한국수자원학회 수자원시스템분과 세미나

데이터 합성을 통한 원격탐사 데이터의 개선

경희대학교 사회기반시스템공학과
김석현 (shynkim@khu.ac.kr)

지구관측 인공위성 원격탐사 개요

“자연과의 화해는 금세기 가장 중요한 과제 (defining task)이며 모든 사람에게서, 모든 곳에서 최우선 순위여야 한다.”

—안토니우 구테흐스
(UN 사무총장)

과학

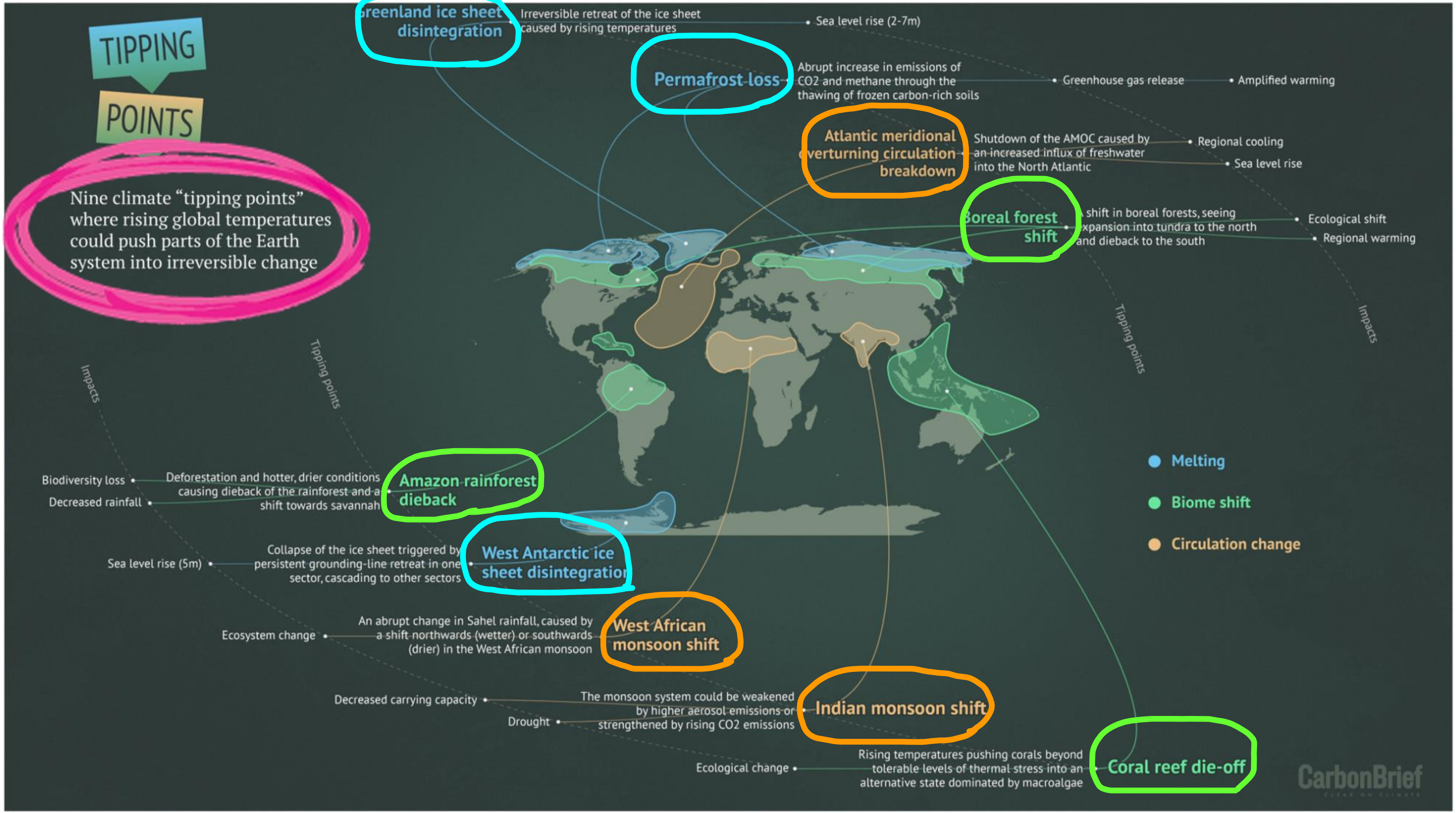
노벨물리학상에 기후변화 연구 급물살 만든 복잡계 물리 연구 선구자들 3명(재종합)

2021.10.05 20:51

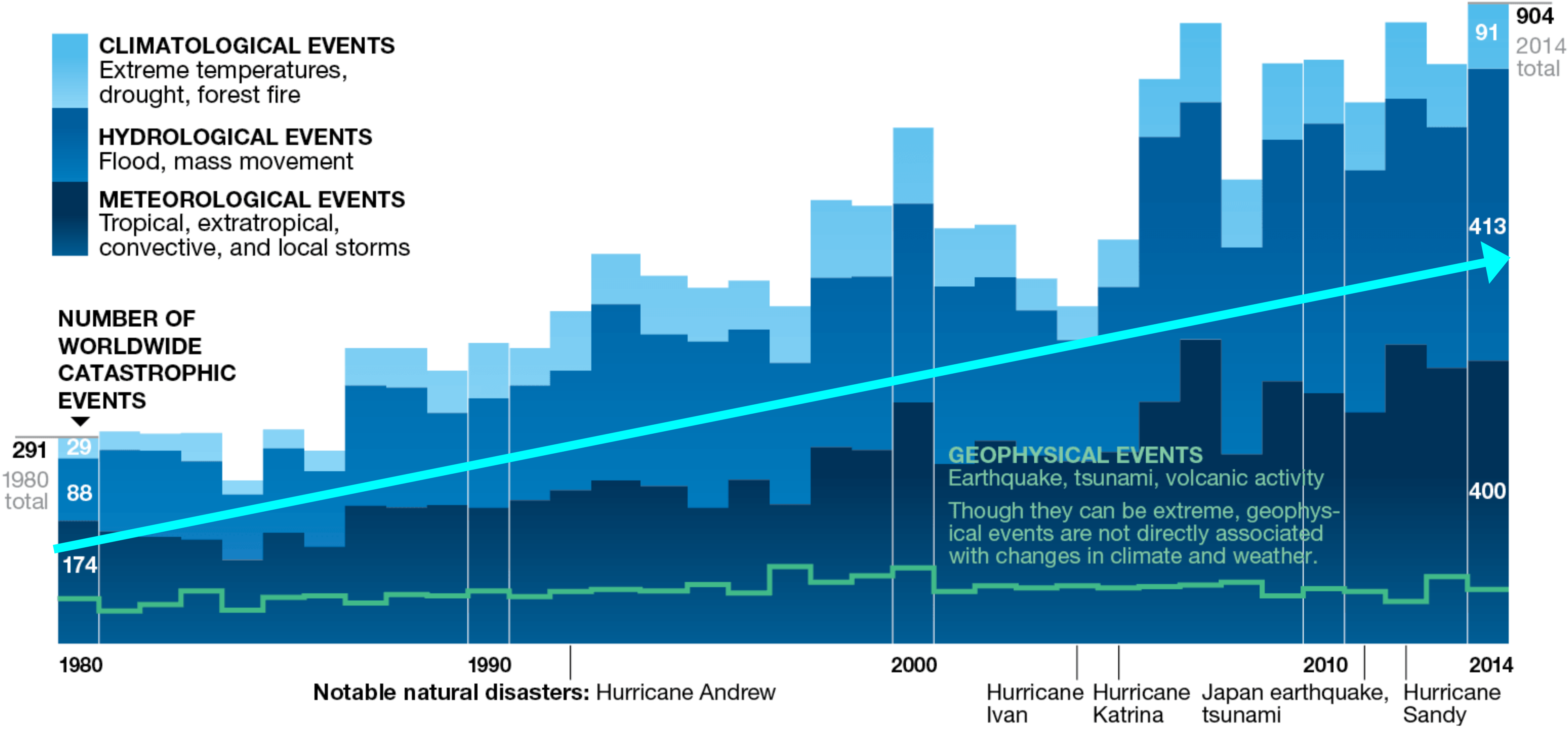
가 가

마나베 슈쿠로·클라우스 하셀만·조르조 파리시

2021 노벨물리학상을 수상한 마나베 슈쿠로 미국 프린스턴대 교수, 클라우스 하셀만 독일 막스플랑크연구소 연구원, 조르조 파리시 이탈리아 사피엔자대 교수. 프린스턴대·막스플랑크연구소·울프재단 제공

