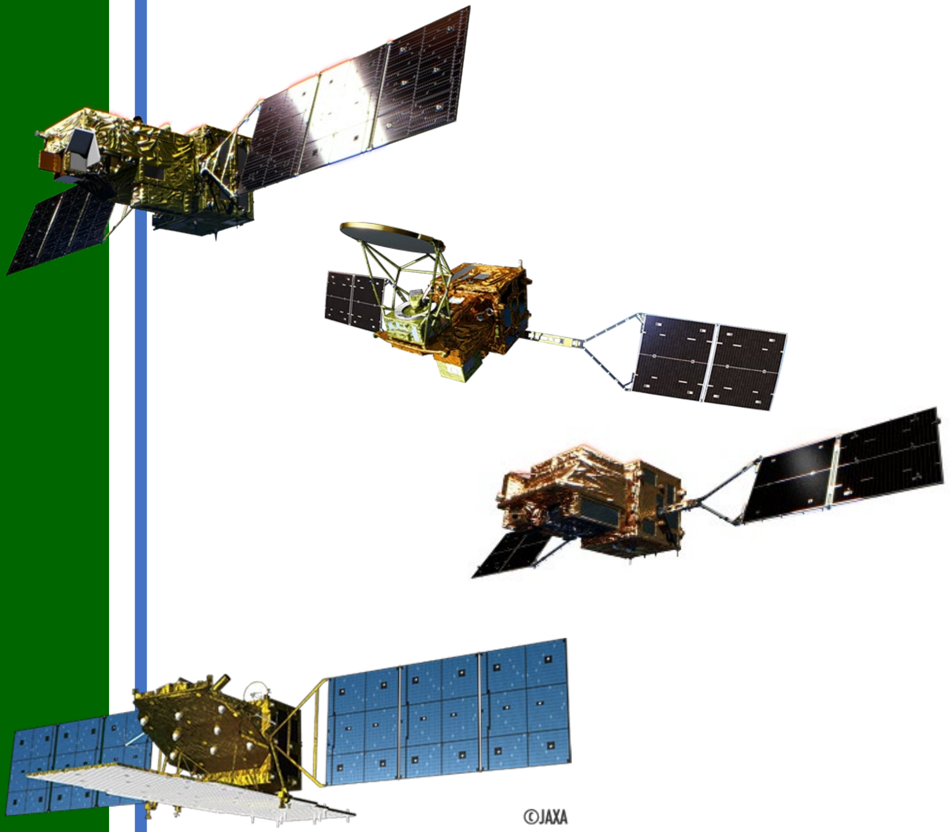
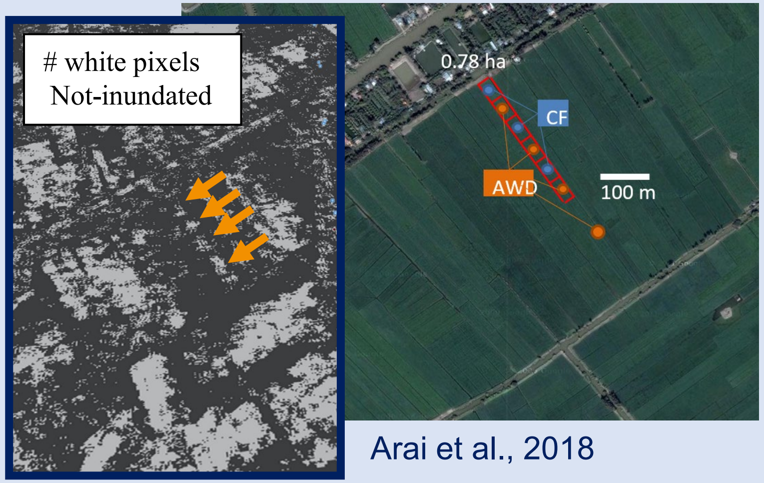
The state of the art of digital-twin technology for sustainable rice production and GHG mitigation



Hironori Arai[1,2], Hung Van Nguyen[1], Thuy LeToan[3], Kei Oyoshi[4], Yoshinobu Kawahara[2], Wataru Takeuchi[5], Kaoru Ichikawa[6], Mehrez Zribi[3], Kim ThuNguyen[7], Nguyen TheCuong[7], Thach NgocTran[7], Tran ThiCamNhung[1], Tamon Fumoto[8], Kazuyuki Inubushi[9], LamDao Nguyen[10], Kengo Shimanoe[6], Shinichi Sobue[4], Bas Bouman[1]

Satellite remote sensing on inundation/phenology



Arai et al., 2018

Satellite rice remote sensing
-> Very well discussed yesterday already!

1:30-5:05	**Session-V: LCLUC, Agriculture and Water Resources** Chair: Chris Justice (University of Maryland College Park)

Keynote Presentation (20-min Presentation; 5-min discussion)

1:30 GEOGLAM and NASA HARVEST Overview – Chris Justice (University of Maryland College Park, USA)

Technical Presentations (15-min Presentation; 5-min discussion)

1:55 Satellite Observations of Changes in Agriculture in the Vietnam Mekong Delta under Human and Climate Pressures - Thuy Le Toan (CESBIO/GlobEO, France)

2:15 Dynamic LULC Mapping For Agriculture In Suphanburi, Thailand Using ALOS-2/PALSAR-2 - Shindai Kanai (University Of Tsukuba, Japan)

2:35 Cropland Mapping Using Landsat Time Series And Land Cover Phenological Pattern Modelling – Nguyen Dinh Duong (Institute Of Geography, VAST, Vietnam)

2:55 Understanding Agricultural Land System By Using Big Remote Sensing Data, Cloud Computing, And Novel Algorithms - Jinwei Dong (Chinese Academy Of Sciences, China)

3:15 Remote Sensing Applications In Rice Production In The Vietnamese Mekong Delta -Nguyen Lam-Dao (Vietnam National Space Center Vietnam, Vietnam)

3:35-4:05

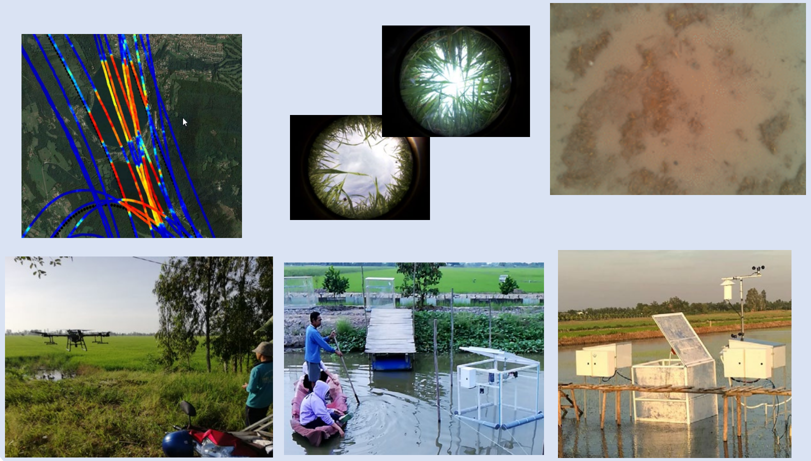
Tea Break

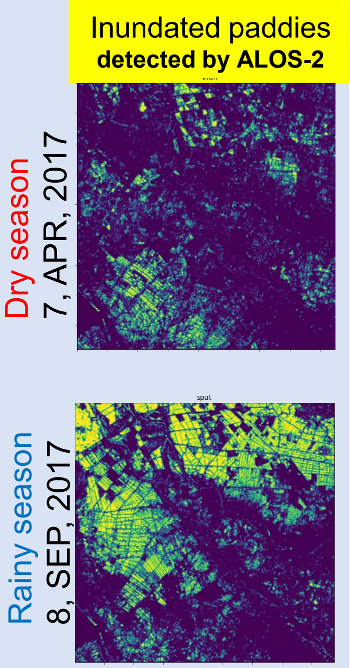
4:05 Assessing Spatial Patterns Of Environmental Consequences Of Hydro Dams In The Mainland Southeast Asia - Jiaguo Qi (Michigan State University, USA)

4:25 Panel Discussion And Open Forum Session – Needs And Priorities For Agriculture LCLUC Synthesis Studies. Panel Lead – Chris Justice (UMd). Panel members: Pat Yeh (Malaysia); Lam Dao Nguyen (Vietnam), Tanapat Tanaratkiattikul (Thailand), Hiranori Arai (The Philippines)

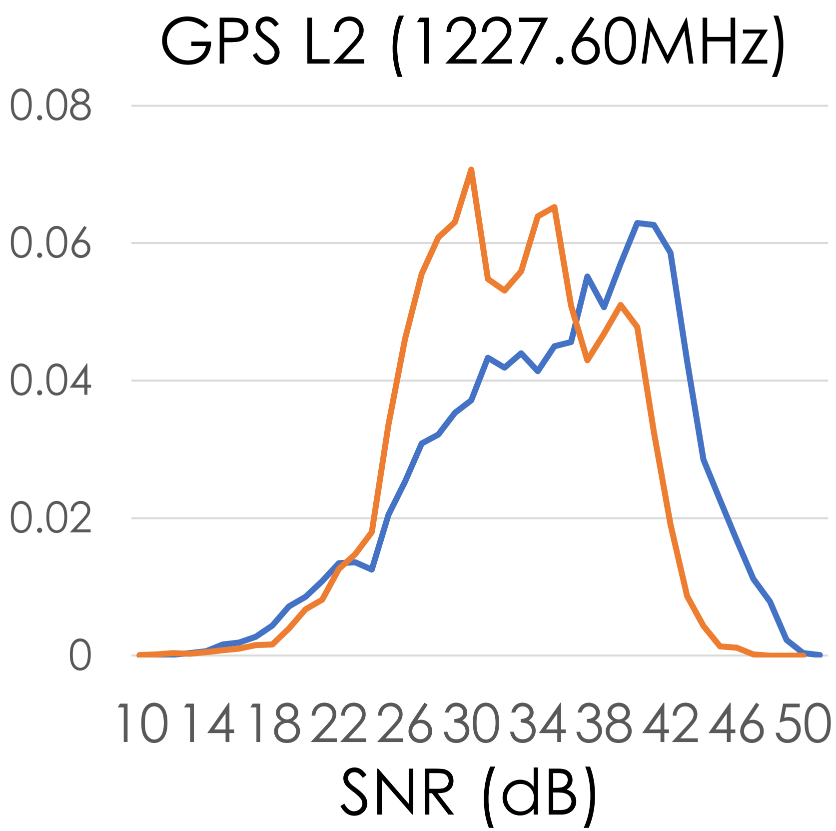
Monitoring by farmers!
Reporting by farmers!
Verification by farmers!

