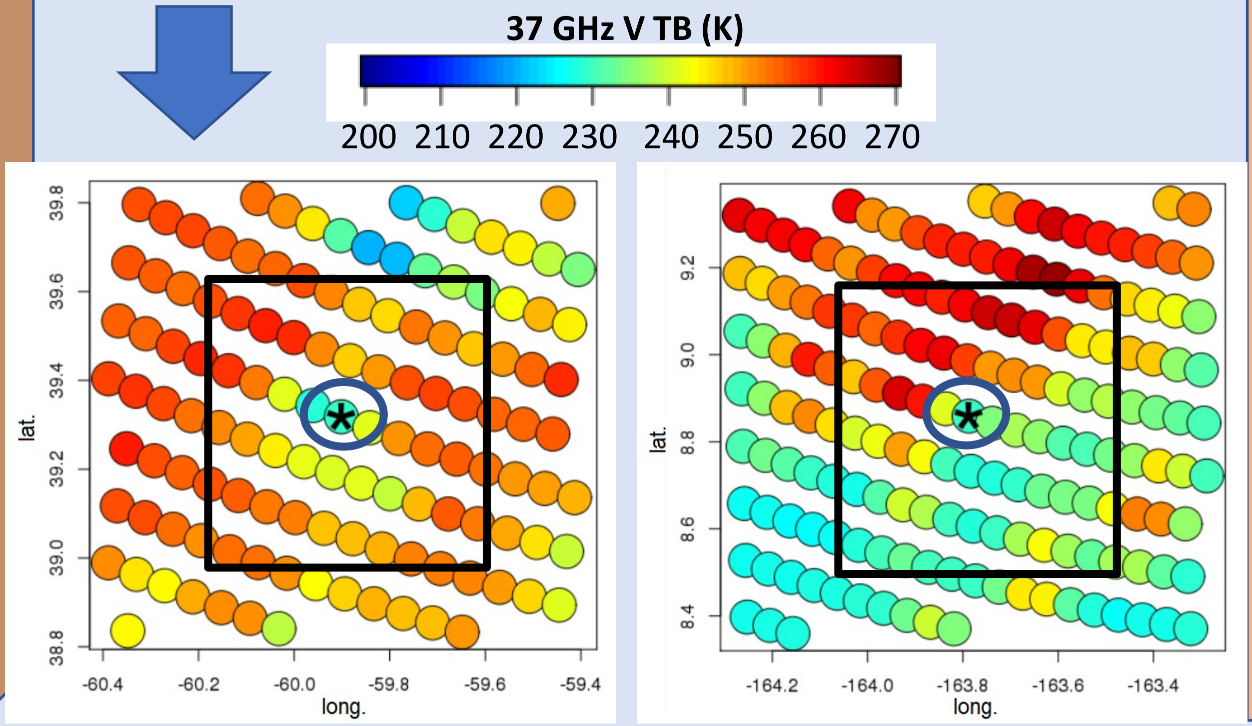
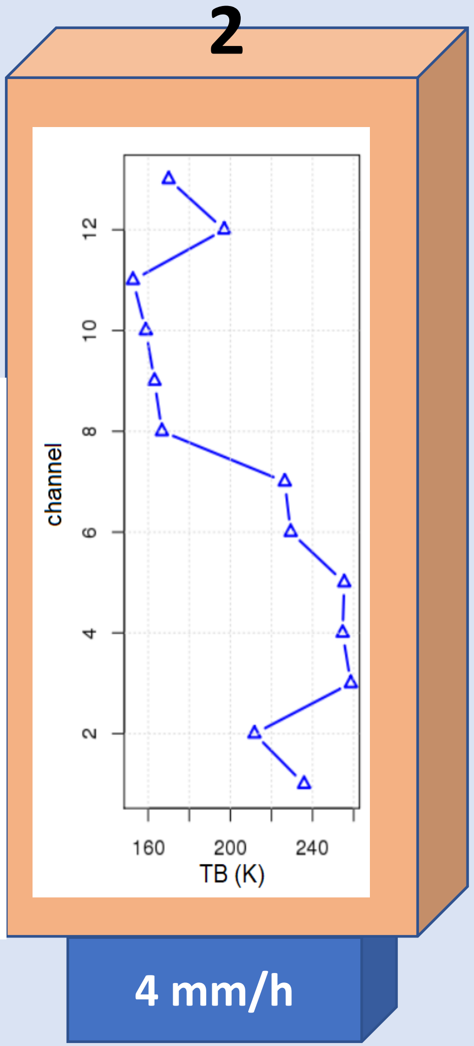


Local depression of the 37 GHz TB = deep convection





The challenge becomes:

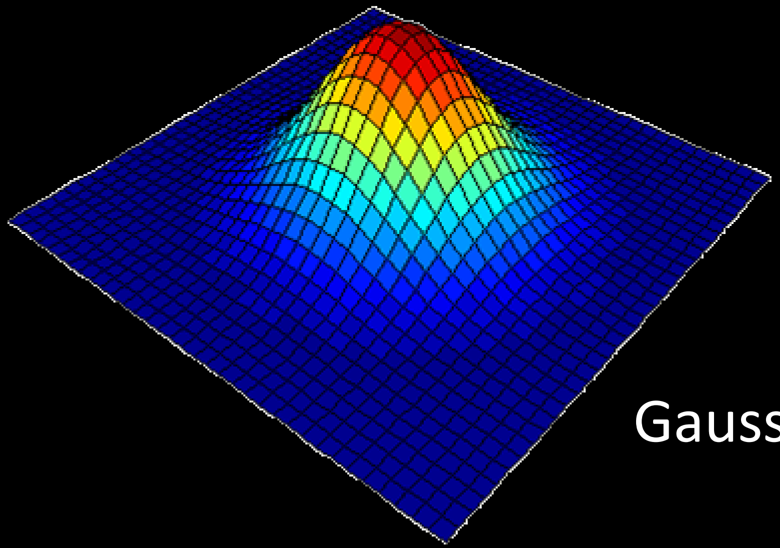
How to extract:

-- the most informative <u>non-local parameters </u>from the TB patterns

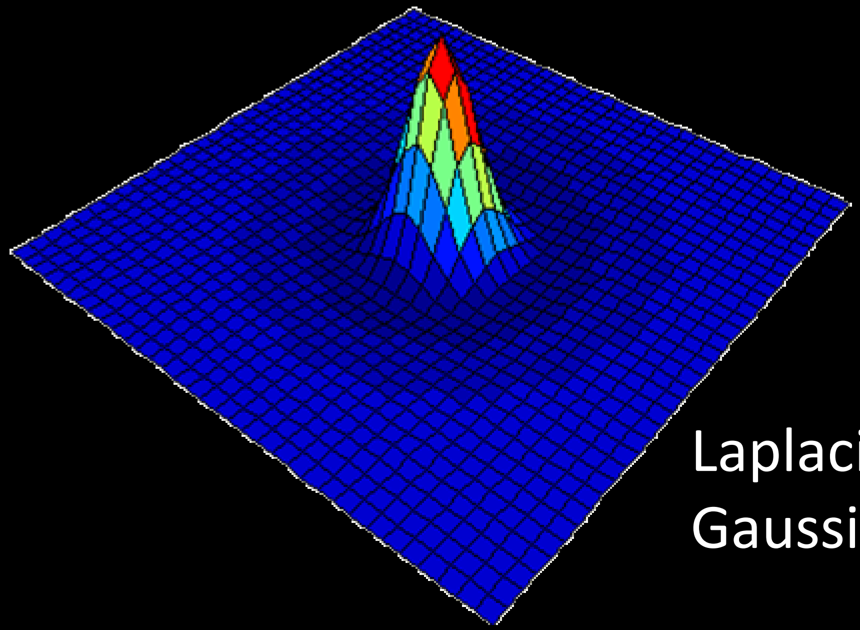
-- to increase identifiability and reduce retrieval uncertainty?

Convolution filters to extract spatial information from fields of TB

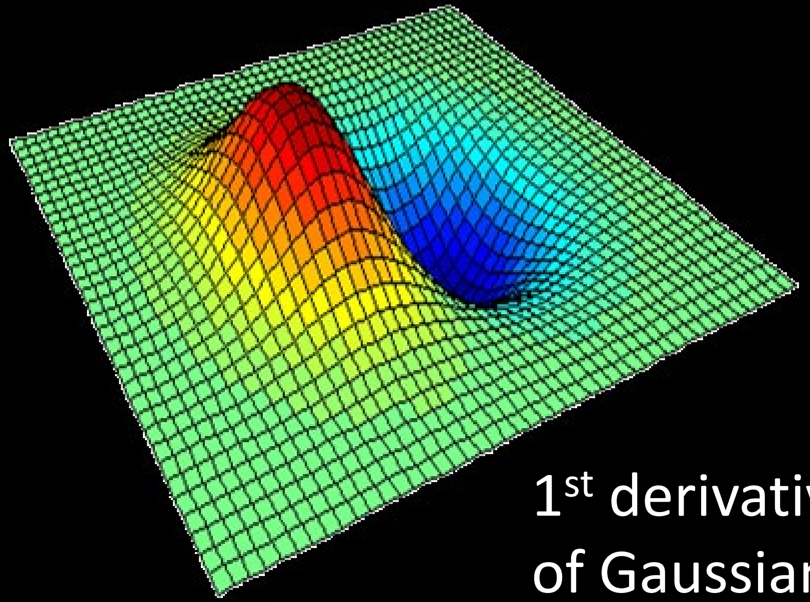
- Pattern extraction
- Spatial averaging / smoothing
- Spatial differentiation / edge detections / gradients extraction
- Multiscale decompositions (wavelets)



Gaussian

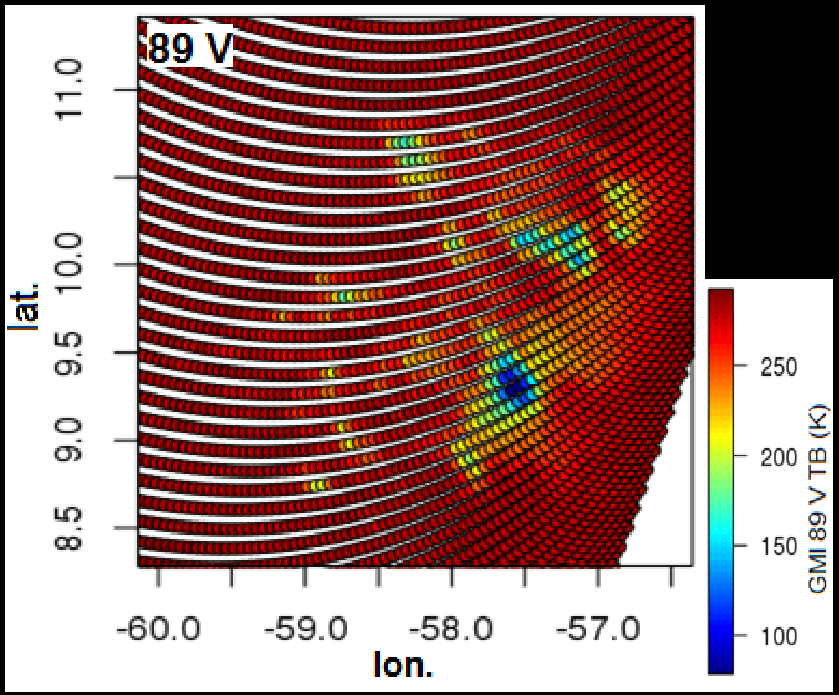


Laplacian of Gaussian

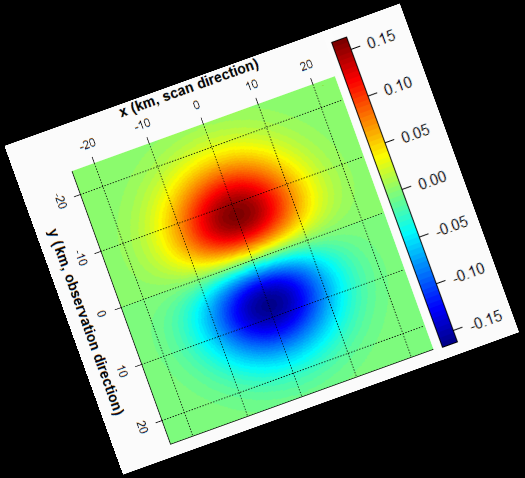


1st derivative of Gaussian

Convolution filters to extract spatial information from fields of TB

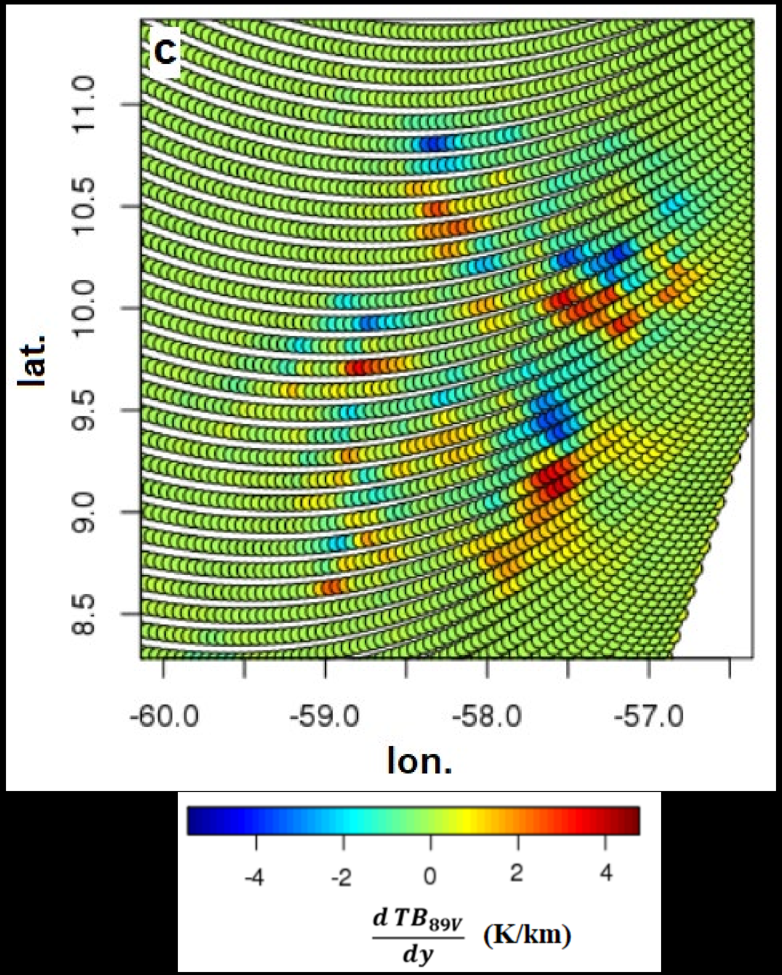


*



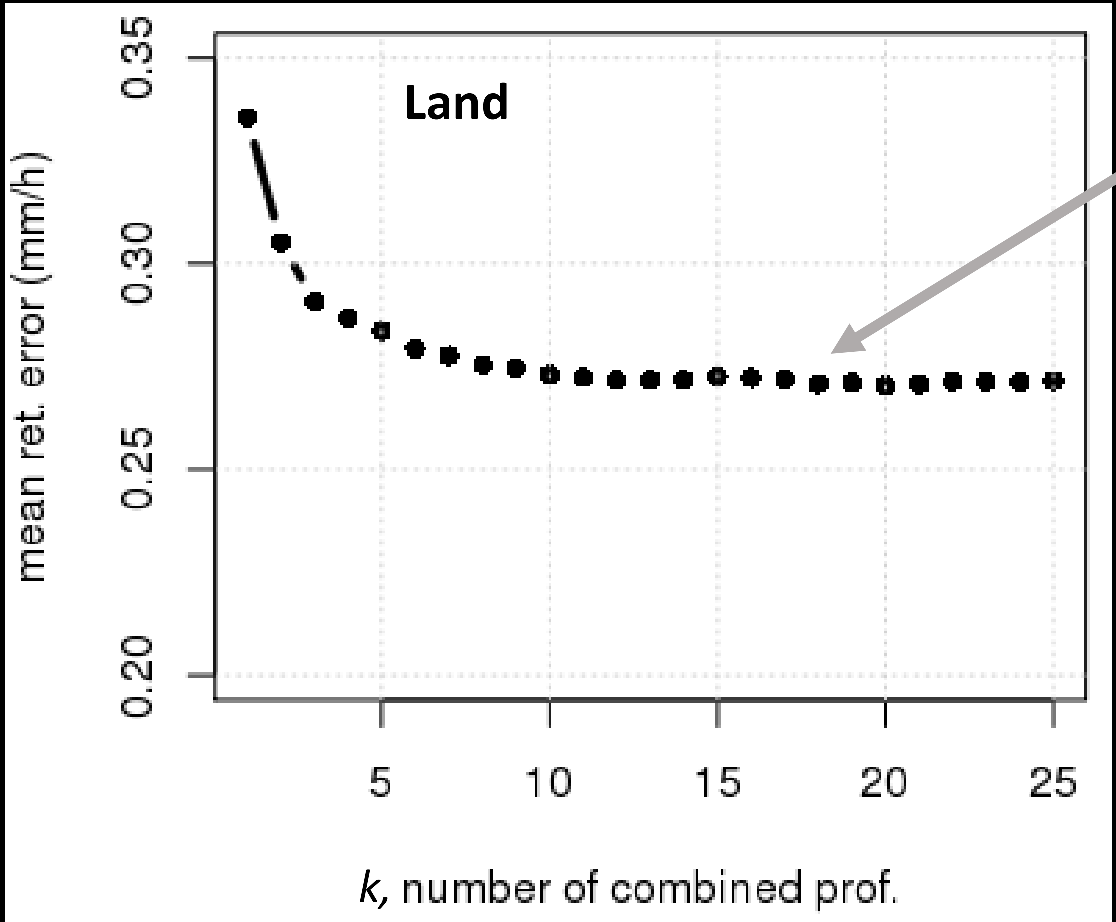
=

“nonlocal” parameter



KNN retrieval from GMI with a 700 000 profile database

MEAN ABSOLUTE ERROR



13 “pixel” TBs
+ 2m temp. + surf. type

KNN retrieval from GMI with a 700 000 profile database

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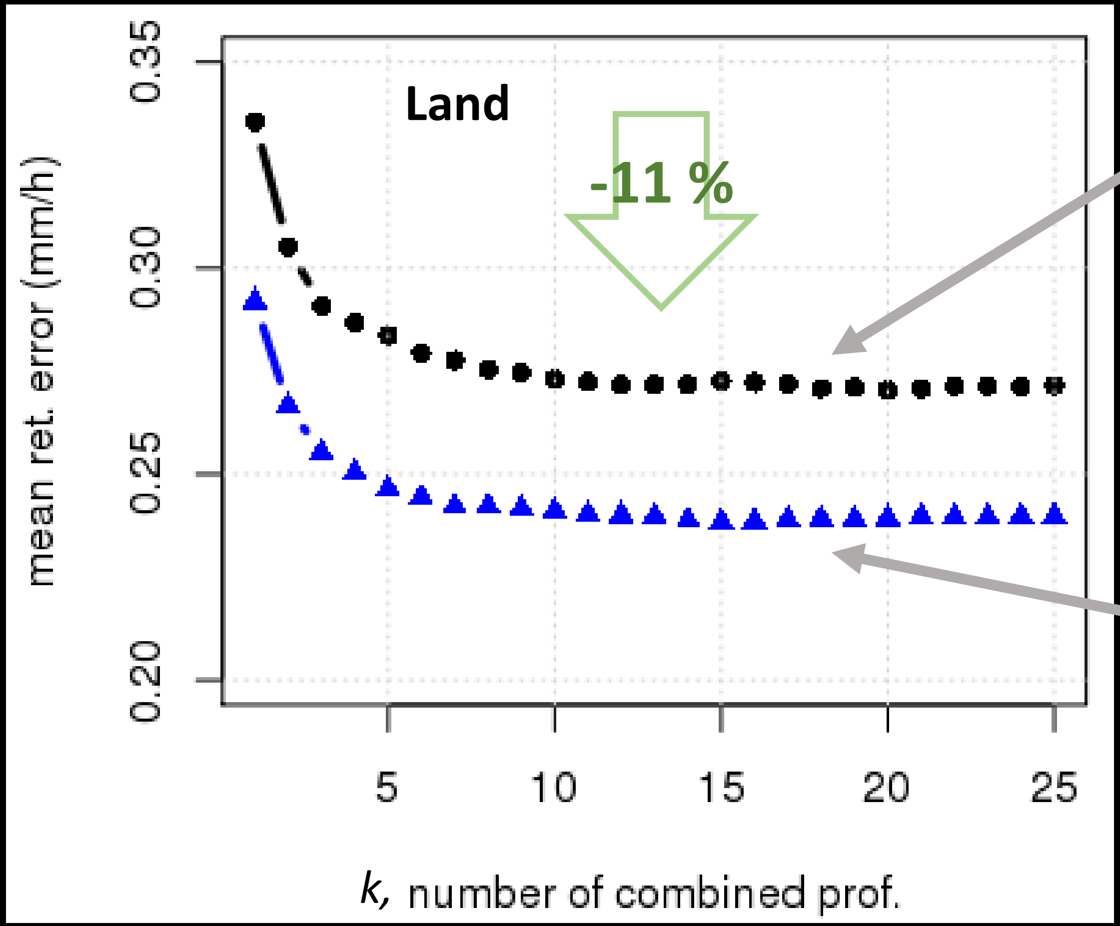