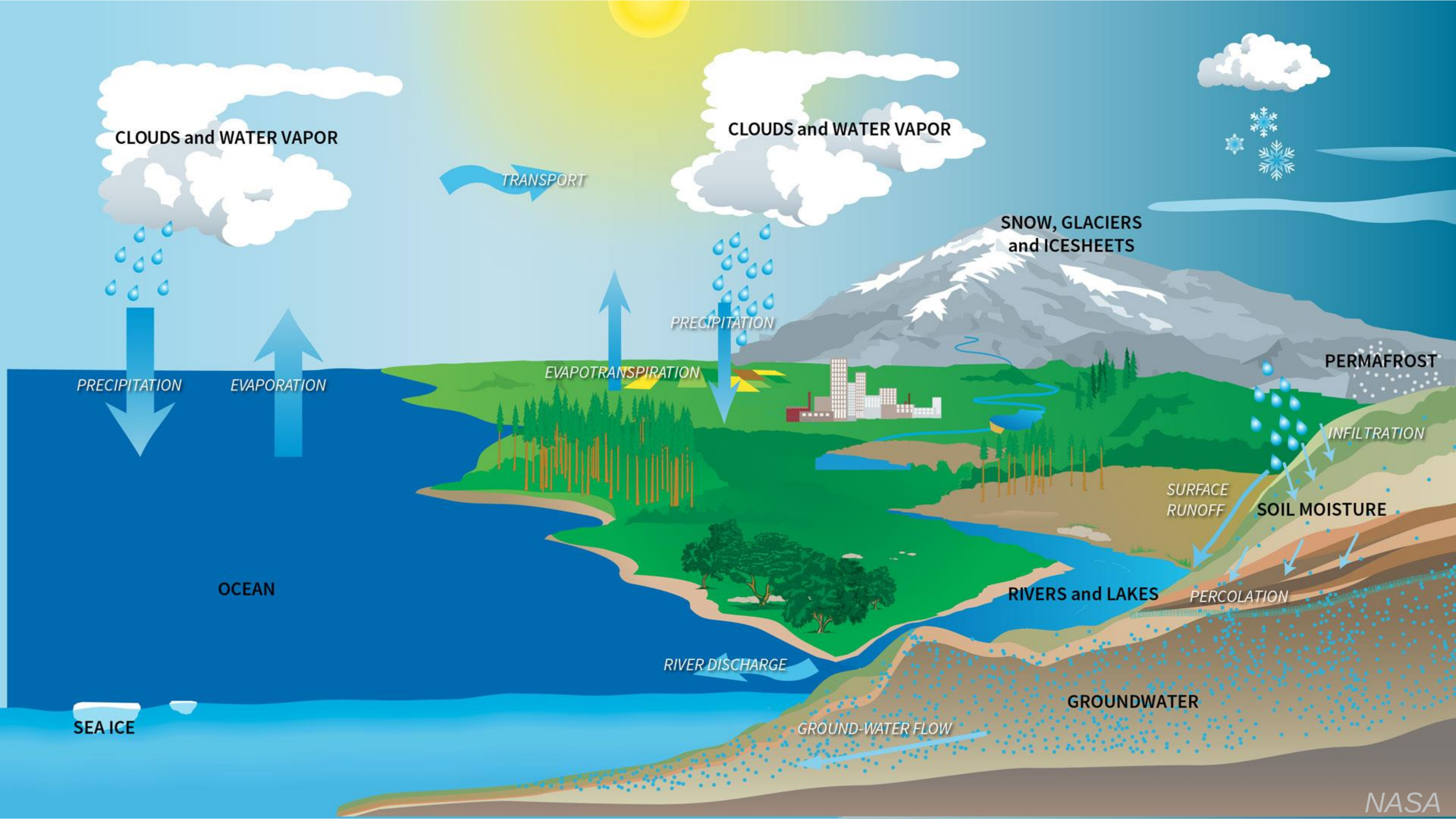


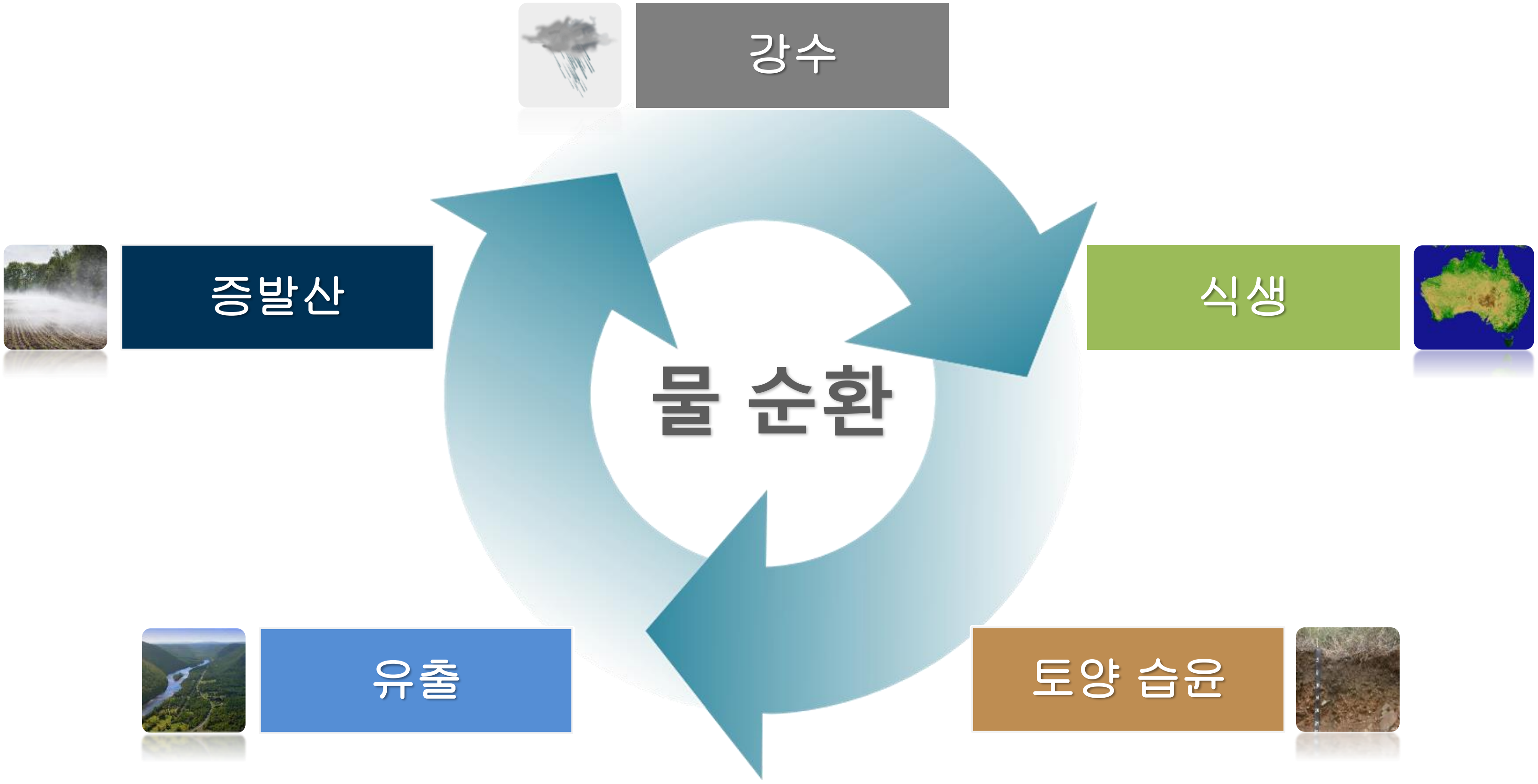
TIPPING
POINTS
Nine climate "tipping points" where rising global temperatures could push parts of the Earth system into irreversible change
reenland ice sheet disintegration
Irreversible retreat of the ice sheet caused by rising temperatures
Sea level rise (2-7m)
Permafrost loss
Abrupt increase in emissions of CO2 and methane through the thawing of frozen carbon-rich soils
Greenhouse gas release
Amplified warming
Atlantic meridional verturning circulation breakdown
Shutdown of the AMOC caused by an increased influx of freshwater into the North Atlantic
Regional cooling
Sea level rise
oreal forest shift
shift in boreal forests, seeing xpansion into tundra to the north and dieback to the south
Ecological shift
Regional warming
Tipping points
Impacts
Melting
Biome shift
Circulation change
Impacts
Tipping points
Biodiversity loss
Decreased rainfall
Deforestation and hotter, drier conditions causing dieback of the rainforest and a shift towards savannah
Amazon rainforest dieback
Sea level rise (5m)
Collapse of the ice sheet triggered by persistent grounding-line retreat in one sector, cascading to other sectors
West Antarctic ice sheet disintegratio
Ecosystem change
An abrupt change in Sahel rainfall, caused by a shift northwards (wetter) or southwards (drier) in the West African monsoon
West African monsoon shift
Decreased carrying capacity
Drought
The monsoon system could be weakened by higher aerosol emissions or strengthened by rising CO2 emissions
Indian monsoon shift
Ecological change
Rising temperatures pushing corals beyond tolerable levels of thermal stress into an alternative state dominated by macroalgae
Coral reef die-off
CarbonBrief



CLIMATOLOGICAL EVENTS
Extreme temperatures, drought, forest fire
HYDROLOGICAL EVENTS
Flood, mass movement
METEOROLOGICAL EVENTS
Tropical, extratropical, convective, and local storms
NUMBER OF WORLDWIDE CATASTROPHIC EVENTS
291
1980 total
29
88
174
904
2014 total
91
413
400
GEOPHYSICAL EVENTS
Earthquake, tsunami, volcanic activity
Though they can be extreme, geophysical events are not directly associated with changes in climate and weather.
1980
1990
2000
2010
2014
Notable natural disasters: Hurricane Andrew
Hurricane Ivan
Hurricane Katrina
Japan earthquake, tsunami
Hurricane Sandy

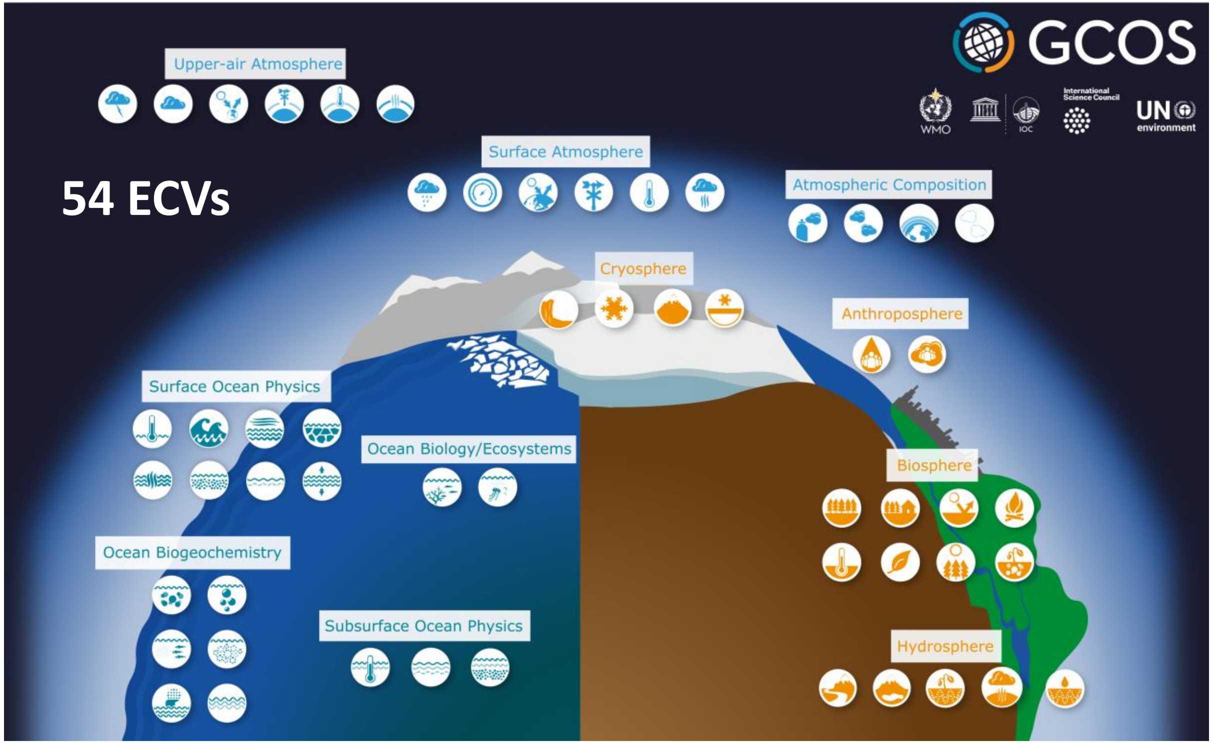
우리의 미래는?


CLOUDS and WATER VAPOR
TRANSPORT
CLOUDS and WATER VAPOR
SNOW, GLACIERS and ICESHEETS
PRECIPITATION
EVAPORATION
EVAPOTRANSPIRATION
PRECIPITATION
PERMAFROST
INFILTRATION
SURFACE RUNOFF
SOIL MOISTURE
OCEAN
RIVERS and LAKES
PERCOLATION
RIVER DISCHARGE
GROUNDWATER
GROUND-WATER FLOW
SEA ICE
NASA


강수
증발산
식생
물 순환
유출
토양 습윤

Essential Climate Variables (ECV)

- ECV는 물리적, 화학적, 생물학적 또는 지구의 기후 특성화에 결정적으로 기여하는 인자



https://public.wmo.int/en/programmes/global-climate-observing-system/essential-climate-variables

Atmosphere (16)

Surface

- Precipitation
- Pressure
- Radiation budget
- Temperature
- Water vapour
- Wind speed and direction

Upper-air

- Earth radiation budget
- Lightning
- Temperature
- Water vapor
- Wind speed and direction

Atmospheric Composition

- Aerosols
- Carbon dioxide, methane and other greenhouse gases
- Clouds
- Ozone
- Precursors for aerosols and ozone

Land (19)

Hydrosphere

- Groundwater
- Lakes
- River discharge

Cryosphere

- Glaciers
- Ice sheets and ice shelves
- Permafrost
- Snow

Biosphere

- Above-ground biomass
- Albedo
- Evaporation from land
- Fire
- Fraction of absorbed photosynthetically active radiation (FAPAR)
- Land cover
- Land surface temperature
- Leaf area index
- Soil carbon
- Soil moisture

Anthroposphere

- Anthropogenic Greenhouse gas fluxes
- Anthropogenic water use

Ocean (19)

Physical

- Ocean surface heat flux
- Sea ice
- Sea level
- Sea state
- Sea surface currents
- Sea surface salinity
- Sea surface stress
- Sea surface temperature
- Subsurface currents
- Subsurface salinity
- Subsurface temperature

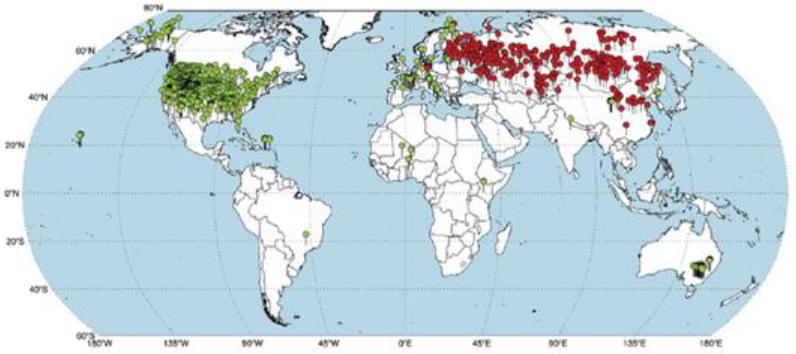
Biogeochemical

- Inorganic carbon
- Nitrous oxide
- Nutrients
- Ocean colour
- Oxygen
- Transient tracers

Biological/ecosystems

- Marine habitats
- Plankton

International Soil Moisture Network (ISMN)



지구관측을 위한 원격탐사

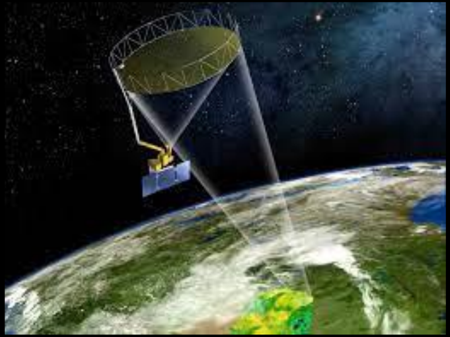
원격탐사
(Remote Sensing)

