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MAPPING SPATIAL VARIABILITY IN CROP EVAPOTRANSPIRATION AND DEFINING SPATIAL RESOLUTION UNITS FOR CROP WATER FOOTPRINT ASSESSMENT AT RIVER BASIN SCALE

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ABSTRACT

Aim of this study was to develop amethodologyfor defining the spatial resolutionunit (SRU)for WF assessment at river basin scale. On the basis of soil type and agro-ecology, the Betwa river basin was divided in to smaller but homogeneous agriculture production units (APU). Spatial variability in ETc of 12 major crops was mapped using geostatistical interpolation.K-means clustering was applied to combine the APUs to form the SRU such that ETc variation within the SRU is minimum. Four distinct SRUs were identified for *kharif* and *rabi* crops.Variation in ETc of crop within the AESRs of the basin ranged between 22.0 (AESR 10.3) to 33.9 mm (AESR 4.4) while it reduced to 11.7 (SRU1) to 18.6 mm (SRU4) within the delineated SRUs. Based on the tests of significance, SRUs were found to be a better resolution unit for WF assessment at river basin scale. The proposed methodology of SRU delineation is robust and can be replicated in other river basins.

KEY WORDS
Water footprint
Spatial resolution
Variability mapping
Cluster analysis

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INTRODUCTION

Changing climatic conditions, increasing population, over exploitation and pollution is leading to recurring water shortages in many river basins of the India. To overcome the problems of water scarcity, water resources are exploited for consumption in an unsustainable way (Dutta *et al.,* 2009). Researchers have used water accounting approach to study the sustainability of water consumption pattern (Hazra and Avishek, 2010). In recent past, new paradigms and approaches like virtual water content (VWC) and water footprint (WF) are increasingly being used to address the problem of water sacristy. Crop WF is a function of crop evapotranspiration (ETc) which varies with soil, climate and crop factors (Allen *et al.,* 1998). This implies that crop evapotranspiration needs to be estimated in a spatially explicit way.

At river basin scale researchers have used different spatial resolutions for ETc estimation and consequent assessment of WF. Feng *et al.* (2012) divided the yellow river basin in to upper, middle and lower regions based on characteristics like water resources, economic structure and household incomes and consumption patterns. Aldaya and Llamas (2008) carried out analysis of water footprint for Gaudiana river basin in Spain using ETc estimated at provincial level. Spatial resolution at which ETc is estimated significantly influences the WF estimates. Global WF of wheat at resolution of 5′x5′ was estimated as 941.42 km^3 (Siebert and Doll, 2010) while at 30′X30′ resolution it was estimated as 678.3 km^3 (Fader *et al.,* 2011).In most of the recent WF studies, decision on spatial resolution at which the ETc was estimated was based mainly on spatial scale at which the data was available. Systematic study on development of procedure for delineation of spatial resolution units for WF assessment has been reported so far.

Water footprint is most sensitive to reference crop evapotranspiration (ET_0) and crop coefficient (Kc) (Zhuo *et al.,* 2014). In view of considerable spatial variation in variation in soil and climate,WF assessmentat the spatial resolution of adistrict, province or countrymay lead to unrealistic WF estimates. Therefore, the spatial resolution unit should be delineated for basin such that intra-unit ETc variationiswithin acceptable limit. Delineation of such homogeneous areas will not only reduce the time and money involved but also help managers to formulate the guidelines for data collection and allocate budget and manpower for the purpose of WF assessment. This study is a first attempt to develop the systematic procedure for defining the spatial resolution units for WF assessment.

This paper demonstrates a framework for delineation of appropriate spatial resolution for WF assessment at river basin scale. In this study, a methodology consisting of geostatistical interpolation, principal component analysis and cluster analysis is proposed for delineation of appropriate spatial resolution units within a river basin. This study was planned tomodel the spatial variability in ETc within the basin and to define the spatial resolution units for WF assessment at river basin scale.