13 “pixel” TBs
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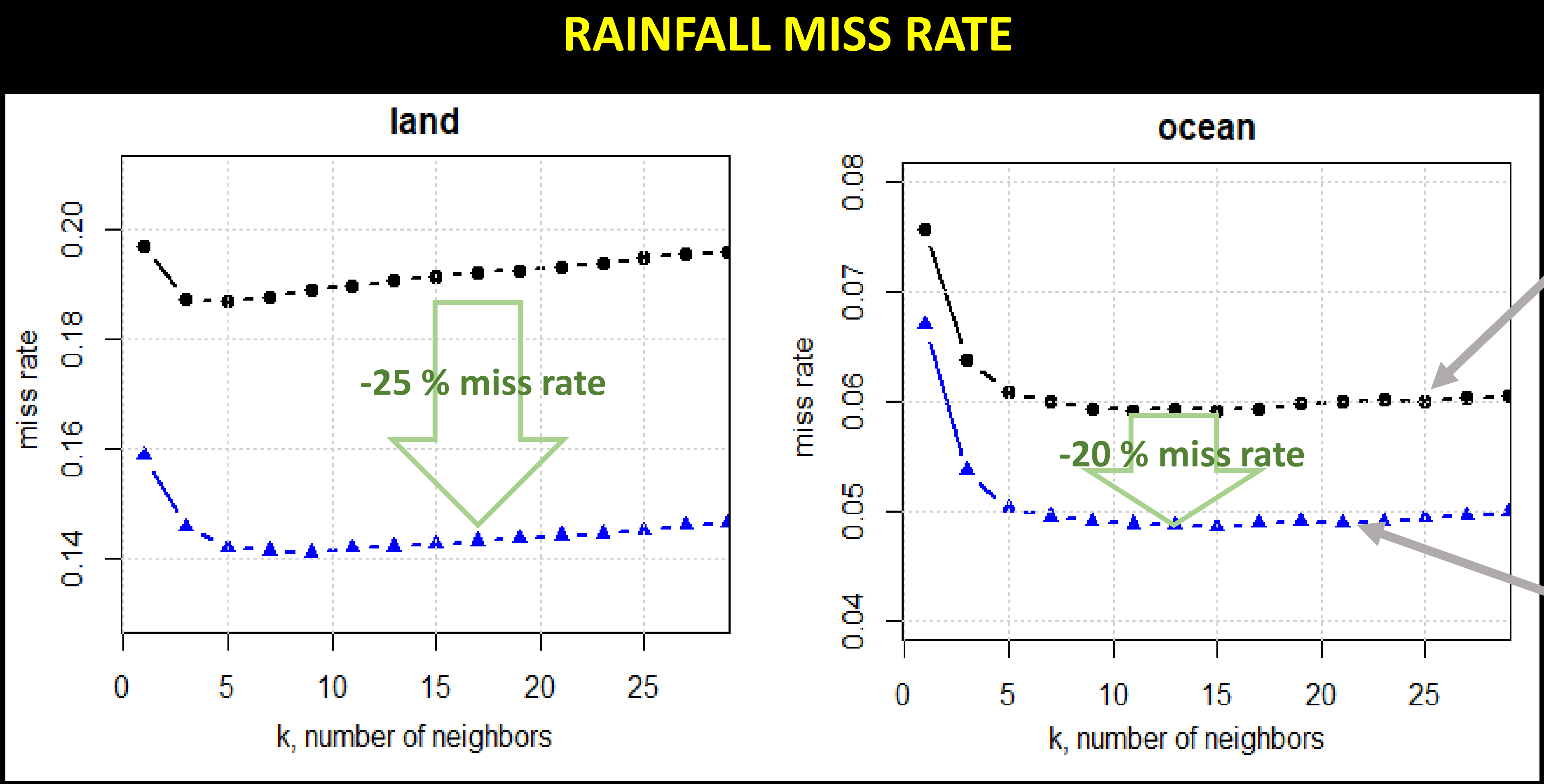
13 “pixel” TBs
+ 2m temp. + surf. type
+ 3 nonlocal param. (at 37 and 89 V GHz)

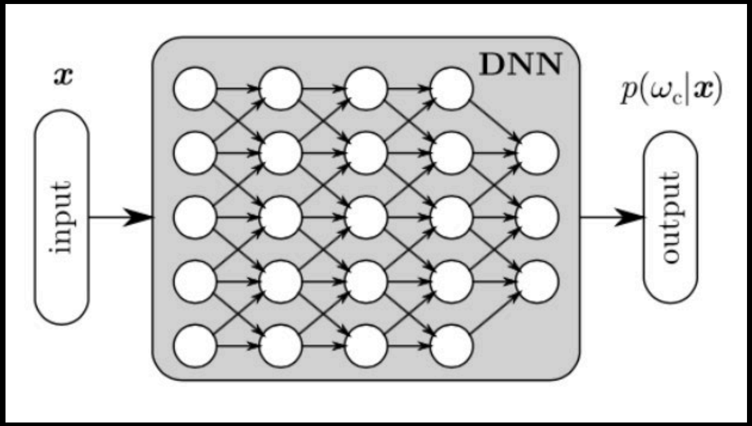
KNN retrieval from GMI with a 700 000 profile database



13 “pixel” TBs
+ 2m temp. + surf. type

13 “pixel” TBs
+ 2m temp. + surf. type
+ **3 nonlocal param.** (at 37 and 89 V GHz)

What's next?



- Is Machine Learning (ML) the solution?
- Eventually maybe, but not without physically-based dimensionality reduction first
- Train Convolutional Neural Networks (CNNs) and by backpropagation methods learn what patterns were retained in the training (attribution methods)
- Could work on specific storm systems, e.g., snowstorms and learn patterns that "detect snow", etc.
- Error diagnostics for multi-sensor merging (IMERG)

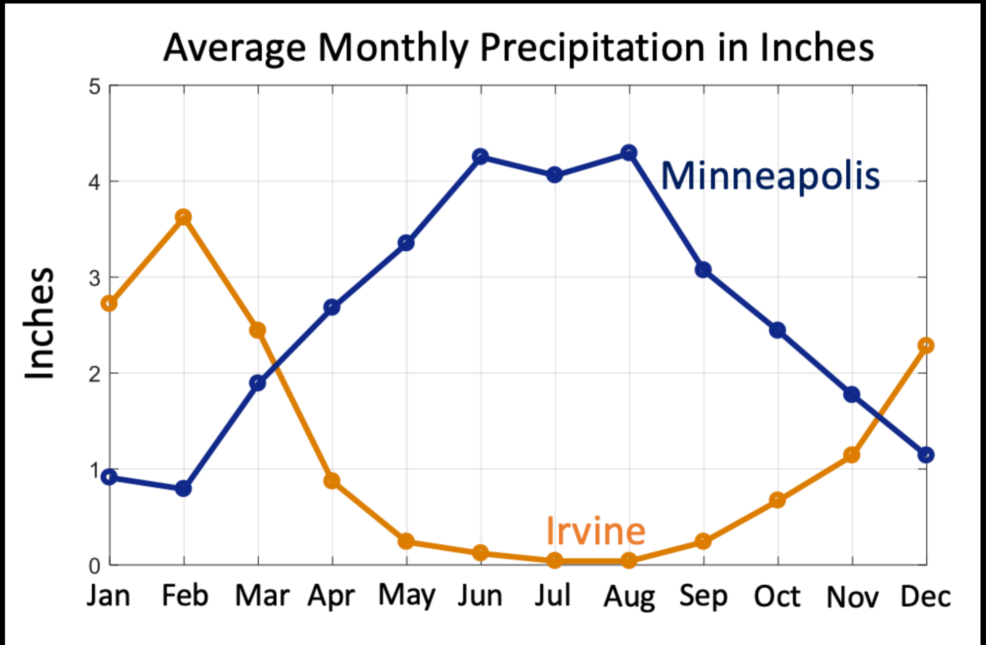
Today's focus:

RAINFALL

1. Global estimation from space
2. **Seasonal prediction**

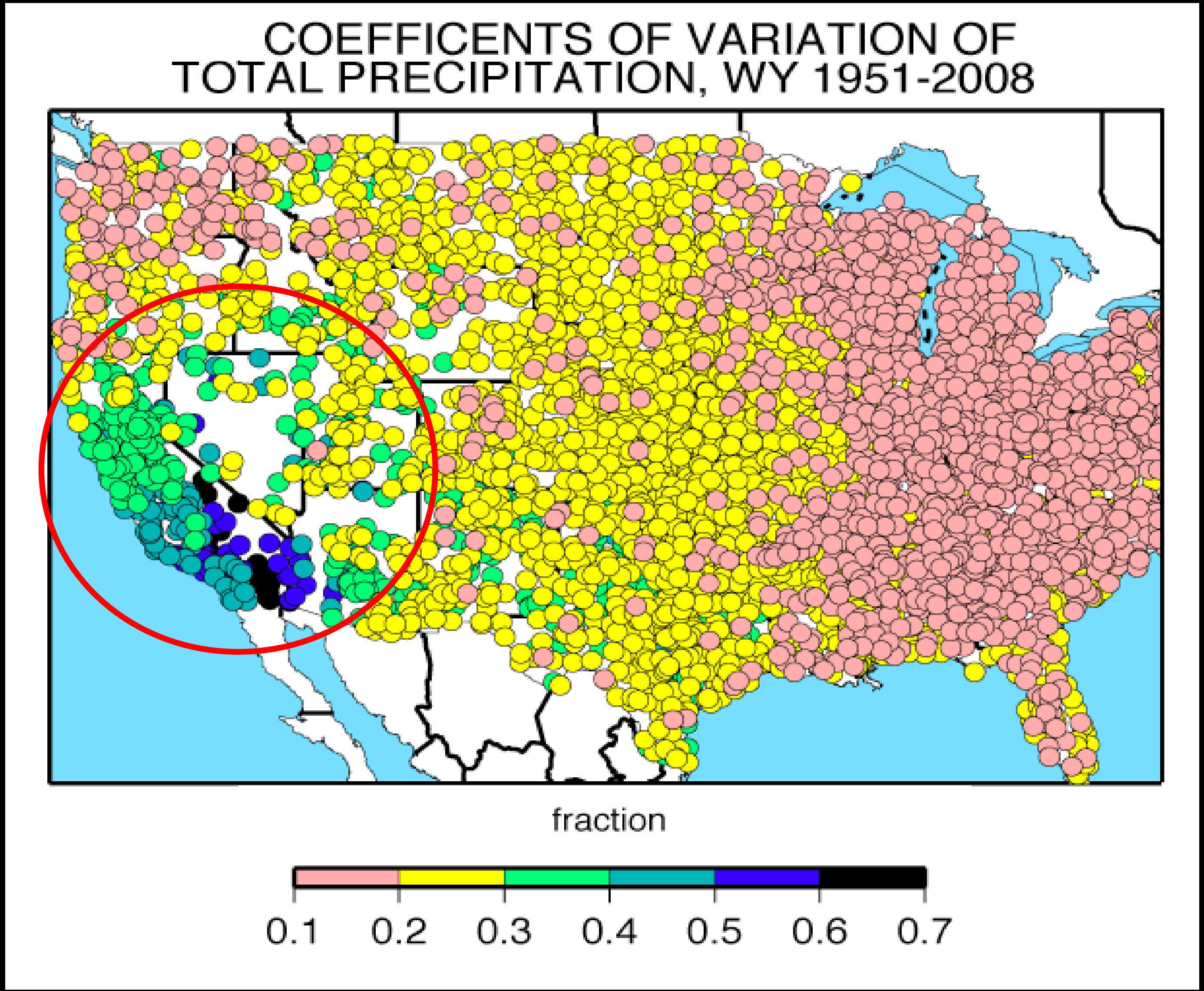

30 years
3 years
CANADA
MEXICO
Pacific Ocean
Atlantic Ocean
Gulf of Mexico
Gulf of California
Lake Superior
Lake Michigan
Lake Huron
Lake Erie
Lake Ontario
St. Lawrence
Columbia Plateau
Colorado Plateau
Great Basin
Edwards Plateau
Ozarks Plateau
Allegheny Plateau
Cascade Range
Coastal Range
Sierra Nevada
Rocky Mountains
Appalachian Mountains
Piedmont
Atlantic Coastal Plain
Great Plains
Badlands
WA
OR
CA
NV
ID
MT
WY
UT
CO
AZ
NM
ND
SD
NE
KS
OK
TX
MN
IA
MO
AR
LA
WI
IL
MI
IN
OH
KY
TN
MS
AL
GA
FL
SC
NC
VA
WV
PA
NY
VT
NH
ME
MA
CT
RI
NJ
DE
MD
DC
WASHINGTON
Olympia
Portland
Salem
Boise
Helena
Bismark
Pierre
Cheyenne
Salt Lake City
Denver
Carson City
Sacramento
San Francisco
Las Vegas
Los Angeles
San Diego
Phoenix
Santa Fe
Albuquerque
El Paso
Lincoln
Topeka
Kansas City
Jefferson City
St. Louis
Oklahoma City
Dallas
Austin
San Antonio
Houston
Little Rock
Memphis
Jackson
Baton Rouge
New Orleans
Des Moines
Paul
Madison
Milwaukee
Chicago
Springfield
Indianapolis
Lansing
Detroit
Cleveland
Columbus
Pittsburgh
Frankfort
Charleston
Nashville
Atlanta
Montgomery
Tallahassee
Columbia
Raleigh
Richmond
Harrisburg
Trenton
Philadelphia
Baltimore
Annapolis
Dover
New York
Albany
Hartford
Providence
Boston
Concord
Montpelier
Portland
Orlando
Tampa
Miami
Florida Strait
THE BAHAMAS
Yellowstone
Missouri
Mississippi
Platte
N. Platte
S. Platte
Arkansas
Red River
Colorado
Rio Grande
Ohio
Tennessee
Alabama
Snake
Great Salt Lake
Mojave Desert
Chukchi Sea
Beaufort Sea
Bering Sea
Gulf of Alaska
RUSSIA
Brooks Range
Alaska Range
AL
Fairbanks
Anchorage
Juneau
country capital
regional capital
city/town
6.000 m
4.000
3.000
2.000
1.000

	Minneapolis	Irvine
Rain	32 inches	12 inches
Snow	53 inches	0 inches
Prec days	112 days	36 days
Avg T Jan	7 degrees F	46 degrees F

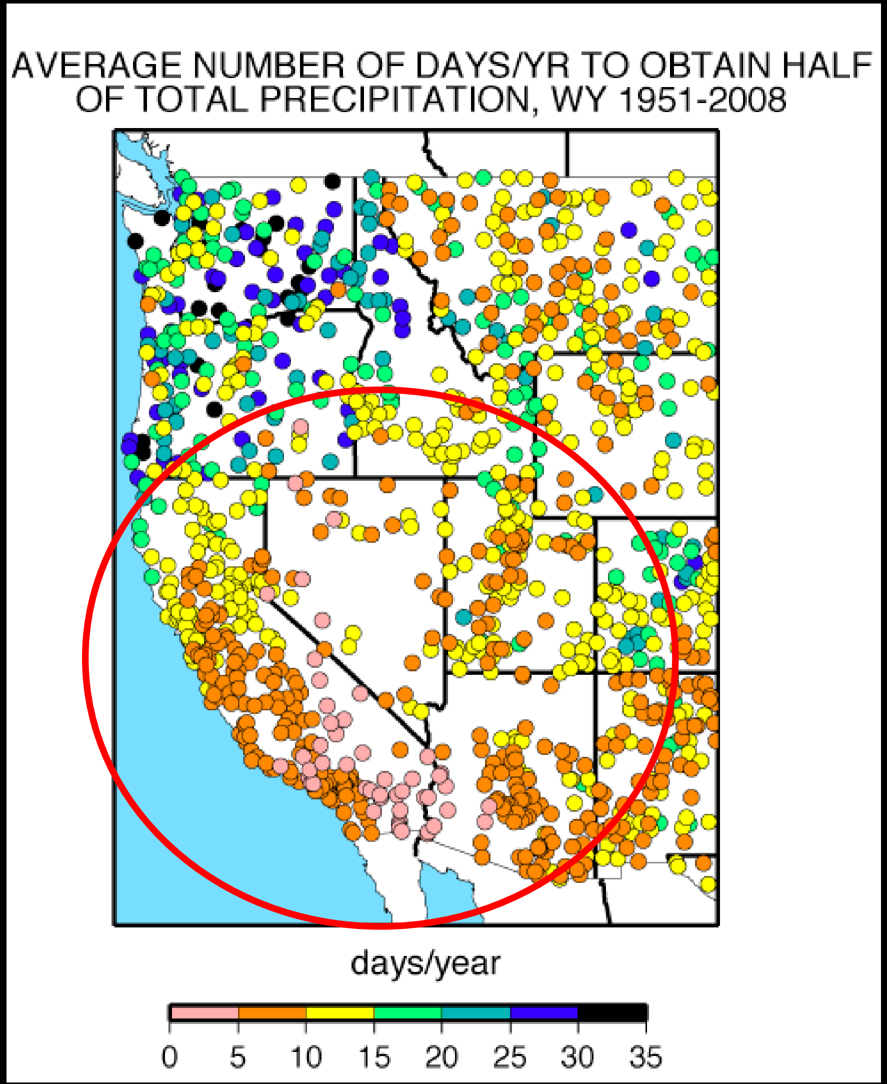


https://www.usclimatedata.com/

Large interannual variability



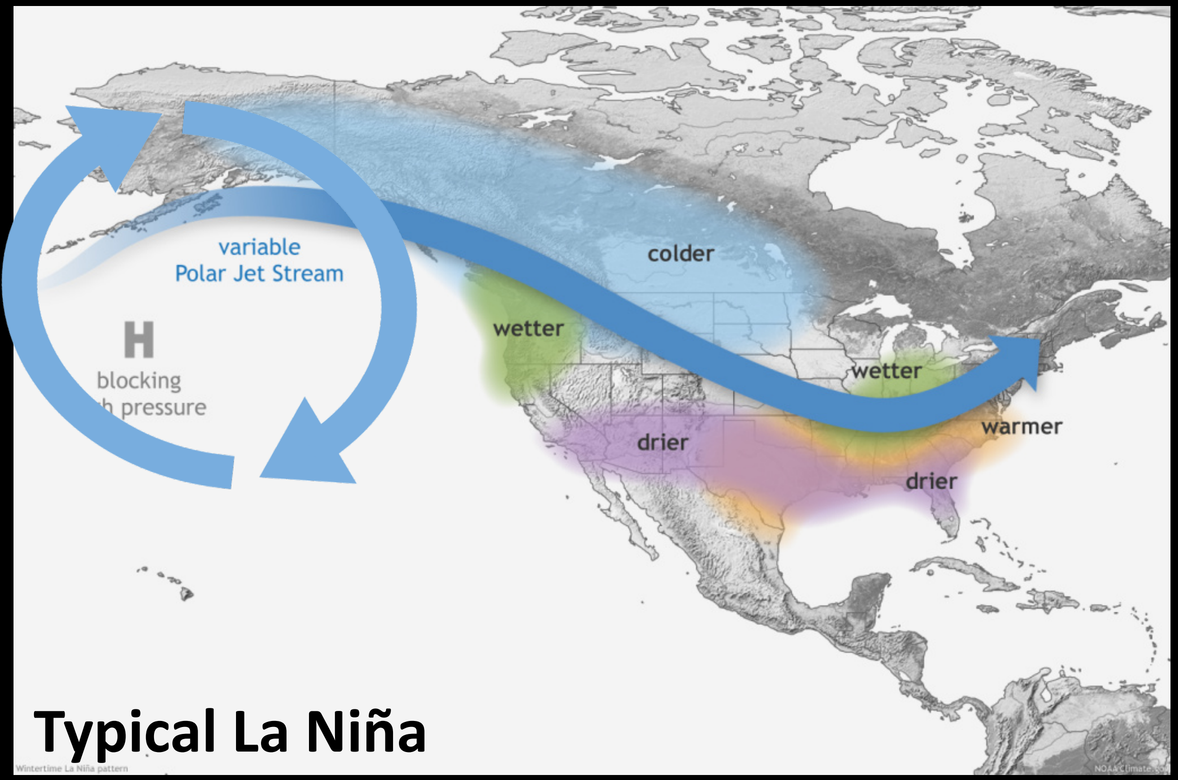
Half of annual rain in 5-10 days

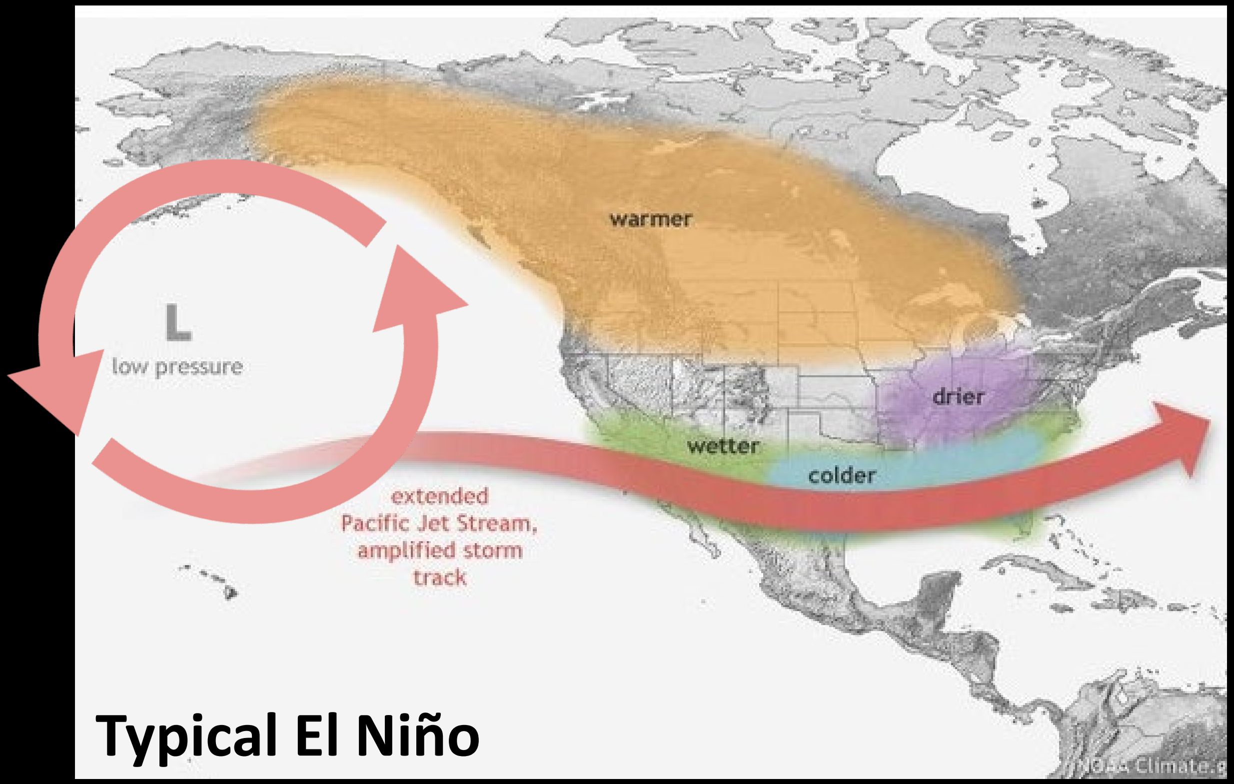


Precipitation in SWUS: It all comes down to Pressure…

Persistent H/L-pressure ridges/troughs over the Gulf of Alaska
affect the jet stream diverting it to the N or S relative to its average latitudinal location