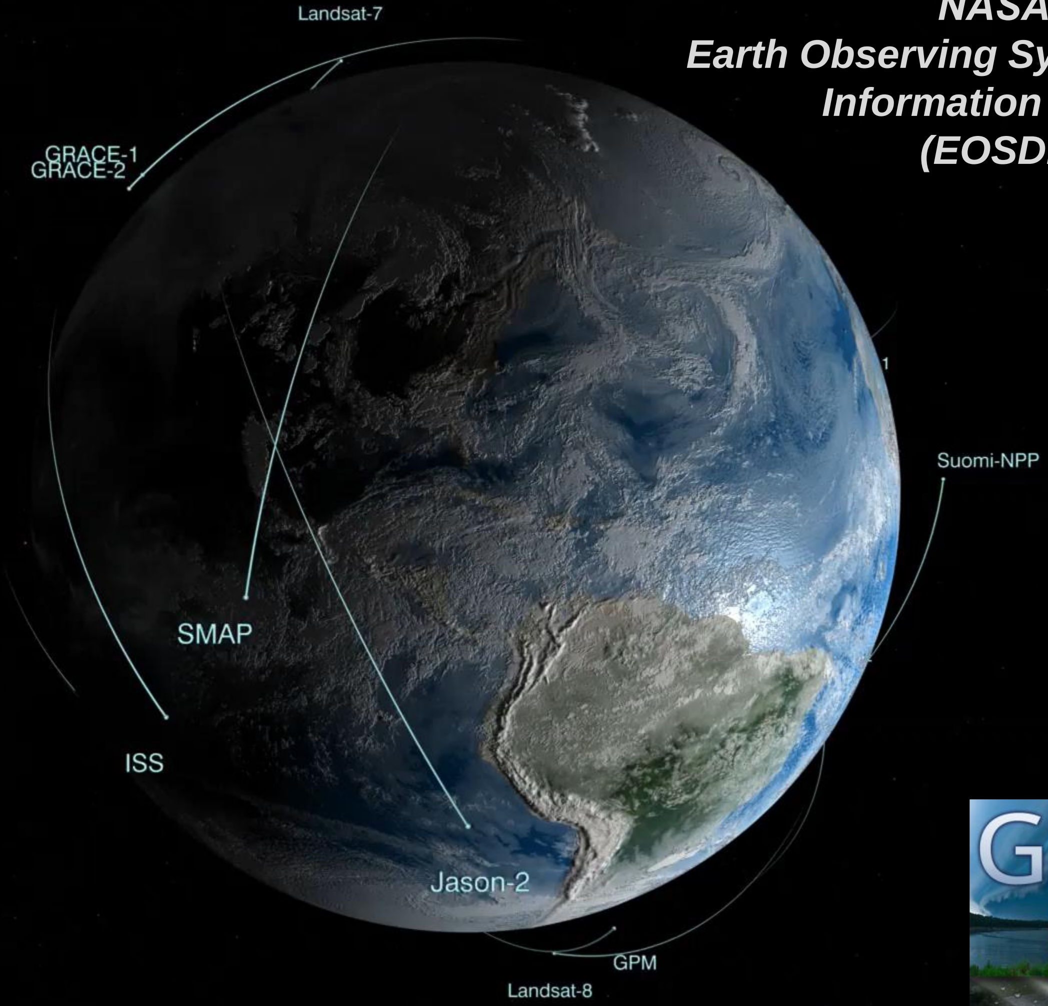
“물체와 물리적 접촉 없이
정보 획득”

Yang, J. et al. (2013)

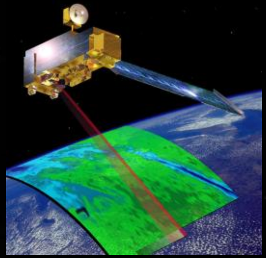
NASA's Earth Observing System Data and Information System (EOSDIS)

SMAP (토양 습윤)

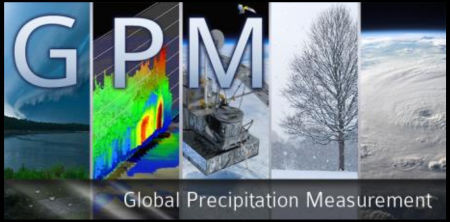




MODIS
(식생지표)

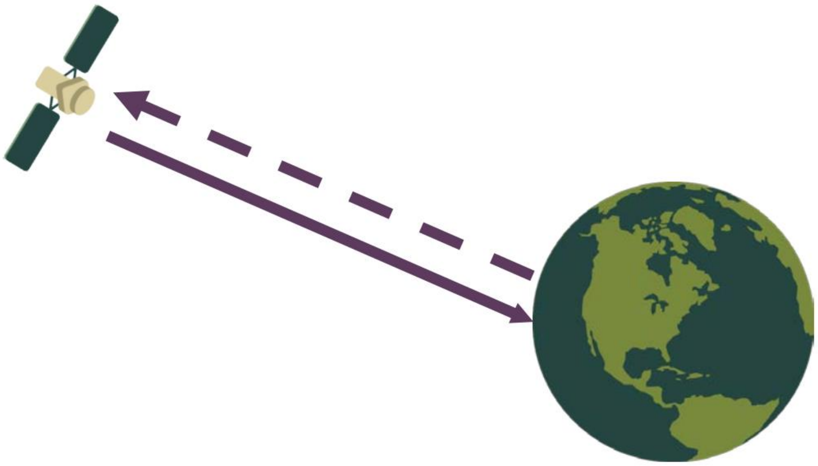


GPM (강우)



원격탐사의 방식

Active Sensors

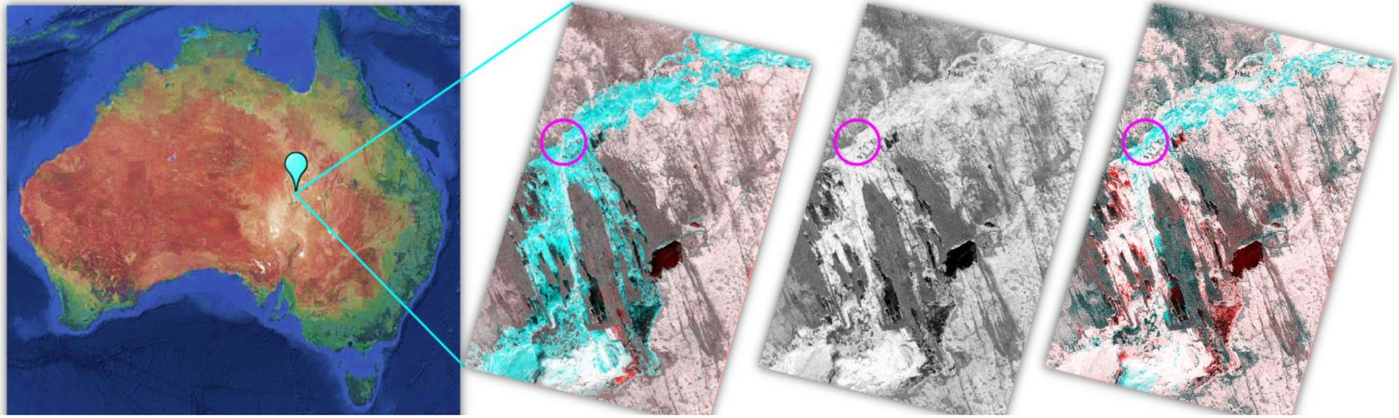


25%

Passive Sensors

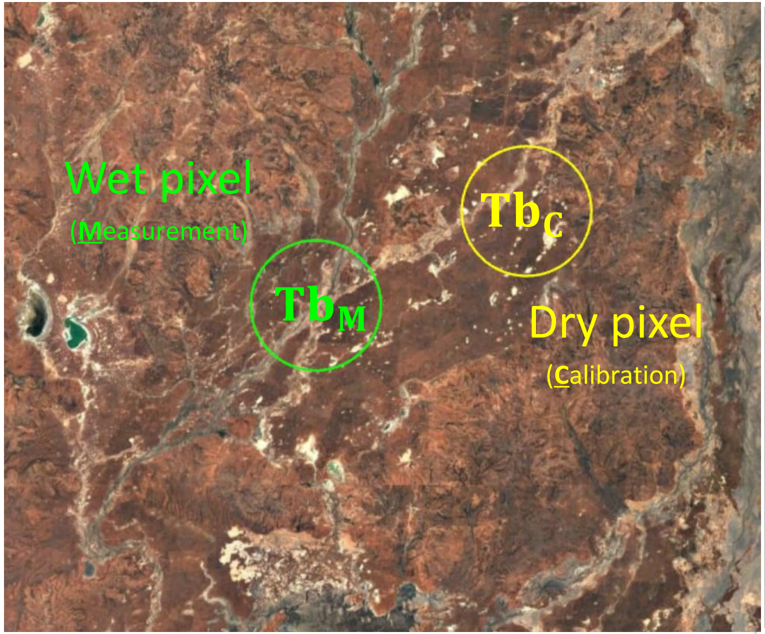
75%

https://earthdata.nasa.gov/learn/remote-sensors



Sentinel-1 C-band SAR를 이용한 홍수범위 탐지 (Active)

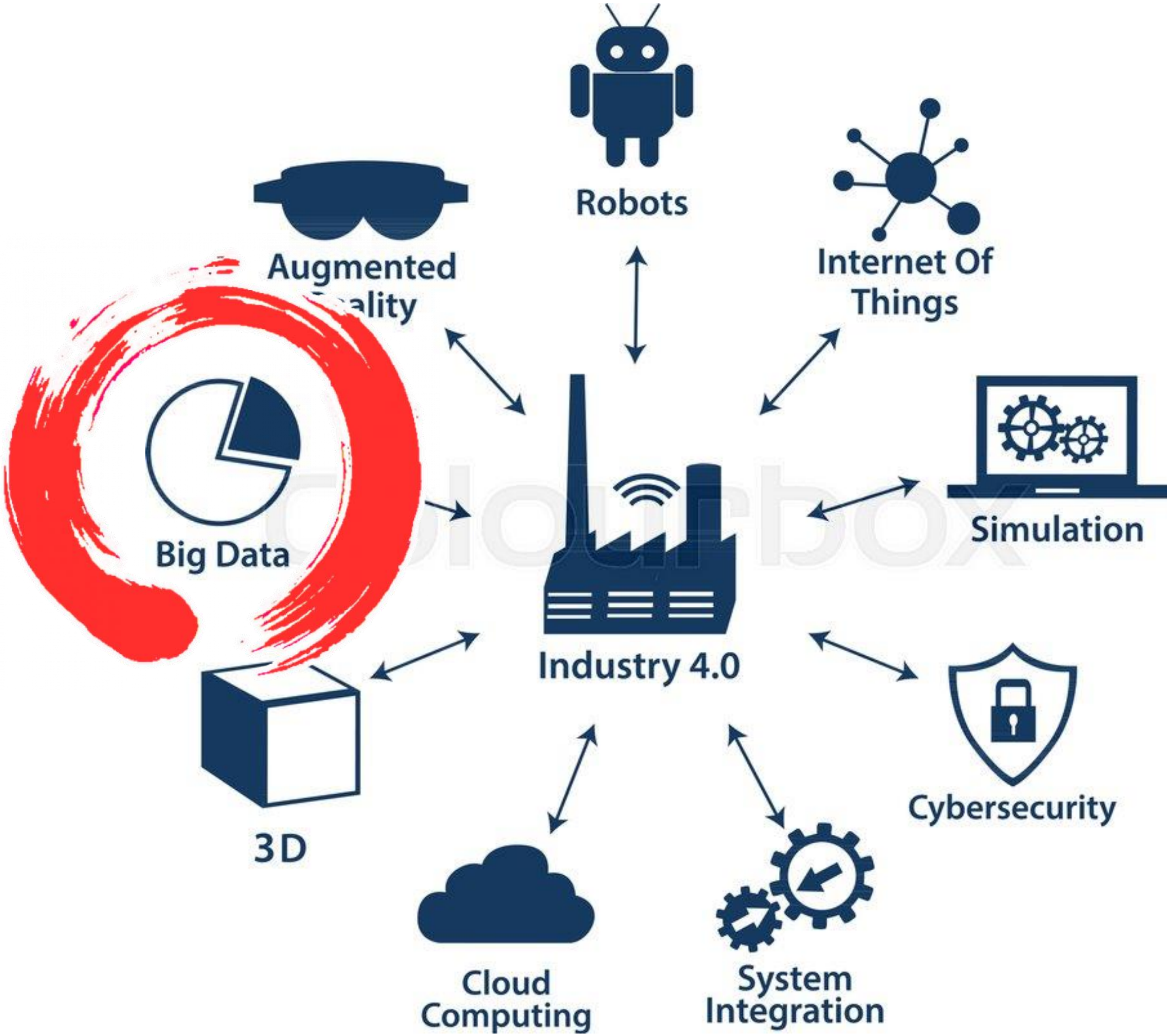
홍수감지를 위한 마이크로파 (passive)



