23-24 Jan 2023

Training Workshop to PMFBY Stake holders

YES-TECH

Yield Estimation System based on Technology

Outline of this presentation

- Technology interventions in PMFBY in recent years – a quick recap
- New initiatives from 2023
- YES-TECH
    - Rationale
    - Brief overview of approaches
    - Key considerations
    - Implementation framework
    - Other issues

Way forward

Technology Interventions in PMFBY: Recap

2016
- Road map for Technology Solutions defined
- Introduction of smart phones to monitor CCE system

2017
- SOP for Yield dispute resolution
- R&D for Smart Sampling

2018
- CCE-Agri App
- Smart Sampling Technique (SST) in Odisha
- R&D studies on CCE optimisation

2019
- Nation wide roll-out of SST
- R&D studies on Tech. based yield estimation

2020
- Revamped PMFBY
- Scaled-up Technology based Yield estimates

2021
- Tech. based yld. estimation pilots to non-cereal crops

2022
- Introduction of Tech. based yield estimation in to PMFBY

2023 plans
- YES-TECH
- WINDS
- CROPIC

Technology interventions: near-future plans

2023-24

Next level of Technology adoption

- Data driven and evidence based crop loss assessments
- Reduce dependency on manual assessments
- Automation, Transparency, timeliness and cost effectiveness

Three major initiatives

YES-TECH — Yield Estimation System based on Technology

I. Nation wide implementation of technology based yield estimation

WINDS

II. Augmentation of weather data infrastructure, data collection and data repository

CROPIC

III. Smart phone based crop data repository and assessments

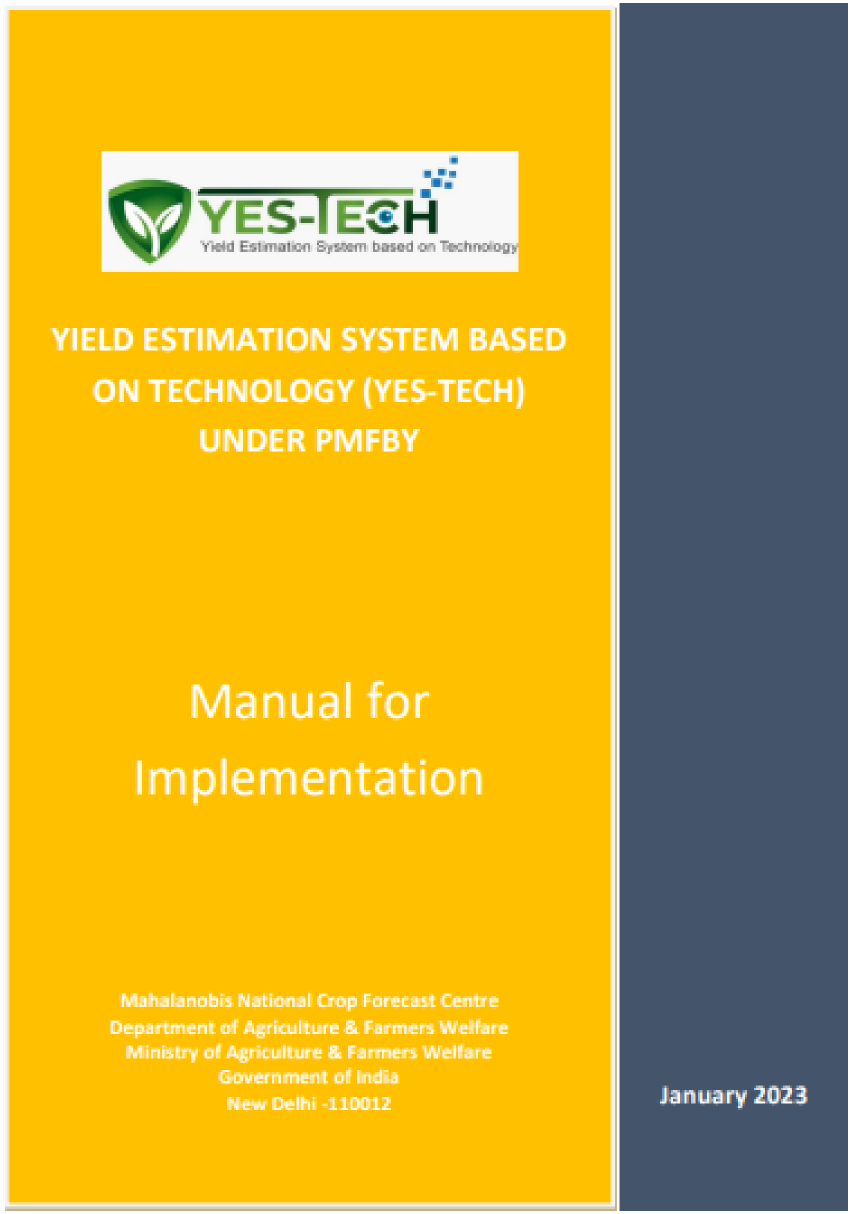
Nation wide implementation of technology based yield estimation for paddy and wheat and integration with crop loss assessments under PMFBY

Targeted outcomes

- Improve the data of crop yield estimates for rice and wheat from 2023 onwards
- Gradually reduce dependence on manual system

<u>Expert Committee for preparing the Manual</u>

S. No	Name of Expert	Designation
1	Dr. C. S. Murthy, Director, MNCFC	Chair
2	Dr. Rajendra Prasad, Director, IASRI (ICAR)	Member
3	Dr. Bimal Bhattacharya, Group Director, SAC	Member
4	Dr. Karun Kumar Choudhary, Head, Crops Div., NRSC	Member
5	Dr. Paresh Shirsath, Scientist BISA-CIMMYT	Member
6	Dr. Maheswaran, R. Asstt. Prof. IIT Hyderabad	Member
7	Dr. Sunil Kumar, Asst. Comm. DA & FW	Member
8	Commissioner Agriculture Maharashtra	Member
9	Director of Agriculture, Odisha	Member
10	Dr. Sunil Dubey, Deputy Director, MNCFC	Member Secretary


YES-TECH
Yield Estimation System based on Technology

YIELD ESTIMATION SYSTEM BASED ON TECHNOLOGY (YES-TECH) UNDER PMFBY

Manual for Implementation

Mahalanobis National Crop Forecast Centre
Department of Agriculture & Farmers Welfare
Ministry of Agriculture & Farmers Welfare
Government of India
New Delhi -110012

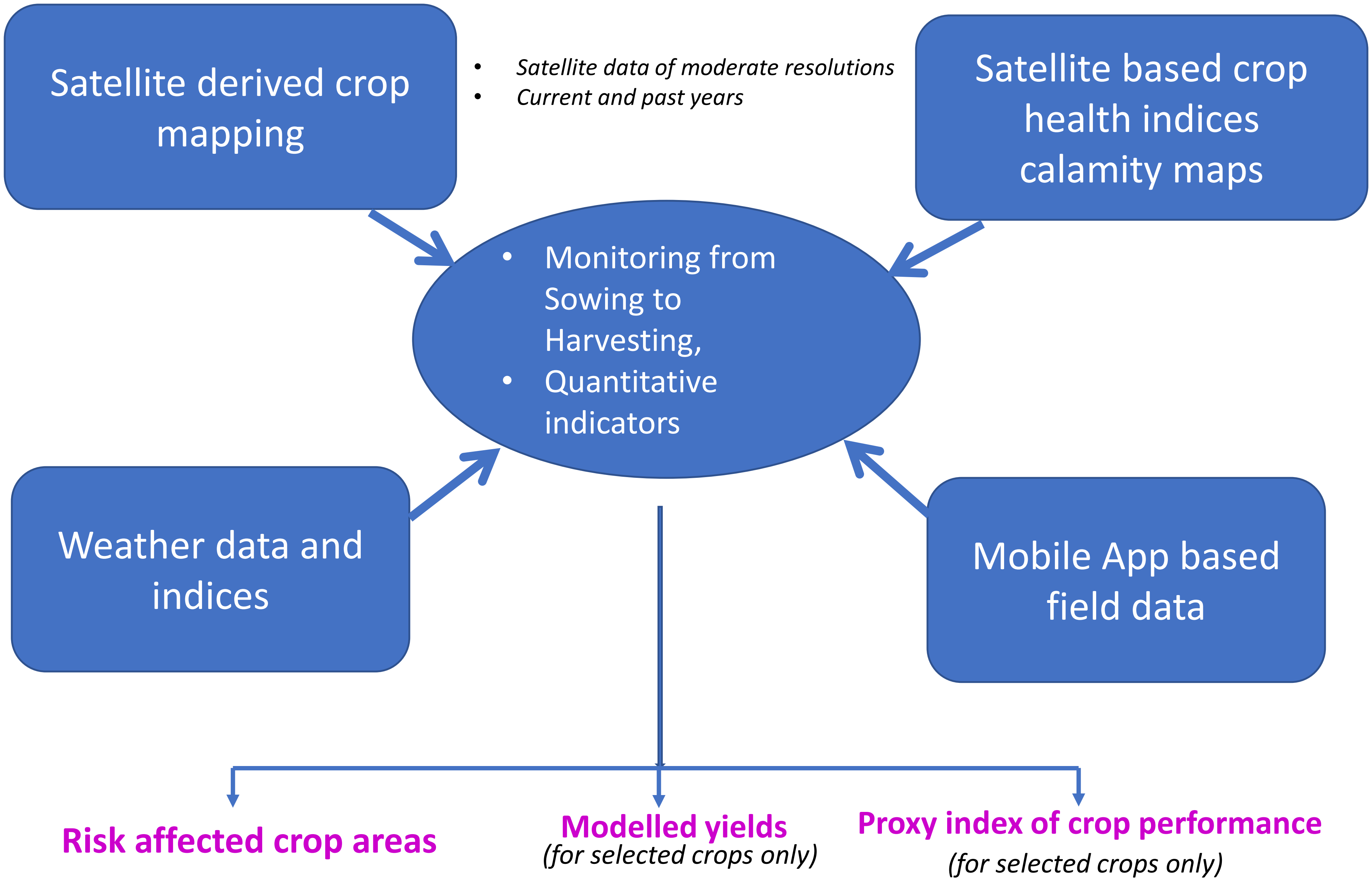
January 2023

Rationale behind the YES-Tech initiative

- Results of pilot studies on technology-based yield estimation for paddy and wheat crops are promising as observed by the Expert Committee constituted by DA&FW.
- Results of the models implemented by other agencies like NRSC (ISRO) and other agencies are already published in peer reviewed international journals.
- Increasing acceptance of technology-based yield estimation by states and other stakeholders
- Proactive steps taken by some of the states like Maharashtra and Madhya Pradesh to adopt technology-based yield estimation

Overview of YES-TECH implementation

Data analysis framework



Satellite data

ESA Sentinels				
Satellites	Sensor	Spatial	Freq.	Swath
Sentinel	MSI	10m	5	300 km
	SAR	20m	12	300 km
Sentinel-3	MSI	300m	10	300 km

Landsat				
Satellites	Sensor	Spatial	Freq.	Swath
LANDSAT 8 & 9	OLI	30 m	8 days	185 km

Indian Satellites				
Satellites	Sensor	Spatial resolution	Temporal resolution	Swath
RISAT 1A	SAR	20 m	16 days	200 km

Prominent spectral indices for crop assessment

NDVI – Normalised Difference Vegetation Index - chlorophyll based crop vigour index derived from the reflectance of red and Near Infra-Red (NIR) bands

LSWI – Land Surface Water/ Wetness Index - surface/canopy moisture index

RADAR backscatter – Responsive to crop growth due to volumetric scattering caused by canopy geometry, roughness and wetness, represents biophysical crop condition

fAPAR **–** Fraction of Absorbed Photosynthetic Active Radiation absorbed by the crop canopy. Determined by canopy structure/status and illumination conditions. A biophysical variable closely associated with biomass production

Crop mapping

- Use data of 30m and better
- Capture the spectral variability at GP/IU level and define classification rules
- Commission error should always be less than 10%
- Omission error should always be less than 20%

Recommended models under YES-TECH

Semi-physical / Semi-empirical

- Light use efficiency models.
- Radiation, absorbed radiation by crop, efficiency factor, biomass production and yield.

Machine Learning / Deep Learning

- Non-parametric techniques
- Model parameterisation
- Training data and validation data are critical factors

Crop simulation

- Plant process based modelling.
- Intensive parametrisation

Ensembled models

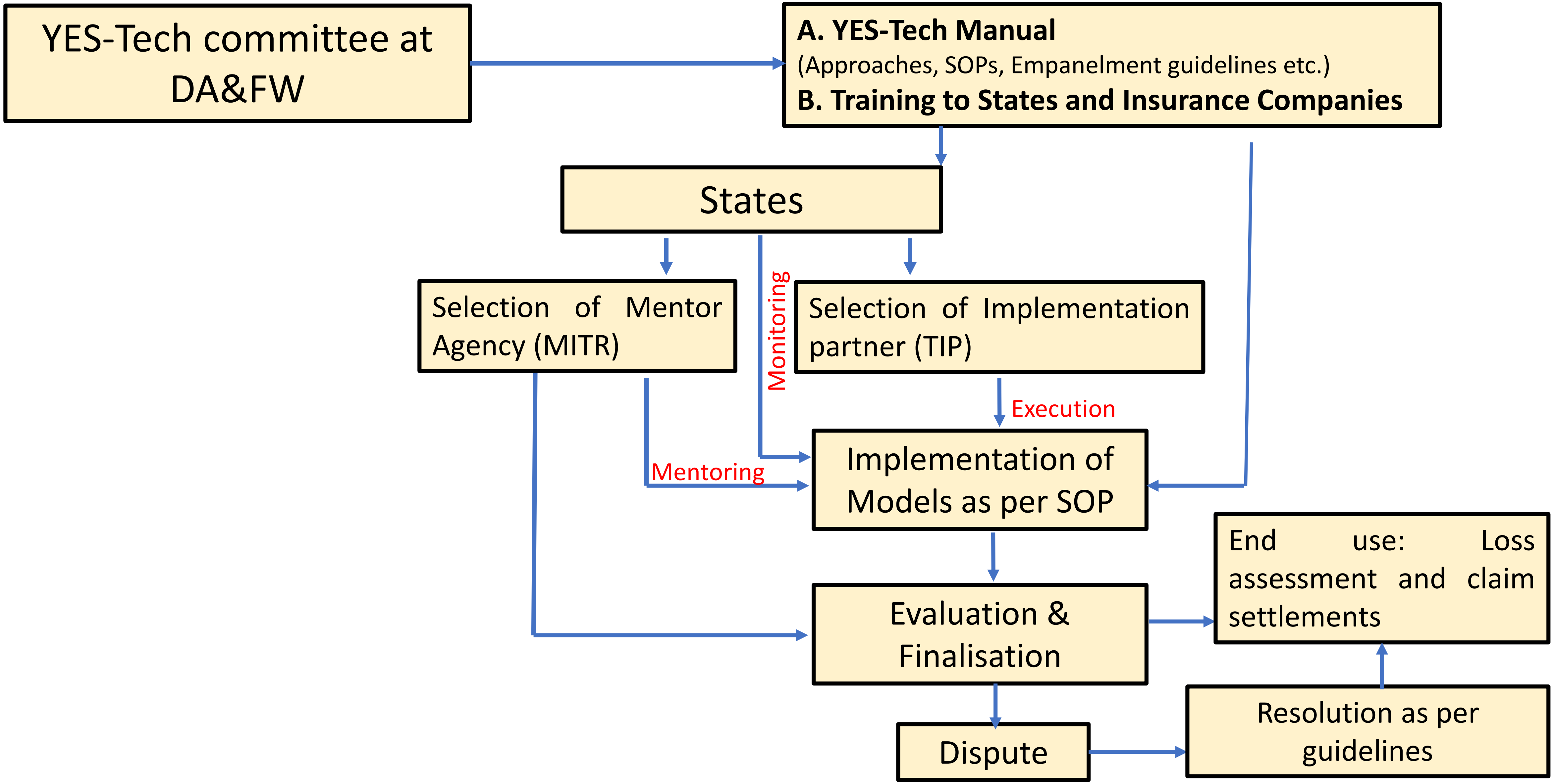
- Combination of models

Parametric indexing approach - CHF

- Plant process based modelling.
- Intensive parametrisation

Expert Committees' observation: All the tested technology based approaches were similar in performance for large majority of the area with an error margin is 20%.

Implementation framework



Key considerations

Choice of models: Selection of model is at the discretion of States. It is mandatory to declare the selected model in the beginning of crop season in order to maintain transparency in the system.

Model implementation for past years: It is mandatory to implement these models for the current and past years from 2017 onwards. This is to ensure consistency in the model performance and outputs.

N.B: the purpose of adopting models is to improve yield estimates for loss assessment from 2023. Not meant for changing AY and TY values.

Recommended end use of model outputs

Blending of modelled crop yields or CHF with CCE-yield estimates is suggested for arriving at crop loss and claim assessments from the 2023 crop season.

Modelled yields - 70% weightage to CCE yield and 30% weightage to modelled yield

CHF - 70% weightage to CCE-yield deviation from the threshold and 30% weightage to CHF deviation from the threshold.

The blending approach would lead to improving the loss assessment mechanism under PMFBY. **It reduces dependence on estimates of CCE**

The scientific basis for assigning 30% weightage to technology can be drawn from the facts; (a) to result in a **meaningful impact on the final loss assessment**, (b) the benefit of technology adoption can be possible only when the **minimum possible and significant weightage** is assigned to the outcome.

Implementing Agencies

- Technology Implementation Partner (TIP) – Agencies/Companies having capabilities for implementing yield estimation models
- Empanelment Criteria
- MNCFC to empanel the implementing agencies
- Selected TIP will implement models as per Manual

Technology Implementation Partner (TIP)

a. TIP will participate in the closed bid floated by the respective State / UT
b. TIP will consult with the State / UT for the area distribution if more than one agency is selected by State / UT
c. TIP will request administrative boundary, historical yield/crop data from the State /UT
d. TIP will conduct a kick-off meeting with State / UT representative, MITR organization, and other relevant stakeholders where TIP will briefly explain the selected methodology, planning for the milestone deliverables, inputs required, required authorization letters from the State, etc.
e. TIP will consult State / UT for the necessary approvals related to the field activities such as field data collection, drone survey, CCE sample collection, etc.
f. TIP will submit the results as per the defined timeline and it will participate in the review meeting with the State, MITR Organization, and other stakeholders at a regular interval
g. TIP will consult the MITR organization / State if the results are not satisfactory and TIP will submit a plan to improve it
h. TIP will hand over the data collected from the field at the end of the project
i. TIP will push the results to MNCFC where MNCFC will store them in the central repository

Mentor Agencies

Agencies having expertise in tech based crop yield estimation

- NRSC - ML/DL Models, CHF
- SAC - Semi-physical models, Crop Simulation models, ensembled models
- CRIDA - Crop Simulation models, ensembled models
- IARI -Crop Simulation models, ensembled models
- State Agril. Universities

MNCFC will facilitate engaging MITR by States

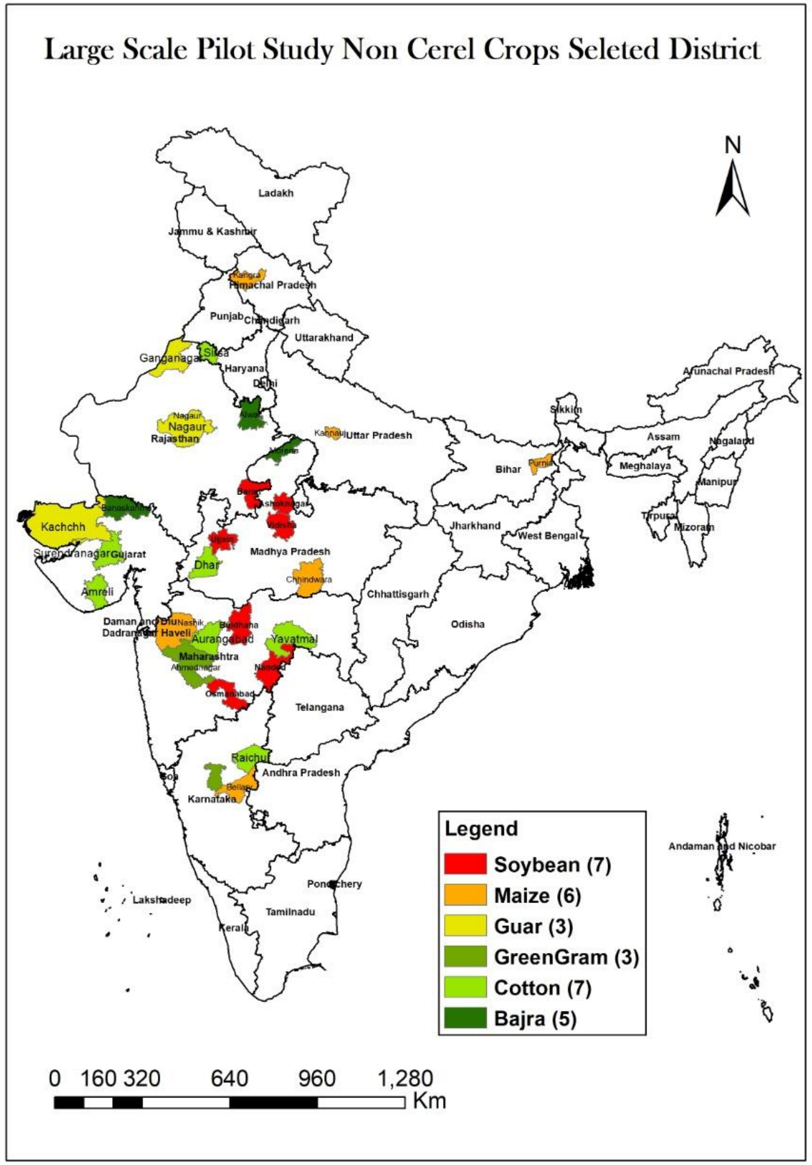
MITR’s Responsibilities

a. MITR organization will inform MNCFC about their association with multiple States / UT in the scheme implementation
b. MITR organization will serve as a **State Advisory Committee (SAC)** and will ensure the necessary infrastructure and expertise
c. MITR organization will understand the methodology to be implemented, expectations in the milestone delivery from the State / UT
d. MITR organization will understand the overall approach of delivery, inputs to be used from the selected agency
e. MITR organization will identify a Single Point of Contact (SPOC) for each state
f. MITR organization will participate in the review meetings as per the State / UT’s predefined timeline
g. MITR organization will evaluate the methodology and produce results technically and approve/reject the results
h. MITR organization will provide technical guidance to the selected agency if the results are rejected and MITR organization will also ensure the improvement in the deliverables to the State / UT

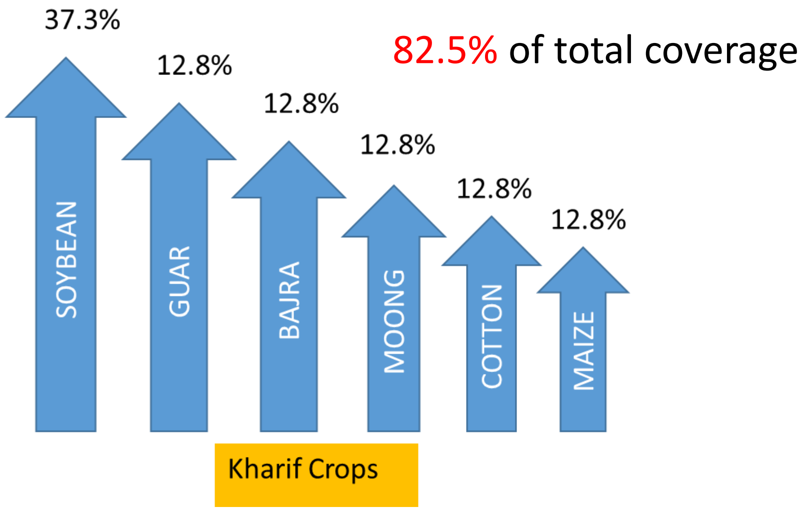
Way Forward

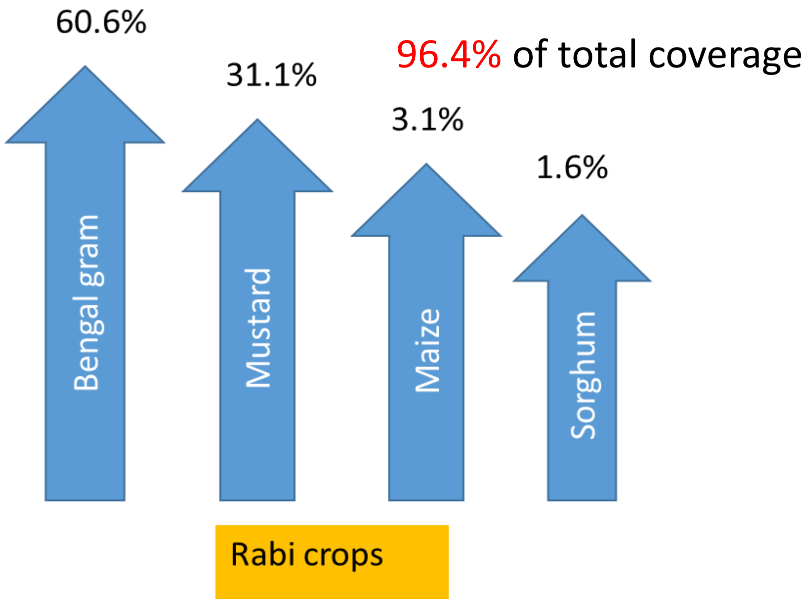
▪ **Dec 2022**	Draft manual
▪ **Dec 2022 / Jan 2023**	Stakeholder consultation
▪ **Jan/Feb 2023**	Final manual
▪ **Jan/Feb 2023**	Notification in Operational Guidelines
▪ **Feb 2023**	Notification in PMFBY tenders
▪ **April/May 2023**	Implementation

Yield estimation for Non-Cereal crops - pilots initiated



Crops Covered

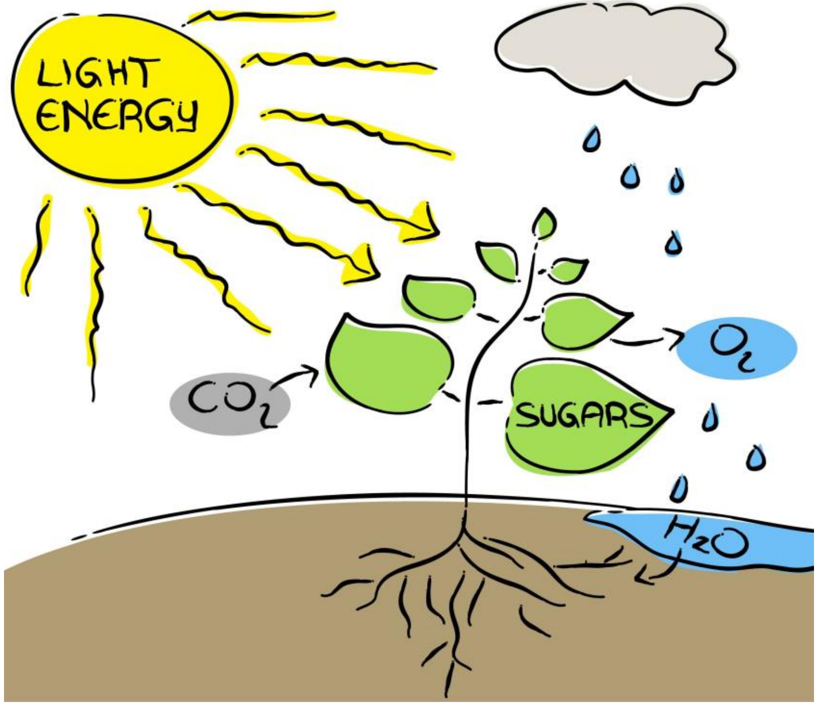




- 20 agencies (10 Govt. and 10 Private)
- 25 districts from 8 states in kharif
- 20 districts in rabi
- 50 GPs in each district
- Mid-term review agencies has been conducted by the expert committee

Thank You

Semi Physical Crop Model for Yield Estimation (Process based Model)



Sunil Kumar Dubey
Deputy Director, MNCFC

Outline

- Introduction
- Why Semi Physical Model
- Functioning of Semi Physical Model
- Overview of the Model
- Data Requirement of Model
- Explanation of Model Inputs and Function
- Benefits of Model

Introduction

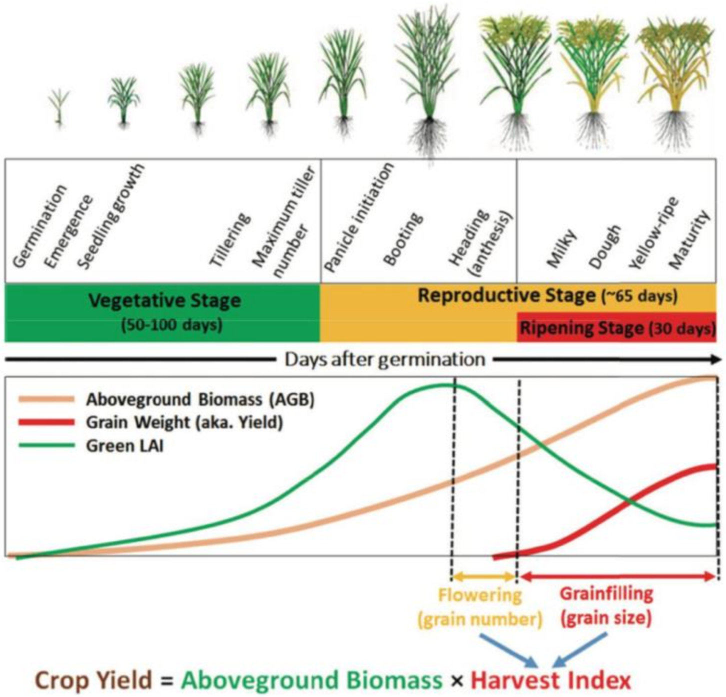
➢ Semi physical model is based on the concept that, the biomass produced by a crop is a function of the amount of photo synthetically active radiation (PAR) absorbed, which depends on incoming radiation and the crop's PAR interception capacity.

