

# 5

## GeoSpatial Technology Landscape – R&D and its Linkages across Domains

#### **Prof. K S RAJAN**

Professor and Registrar, IIIT Hyderabad

Lab for Spatial Informatics,

Chairman, KAIINOS Geospatial Tech Pvt. Ltd.

ISRS, ISG, OSGeo, IEEE GRSS-CIS, ISPRS-WG V/8, CSI-SIG-BDA, FSMI, Geo4All, ISSE

RAJAN@IIIT.AC.IN



## Evolving world of Geospatial Technology

	Sensing Systems & Digital Image Processing						
-ield Measurements GPS - Total	Aerial Photogrammetry	Digital Maps – Desktop to Web Geo Services					
Stations Mobile	Remote Sensing Digital Data	CAD GIS	Location as a	GeoAl			
platforms & IoT	Models Change Studies 	Interactive Maps Web mashups	Variable Consumerisation of Maps 	Spatio-temporal Data Science Analytics for Science Analytics for Decision Making			



## Geospatial Landscape in India

### **Major Players**

- Cartography and Mapping
  - Survey of India (since 18<sup>th</sup> century)
- Aerial Photogrammetry and Satellite Technology
  - ISRO
  - National Remote Sensing Center
- Solution Providers
  - Multiple Agencies like GSI, FSI, and others
  - Academia, RnD
  - Industry



### **Technology Evolution**

- Aerial and Satellite Image Processing
  - Map as a Product
- GIS as a System
  - Mapping to Spatial Analysis
- Information Technology
  - Static to Interactive Maps (WebGIS)
  - GeoSpatial Services
- Spatial Data Science and GeoAl
  - Geospatial as a Science



## RnD in GeoSpatial Technology

- Operational RnD
  - Adopting the technology to the Indian Conditions
  - Customisation of Processes
- Thematic or Domain driven RnD
  - Land Use Studies and Mapping
    - Land use products
  - Water Resources and Water Use
  - Agricultural Programs
  - Forestry Fires, Field integration and so on
- Fundamental Technology Developments





## Emerging field of Spatial Data Sciences

- Spatial Big Data Analytics
  - Mining the data for (cause-effect) relationships
  - Is it driven by the known or the Unknown (processes?)?
  - Discovering Knowledge from Data
- GeoAl or Geo+Al?

**Processes**??

- Brings together GIS/Spatial Science, Data Mining, AI, HPC
- Extracting/Detecting/Identify Spatial Objects from Spatial and Temporal Data
- Data Gap filling / Estimation / Prediction Modelling
- Locational Intelligence to Decision Support
- Can AI/ML/DL change the way we look at GeoSpatial Data and



### Lets, take Spatial Solutions in Aviation as an Example



#### • GIS Data uses in Airport environment (Understanding GIS requirements for Aviation)





٠

٠

- Asset maintenance
- Asset monitoring
- Logistics
- Utilities
- Pavement management
- Repair and Constructions

- Land and airspace planning
- Landside access planning
- Airspace regulations
- Environmental regulations
- Noise regulations
- Cargo handling
- Obstruction surface Creation/Modification
- Obstruction Analysis/Evaluation

Source: Report by Durga Prasad, Dhulipudi, KS Rajan



## Accelerated Mapping

- We investigated the identification and classification of key Runway features automatically using **Machine Learning** and Computer Vision approaches.
- Durga & Rajan (2020,2021) studied the method of automatic airport feature extraction from satellite images.
  - Training Data Preparation
  - Transfer Learning Model
  - CNN



**Outstanding Paper Award: Durga Prasad Dhulipudi**., **& K S Rajan**. (2021). Geospatial Object Detection Using Machine Learning-Aviation Case Study. 2021 Integrated Communications Navigation and Surveillance Conference (ICNS), 1-8.