These pressure patterns are typically related to ENSO



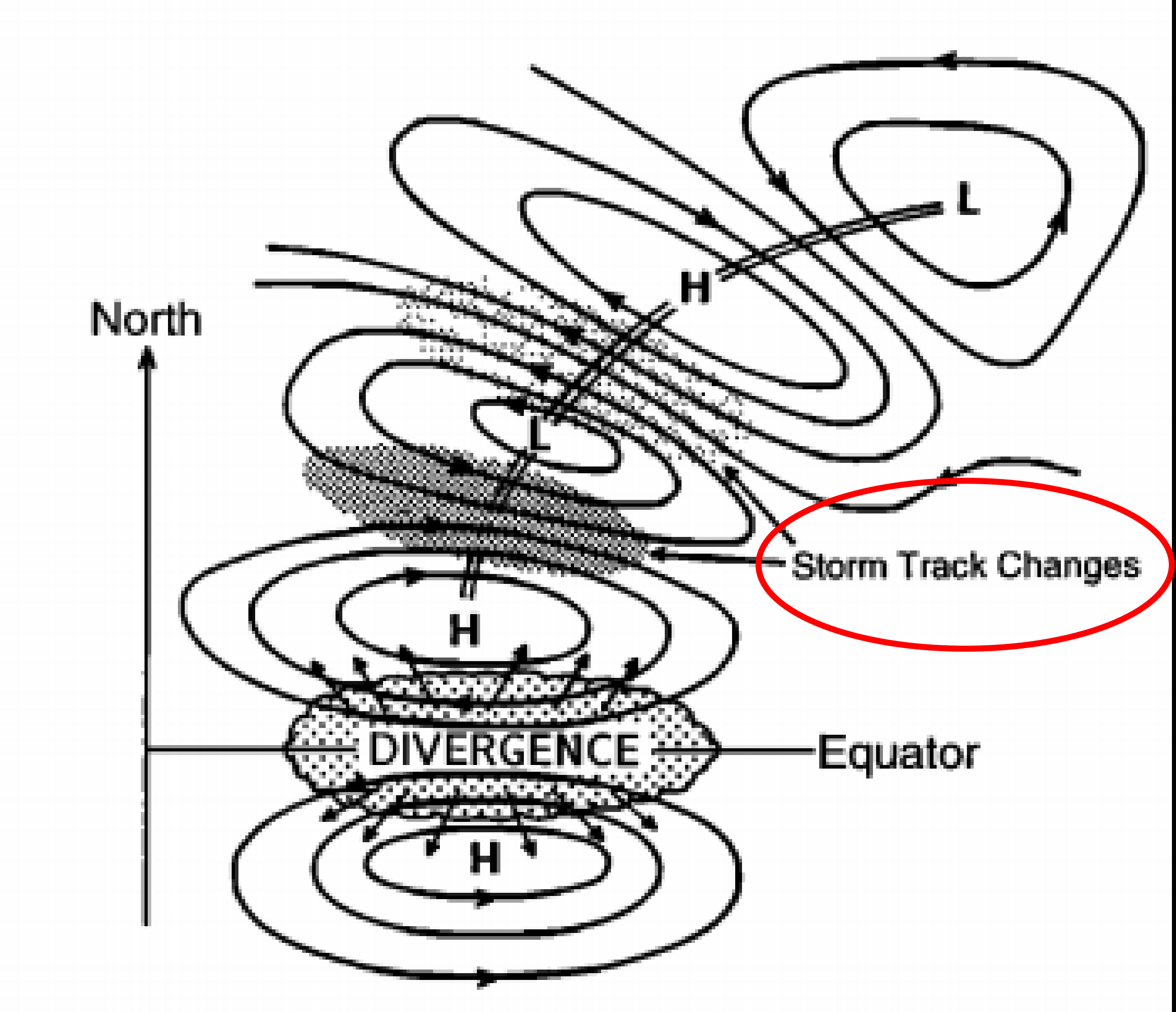


Figures are from Lindsey, 2016.

Precipitation in SWUS: It all comes down to Pressure…

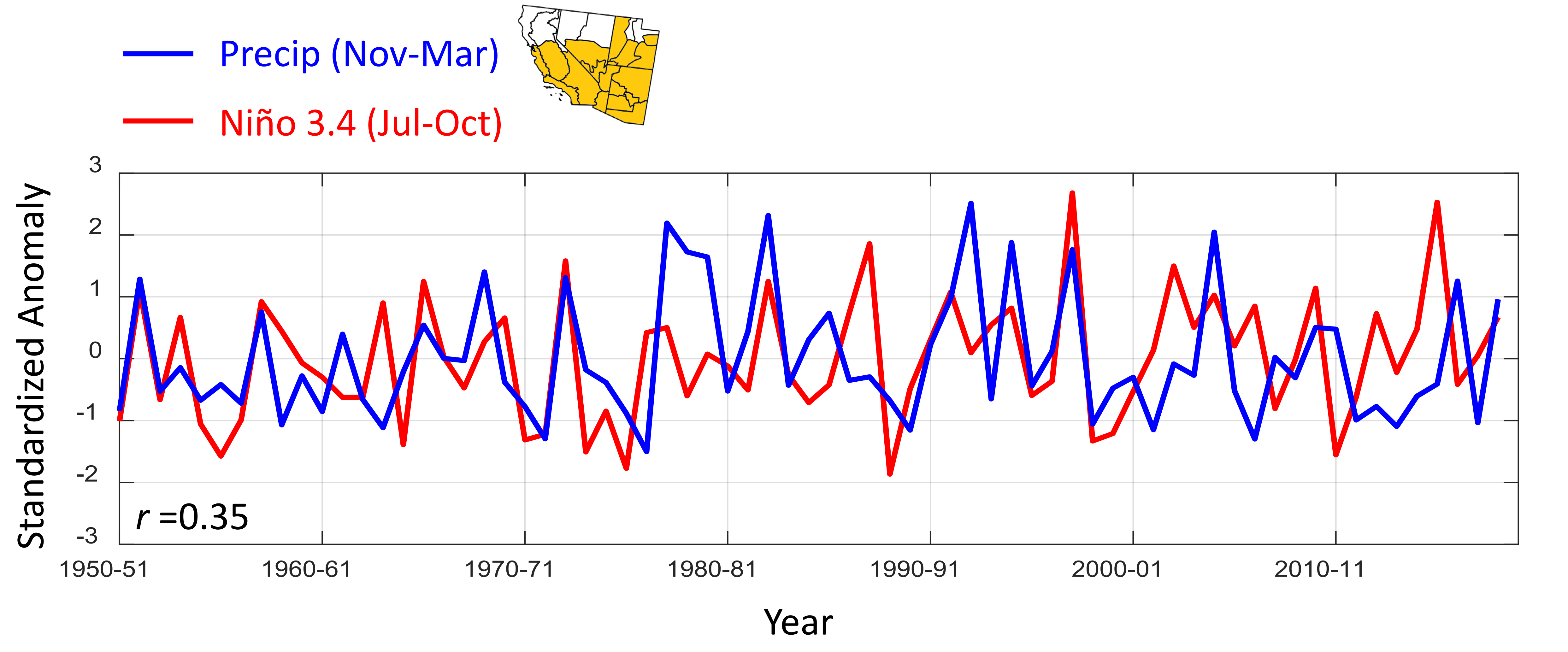
Above normal SSTs in the tropical Pacific **increase convergence** in the surface which enhances air convection and leads to **anomalous divergence in the top of the troposphere.**

A **quasi-stationary Rossby wave** of alternating anticyclonic and cyclonic patterns forms, which is associated with a southward **shift of the storm tracks in the subtropical regions.**

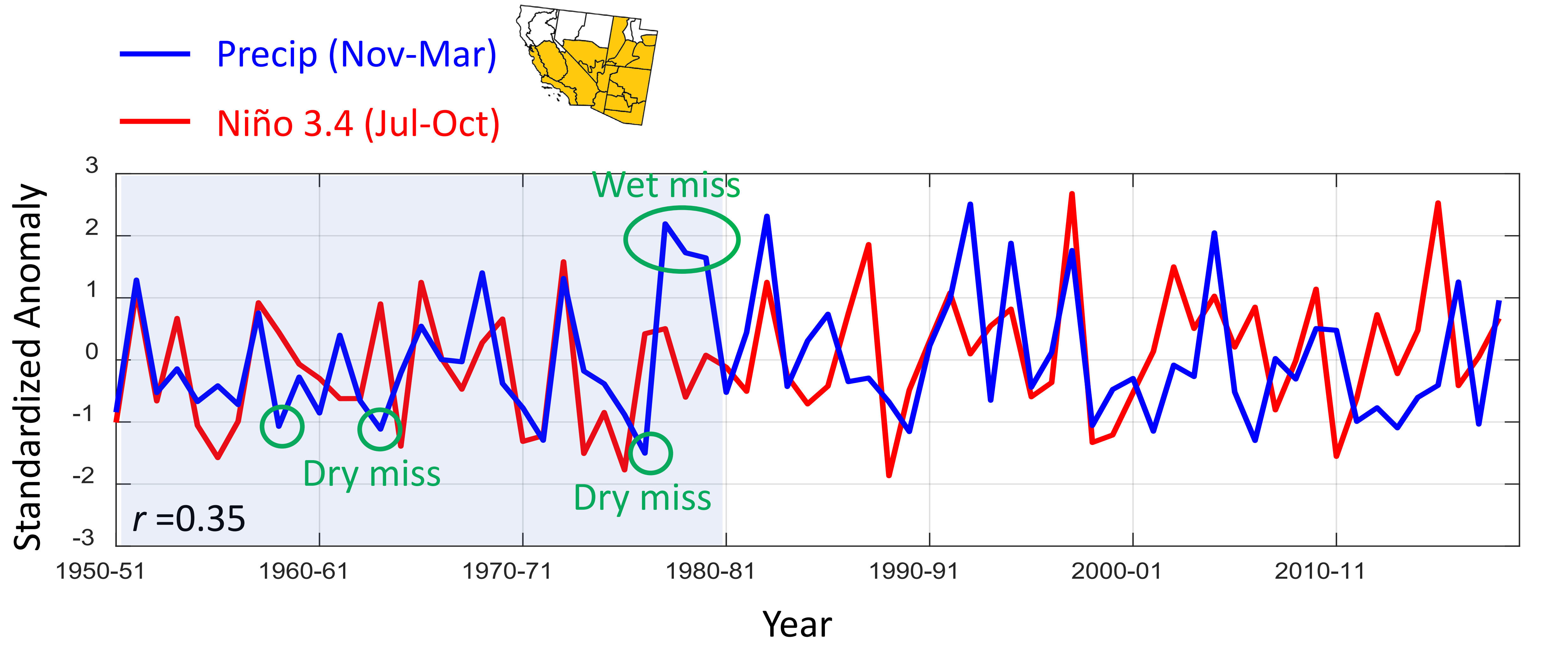


(Trenberth et al., 1998)

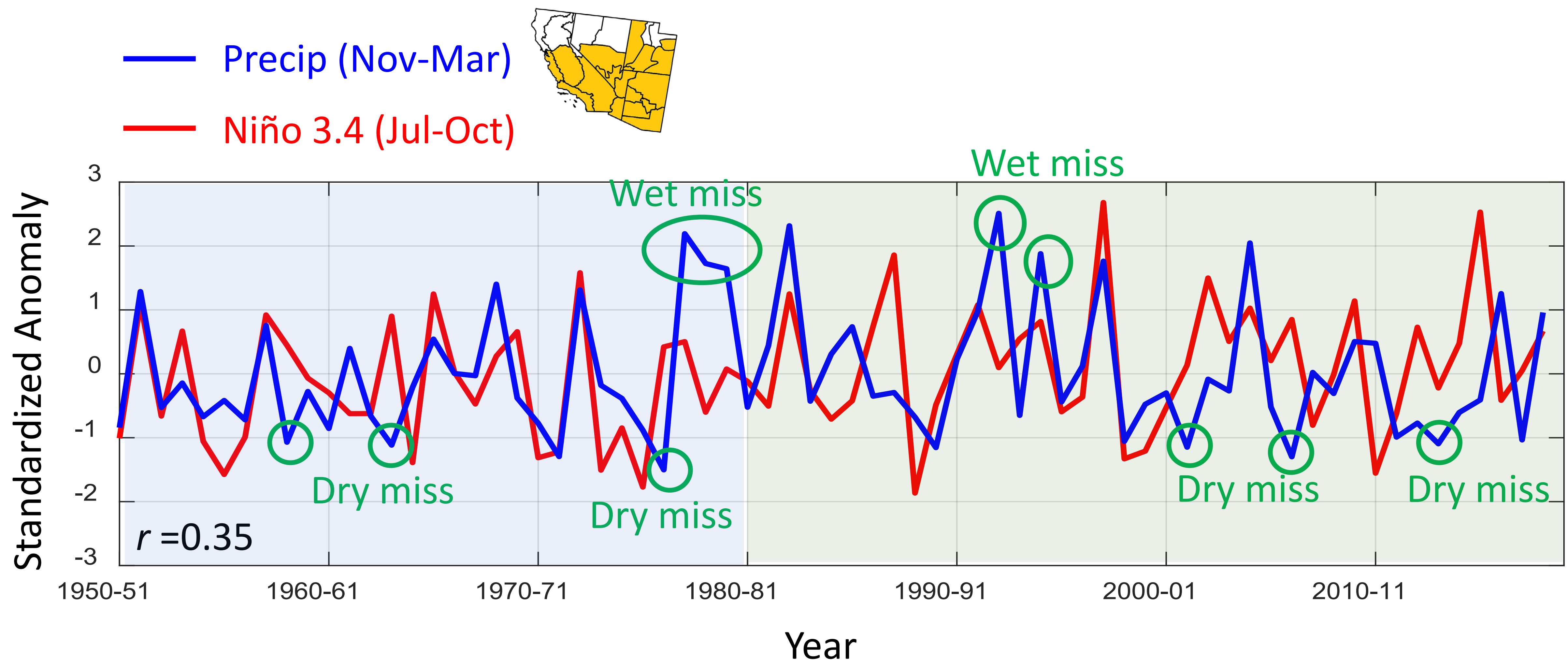
Low predictive ability by ENSO



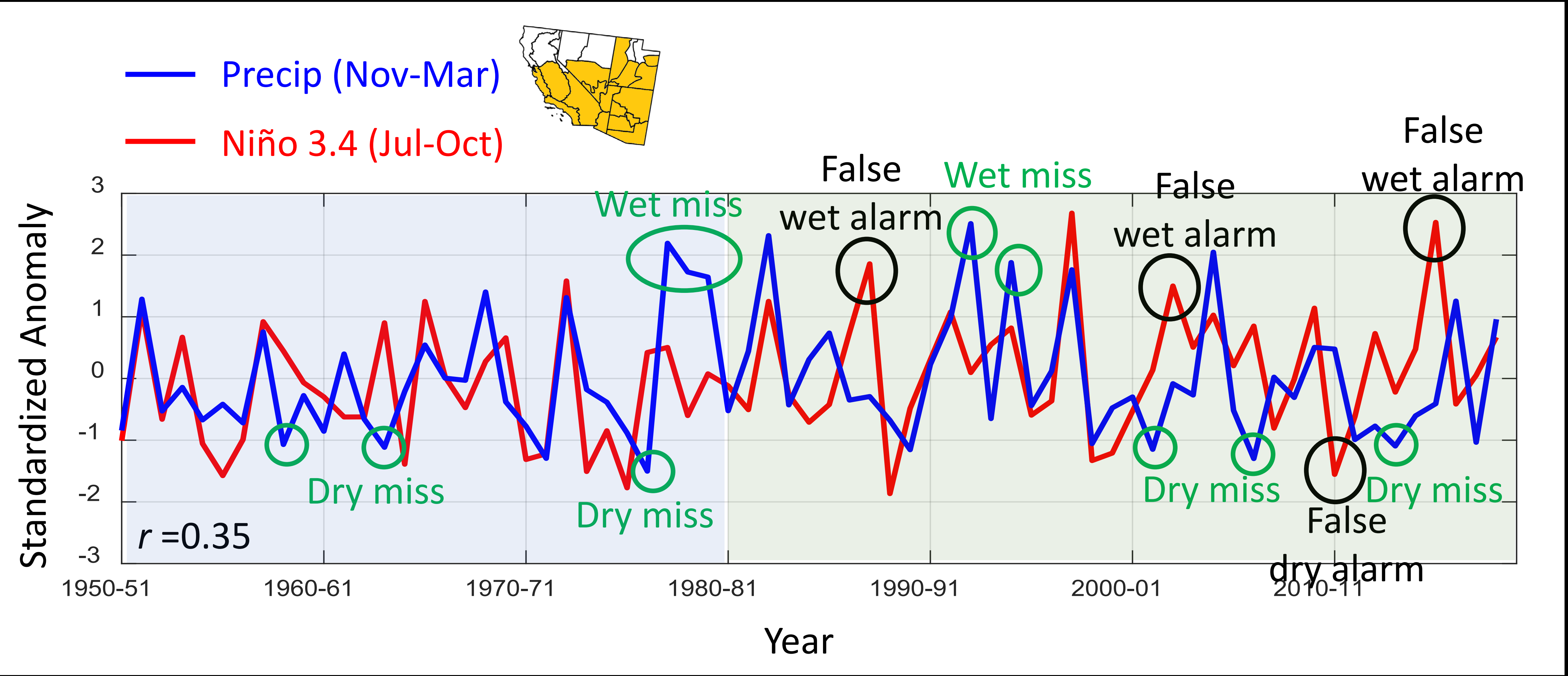
Low predictive ability by ENSO



Low predictive ability by ENSO

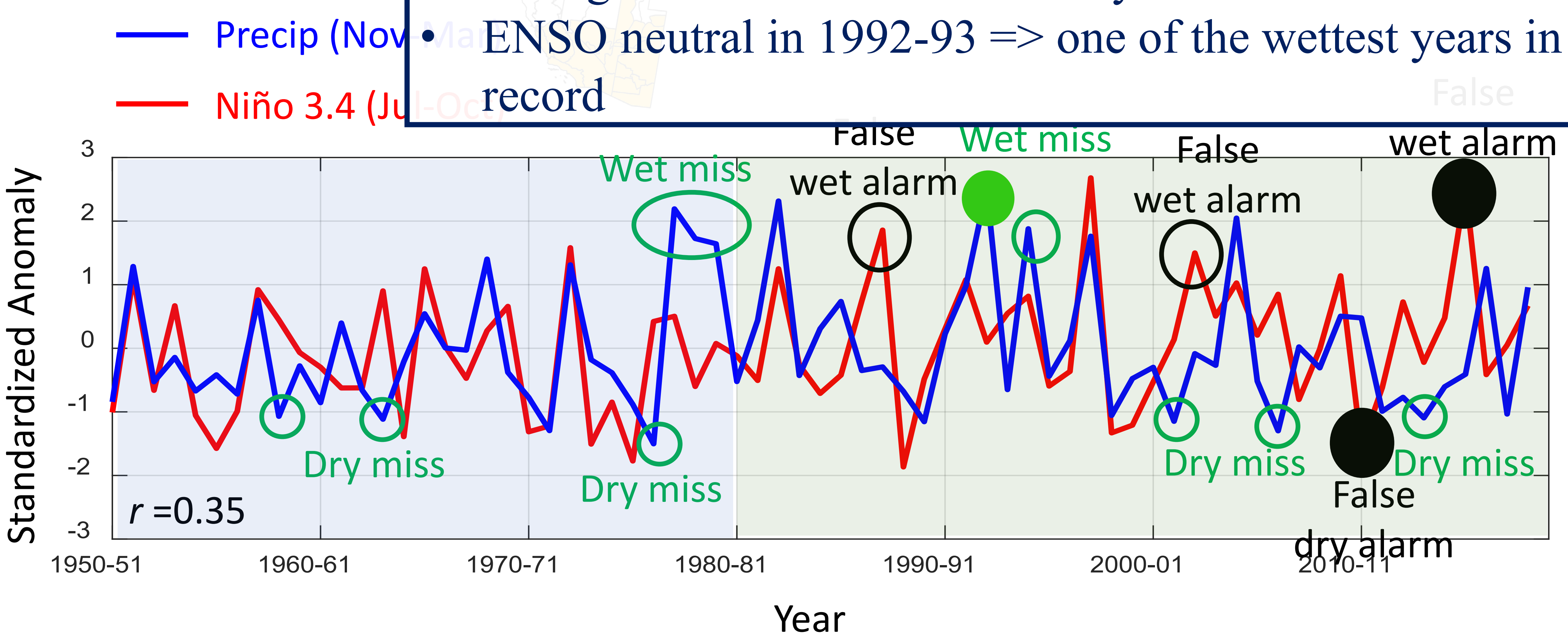


Low predictive ability by ENSO



Low predictive ability by ENSO

- Mega El Niño 2015-16 => dry year
- Strong La Niña 2010-11 => wet year
- ENSO neutral in 1992-93 => one of the wettest years in record



The increasing importance of Western Pacific

AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2014GL059748

Key Points:
- The drought-inducing ridge is recurrent
- The ridge is linked to an ENSO precursor
- The link of the ridge with ENSO precursor has grown

Probable causes of the abnormal ridge accompanying the 2013–2014 California drought: ENSO precursor and anthropogenic warming footprint

S.-Y. Wang[1,2], Lawrence Hipps[2], Robert R Gillies[1,2], and Jin-Ho Yoon[3]

[1]Utah Climate Center, Utah State University, Logan, Utah, USA, [2]Department of Plants, Soils and Climate, Utah State University, Logan, Utah, USA, [3]Pacific Northwest National Laboratory, Richland, Washington, USA

Journal of Geophysical Research: Atmospheres

RESEARCH ARTICLE
10.1002/2017JD026575

Key Points:
- North Pacific atmospheric high pressure similar to that responsible for the 2013–2016 California drought

Remote Linkages to Anomalous Winter Atmospheric Ridging Over the Northeastern Pacific

Daniel L. Swain[1,2], Deepti Singh[1,3], Daniel E. Horton[4], Justin S. Mankin[3,5], Tristan C. Ballard[1], and Noah S. Diffenbaugh[1,6]

Causes of Extreme Ridges That Induce California Droughts

HAIYAN TENG AND GRANT BRANSTATOR

National Center for Atmospheric Research,[a] Boulder, Colorado

INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **19**: 1399–1410 (1999)

DECADAL VARIATIONS IN THE STRENGTH OF ENSO TELECONNECTIONS WITH PRECIPITATION IN THE WESTERN UNITED STATES

GREGORY J. McCABE[a,*] and MICHAEL D. DETTINGER[b,†]
[a] *US Geological Survey, Denver Federal Center, MS 412, Denver, CO 80225, USA*
[b] *US Geological Survey, Scripps Institution of Oceanography, La Jolla, CA 92093-0227, USA*

SAN FRANCISCO ESTUARY & WATERSHED SCIENCE
Sponsored by the Delta Science Program and the UC Davis John Muir Institute of the Environment

Drought and the California Delta—A Matter of Extremes

Michael Dettinger[1,*] and Daniel R. Cayan[1]

"And it never failed that during the dry years the people forgot about the rich years and during the wet years they

atmosphere
MDPI

Article

Impacts of Pacific SSTs on Atmospheric Circulations Leading to California Winter Precipitation Variability: A Diagnostic Modeling

Boksoon Myoung [1,*], Sang-Wook Yeh [2], Ji
1 APEC Climate Center, Busan 48058, Korea
2 Department of Marine Sciences and Conver

Is There a Role for Human-Induced Climate Change in the Precipitatio Decline that Drove the California Drought?

