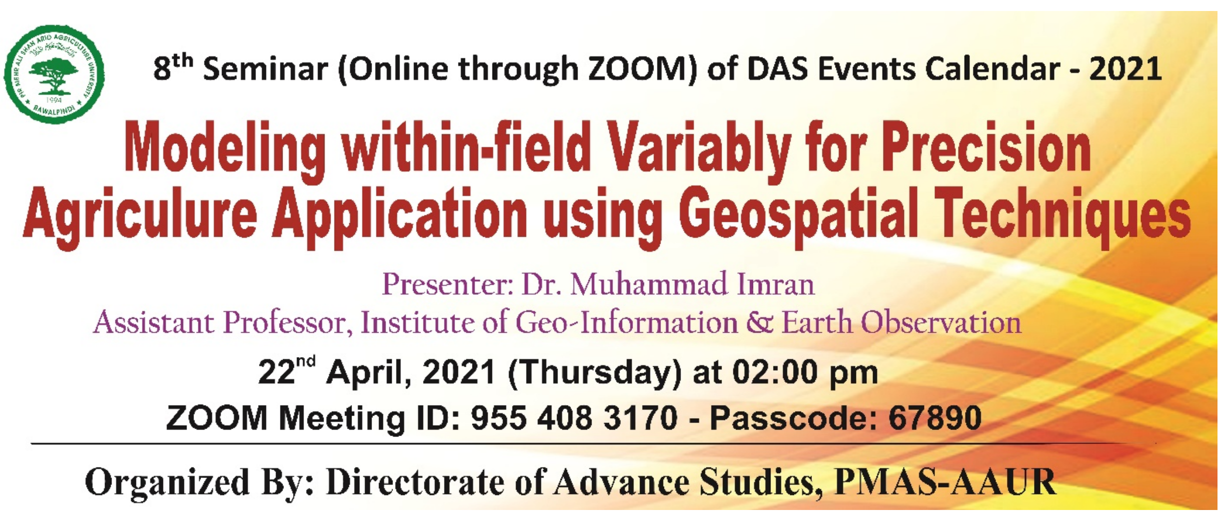
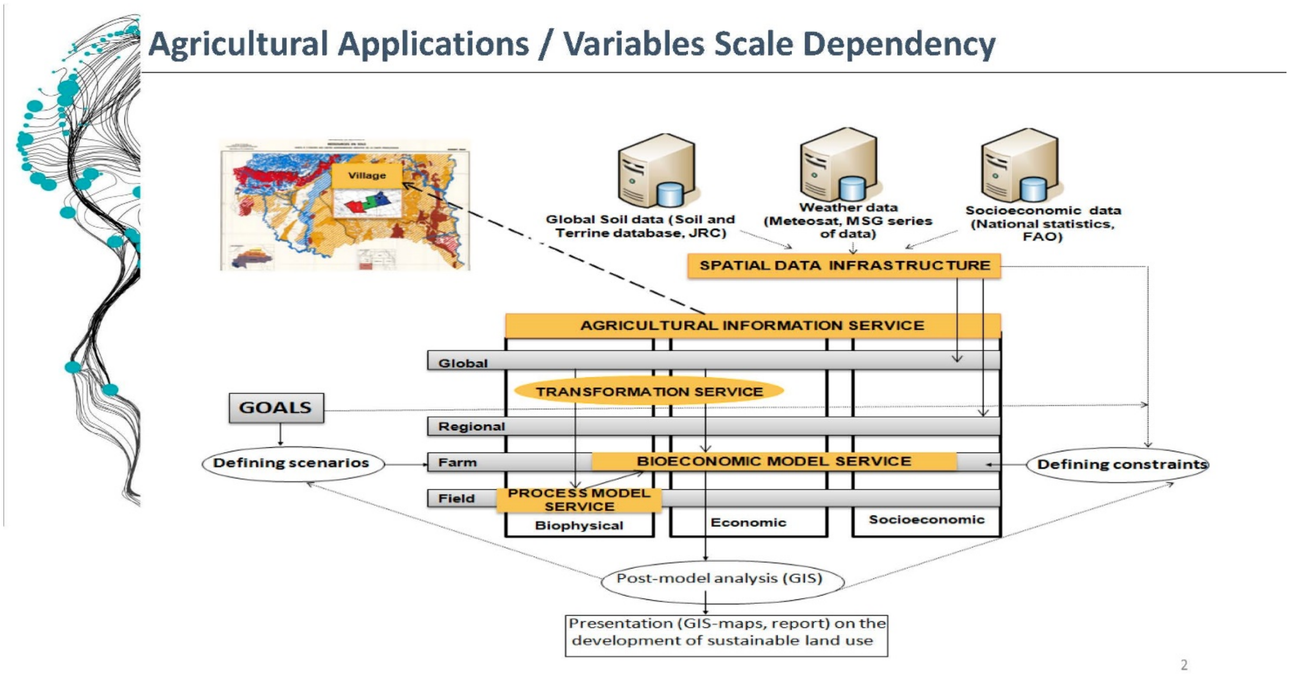
DIRECTORATE OF ADVANCED STUDIES
EVENT CATALOGUE
2021