➢ Biomass is a function of the total photo synthetically active radiation (PAR) and the ability of the plant to absorb (fAPAR) this radiation and convert this radiation to dry matter (RUE)

➢ Yield is a function of net dry matter and the harvest index (HI) of the crop.

➢ Water Scalar and Temperature Scalar derived from satellite/observed sources will be used as a limiting factor of crop yield.

➢ Major factors of crop growth (i.e.) the radiation and the ability of the crop to convert the absorbed radiation into dry matter) are derived and used for estimating the yield.



Why Semi Physical Model

There are many methods of crop yield estimation prior to harvest using remote sensing such as.

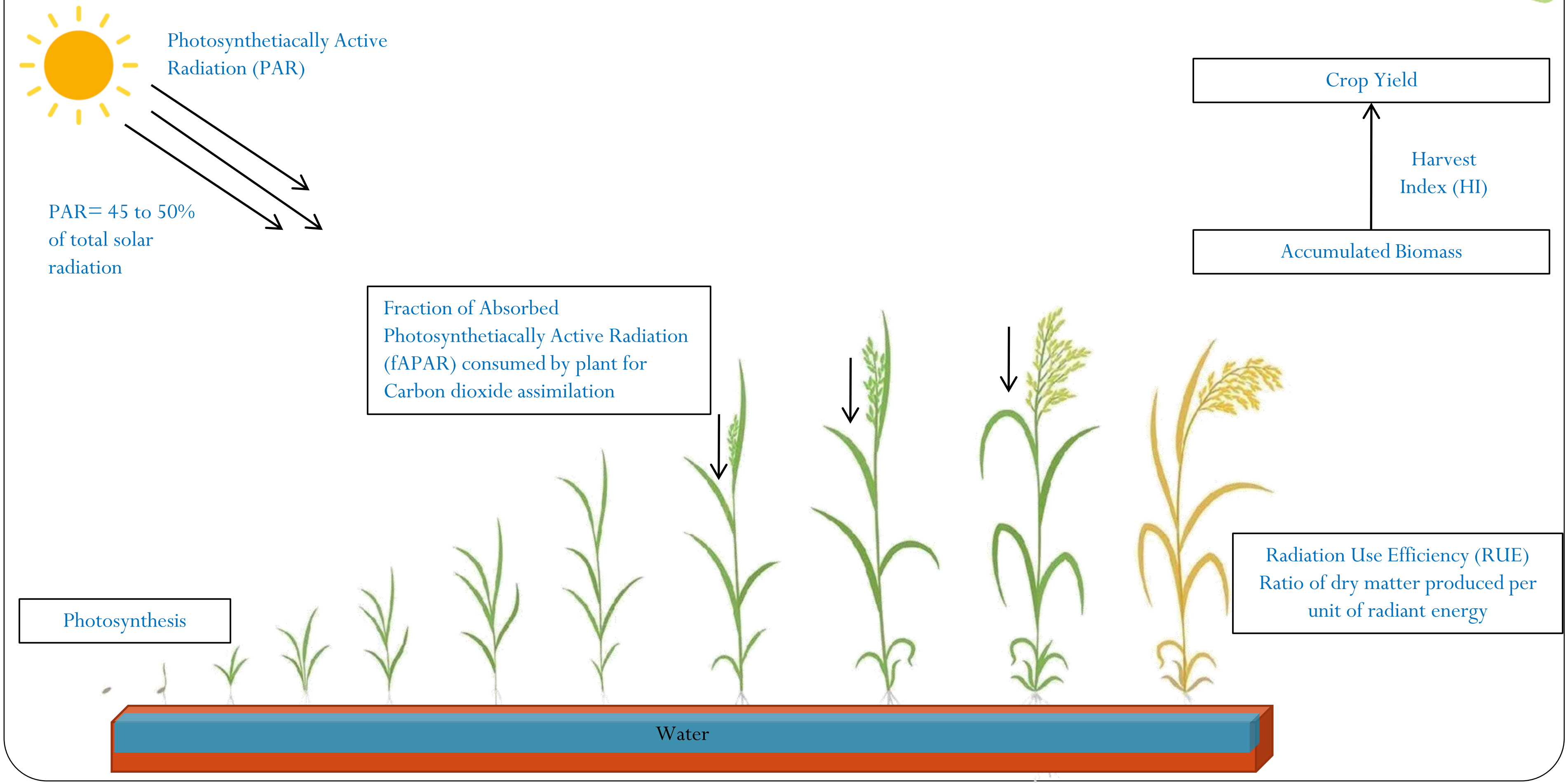
1. Empirical models
2. Mechanistic and dynamic crop growth model (CSM)
3. Semi-physical model

✓Empirical models based on the vegetation index (VI) are location-specific and cannot be generalized with sufficient accuracy over larger areas.

✓Crop simulation models describe the primary physiological mechanisms of crop growth and development in a computational loop, the difficulties of adopting CSM has usually been associated with the intensive data requirement for models' parameterization. The need for calibration can be quite data extensive and hence not applicable for large area yield estimation.

✓ Semi-physical method for yield estimation, which is based on remote sensing and physiological concepts such as PAR and the fraction of PAR absorbed by the crop (fAPAR). PAR and fAPAR can help to assess the real-time information of the crop growing conditions at any stage during the crop growing season. The parameters of model were not empirical estimates, but were derived using physiological concepts.

Functioning of Semi Physical Crop Model



Mathematically can be written as-

$$Biomass = RUE * fAPAR * PAR * Wscalar$$

$$Yield = Biomass * HI$$

HI= EconomicYield/Biological yield

Photosynthetiacally Active Radiation (PAR)

- Photo-synthetically active radiation (PAR) is the part of electromagnetic radiation that can be used as the source of energy for photosynthesis by green plants.

- PAR is calculated at daily basis using Insolation data and can be calculated.

$$\boldsymbol{PAR} = Total\ Solar\ Irradiance * 0.48$$

Fraction of Absorbed Photosynthetiacally Active Radiation (fAPAR)

- The fAPAR quantifies the fraction of the solar radiation absorbed by live leaves for the photosynthesis activity and it refers only to the green and alive elements of the canopy.

- The fAPAR characterizes the energy absorption capacity of vegetation canopy. It is a basic physiological variable describing the vegetation structure and related material and energy exchange processes.

- It is an important parameter for estimating the plant biomass

Water Scalar

LSWI Index :

- LSWI index has been used as canopy water stress in the model to incorporate the effect of moisture stress in the plant.

- LSWI index computed from the near range Infrared band and short-wave infrared (SWIR) regions of electromagnetic. This index is sensitive for the total amount of vegetation liquid and also for soil background.

$$LSWI = \frac{NIR - SWIR}{NIR + SWIR}$$

Water Scalar:

Estimated LSWI had used further in deriving the water stress scalar.

$$Wscalar = \frac{1 + LSWI}{1 + LSWI_{max}}$$

Radiation Use Efficiency (RUE)

- Plant biomass production can be modelled as a linear function of intercepted Photosynthetically active radiation (PAR).
- The slope of this relationship is the RUE , which is approximately constant for forests and natural ecosystems, and particularly for crops when growth is not limited by environmental conditions.

- Radiation-use efficiency (RUE)is defined as the ratio of dry matter produced per unit of radiant energy used in its production. Because efficiency should be dimensionless, the term of "dry matter: radiation quotient" was suggested (Russell et al. (1989), however, RUE is used widely and considered a useful tool for simulating crop growth.

Crop Biomass and Crop Yield

Crop Biomass estimation:

- Biomass is a function of the total photo synthetically active radiation (PAR) and the ability of the plant to absorb (fAPAR) this radiation and convert this radiation to dry matter (RUE) .Radiation Use Efficiency was the capacity of the plant to convert radiation into dry matter. The biomass had been calculated from the following equation.

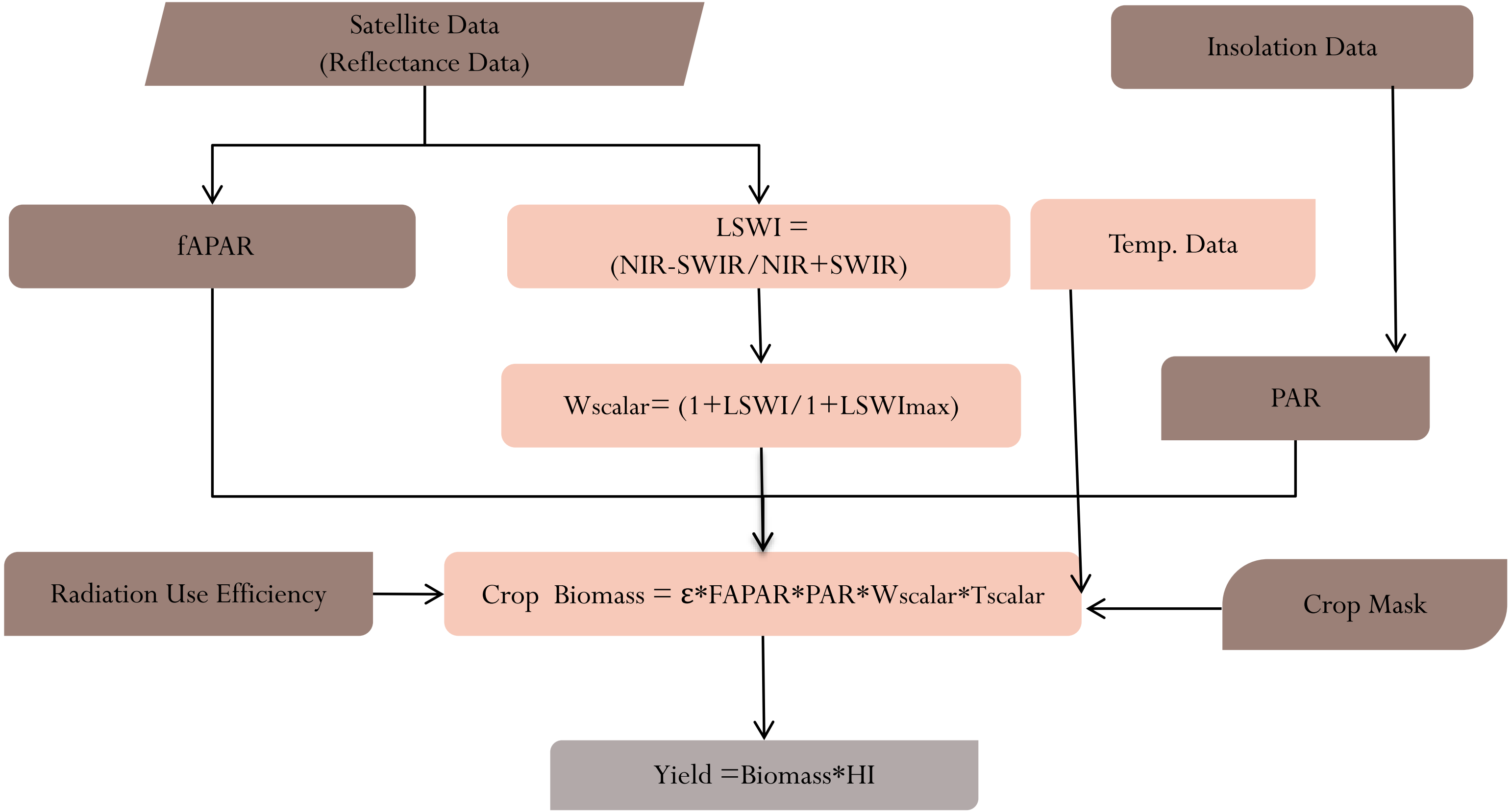
$$\boldsymbol{Biomass} = RUE * fAPAR * PAR * Wscalar$$

Crop Yield estimation:

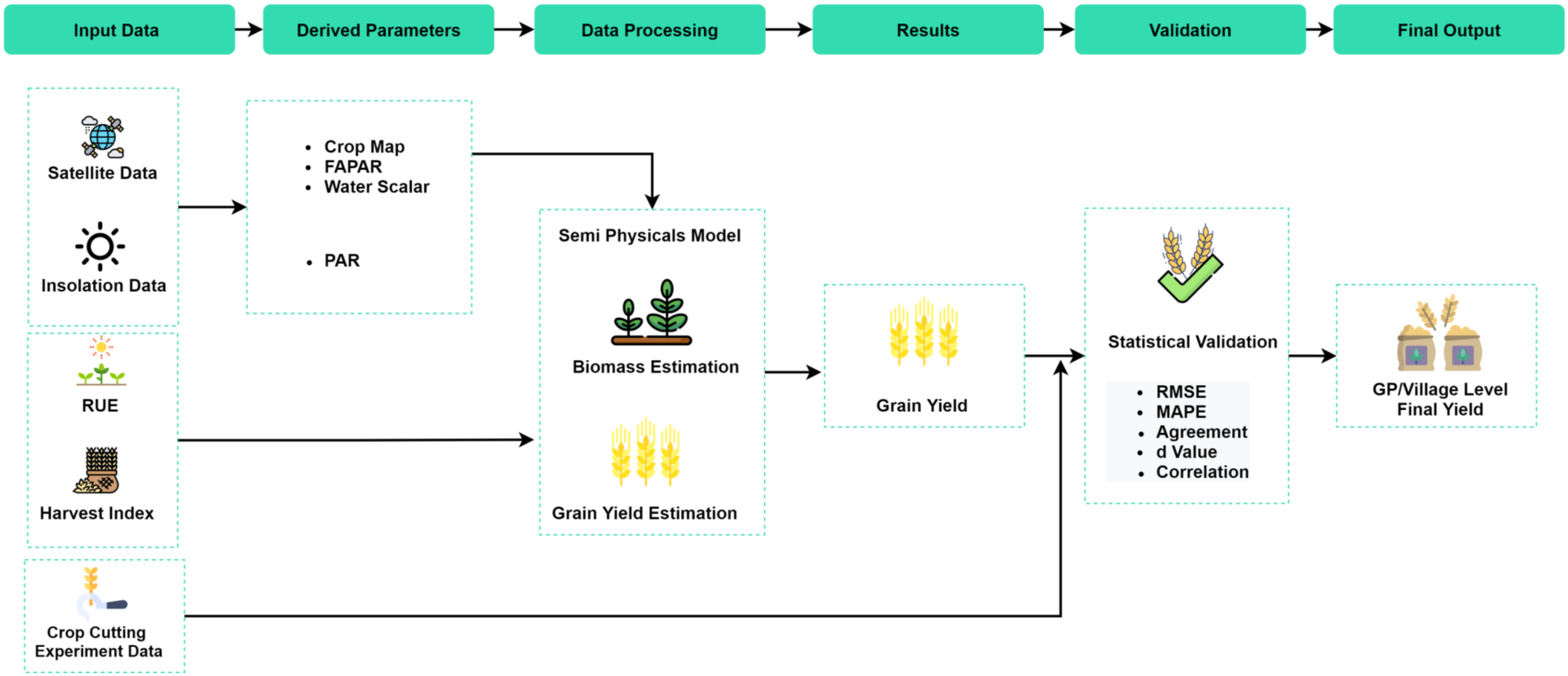
- Yield is a function of net dry matter and the harvest index (HI) of the crop. Harvest index is the ratio of crop grain yield and crop biomass. The crop yield had been calculated from the following equation.

$$\boldsymbol{Yield} = Biomass * HI$$

Overview: Semi Physical Model



Yield Modelling Approach



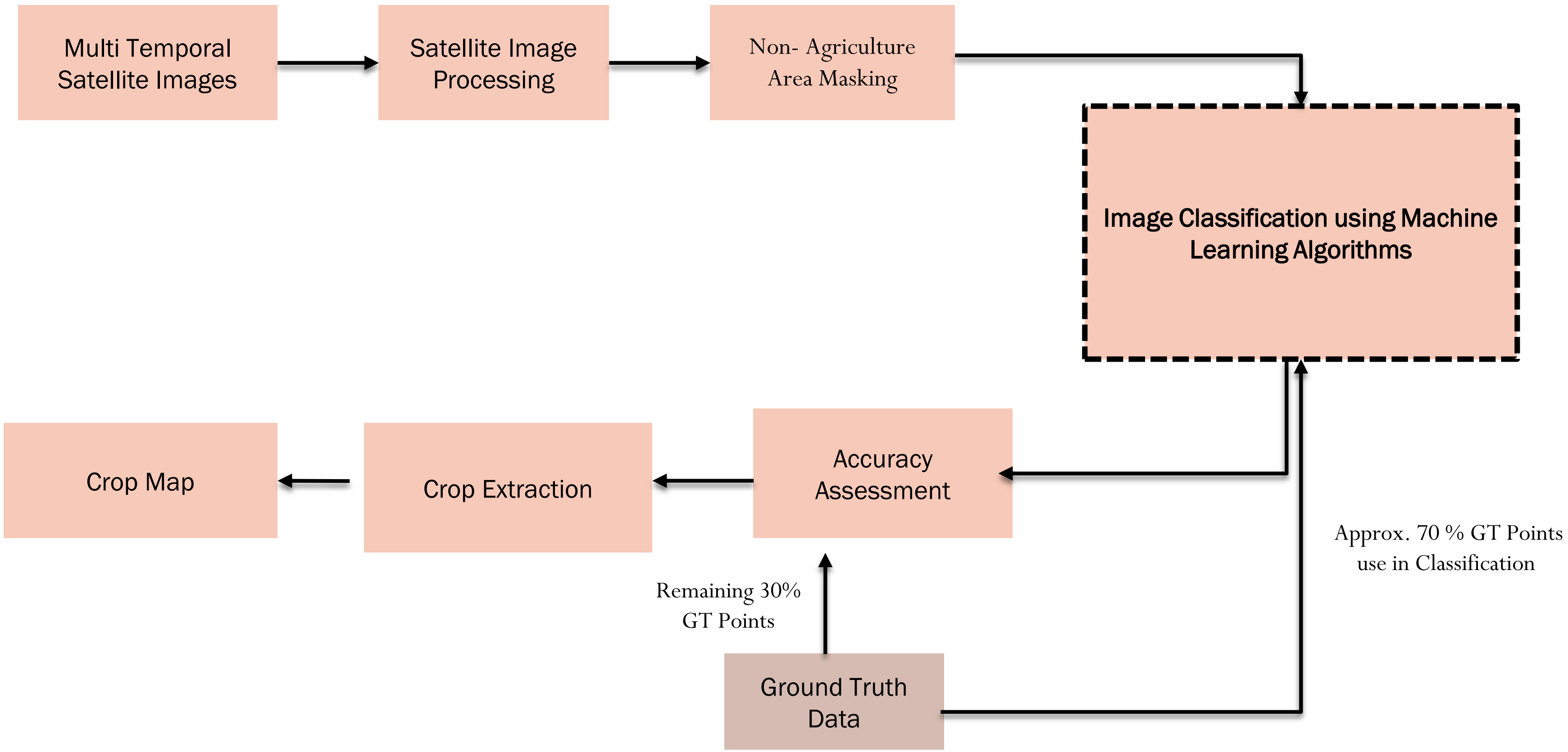
Input Data Requirement

Data /Product	Satellite/ Ground	Sensor	Resolution	Source
Daily integrated Insolation	INSAT 3D	Imager	1 km	MOSDAC
8-days composite FAPAR	Terra Sentinel 3	MODIS OLCI	0.5 km 0.3 km	NASA-EARTHDATA ESA
8-days composite surface reflectance	Terra Sentinel 2	MODIS MSI	0.5 km 10-20m	NASA-EARTHDATA To be developed by TIP
NDVI & LSWI during Maximum Vegetative Stage	Sentinel 2 Landsat 8	MSI OLI	10-20 m 30 m	ESA NASA-EARTHDATA
Crop mask (5-30 meter) resolutions	Sentinel 1 Sentinel 2 Landsat 8	SAR MSI OLI	20 m 10 m 30 m	To be developed by TIP
Crop Sowing Date	Sentinel 1 Sentinel 2 Landsat 8	SAR MSI OLI	20 m 10 m 30 m	To be developed by TIP
Harvest Index	Ground Data CCE	---	District Level	CCEs conducted by TIP
Daily Tmin and Tmax	Gridded Data	---	0.5o x 0.5o 5 km Grid	IMD Pune Website WRF short-range forecast of SAC

Satellite Data

- Multi date optical/ microwave satellite images covering entire crop growth stages will be use.
- Satellite image will be use for crop type mapping, fAPAR estimation and water scalar estimation.
- The major bands required in optical satellite images are Blue, Green, Red, Near infrared and Short wave infrared .

Crop Map Generation



Benefits of Semi Physical Model

- Less requirements of input data as compare to other model.

- There is no dependency of model on crop cutting experiment data

- Model results are validated at Gram panchayat/ village level for estimating the crop yield in multiple years.

Critical Aspects in Semi physical model

- Data of various resolutions are being used, better to use higher resolution.
- The model operates at pixel level, crop map should be of higher resolutions.
- Dynamic model, assessing the situation of crop from start to end.
- Authentic source of HI value is requires.
- Determine the start and end of season judicially


Thank you.
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Workshop for YES-Tech initiative and its implementation modalities

23-24 Jan, 2023, New Delhi

Technology based crop yield estimation: Machine Learning approach

KK Choudhary

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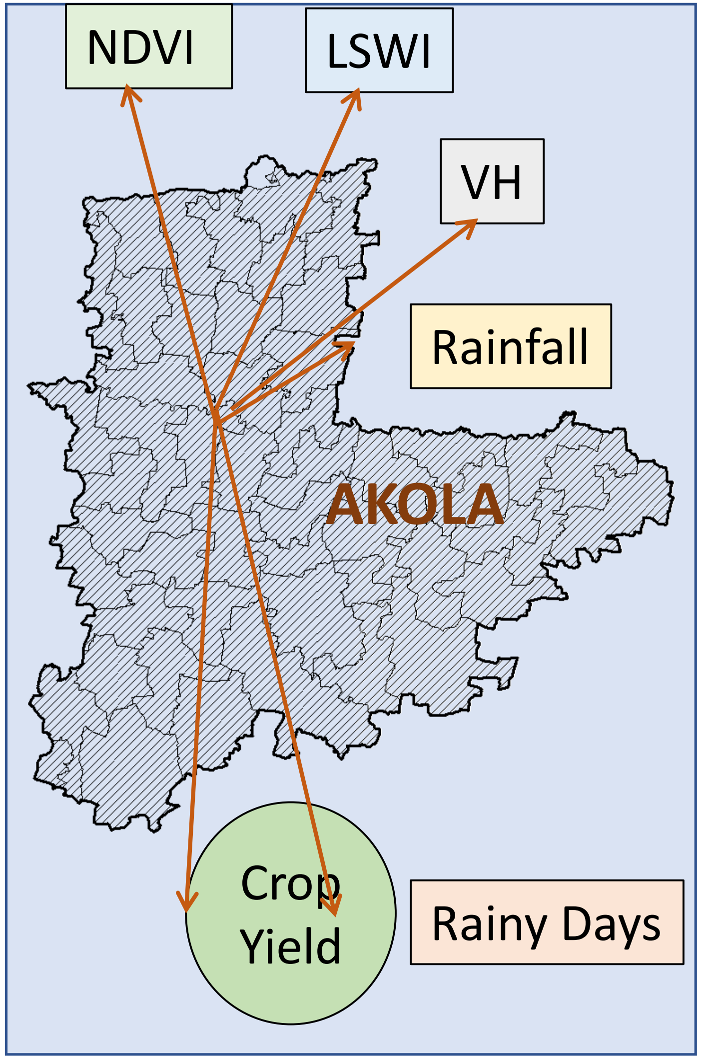
Why Machine Learning?