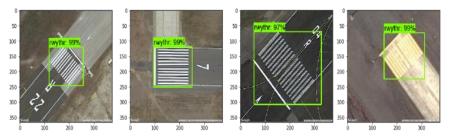
#### ACCELERATED MAPPING



### Geospatial Object Detection Using Machine Learning-Aviation Case Study Phase II Improved accuracies with more samples (GPU)



150 200



	SUMMARY OF PHASE1 CONFIGURATION AND RESULTS		SUMMARY OF PHASE2 CONFIGURATION AND RESULTS
System Configuration	E5470 - Intel HD Graphics 520. Core i5 6300U - 8 GB RAM - 256 GB SSD RAM, 2.4ghz, Windows 10 Enterprise 64 Bit	System Configuration	Dell Intel64 Family 6 Model ~2200 Mhz, Windows 10 Enterprise 64 Bit, Precision Tower 5810, Microsoft Windows 10 Enterprise, 64GB RAM
Model used	Transfer learning with Faster R-CNN ResNet	Model used	Transfer learning with Faster R-CNN ResNet
Training time	2 E bours	Training time	~33 minutes
	2.5 hours	Dataset Size	1025 images
Dataset Size	200 images	Train Test ratio	80% & 20%
Train Test ratio	80% & 20%	Iterations	2000
Iterations	200	Confidence	>94%
Confidence	>85%	ТР	>92%
ТР	>60%	Failure	Localization requires improvement
Failure	Localization requires improvement		

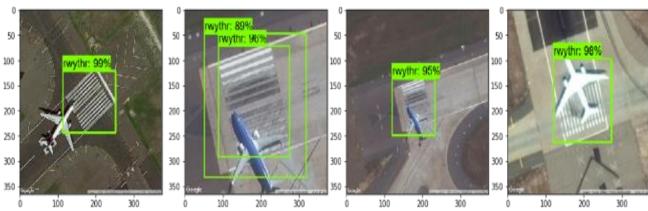




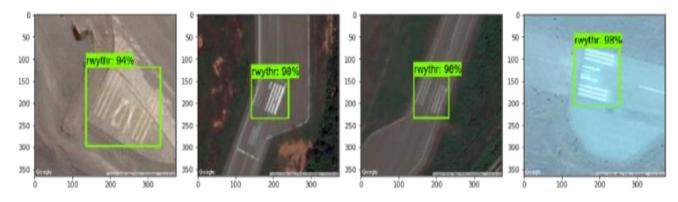
### **Geospatial Object Detection Using Machine Learning-Aviation Case Study**

#### Phase II

With more samples and increasing the variety, we noticed accuracies **above 95%** even in the case of <u>occlusions</u> also.



Similar level of true positives detected in case of highly **unclear ambiguous** images .





• Model inference in Occlusions and Ambiguity- Work In Progress



## Agriculture: What is a Good Monitoring System ?

- A good baseline data
  - Coverage, periodic updates, record of causes of changes, if any
- Is Crop-calendar a good baseline?
  - esp. if it is one calendar for the whole district
- What about uncertainties in the crop calendar?
- Can Phenology be a good growth parameter ?

How Events like droughts affect Cropping patterns in a region?

- > All are areas affected similarly/homogenously ?
- Can such analysis help us identify the Causative and underlying factors?



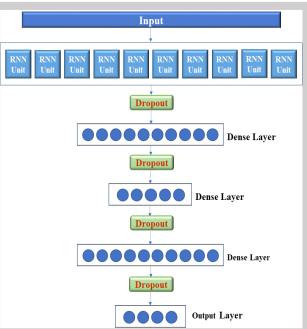


## Deep Learning Approach for Cropping practices

Used 3 Deep Learning methods –

- 1-Dimensional Convolutional Neural
- Long Short Term Memory Networks (LSTM)
- Gated Recurrent Units (GRU)

Image Type	MODIS EVI
Ground truth	NRSC LULC
Resolution	500m
Time Period	12 years
No. of Images	276 (12 X 23)



#### **Results Showed -**



LSTM performs better (63% accuracy) Trade-off between Image resolution, GT and Model appropriateness