8^{TH} SEMINAR OF DAS EVENTS CALENDAR – 2021

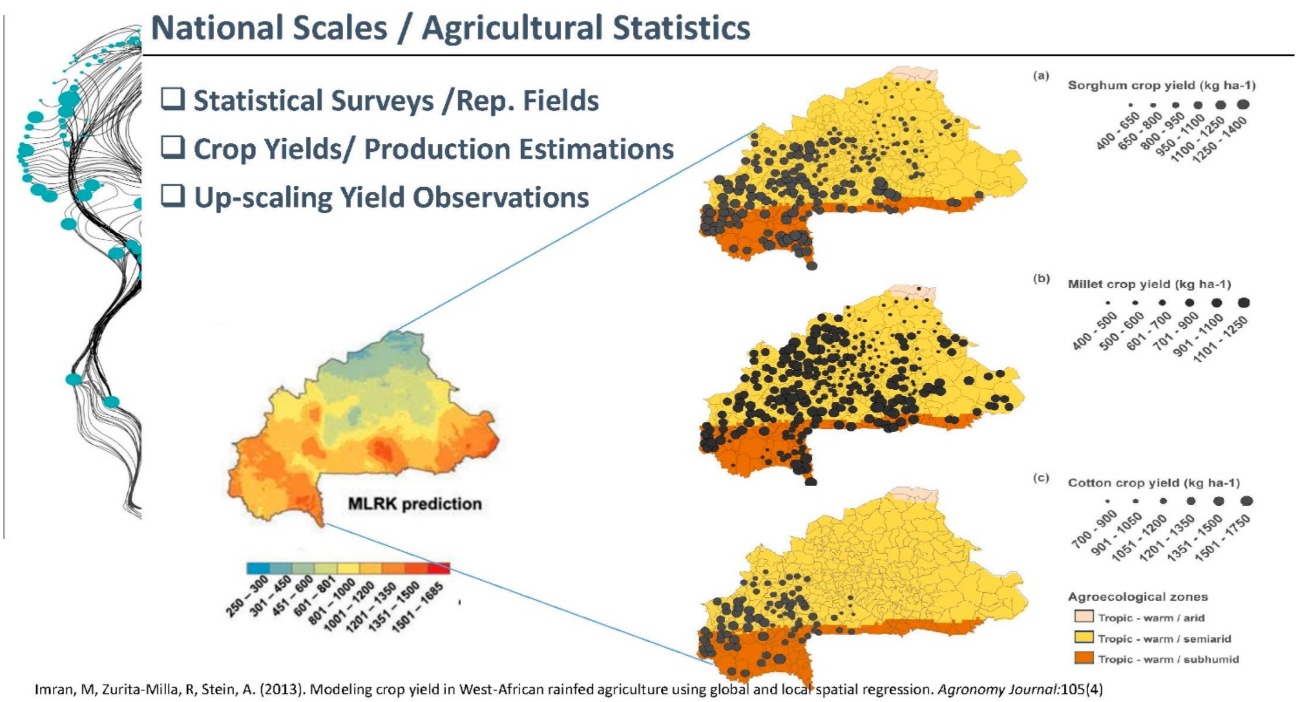
MODELING WITHIN-FIELD VARIABLY FOR PRECISION AGRICULTURE APPLICATION USING GEOSPATIAL TECHNIQUES