MATERIALS AND METHODS

The study was carried out for Betwa river basin located in semi-arid region of Central India (Fig. 1). The basin drains an area of about 43120 km² out of which 29329 km² is in Madhya Pradesh and 13791 km² is in Uttar Pradesh state. Average rainfall of the basin is about 1138 mm. Twelve major crops covering about 80.1 % of the gross cropped area of the basin were selected for the purpose of defining spatial resolution.

On the basis of homogeneity in soil, agro-ecological conditions and district boundaries, the Betwa basin was divided in to smaller homogeneous units named as Agricultural Production Units (APU).The APU was considered as the smallest unit (highest resolution) for assessment of ETc.Intersect of thematic layers pertaining to soil type, AESR, basin and district boundary was carried out in ArcGIS™ to delineate the APU polygons for each district. Using this approach, the Betwa basin was divided in to 27 APUs (Fig. 2). Evapotranspiration of selected crops (ETc) was estimated for each APU basin using FAO CROPWAT model (Allen *et al.,* 1998; FAO, 2012). CROPWAT model estimates reference crop evapotranspiration (ET_0) over the cropping season using Penman-Monteith equation and crop coefficients. Crop coefficients at different crop development stages (initial, middle and late stage), length of crop development stage and crop rooting depths were taken from FAO (Allen *et al.,* 1998). The crop planting and harvesting dates for the state of Uttar Pradesh and Madhya Pradesh were adopted from information published by Department of Economics and Statistics, Ministry of Agriculture, Government of India (MoA, 2011) and ICAR. The gridded daily time series data on climatic parameters was taken from NICRA project (NICRA-ICAR, 2012).

Spatial Variability in ETc

Ordinary Kriging (OK) and Ordinary Co-Kriging (OCK) interpolation methods were evaluated using cross-validationstatistics (Deutsch and Journel 1998). Spherical semivariogram model was used in kriging as it is one of the most widely used semivariogram models (Goovaerts, 2000) and is commonly available in many geostatistical software packages. In case of ordinary co-kriging, mean maximum (T_{max}) and mean minimum (T_{min}) temperature were used as covariates. The variability maps were developed using the best performing kriging method in terms of mean error (ME) and Root Mean Squared Error (RMSE) and using the geostatistical analysis extension module of ArcGIS™.

Delineation of spatial resolution unit

Principal component analysis (PCA) was used to combine the information on APU level spatial estimates of ETc of 12 crops to derive more meaningful datasets to be used in delineation of SRU. Optimum number of PCs were determined by the Scree plots and Kaiser Criterion (Kaiser, 1960) where only the PCs with eigenvalues greater than unity are retained.K-means statistical clustering of the scores of derived PCs at each APU were used to combine the delineated APUs to form SRUs. Here, the goal was to form the groups (clusters)of APUs such that the ETc variation within a SRUis reduced and between the SRUsit is maximised.

RESULTS AND DISCUSSION

Crop evapotranspiration variation within AESRs

Considerable variation in ETc was observed within the AESR (Table 1). Being smaller in size, the AESR 4.3 showed only slight variation in ETc of all the crops. In case of *kharif* crop maximum ETc was observed in AESR 4. 3 while in case of*Rabi* crops the maximum ETc was in AESR 10.1. Although, the range of ETc variation *within* AESRs was very high, there is lack of clear cut difference in ETc *between* the AESRs. This shows that AESR are not able to capture the spatial variation in the ETc of crops. Sharma and Irmak (2012) also observed significant differences in reference crop evapotranspiration among different counties of Nebraska. Therefore, at a river basin scale, AESR cannot be used as an ideal spatial resolution for assessment of agricultural WFP.