Limitations of conventional multivariate regressions



Circle	NDVI	LSWI	VH	RF	RD	Yld(Kg/Ha)
C_1	0.65	0.62	0.035	1154	75	780
C_2	0.71	0.58	0.042	895	79	854
C_3	0.68	0.64	0.058	1059	78	1159
……	……	……	……	……	……	……
……	……	……	……	……	……	……
C_n	0.75	0.71	0.049	958	76	942

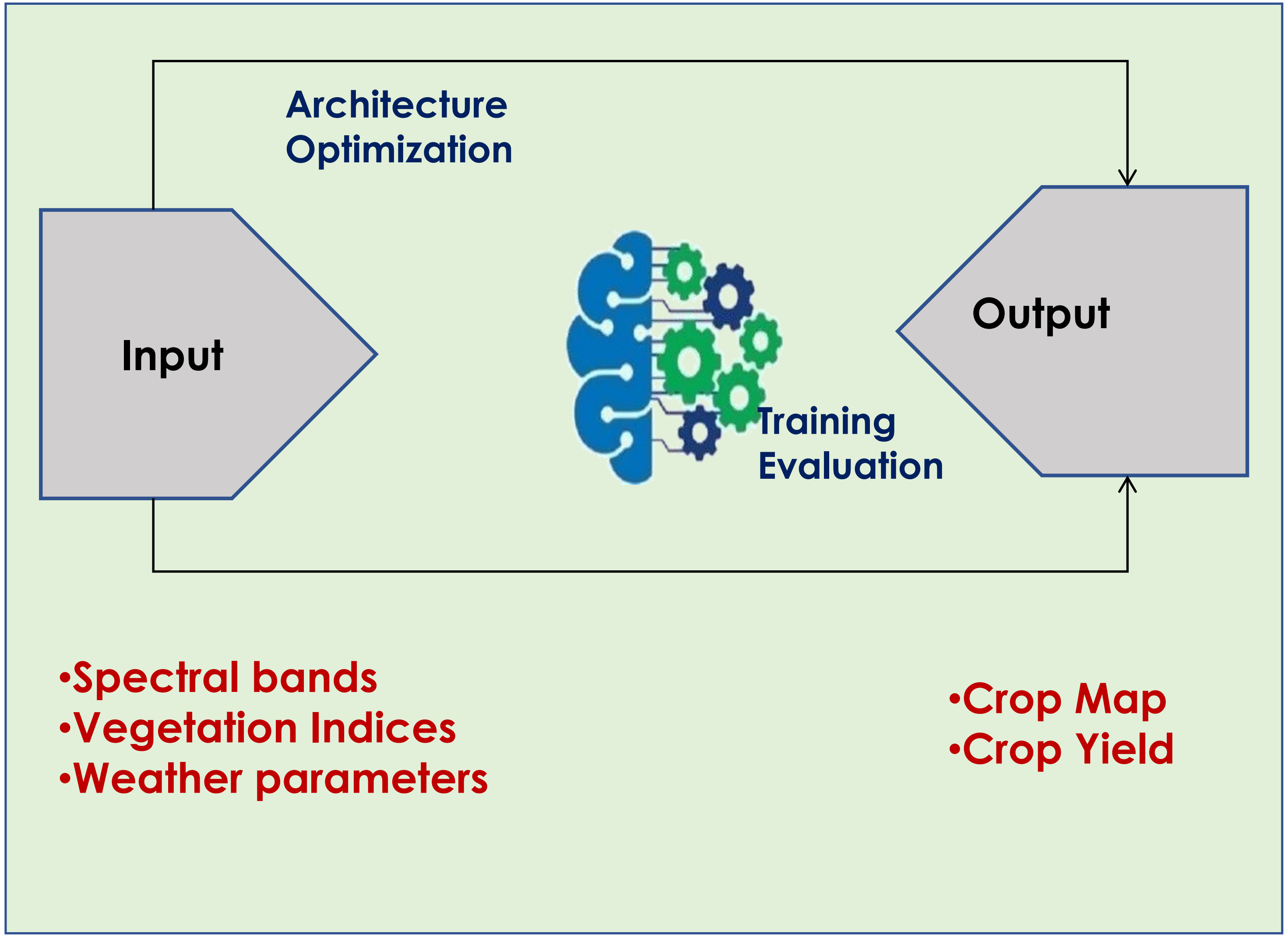
$$Yield = w_1*ndvi + w_2*lswi + w_3*vh + w_4*rf + w_5*rd + k$$

Countable number of parameters
Assume some data distribution for each feature
Low accuracy in case:

- Non-linear relations
- Inter correlation among input features
- Dimension of feature space in high.

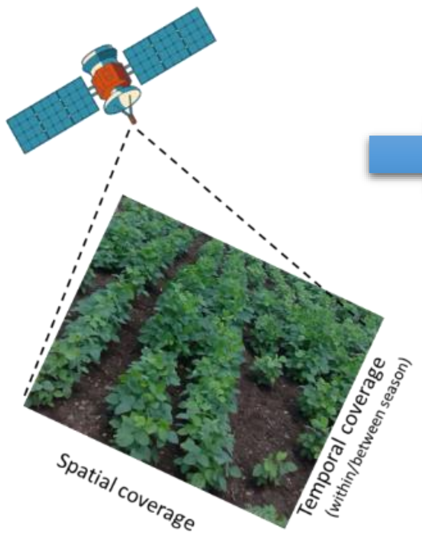
Why Machine Learning?

- ❖ Ability of a system to learn itself from the data.
- ❖ Independent of data distribution
- ❖ Complex non-linear relations
- ❖ Can handle high data dimensions
- ❖ Independent of multi-collinearity
- ❖ Used globally for large scale crop yield estimation
- ❖ Used in pilot studies by several agencies



Machine Learning: Framework

Features collection

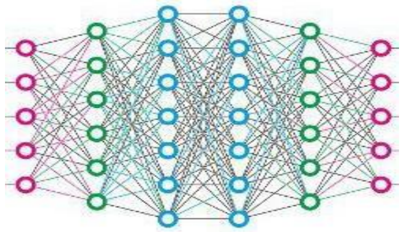


Input layer (historical years)

- **Satellite Bands, Indices and crop map**
- **Weather** (RF, RD etc)
- **Environment** (Soil)
- **Ground Data**

ML Models

(Deep Neural Network, Random forest,



Task

Crop Yield prediction at aggregated and disaggregated level

ML Models

Model Selection

Feature Selection

Feature Engineering

Hyper-parametrization

Testing & Evaluation

Popular Machine learning models

Genre	ML models
Decision trees	Classification and Regression tree (CART) Random forest
Neural Networks	Fully connected, Sparsely connected, Sequential learning
Adaptive Models	Boosting
Kernel based	Support Vector machine, KRR, GPR

ML Models

Model Selection

Feature Selection

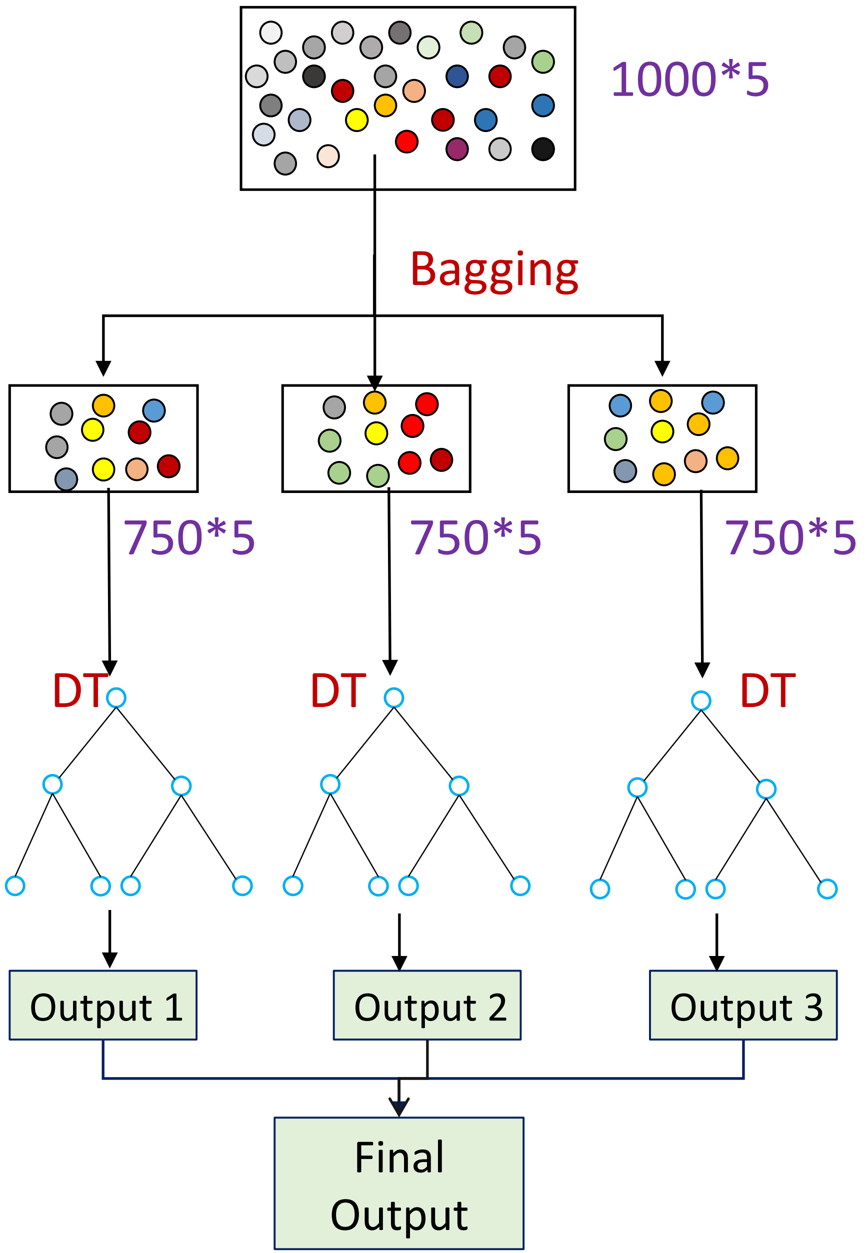
Feature Engineering

Hyper-parametrization

Testing & Evaluation

Random Forest (RF)

- ❖ Several subsets of input data (bags) are created Bootstrap Aggravation
- ❖ For each of the bags, a very deep decision tree is grown
- ❖ While making the decision, at every split point in the decision tree the learning algorithm looks through only random subsample of the feature space.
- ❖ The decision is made by looking the Gini Index value for each feature
- ❖ The final output is the ensembled output of each of the decision tree.
- ❖ Less prone to overfitting



Neural Network (NN)

ML Models

Model Selection

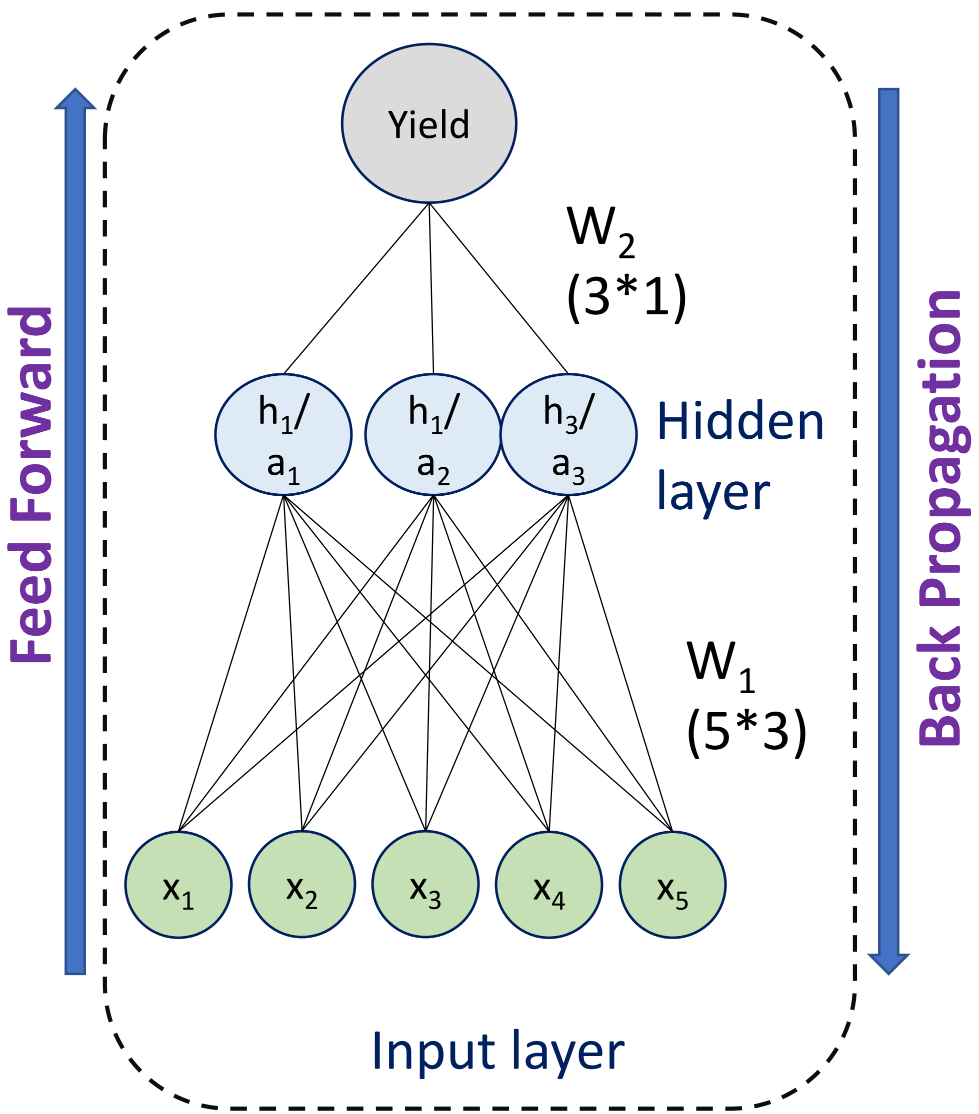
Feature Selection

Feature Engineering

Hyper-parametrization

Testing & Evaluation

- Utilizes the principle of universal approximation
- Mimic the biological neurons signal transfer (Brain)
- Comprised of a node layers, containing an input layer, one or more hidden layers, and an output layer.
- Each node has an associated weight and threshold.
- If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network
- Learning algorithms to optimize the weights and bias of the model: Gradient descent, ADAM etc



Which ML model to select?

- ML Models
- **Model Selection**
- Feature Selection
- Feature Engineering
- Hyper-parametrization
- Testing & Evaluation

❖ Tree based or neural network

❖ Fully connected or sparsely connected

❖ Performance of multiple models needs to be compared

❖ Model that works well for Tabular data

- ML Models
- Model Selection
- **Feature Selection**
- Feature Engineering
- Hyper-parametrization
- Testing & Evaluation

Category	Features	Source
Satellite based	Reflectance bands	Sentinel-2, Landsat-8, MODIS
	Vegetation Indices-Greenness (NDVI, EVI, Red edge index)	Sentinel-2, Landsat-8, MODIS
	Vegetation Indices-wetness (NDWI, LSWI, etc)	Sentinel-2, Landsat-8, MODIS
	Radar backscatter (VH, VV, RVI etc)	Sentinel-1, EOS-4
Meteorological	Rainfall, Rainy Days	IMD gridded, CHIRPS, any other gridded/reanalysis data
	Dry-spell/Wet-spell	IMD gridded, CHIRPS, any other gridded/reanalysis data
	Temperature	IMD gridded, any other gridded/reanalysis data
	Growing degree days	IMD gridded, CHIRPS, any other gridded/reanalysis data
	Heat wave/cold wave	IMD gridded, CHIRPS, any other gridded/reanalysis data
Bio-physical	FAPAR	PROVA/Sentinel-3, MODIS, Sentinel-2
	LAI	PROVA/Sentinel-3, MODIS, Sentinel-2
Edaphic	Soil (texture, depth, AWC, etc)	NBSSLUP (1: 250K, 1:50K)
	DEM	SRTM, DEM
	Soil moisture	SMAP, AMSR-E

ML Models

Model Selection

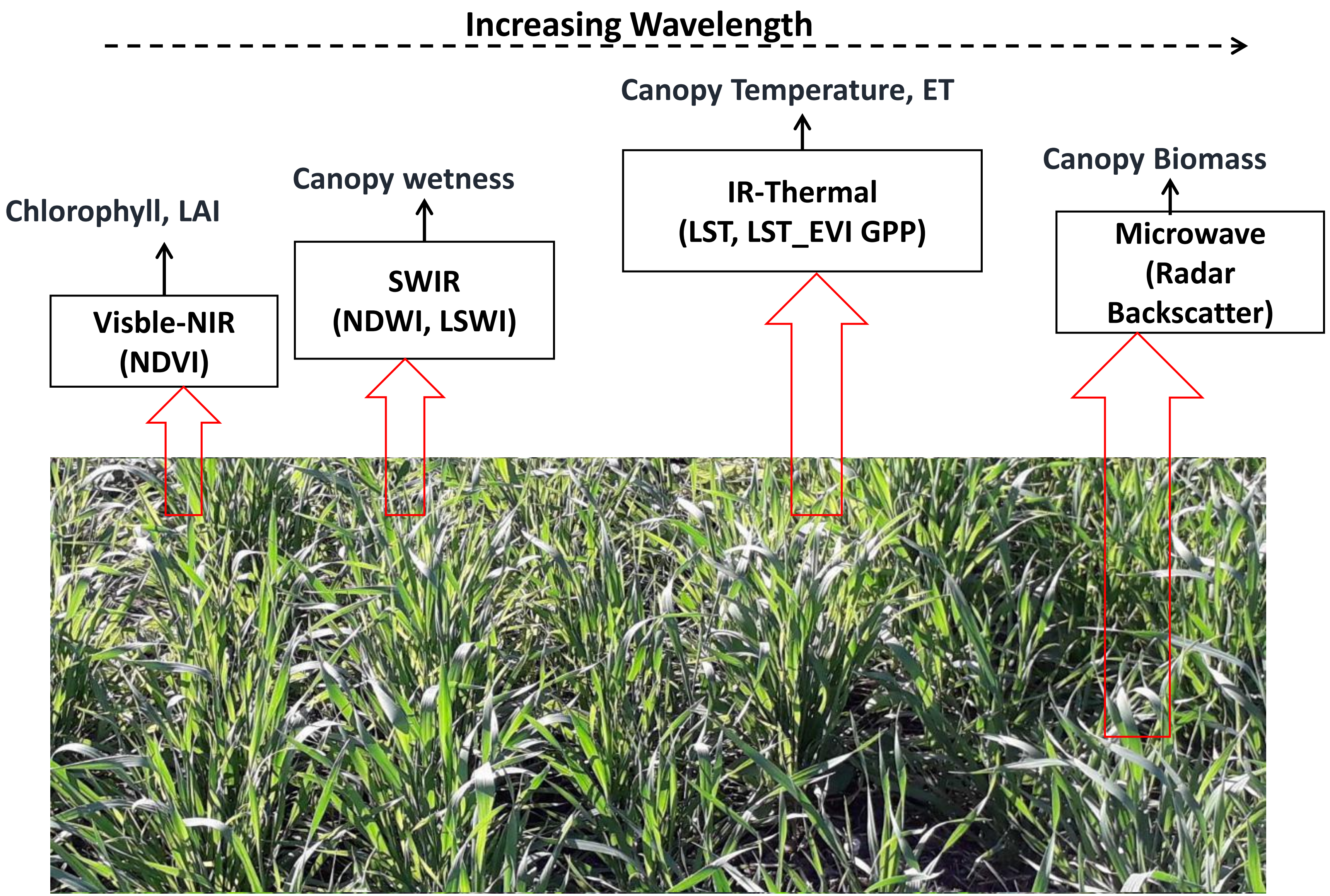
Feature Selection

Feature Engineering

Hyper-parametrization

Testing & Evaluation

Satellite based crop condition indicators



ML Models

Model Selection

Feature Selection

Feature Engineering

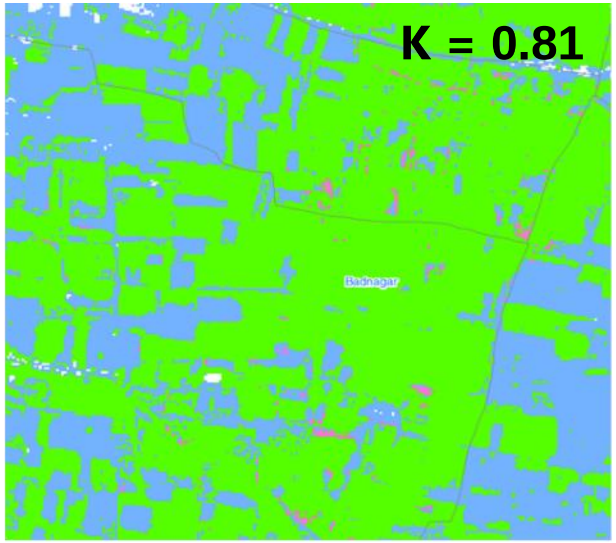
Hyper-parametrization

Testing & Evaluation

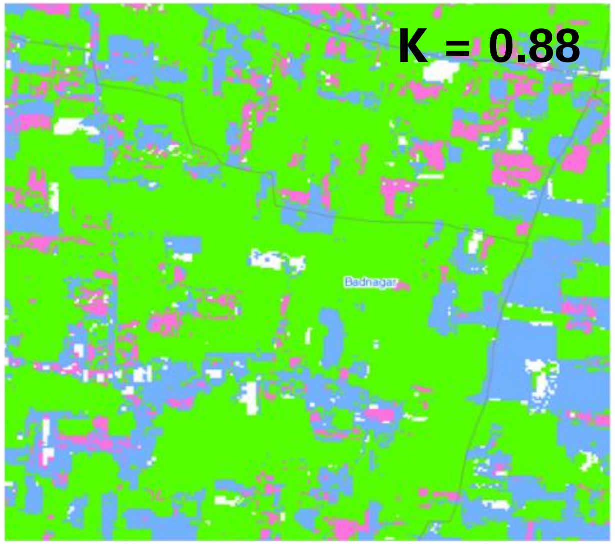
Crop mapping

- ❖ Features extraction for only specific crop pixels
- ❖ Multiple years crop maps to be prepared
- ❖ Only medium resolution satellite data need to be exploited for mapping
- ❖ Classification accuracies should be higher at disaggregated level

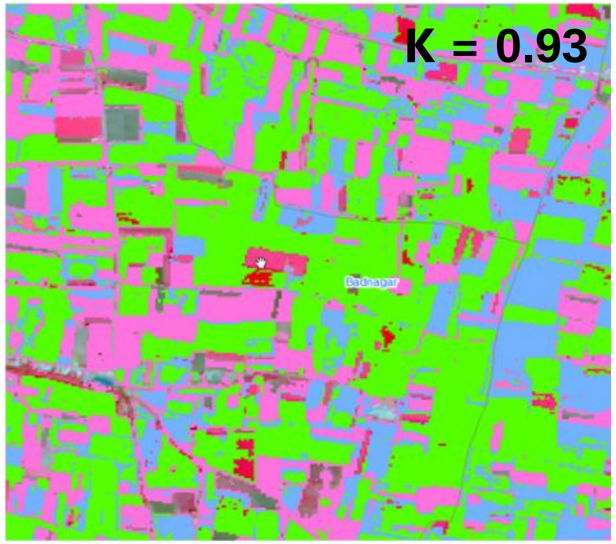
FCC: 26-Dec-2017



Classified with Decision rule



Classified with SAM

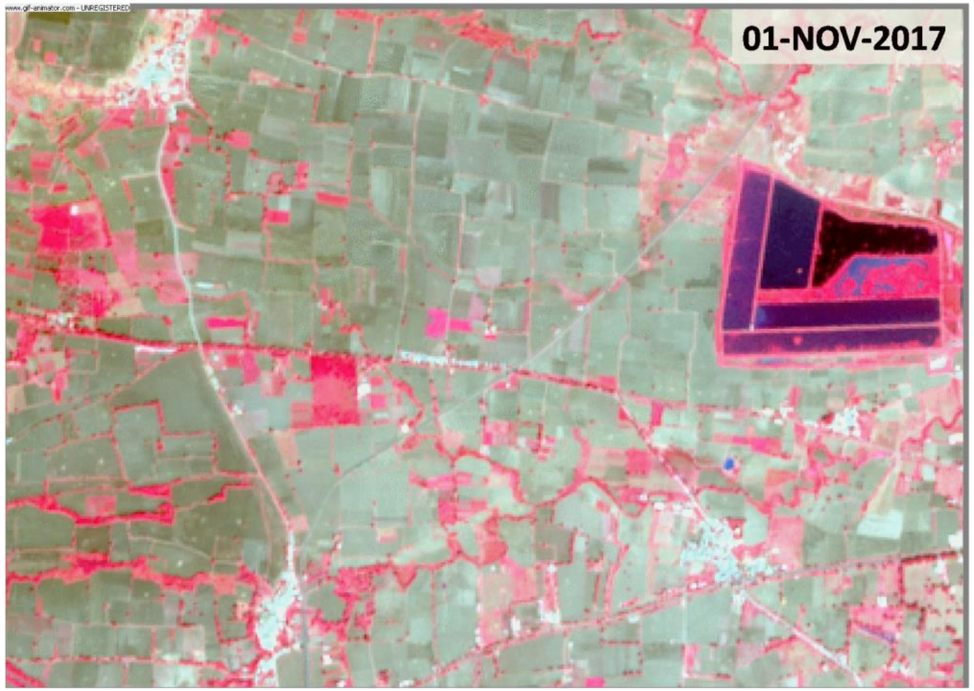


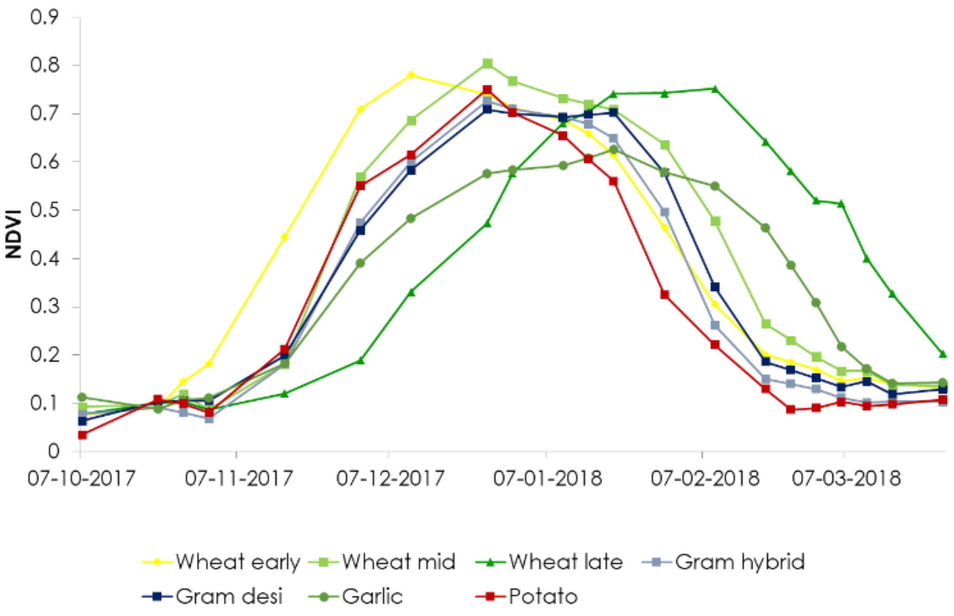
Classified with RF

Wheat Gram Garlic

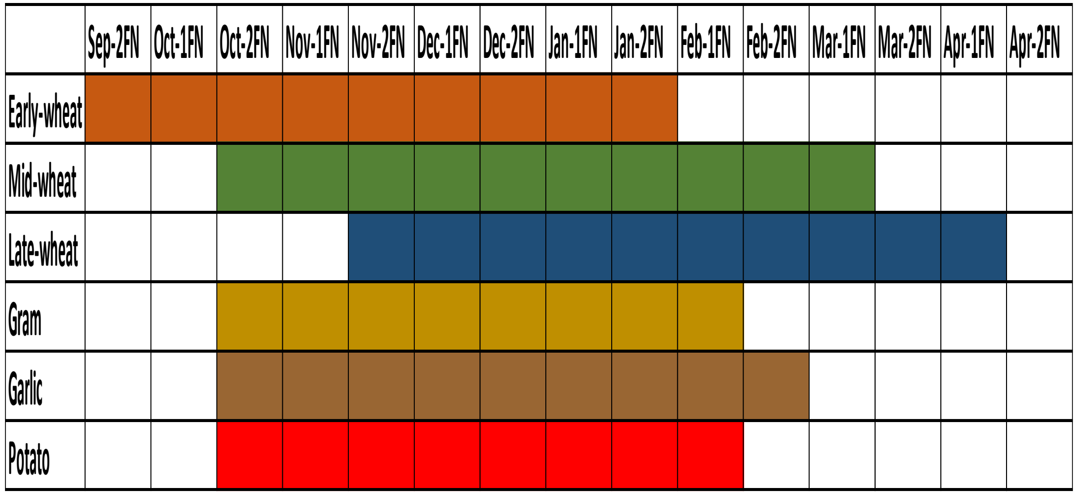
Considering crop window

- ML Models
- Model Selection
- **Feature Selection**
- Feature Engineering
- Hyper-parametrization
- Testing & Evaluation