ACTIVITIES



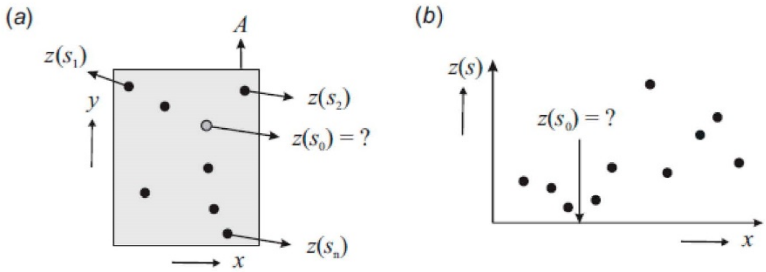
Agricultural Applications / Variables Scale Dependency
Village
Global Soil data (Soil and Terrine database, JRC)
Weather data (Meteosat, MSG series of data)
Socioeconomic data (National statistics, FAO)
SPATIAL DATA INFRASTRUCTURE
AGRICULTURAL INFORMATION SERVICE
Global
TRANSFORMATION SERVICE
GOALS
Regional
Defining scenarios
Farm
BIOECONOMIC MODEL SERVICE
Defining constraints
Field
PROCESS MODEL SERVICE
Biophysical
Economic
Socioeconomic
Post-model analysis (GIS)
Presentation (GIS-maps, report) on the development of sustainable land use
2

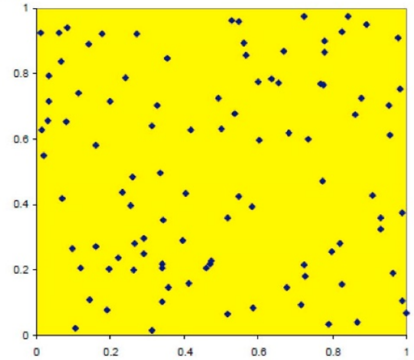


National Scales / Agricultural Statistics
❑ Statistical Surveys /Rep. Fields
❑ Crop Yields/ Production Estimations
❑ Up-scaling Yield Observations
MLRK prediction
250 - 300
301 - 450
451 - 600
601 - 801
801 - 1000
1001 - 1200
1201 - 1350
1351 - 1500
1501 - 1685
(a)
Sorghum crop yield (kg ha-1)
400 - 650
650 - 800
800 - 950
950 - 1100
1100 - 1250
1250 - 1400
(b)
Millet crop yield (kg ha-1)
400 - 500
500 - 600
601 - 700
701 - 900
901 - 1100
1101 - 1250
(c)
Cotton crop yield (kg ha-1)
700 - 900
901 - 1050
1051 - 1200
1201 - 1350
1351 - 1500
1501 - 1750
Agroecological zones
Tropic - warm / arid
Tropic - warm / semiarid
Tropic - warm / subhumid
Imran, M, Zurita-Milla, R, Stein, A. (2013). Modeling crop yield in West-African rainfed agriculture using global and local spatial regression. Agronomy Journal:105(4)

Field / Farm Scales / Precision Agriculture

- ❑ Field data collected at, for example, small farms or individual soil pits
- ❑ Extrapolations for precision agriculture equipments / VRT

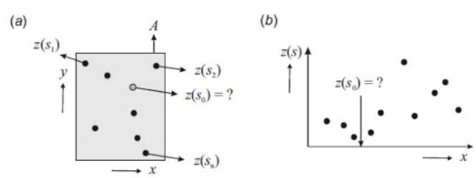



Complete Random Sampling

Imran, M, Zurita-Milla, R, Stein, A. (2013). Modeling crop yield in West-African rainfed agriculture using global and local spatial regression. *Agronomy Journal*:105(4)