MC ratio

⇩

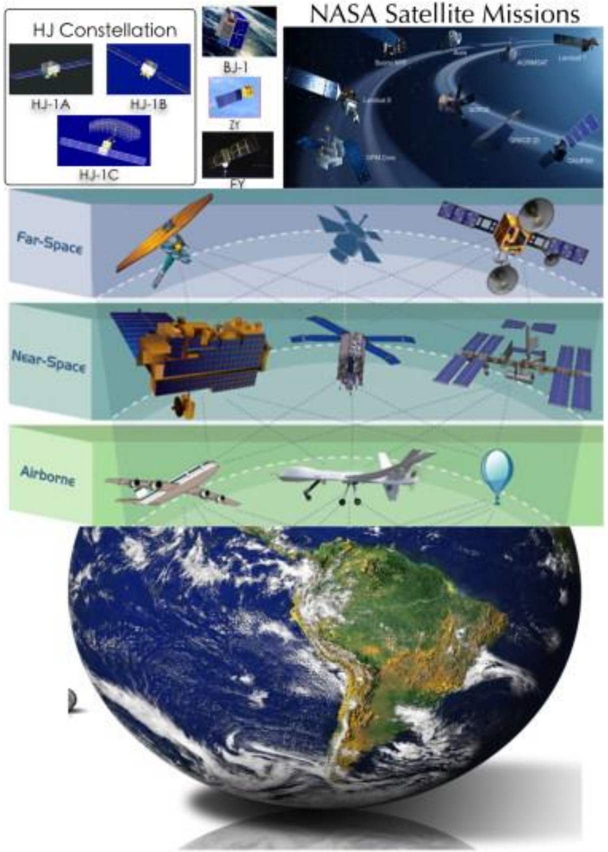
$\propto Q$

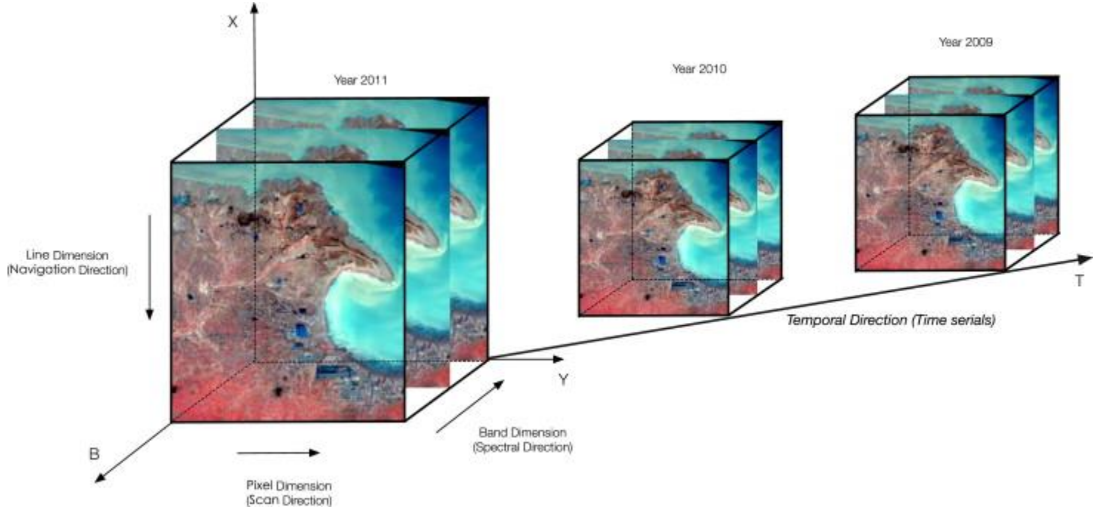


4차 산업혁명
(Industry 4)

현대 스마트 기술에 초점을 맞춘 새로운 산업혁명

원격탐사: 환경 빅 데이터 원천





Ma, Y.et al. (2015). Remote sensing big data computing: Challenges and opportunities. *Future Generation Computer Systems*, *51*, 47-60.

한국의 인공위성

20개 이상의 인공위성 운영 중

세계 7위의 인공위성 개발/운영 능력

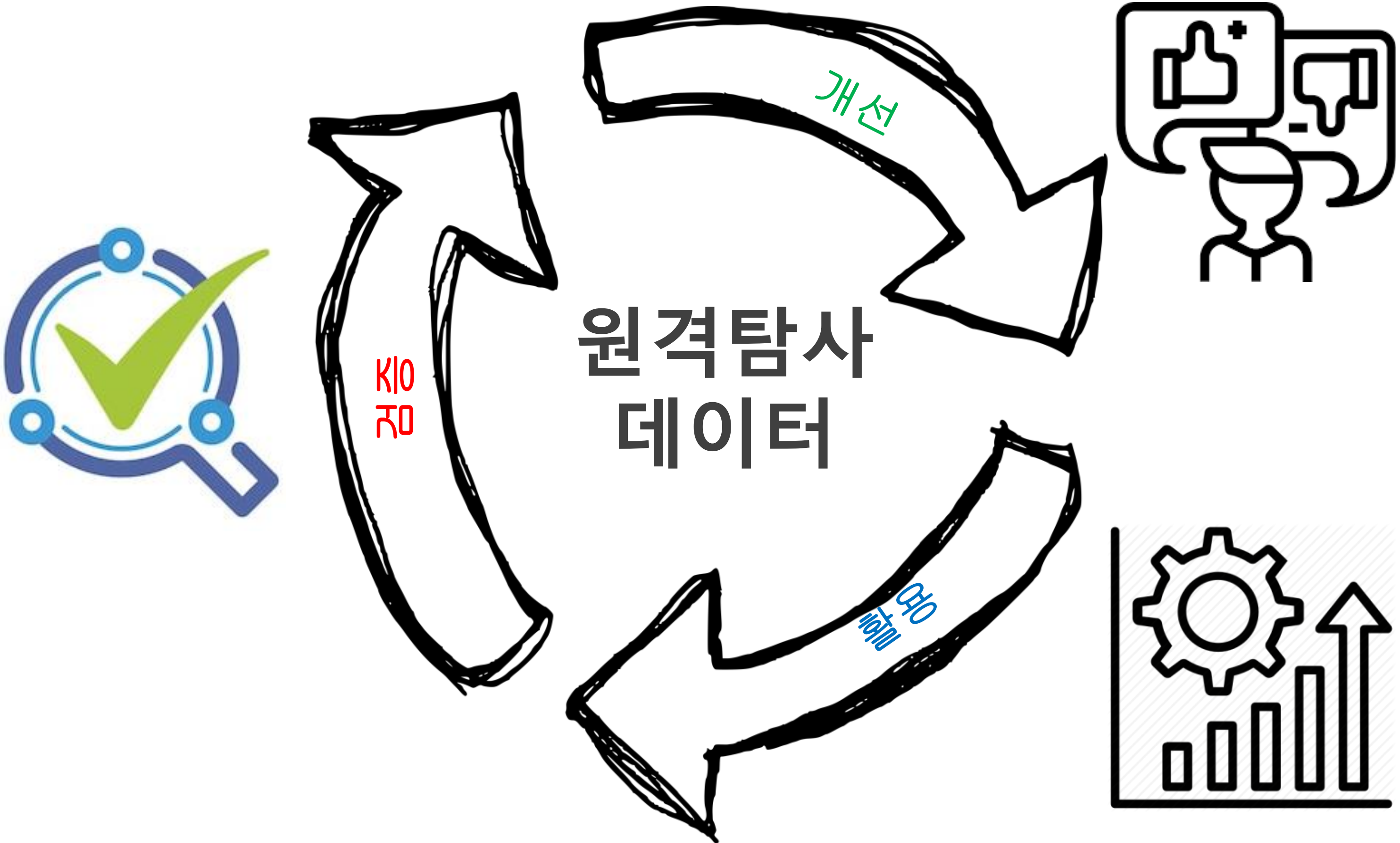
지구관측용 인공위성 개발을 위한
지속적인 연구개발

수자원/재난 모니터링 전용 인공위성

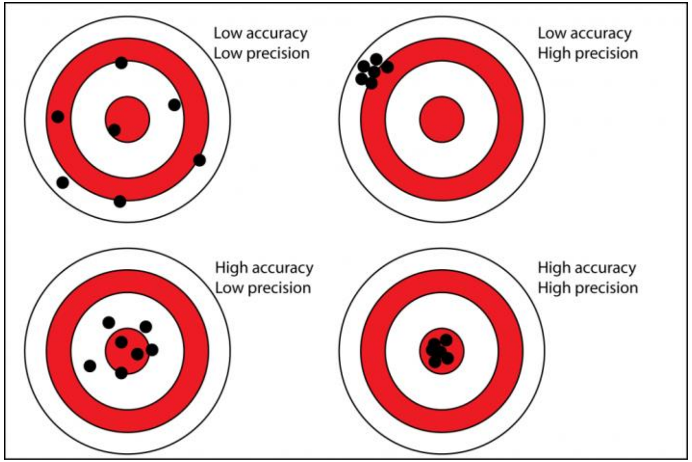
정부, 수자원위성 개발에 5545억원 투입…기후변화 대응

| 2025~27년까지 중형위성 5호·천리안 3호 개발

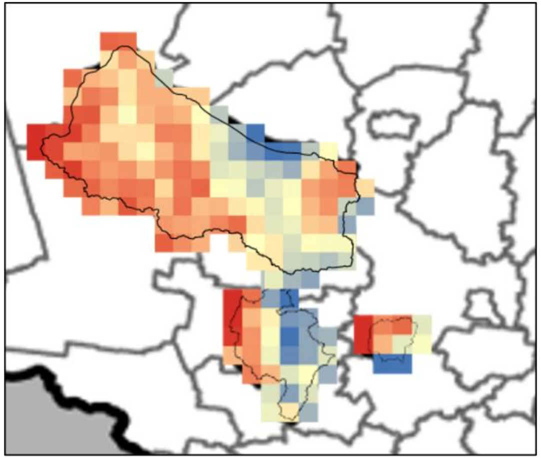
원격탐사 연구분야



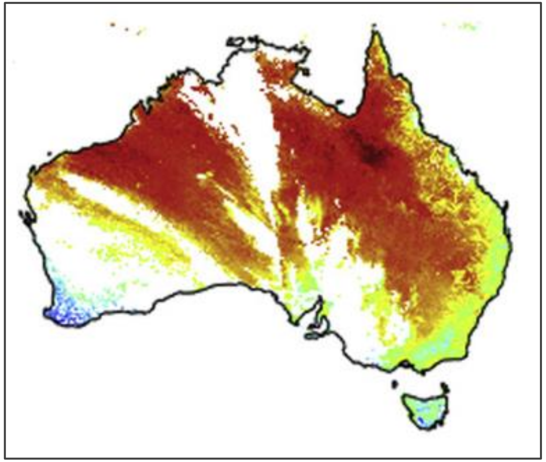
원격탐사 데이터의 개선



Accuracy (정확도) / precision (정밀도)



Spatial disaggregation



Gap-filling

데이터 합성을 통한 원격탐사 데이터의 개선

Rethinking Satellite Data Merging: From Averaging to SNR Optimization

Seokhyeon Kim, Ashish Sharma, Yi Y. Liu, and Sean I. Young

Original combination – minimizing MSE (Bates and Granger, 1969)

The Combination of Forecasts

J. M. BATES and C. W. J. GRANGER
Department of Economics, University of Nottingham

Two separate sets of forecasts of airline passenger data have been combined to form a composite set of forecasts. The main conclusion is that the composite set of forecasts can yield lower mean-square error than either of the original forecasts. Past errors of each of the original forecasts are used to determine the weights to attach to these two original forecasts in forming the combined forecasts, and different methods of deriving these weights are examined.

in the second set. The choice of k should be made so that the errors of the combined forecasts are small: more specifically, we chose to minimize the overall variance, σ_c^2. Differentiating with respect to k, and equating to zero, we get the minimum of σ_c^2 occurring when:

$$k = \frac{\sigma_2^2 - \rho\sigma_1\sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2}. \qquad (1)$$

In the case where $\rho = 0$, this reduces to:

$$k = \sigma_2^2/(\sigma_1^2 + \sigma_2^2). \qquad (2)$$

It can be shown that if k is determined by equation (1), the value of σ_c^2 is no greater than the smaller of the two *individual* variances. The algebra demonstrating this is recorded in Section 2 of the Appendix.