- ❖ SOS and EOS needs to be derived at disaggregated level
- ❖ Features should represent the crop growing window



ML Models

Model Selection

Feature Selection

Feature Engineering

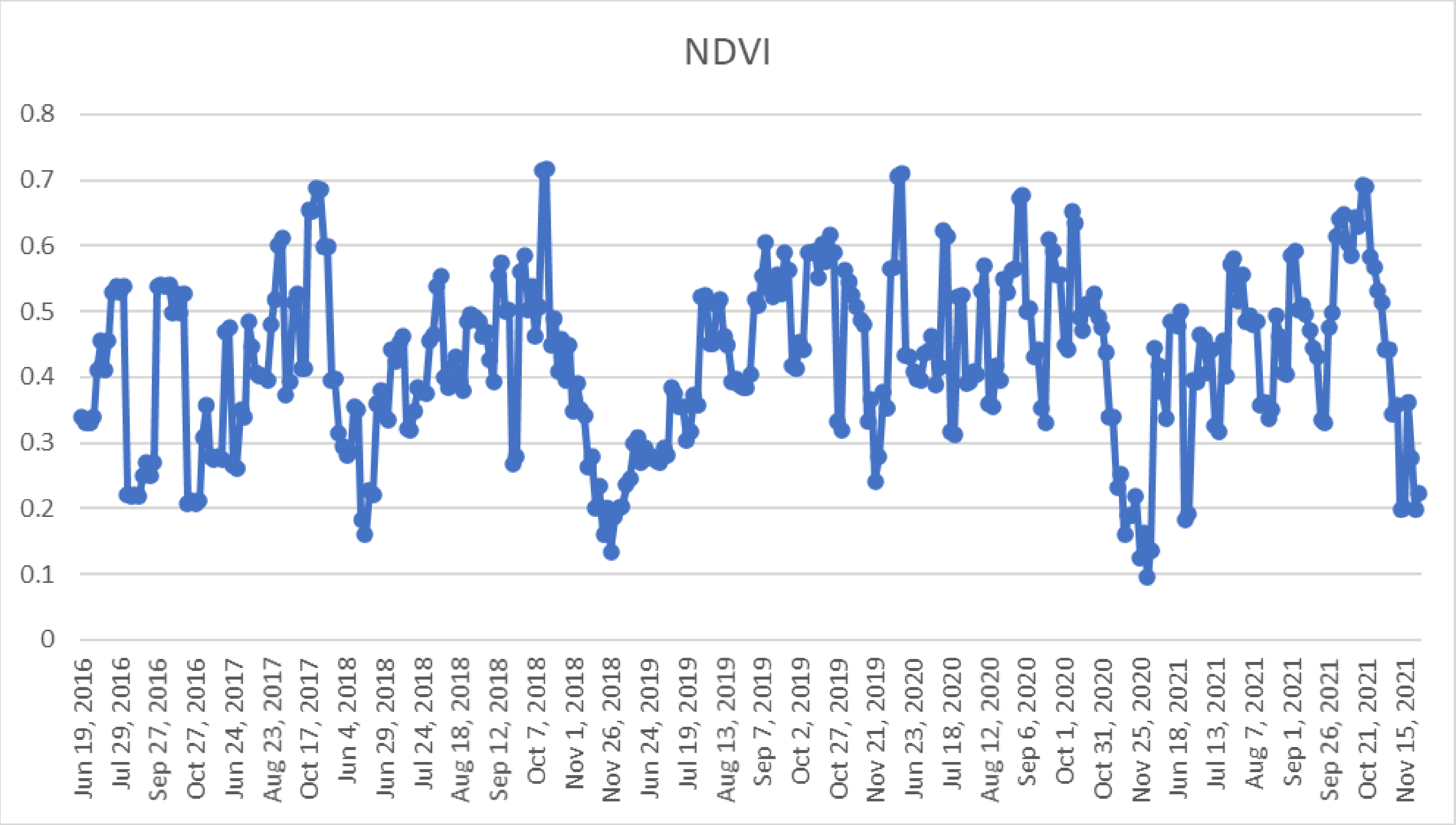
Hyper-parametrization

Testing & Evaluation

Need for feature engineering

GP: Guskara (m)

Dist: Purba Bardhaman



Need for feature engineering

ML Models

Model Selection

Feature Selection

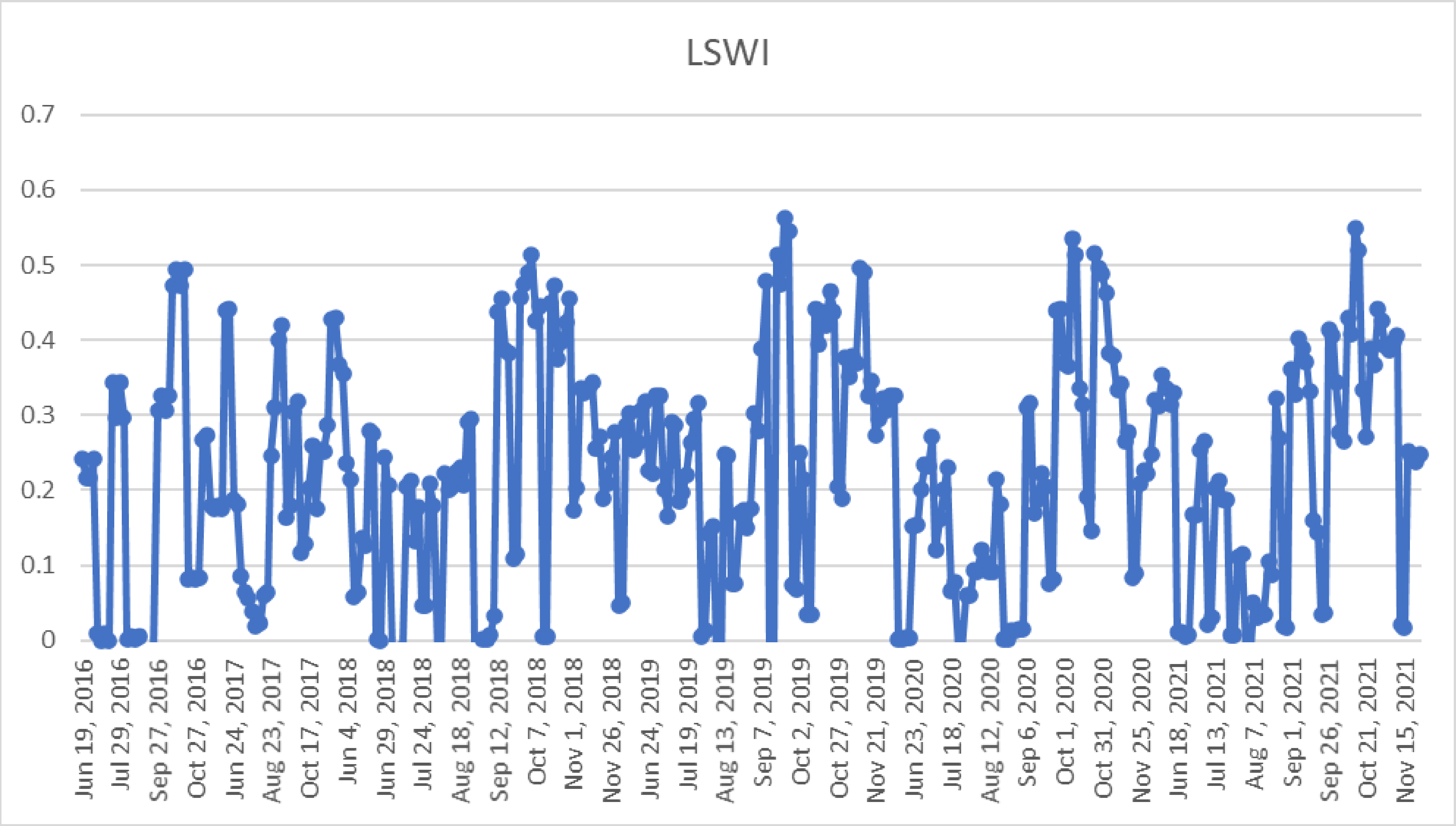
Feature Engineering

Hyper-parametrization

Testing & Evaluation

GP: Guskara (m)

Dist: Purba Bardhaman

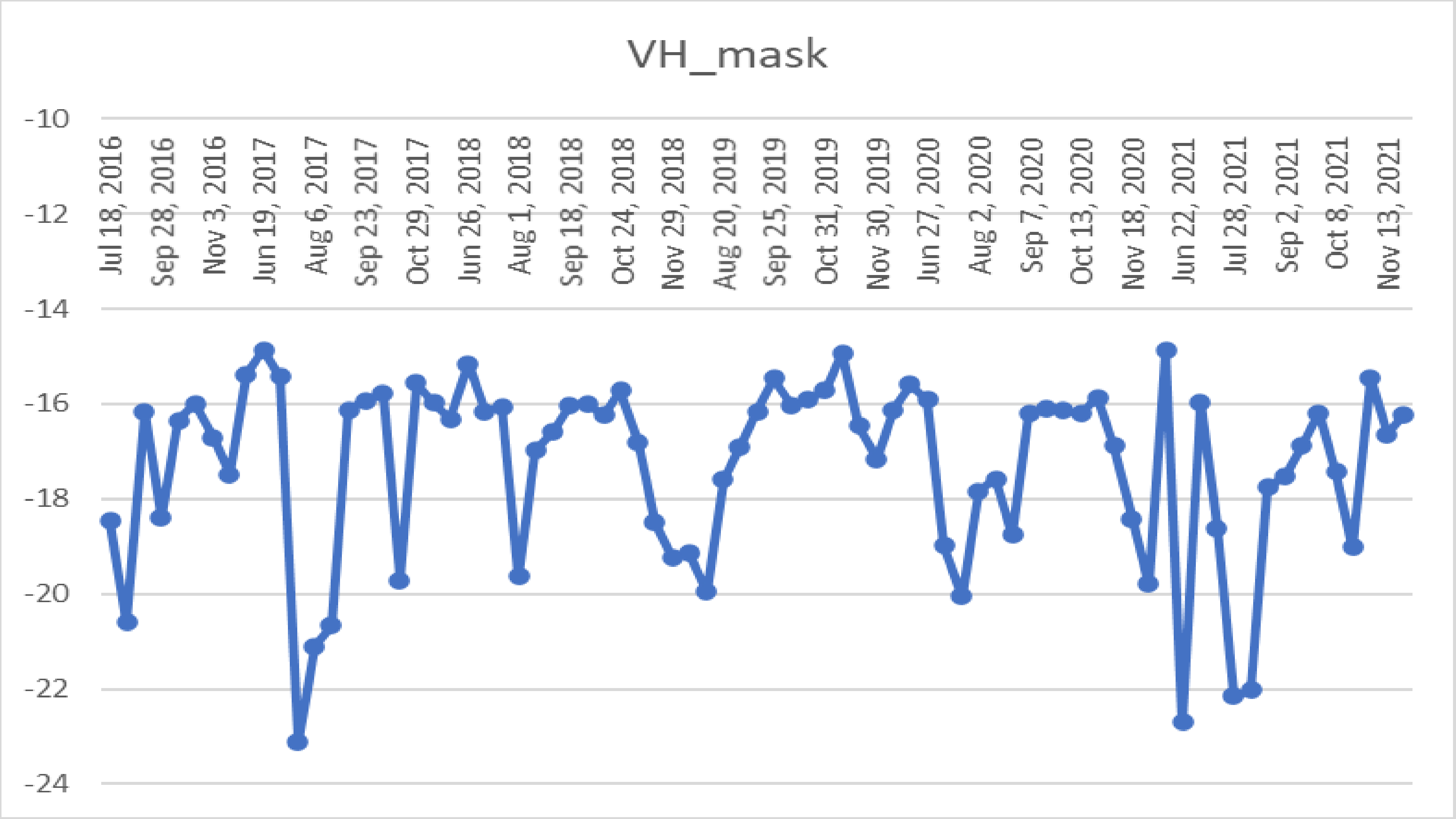


Need for feature engineering

- ML Models
- Model Selection
- Feature Selection
- **Feature Engineering**
- Hyper-parametrization
- Testing & Evaluation

GP: Guskara (m)

Dist: Purba Bardhaman



ML Models

Model Selection

Feature Selection

Feature Engineering

Hyper-parametrization

Testing & Evaluation

Feature engineering: Example

1
Maximum Red
Bare soil at sowing preparation

2
Max. positive Slope
Fastest growth of vegetation

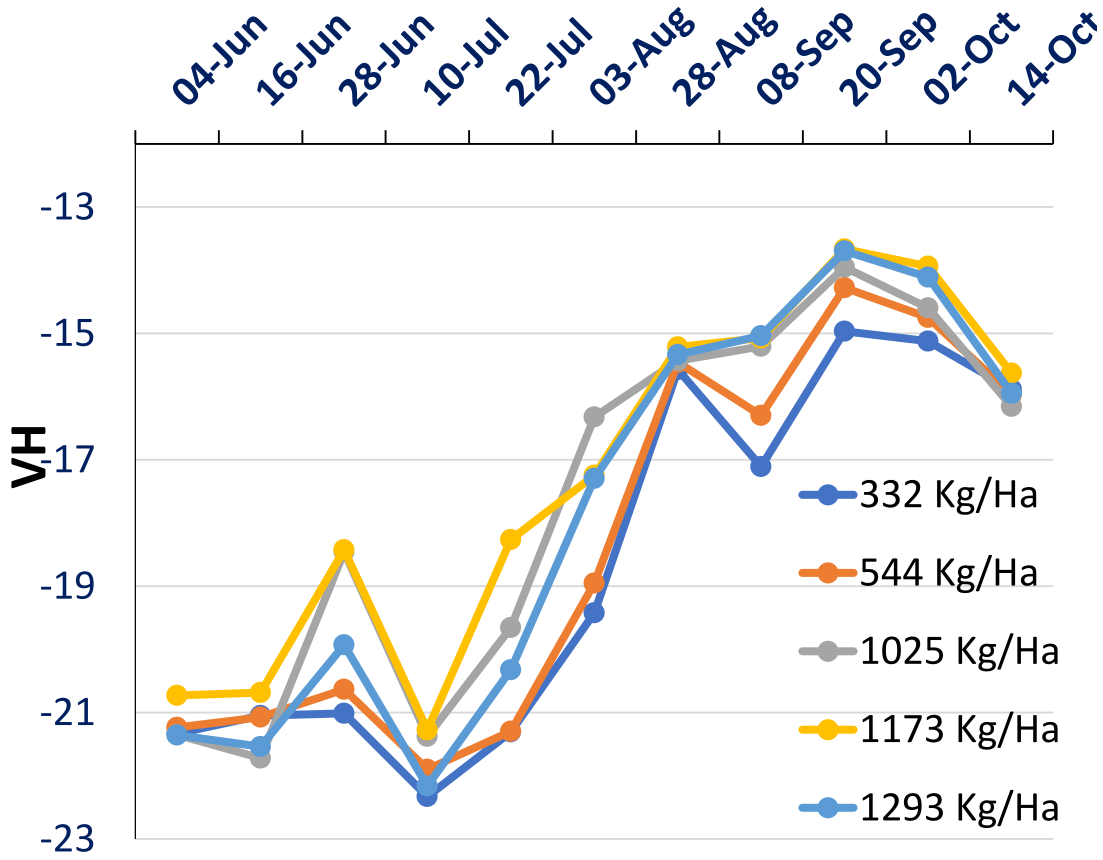
3
Maximum NDVI
(average ß max.)
Maximum biomass

4
Max. Negative Slope
Fastest reduction of greeness

5
Minimum NDVI
(average)
Harvest crop or non green residue

Feature engineering: Example

- ML Models
- Model Selection
- Feature Selection
- **Feature Engineering**
- Hyper-parametrization
- Testing & Evaluation



Feature Extracted

1. Season Maximum VH (Smax VH)
2. Dynamic range of VH (Range_VH)
3. Area under the VH curve (AUC)

Tuning of Hyper-parameters

- ML Models
- Model Selection
- Feature Selection
- Feature Engineering
- Hyper-parametrization
- Testing & Evaluation

ML Model	Hyper-parametrs
Random Forest	•Number of trees •No. of features selected at each node •Minimum Leaf size
Deep Neural Network	▪Network Architecture: ▪Activation function {Sigmoid, Tanh, ReLu, L-ReLU): convert input into non-linear ▪Learning Algorithm {GD, Momentum, Adam}: ▪Learning rate {between 0-1} ▪Loss Function {RMSE, Cross-Entropy} ▪Regularization criteria {dropout, batch normalization, early stopping} ▪Number of training epochs (number of cycle for model tuning) ▪Batch size

- ML Models
- Model Selection
- Feature Selection
- Feature Engineering
- Hyper-parametrization
- **Testing & Evaluation**

Training and Validation approach

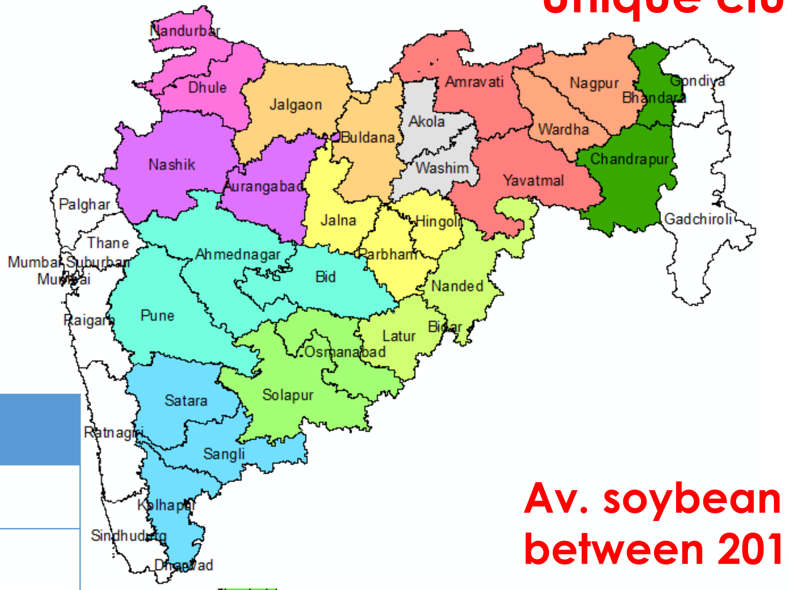
- Model accuracy need to be tested based on MAE/RMSE/ NRMSE
- For model training and validation, stratified random sampling approach from different yield classes need to be followed.
- From each yield class range at least 30% randomly selected dataset should be used for model validation and the rest for training.
- A good quality training yield data (CCE/IU averaged) as vetted by the state agricultural department from historical crop season should be used.
- **The validated model needs to be run for the current season and the final deliverables will be the modelled yield of insurance units for the current and historical (at least 5 years) years.**

Case Study

Machine Learning based Soybean yield estimation in Maharashtra

- All the major soybean growing districts of Maharashtra are divided into 12 clusters based upon AESR zones
- For each group, a separate ML model was trained by using the crop yield data from 2017 onwards.

Unique clusters

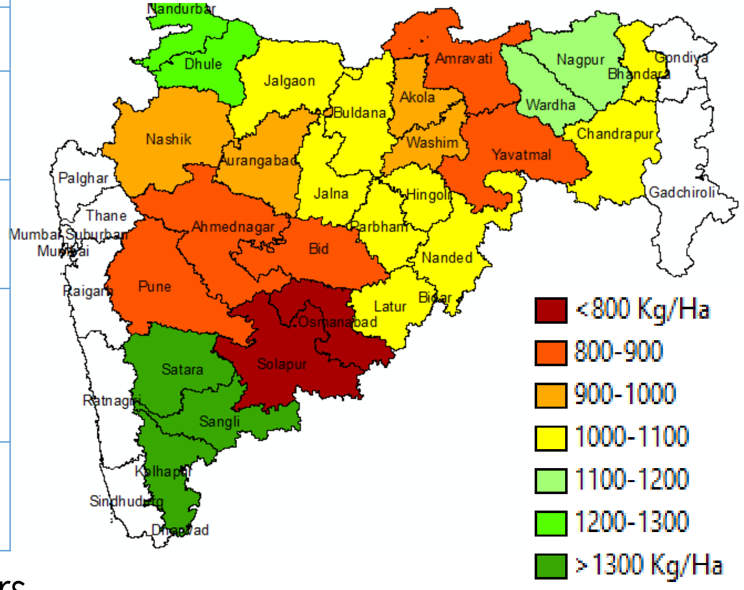


Dataset used

Datasets	Source	Feature derived
Temporal VH	Sentinel 1	Monthly max VH from June to October
NDVI	Sentinel-2	Season max NDVI from June to October
LSWI	Sentinel-2	Season max LSWI from June to October
Rainfall	State Agril Dept.	Monthly rainfall during June to October
Rainy Days	Derived from rainfall	Monthly rainy days during June to October
Profile Available water capacity	NBSSLUP	Profile Available water capacity
Soybean crop yield	State Agril Dept.	Soybean frop yield at circle level from 2017 onwards.

Soybean crop map derived from Sentinel-1 & Sentinel-2 data for all the years

Av. soybean yield between 2017-2020



Case Study

Machine Learning based Soybean yield estimation in Maharashtra

Methodology

Temporal VH

Weather data (RF&RD)

Smax NDVI

Smax LSWI

PAWC

Data preprocessing (gap filling, outlier removal, data normalization etc)

Model Training

ML model training & validation

- Model parameter optimization
- **2017-2020 soybean yield data**

Model deployment

Current Year datamatrix → **Trained ML model** → **Soybean crop yield estimate for current year**

Case Study

Machine Learning based Soybean yield estimation in Maharashtra

Model Hyper-parameters

DNN Architecture	18-36-18-9-1
Activation function	Leaky ReLU
Learning Algorithm	Adam
Learning rate	0.001
Loss Function	RMSE
Regularization	Dropout of 0.2
training epochs	500
Batch size	8

Based upon the accuracies observed during model training process, these architecture were further modified for each clusters

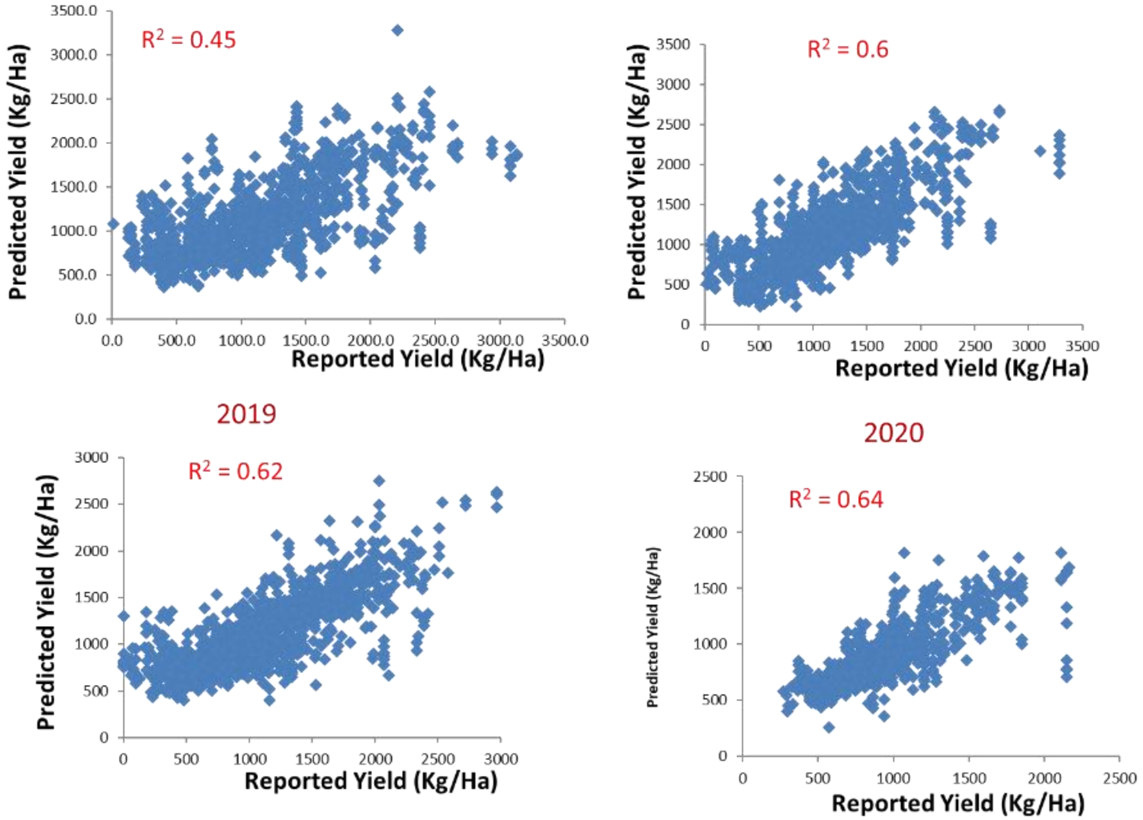
Case Study

Machine Learning based Soybean yield estimation in Maharashtra

Results

Cluster	Training RMSE (Kg/Ha)	Validation RMSE (Kg/Ha)
Akola-Washim	228	283
Amravati-Yavatmal	165	240
Nagpur,Wardha	203	240
Jalgaon,Buldana	214	287
Parbhani-Jalna-Hingoli	228	259
Latur-Nanded	187	280
Osmanabad-Solapur	140	246
Beed,Ahmednagar-Pune	231	244
Satara-Sangli-Kolhapur	311	430
Nashik,Aurangabad	308	388
Nandurbar-Dhule	346	374
Chandarpur-Bhandara	293	305