Spatial variability in ETc within the basin

The point values of ETcin each of the 27 APUs wassubjected to ordinary kriging (OK) and ordinary co-kriging (OCK). The cross validation statistics revealed that OCKwith Tmax as covariate performed betterin terms of ME and RMSE (Table 2).In ordinary co-kriging, use of T_{max} as covariate resulted in

Table 1: Mean crop evapotranspiration (*μ*) and variation (R) in ETc (mm) in different agro-ecological sub regions

	AESR 4.3		AESR 4.4		AESR 10.1		AESR 10.3	
	μ	R	*μ*	R	*μ*	R	*μ*	R
Paddy	508.8b	3.1	507.6b	45.0	477.1a	34.1	502.8 b	35.2
Sorghum	382.4b	1.5	383.5b	35.3	368.3a	20.5	379.5ab	25.7
Maize	392.3ab	2.6	400.0c	17.9	387.2a	12.3	399.0bc	11.
Groundnut	535.7b	1.8	534.8b	40.1	512.8a	25.4	529.9b	24.6
Pigeon pea	569.5b	1.5	570.6b	48.0	541.4a	34.3	565.4b	35.3
Sesame	357.4a	6.0	394.0bc	51.8	378.9b	18.8	396.4c	22.1
Soybean	483.9b	2.6	481.1b	44.3	452.1a	29.0	476.0b	32.0
Wheat	393.2a	0.2	399.9a	29.0	421.3b	26.3	401.7a	20.6
Chickpea	302.2a	0.1	309.7ab	18.8	324.8c	19.0	310.8b	14.1
Lentil	373.3a	1.9	387.8b	33.0	404.9c	17.5	390.0b	23.2
Mustard	305.9a	2.5	318.2b	22.7	334.5c	13.3	318.7b	16.8
Peas	293.5a	4.2	306.9b	28.9	326.7c	16.8	309.2b	23.1

Note: Within a row, means followed with same letter are not significantly different ($p < 0.05$).

lowest ME (-0.3 to 0.7 mm) and RMSE (2.9 to 25 mm) for *kharif* and *rabi* season crops. Hence, OCK interpolation algorithm with T_{max} as covariate was used to develop the spatial variability maps of the ETc within the basin (Fig. 3). The ETc of all the *kharif* crops increased from southeast part to northern part of the basin. The *rabi* crops showed reversed trend with ETc increasing from north-eastern part to southwest part of the basin. The three major crops grown in Betwa basin viz. wheat, chickpea and rapeseed showed large spatial variability in ETc with the variation ranging from 370 to 433 mm, 289-335 mm and 297-340 mm respectively. Substantial difference in spatially interpolated maximum and minimum values of ETc was observed in case of rice (71 mm) and pigeon pea (74 mm). For other crop this difference varied from 43 mm (rapeseed) to 66 mm (soybean).