Up-scaling Field Observations / Modeling Spatial Variability

- Use of agricultural data requires up-scaling towards the scale of application.
- The solution is to model spatial variability of agricultural variables and use it in the process of extrapolation.



$$Z(s) = m(s) + \varepsilon(s)$$

dependent, target variable

trend, explanatory part

stochastic residual, unexplanatory part, can be spatially correlated!

$$\hat{z}(\mathbf{s}_0) = \sum_{i=1}^{n} \lambda_i(\mathbf{s}_0) \cdot z(\mathbf{s}_i)$$

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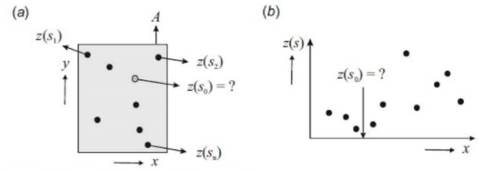
Modeling Spatial Variability / Geostatistical Approaches

Weights governing the spatial variation of a variable can be quantified using the so-called semivariance, this is half the expected squared difference between the values of the variable of interest at two locations



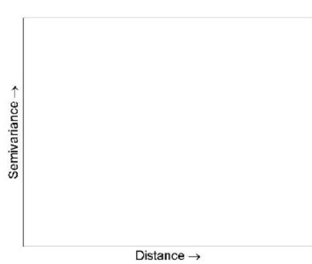
$$\gamma(h) = \frac{1}{2} E\left[\left(Y(s) - Y(s+h)\right)^2\right]$$

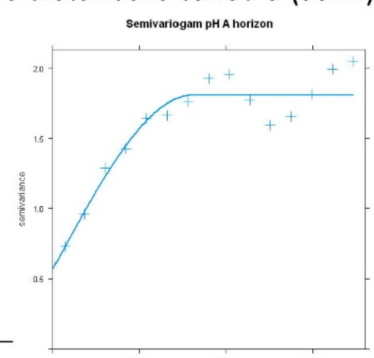
measurement at location S

measurement at location s+h

The variogram - γ(h) / Ordinary Kriging

- The tool we use to represent and model spatial variation
- The semivariance of Z(s) and Z(s+h) only depends on the distance h and not on the locations s and s+h.
- In other words we assume spatial non-stationarity, i.e., mean or trend component is constant
- Plot of semivariance as a function of the distance is called a (semi)-variogram





Modeling Uncertainty in Up-scaling Yield Observations

- The kriging variance at each point is automatically generated as part of the process of computing the weights. This kriging variance gives a measure of prediction error (Uncertainty).

$$\sigma^2_{OK}(s_0) = E\left[(Z(s_0) - \hat{Z}(s_0))^2\right] = \sum_{i=1}^{n} \lambda_i \cdot \overbrace{\gamma(s_i - s_0)}^{\text{semivariance at distance } s_i - s_0} + \varphi$$