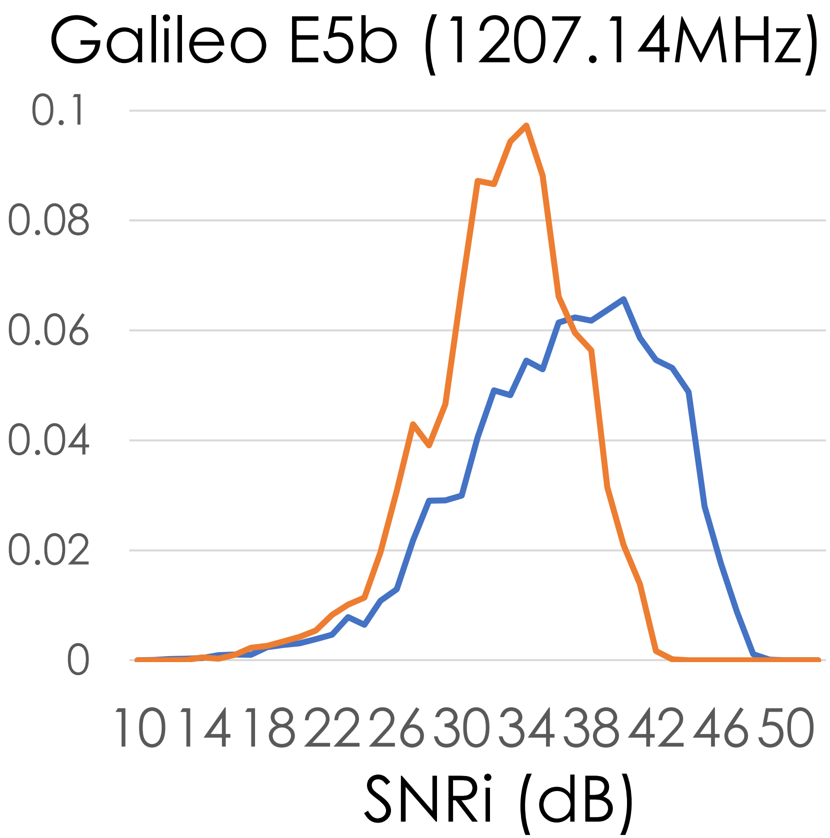
low cost UAV & IoT tech.





Drone, Finally! *- preliminary GNSS-R test -* *Towards RADAR remote sensing by farmers !*





CF (inun. paddies)
AWD (inun. + non-inun.)

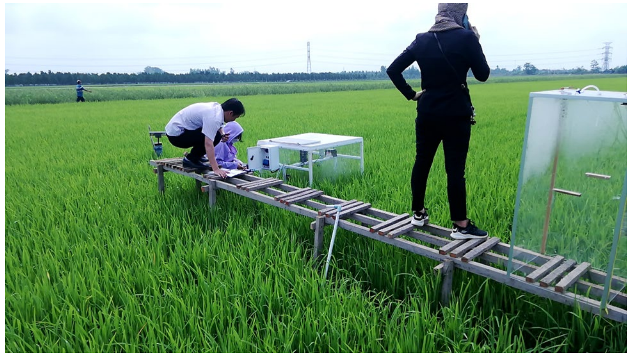
9th and 12th Jan. 2024
40 - 43 DAS
(reproductive stage)

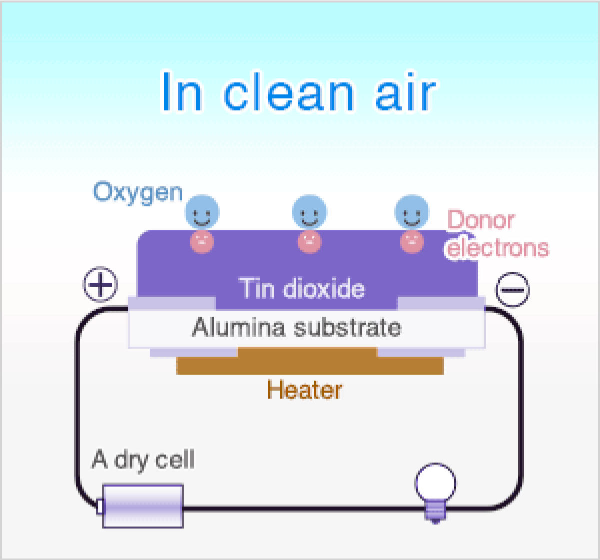
 # Note

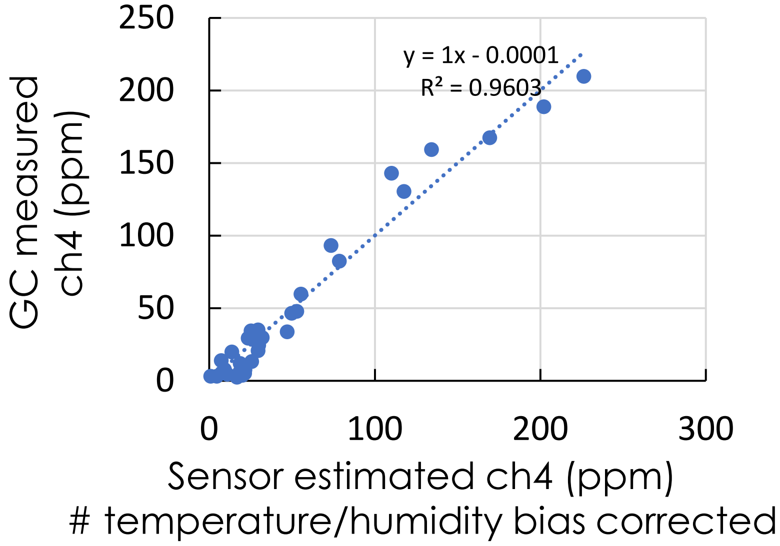
- Composites of SPs with varied **incidence-angle (0-85 degree)** and delay time were plotted here without any of correction/normalization/QC ***-> delay/incidence-angle mapping and correl. Power analysis, altimetry approach***

Low cost Waterlevel & CH4 automated wireless chambers

All electrical components commercially available for VN farmers







Noboru Yamazoe, Kengo Shimanoe, Basic approach to the transducer function of oxide semiconductor gas sensors, Sensors and Actuators B 160 (2011) 1352-1362

$$R = \frac{R_S}{R_0} = \frac{\left(\frac{V_C}{V_L} - 1\right)}{\left(\frac{V_C}{V_0} - 1\right)}.$$

$$CH_4 = aR^b + cH(aR^b) + dT(aR^b) + K$$

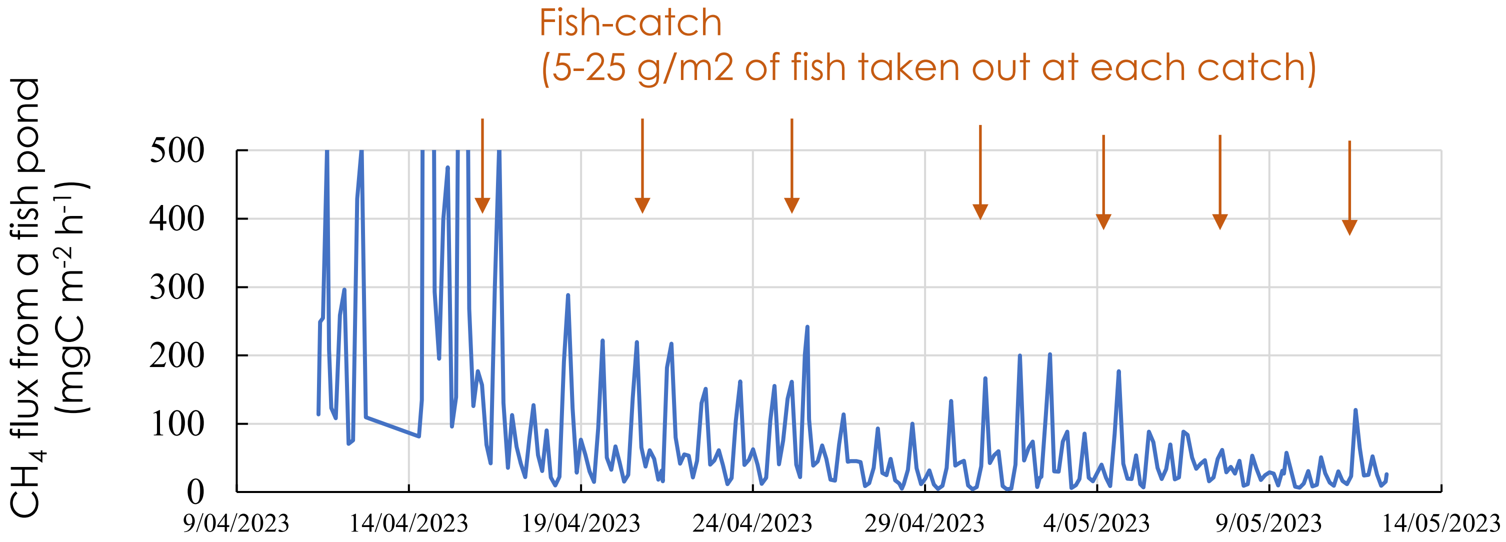
Diel variability of methane emissions from lakes