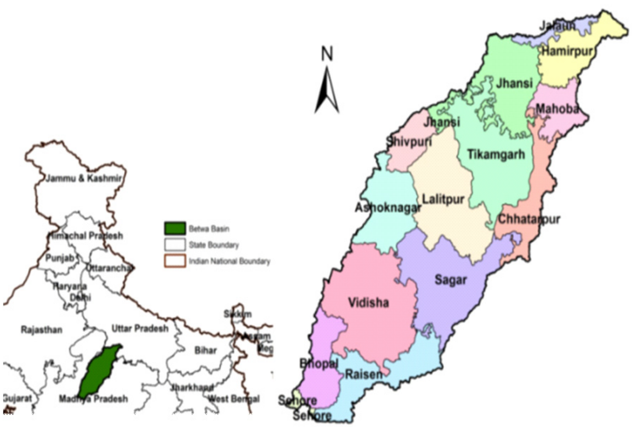

Figure 1: Location of the Betwa basin showing the administrative districts

Table 2: Cross validation results of ordinary kriging and ordinary co-kriging

Crop	Ordinary Kriging ME	Ordinary Kriging RMSE	Ordinary co-kriging T_{min} ME	T_{min} RMSE	T_{max} ME	T_{max} RMSE
Paddy	0.1	9.5	0.0	6.4	0.1	5.2
Maize	0.3	13.3	0.5	13.5	0.4	13.2
Groundnut	0.0	8.6	0.0	6.5	0.0	5.9
Pigeon Pea	0.1	9.5	0.1	6.8	0.1	5.8
Sorghum	0.1	8.1	0.2	6.8	0.1	6.7
Sesame	0.8	25.6	0.7	25.3	0.7	25.0
Black gram	0.0	7.1	0.0	4.5	0.1	3.7
Soybean	0.1	9.5	0.1	6.4	0.1	5.6
Wheat	-0.2	5.8	-0.3	5.4	-0.1	4.2
Chickpea	-0.2	4.0	-0.2	3.8	-0.1	3.1
Mustard	-0.1	4.8	-0.2	3.7	0.0	2.9
Peas	0.0	6.1	-0.1	4.1	0.0	4.0
Lentil	-0.4	8.7	-0.1	8.5	-0.3	7.1

Note: ME: mean error, RMSE: root mean square error, T_{max}: mean maximum temperature, T_{min}: mean minimum temperature.

Delineation of SRUs within the basin

Principal component analysis was applied separately to *kharif* and *rabi* crops and one principal component was retained for each season. The PCs so obtained explained about 99.7% and 98.8% of variance and were useful in removing the co-linearity in the data as found by Wang *et al.* (2013). According to the elbow rule (Madhulatha and Soni, 2012) fournumber of clusters were identified for both PCs representing kharif and rabi the seasons. The K-means clustering produced asubdivision of the basini nto four distinct SRUs with significantly different mean ETc values (Fig. 4). This partition best accorded with the description of spatial variation of ETc in the field. For all the selected crops, the mean ETC at each SRU was significantly different. The mean ETc decreased from SRU 1 to SRU 4 for *kharif* crops while there was reverse trend in case of *rabi* crops (Table 3).