### Events (Drought) and Cropping Practices agricultural-year 2008-09 to 2011-12 (4 crop years)

10

5

No. of pixels (%) 7.5 8 02

6 1

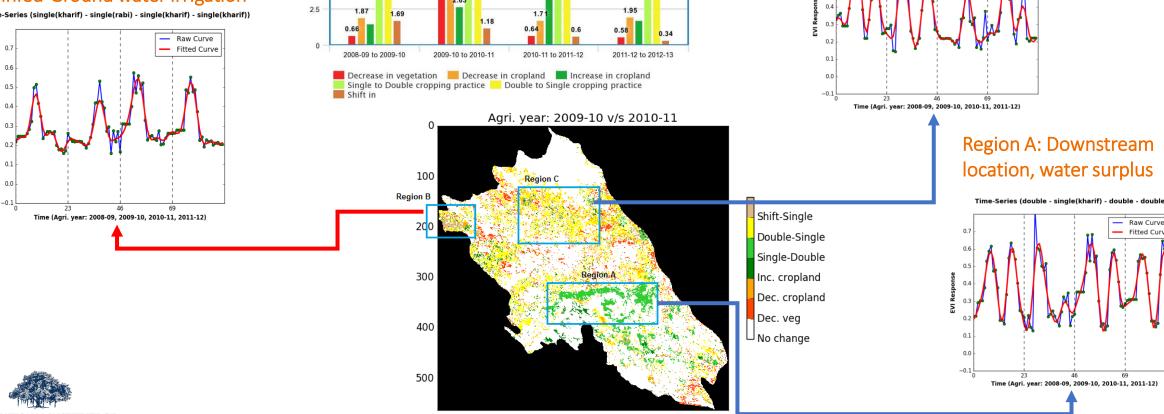
11.58

4.99

3.91

#### **Region B: Away from River, Rainfed-Ground water irrigation**

Time-Series (single(kharif) - single(rabi) - single(kharif) - single(kharif))



3.82



D Baheti, KS Rajan. 2017. A Shape-Based Approach to Spatio-Temporal Data Analysis Using Satellite Imagery. Proceedings of the 4<sup>th</sup> IEEE International Conference on Data Science and Advanced Analytics (DSAA), Tokyo, Japan. Oct 19-21, 2017.

5.16



Raw Curve itted Curv

Region C: Upstream, Mostly Irrigation

Raw Curve

Fitted Curve

(canal/ground water) based

me-Series (double - double - single(rabi) - double)



## Spatio-Temporal Data Analytics of Crop Yields

- Are all FOOD PRODUCING Regions/Districts in India Sustainable?

- How can we Assess Food Production / Crop Yields ?
- Are current methods/tools useful to do this?

- Are they **consistent Performers** or change over Space and time?



### FACTORS AFFECTING YIELD

- Ecological factors
  - Availability of water resources (Rainfall, Irrigation mechanisms)
  - Type and quality of Soil
  - Temperature
  - Fertilizers, etc.
- Non-ecological factors Management Practices
  - Cropping practices
  - Allocation of funds and resources
  - Training and education by government
  - Other socio-economic factors