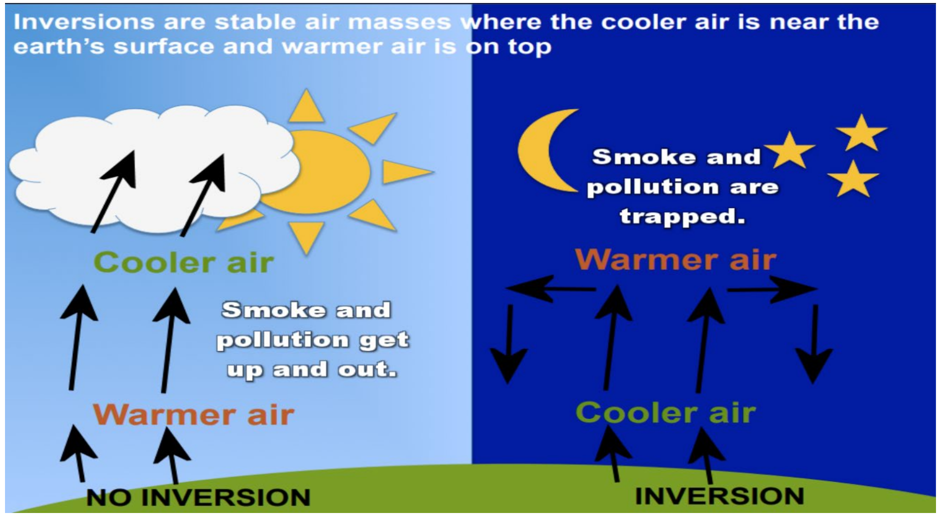
Anna K. Sieczko[a,1], Nguyen Thanh Duc[a], Jonathan Schenk[a], Gustav Pajala[a], David Rudberg[a], Henrique O. Sawakuchi[a,b], and David Bastviken[a]

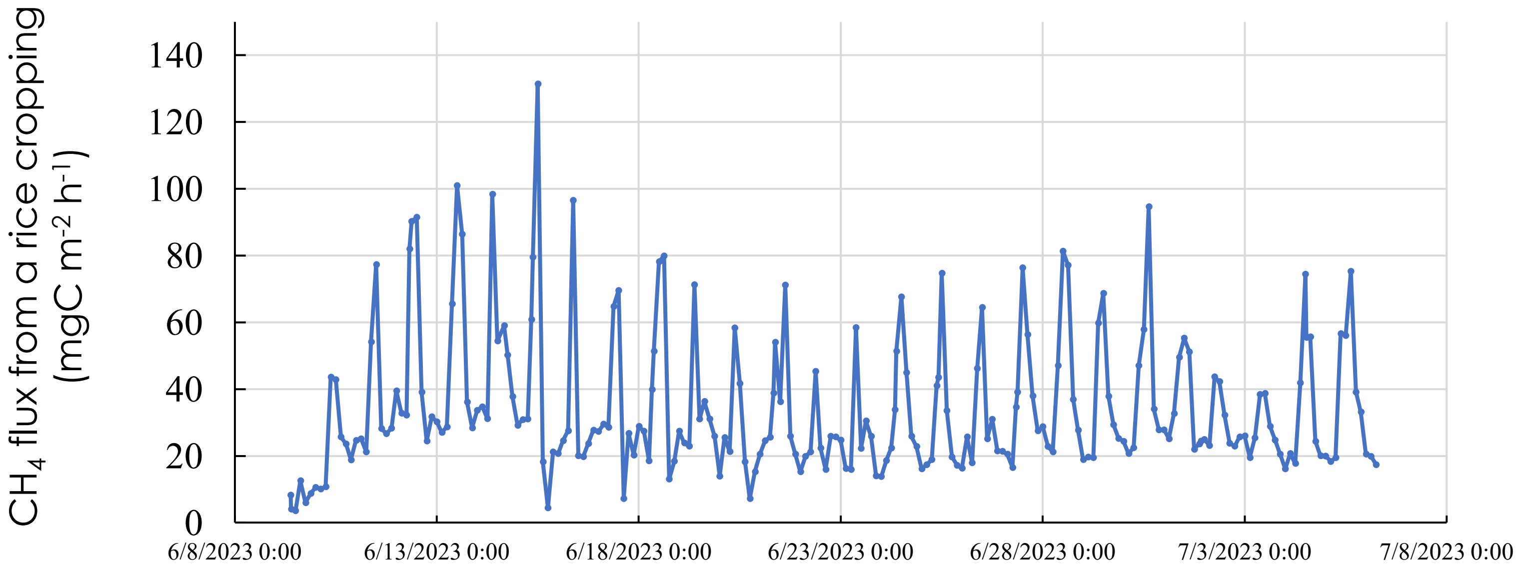
[a]Department of Thematic Studies–Environmental Change, Linköping University, 58183 Linköping, Sweden; and [b]Department of Ecology and Environmental Sciences, Umeå Universitet, 901 87 Umeå, Sweden

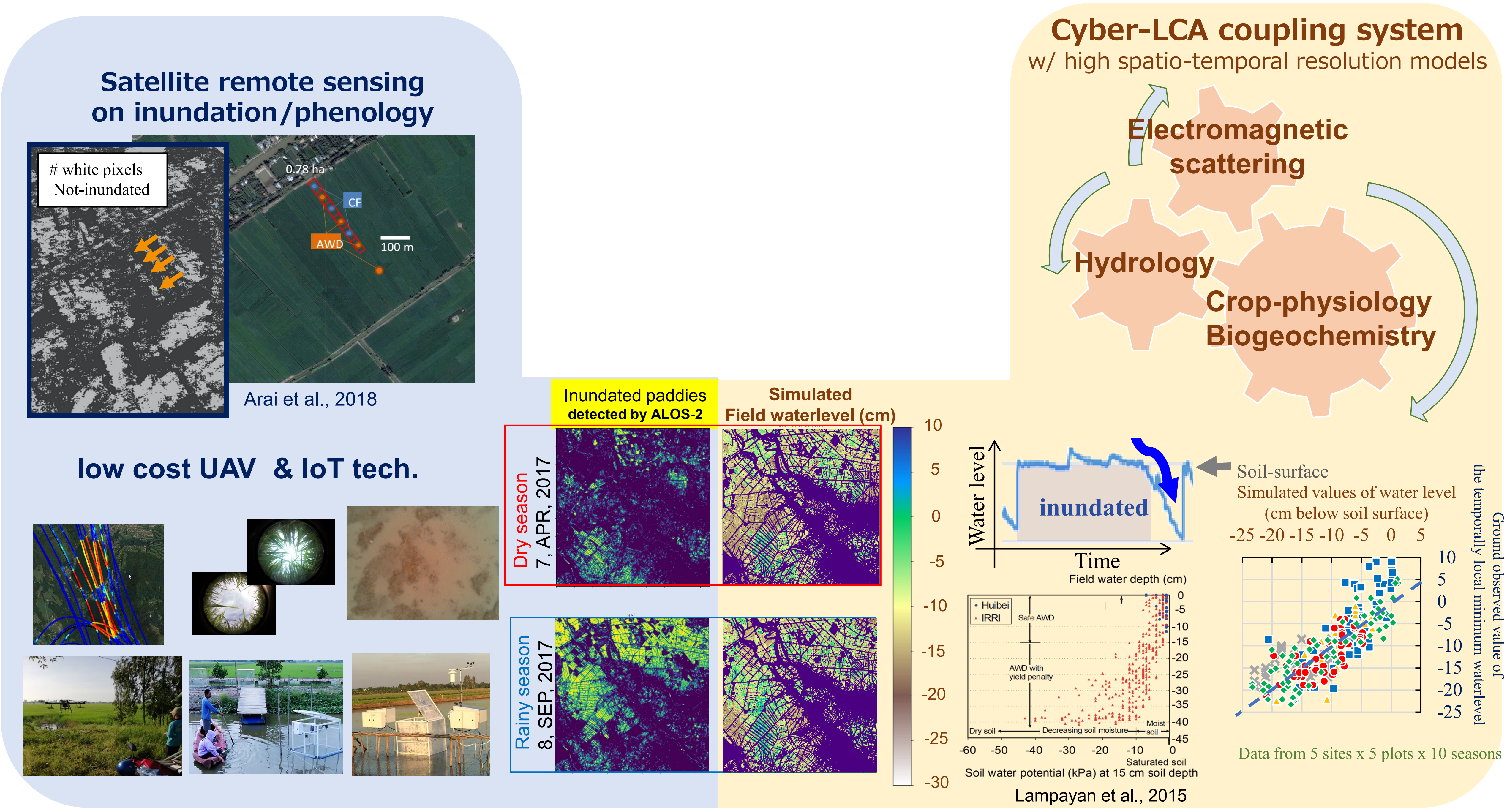
Towards Monitoring/Reporting/Verification by farmers !