The optimum value for k is not known at the commencement of combining forecasts. The value given to the weight k would change as evidence was accumulated about the relative performance of the two original forecasts. Thus the combined forecast for time period T, C_T, is more correctly written as:

$$C_T = k_T f_{1,T} + (1 - k_T) f_{2,T},$$

다양한 분야에서의 활용

AGU PUBLICATIONS
Geophysical Research Letters
RESEARCH LETTER
10.1002/2015GL064981

A framework for combining multiple soil moisture retrievals based on maximizing temporal correlation

Seokhyeon Kim[1], Robert M. Parinussa[1], Yi. Y. Liu[2], Fiona M. Johnson[1], and Ashish Sharma[1]

Key Points:
- Two existing remote sensing products

Remote Sensing of Environment 204 (2018) 260–275
Contents lists available at ScienceDirect
Remote Sensing of Environment
journal homepage: www.elsevier.com/locate/rse

Global-scale assessment and combination of SMAP with ASCAT (active) and AMSR2 (passive) soil moisture products

Hyunglok Kim[a], Robert Parinussa[b], Alexandra G. Konings[c], Wolfgang Wagner[d], Michael H. Cosh[e], Venkat Lakshmi[a], Muhammad Zohaib[f], Minha Choi[f,*]

6780 IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 55, NO. 12, DECEMBER 2017

Triple Collocation-Based Merging of Satellite Soil Moisture Retrievals

Alexander Gruber, Wouter Arnoud Dorigo, Wade Crow, and Wolfgang Wagner, *Senior Member, IEEE*

Review *TRENDS in Ecology and Evolution* Vol.22 No.1
Full text provided by www.sciencedirect.com ScienceDirect

Ensemble forecasting of species distributions

Miguel B. Araújo[1] and Mark New[2]

[1] Department of Biodiversity and Evolutionary Biology, National Museum of Natural Sciences, CSIC, C/Gutiérrez Abascal, 2, 28006, Madrid, Spain
[2] Climate Research Laboratory, Oxford University Centre for the Environment, South Parks Road, Oxford, UK, OX1 3QY

15 May 2014 KHAN ET AL. 3505

Global Sea Surface Temperature Forecasts Using an Improved Multimodel Approach

Mohammad Zaved Kaiser Khan, Rajeshwar Mehrotra, and Ashish Sharma
School of Civil and Environmental Engineering, The University of New South Wales, Sydney, Australia

A. Sankarasubramanian
Department of Civil, Construction and Environmental Engineering, North Carolina State University, Raleigh, North Carolina

WATER RESOURCES RESEARCH, VOL. 45, W10428, doi:10.1029/2008WR007510, 2009

Multisite seasonal forecast of arid river flows using a dynamic model combination approach

Shahadat Chowdhury[1] and Ashish Sharma[1]

Journal of Business & Economic Statistics, January 1986, Vol. 4, No. 1

Combining Economic Forecasts

Robert T. Clemen
College of Business Administration, University of Oregon, Eugene, OR 97403

Robert L. Winkler
Fuqua School of Business, Duke University, Durham, NC 27706

Remote Sensing of Environment 123 (2012) 280–297
Contents lists available at SciVerse ScienceDirect
Remote Sensing of Environment
journal homepage: www.elsevier.com/locate/rse

Trend-preserving blending of passive and active microwave soil moisture retrievals

Y.Y. Liu[a,c,d,e,*], W.A. Dorigo[b], R.M. Parinussa[c], R.A.M. de Jeu[c], W. Wagner[b], M.F. McCabe[a], J.P. Evans[d], A.I.J.M. van Dijk[e]

행렬형식을 통한 가중평균방법 (WA)일반화

$\mathbf{x} = y\mathbf{1} + \mathbf{e}$ 와 $\mathbf{u} \in \mathbb{R}^N$에 대하여, 목적함수와 조건은

$$\text{Minimize } g(\mathbf{u}) = \mathbb{E}(\mathbf{e}^T\mathbf{u})^2 = \mathbb{E}(\mathbf{x}^T\mathbf{u} - y\mathbf{1}^T\mathbf{u})^2$$

$$\text{Subject to } h(\mathbf{u}) = \mathbf{1}^T\mathbf{u} = 1$$

최적해는

$$\boxed{\mathbf{u}^\dagger = (\mathbf{1}^T\mathbb{E}(\mathbf{e}\mathbf{e}^T)^{-1}\mathbf{1})^{-1}\mathbb{E}(\mathbf{e}\mathbf{e}^T)^{-1}\mathbf{1}}$$

모(parent)데이터의 수가 2개일 경우

$$\mathbf{u}^{\dagger} = (\mathbf{1}^T \mathbb{E}(\mathbf{e}\mathbf{e}^T)^{-1}\mathbf{1})^{-1} \mathbb{E}(\mathbf{e}\mathbf{e}^T)^{-1}\mathbf{1}$$

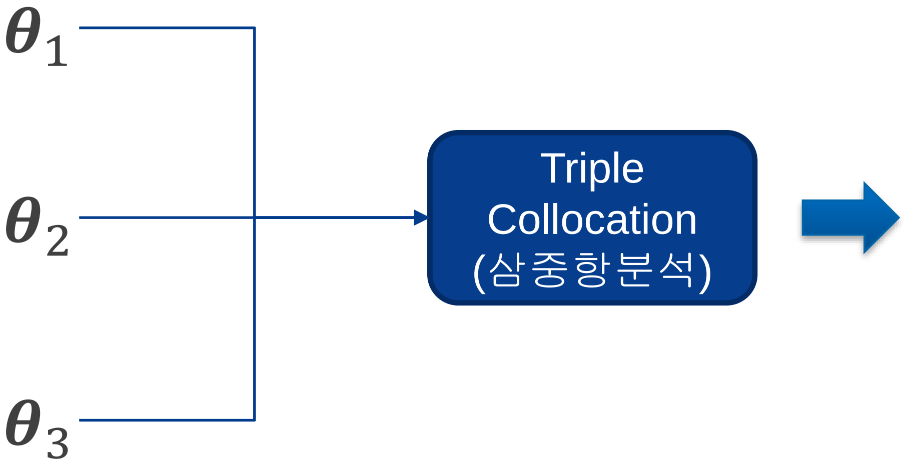
$$u_1 = \frac{{\sigma_{\varepsilon 2}}^2 - \rho_{\varepsilon 1,\varepsilon 2}\sigma_{\varepsilon 1}\sigma_{\varepsilon 2}}{{\sigma_{\varepsilon 1}}^2 + {\sigma_{\varepsilon 2}}^2 - 2\rho_{\varepsilon 1,\varepsilon 2}\sigma_{\varepsilon 1}\sigma_{\varepsilon 2}}$$

$$\rho_{\varepsilon 1,\varepsilon 2} = 0$$

$$u_1 \approx \frac{{\sigma_{\varepsilon 2}}^2}{{\sigma_{\varepsilon 1}}^2 + {\sigma_{\varepsilon 2}}^2}$$

$$k = \frac{\sigma_2^2 - \rho\sigma_1\sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2}.$$

오차 공분산 행렬 ($\mathbb{E}(\mathbf{e}\mathbf{e}^T)$)



$$\boldsymbol{\sigma}_{\varepsilon} = \begin{bmatrix} \sqrt{Q_{11} - \frac{Q_{12}Q_{13}}{Q_{23}}} \\ \sqrt{Q_{22} - \frac{Q_{12}Q_{23}}{Q_{13}}} \\ \sqrt{Q_{33} - \frac{Q_{13}Q_{23}}{Q_{12}}} \end{bmatrix}$$

$$\boldsymbol{\rho}_{t,X} = \pm \begin{bmatrix} \sqrt{\frac{Q_{12}Q_{13}}{Q_{11}Q_{23}}} \\ \mathrm{sign}(Q_{13}Q_{23})\sqrt{\frac{Q_{12}Q_{23}}{Q_{22}Q_{13}}} \\ \mathrm{sign}(Q_{12}Q_{23})\sqrt{\frac{Q_{13}Q_{23}}{Q_{33}Q_{12}}} \end{bmatrix}$$

Stoffelen (1998); McColl et al.(2015)

4개의 TC 가정

- Linearity between observations and the truth: $\boldsymbol{\theta_i} = \alpha_i \boldsymbol{t} + \beta_i + \boldsymbol{\varepsilon_i}$
- Stationarity for $\mathrm{E}[\varepsilon_i]$ and $\mathrm{E}[t]$
- Zero error-cross correlation (ECC): $\rho_{\varepsilon_i,\varepsilon_j} = 0$
- Error-truth orthogonality: $\rho_{\varepsilon_i,t} = 0$

데이터 합성분야의 연구방향

- 데이터 합성방법 개발 (예: min MSE, max R 등)
- 데이터 합성에 필요한 매개변수 추정 (예: TC, Extended TC, QC, Instrument Variable Method, Double Instrument Variable Method, Three-Cornered Hat 등)

기존 가중평균법의 문제점

- 데이터 합성의 목적이 합성된 데이터의 오차를 최소화 하는 것이라면, 가중치의 합이 1이 여야 한다는 조건 (즉, 모데이터의 가중평균)은 불필요하며 이는 오히려 데이터 합성 결과의 최적성을 제한함

- 즉, 목적함수를 세울 때 오차항만 다룰 것이 아니라 합성 데이터 자제를 대입함으로써 문제를 해결할 수 있음

- 이 경우 **신호 대 잡음 비 (signal-to-noise ratios, SNR)**가 데이터 합성을 위한 매개변수가 됨

새로운 방법: SNR-opt

$\hat{y} = \mathbf{x}^T \mathbf{u}$이므로, 목적함수와 조건은

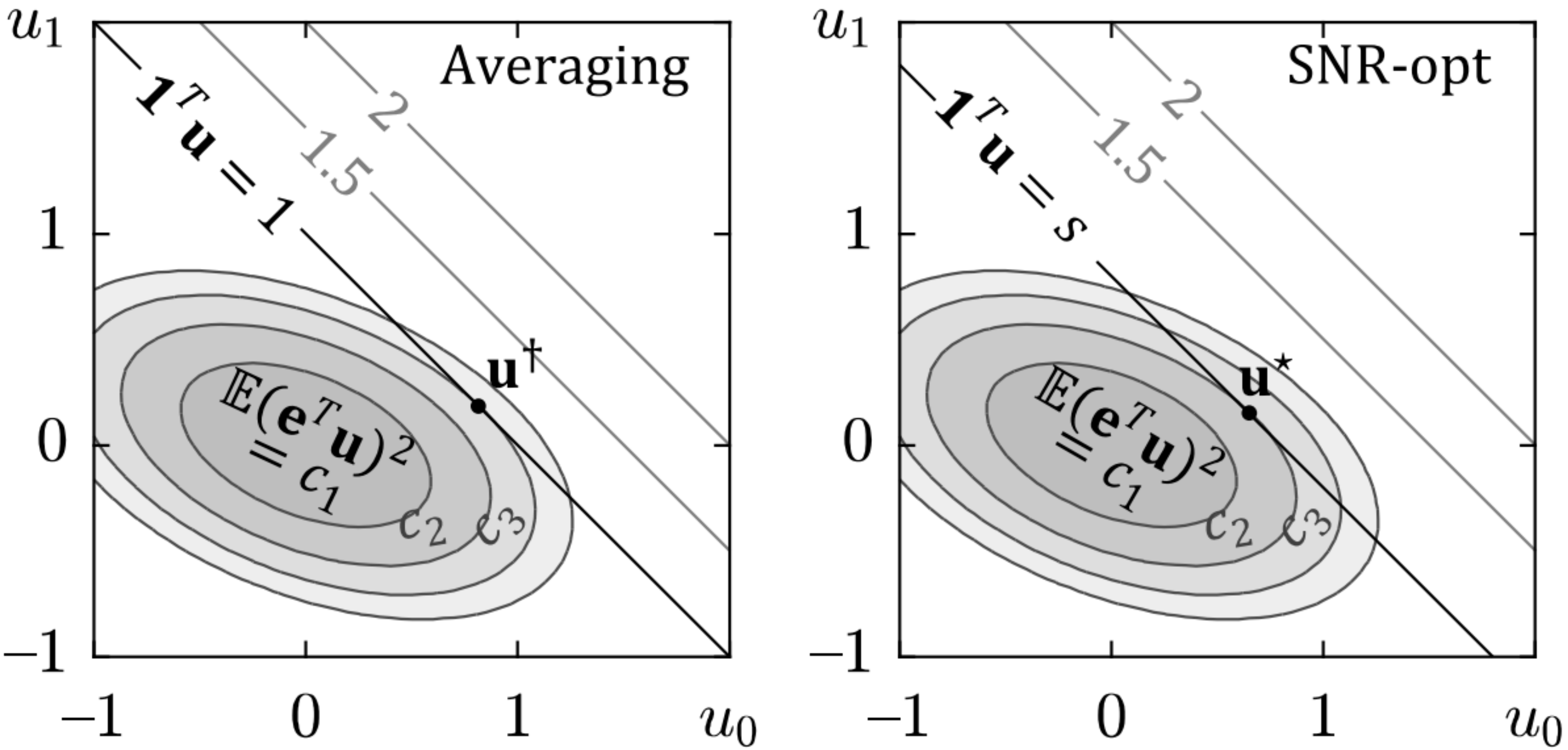
$$\text{Minimize } f(\mathbf{u}) = \mathbb{E}(\mathbf{e}^T \mathbf{u})^2 = \mathbb{E}(\mathbf{x}^T \mathbf{u} - y)^2$$

이에 대한 최적해는

$$\boxed{\mathbf{u}^\star = (\mathbf{N} + \mathbf{a}\mathbf{a}^T)^{-1} \mathbf{a}}$$

여기서 $\mathbf{N} = \mathbb{E}[\mathbf{e}\mathbf{e}^T] / \mathbb{E}(y^2)$ 는 SNR

WA vs. SNR-opt



Averaging
SNR-opt
u_1
u_0
$\mathbf{1}^T\mathbf{u} = 1$
$\mathbf{1}^T\mathbf{u} = s$
2
1.5
$\mathbf{u}^\dagger$
$\mathbf{u}^\star$
$\mathbb{E}(\mathbf{e}^T\mathbf{u})^2 = c_1$
c_2
c_3
1
0
−1

WA vs. SNR-opt

Example 1: $\mathbf{N} \to \infty$ ($\mathbb{E}(\mathbf{e}\mathbf{e}^T) \gg \mathbb{E}(y^2)$)

$\mathbb{E}(y^2) = 0.01; \mathbb{E}(\mathbf{e}\mathbf{e}^T) = \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix}$; $\mathbf{a} = \mathbf{1}$.