Model Performance

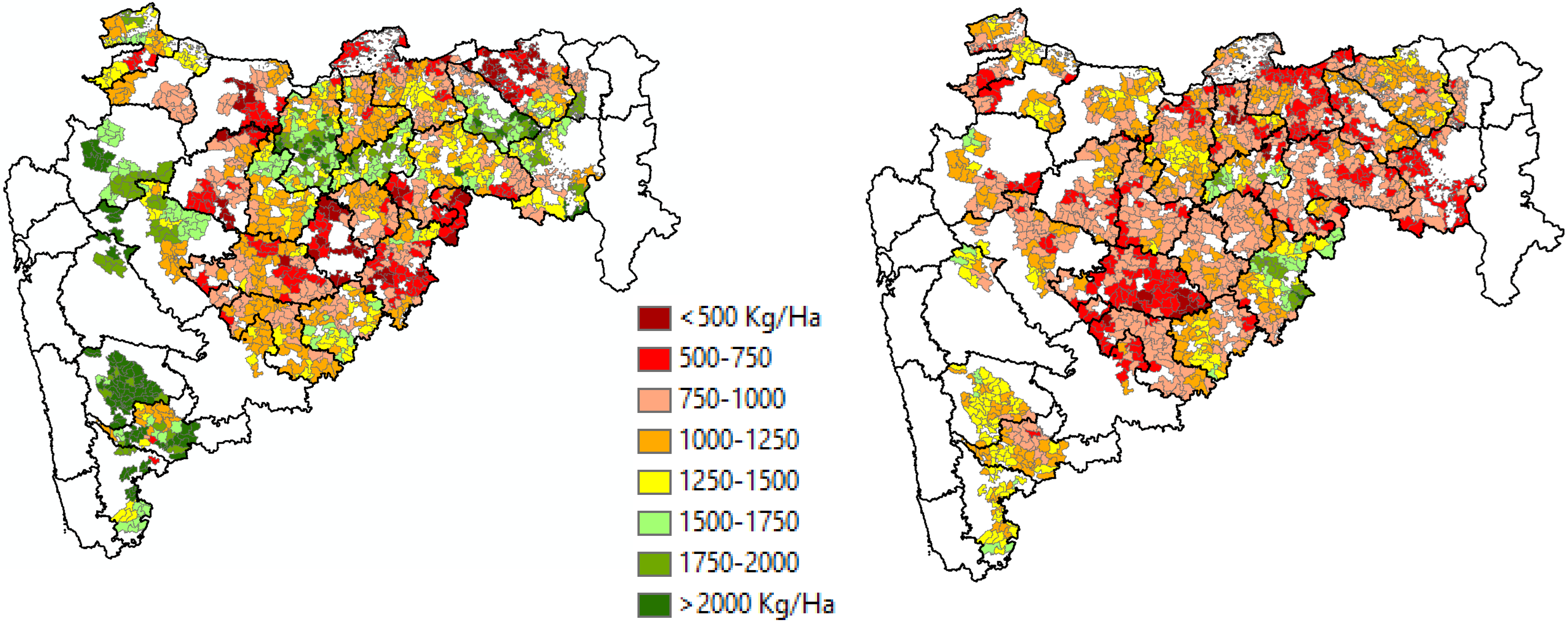


Case Study

Machine Learning based Soybean yield estimation in Maharashtra

Results

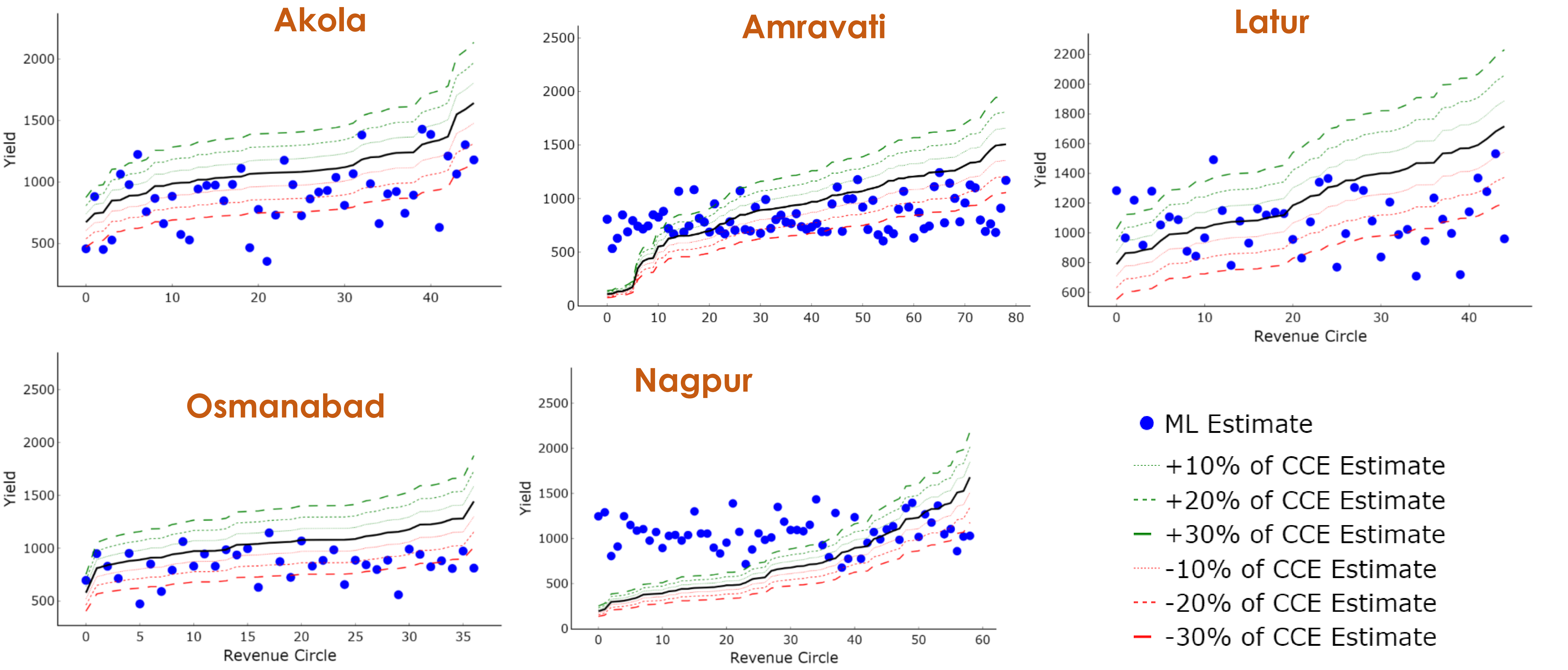
CCE reported soybean yield **2021** MI predicted soybean yield



Case Study

Machine Learning based Soybean yield estimation in Maharashtra

Results (2021)



To Summarize

- Machine learning models can captures the non-linear relationships between the yield and the features influencing the crop yield

- Proper workflow should be carried out which includes pre-processing, feature design, splitting data into training and validation sets, selecting machine learning algorithm, training, optimization, evaluations and testing

- Datasets/features must represent crop growth influencing factors

- Proper feature engineering should be carried out

- Regularization criteria must be followed to check the overfitting of the model. Optimization function should be reflected as an output to visualize the learning rate, batch size etc

- A good quality training yield data must be used

PMFBY
Pradhan Mantri Fasal Bima Yojna

SOP for

Crop Simulation Models

YIELD ESTIMATION SYSTEM BASED ON TECHNOLOGIES

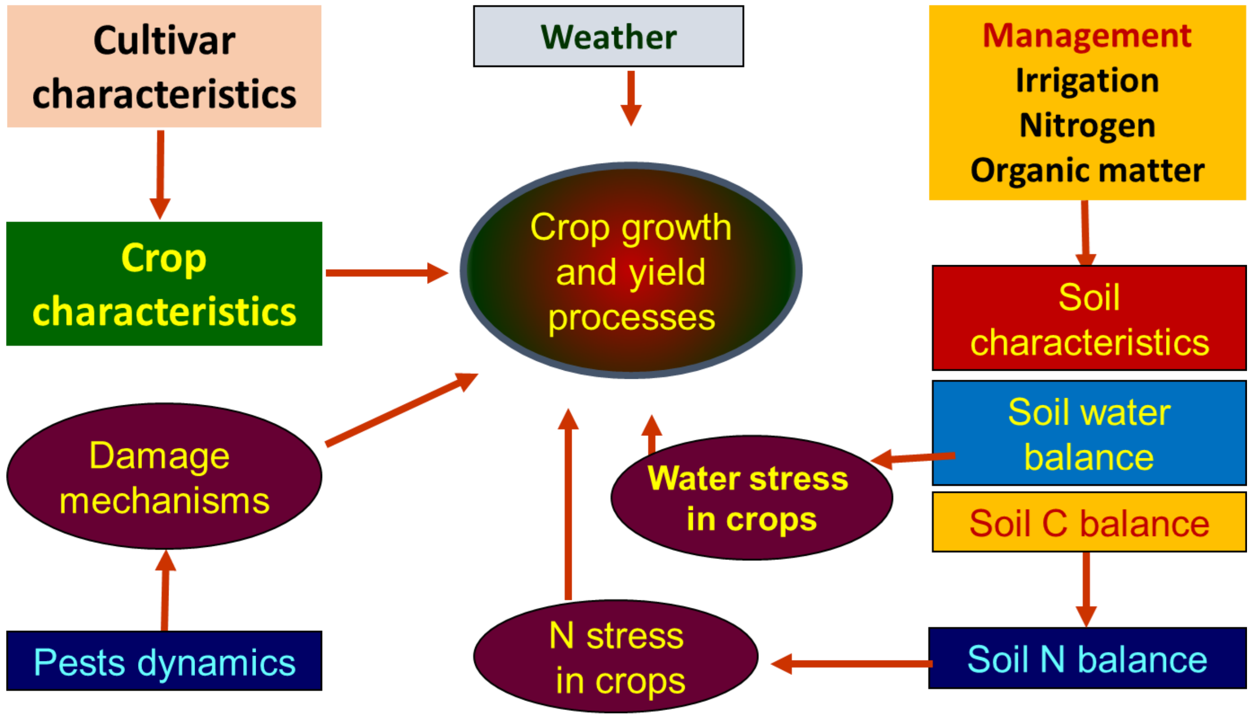
YES-YECH

Presentation outline

1. Introduction
2. Available CSMs
3. Input data
4. Calibration and validation
5. Increasing the granularity of CSMs
6. Spatial simulation tools
7. RS data assimilation
8. Deliverables

Crop Simulation Models

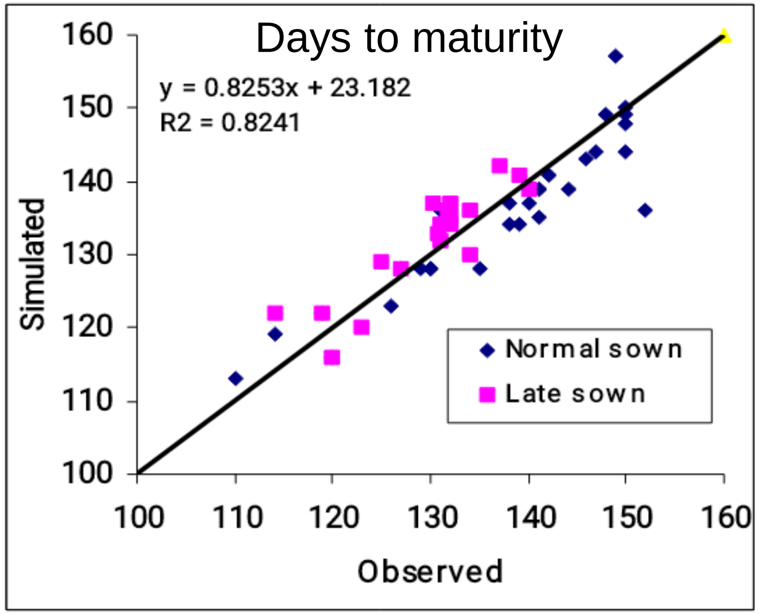
- Crop growth models simulate the plant processes to estimate various bio-physical parameters and final crop yield.
- The following processes are considered in most of these models:
  - Crop growth and development: phenology, photosynthesis, partitioning, leaf area growth, storage organ numbers, source: sink balance, transpiration, uptake, allocation, and redistribution of nitrogen.
  - Effects of water, nitrogen, temperature, flooding, and frost stresses on crop growth and development.
  - Soil water balance: root water uptake, inter-layer movement, drainage, evaporation, runoff, ponding.
  - Soil nitrogen balance: mineralization, uptake, nitrification, volatilization, interlayer movement, denitrification, leaching.
  - Soil organic carbon dynamics: mineralization and immobilization

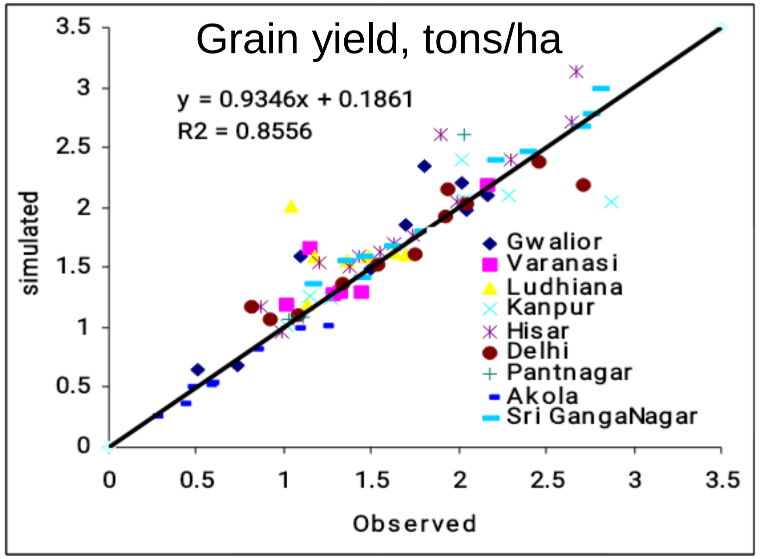


Source: Aggarwal el al., 2006 a, b

Crop-Yield assessment

- Crop Growth and Yield Modelling has been there for long: several empirical and mechanistic models are already available;
- The process-based models require detailed data, which is usually not available beyond research setups;
- Crop insurance created a demand for crop yield/loss assessment at the village scale;
- Crop loss assessment requires multi-disciplinary effort, several methods and their combinations;
- Achieving village/pixel level yield loss assessments using only weather, CSMs is not possible;





Crop: Mustard (Bhoomiraj *et al.* 2008)

Available Simulation Models

- There are several crop-simulation models available in the literature; however, they have varying accuracy, and only a few are tested thoroughly for Indian conditions.

- Emphasis should be given to the use of those models that have proven accuracy and calibrated parameter values (e.g., cultivar coefficients) are available.

SOPs Step 2

Input Datasets – Weather Data

- IMD daily weather data (station) for the current season and historical (more than seven years)
- Real-time and historical satellite/gridded weather data (daily)
- Minimum weather data: Daily rainfall, temperature (maximum and minimum)
- Additional weather data: Solar radiation, wind speed, humidity

Data Source

IMD Station and Gridded Data

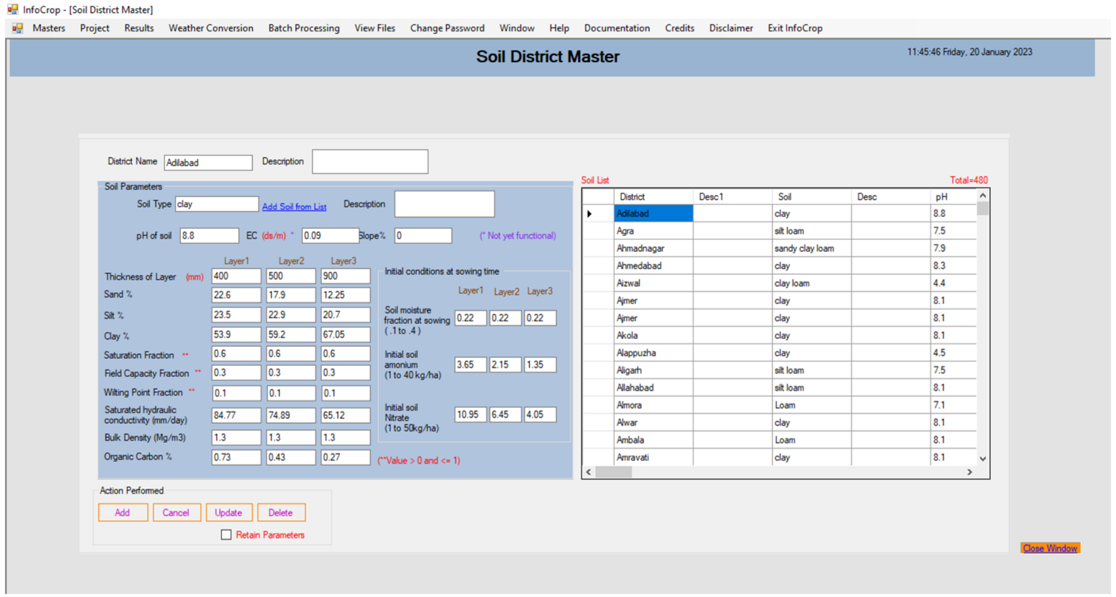
ERA5 or reanalysis data

CPC/CHIRPS or CHIRTS or other satellite/gridded data

SOPs Step 3

Soil Data

- Soil physical properties by layers: Bulk density, soil texture, depth
- Soil chemical properties by layers: Organic carbon, EC, pH



Data Source: NBSSLUP Data, Gridded soil data (SoilGrids), Field survey, Soil Health Card

SOPs Step 4

Crop Management Data

- Cultivar information: primary cultivar
- Agronomic data on fertilizer,

seed rate, crop duration, irrigated area, rained area, cultivars, sowing depth, etc.,

- Sowing dates

Data Source: Field surveys & Information from KVKs, Using the above inputs and RS data

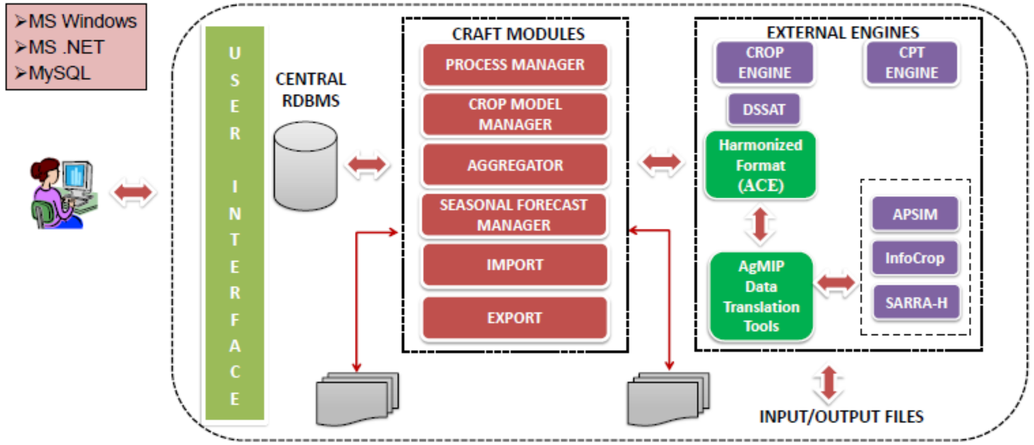
Calibration and Validation

- Model calibration and validation approaches are required for each selected model for the selected crop.
- The simulation models are sensitive to the genetic coefficients of the crop cultivar.
- The calibration process should be done with care and ensure that the parameters do not exceed the biological range.
- A minimum check on crop duration and time to flowering/maturity should be done.
- The datasets from KVK, SAUs, or ICAR institutes should be used to check the quality of the simulation.

SOPs Step 6

Increasing the granularity of CSMs

- The granularity of outputs derived from CSMs depends on the granularity of input datasets.
- To improve the granularity, spatial simulations should be done by considering variations in soil, weather, and other input parameters like sowing dates.
- Several tools are available to do spatial simulations e.g., CRAFT, CAM and AGMIP tools.
- Assimilation of remote sensing data in the crop simulation models, e.g., LAI
- Crop area-based aggregation must be applied to derive final yields at the IU level.



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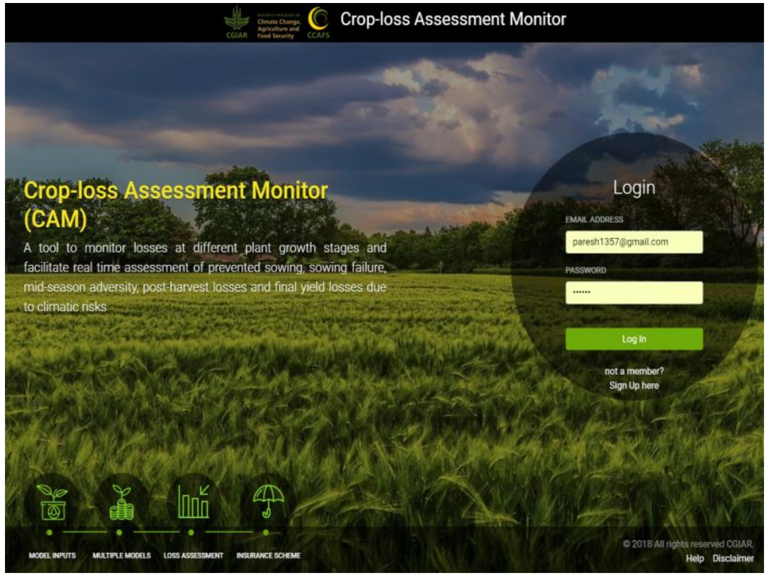
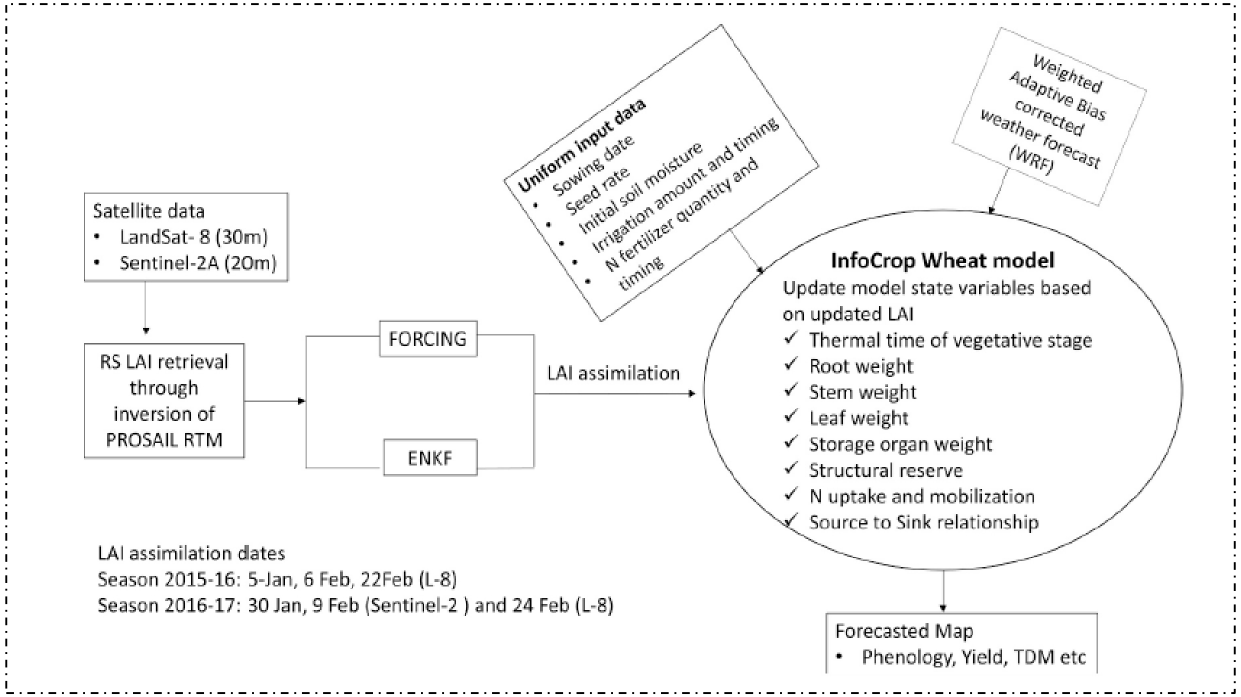


Critical considerations in assimilating RS data in CSM

- Assimilating remote sensing data in CSMs is an accepted way to improve the granularity and capture field-level details.

- LAI and soil moisture are the primary remote sensing variables usually assimilated into the crop simulation models.

- Remote sensing data assimilation and subsequent updating of the state variables in the CSM should be done using methodologies tested and published in peer-reviewed research journals.



Dhakar et al., 2022

Advantages and limitations of using of CSMs

Advantages

- Setting up a CSM platform for crop and agro-ecology initially takes time however, once calibrated and validated, it just needs data updates subsequently
- CSMs provide detailed daily outputs, which adds knowledge to understanding risks and their impact, which otherwise lacks in the data-driven model.
- With remote sensing data assimilation in CSMs can compensate for field-to-field variability in variety, sowing date and management practices even with uniform values specified to model

Limitations

- Achieving granularity needs additional effort and can become tedious in absence of tailored tools.
- Not all risks are simulated in CSMs e.g., many models lack biotic stress modules, local hazards such as hailstorms and others

SOPs Step 8

Deliverables

The final deliverable will be a model yield estimate for the **current** and at least the past five years for the given crop at the IU level.