CH4 emission observation from a Rice-fish rotation system w/ low-cost wireless automatic chamber









Satellite remote sensing
on inundation/phenology
white pixels
Not-inundated
0.78 ha
CF
AWD
100 m
Arai et al., 2018
low cost UAV & IoT tech.
Inundated paddies
detected by ALOS-2
Simulated
Field waterlevel (cm)
Dry season
7, APR, 2017
Rainy season
8, SEP, 2017
10
5
0
-5
-10
-15
-20
-25
-30
Cyber-LCA coupling system
w/ high spatio-temporal resolution models
Electromagnetic
scattering
Hydrology
Crop-physiology
Biogeochemistry
Water level
inundated
Time
Soil-surface
Simulated values of water level
(cm below soil surface)
-25 -20 -15 -10 -5 0 5
Ground observed value of
the temporally local minimum waterlevel
Data from 5 sites x 5 plots x 10 seasons
Field water depth (cm)
Huibei
IRRI
Safe AWD
AWD with
yield penalty
Dry soil
Decreasing soil moisture
Moist
soil
Saturated soil
Soil water potential (kPa) at 15 cm soil depth
-60 -50 -40 -30 -20 -10 0
Lampayan et al., 2015

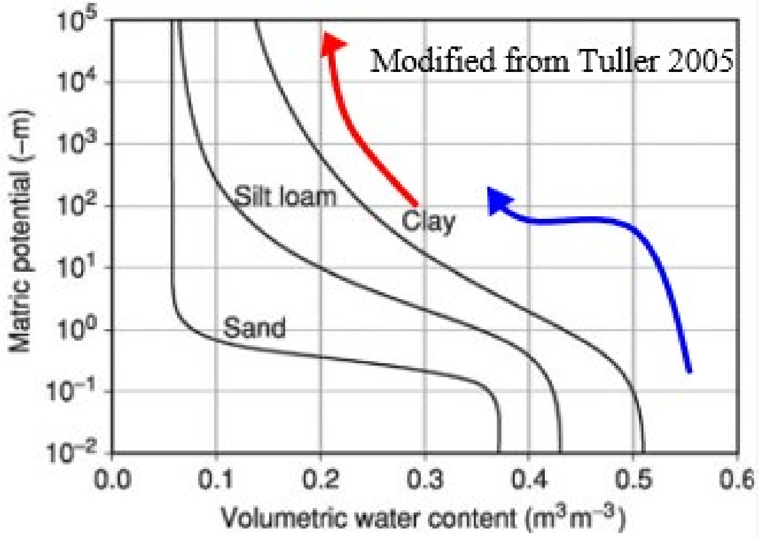
DNDC-rice-SWAT 2/3D model for Hybrid optimization system w/ SAR&GNSS-R observations

- lateral seepage ->3D simulation
- soil water suction/swelling scheme extension
  dynamic hydraulic conductivity
  dynamic bulk density

-> optimization by different scale observation GNSS-R and SAR simultaneously

Saturated swelling soil causing soil water desorption

Unsaturated shrinking soil causing soil water suction



Preparation of non-autonomous hydrological model experiment for rice paddy

A conservation equation for quantity q in two dimensions may be written as

$$\frac{\partial q}{\partial t} + \frac{\partial (uq + U)}{\partial x} + \frac{\partial (vq + V)}{\partial y} = Q, \qquad (1)$$

where Q represents any sources of q, and U and V represent any terms with spatial derivatives that depend on the prognostic variables in the model. In a shallow water context and in the absence of any sources, we wish to conserve the total volume and the total momentum in each direction, so want conservation equations for h, uh and vh. Therefore, the shallow water equations in conservative (or flux) form may be written as:

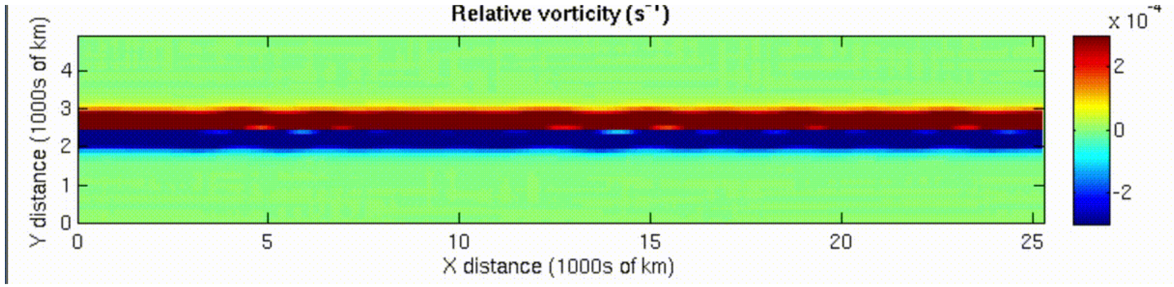
$$\frac{\partial h}{\partial t} + \frac{\partial (uh)}{\partial x} + \frac{\partial (vh)}{\partial y} = 0, \qquad (2)$$

$$\frac{\partial (uh)}{\partial t} + \frac{\partial (u^2 h + gh^2/2)}{\partial x} + \frac{\partial (uvh)}{\partial y} = h\left(fv - g\frac{\partial H}{\partial x}\right), \qquad (3)$$

$$\frac{\partial (vh)}{\partial t} + \frac{\partial (uvh)}{\partial x} + \frac{\partial (v^2 h + gh^2/2)}{\partial y} = h\left(-fu - g\frac{\partial H}{\partial y}\right), \qquad (4)$$

where f is the Coriolis parameter and g is the accelleration due to gravity. In this model, the Coriolis parameter is modelled as varying linearly with y such that $f = f_0 + \beta(y - \bar{y})$. Thus $f = f_0$ in the middle of the domain in the y direction. The pressure gradient terms have been put within the spatial derivatives on the left-hand side.

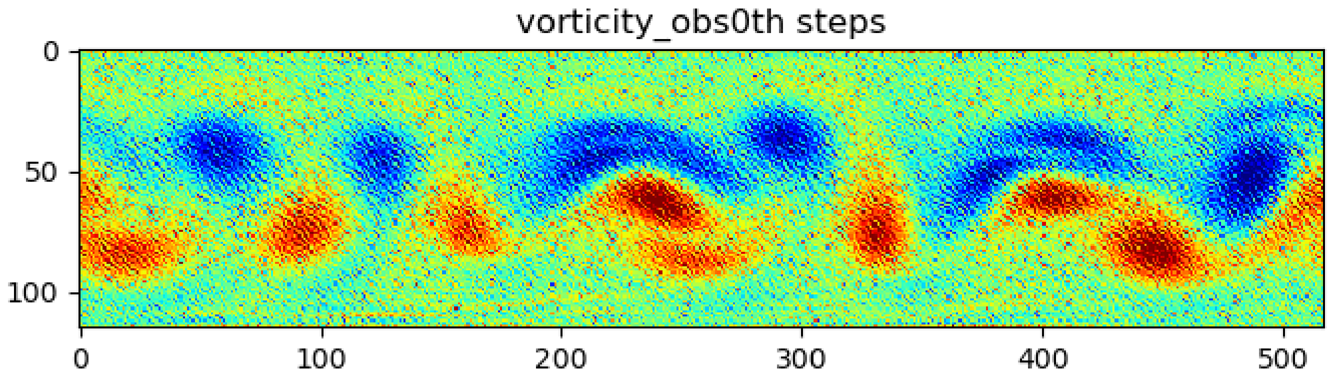
percolation, et -> *g*: Gravity
seepage -> *f*: Coriolis



Simulation

4th order runge kutta + 2nd order Lax-Wendroff

Spatiotemporal noise on 2 parameters (*g*,*f*)
(50 percent gaussian noise)



Localization on extended-DMD for non-autonomous rice system

Inspiration from Li & Jiang 2023

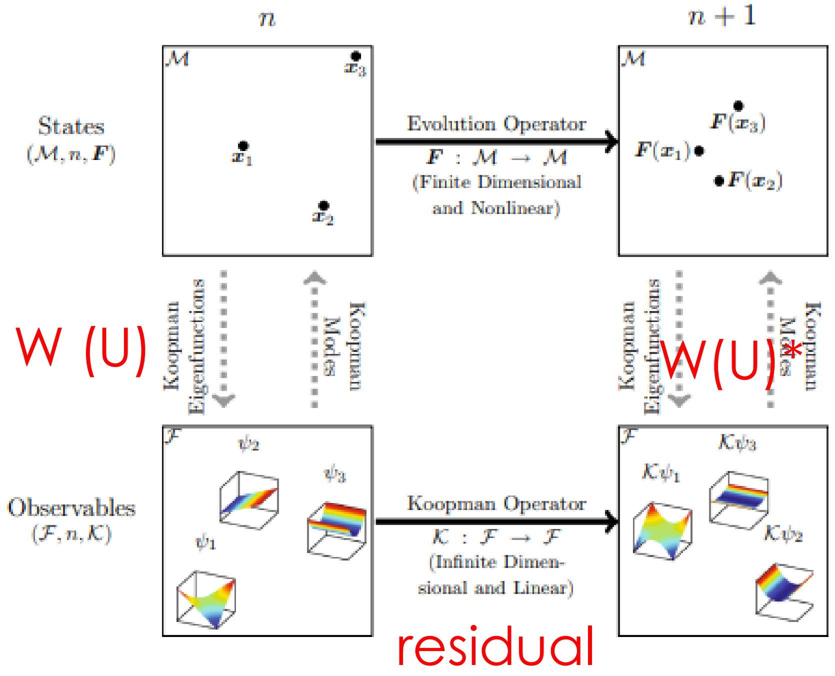
If $\{\lambda_i^{t,t_0}, \mathbf{w}_i^{t,t_0}, \mathbf{v}_i^{t,t_0}\}_{i=1}^{q}$ *are the triple of the eigenvalues, left and right eigenvectors of the matrix* $\mathbf{K}^{t,t_0}$*, then*