Therefore, $\mathbf{N} = \mathbb{E}(\mathbf{e}\mathbf{e}^T)/\mathbb{E}(y^2) = \begin{pmatrix} 100 & 0 \\ 0 & 200 \end{pmatrix}$.

Then, $\mathbf{u}^\dagger = (\mathbf{1}^T \mathbb{E}(\mathbf{e}\mathbf{e}^T)^{-1}\mathbf{1})^{-1}\mathbb{E}(\mathbf{e}\mathbf{e}^T)^{-1}\mathbf{1} = \begin{pmatrix} 0.667 \\ 0.333 \end{pmatrix}$ for the weighted average, and

$\mathbf{u}^\star = (\mathbb{E}(\mathbf{e}\mathbf{e}^T)/\mathbb{E}(y^2) + \mathbf{1}\mathbf{1}^T)^{-1}\mathbf{1} = \begin{pmatrix} 0.010 \\ 0.005 \end{pmatrix}$ for the SNR-opt.

Example 2: $\mathbf{N} \to 0$ ($\mathbb{E}(\mathbf{e}\mathbf{e}^T) \ll \mathbb{E}(y^2)$)

$\mathbb{E}(y^2) = 10; \mathbb{E}(\mathbf{e}\mathbf{e}^T) = \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix}$; $\mathbf{a} = \mathbf{1}$.

Therefore, $\mathbf{N} = \begin{pmatrix} 0.1 & 0 \\ 0 & 0.2 \end{pmatrix}$.

Then, $\mathbf{u}^\dagger = \begin{pmatrix} 0.667 \\ 0.333 \end{pmatrix}$ for the weighted average, and $\mathbf{u}^\star = \begin{pmatrix} 0.625 \\ 0.313 \end{pmatrix}$ for the SNR-opt.

[Box] 상관계수 최대화: max R

$$\text{maximize } r(\mathbf{u}) = \frac{\mathbb{E}(y(\mathbf{x}^T\mathbf{u}))}{\sqrt{\mathbb{E}(y^2)}\sqrt{\mathbb{E}((\mathbf{x}^T\mathbf{u})^2)}}$$

$$\text{maximize } r^2(\mathbf{u}) \propto \frac{\mathbf{u}^T\mathbb{E}(y\mathbf{x})\mathbb{E}(y\mathbf{x})^T\mathbf{u}}{\mathbf{u}^T\mathbb{E}(\mathbf{x}\mathbf{x}^T)\mathbf{u}} = \boxed{\frac{\mathbf{u}^T\mathbf{a}\mathbf{a}^T\mathbf{u}}{\mathbf{u}^T\mathbb{E}(\mathbf{x}\mathbf{x}^T)\mathbf{u}}},$$

일반화된
Rayleigh
몫(quotient)

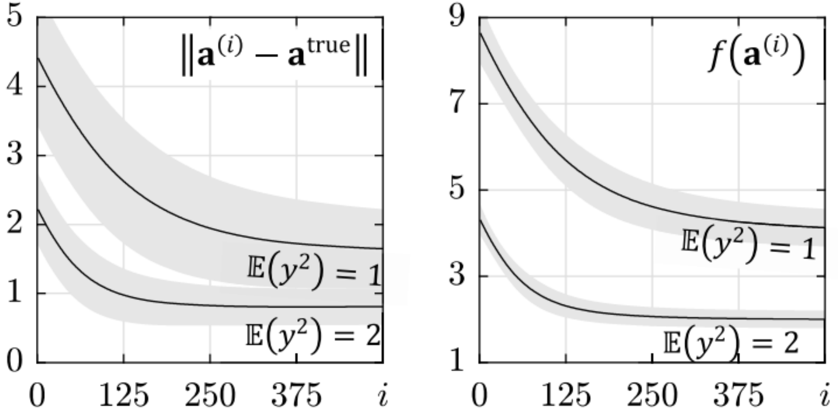
$\mathbf{a}\mathbf{a}^T\boldsymbol{u} = \lambda\mathbb{E}(\mathbf{x}\mathbf{x}^T)\boldsymbol{u}$의 주 고유벡터 =
상관계수를 최대화 하는 가중치

참값 없이 SNR 구하는 방법: SNR-est

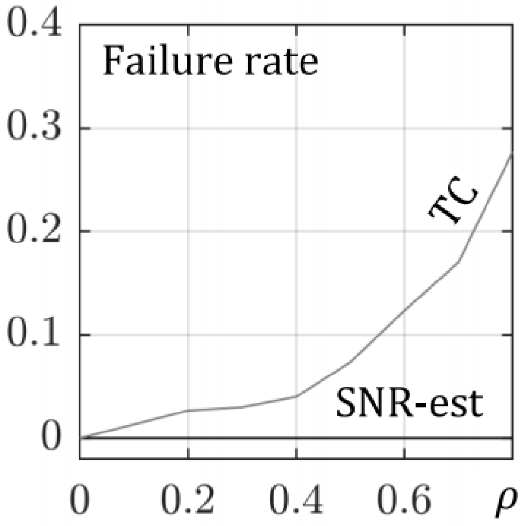
$\mathbf{C} = \widehat{\mathbb{E}(\mathbf{x}\mathbf{x}^T)}/\mathbb{E}(y^2) \approx \mathbf{N} + \mathbf{a}\mathbf{a}^T$에 대해 $\mathbf{N}$의 비 대각성분이 "작다" 라고 가정하고 다음의 최적화를 수행

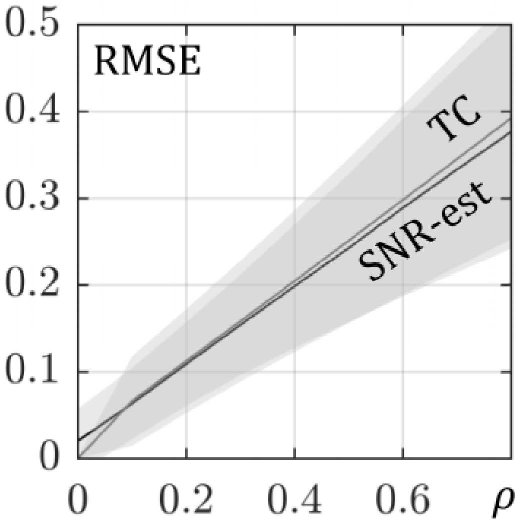
$$\text{minimize} \quad f(\mathbf{a}) = \mathbf{1}^T\left((\mathbf{1}\mathbf{1}^T - \mathbf{I}) \circ \text{abs}(\mathbf{C} - \mathbf{a}\mathbf{a}^T)\right)\mathbf{1}$$

$$\text{subject to } h(\mathbf{a}) = \text{diag}(\mathbf{a}\mathbf{a}^T) - \text{diag}(\mathbf{C}) \leq \mathbf{0}$$



SNR-est vs. TC





- TC와 SNR-est는 비슷한 성능
- 그러나, 오차간 상관성이 증가할 수록 TC는 실패 (음의 오차분산) 케이스 증가
- 이에 반해 SNR-est는 실패 케이스 없음
- 또한 TC는 3개 또는 4개 (QC)의 데이터에만 적용이 용이하지만
- SNR-est는 2개 이상의 데이터에 제한없이 사용가능

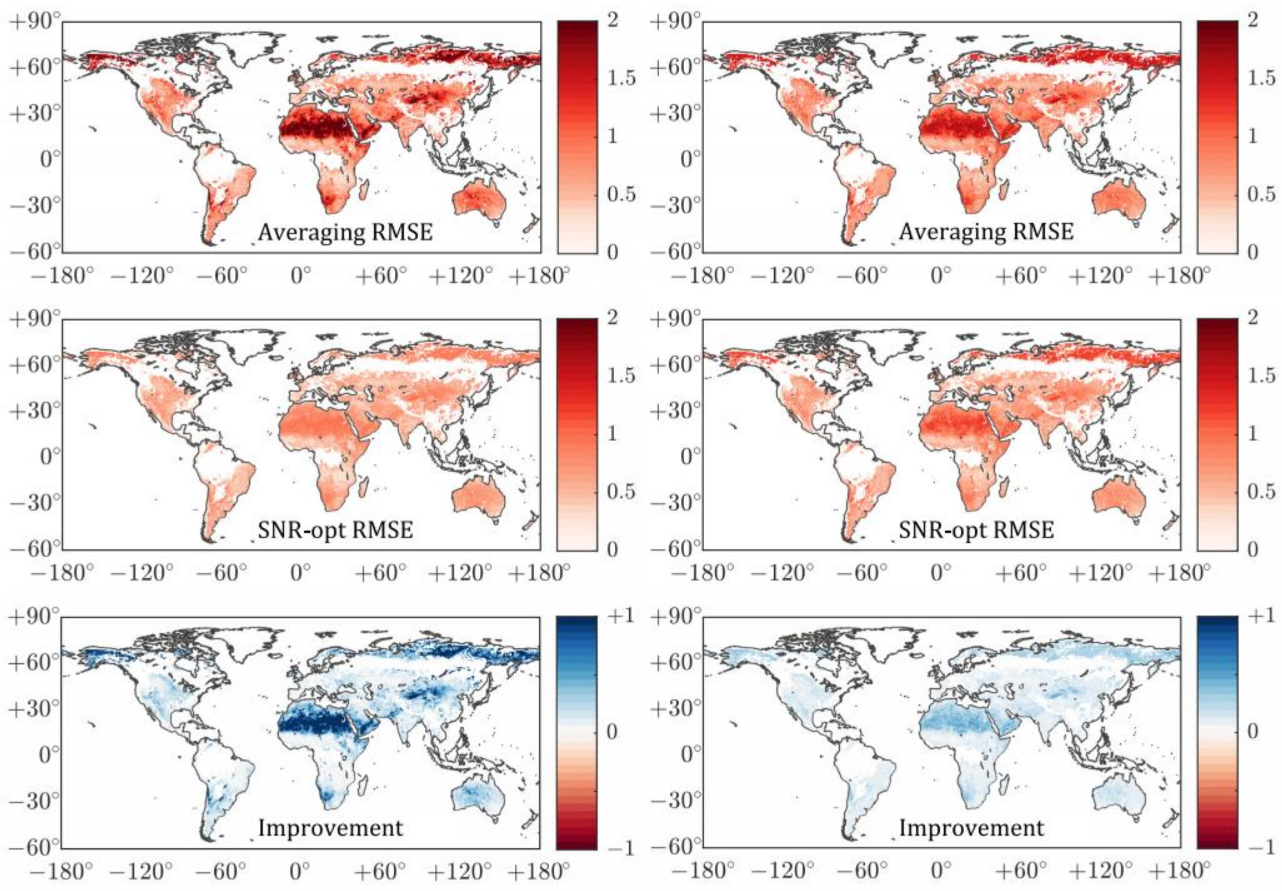
* SNR-est를 약간 변경하면 TC와 동등해짐

적용결과 (1)