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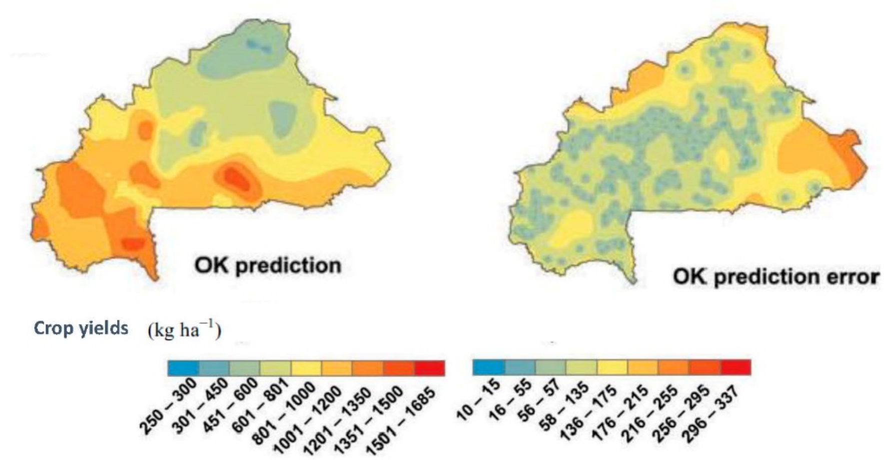
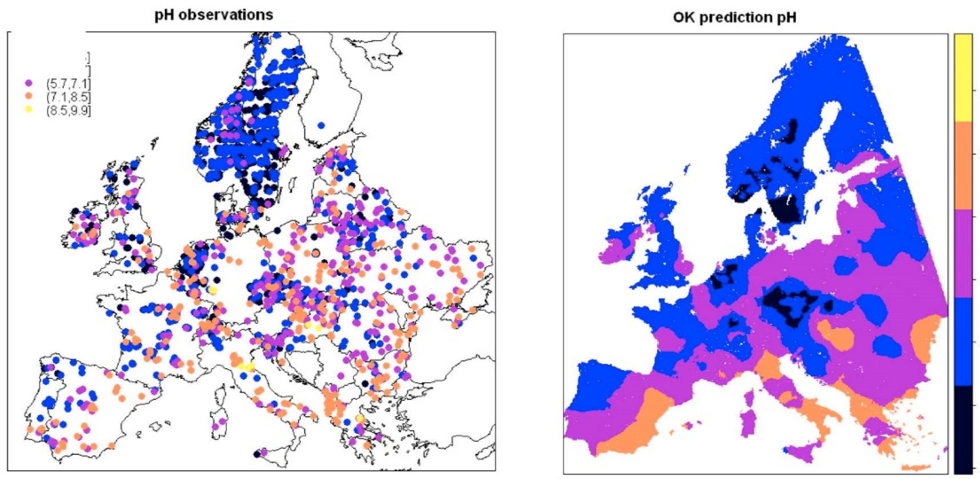
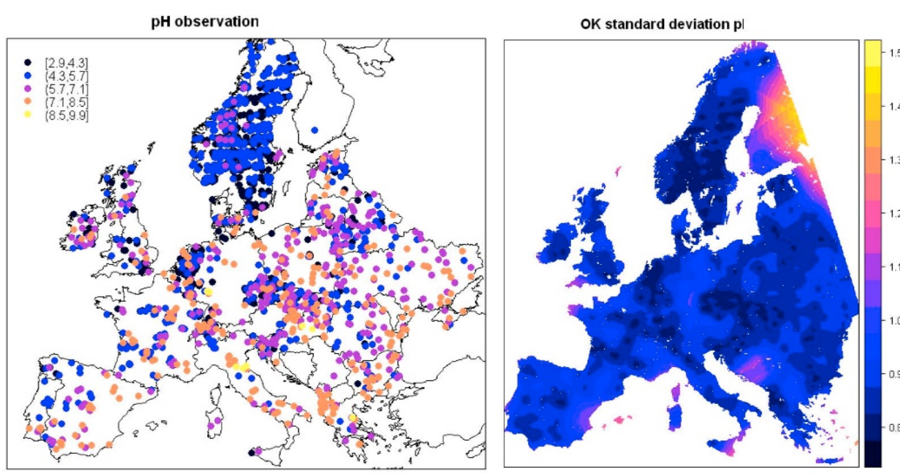
OK-based Crop Yield Extrapolation



OK-based Prediction of Soil Variables – Field Scale



Measurement of Uncertainty



Modeling Spatial Variability / Upscaling Yield Observations

- ❑ When the variable mean is not constant – it varies spatially
  - correlated with location (trend-surface analysis, kriging with a trend);
  - varies with class (e.g., land-cover type, soil type);
  - varies together with a continuous covariate.