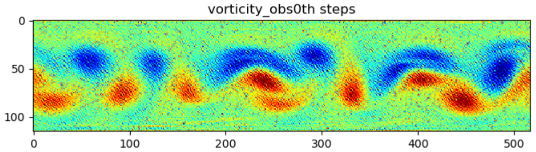
$$\varphi_i^{t,t_0}(z) = (\mathbf{w}_i^{t,t_0})^T \mathbf{g}(z)$$

are the eigenfunctions of the approximate nonautonomous Koopman operator $\mathcal{K}_p^{t,t_0}$ *corresponding to eigenvalues* λ_i^{t,t_0}, $i = 1, 2, \cdots, q$.
Moreover, if matrices $\mathbf{L}(t)$ *commute and are diagonalizable, with eigenvalues* $\theta_i(t)$ *and the corresponding left eigenvectors* $\mathbf{w}_i$*, then*

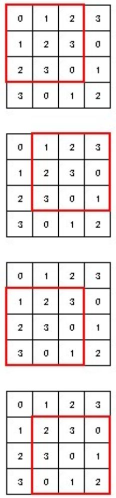
$$\lambda_i^{t,t_0} = \exp\left(\int_{t_0}^{t} \theta_i(\tau)d\tau\right), \quad \mathbf{w}_i^{t,t_0} = \mathbf{w}_i.$$

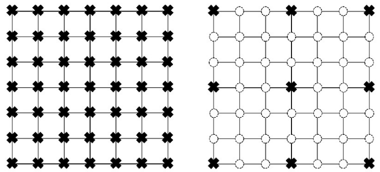
No need to obtain V -> ***compatible with randomized SVD***



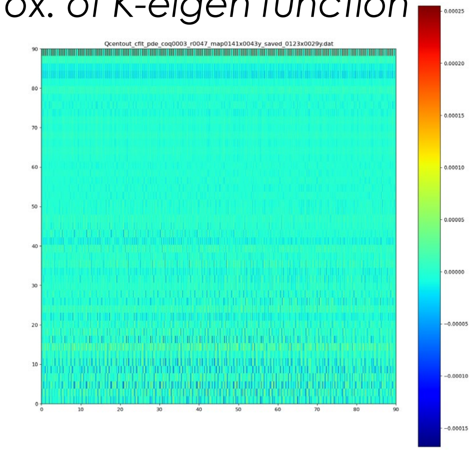


Dilated Convolution & interpolation!

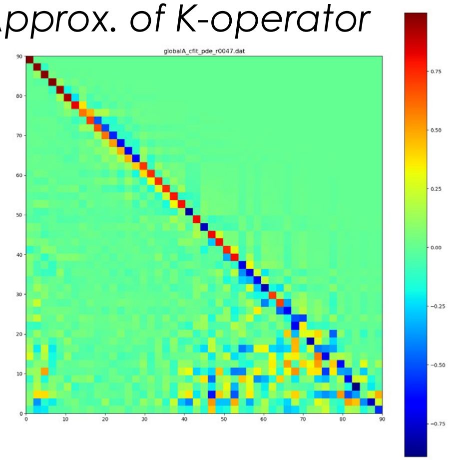




Approx. of K-eigen function



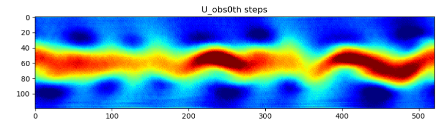
Approx. of K-operator



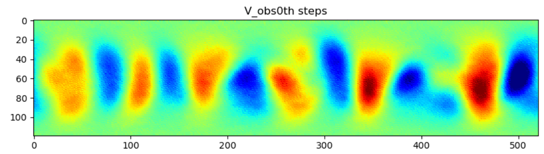
Memory saving!