A Customer Centric Lens for Good Agricultural Practices

September 2019



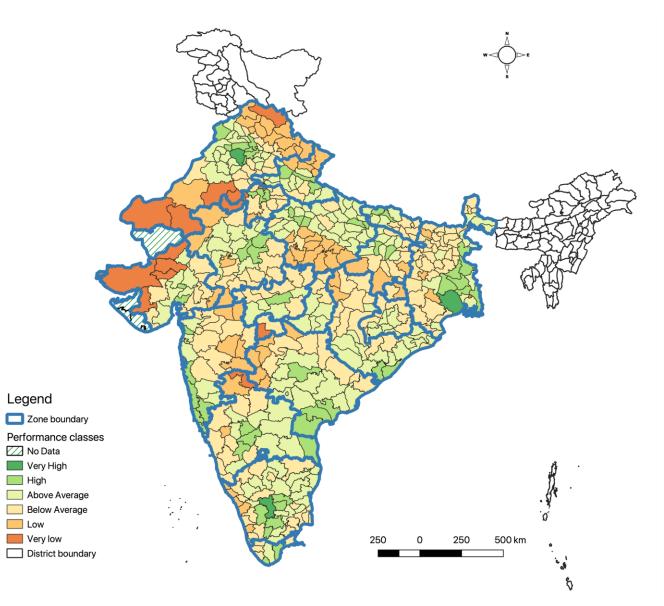


MERA 🔀 IDRC | CRDI Installard Development Instantication



#### RESULTS

#### R2. PERFORMANCE CLASSES WITHIN ZONES

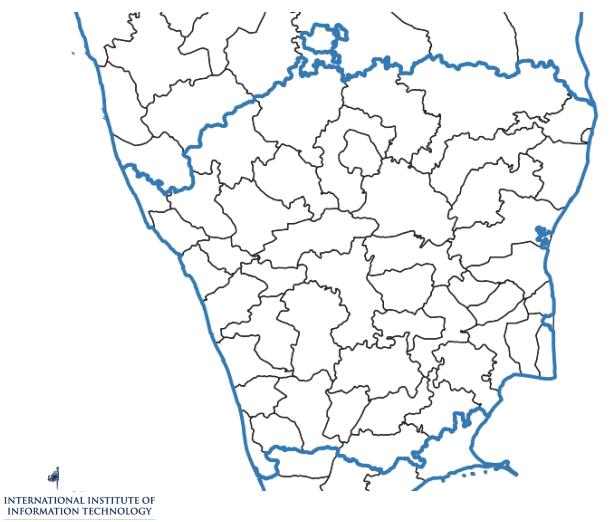


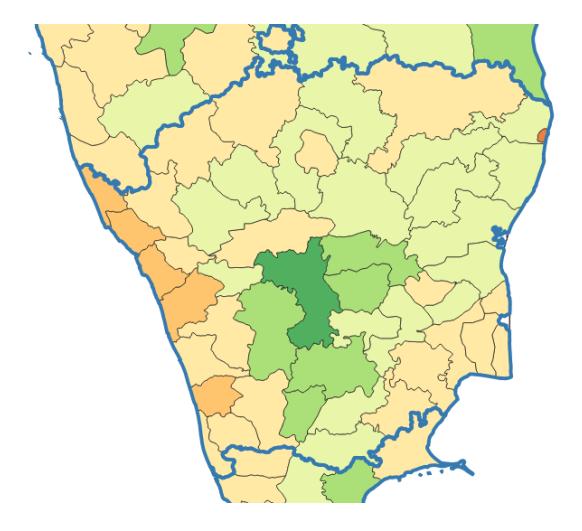




#### RESULTS

#### R2. Classification for a zone





HYDERABAD



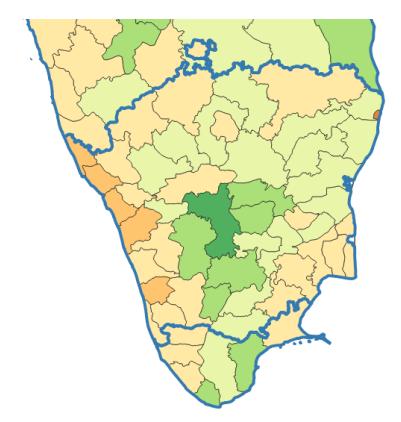
### Re-Analysis of TEMPORAL TRENDS

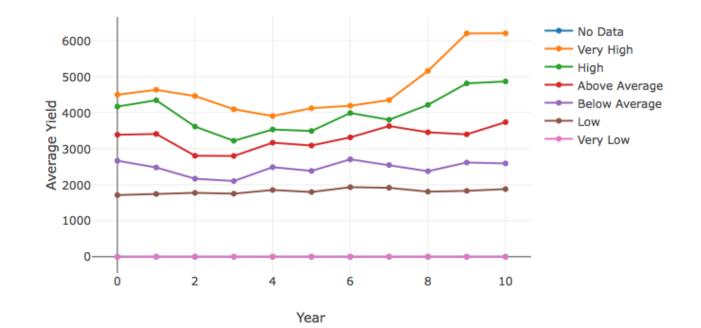
- For a specific zone,
  - We have performance classes
  - i.e., groups of homogeneous districts
- Performance may
  - remain consistent
  - Increase/decrease
- Observe effects on performance of each class
  - Drought/Flood years
- Within a zone
  - For the districts of a performance class
- Plot their annual average with time