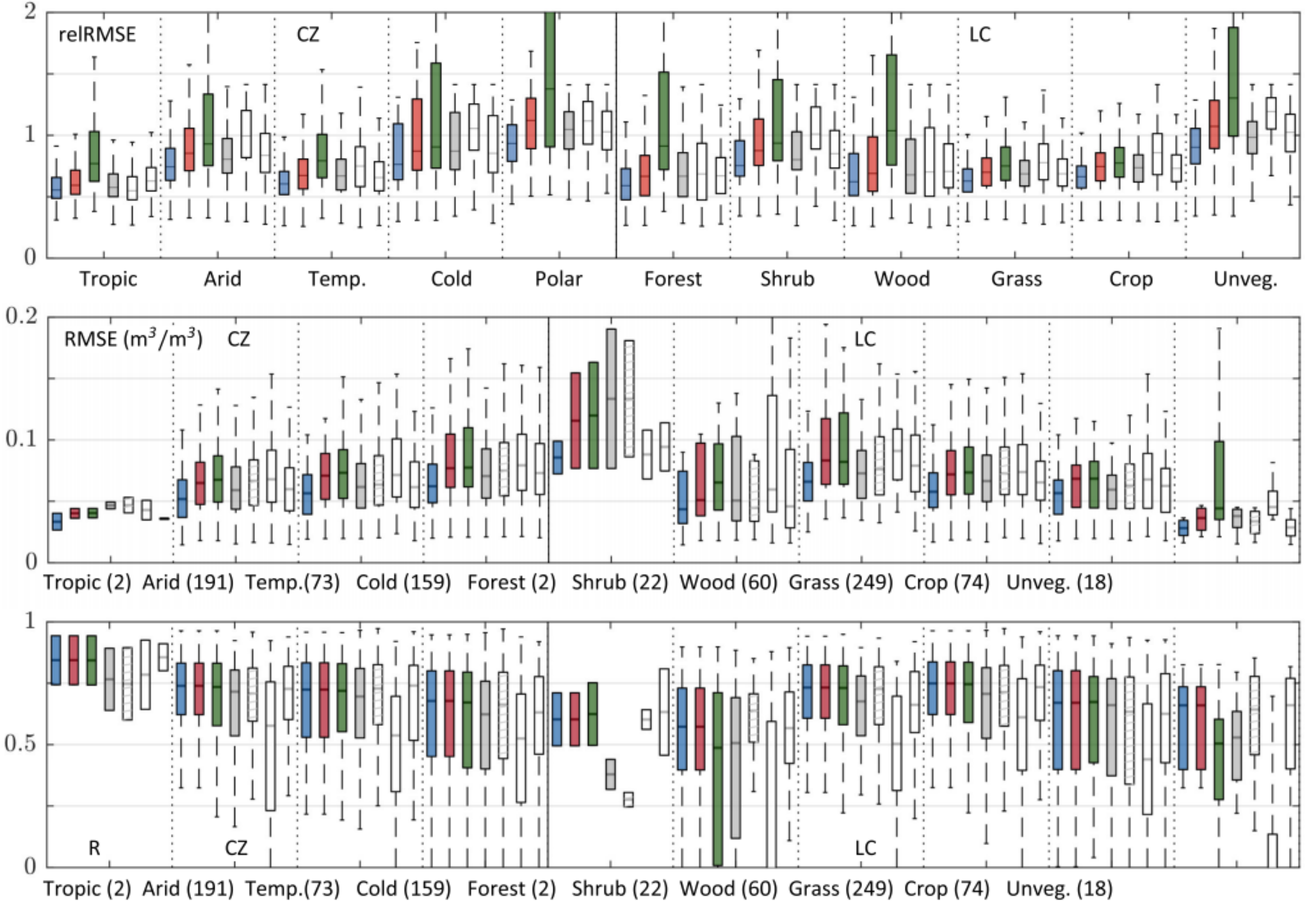
TABLE I
SUMMARY OF PARENT, REFERENCE, ANCILLARY AND VALIDATION DATASETS USED IN THIS WORK

	Product name	Resolutions (temporal/spatial)		Details
Parent datasets	**ASCAT** (Advanced SCATterometers) Level 2 V5 SM index product H103 [61]	Daily/overpass (ascend/descend) at 9:30 PM/AM (local time)	0.25°×0.25°	Active C-band (5.3 GHz) radar backscatter from ASCAT on board MetOp-B
	SMAP (Soil Moisture Active Passive) Level 3 Radiometer Global Daily SM/LST V3 [62]	Daily/overpass (ascend/descend) at 6 PM/AM (local time)	36km×36km EASEv2-Grid	Passive L-band (1.41 GHz)
	LPRM (Land Parameter Retrieval Model) Level 3 Daily SM/LST V1 [63]	Daily/overpass (ascend/descend) at 1:30 PM/AM (local time)	0.25°×0.25°	Passive X-band (10.65 GHz) from AMSR2 on GCOM-W
Ref	**ERA5-Land** (European Centre for Medium-Range Weather Forecasts Re-Analysis 5 Land) [51]	Hourly	0.1°×0.1°	Volumetric soil water content in layer 1 (0–0.07m), Skin temperature
Ancillary data	**CZ** Updated Köppen–Geiger climate classification [64]	–	0.25°×0.25°	5 primary classes: tropical, arid, temperate, cold, and polar regions
	MCD12C1 (Moderate Resolution Spectroradiometer Terra+Aqua land cover climate modeling grid) V1 [65]	Yearly (2015)	0.05°×0.05°	6 primary classes: forest, shrublands, woodlands, grasslands, croplands, and unvegetated regions
Validation data	**ESA CCI SM** (European Space Agency Climate Change Initiative Soil Moisture) V05.2 [41, 66, 67]	Daily	0.25°×0.25°	Active–passive combined surface SM product
	ISMN (International Soil Moisture Network) [68, 69] and [70-82]	Hourly	425 stations across 18 networks:	SNOTEL[128], SCAN[111], PBO-H2O[79], USCRN[51], RSMN[18], OZNET[8], SMOSMANIA[7], RISMA[5], SOILSCAPE[2], GROW[3], REMEDHUS[3], AMMA-CATCH[2], HOBE[2], IPE[2], BIEBRZA-S-1[1], COSMOS[1], DAHRA[1], and TERENO[1]

적용결과 (2)

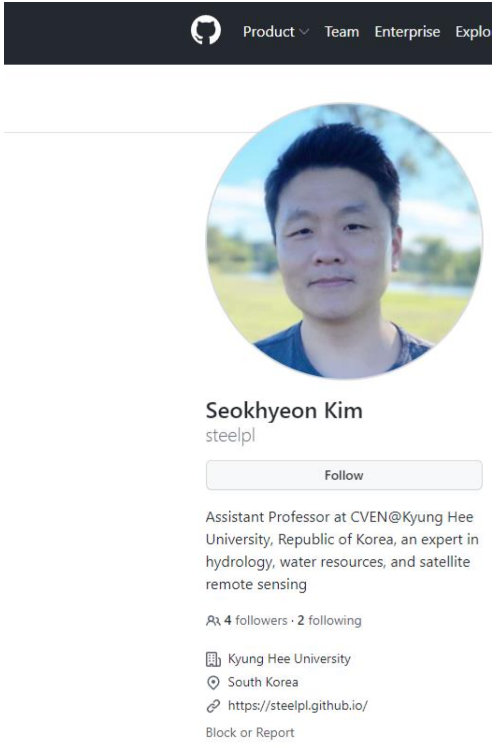

Averaging RMSE
Averaging RMSE
SNR-opt RMSE
SNR-opt RMSE
Improvement
Improvement
+90° +60° +30° 0° −30° −60°
−180° −120° −60° 0° +60° +120° +180°
2 1.5 1 0.5 0
+1 0 −1

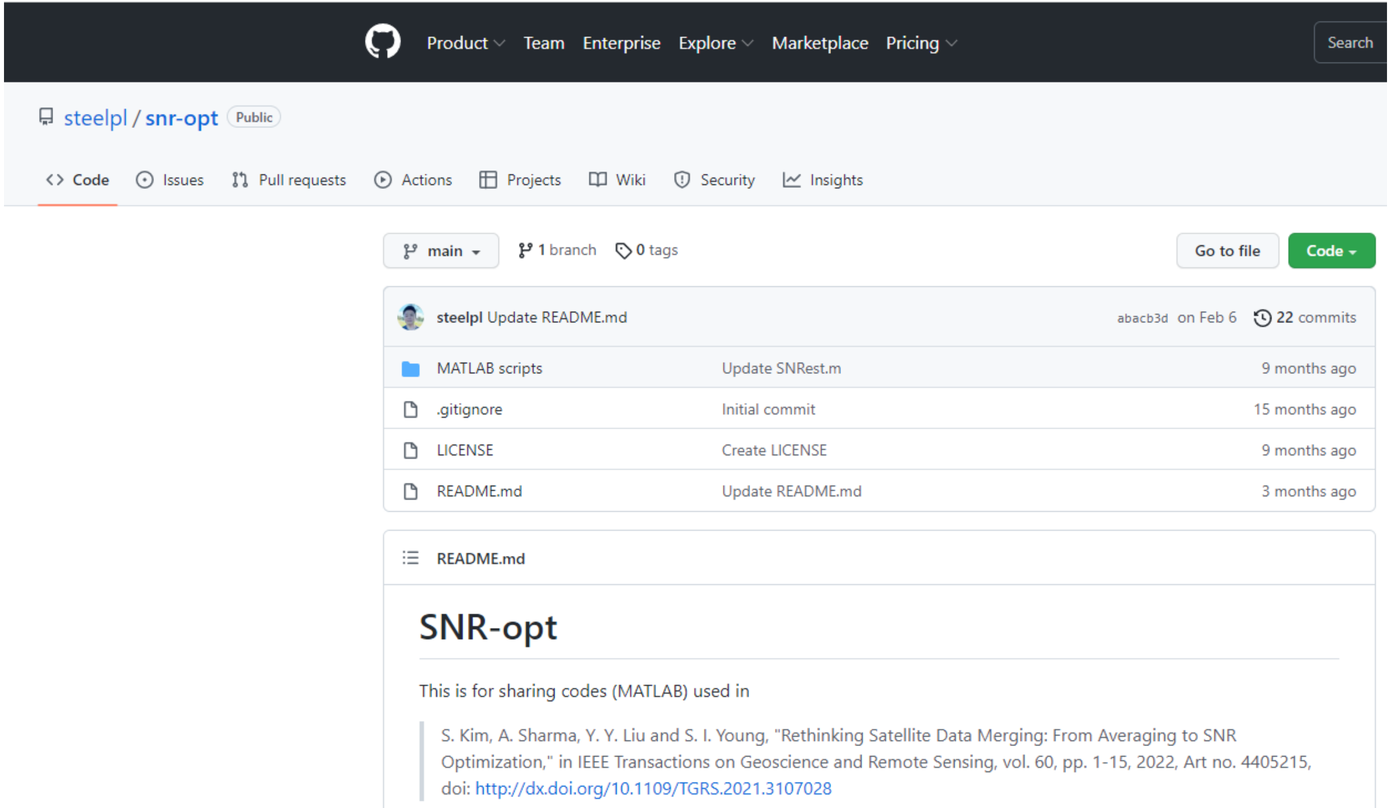
적용결과 (3)



relRMSE
CZ
LC
2
1
0
Tropic
Arid
Temp.
Cold
Polar
Forest
Shrub
Wood
Grass
Crop
Unveg.
RMSE (m3/m3)
CZ
LC
0.2
0.1
0
Tropic (2) Arid (191) Temp.(73) Cold (159) Forest (2) Shrub (22) Wood (60) Grass (249) Crop (74) Unveg. (18)
R
CZ
LC
1
0.5
0
Tropic (2) Arid (191) Temp.(73) Cold (159) Forest (2) Shrub (22) Wood (60) Grass (249) Crop (74) Unveg. (18)

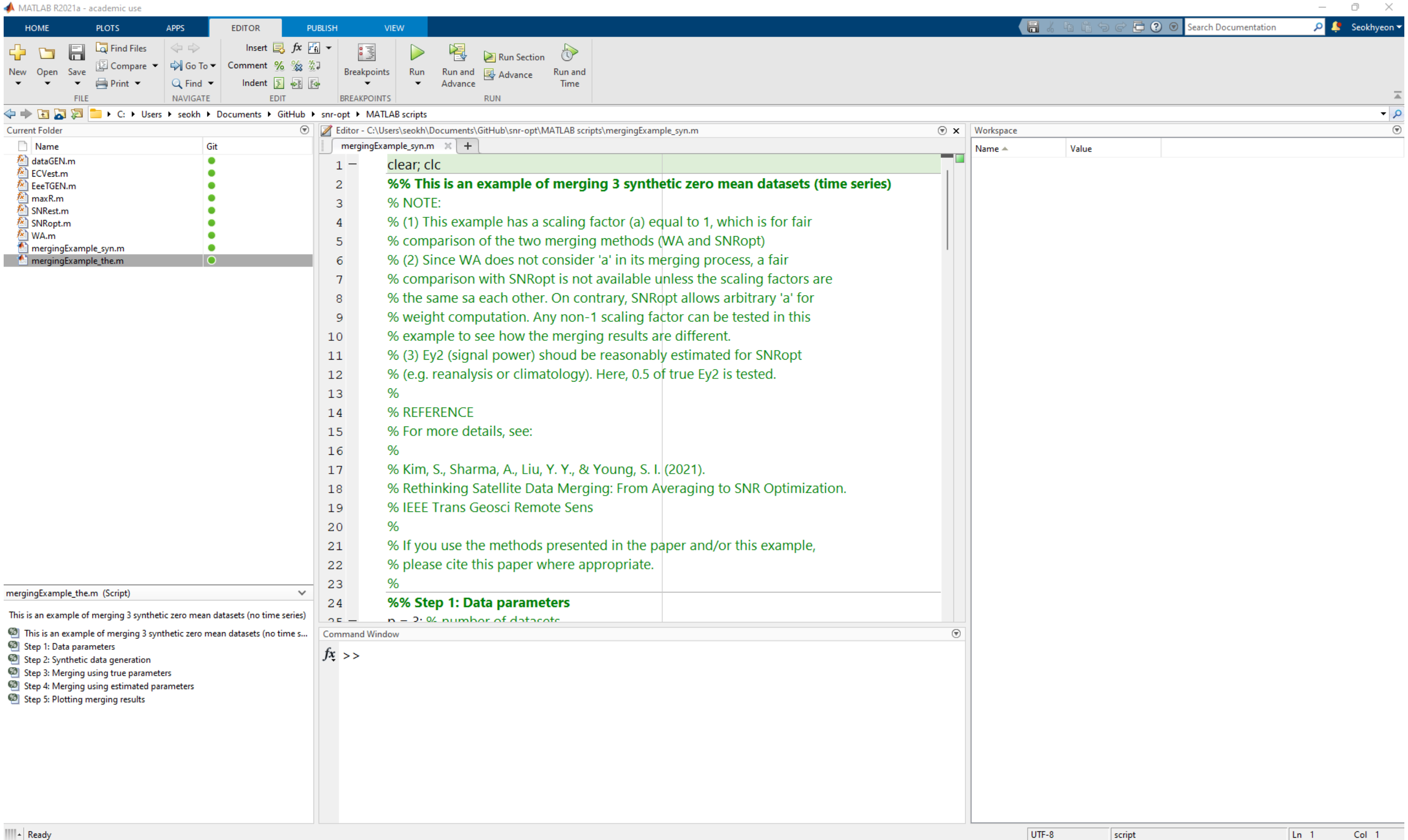
개발된 툴 (1)