truth

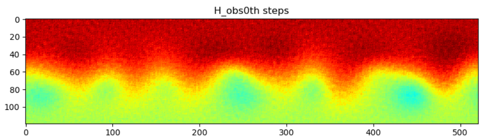
U



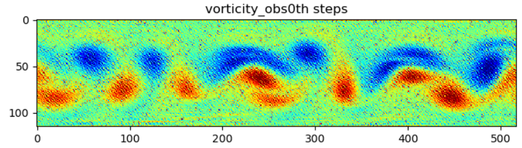
V



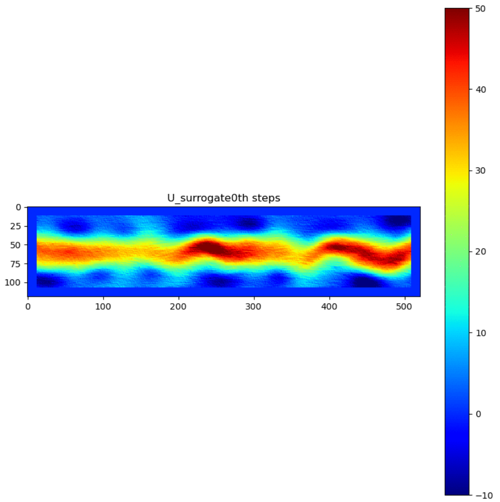
H

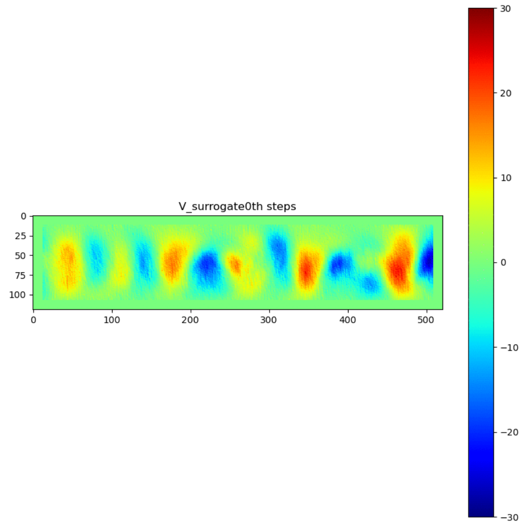


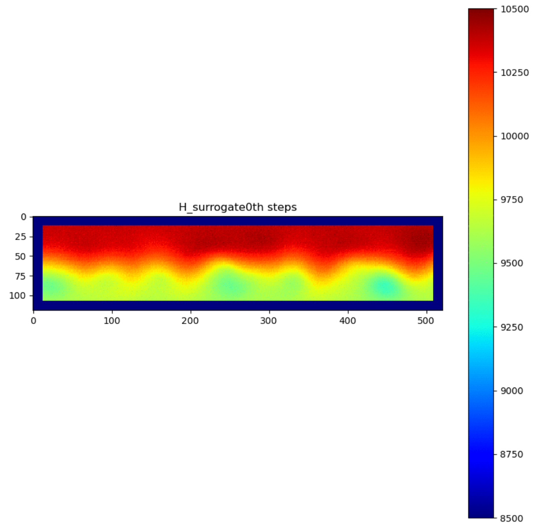
vorticity

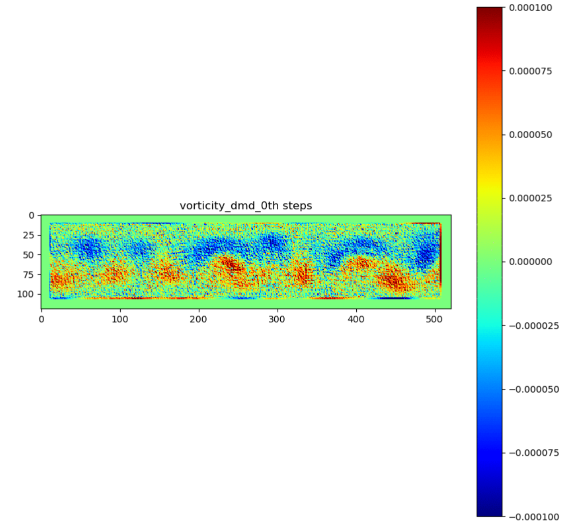


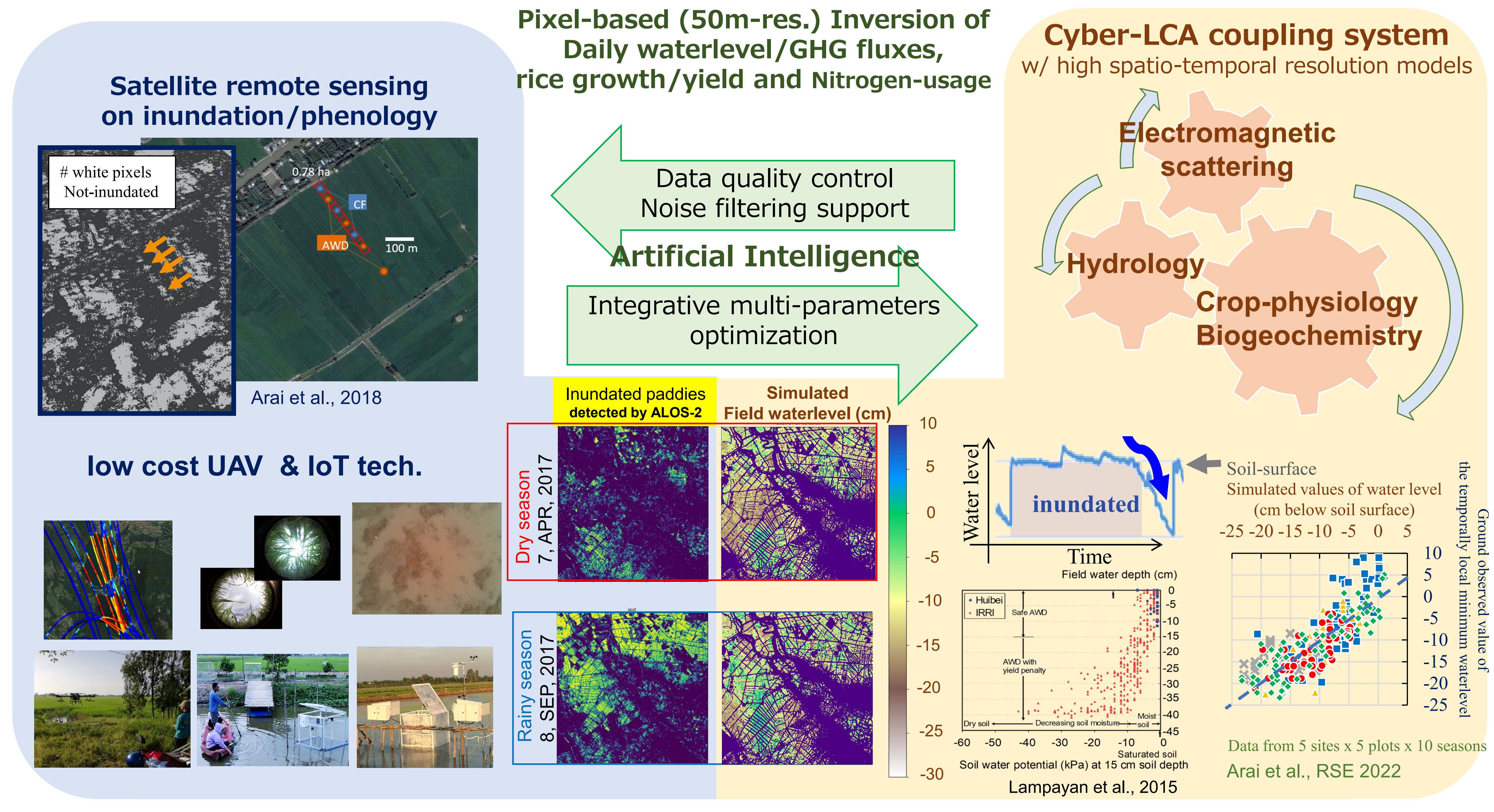
Localized-EDMD (10% SVD-truncation, 2 grid strides/interpolation)











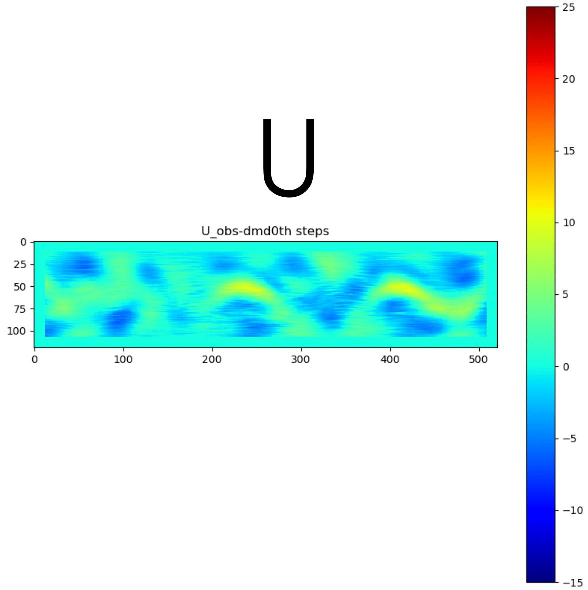
Pixel-based (50m-res.) Inversion of
Daily waterlevel/GHG fluxes,
rice growth/yield and Nitrogen-usage
Satellite remote sensing
on inundation/phenology
white pixels
Not-inundated
0.78 ha
CF
AWD
100 m
Arai et al., 2018
Data quality control
Noise filtering support
Artificial Intelligence
Integrative multi-parameters
optimization
Cyber-LCA coupling system
w/ high spatio-temporal resolution models
Electromagnetic
scattering
Hydrology
Crop-physiology
Biogeochemistry
low cost UAV & IoT tech.
Inundated paddies
detected by ALOS-2
Simulated
Field waterlevel (cm)
Dry season
7, APR, 2017
Rainy season
8, SEP, 2017
10
5
0
-5
-10
-15
-20
-25
-30
Water level
inundated
Time
Soil-surface
Simulated values of water level
(cm below soil surface)
-25 -20 -15 -10 -5 0 5
Ground observed value of
the temporally local minimum waterlevel
Field water depth (cm)
Huibei
IRRI
Safe AWD
AWD with
yield penalty
Dry soil
Decreasing soil moisture
Moist
soil
Saturated soil
-60 -50 -40 -30 -20 -10 0
Soil water potential (kPa) at 15 cm soil depth
Lampayan et al., 2015
Data from 5 sites x 5 plots x 10 seasons
Arai et al., RSE 2022

Bias/non-linearity (i.e., truth - EDMD surrogate)

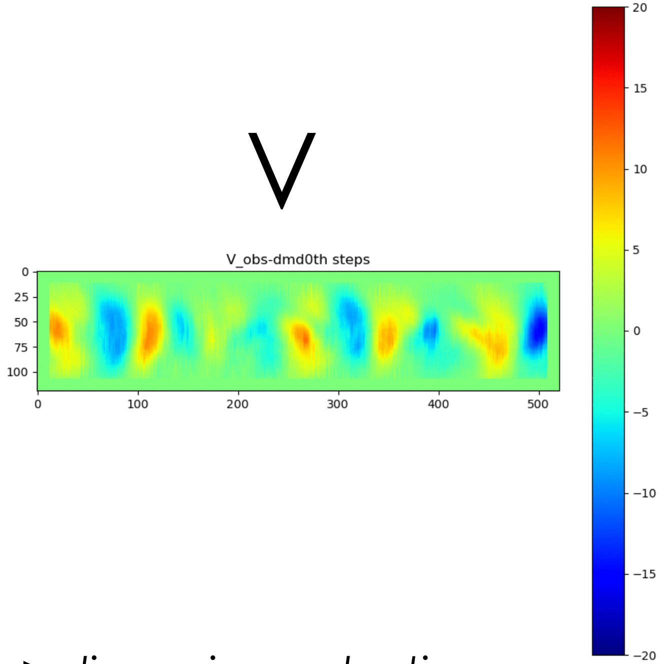
-> Back ground error covariance computation in flow dependent

-> for rejuvenation of LPF

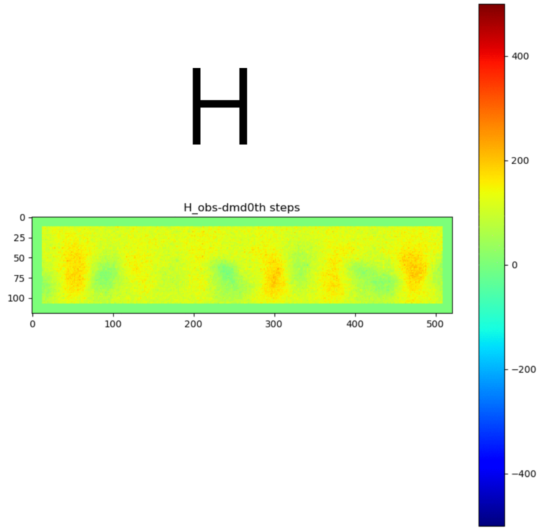
U



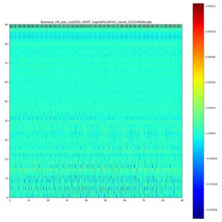
V

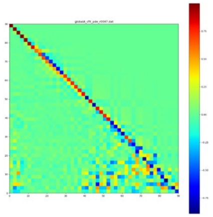


H



Approx. of K-eigen function / operator -> dimension reduction





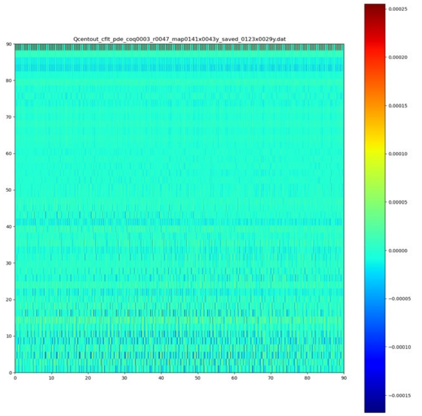
- ➔ Resampling in reduced dimension for LPF
- ➔ TLM/ADJ/Simplification operator for 4DVAR
- ➔ Hybrid LPF-EDMD-4DVAR!