CSM Expertise in India (indicative list)

- ICAR Institutes: IARI, CRIDA, IIRI, IIFSR and others
- ISRO Institutes: SAC, NRSC, IIRS, RRSCs and State Remote Sensing Centers
- IITs (IITKGP, IITR and others)
- SAUs (TNAU, PAU, MPKV and others)
- CGIAR – CIMMYT, ICRISAT, IWMI, (BISA)
- And many more …

Thank You

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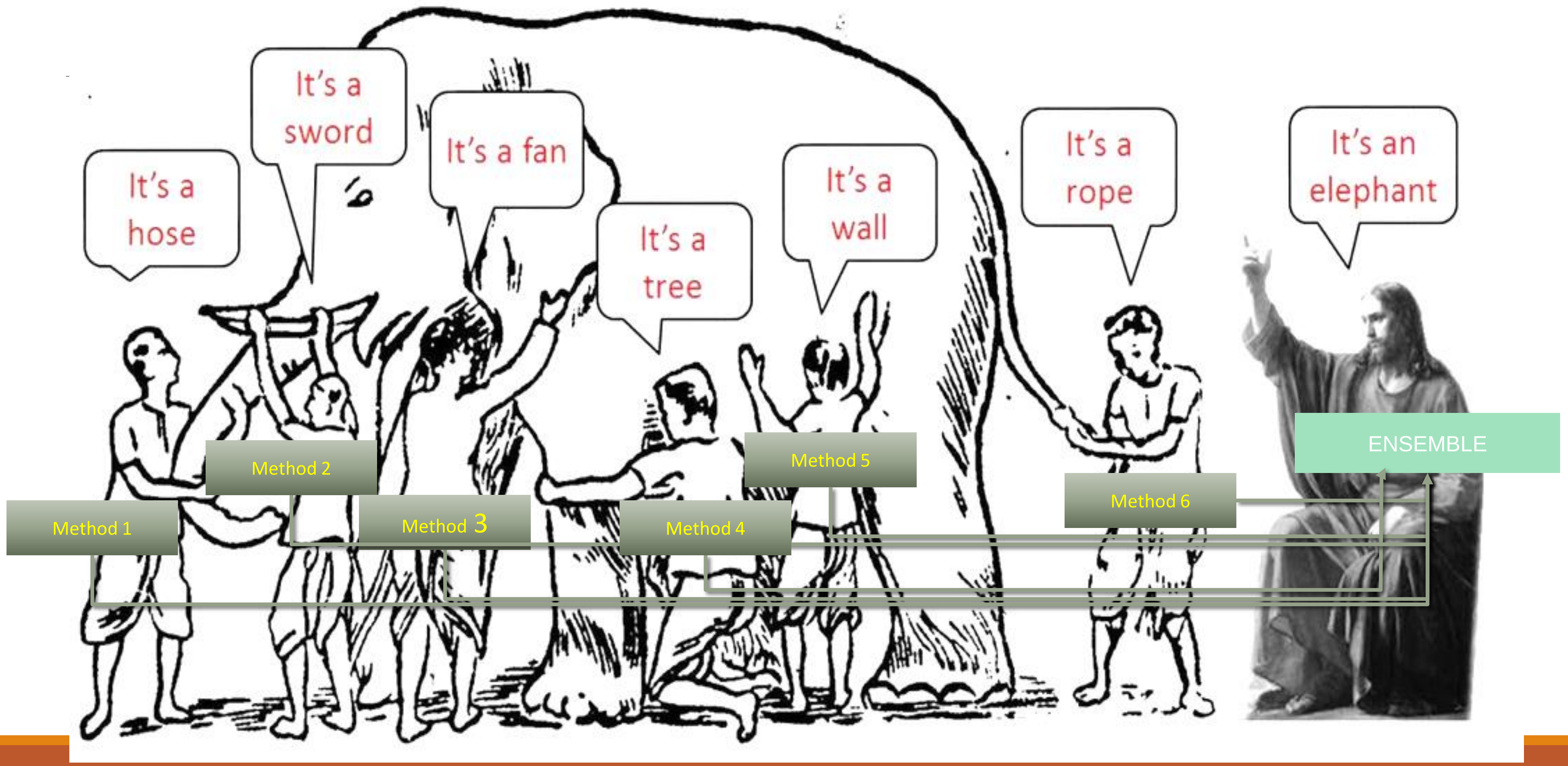
Ensembled approach of crop yield estimation

AN OUTCOME OF PILOT STUDIES

sunil.dubey86@gov.in

The Ancient Parable "The Blind and The Elephant", Illustrating The Method of Ensembling



What are Ensemble Methods?

Ensemble methods are techniques that create multiple models and then combine them to produce improved results.

This approach allows the production of **better predictive performance compared to a single model**.

Ensemble methods **usually produce more accurate solutions than a single model would**.

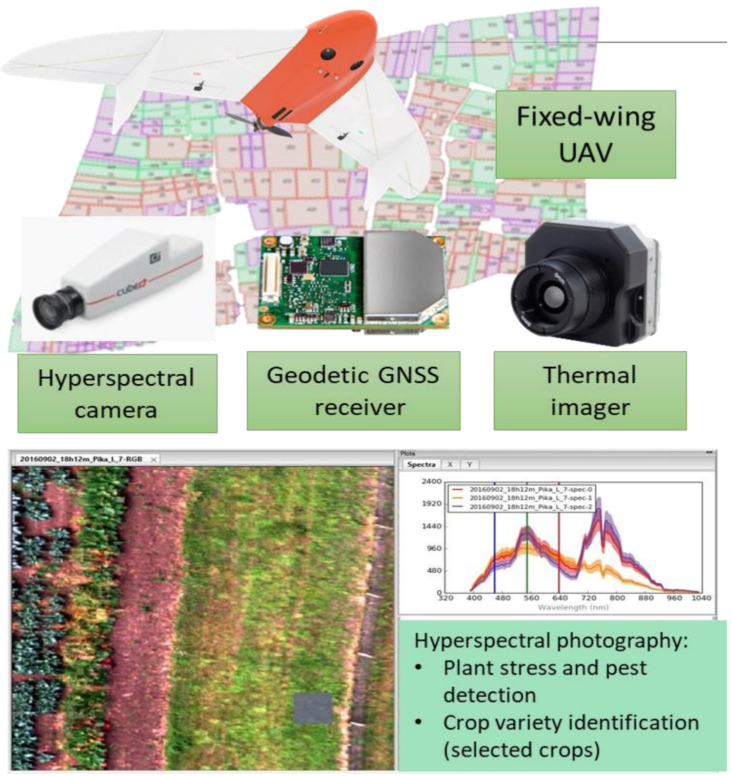
This has been the case in many machine learning competitions, where the winning solutions used ensemble methods.

Ensemble Methods used in the technology:

1. **Bucket of models**: pick the model with best metrics for each region.
2. **Bagging:** sequential sampling of pre-trained algorithms followed by a weighted stacking
3. **Stacking:** linear (or custom) model on predictions by various pre-trained algorithms.

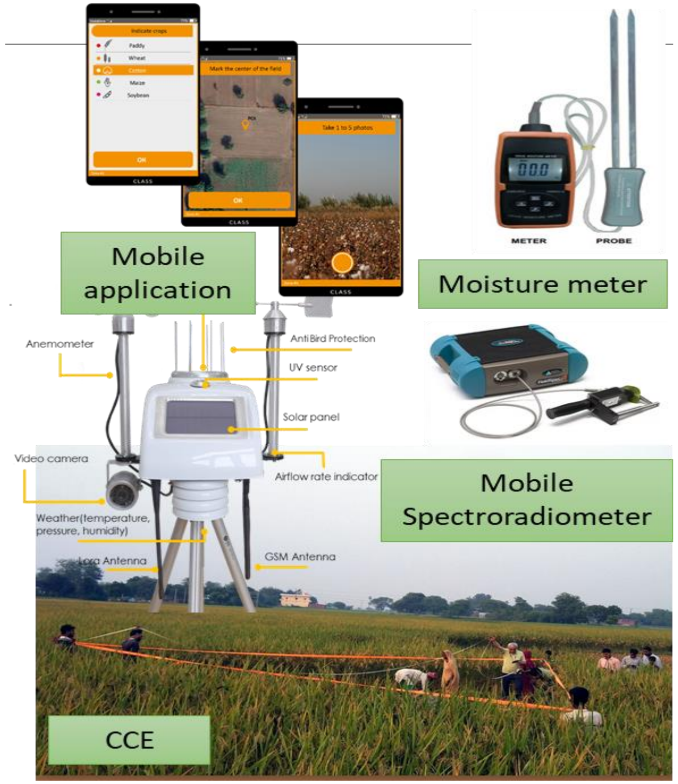
Proposed Analytics

IN THE AIR



- DGCA-compliant UAV 90+min endurance
- Weekly monitoring of plots to track dynamics
- Hyperspectral & RGB cameras of required specifications
- 2-2,5 tsd. of spectrum images per crop variety

IN THE FIELD

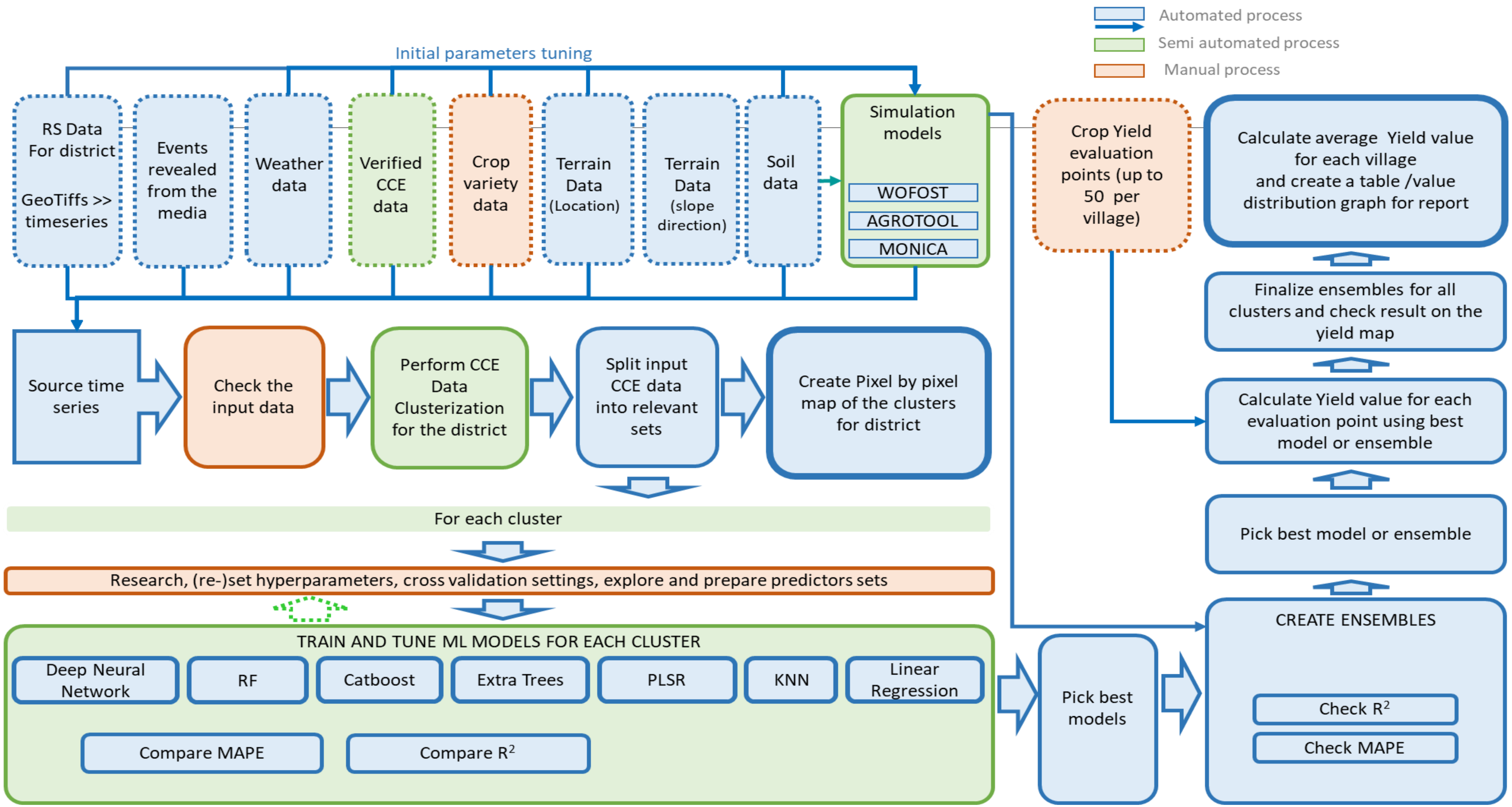


- Customized mobile application
- Crop classification & Stress type detection
- Test-beds for vegetation patterns study
- Soil cards
- Meteo data
- Fertilizer/Pesticide use (type and intensity)

IN CYBERSPACE

- Digital maps as basic matrix
- Cloud data storage (est. 800 Gb)
- Powerful processing software (e.g. CLASS)
- Binary classificatory arrays for clustering
- ML-based selection of valid predictor sets
- Absorption of heterogeneous info

Comprehensive Crop yield modeling approach

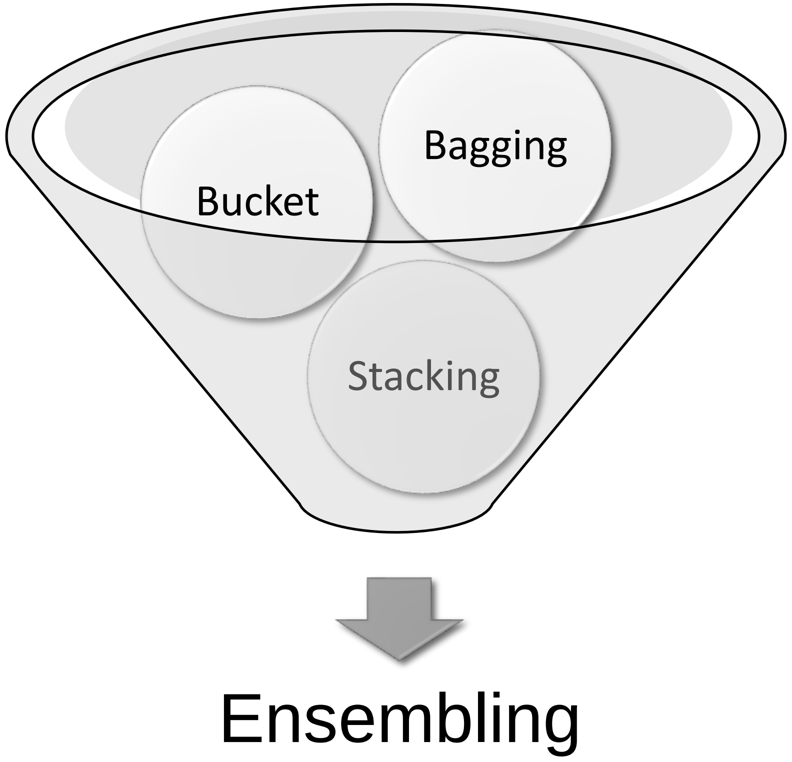


AI-based computation avails high level of automated operations in the modeling process

Ensembled approach tested in Pilot study

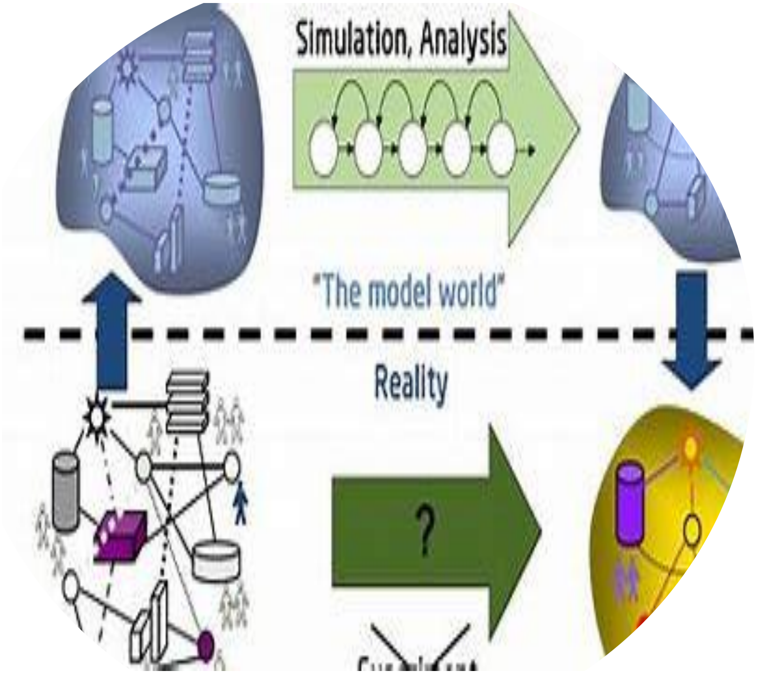
YIELD MODELLING APPROACH

MODELING METHOD	BRIEF DESCRIPTION
RANDOM FOREST	Constructing a multitude of decision trees at training time and outputting the average prediction of the individual trees.
LINEAR REGRESSION	Modelling linear relationship between a scalar response and explanatory variables.
DEEP NEURAL NETWORKS	Artificial neural network with multiple layers between the input and output layers.
CATBOOST	Gradient boosting algorithm. Produces a prediction model in the form of an ensemble of decision trees.
EXTRATREES	Extremely Randomized Trees, or Extra Trees, is an ensemble machine learning algorithm. It is an ensemble of decision trees.
K NEAREST NEIGHBORS	KNN - K nearest neighbors is an algorithm that stores all available cases and predict the numerical target based on a similarity measure (e.g., distance functions).
ORYZA Imitation model *by International Rice Research Institute*	ORYZA is a crop model for rice, which embodies more than 30 years of global research.
WOFOST Imitation model *by Center for World Food Studies (CWFS) in cooperation with the Wageningen University.*	It is a mechanistic, dynamic model that explains daily crop growth on the basis of the underlying processes, such as photosynthesis, respiration and how these processes are influenced by environmental conditions.
ENSEMBLES	Ensembles are multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms alone.



! Highest accuracy for yield modelling is achieved via use of ensembling methods

Thank you



Parametric index (CHF model)

Parametric-index based crop insurance: Research findings?

- **Crop loss assessment and insurance payouts based on crop performance proxies rather than measured /modelled yield** data are more promising.
- **Index-based insurance envisages pay-outs based on objectively measured index** reflecting the crop losses and overcomes many problems encountered with the pay-outs based on measured losses (Hess and Syroka 2005, Hazell et al. 2010, Miranda and Farrin, 2012, Ibarra and Skees 2007, Barnett et al. 2007, Leblois et al. 2014).

commentary

Science-based insurance

Molly E. Brown, Daniel E. Osgood and Miguel A. Carriquiry

Crops are at risk in a changing climate. Farmers in the developing world will be able to insure against harvest failure if robust insurance packages, based on a geophysical index rather than individual loss, become widely available.

comment

Satellite support to insure farmers against extreme droughts

Agricultural insurance is a valuable strategy to cope with extreme weather risks. Improved satellite observation capabilities can be particularly helpful with droughts, but will not translate into better insurance unless key challenges are overcome.

Willemijn Vroege, Anton Vrieling and Robert Finger

Extreme weather events are a major risk to agricultural production. Droughts, for example, can ruin a whole year's continuous stream of high-resolution openly accessible data that can be transformed into relevant and validated information for that insured farmers are not fully covered for their losses.

High-resolution satellite imagery can

SCIENTIFIC REPORTS

OPEN

Phenology Information Contributes to Reduce Temporal Basis Risk in Agricultural Weather Index Insurance

Received: 22 September 2017
Accepted: 14 December 2017
Published online: 08 January 2018

Tobias Dalhaus[1], Oliver Musshoff[2] & Robert Finger[1]

Weather risks are an essential and increasingly important driver of agricultural income volatility. Agricultural insurances contribute to support farmers to cope with these risks. Among these insurances, weather index insurances (WII) are an innovative tool to cope with climatic risks in agriculture. Using WII, farmers receive an indemnification not based on actual yield reductions but are compensated based on a measured weather index, such as rainfall at a nearby weather station. The discrepancy between experienced losses and actual indemnification, basis risk, is a key challenge. In particular, specifications of WII used so far do not capture critical plant growth phases adequately. Here, we contribute to reduce basis risk by proposing novel procedures how occurrence dates and shifts of growth phases over time and space can be considered and test for their risk reducing potential. Our empirical example addresses drought risks in the critical growth phase around the anthesis stage in winter wheat production in Germany. We find spatially explicit, public and open databases of phenology reports to contribute to reduce basis risk and thus improve the attractiveness of WII. In contrast, we find growth stage modelling based on growing degree days (thermal time) not to result in significant improvements.

Remote Sensing in crop insurance: Research findings

Roumiguie et al. 2015, developed ***Forage Production Index using fractional green vegetation cover integral*** from medium resolution data for index-based insurance over grasslands.

Bokusheva et al. (2016) developed index-insurance contracts for wheat crop using satellite-derived vegetation condition index ***(VCI)*** and temperature condition index ***(TCI)*** covering Northern Kazakhstan. Copula approach was adopted to model wheat yield and satellite indices, and the results indicated substantial risk reduction in these new contracts. The study also suggests that satellite data of higher spatial resolutions would enhance the effectiveness of insurance contracts.

Some operational ***index-based insurance products for grasslands using NDVI / Rainfall*** in Spain, Mexico, the U.S.A., Canada are summarized in Roumiguie et al. (2017).

Mollmann et al. (2019) - used *remote sensing-based vegetation health indices* performed better than weather indices like temperature and precipitation.

Kolle et al. (2020) reported that satellite indices ***VCI and TCI*** outperformed the meteorological indices in crop risk management through index-based insurance, covering non-irrigated olive trees in Spain.

Rationale behind parametric index generation

(a) objectively measured yield-proxy-index is a better choice than subjectivity-prone manual yield estimates to design crop insurance contracts,

(b) currently satellite and weather datasets permit more objective assessment of crop health at moderate spatial and temporal scales,

(c) composite indicators are effective to simplify the complex processes into easily understandable simple comparisons.

Parametric index "Crop Health Factor (CHF)" implemented in West Bengal

Data sets

- Remote Sensing
- Weather data
- Mobile based field data
- Other data sets
- Spatial analytics
- ....

Alternate mechanism

Abundant satellite data for the current and past seasons, weather datasets and user friendly Mobile Apps for fast and efficient field data collection permit close monitoring of crops through out the season capturing most of the crop risks.

CHF is a bio-physical composite index derived from multiple parameters of crop status from sowing to harvesting. It is a quantitative and objective measure on crop health and its overall performance. It is a close proxy of crop yield.

Area-yield index to be transformed as Area-crop performance index

Input indicators of CHF - Paddy

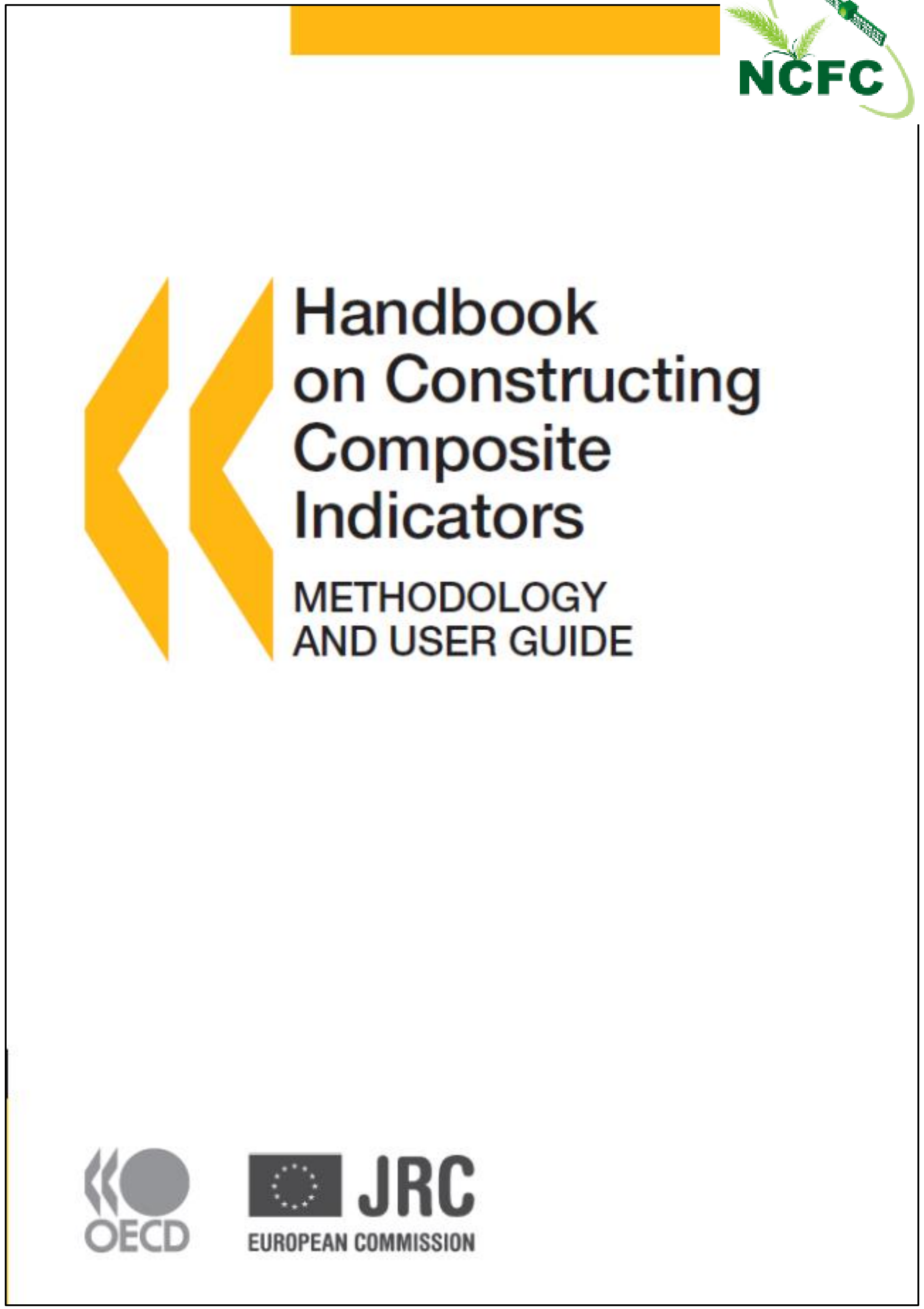
	Input indicator
1	Seasons' maximum NDVI
2	Season's maximum LSWI
3	Season's maximum VH backscatter
4	Integrated VH backscatter
5	Integrated FAPAR
6	Crop condition variability
7	Rainfall
8	Rainy days