- ❑ Deterministic or empirical relationship / Trend:
  - deterministic
  - empirical - regression modeling

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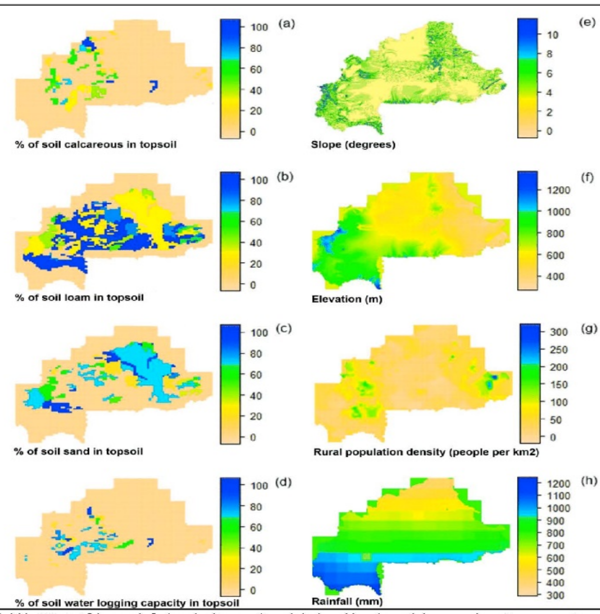
Crop Yield Estimations with Trends



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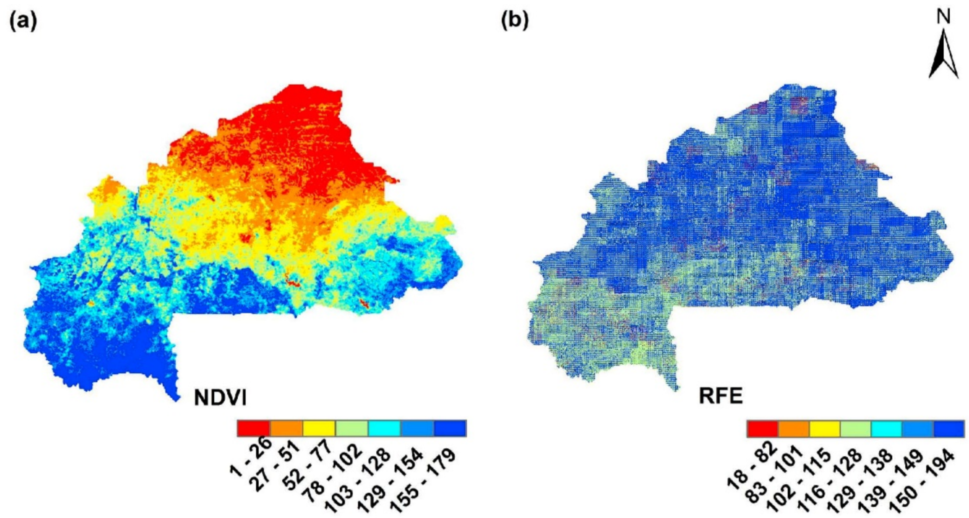
Satellite Data



Imran, M., Basit, I., Khan, M.R., Ahmad, S.R.Analyzing the Impact of Spatio-Temporal Climate Variations on the Rice Crop Calendar in Pakistan . Accepted for presentation in at the 20th International Conference on Sustainable Agriculture Environment & Forestry, London, UK. 28-29 June 2011,Londn, UK.

Modeling trend with deterministic methods
Multiple Linear Regression Kriging (MLRK)

$$Y(s) = f(NDVI.PC(s), PERC(s), ELEV(s), RURP(s), PHCR(s), MARK(s)) + H(s),$$

$$\hat{z}(\mathbf{s}_0) = \hat{m}(\mathbf{s}_0) + \hat{e}(\mathbf{s}_0) = \sum_{k=0}^{p} \hat{\beta}_k \cdot q_k(\mathbf{s}_0) + \sum_{i=1}^{n} \lambda_i \cdot e(\mathbf{s}_i)$$