# TEMPORAL TRENDS (1/2)

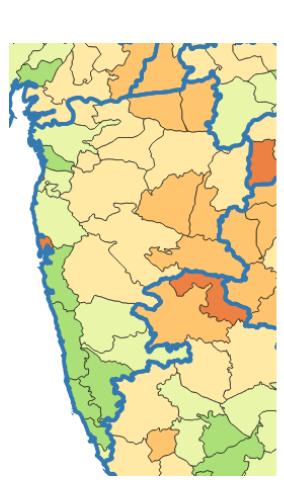


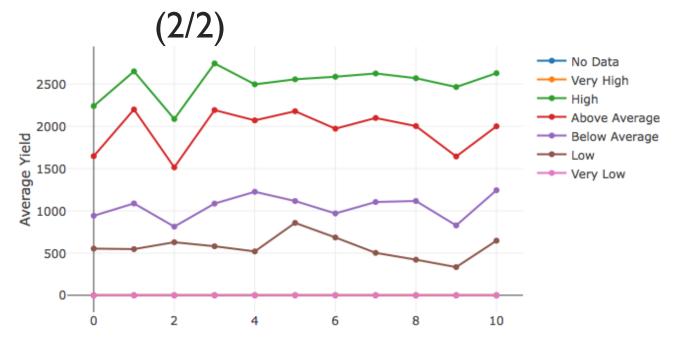


INTERNATIONAL INSTITUTE OF INFORMATION TECHNOLOGY H Y D E R A B A D



#### **TEMPORAL TRENDS**





Class ID	No of districts	Min (in kg/ha)	Max (in kg/Ha)
1	0	-	-
2	6	1889.2	3171.4
3	7	1080	2827.4
4	9	489.8	2420.6
5	5	319.1	1014.4
6	0	-	-







### Observations from Spatio-Temporal Analysis

- Spatio-Temporal output analysis
  - gives an understanding of yield patterns across the country
- Good and poor performing districts
  - In a given neighborhood
  - High performers close to the center of the zones
  - Performance deteriorates near the boundary
- Performance Statistics
  - Low 87 ( Combines 'Very Low' and 'Low' )
  - Moderate 344 (Combines 'Above average' and 'Below Average')
  - High 61 (Combines 'High' and 'Very High')
- High remains high; Low remains low
  - Performance resilient with time; lines do not intersect
  - No drastic changes even in extreme events
  - External factors not predominant
  - Irrespective of the amount of inputs provided





## $Geo \leftrightarrow AI$ : Where to go from here

- Early stages of Adoption of AI/ML/DL methods
  - Using more like a black box / model
    - Works well for general solutions
    - Supports Large data analysis and Computationally heavy processes
  - While results give good insights, throws-up more questions
    - When it fails to capture key Features and its context
- Geo←→Al true Integration when Domain Adaptation of these Algorithms are possible
  - Spatial context
  - Temporal uncertainties
  - Processes capture or Indicative factors
  - From Data Analysis → Information generation → Knowledge discovery that supports/advances Science





Land Use

Modelling

Urban,

**vgricultural** 

## Lab for Spatial Informatics - Research Overview

✤ Spatial Data Science/ Geo-AI **GeoSpatial Science** Spatio-temporal Analytics / Data Mining / Databases Health, Crop Yield analysis, Climate, Crime and Technology Platforms developed Remote Sensing and IoT for Water Quality Forest Dynam Geo-Visualization ✤ 4D Flood Visualization Deep Learning on Terrain Super Resolution 3D realistic terrains/topography **Optical Imagery** Geo-Governance - Web/Mobile GIS Feature Extraction – Roads. FOSS4G Air Pollution and Human Health **Buildings** Water Quality and Quantity p Modelling Time-series Analysis – Crop Environmental phenology & Season Cale OBIA Policy **Spatial Modelling**  $\checkmark$ HyperSpectral Sensing **Strategic Environmental Assessments** Key Parameter **River Basin Hydrology** Characterisation - Vegetatio **Cli**mate Extremes and Impacts **RS** – Parameter Estimation Water Quality in Inland waterbodies **Spatial Modelling Remote Sensing Faculty at LSI:** & Simulations



IoT and Air Pollution Monitoring / Evaluation

+ Collaborations with Other Institutions and Organisations

Prof. KS Rajan

Dr. RC Prasad Dr. S Rehana

ana Dr. R Nagaraja



Lab for Spatial Informatics

### Thank You!



### Contact Info: K S Rajan (rajan@iiit.ac.in)