RICHARD SEAGER, NAOMI HENDERSON, MARK A. CANE, HAIBO LIU, AND JENNIFER NAKAMURA

Key Role of the North Pacific Oscillation–West Pacific Pattern the Extreme 2013/14 North American Winter

STEPHEN BAXTER

Climate Prediction Center, NOAA/NWS/NCEP, College Park, Maryland

SUMANT NIGAM

Geophysical Research Letters

RESEARCH LETTER
10.1029/2019GL084021

Key Points:
- Tropical Pacific zonal sea surface temperature gradients modulate tropical atmospheric patterns traditionally associated with El Niño
- An anomalously strong tropical

On the Delayed Coupling Between Ocean and Atmosphere in Recent Weak El Niño Episodes

N. C. Johnson[1,2], M. L. L'Heureux[3], C.-H. Chang[4], and Z.-Z. Hu[3]

[1]Atmospheric and Oceanic Sciences Program, Princeton University, Princeton, NJ, USA, [2]NOAA Geophysical Fluid Dynamics Laboratory, Princeton, NJ, USA, [3]NOAA/NCEP Climate Prediction Center, College Park, MD, USA, [4]Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, South Korea

ica that

The increasing importance of Western Pacific

*"Our analysis **cautions against** succumbing to the post-1980–90s temptation of **ascribing various extratropical anomalies in the Pacific–North American sector to ENSO**—a favorite go-to mechanism…"* – **Baxter and Nigam, J. Climate (2015)**

*"…there are tropical **heating anomalies that do not depend on ENSO** that may excite extratropical responses **that include extreme west coast ridges**."* -- **Teng and Branstator, J. Climate, (2017)**

*"There exists a **cross-Pacific pathway of Rossby wave energy, propagating from the western subtropical Pacific** toward the Gulf of Alaska…"* – **Wang et al., GRL, (2014)** on the extreme 2013/2014 North American drought

Similar notes by **Barsugli and Sardeshmukh (2002)**, **Hoerling and Kumar (2002)**, **Seager et al., (2014)**, **Seager et al., (2017)**, **Swain et al., (2017)**, **Myoung et al., (2018)** and **many more…**

Our study

2018

nature COMMUNICATIONS

ARTICLE

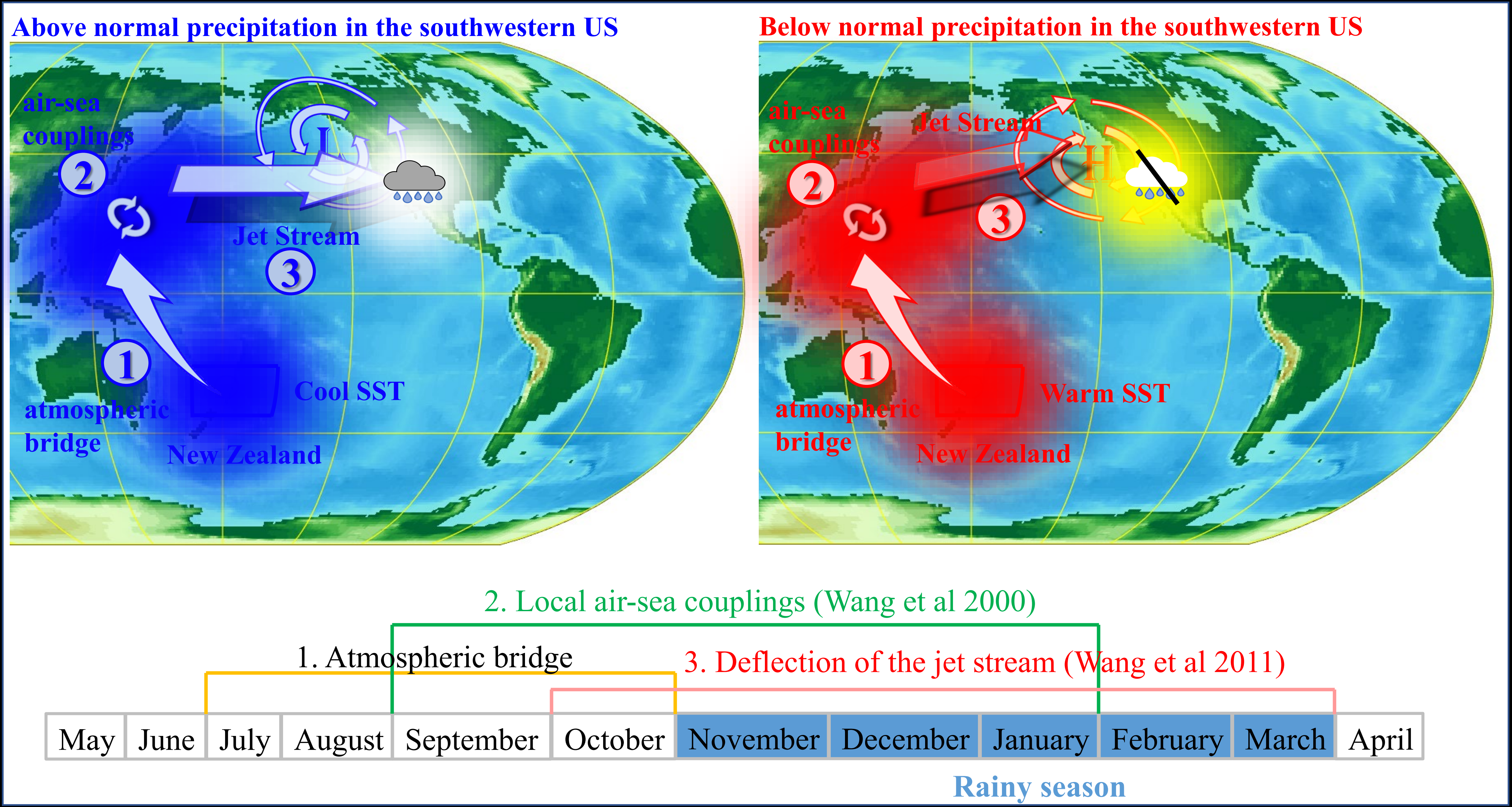
DOI: 10.1038/s41467-018-04722-7 OPEN

A new interhemispheric teleconnection increases predictability of winter precipitation in southwestern US

Antonios Mamalakis [1], Jin-Yi Yu [2], James T. Randerson [2], Amir AghaKouchak [1,2] & Efi Foufoula-Georgiou [1,2]

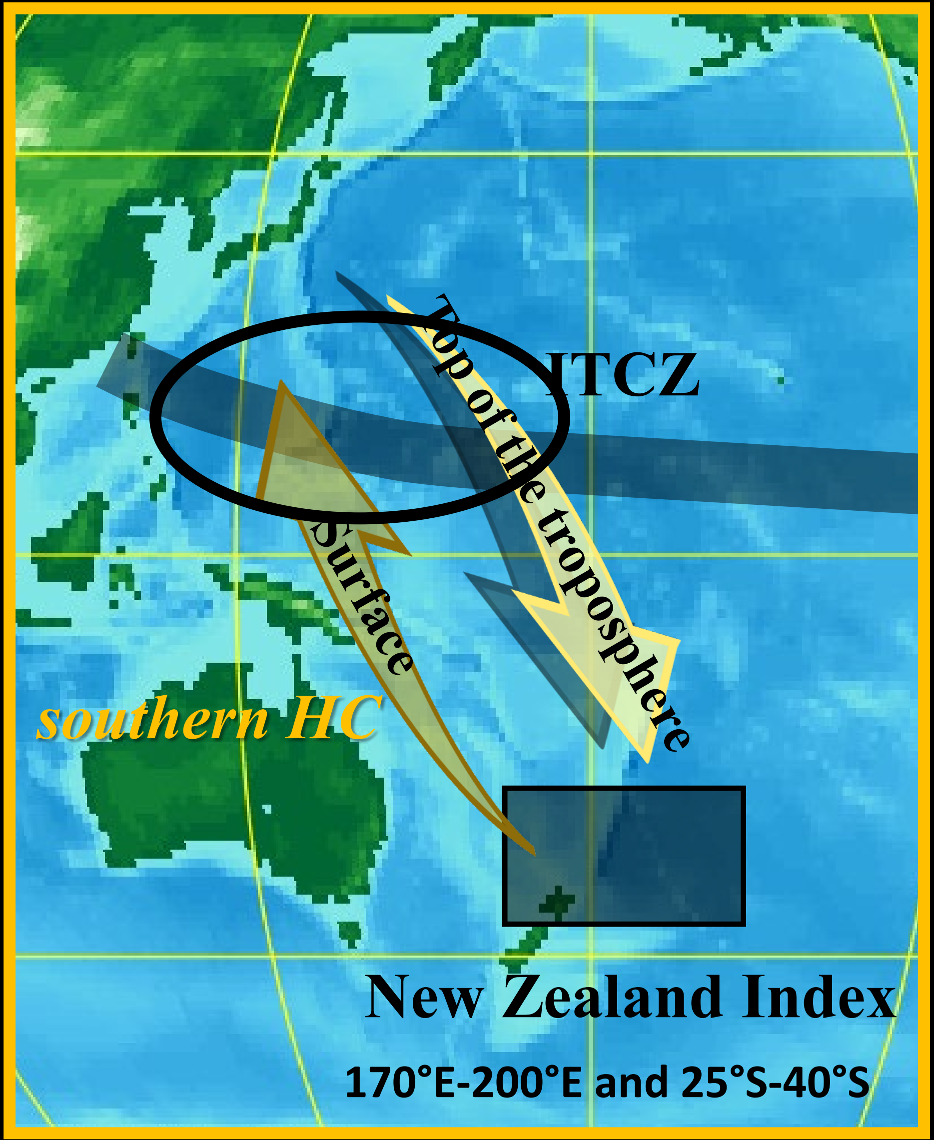
Western Pacific pathway

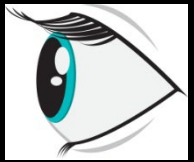
Mamalakis et al., 2018, *Nat. Communications*

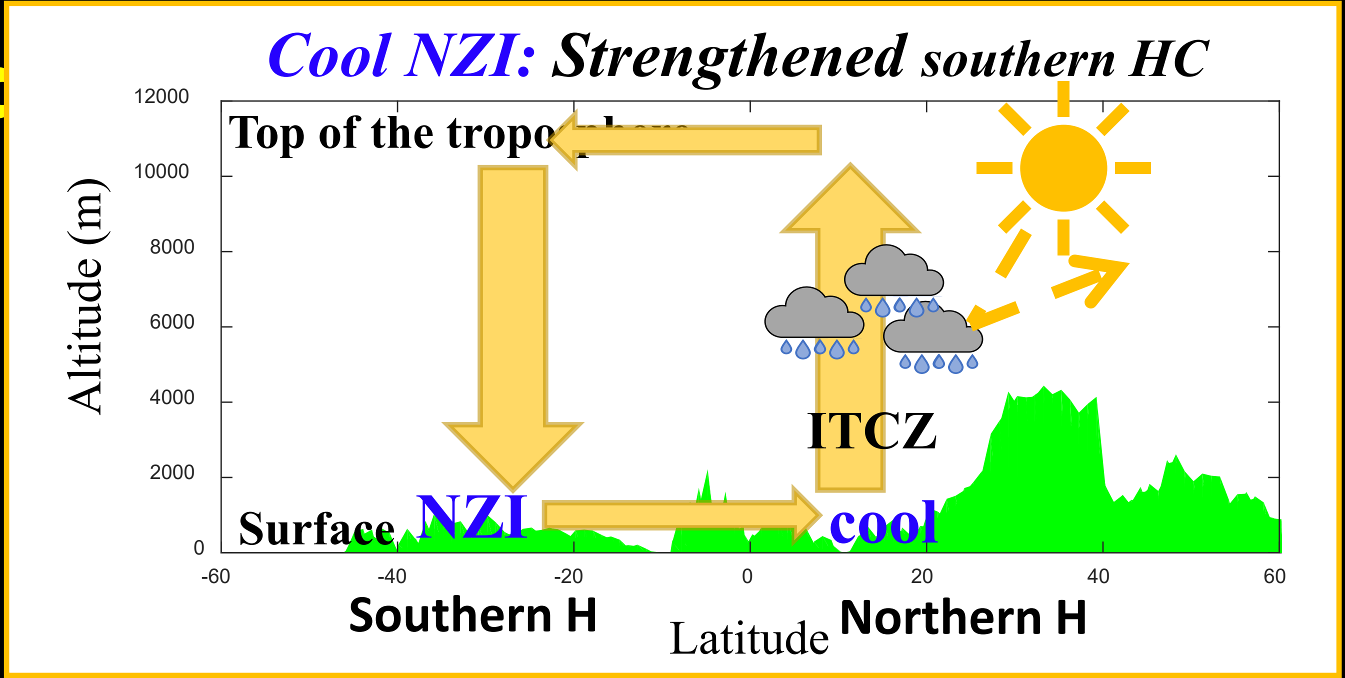


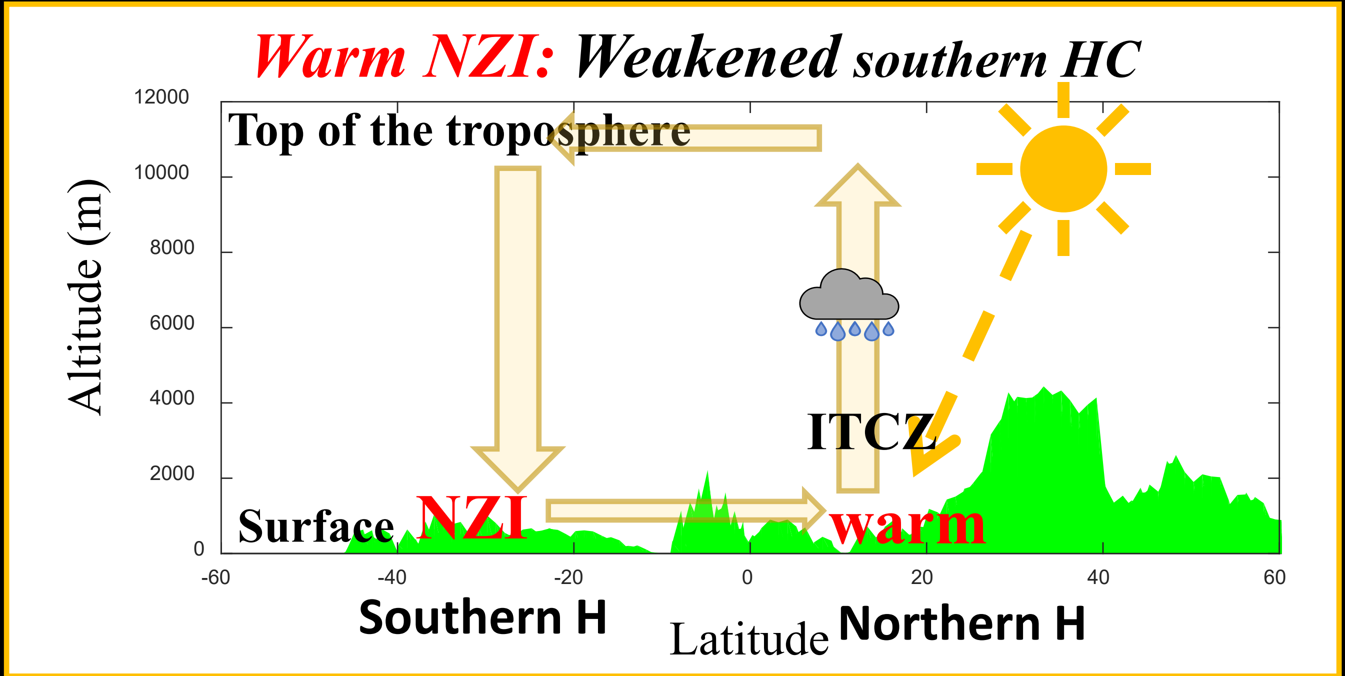
Western Pacific pathwa

Late boreal summer





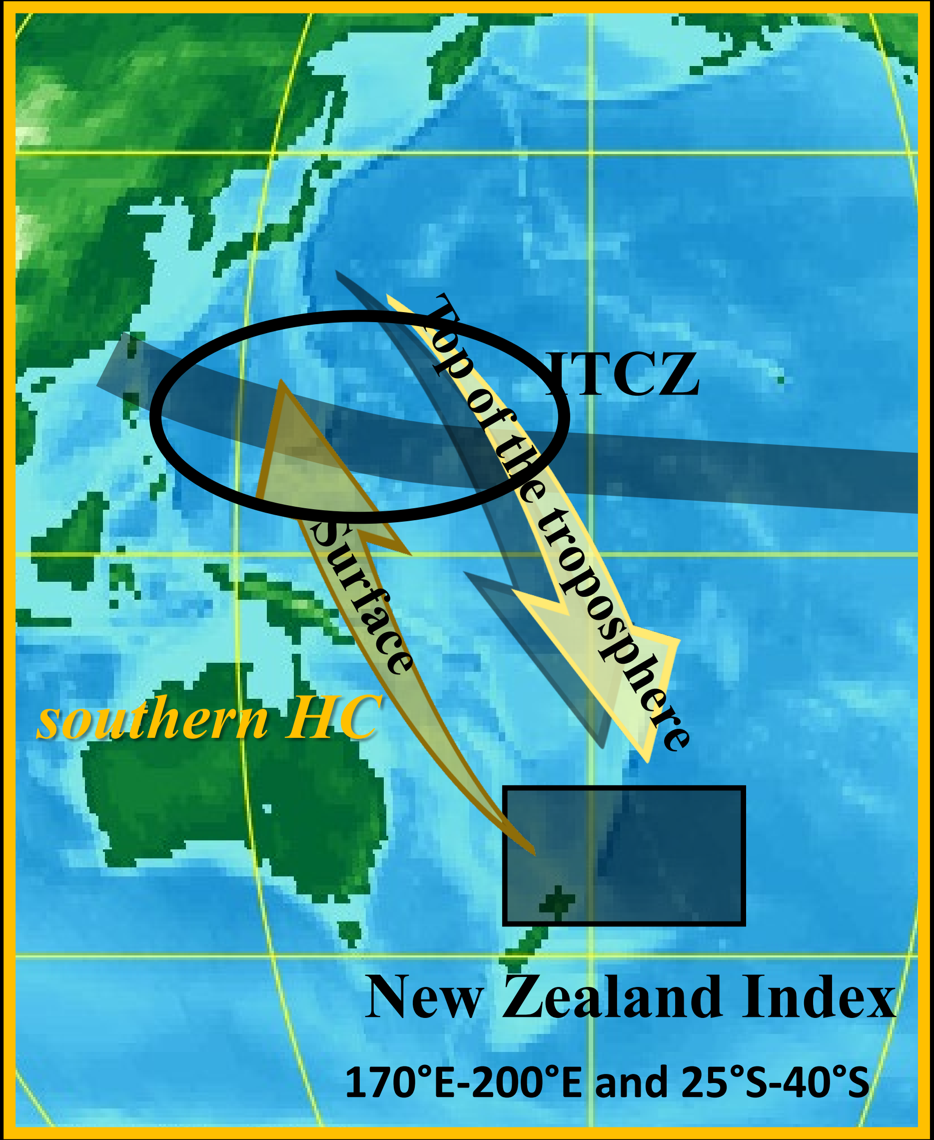


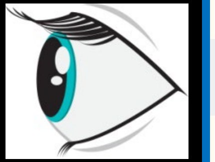


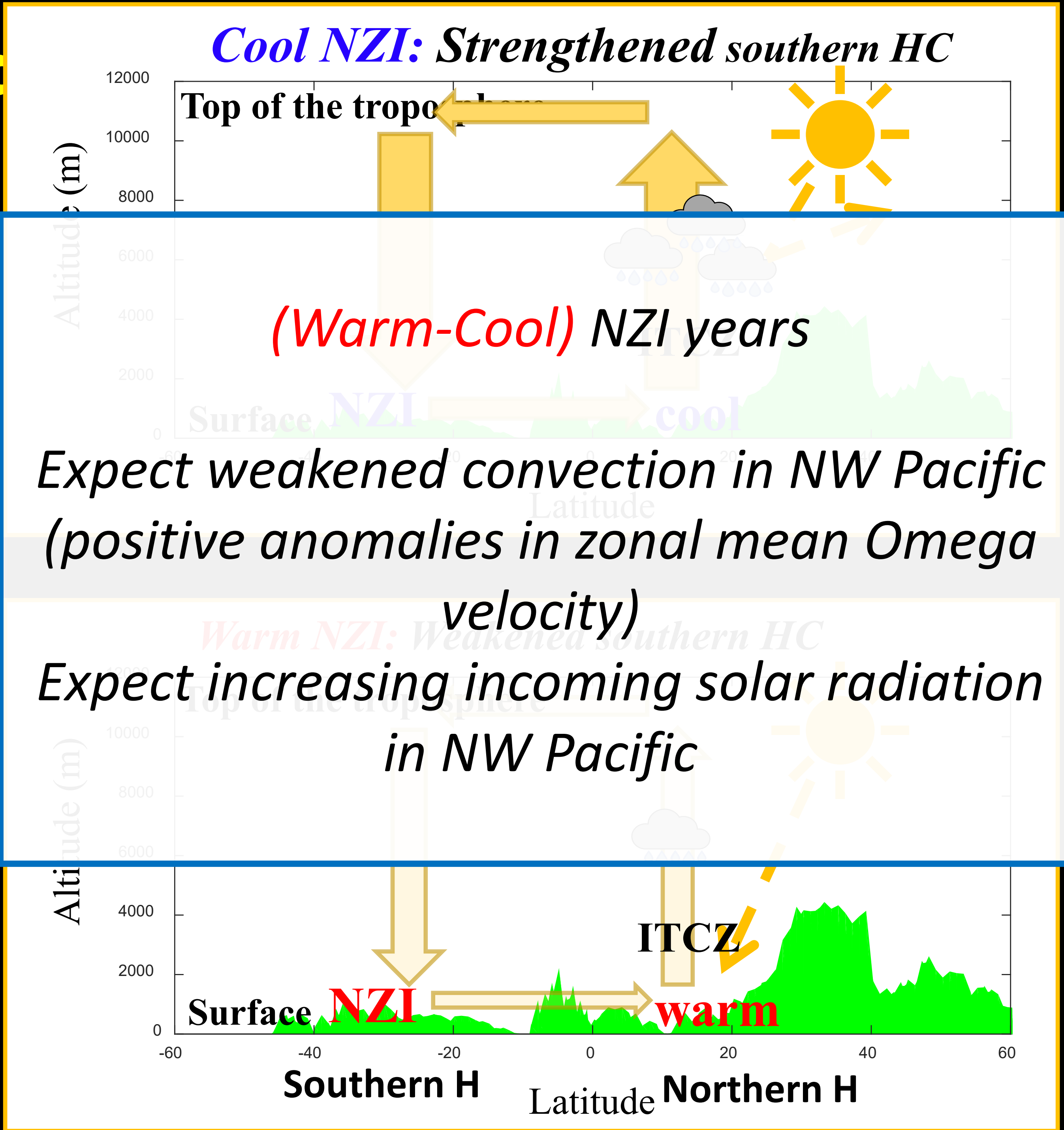
Mamalakis et al., 2018, *Nat. Communications*