$$\hat{Y}_{RK}(s) = x_{\circ}(s)^T \hat{\beta}_{MLR}(s) + \hat{H}_{OK}(s),$$

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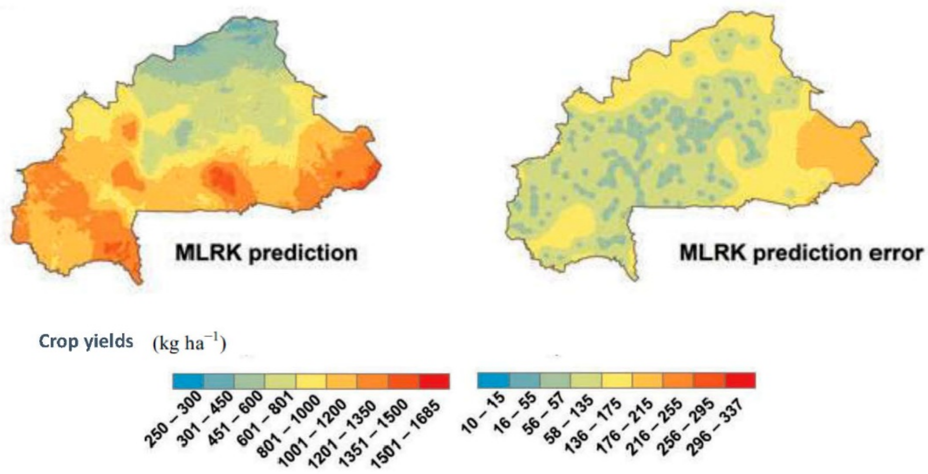
MLRK-based Crop Yield Extrapolation



Modeling Spatial Variability – Geostatistical Approaches

- Geostatistical approaches include the distance between two observations for the quantification of spatial variability.

- These methods however do not consider spatial variations with respect to the geographical coordinates.

$$\gamma(h) = \frac{1}{2} E\left[\left(Y(s) - Y(s+h) \right)^2 \right]$$

measurement at location s

measurement at location s+h

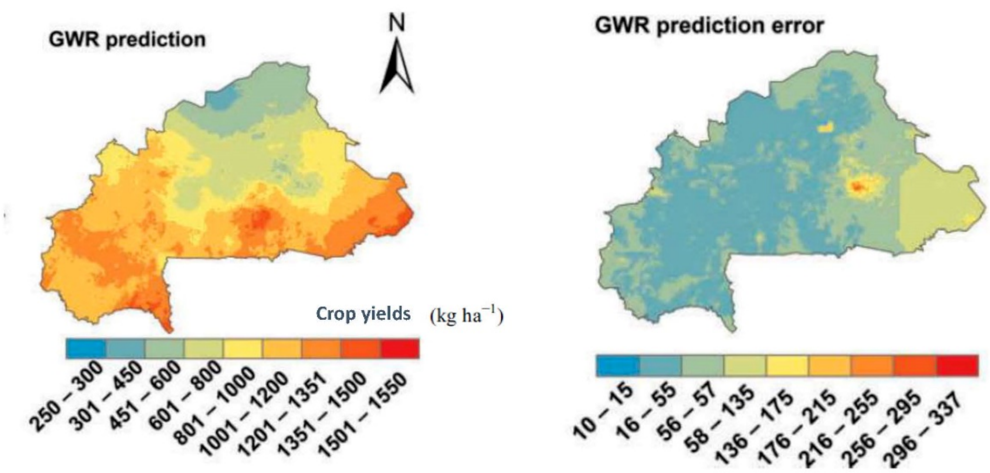
Modeling Spatial Variability – Spatial Statistoc Approaches Geographical Weighted Regression (GWR)

$$Y(s) = f(NDVI.PC(s), PERC(s), ELEV(s), RURP(s), PHCR(s), MARK(s)) + H(s),$$

$$Y(s) = \beta_0 + \sum_k \beta_k X_k(s) + \epsilon_s,$$

$$Y(s) = \beta_0(s) + \sum_k \beta_k(s) X_k(s) + \epsilon(s),$$

GWR Crop Yield Extrapolation



Concluding remarks

- Spatial statistical tools help to model spatial variability of variables.

- Geostatistical approaches uses the quantified spatial variability to extrapolate variables from field to regional scales.

- Remote sensing imagery can be used to assist in scaling-up and scaling-down spatial information.