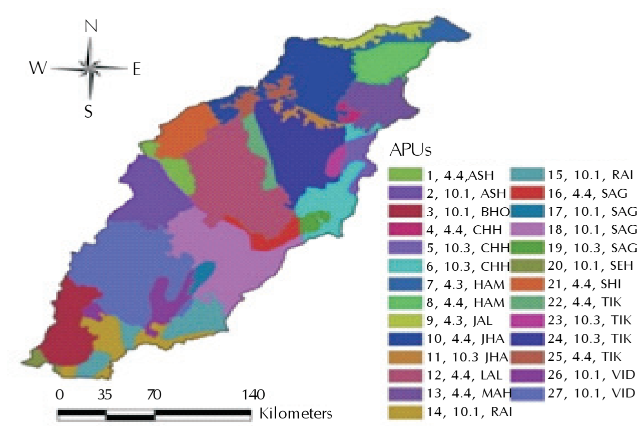

Figure 2: Delineated Agricultural Production Units (APU) in Betwa basin

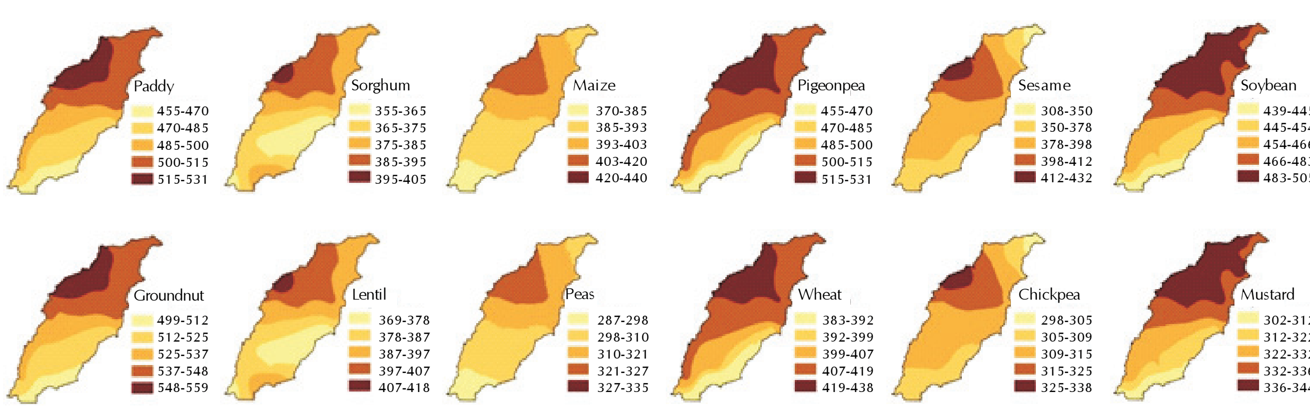

Figure 3: Spatial distribution pattern of crop evapotranspiration in mm (ET_c) of different crops in the Betwa basin

Table 3: Mean (μ) and range (R) of crop evapotranspiration (mm) in different SRUs

	SRU1		SRU 2		SRU 3		SRU 4	
	μ	R	μ	R	μ	R	μ	R
Paddy	517.5[†]	8.4	506.3	16.2	478.7	7.8	467.3	6.3
Sorghum	390.6	8.6	382.3	12.6	364.4	7.4	369.9	19.5
Maize	405.9	7.4	397.4	14.9	388.9	8.5	383.9	2.7
Groundnut	541.4	14.5	533.7	12.2	513.1	7.9	506.0	6.3
Pigeon pea	580.0	11.3	569.2	17.4	541.8	9.0	532.5	6.6
Sesame	406.3	14.4	395.8	26.3	380.1	6.7	373.9	1.9
Soybean	489.7	11.0	480.0	15.5	453.4	6.3	443.4	0.9
Wheat	392.2	5.7	416.1	15.8	431.2	10.1	398.5	9.4
Chickpea	302.5	2.8	320.7	10.6	333.2	6.7	309.2	8.0
Lentil	375.4	7.5	403.2	11.9	406.7	17.0	386.9	10.7
Mustard	307.5	5.0	331.0	10.2	340.9	4.9	317.3	10.4
Peas	295.4	5.9	322.8	13.7	333.7	2.5	306.1	13.5

†For all the crops the means are significantly different ($P<0.05$)

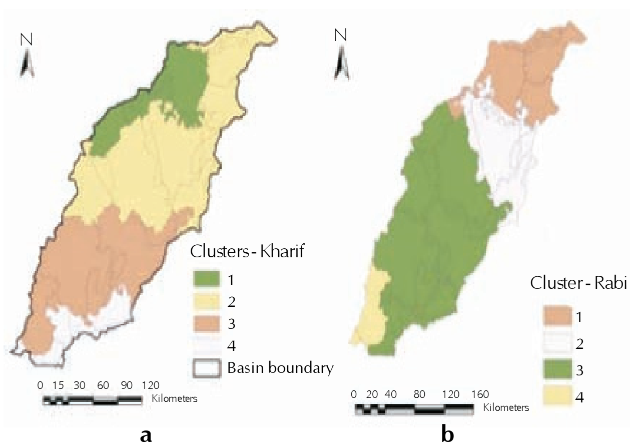

Figure 4: Homogeneous units identified using cluster analysis for *kharif* (a) and *rabi* (b) season

In previous sections it was shown that ETc estimated at AESR level did not capture the variability of ETc at basin scale. This implies that, at basin scale, the spatial heterogeneity in climatic parameters is not well represented by AESRs. Hence, AESR cannot be considered as an appropriate spatial resolution unit for ETc estimation at river basin scale.It was obvious that the spatial extent of SRUs as obtained by combining of APUs was a coarser resolution than APUs. Still, SRU is a better option in the sense that ETc variability within the SRU was within the acceptable limits. With the help of statistical clustering, it is possible to merge the high resolution units (APUs) into SRUs without sacrificing the spatial variability in ETc. Therefore, in terms of accuracy of WF assessment, SRUs is a better spatial resolution unit as compared to entire basin or AESR. Considering the time, efforts and cost involved in the process of WF assessment, the SRU is more advantageous. Since, population and crop related statistics are maintained at district level, the concept of APUs proposed in this study will be useful in downscaling of such administrative unit level data to SRU or river basin level. Based on the ETc and crop yield data, the WF of crops can be estimated at SRU level and hence for the entire basin. Therefore, the proposed methodology is an improvement over clustering of gridded (interpolated) values as used by Shi and Zeng(2014).It is robust and takes into account the natural variation in soil, climate. Developed methodology can be viewed as a step towards improving the accuracy of WF assessment.