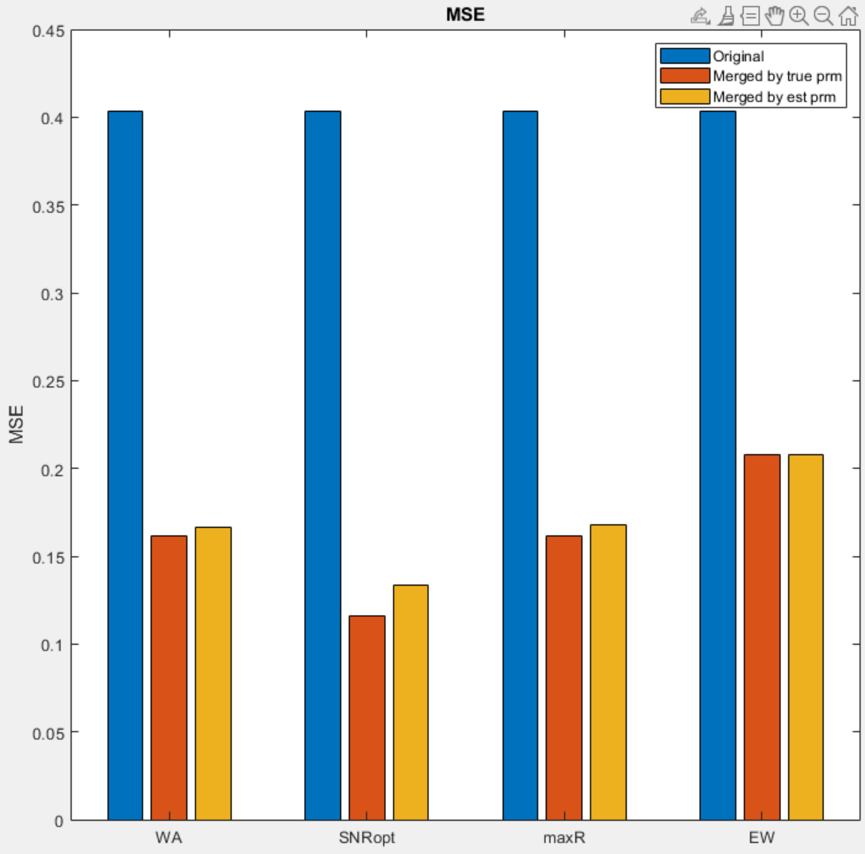


https://github.com/steelpl

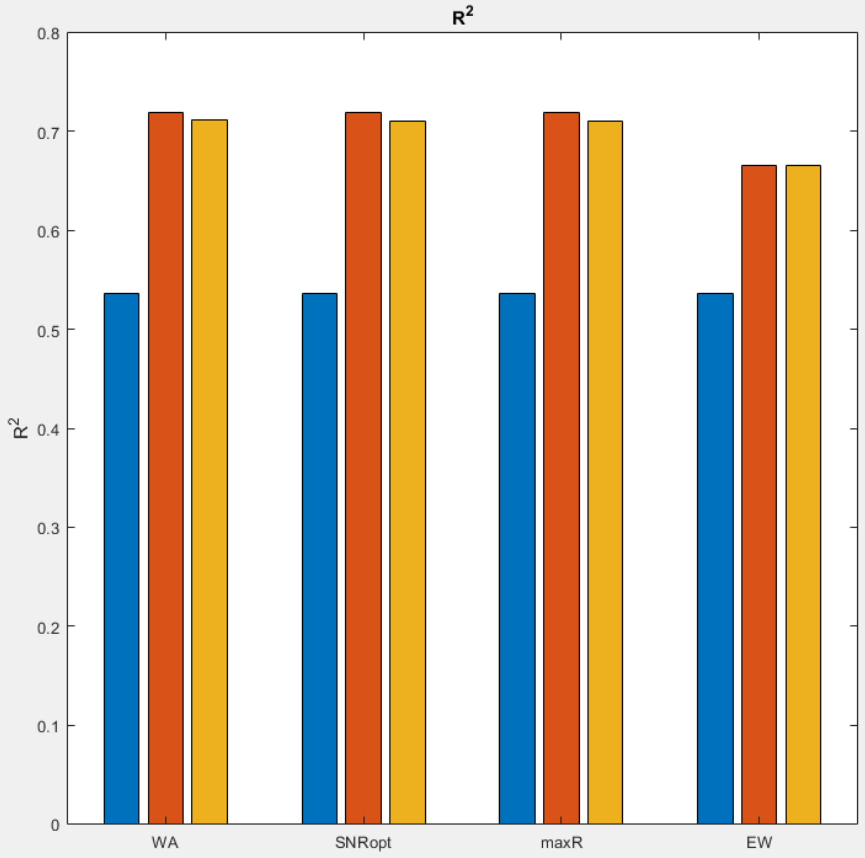
개발된 툴 (2)


MATLAB R2021a - academic use
HOME
PLOTS
APPS
EDITOR
PUBLISH
VIEW
Search Documentation
Seokhyeon
New
Open
Save
Find Files
Compare
Print
FILE
Go To
Find
NAVIGATE
Insert
Comment
Indent
EDIT
Breakpoints
BREAKPOINTS
Run
Run and Advance
Run Section
Advance
Run and Time
RUN
C: ▸ Users ▸ seokh ▸ Documents ▸ GitHub ▸ snr-opt ▸ MATLAB scripts
Current Folder
Name
Git
dataGEN.m
ECVest.m
EeeTGEN.m
maxR.m
SNRest.m
SNRopt.m
WA.m
mergingExample_syn.m
mergingExample_the.m
Editor - C:\Users\seokh\Documents\GitHub\snr-opt\MATLAB scripts\mergingExample_syn.m
mergingExample_syn.m
clear; clc
%% This is an example of merging 3 synthetic zero mean datasets (time series)
% NOTE:
% (1) This example has a scaling factor (a) equal to 1, which is for fair
% comparison of the two merging methods (WA and SNRopt)
% (2) Since WA does not consider 'a' in its merging process, a fair
% comparison with SNRopt is not available unless the scaling factors are
% the same sa each other. On contrary, SNRopt allows arbitrary 'a' for
% weight computation. Any non-1 scaling factor can be tested in this
% example to see how the merging results are different.
% (3) Ey2 (signal power) shoud be reasonably estimated for SNRopt
% (e.g. reanalysis or climatology). Here, 0.5 of true Ey2 is tested.
%
% REFERENCE
% For more details, see:
%
% Kim, S., Sharma, A., Liu, Y. Y., & Young, S. I. (2021).
% Rethinking Satellite Data Merging: From Averaging to SNR Optimization.
% IEEE Trans Geosci Remote Sens
%
% If you use the methods presented in the paper and/or this example,
% please cite this paper where appropriate.
%
%% Step 1: Data parameters
Workspace
Name
Value
mergingExample_the.m (Script)
This is an example of merging 3 synthetic zero mean datasets (no time series)
This is an example of merging 3 synthetic zero mean datasets (no time s...
Step 1: Data parameters
Step 2: Synthetic data generation
Step 3: Merging using true parameters
Step 4: Merging using estimated parameters
Step 5: Plotting merging results
Command Window
fx >>
Ready
UTF-8
script
Ln 1
Col 1

개발된 툴 (3): a=1

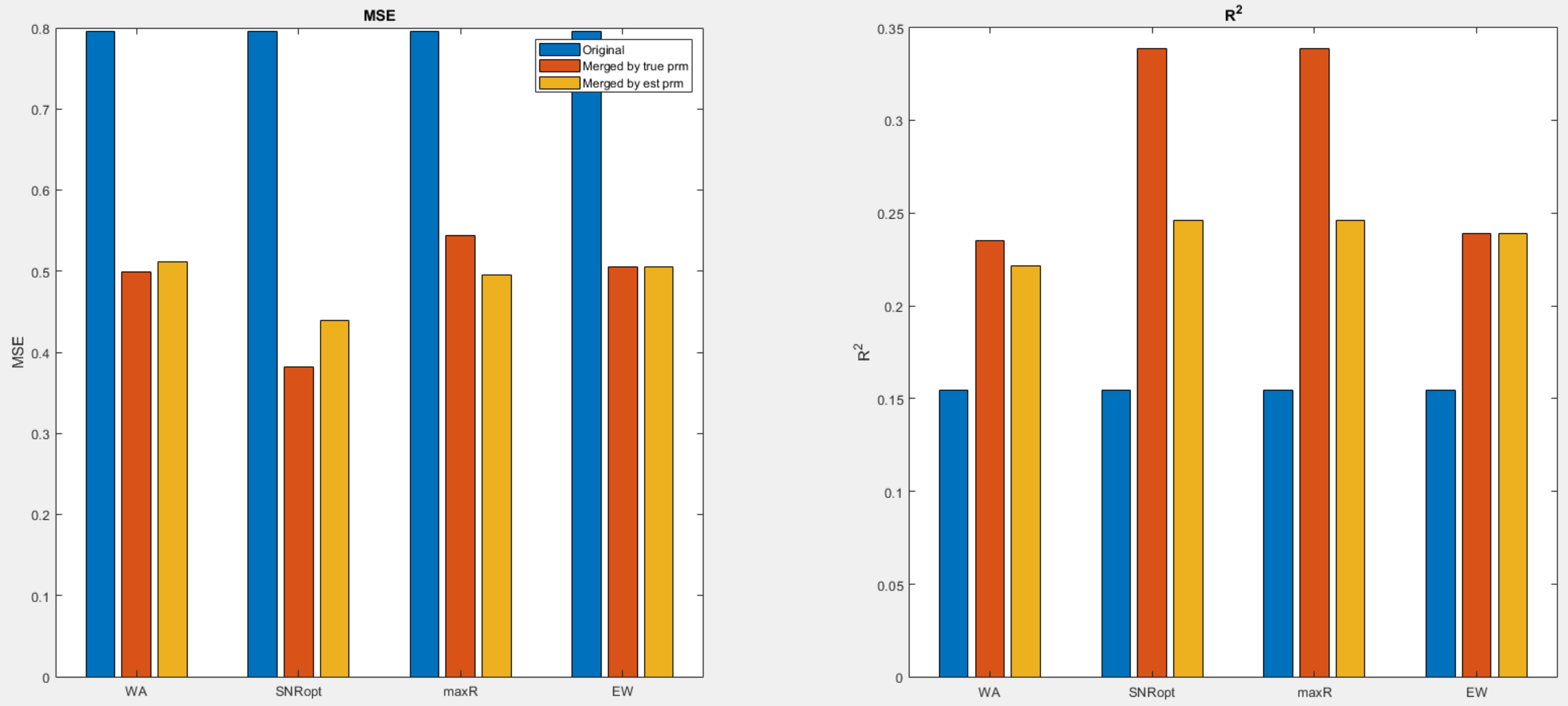


MSE
Original
Merged by true prm
Merged by est prm
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
MSE
WA
SNRopt
maxR
EW



R2
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
R2
WA
SNRopt
maxR
EW

개발된 툴 (4): a≠1



MSE
Original
Merged by true prm
Merged by est prm
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
MSE
WA
SNRopt
maxR
EW
R2
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
R2
WA
SNRopt
maxR
EW

요약

- 기후변화/수자원 연구에서 원격탐사의 역할 증대
- 환경 빅 데이터의 소스, 한국의 세계적 수준의 인공위성 개발능력
- 원격탐사는 기존 관측 체계를 보완/대체할 수 있으나 개선할 필요가 있음
- 데이터 합성은 데이터의 성능을 향상시킬 수 있는 간단하지만 유용한 도구
- 새롭게 제안한 SNR-opt + SNR-est는 기존의 가중평균법보다 나은 성능을 보여줌