Western Pacific pathwa

Late boreal summer







(Warm-Cool) NZI years

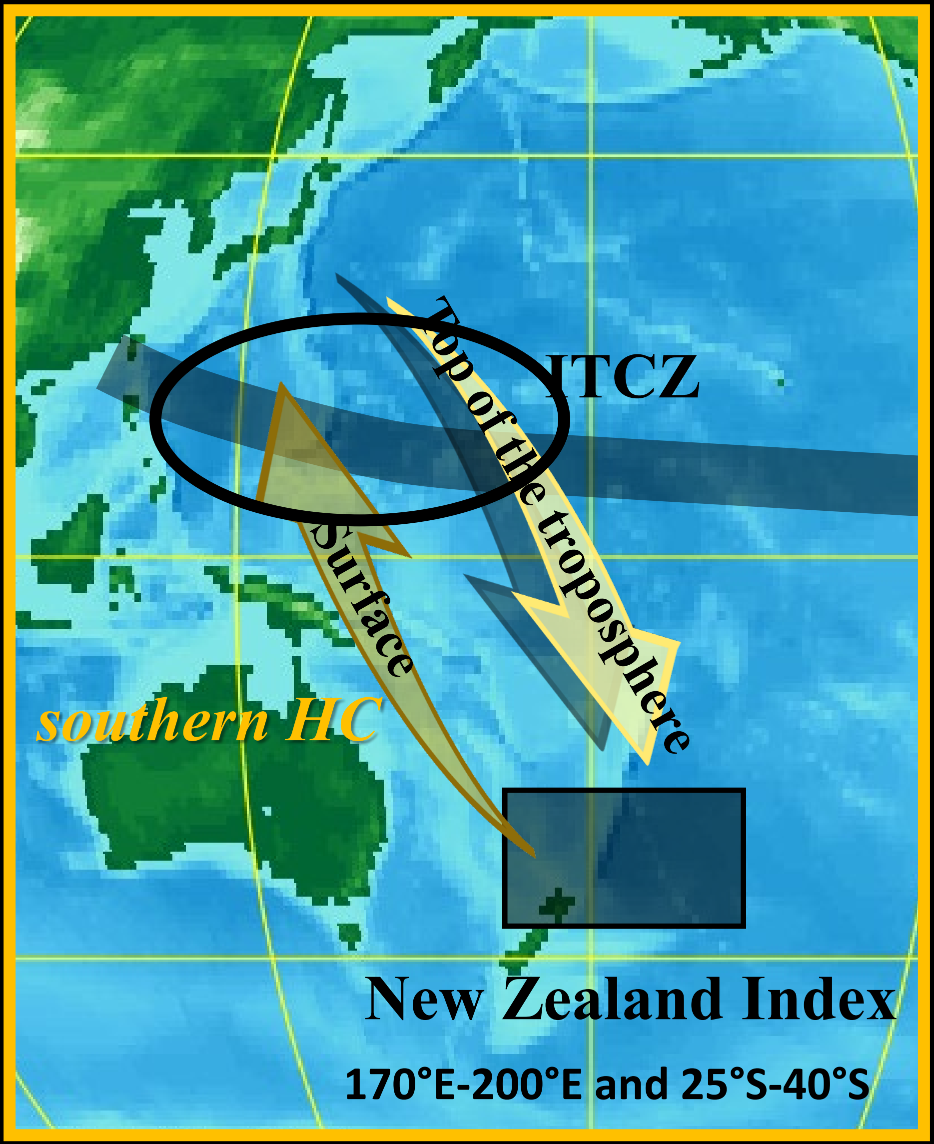
Expect weakened convection in NW Pacific (positive anomalies in zonal mean Omega velocity)

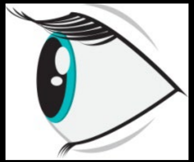
Expect increasing incoming solar radiation in NW Pacific

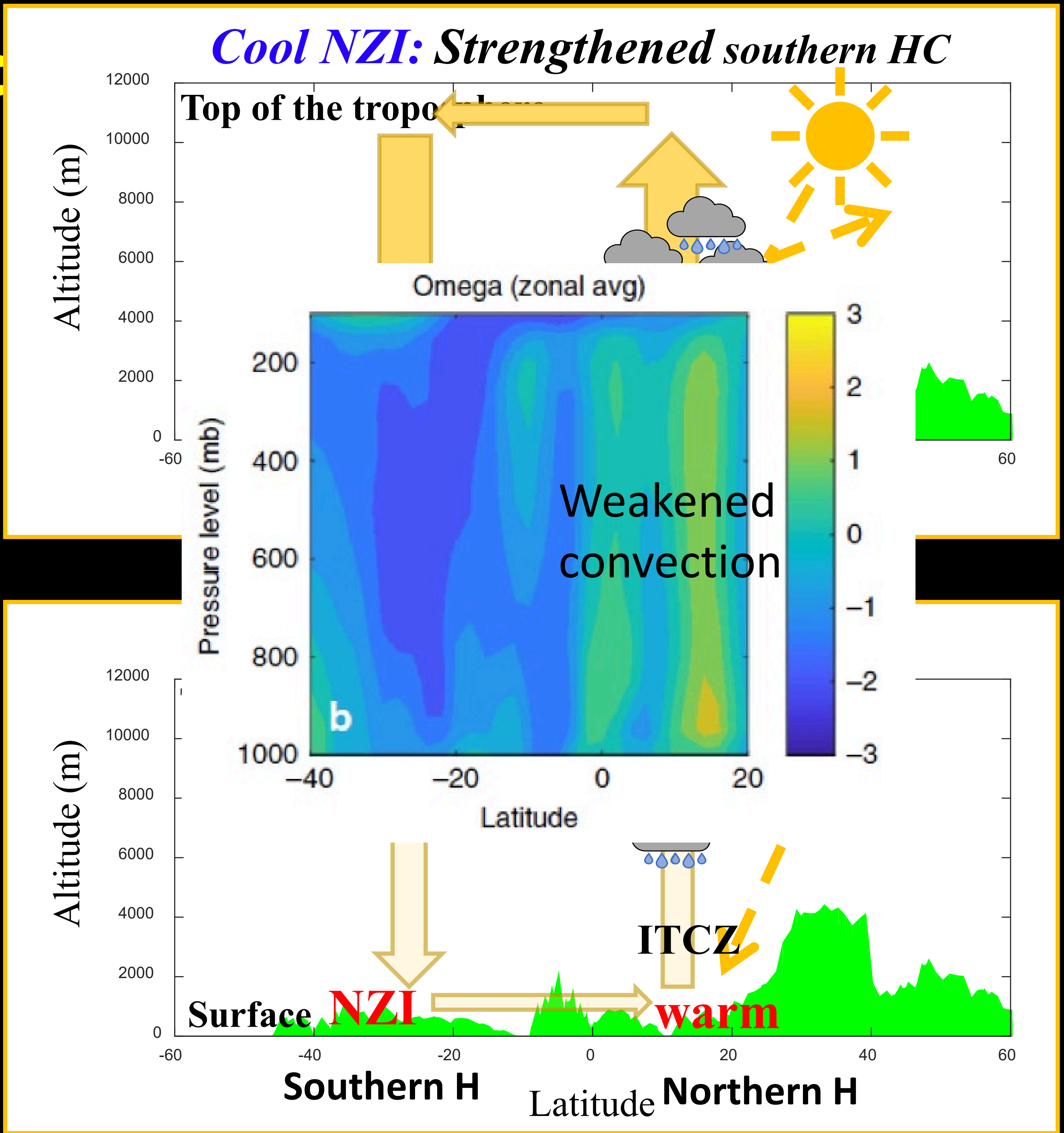
Mamalakis et al., 2018, *Nat. Communications*

Western Pacific pathw

Late boreal summer



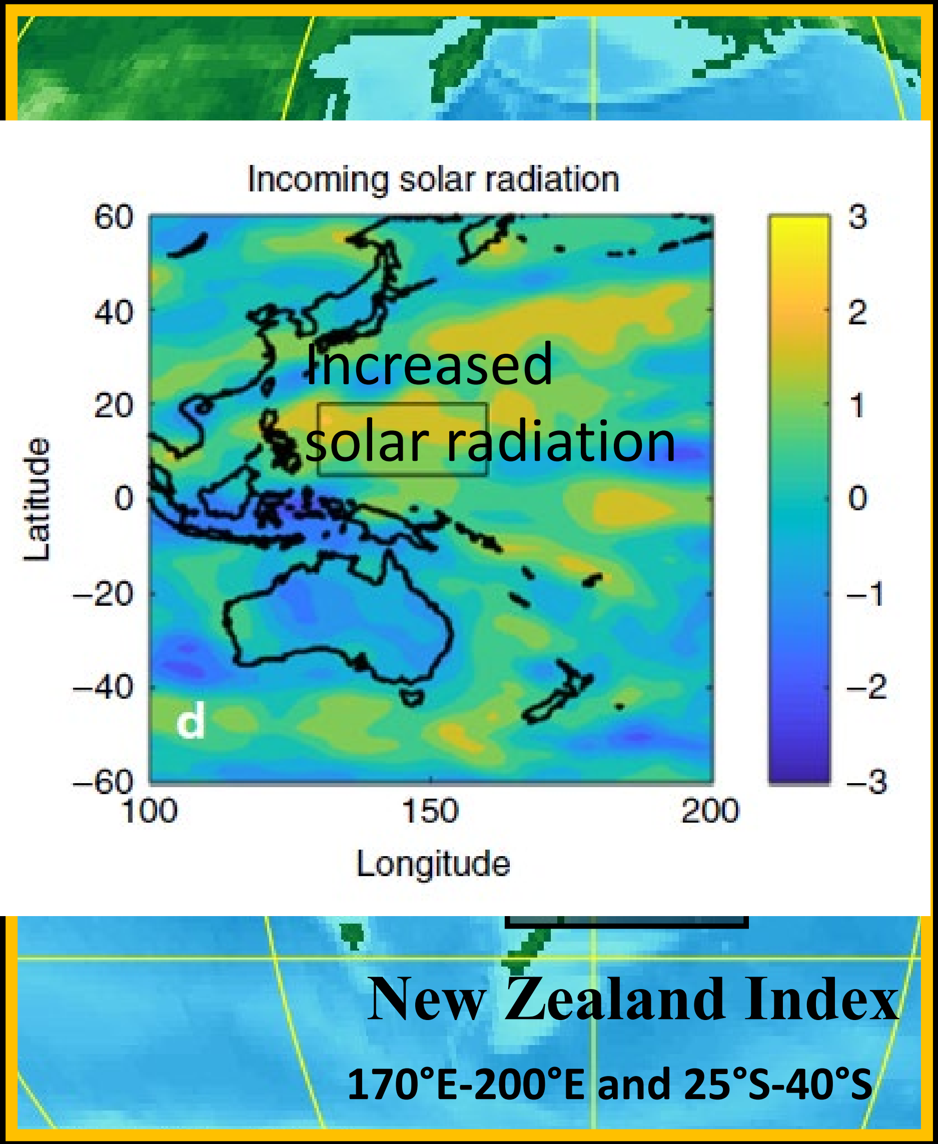


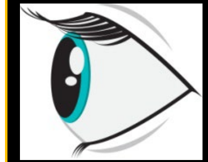


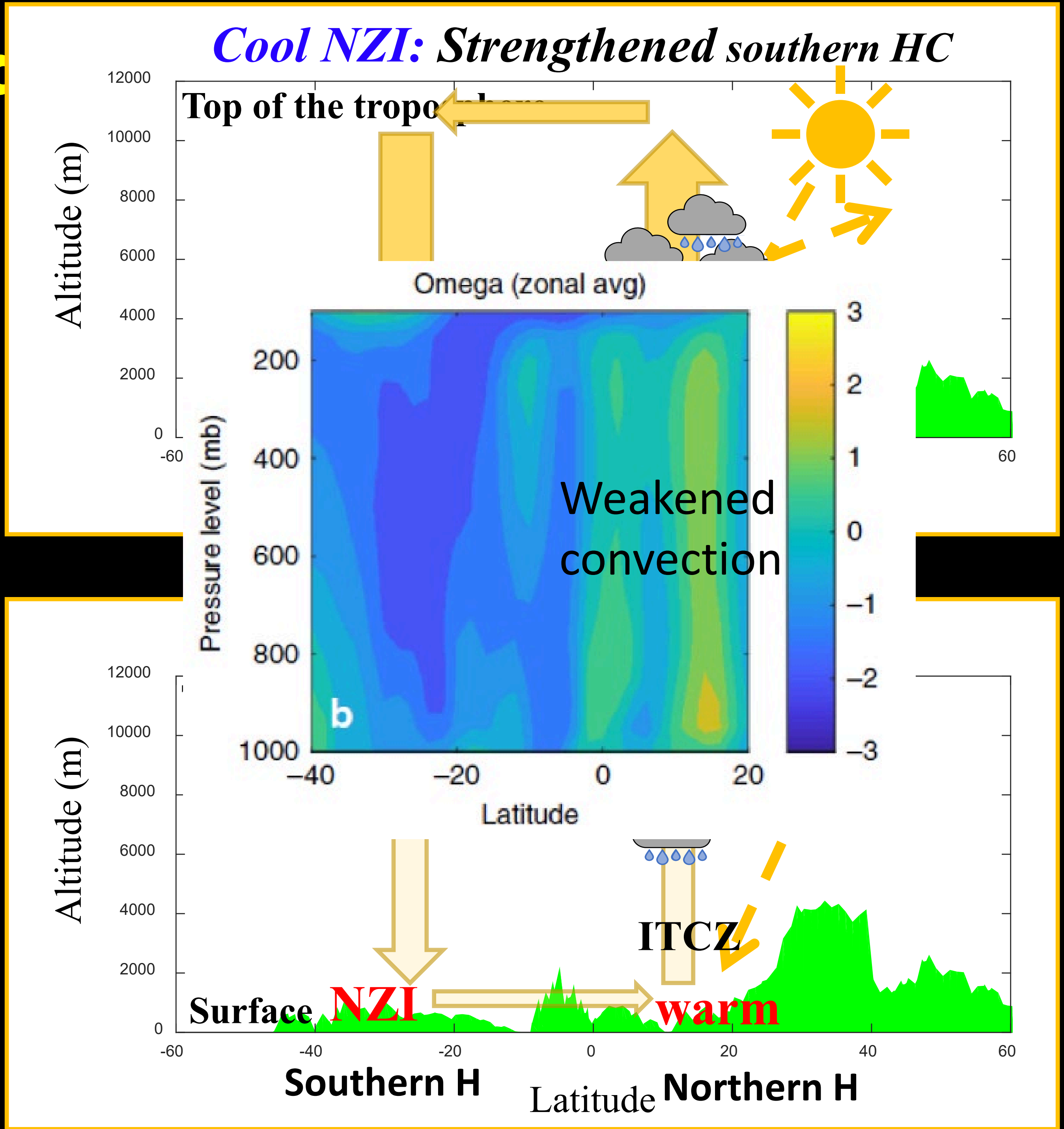
Mamalakis et al., 2018, *Nat. Communications*

Western Pacific pathwa

Late boreal summer



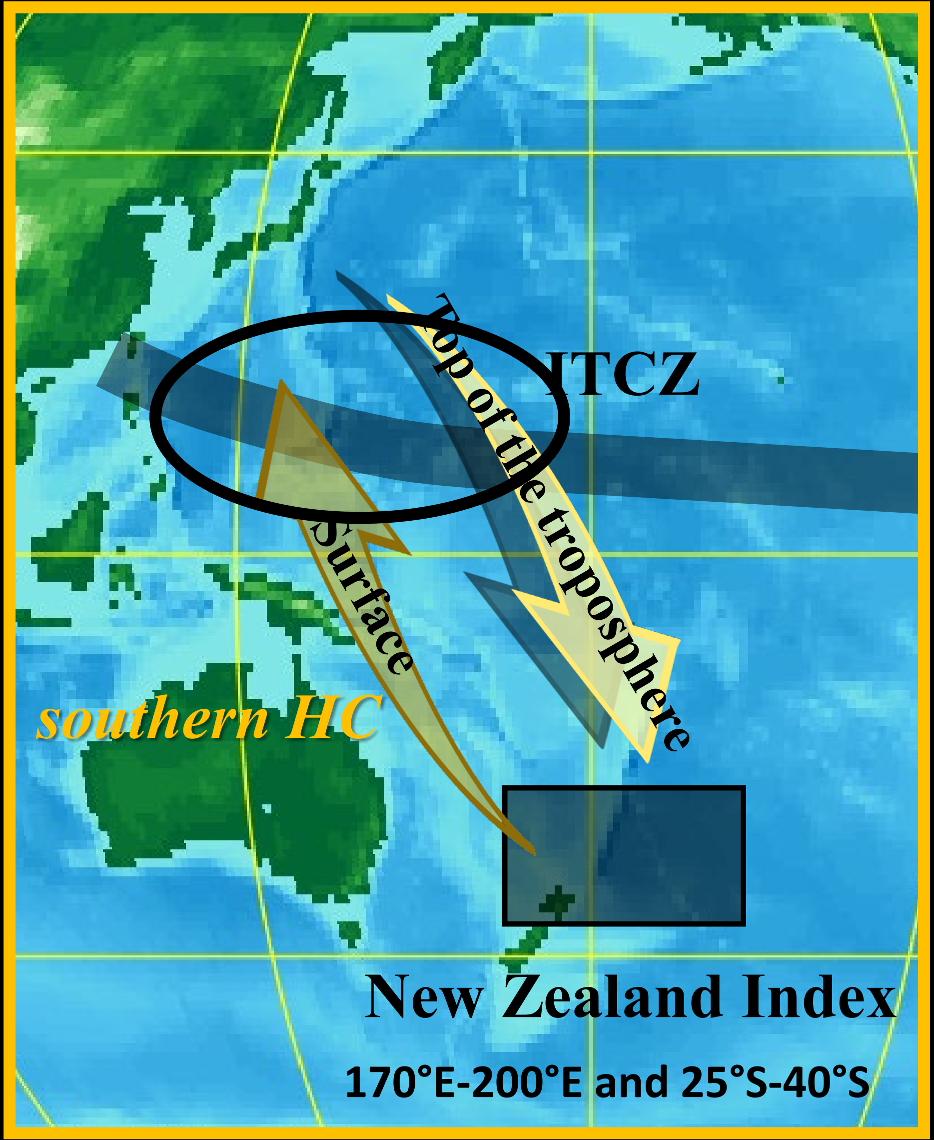




Mamalakis et al., 2018, *Nat. Communications*

Is the WP Pathway "independent"of ENSO?