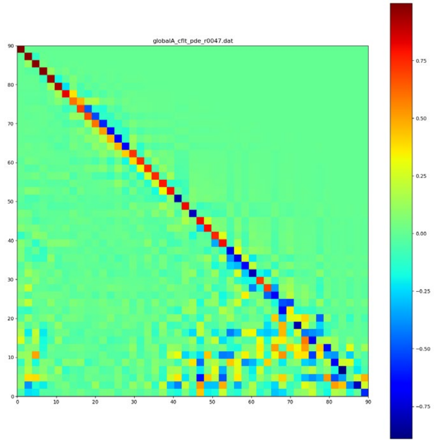
$$\hat{A}\Psi = a\Psi$$

Hybrid with deep dictionary learning

DA w/ parameter estimation

- changes in the attractor



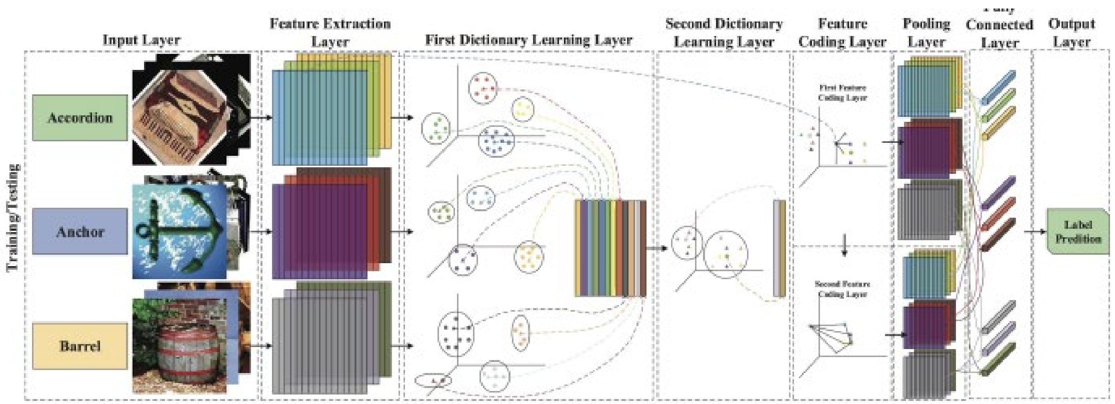


States updated by DA

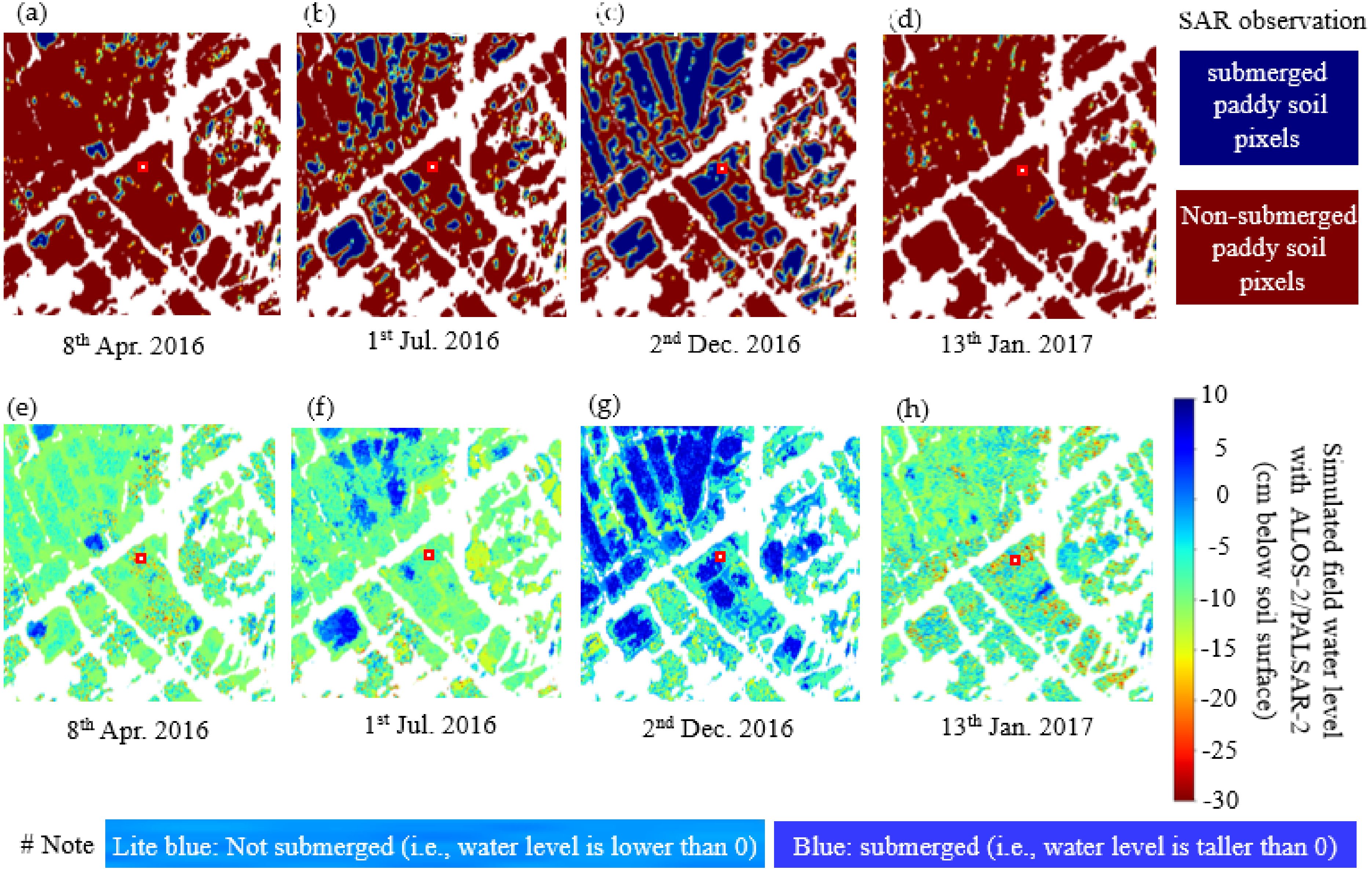
- separation from the attractor

Prediction of DA-increment on eigen-function and K-matrix

-> deep dictionary learning

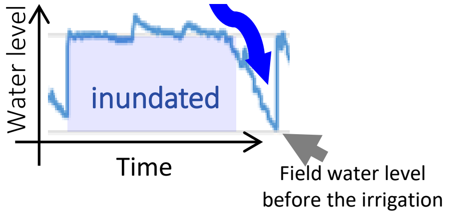


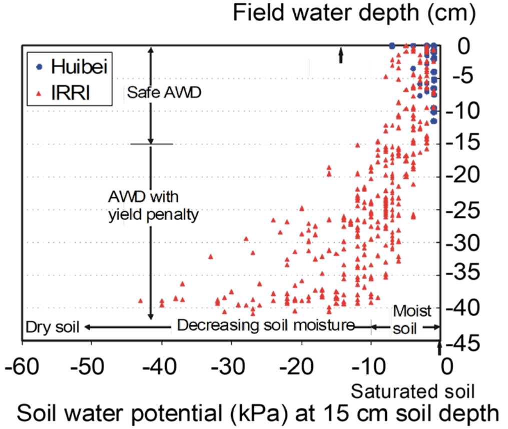
SAR data assimilation of field water level simulation

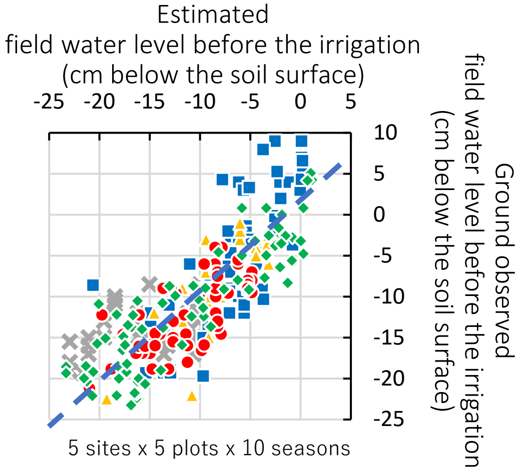


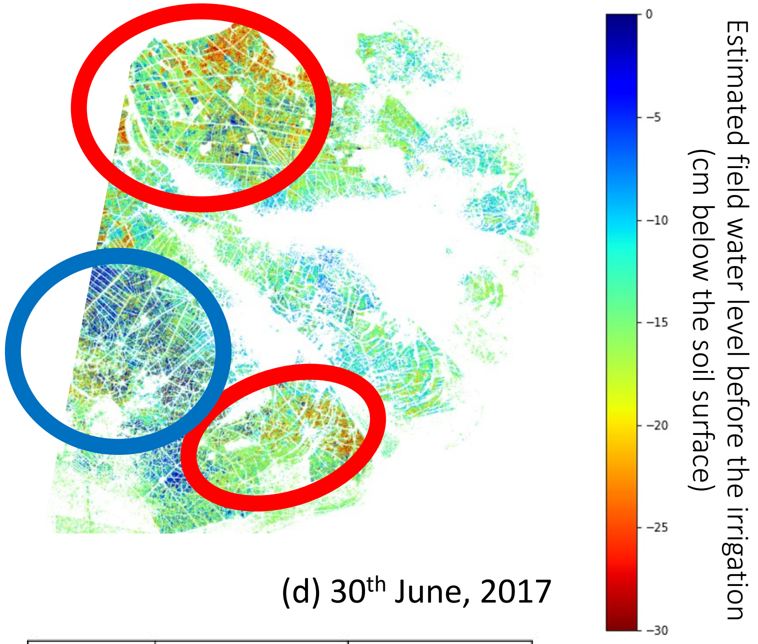
Arai et al., RSI 2022

How deep the field water was dropped by next irrigation?
– Estimation by DA model parameter estimation -