Crop risks being captured

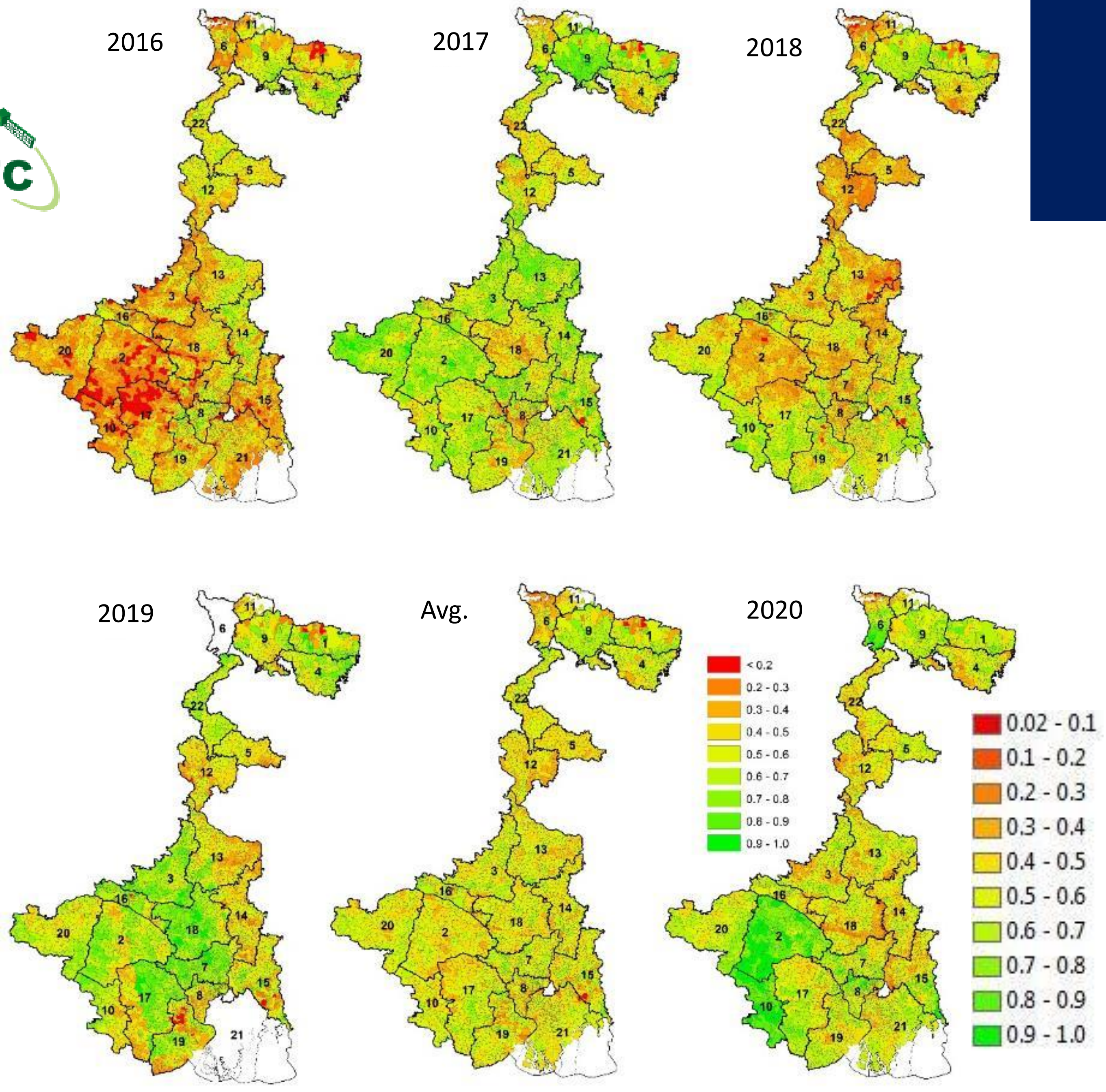
1	Partial submergence
2	Lodging
3	Excess rains causing moist canopy
4	Poor crop condition (wilting)
5	Poor crop condition (structural damage)
6	Poor growth

CHF Analysis framework

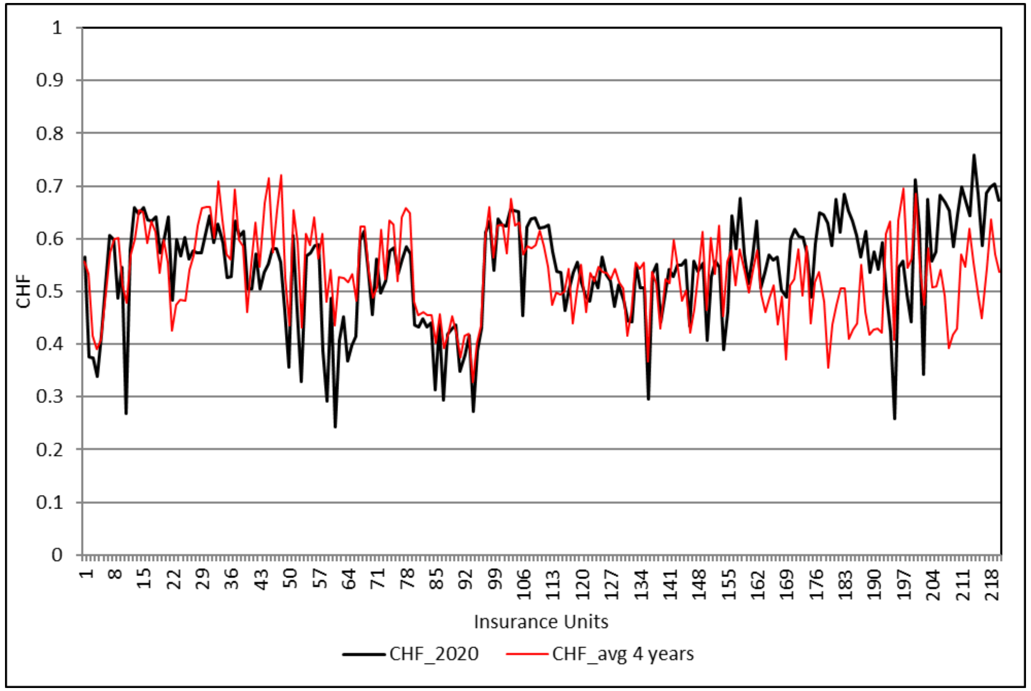
- Zonification of districts – similar crop growing environments
- Input variables – NDVI, LSWI, VH, rainfall, rainy days etc..
- Data Matrix – current and previous years
- Weights generation - entropy analysis
- Index for the current and historic seasons
- Sensitivity analysis – spatial consistency, year to year consistency



Maps of Aman Paddy Crop Health Factor of Insurance Units

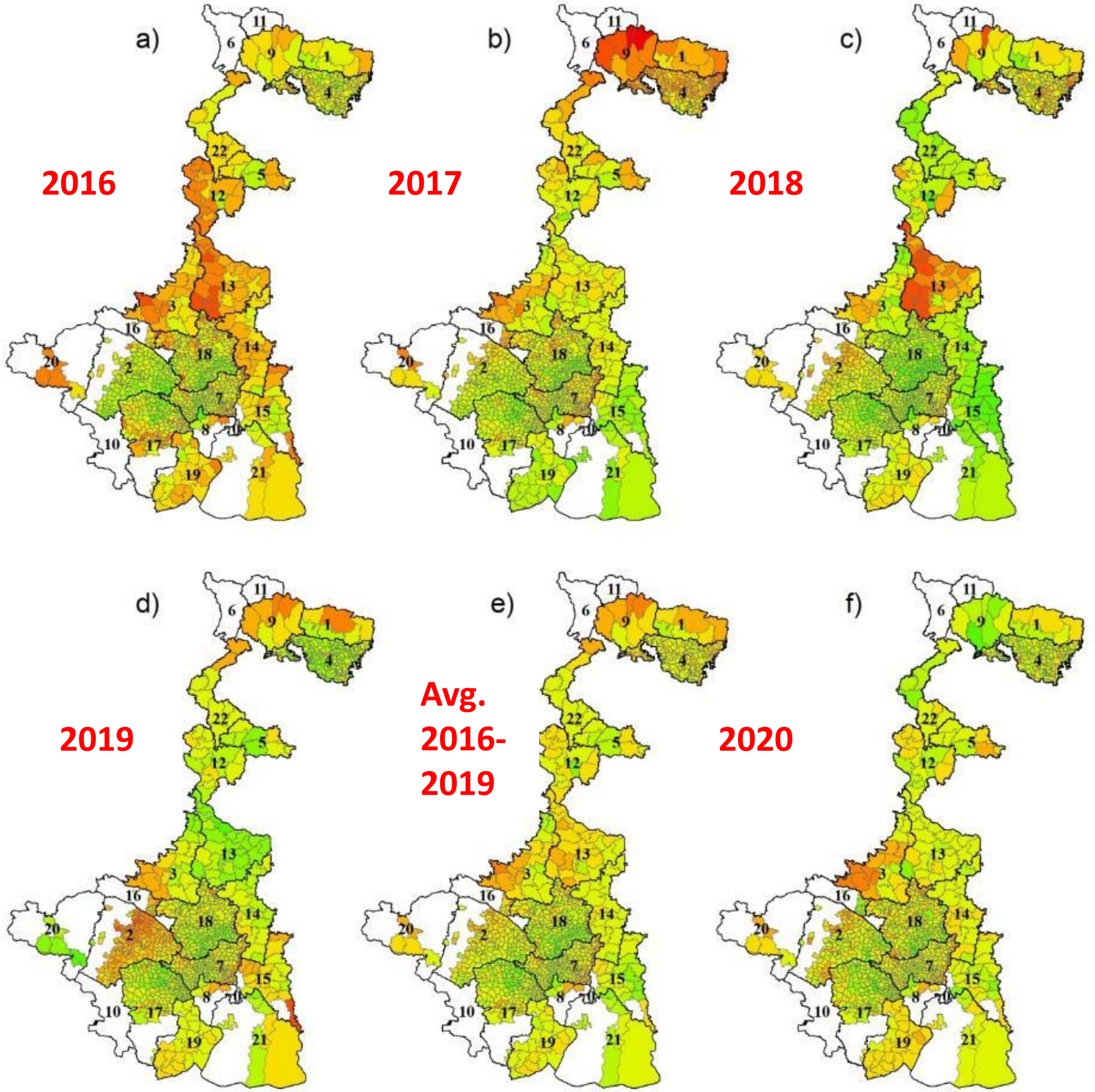


Comparison of CHF: Current year with the past 4-years average - Purba Bardhaman district

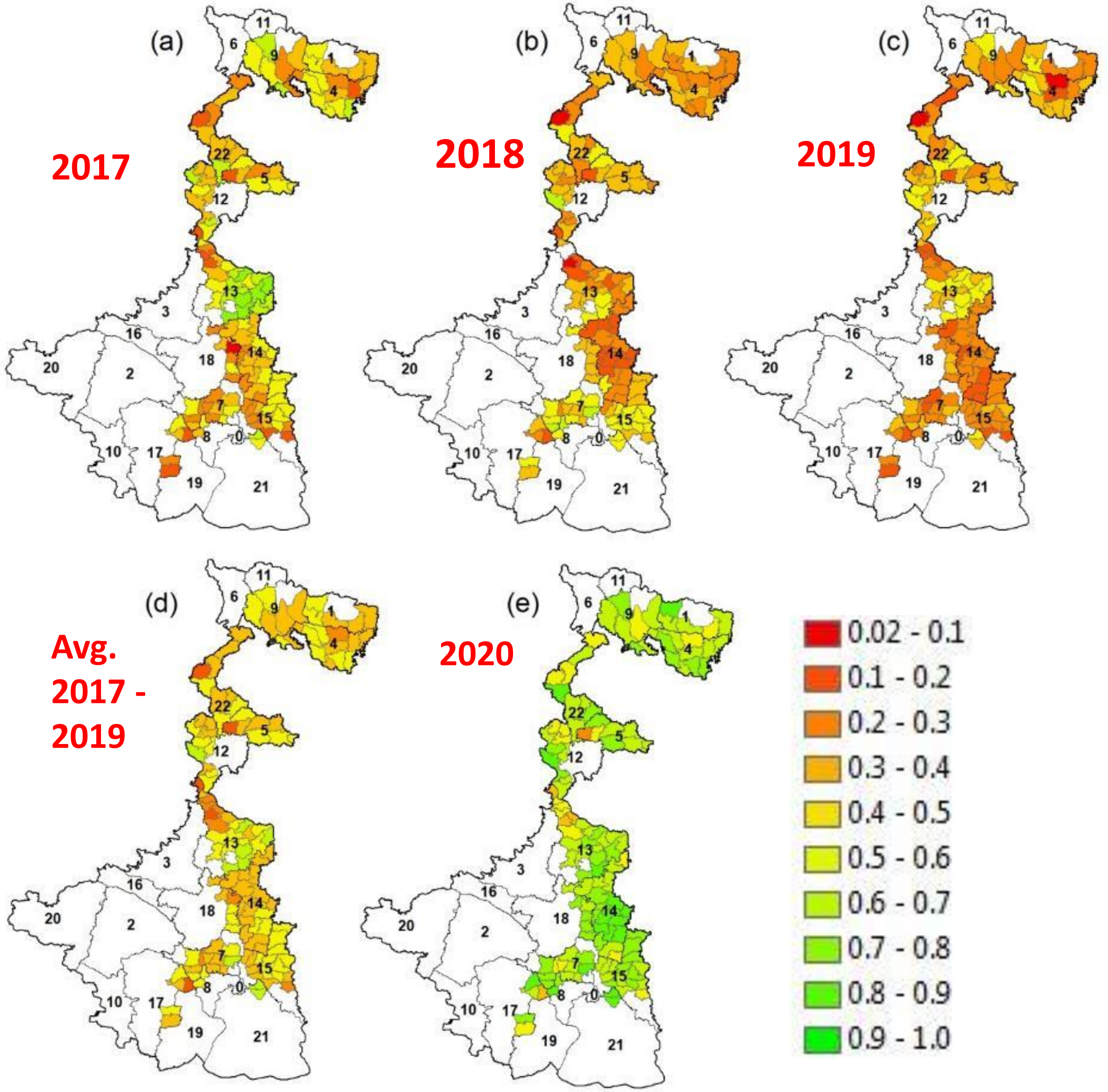


CHF for different insurance units and years

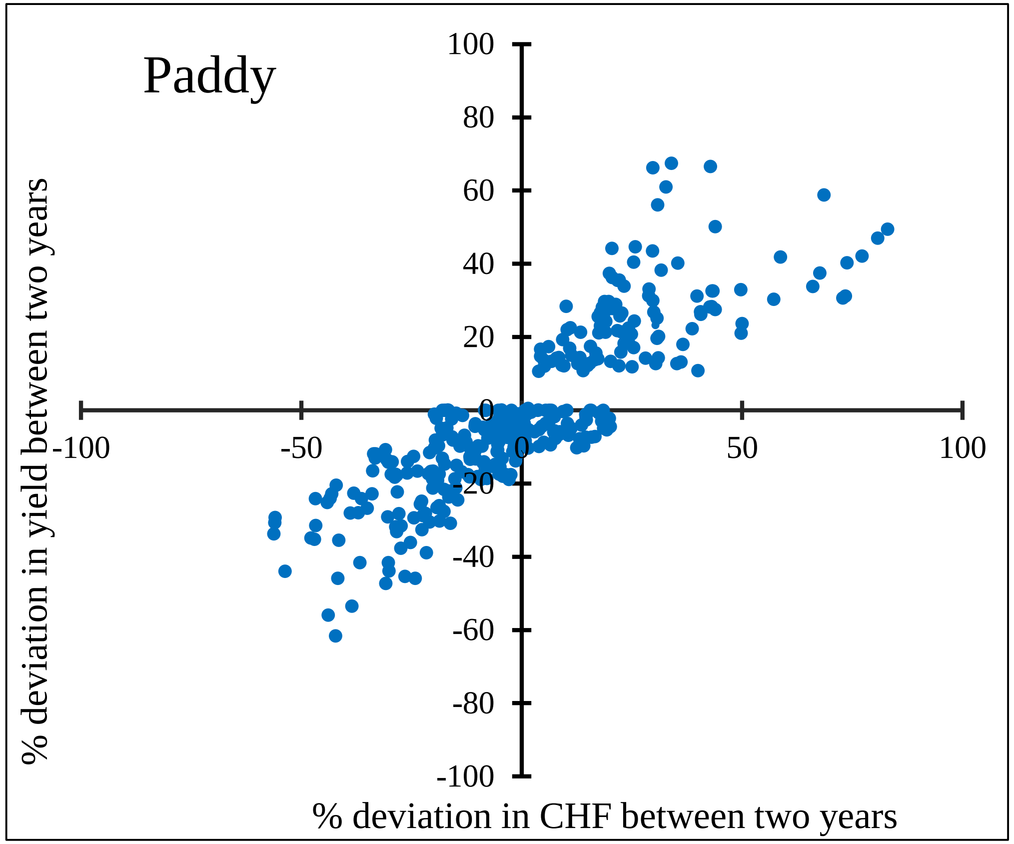
Potato

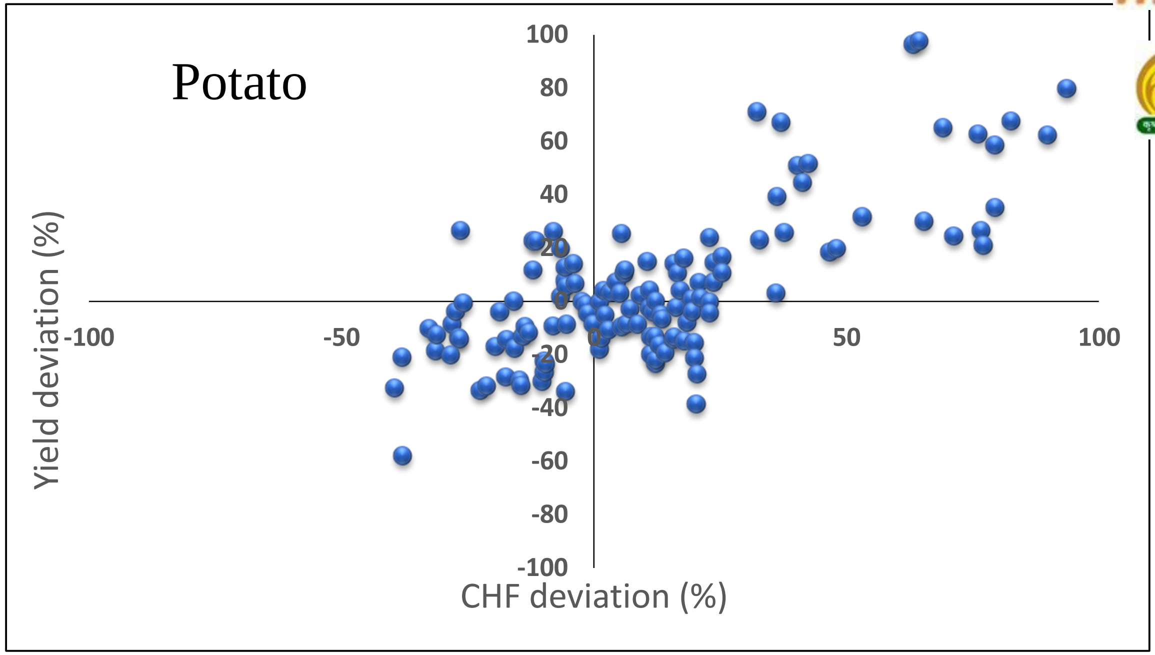


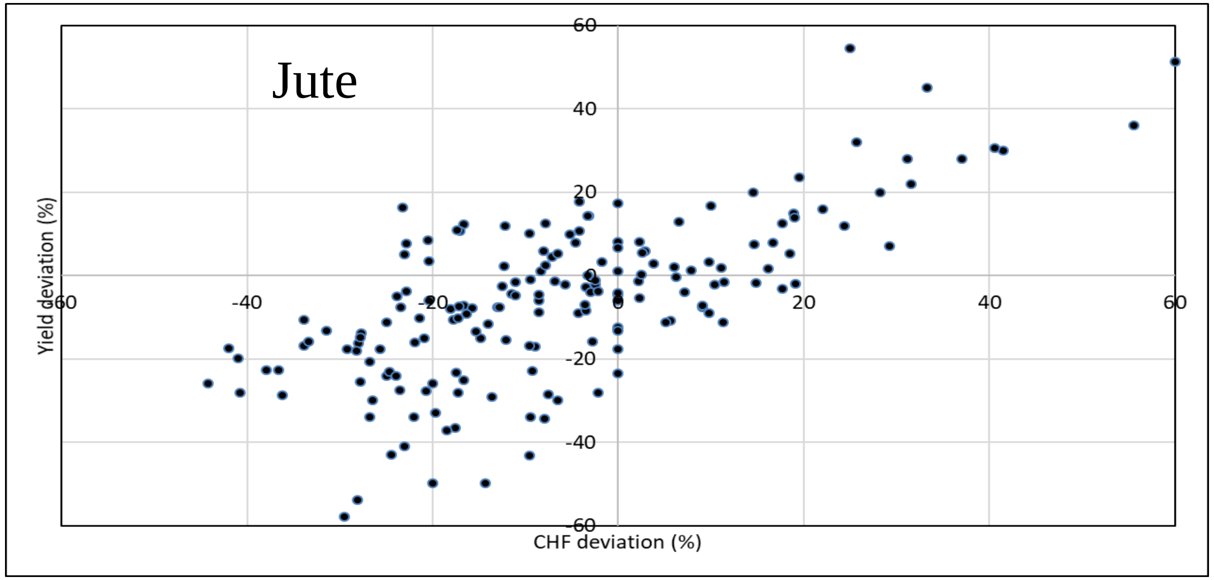
Jute



Relation between CHF and crop yield deviations







Yield changes and CHF changes are well correlated!

Crop loss assessment and insurance claim payout details, 2020-21

(a) Aman paddy

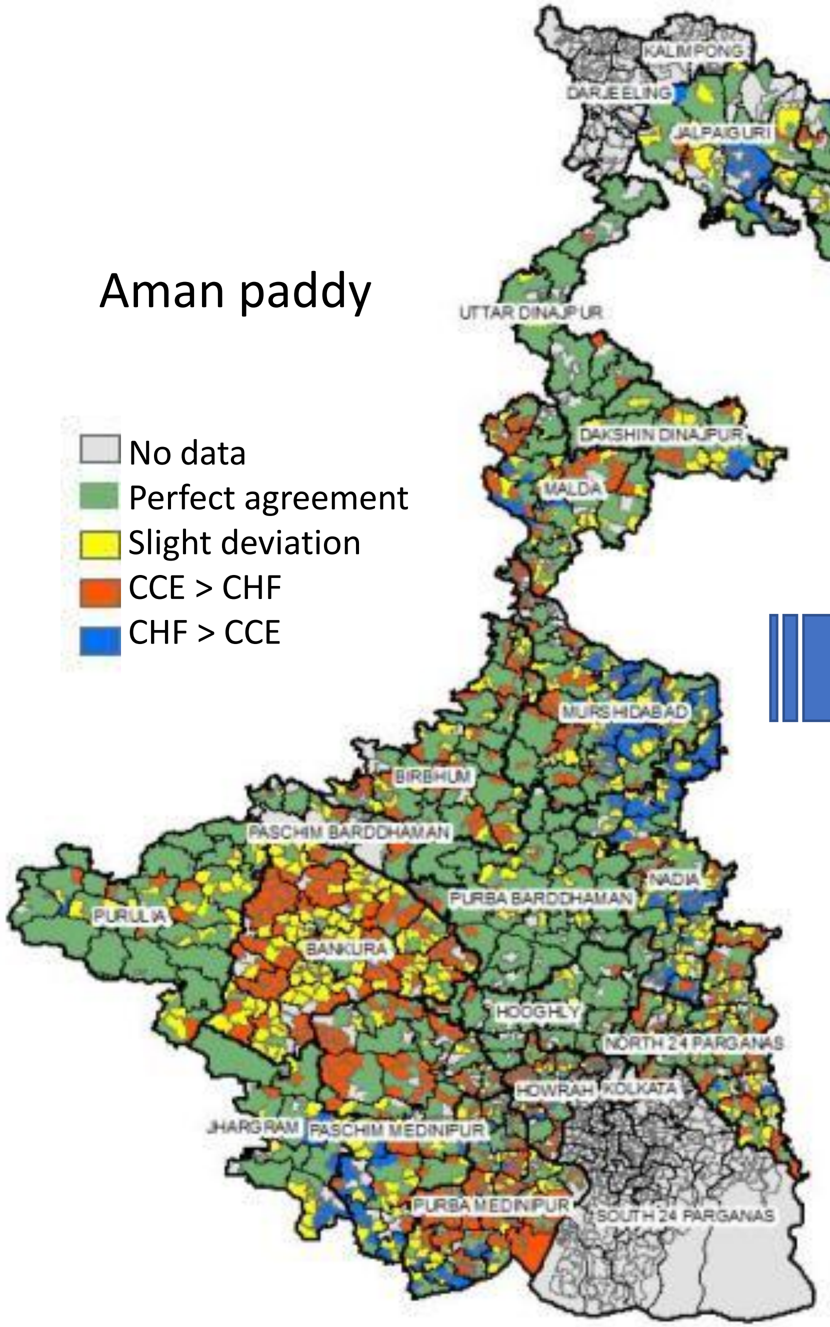
Details	Values
Sum insured per Hectare	INR 50000
Average CHF of past crop seasons	0.80
CHF of 2020 crop season for the IU	0.55
Threshold CHF with indemnity factor @80% of past years average	0.8*0.8 = 0.64
Loss Cost percentage for 2020 crop season	(0.64-0.55)/ (0.64)*100 = 14.06%
Claim payable per Hectare	INR 7031.25

(b) Potato

Details of Potato	Values
Sum insured per Hectare	INR 90000
Average CHF of past four crop seasons (2016 to 2019) for the IU	0.80
CHF of2020 crop season for the IU	0.50
Threshold CHF for 2020 crop season with indemnity factor @70% of past years average	0.8*0.7 = 0.56
Loss Cost percentage for 2020 crop season	(0.56-0.5)/ (0.56)*100 = 10.91%
Claim payable per Hectare	INR 9818

Hedging patterns of CHF and CCE-yield

Aman paddy



Using the data of 2016 to 2019

Agreement between CHF and
CCE-Yield based insurance loss assessments among the IUs

Agreement status	No. of GPs	Implications
Class – I: Perfect agreement	1466 (54%)	CHF based and CCE based pay-outs are close to each other.
Class – II Slight deviation in Agreement +/- one class	519 (19%)	Slight difference between CHF based and CCE based pay-outs.
Class – III: No agreement – CCE-Yield loss is more than that of CHF	518 (19%)	CCE based pay-outs are significantly higher than that of CHF based.
Class – IV: No agreement – CHF loss is more than that of CCE yield	203 (8%)	CHF based pay-outs are significantly higher than that of CCE based.

Accounting for end-of-season crop risks in CHF

What are the crop risks that need to be accounted separately in CHF?