Late boreal summer

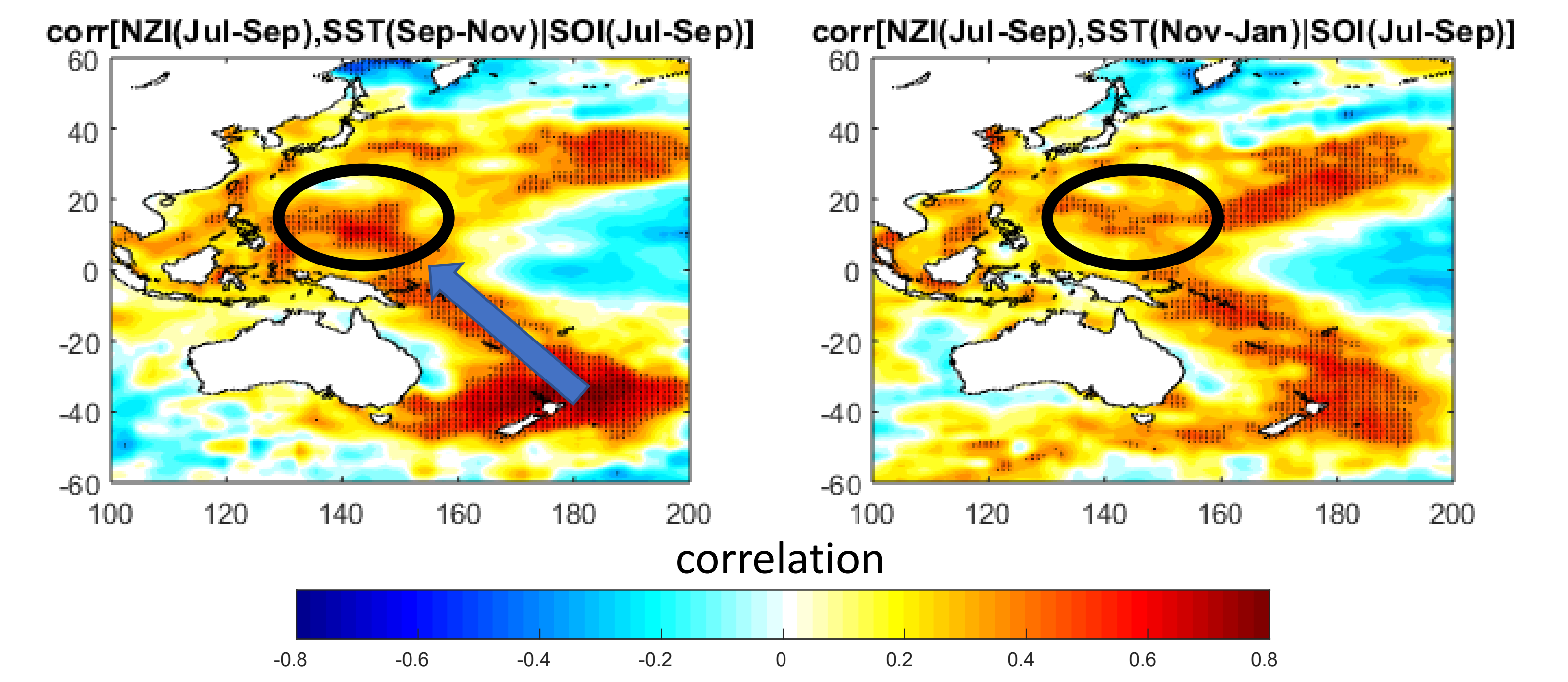


Cascading of NZI SST anomalies in north Pacific is significant even after accounting for ENSO

Corr [NZI(Jul-Sep), SST(2, 4 months later)|**ENSO(Jul-Sep)**]

2 months later
NZI anomalies cascade to NH

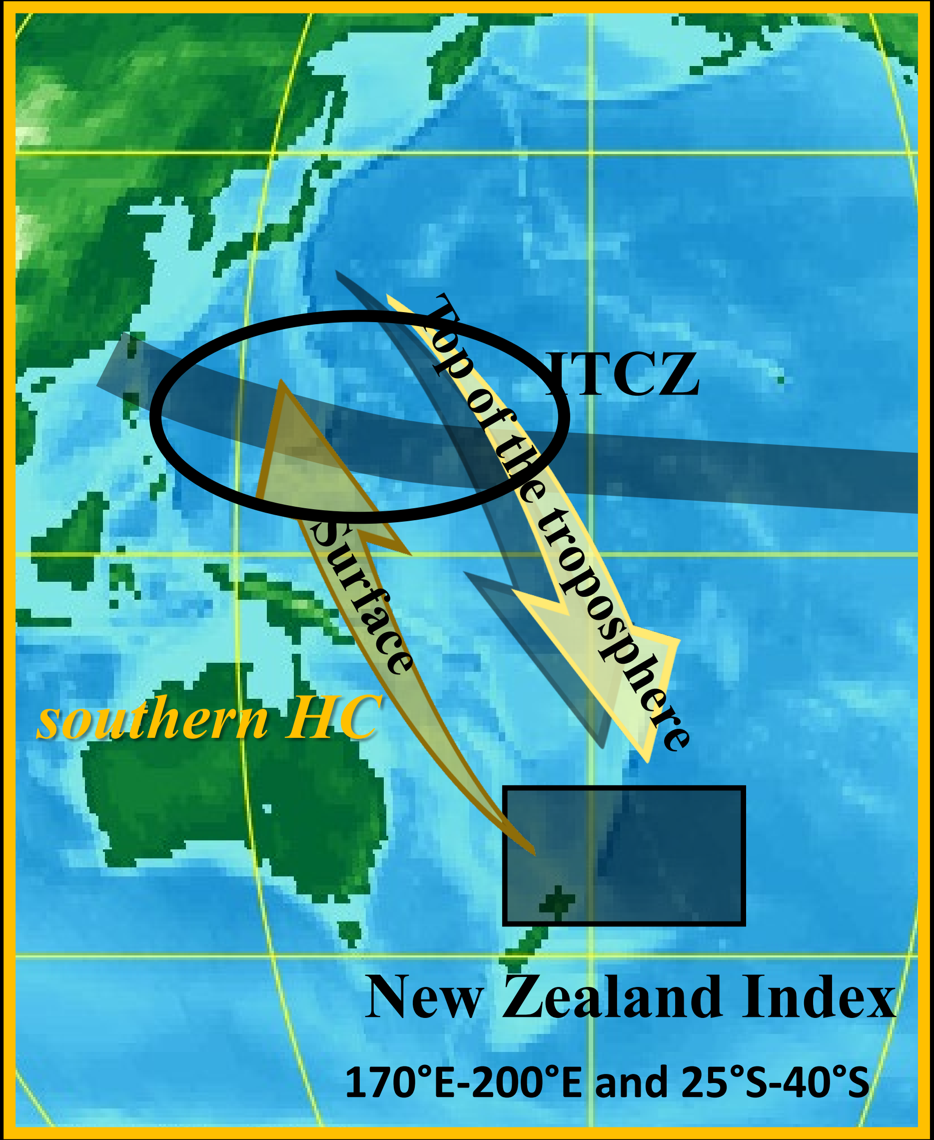
4 months later
NH anomalies sustained



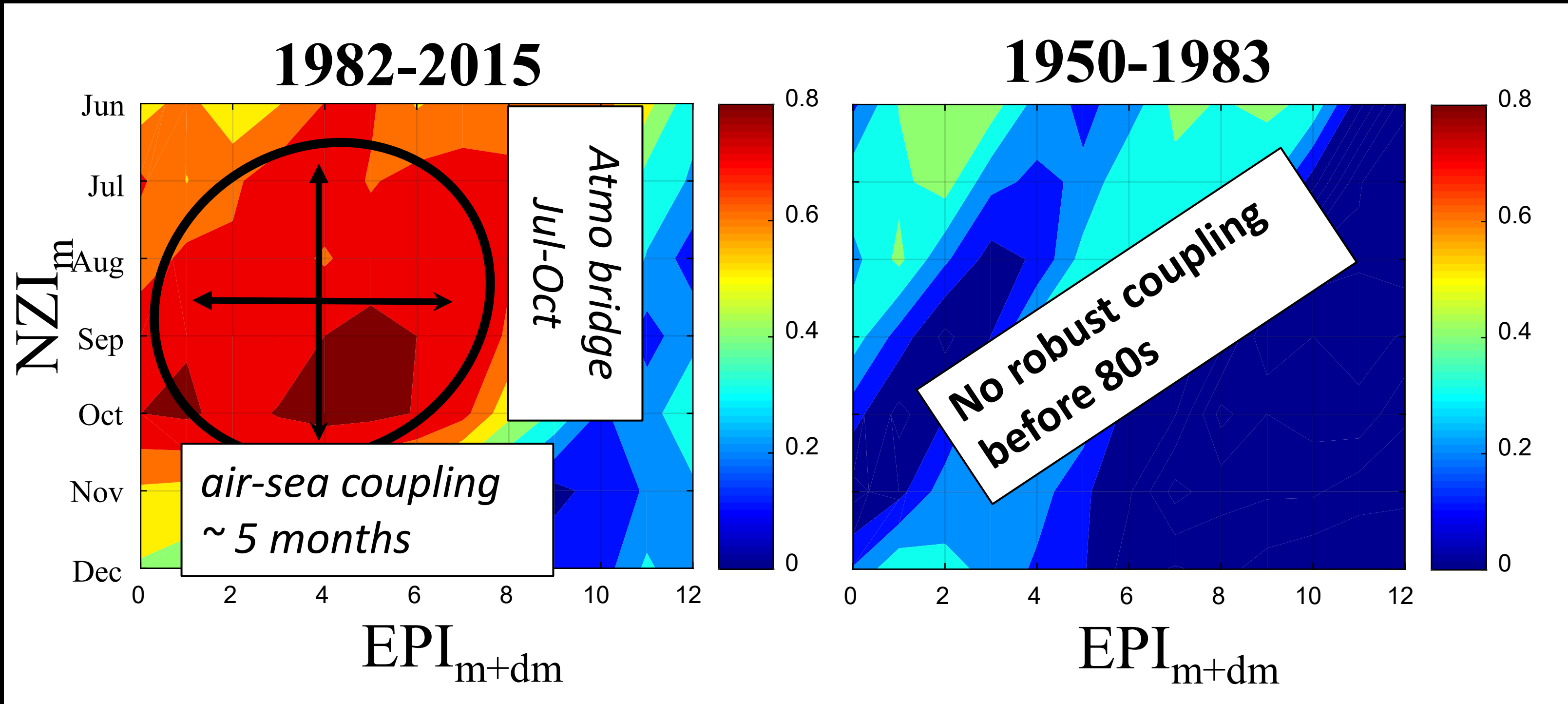
Mamalakis et al., 2018, *Nat. Communications*

Has the WP Pathway amplified?

Late boreal summer



Based on Observations



-- Internal variability?

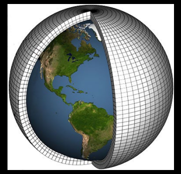
-- External forcing?

-- Data quality?

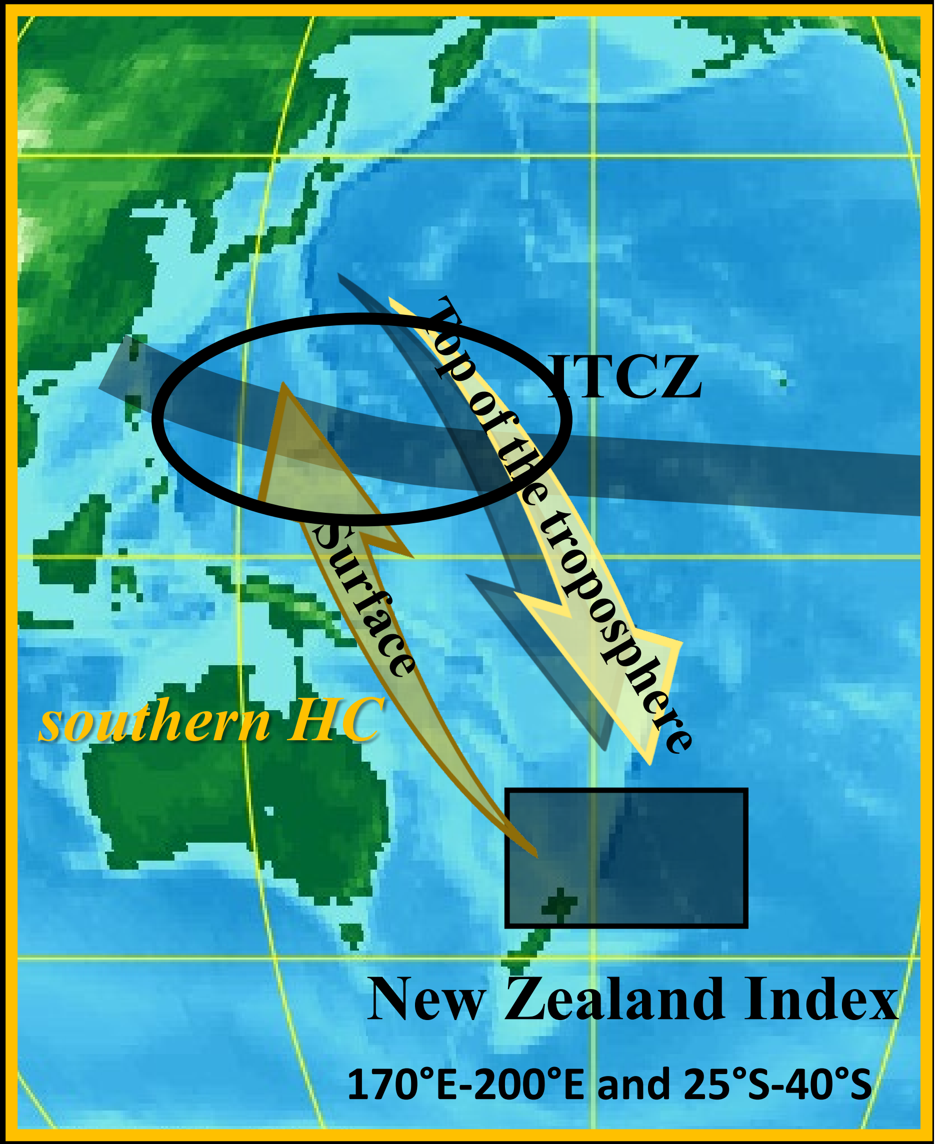
Mamalakis et al., 2018, *Nat. Communications*

Has the WP Pathway amplified?

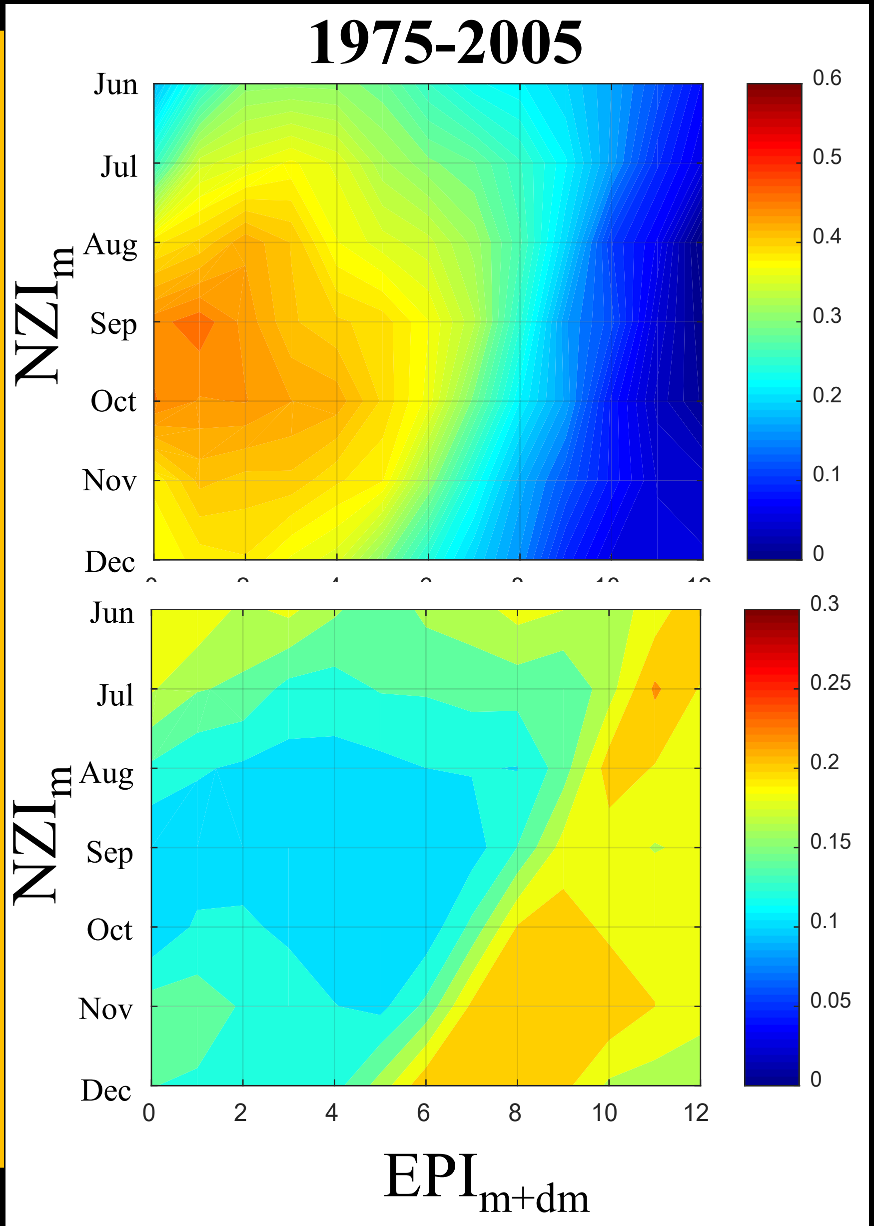
Based on Models: CESMv1 Large Ensemble



Late boreal summer



Mamalakis et al., 2018, *Nat. Communications*



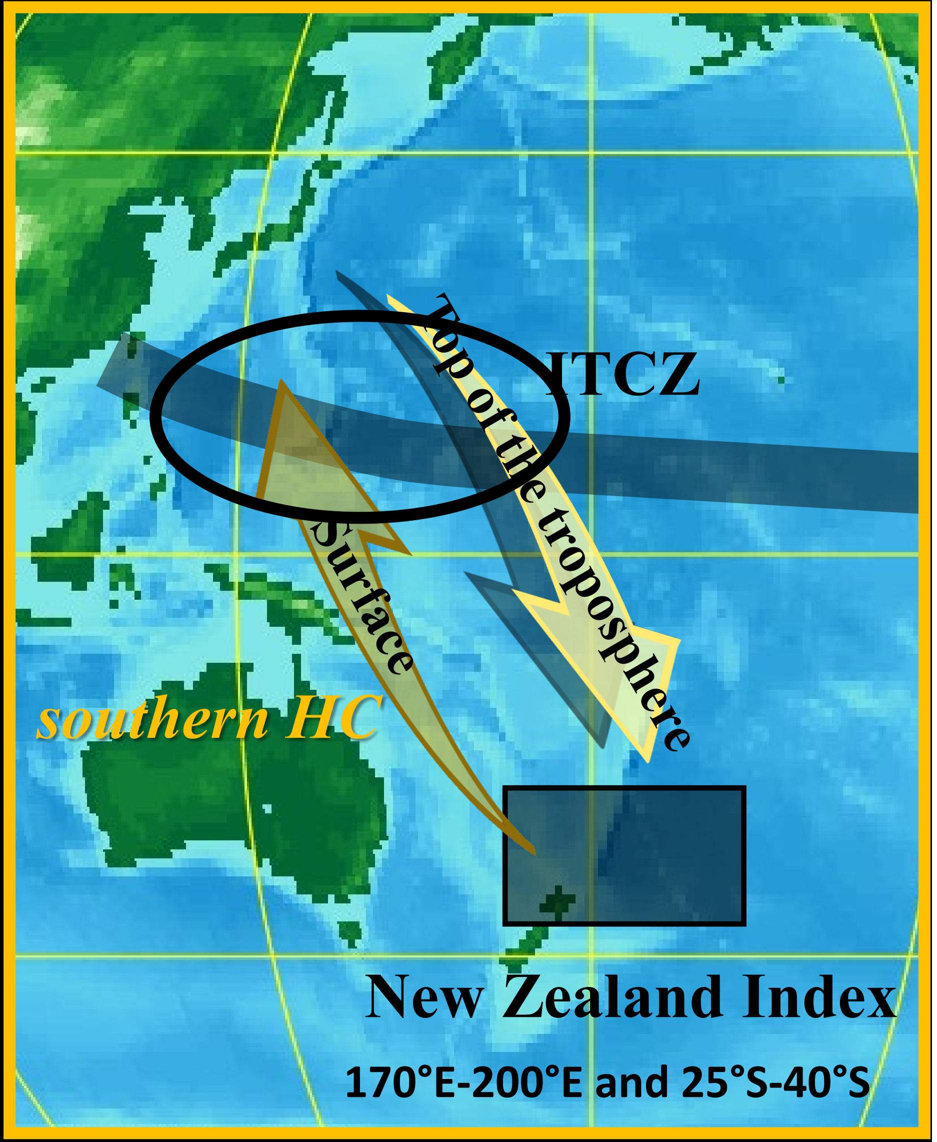
Ensemble mean of correlation **NZI**$_m$ and **EPI**$_{m+dm}$

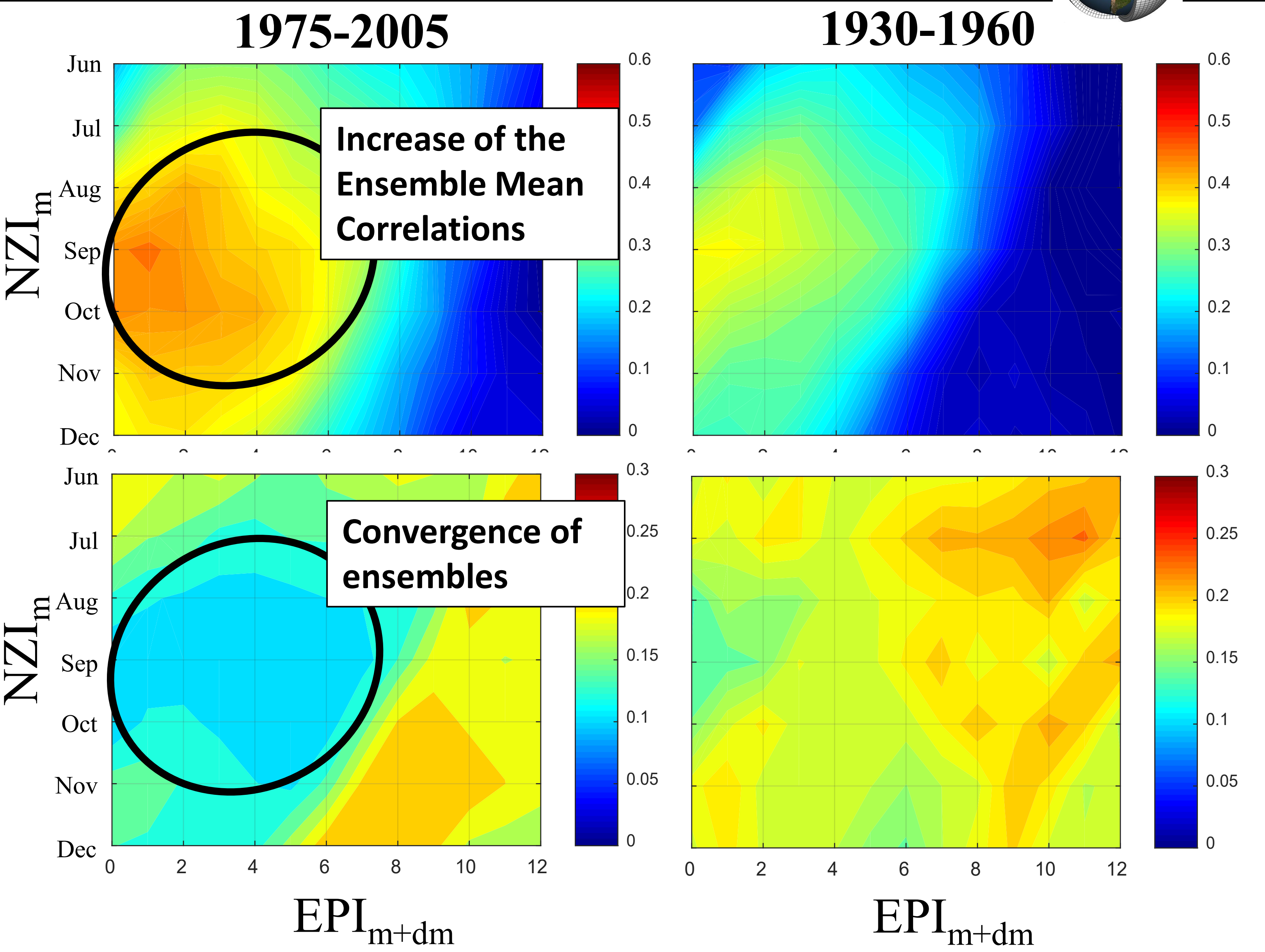
Ensemble st. deviation of correlation **NZI**$_m$ and **EPI**$_{m+dm}$

Has the WP Pathway amplified?