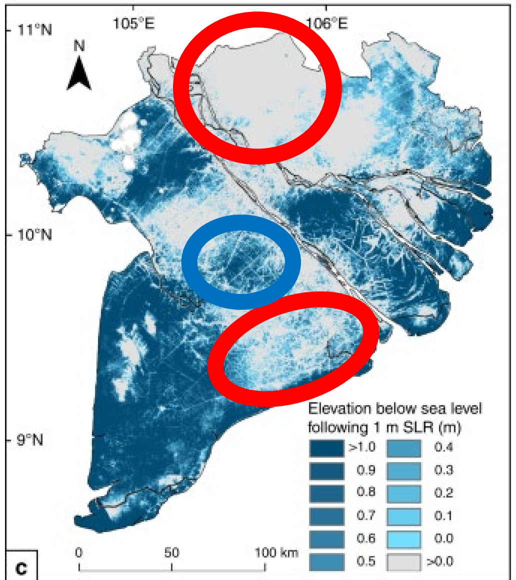


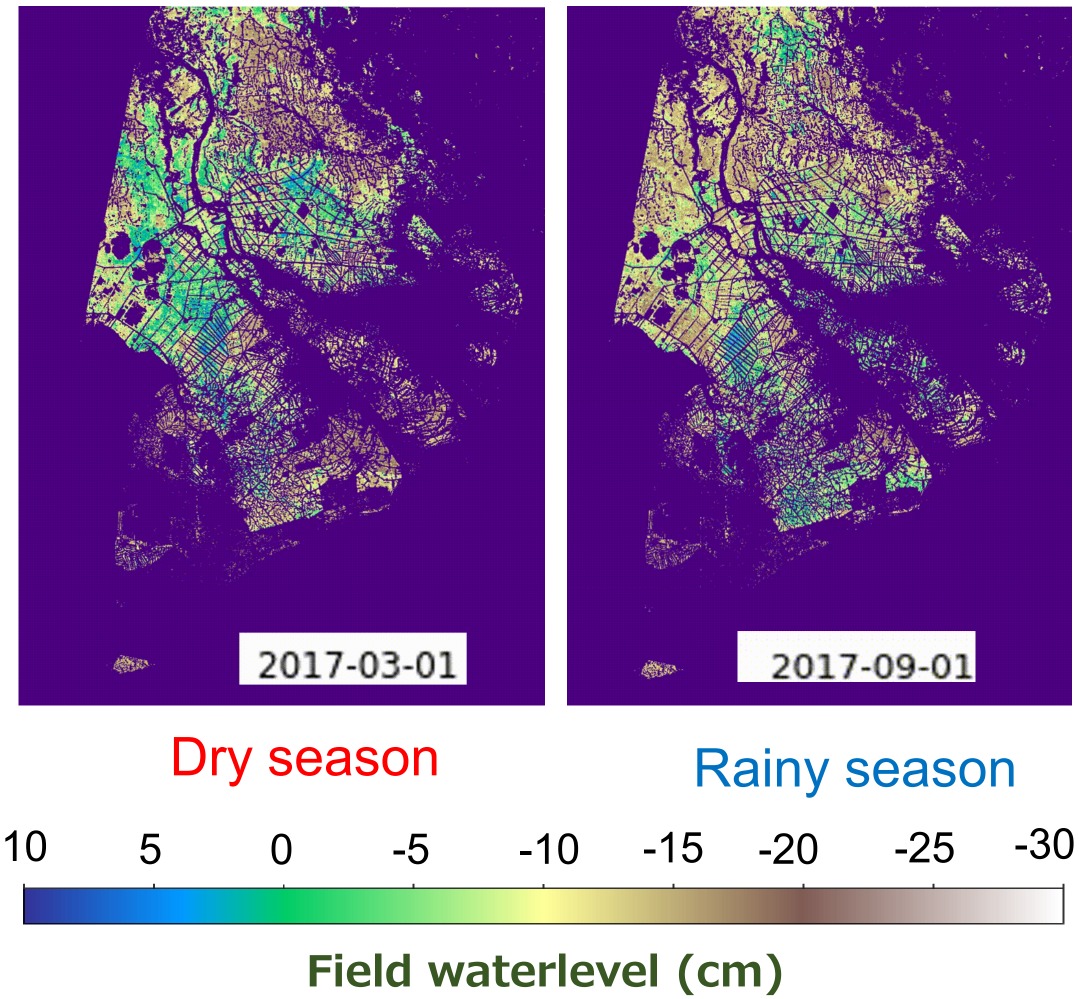






(d) 30th June, 2017





Arai et al., RSE 2022

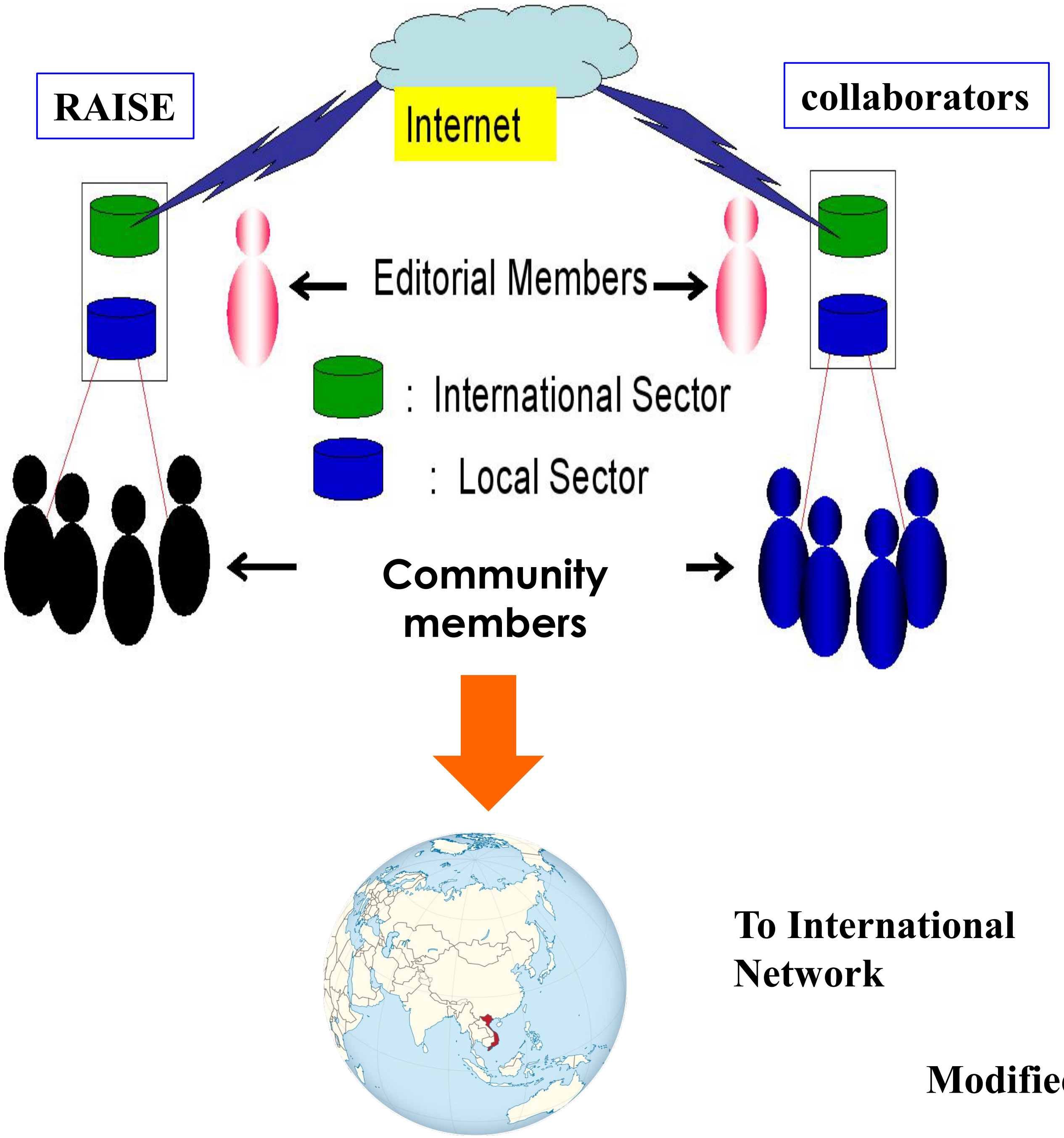
AI algorithm designed for rice, the non-autonomous dynamic system

-> can be used not only for improvement of simulation/model optimization with RS data,
but also for tractors' system-identification/automatic-driving, decision-making with carbon credit

IRRI

Remote sensing & AI System for agricultural Extension (RAISE)

- calling for an AI scientist globally -



Modified from Osaki 2015

Conclusion

The problem/gaps of current public/commercial MRV systems

- Lack of **Transparency** and **permanence**

Technology to address and what it can help

- Low cost IoT monitoring system development and implementation by farmers.
- Satellite/IoT data based digital-twin technology to evaluate/project anthropogenic impacts.
- Real time decision making support with different scale stake-holders.

What's next

- Decision support system based on evidence/BIG-data
  (seamless integration from monitoring to decision-making among different scale stake-holders).
- Multi-variate decision making criteria across different disciplines/scales.