End of season crop risks during the last 30 days of the season

- Unseasonal rains/Floods/Cyclones (submergence, lodging, panic harvest etc)
- Weather aberrations such as hot and dry winds, rise in temperatures (poor grain setting and grain development)
- Weather induced pest/disease incidence
- Pest incidence following floods (BPH in rice)

CHF Correction Factor approach is adopted

Accounting certain crop risks in CHF contd…

CHF Correction Factor framework

Weather - Rainfall, wind speed, temperature, humidity based loss matrix

Satellite based harvest area progression weekly/fortnightly

Satellite based indices

Smart phone based field data showing crop damage

Other data / reports

Affected/ exposed area fraction

Crop yield loss fraction

Insurance Unit wise CHF correction (area weighted approach)

Operates in Hybrid mode – Index based and Indemnity based, when localised risks occur

Strengths of CHF

1. A quantitative measure of crop performance synthesised from multiple crop health attributes – physical and biological.
2. Input attributes cover all crop stages – sowing to harvest, accounting many of the crop risks
3. Observation data at pixel level – 10 to 30 m, 5-12 days freq.
4. Total enumeration system involving all crop fields
5. Comparability with the CHF/CPI of past years is high because methodology and inputs are same for the current and past years
6. Scope for improvements from year to year and recalibration with historic data is easier
7. Less prone to moral hazard
8. Transparency, objectivity and timeliness
9. Less scope for disputes

Taylor & Francis
Taylor & Francis Group

Geomatics, Natural Hazards and Risk

Peer review & Outreach of new model

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tgnh20

Paddy crop insurance using satellite-based composite index of crop performance

C. S. Murthy, Malay Kumar Poddar, Karun Kumar Choudhary, Varun Pandey, P. Srikanth, Siddesh Ramasubramanian & G. Senthil Kumar

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Remote sensing based crop insurance for jute (*Corchorus olitorius*) crop in India

C.S. Murthy [a,*], M.K. Poddar [b], Karun Kumar Choudhary [a], P. Srikanth [a], Varun Pandey [a], Siddesh Ramasubramanian [b], G. Senthil Kumar [b]

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ARTICLE INFO

Keywords:

ABSTRACT

Jute (*Corchorus olitorius*) is an eco-friendly commercial crop largely grown in the West Bengal

34 | Asia Insurance Review | January 2022

Asia Insurance Review Magazine, Jan 2022

MARKET PROFILE – INDIA

For an agrarian economy like India, crop insurance has been practiced as an indispensable risk management tool with varying and pests. Most commonly used indices are Normalised Difference Vegetation Index, Land Surface Wetness Index, Synthetic Aperture of agriculture, Government of Maharashtra, initiated in 2019 with Maharashtra State Remote Sensing Centre and National Remote Sensing

Knowledge dissemination through
Training Programme at NIA, Pune, 07-11 March 2022

Conclusions

- ❑ Data driven and evidence based index
- ❑ Entry point for transformative solutions
- ❑ Immense scope for improvements
- ❑ Objective yield proxy data to replace subjective yield estimates
- ❑ Procedure can be improved year-after-year and stabilized in 2 years time span.
- ❑ Reduces moral hazards, turn-around time, transaction costs and eventually premium rates

way forward

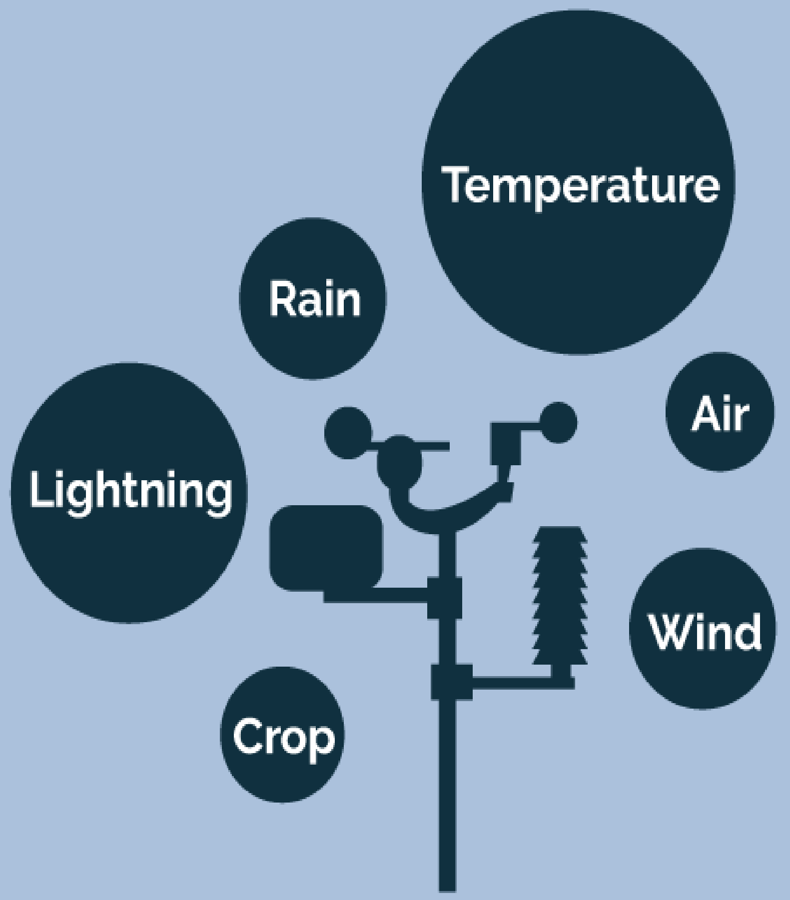
Scalability of CHF

- Paddy, Wheat, Rabi jowar
- Potato, Jute
- Work in progress for other crops – Soybean, Cotton

Implementation choices

- ❖ Replace CCE system
- ❖ Hybrid models – Blending of CCE est. and CHF in certain proportions (80:20, 70:30 etc)

Thank you



PROPOSED GUIDELINES- PAN-INDIA AWS/ARG NETWORK CREATION

AGENDA POINTS

- Realization of WINDS
- AWS/ARG Distribution
- Siting Conditions
- AWS/ARG Technical Specifications
- Maintenance & Calibration
- Data Transmission & quality validation
- Third Party Verification
- Commercial Models

Objective

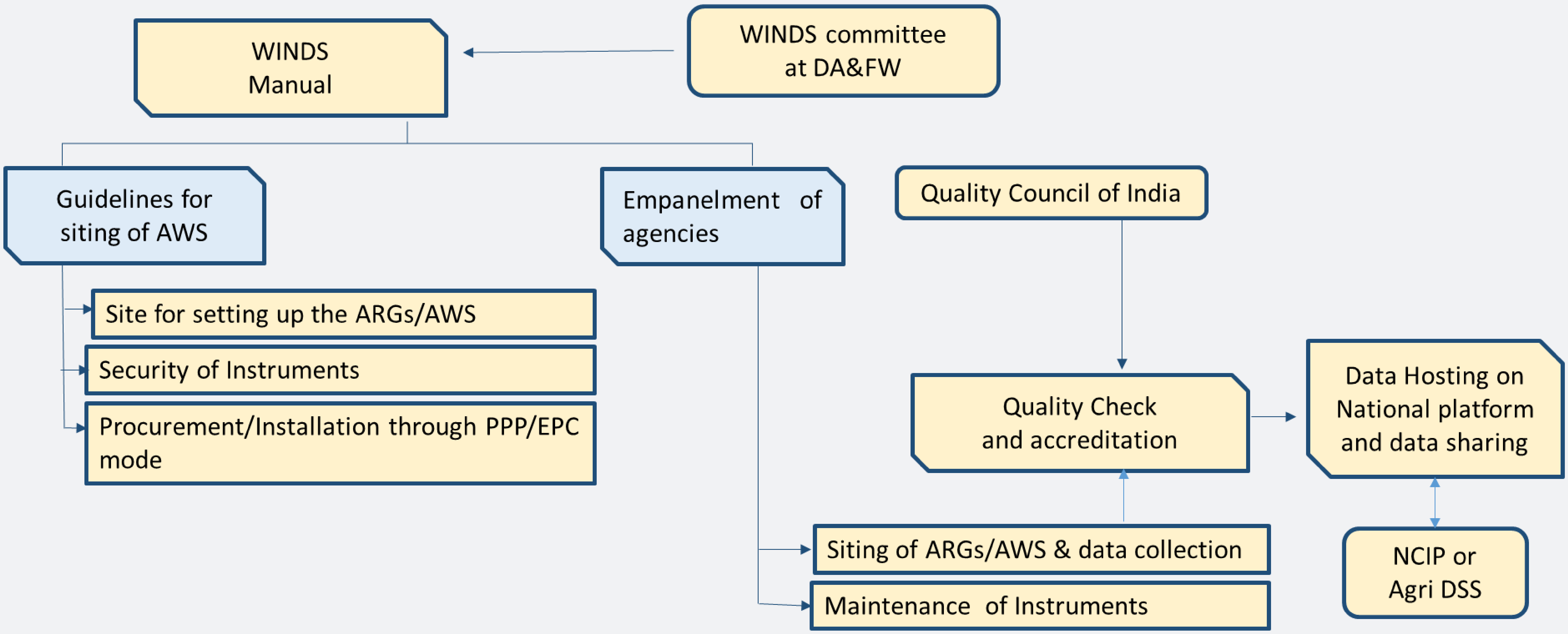
Too little data, even the most basic weather data

Climate Change

Extreme events becoming more common

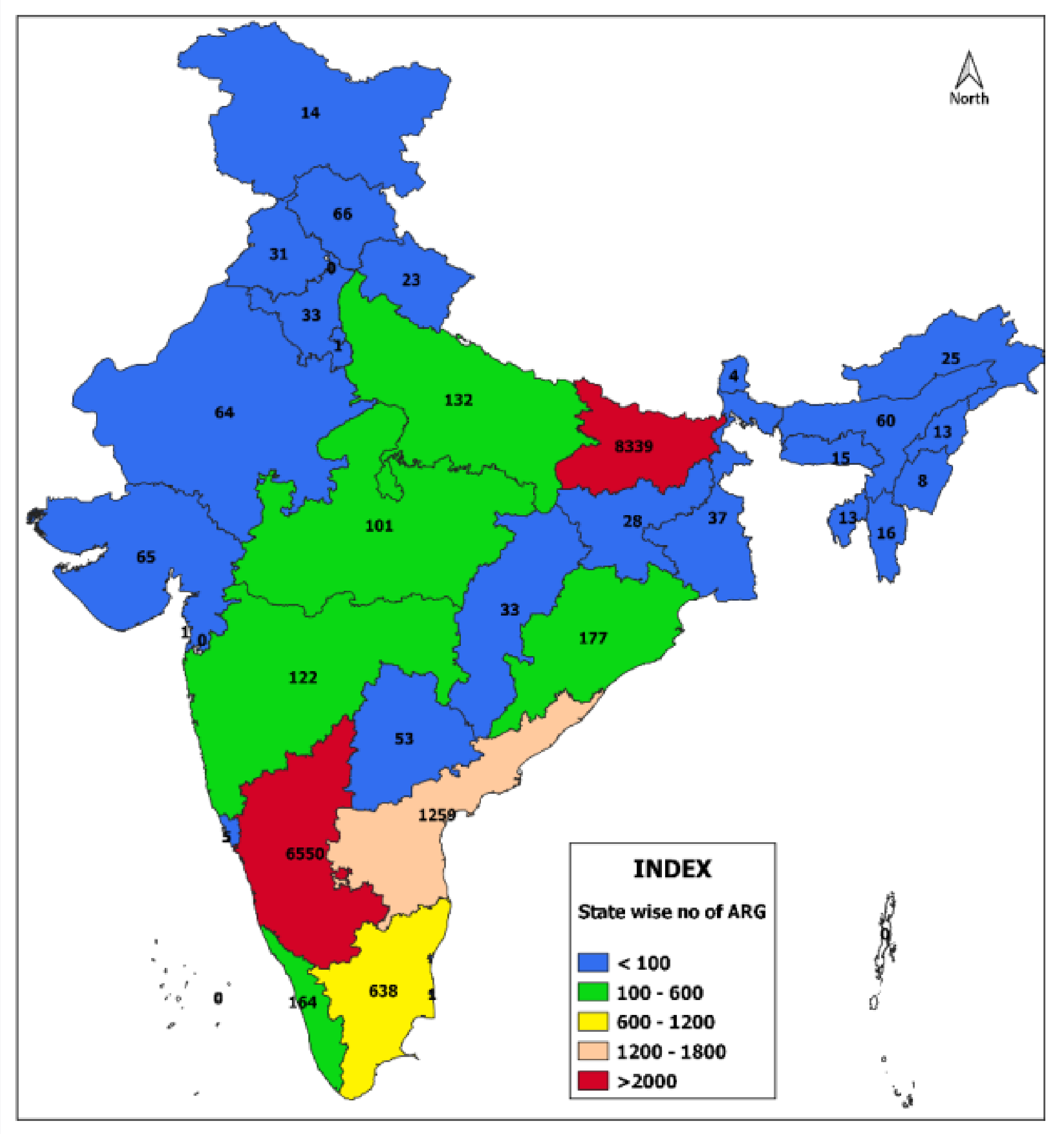
We were finding it difficult to know this in advance because there isn't enough scientifically measured weather data!

Realisation of WINDS objectives

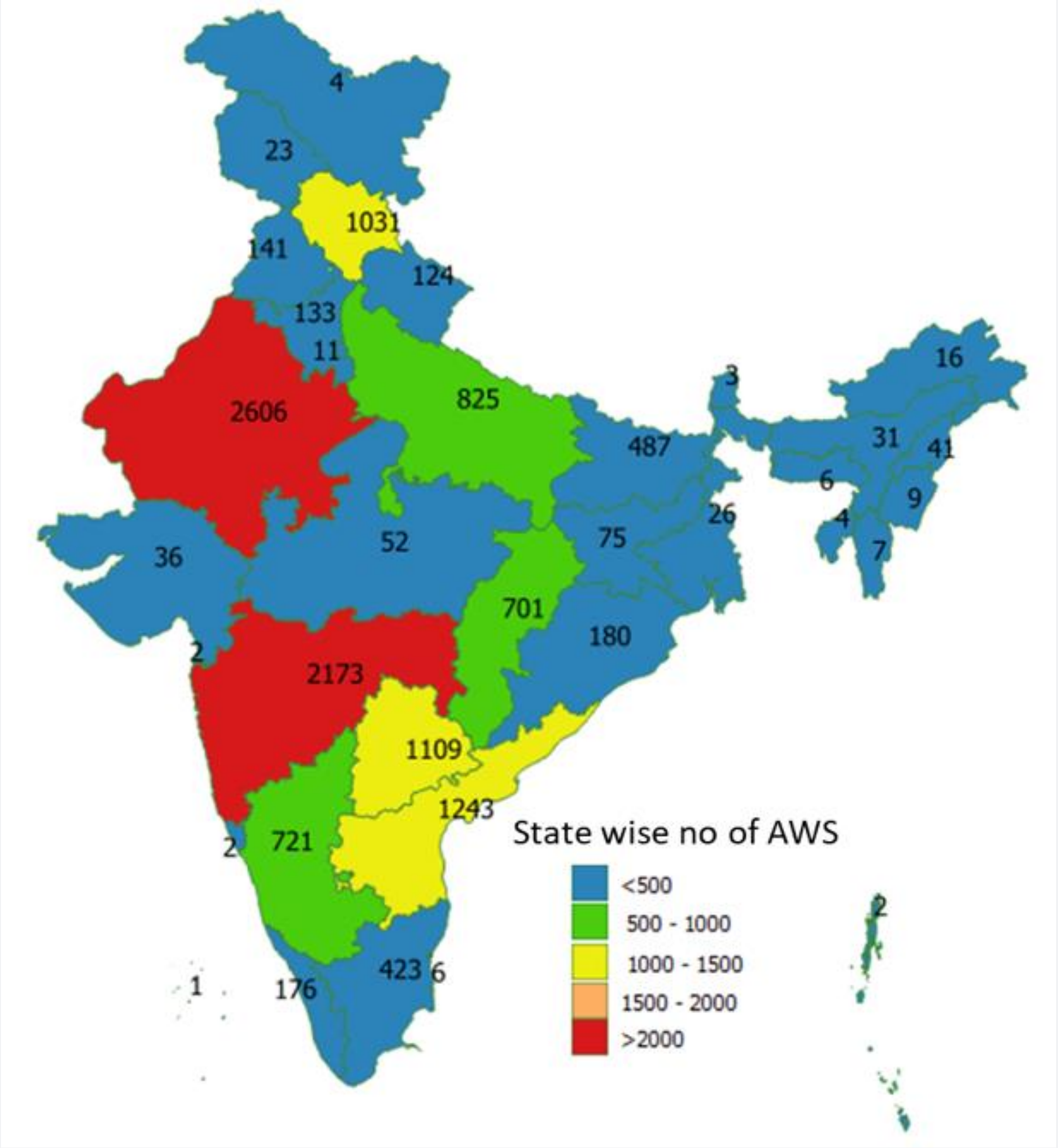


AWS/ARG Distribution

- AWS at every block level. The AWS will be measuring Air Temperature, Relative Humidity, Wind Speed & Direction and Rainfall.
- ~7235 AWS need to be installed at every block of India.
- ARG at every Gram Panchayat level.
- ~283926 ARGs need to be installed at every GP of India.
- **We propose to incorporate existing network AWS & ARG (Complying with WINDS Technical Specifications) created by Central/State Govt, Private Players, Research Institutes etc. to avoid any duplication of network.**



Present status of ARG network in India.



Present status of AWS network in India

Siting Conditions- AWS & ARG

- **There wasn't any change recommended in the siting condition of AWS as per the 2015 guidelines**. Getting one suitable site at block level as per the standard IMD/WMO guideline is possible.

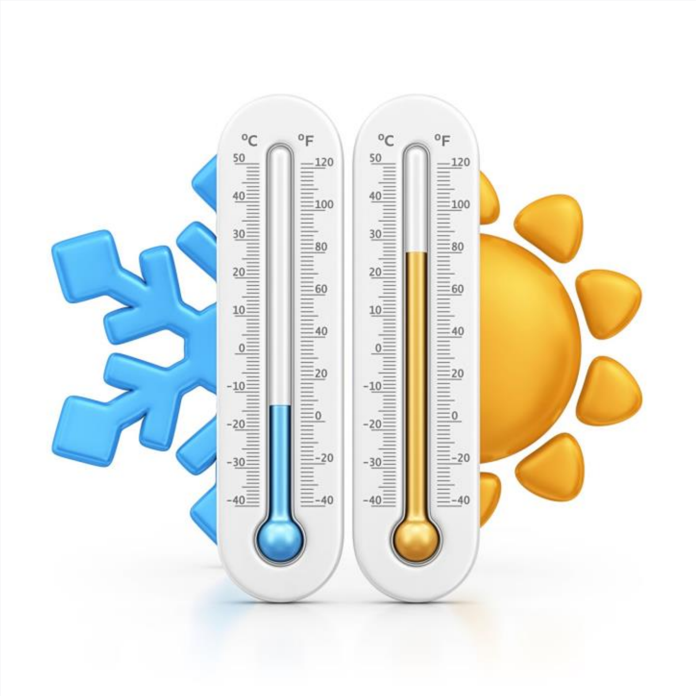
- **We are recommending that the suitable site and the security of the AWS is the responsibility of tendering authority/state/central govt**.

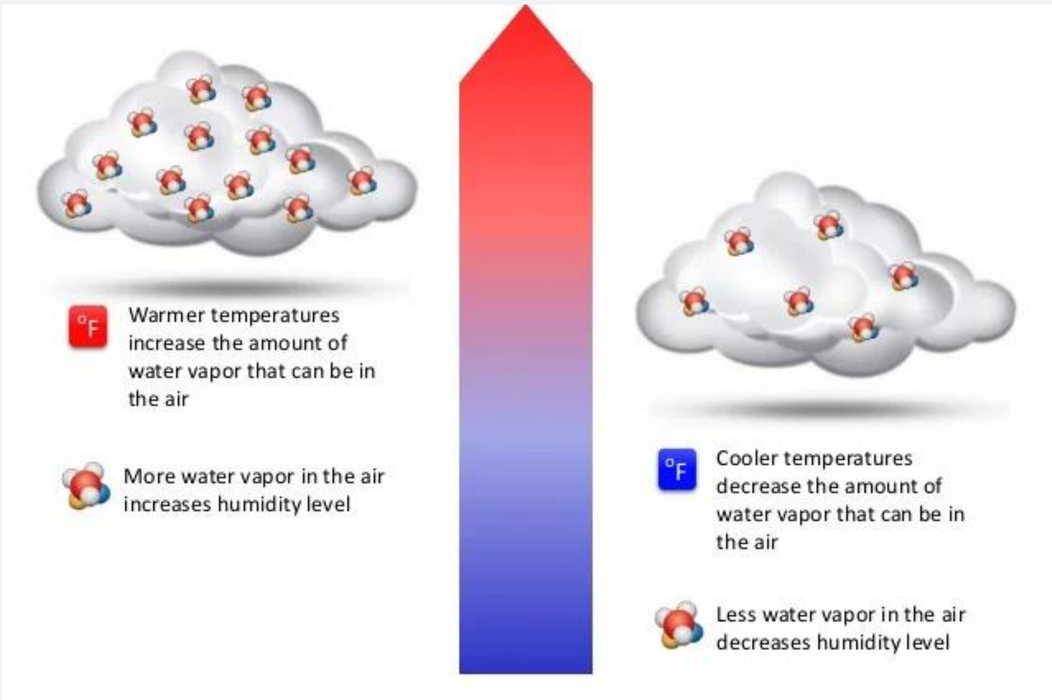
- The ARG will be installed on at **minimum height of 30 cm from ground. The maximum height of ARG can be rooftop of the one-story building** (about 10 feet height from the ground)

- Also, **WMO has recommended to install rain gauge above 30 cm from surface. There is no recommended maximum height for installation**. CWC, Karnataka & Bihar had gone for roof-top ARG installations wherever they couldn't find suitable site on ground and found no impact of height on the rain measurements.

AWS/ARG Technical Specifications

Parameter	Type	Tech Specs/Remark
Air Temperature	PT-100/MEMS Type	In line with BIS/existing IMD guidelines
Relative Humidity	Capacitive / Solid state	In line with BIS/existing IMD guidelines
Wind Speed & Direction	Ultrasonic	In line with BIS/existing IMD guidelines
Rainfall	Tipping Bucket	In line with BIS/existing IMD guideline





Maintenance & Calibrations

- **Preventive Maintenance :** Preventive maintenance should be done **quarterly**

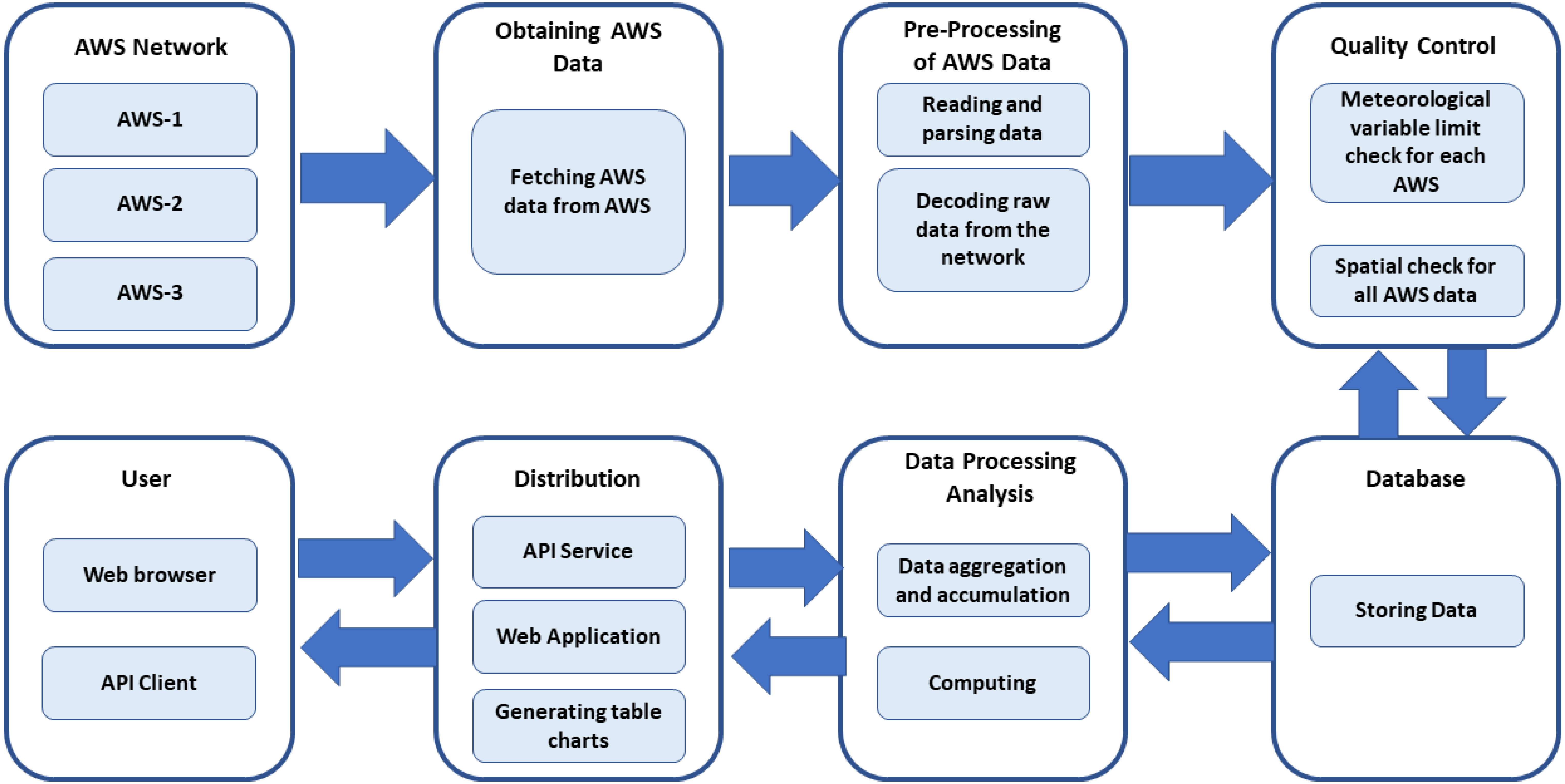
- **Corrective Maintenance :** Corrective maintenance should be on call there is no constraints. Corrective maintenance must be attended within **3 working days from the day of fault/breakdown reported**

- **Adaptive Maintenance :** Adaptive maintenance is **required to consider the rapid changes in technology and the availability of spare parts after a few years.**

- Government of India or respective state government should be provided access to online maintenance logs on a web portal for the maintenance of AWS.

- **Calibration-** Both field inspection with traveling standards and laboratory inspection will be conducted at regular interval.

Data Transmission & Quality Validations



workflow showing detailed steps for the data integration and dissemination

- AWS/ARG will archive and transmit the data at 15-minute interval

Third-Party Verification

- We are recommending to conduct **third party verification of the AWS/ARG network by Quality Council of India or any other third party appointed by them**.
- **The cost of such verification shall be borne by the state/central govt** or the client whoever has initiated the verification process
- **At present there is no accredited third-party auditor of AWS/ARG in the country**

Commercial Models

- Public-Private Partnership Model
- Engineering, Procurement & Construction (EPC) Model

Public-Private Partnership Model

- Financial Risk associate with design & development is transferred to Private Sector
- The concessionaire may obtain its revenues through a fee charged to the user for accessing the data; Govt. will get the data with out any additional charges. Government will notify the AWS network as an official network of the state/center for crop insurance schemes or any other Govt supported scheme
- The payments will be **performance linked & performance standards** are clearly mentioned in the agreement
- Project duration can be of longer period (**7-10 years**)
- **We recommend to initiate the empanelment/RFP process at the center level to keep the uniformity in rates & technical aspects.**

Engineering, Procurement & Construction (EPC) Model

- **This is the most common model adopted in creating AWS/ARG network by Govt.**
- Generally, this model **executed through RFP mode**
- Project duration **can be minimum 5 years.**
- Govt. **must provide the required site/land for installation** of AWSs/ARGs.
- Govt. **needs to develop internal technical skillsets & capacity for managing** the project post commissioning
- Majority of the **project cost needs to be borne by Govt. in first 3 years**/at the time commissioning
- **All IMD and most of the State Govt AWS deployments are under EPC model**

- **We recommend to initiate the empanelment/RFP process at the center level to keep the uniformity in rates & technical aspects.**

Thanks!

Agency Empanelment

- The Applicant should be a body corporate, incorporated under Indian Laws and having principal place of business and control in India (Make in India). He should be in the business of selling of weather data for at least last 7 years.

- The Applicant should be profitable in at least one financial year in previous 3 financial years.

- The Applicant should be having positive net worth.

- The Applicant should have previous experience in maintaining a meteorological network of at least 1000 Automatic Weather Stations used for providing weather data to Government sponsored/ promoted/ subsided Crop Insurance in previous 3 years

- The Applicant should not have been blacklisted by any Statutory Body /Government Ministry/ Government Department/ Central or State PSU.