Based on Models: CESMv1 Large Ensemble

Late boreal summer



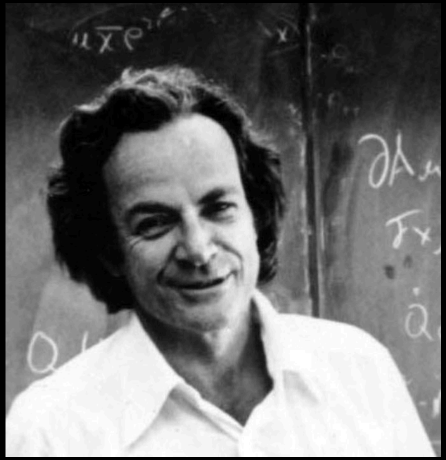


Mamalakis et al., 2018, *Nat. Communications*

“We are trying to prove ourselves wrong as quickly as possible, because only in that way we can find progress”

Richard P. Feynman

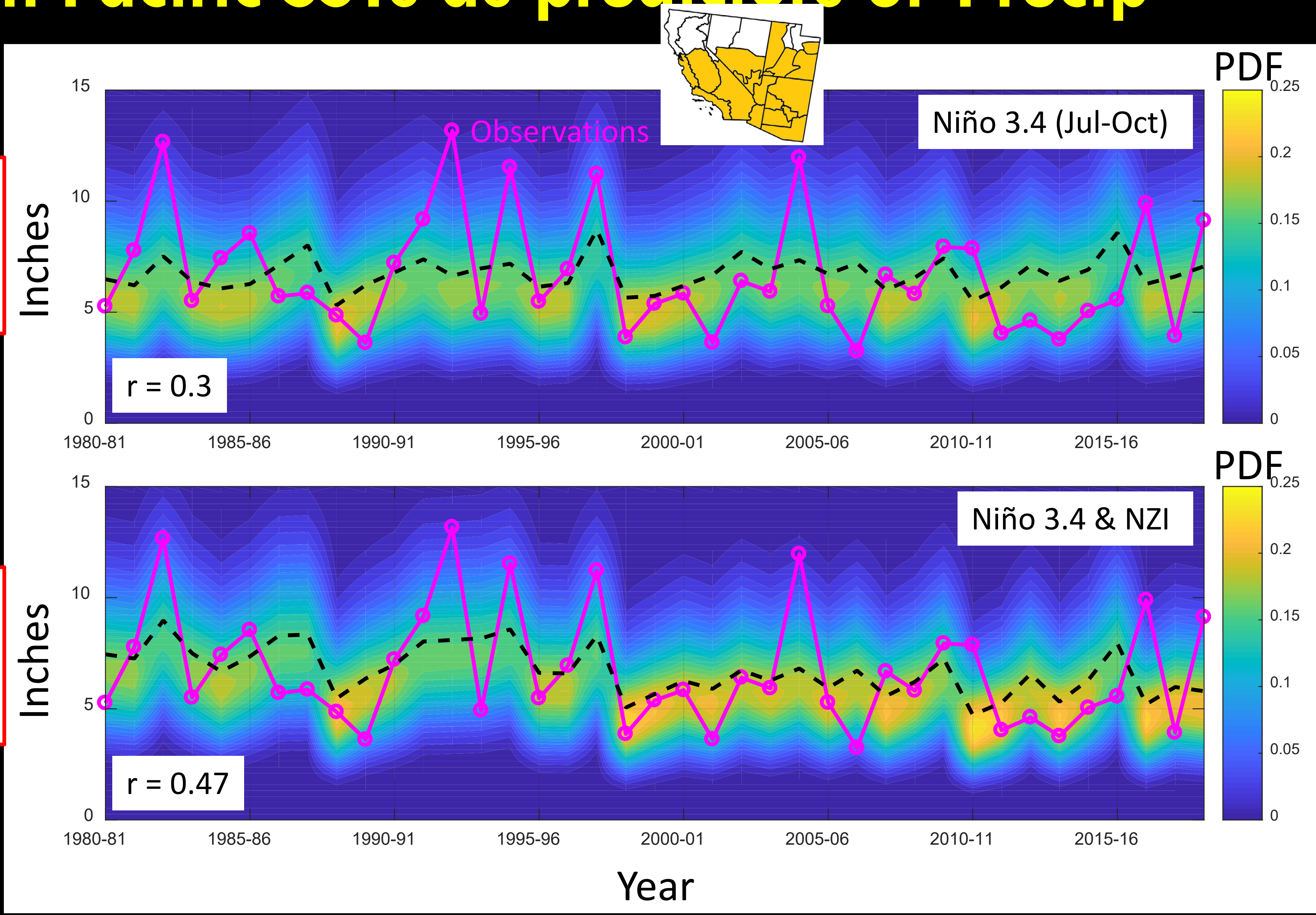
On the Scientific method



Adding Western Pacific SSTs as predictors of Precip

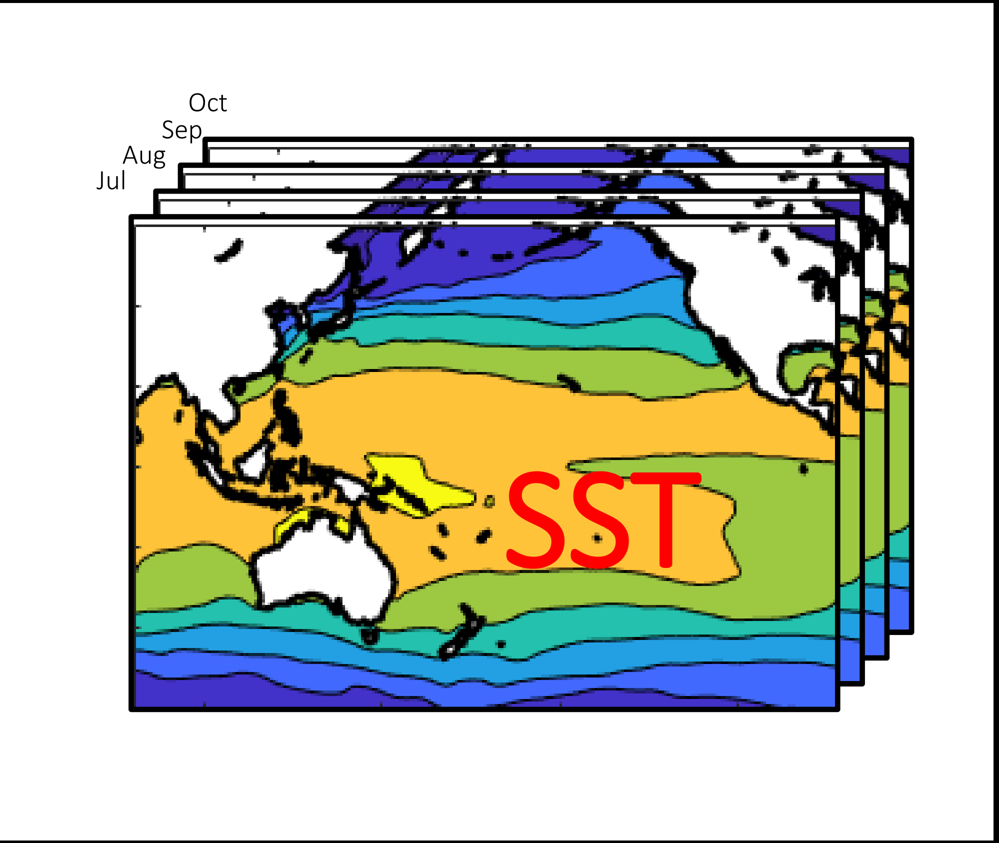
Explained var: 9%
Dry success rate: 28%
Wet success rate: 30%

Explained var: 22%
Dry success rate: 34%
Wet success rate: 34%



Is this the best we can do?

Explore the whole Pacific?



Winter precipitation

Weights

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

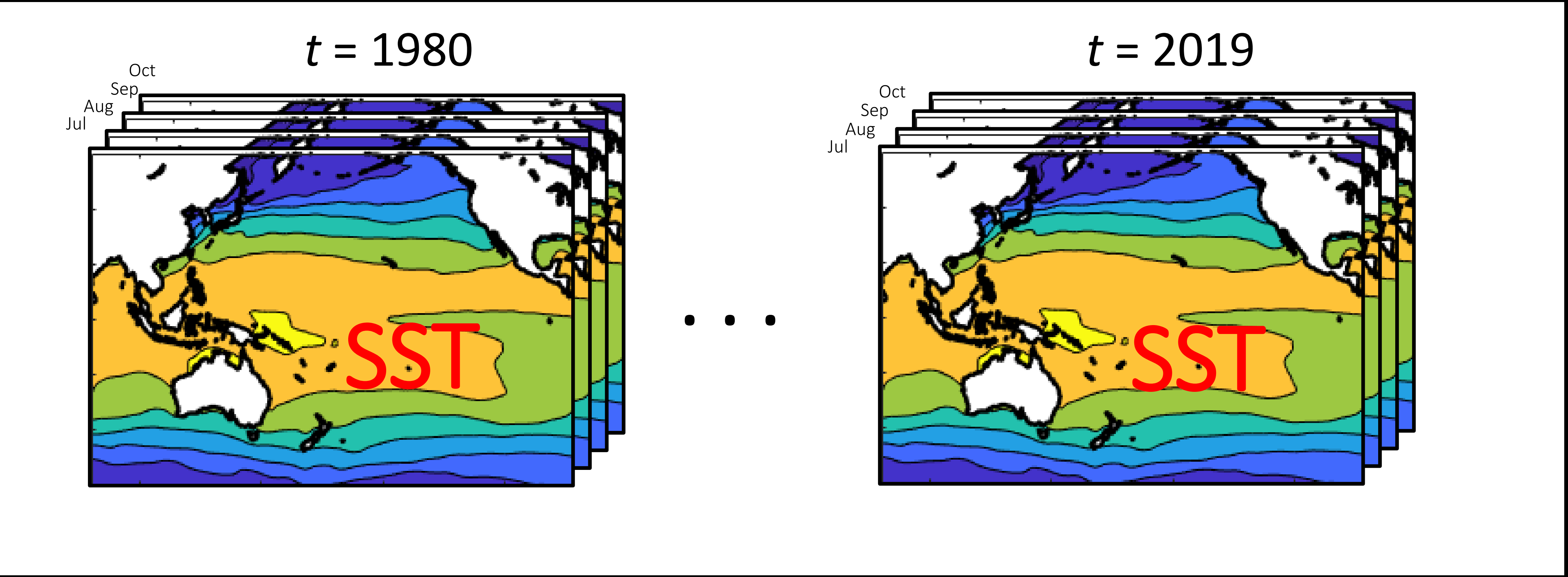
Climate predictors (e.g. SSTs, GPHs in Pacific ocean)

Very high dimensional problem

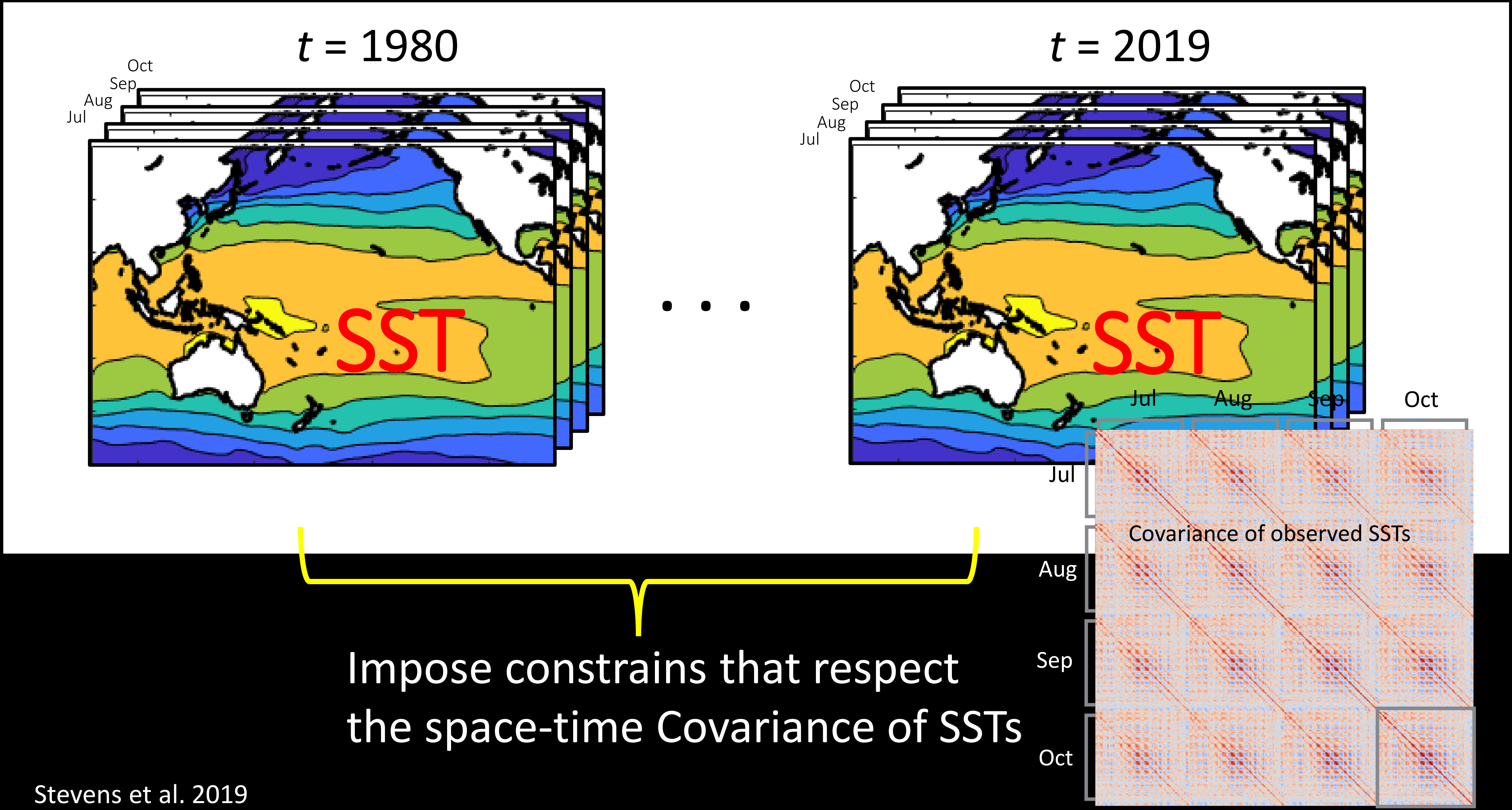
SSTs @ 2x2° x 4 months=>

5612 x4=22,448 predictors

Dimensionality Reduction



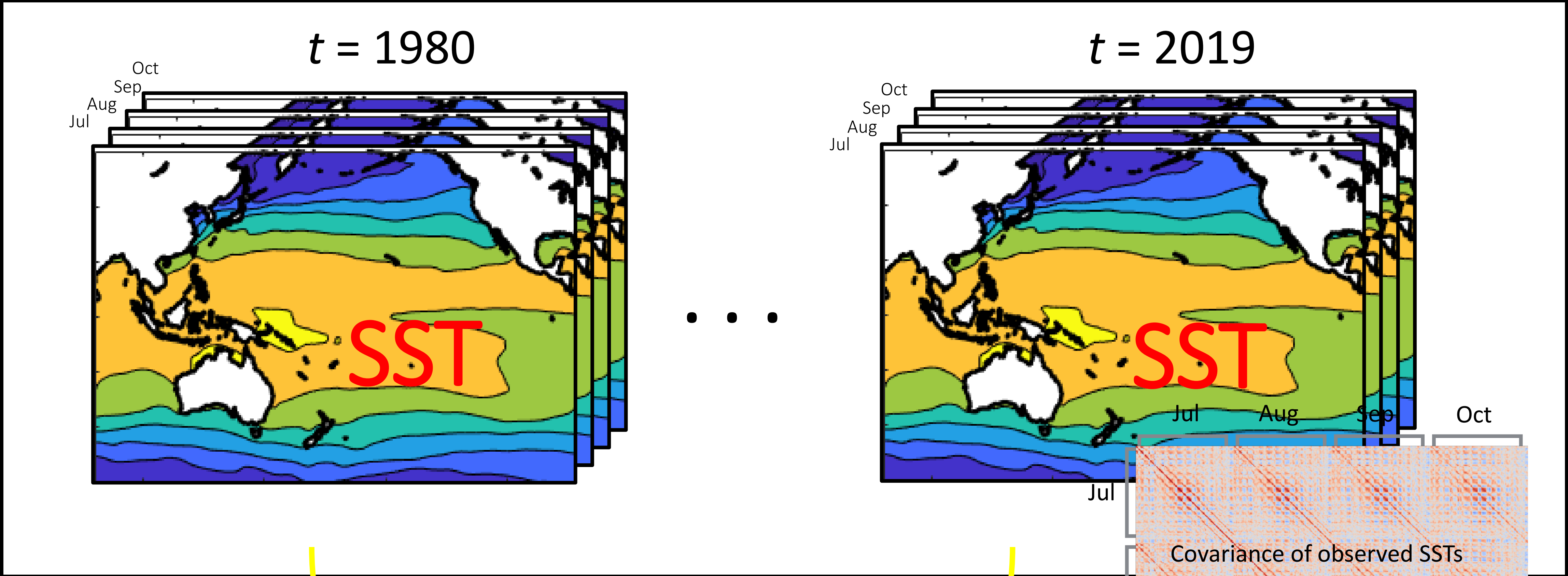
Dimensionality Reduction

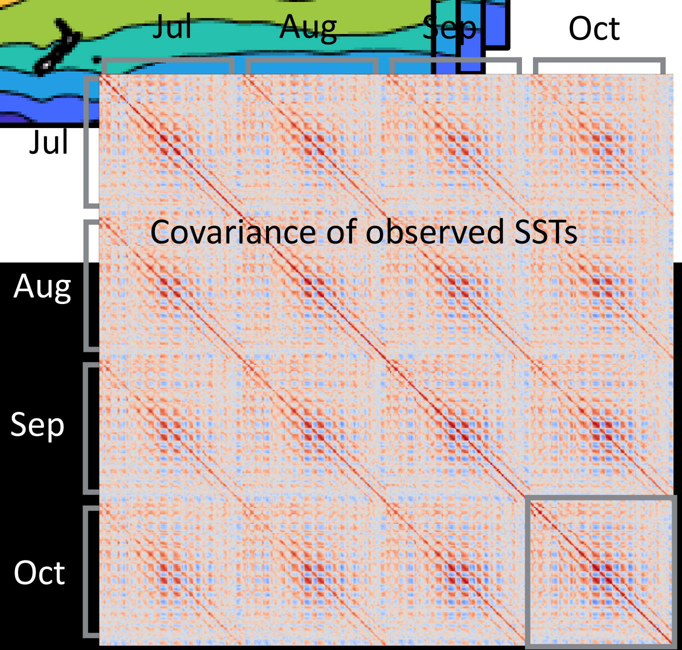


Impose constrains that respect the space-time Covariance of SSTs

Stevens et al. 2019

Dimensionality Reduction





Promote similar **β** for highly correlated predictors to enforce sparsity and unravel the most explanatory features w/out specifying them a-priori

Stevens et al. 2019

Data-driven prediction

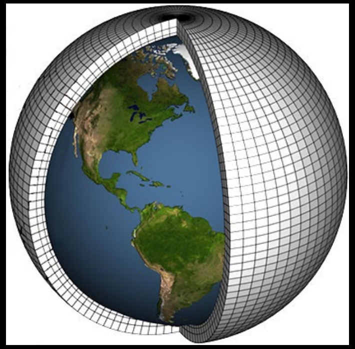
Climate predictors (e.g. SSTs, GPHs in Pacific ocean)

Winter precipitation

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

$$\hat{\boldsymbol{\beta}} = \underset{\boldsymbol{\beta}}{arg\,min}\ \{\underbrace{\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2}_{\text{Data fitting}} + \underbrace{\lambda_1 \|\boldsymbol{\beta}\|_1}_{\text{L1 regularizer (LASSO)}} + \underbrace{\lambda_{TV} \sum_{j,k} \left|\hat{C}_{j,k}\right|^{1/2} \left|\beta_j - \hat{s}_{j,k}\beta_k\right|}_{\text{Graph Total Variation (GTV)}}\}$$

$\hat{\mathbf{C}}$ = covariance matrix of $\mathbf{X}$



$$\hat{s}_{j,k} = sign(\hat{C}_{j,k})$$

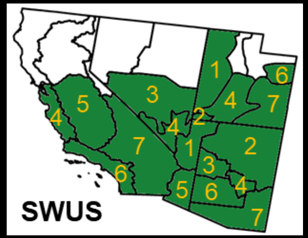
TRIPODS+CLIMATE project

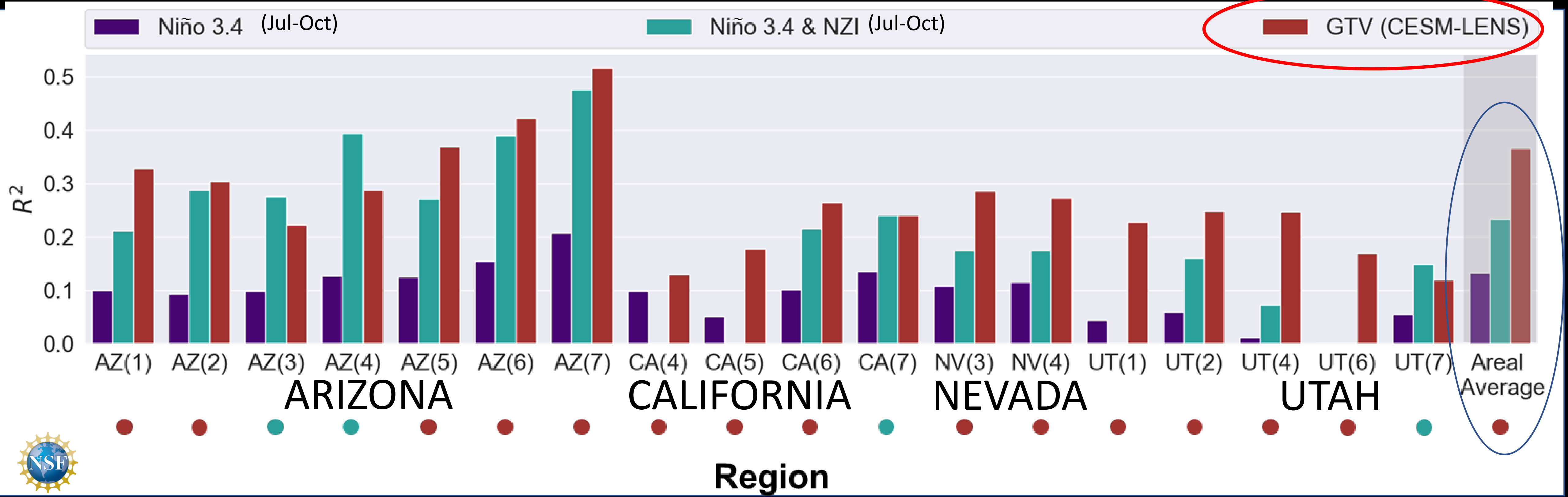
Stevens et al. 2019

Data-driven prediction

Training period: 1940-1990
(with a non-stationarity filter)
Testing period: 1991-2019

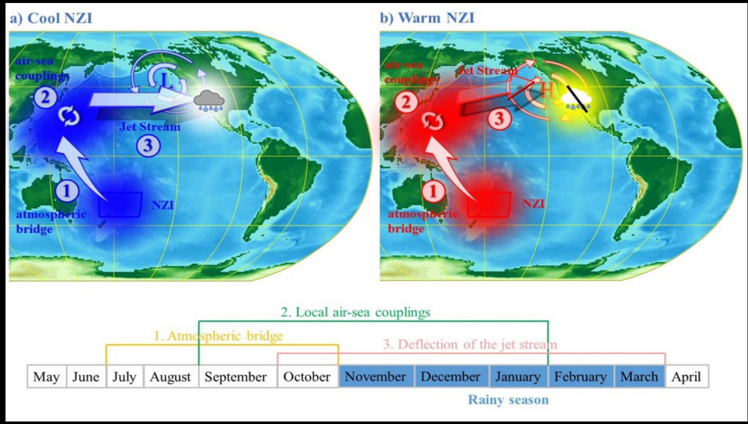
GTV captures almost 40% of the variability in the out-sample period



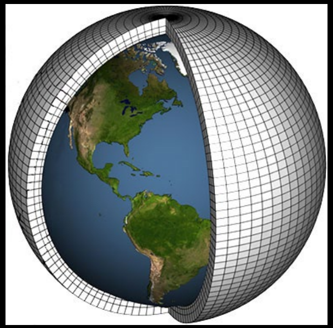


Stevens et al. 2019

What's next?



- Is Machine Learning (ML) the solution?
- Eventually maybe, but not without testing the causality of hypothesized mechanisms & predictors
- Perform idealized perturbation experiments designed to understand the process chain of the WP teleconnection (e.g, differentiate between Rossby-wave vs. HC mediated interhemispheric propagation)
- Study CMIP6 outputs (historical and future projections) to understand time-evolving dynamics relevant to prediction, spectral PCA
- Probabilistic prediction for water resources planning



U34B - Data Analytics and Machine Learning Innovation for Climate and Earth Surface Processes

Wednesday, 11 December 2019 - 16:00 - 18:00

Moscone South - 303-304, L3

MARKUS REICHSTEIN
Max Planck Institute

MATTHEW HANCHER
Google Earth Engine

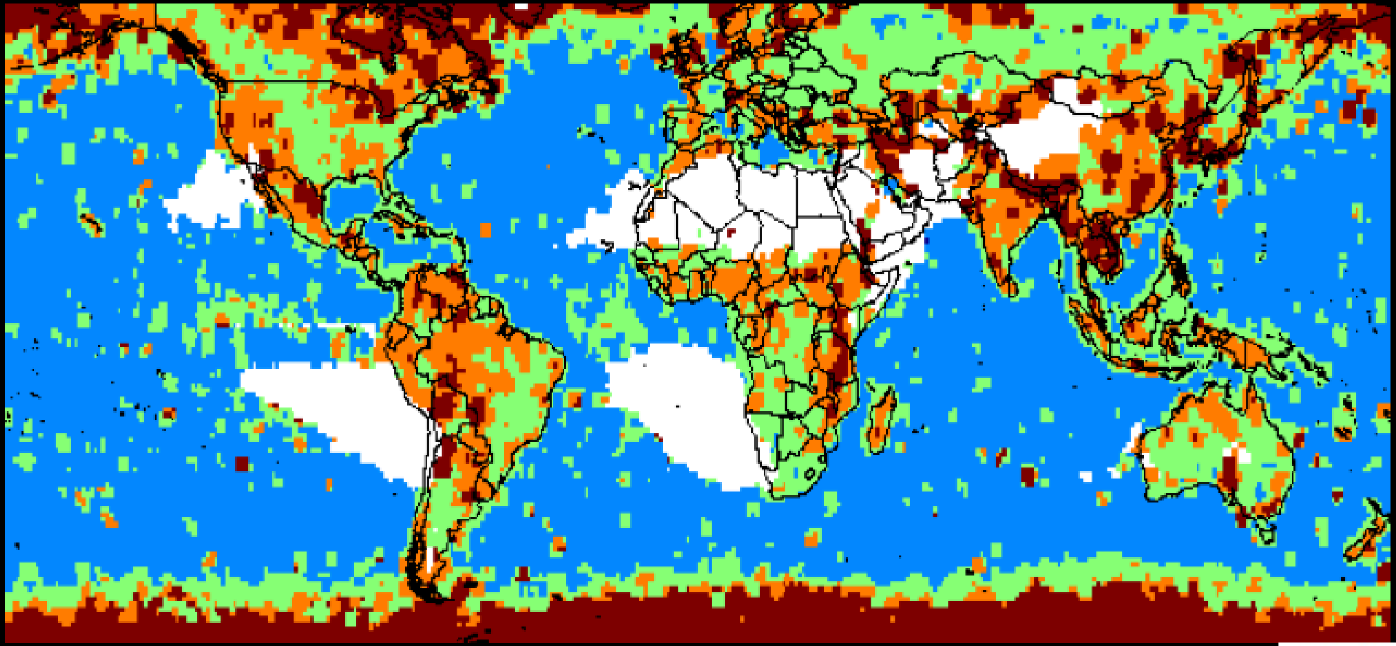
GRÉGOIRE MARIETHOZ
University of Lausanne

EVAN B. GOLDSTEIN
University of North Carolina

CLAIRE MONTELEONI
University of Colorado Boulder

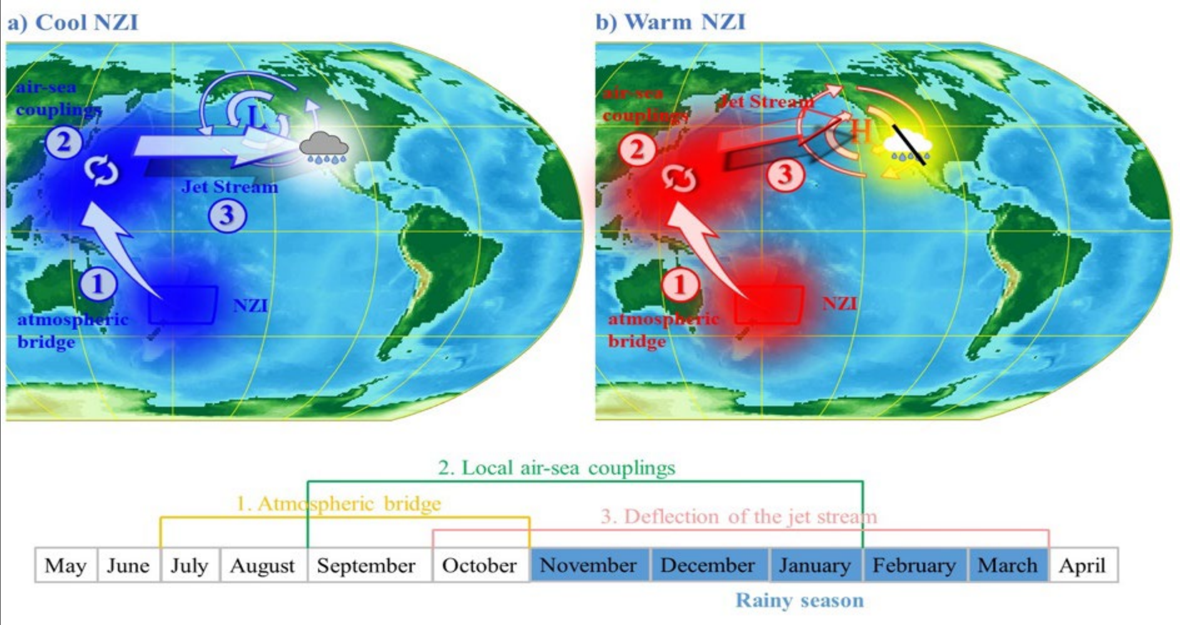
VERONIKA EYRING
German Aerospace Center DLR

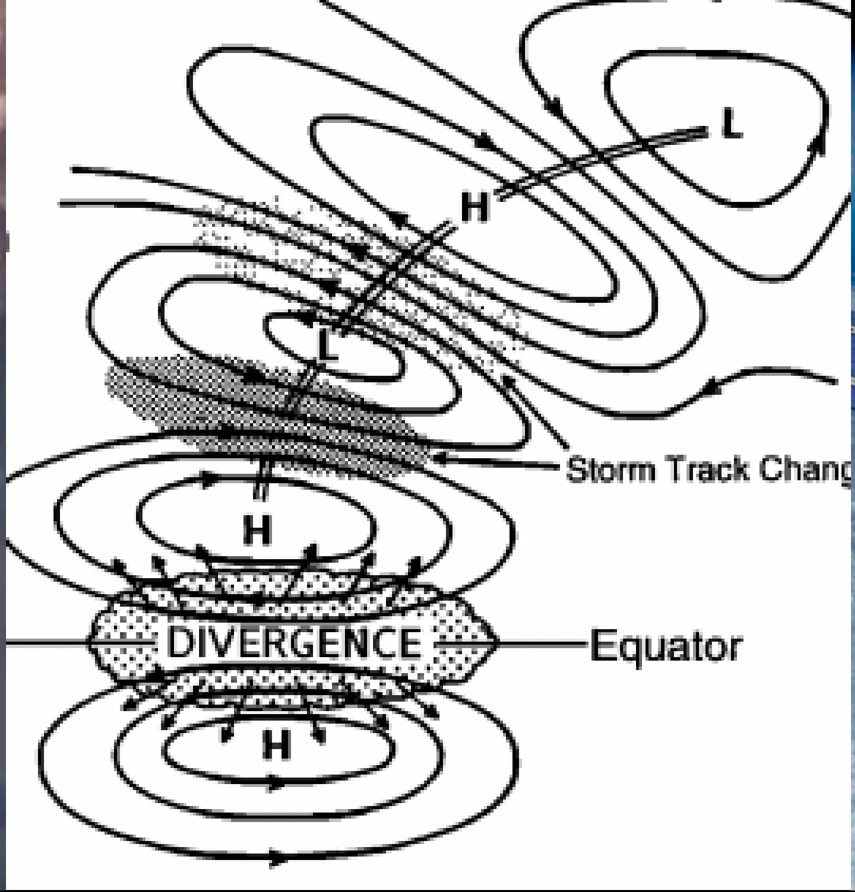
ELIZABETH A BARNES
Colorado State University

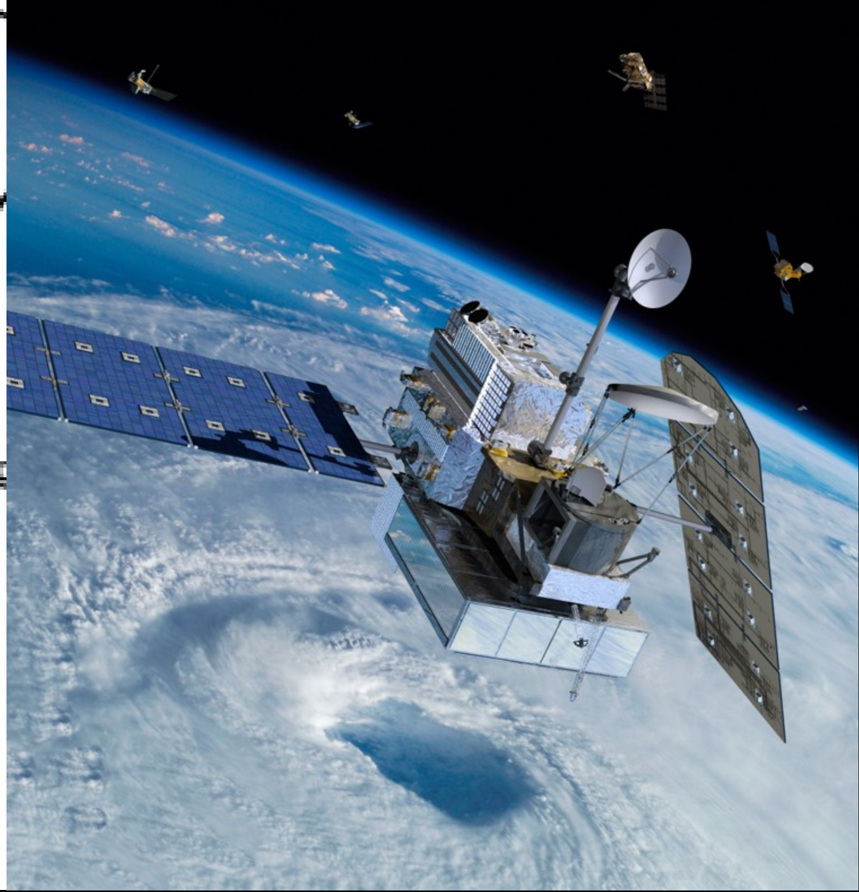


Beyond the pixel

Beyond ENSO







Measuring the unmeasurable and predicting the unpredictable

Efi Foufoula-Georgiou
University of California, Irvine

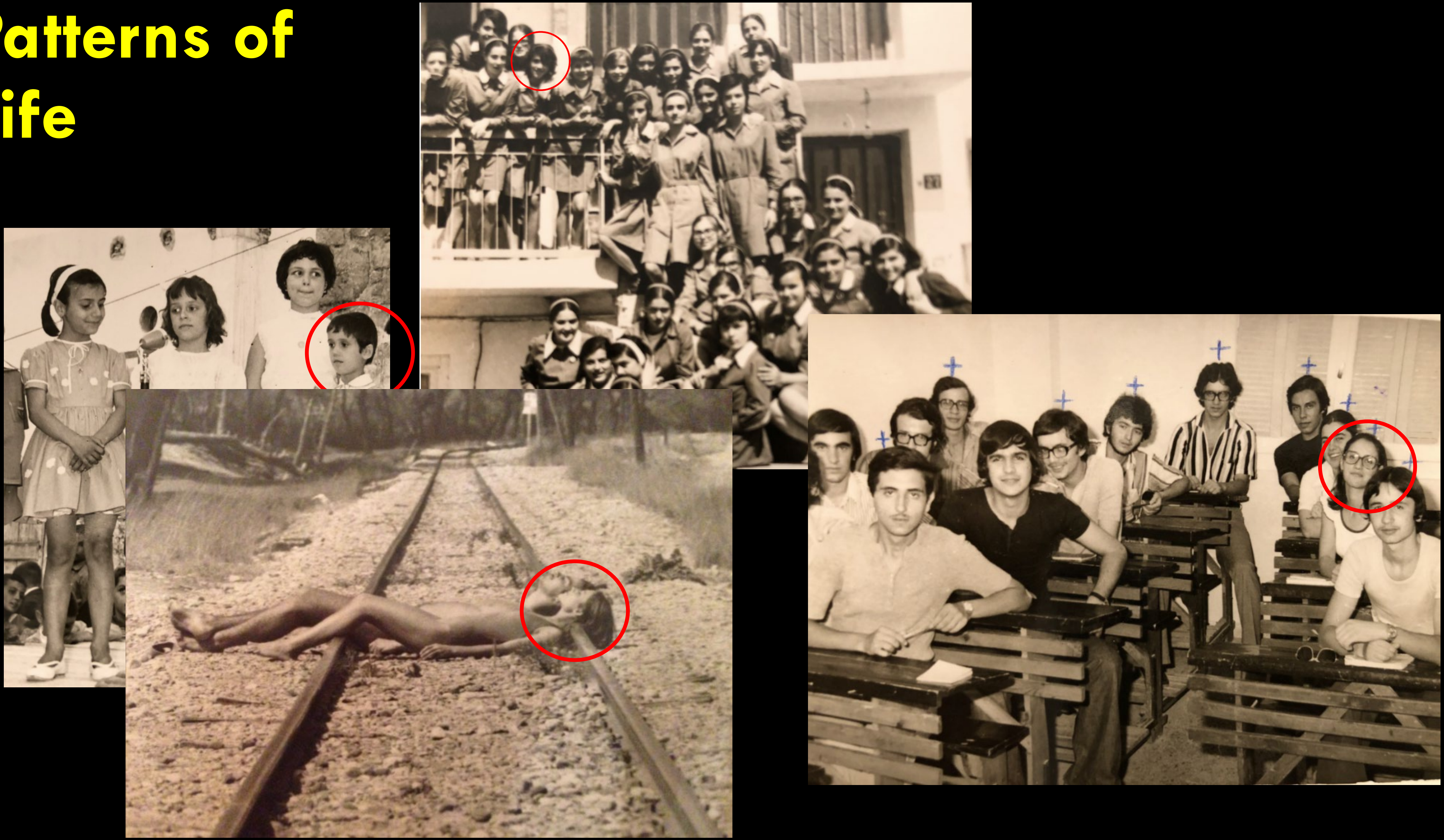
Langbein Lecture
2019 AGU

Patterns of Life

Patterns of Life

Patterns of Life

Patterns of Life




PETZL


BLUE MOON

Efi's Group -- Positive covariances

✓ Whole > Sum (parts)?

X1 = contribution of member 1

X2 = contribution of member 2

$X = X1 + X2$ X = overall contribution

$Mean(X) = Mean(X1) + Mean(X2);$

$Var(X) = Var(X1) + Var(X2) + \underline{COV(X1,X2)}$

Whole > sum of its parts Iff *COV* (+)

Figure 1. Incoming PhD students must complete a BINGO, defined by marking of five squares in a straight or diagonal line, before a PhD degree may be awarded. Squares with quotation marks indicate precise, standalone phrases that must be directed to you. If you are in doubt, it doesn't count--you'll know when you hear it. Pictures of Efi are free squares. The grid was designed to maximize entropy such that each possible bingo has approximately the same probability.

Figure 1. Incoming PhD students must complete a BINGO, defined by marking of five squares in a straight or diagonal line, before a PhD degree may be awarded. Squares with quotation marks indicate precise, standalone phrases that must be directed to you. If you are in doubt, it doesn't count--you'll know when you hear it. Pictures of Efi are free squares. The grid was designed to maximize entropy such that each possible bingo has approximately the same probability.

* Efficient Fear Injector

Figure 1. Incoming PhD students must complete a BINGO, defined by marking of five squares in a straight or diagonal line, before a PhD degree may be awarded. Squares with quotation marks indicate precise, standalone phrases that must be directed to you. If you are in doubt, it doesn't count--you'll know when you hear it. Pictures of Efi are free squares. The grid was designed to maximize entropy such that each possible bingo has approximately the same probability.

Thanks to my extended family & sponsors

PhD students

-- Praveen Kumar (1993)
-- Sanja Perica (1995)
-- Alin Carsteanu (1997)
-- Venu Venugopal (1998)
-- Deborah Nykanen (2000)
-- Boyko Dodov (2003)
-- Sukanta Basu (2004)
-- Chandana Gangodagamage (2009)
-- Paola Passalacqua (2009)
-- Arvind Singh (2011)
-- Vamsi Ganti (2012)
-- Ardeshir Mo Ebtehaj (2013)
-- Jon Czuba (2015)
-- Jon Schwenk (2016)
-- Mohammad Danesh (2017)
-- Zeinab Takbiri (2018)
-- Lawrence Vulis
-- Antonios Mamalakis

Post-doctoral fellows

-- Victor Sapozhnikov
-- Daniel Harris
-- Shuxia Zhang
-- Rohan Shreshtha
-- Ian Iorgulescu
-- Kurt Fienberg
-- Bruno Lashermes
-- Stefano Zanardo
-- Mahesh Rathinasamy
-- Zi Wu
-- Yiannis Dialynas
-- Amy Hansen
-- Leichen Guo
-- Anthony Longjas
-- Simon Papalexiou
-- Alex Tejedor
-- Clement Guilloteau

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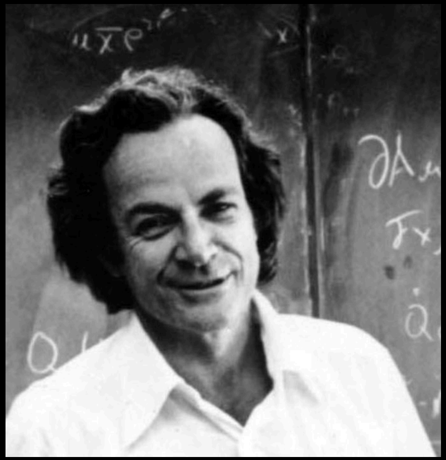
THANK YOU!

"Study hard what interests you the most in the most undisciplined, irreverent and original manner possible"

Richard P. Feynman



2019-20 winter precip. prediction in Irvine?