REFERENCES

Aldaya, M. M. and Llamas, M. R. 2008. Water footprint analysis for the Guadiana river basin. *Value of Water Research Report Series No. 35, UNESCO–IHE Delft, The Netherlands.*

Allen, R. G., Pereira, L. S., Raes, D. and Smith, M. 1998. Crop Evapotranspiration: Guidelines for computing crop water requirements, Irrigation and Drainage Food and Agriculture Organization of the United Nations, Rome, Italy. p. 56.

Deutsch, C. V. and Journel, A. G. 1998. GSLIB, Geostatistical software library and user's guide, 2nd Ed., Oxford University Press, Oxford, UK.

Dutta, S. P. S., Khullar, M. and Sharma, J. 2009. Limnology of two springs adjacent to Chattha nullah, Jammu part I. Water chemistry. *The Ecoscan.* **3(3&4):** 241-246.

Fader, M., Gerten, D., Thammer, M., Heinke, J., Lotze-Campen, H., Lucht, W. and Cramer, W. 2011. Internal and external green-blue agricultural water footprints of nations, and related water and land savings through trade. *Hydrol. Earth Syst. Sci.* **15:** 1641-1660.

FAO. 2012. CROPWAT 8.0, Food and Agriculture Organization of the United Nations, Rome, Italy, [web address]www.fao.org.

Feng, K., Siu, Y. L., Guan, D. and Hubacek, K. 2012. Assessing regional virtual water flows and water footprints in the Yellow River Basin, China: A consumption based approach. *Appl. Geogr.* **32:** 691-701.

Goovaerts, P. 2000. Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. *J. Hydro.* **228(1-2):** 113-129.

Hazra, M. and Avishek, K. 2011. Water resources evaluation through water accounting: a means to achieve sustainable development. *The Bioscan.* **(1):** 4 3-50.

Kaiser, H. F. 1960. The application of electronic computers to factor analysis. *Edu. and Psychol. Measurement.* **20:** 141-151.

Madhulatha, T. and Soni, A. N. 2012. Overview on clustering methods. *IOSR. J. Eng.* **2:** 719-725.

MOA. 2011. Agricultural Statistics at a Glance-2011, Department of Economics and Statistics, Ministry of Agriculture, Govt of India. *[web address]http://eands.dacnet.nic.in.*

NICRA-ICAR 2012. District wise daily weather data, Tools and Services, National Initiative on Climate Resilient Agriculture, Indian Council of Agricultural Research, New Delhi India. *[web address]* *http://www.nicra-icar.in/.*

Sharma, V. and Irmak, S. 2012. Mapping spatially interpolated precipitation, referenceevapotraspiraion, actual crop evapotraspiraion, and net irrigation requirements inNebraska,Part I. Precipitation and Reference Evapotraspiraion" (2012). *Biol Syst Eng: papers and publications. Paper 295. [Web address] htt://digitalcommons.unl.edu/ biosysengfacpub/295*

Shi, W. and Zeng, W. 2014. Application of k-means clustering to environmental risk zoning of the chemical industrial area. *Frontiers of Env. Sci. and Eng.* **8:** 117-127.

Siebert, S. and Doll, P. 2010. Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation. *J. Hydrology.* **384:** 198-207.

Wang, J. L., Kang, S. Z., Sun, J. S. and Chen, Z. F. 2013. Estimation of crop water requirement based on principal component analysis and geographically weighted regression.*Chin Sci Bull.* doi: 10.1007/ s11434-013-5750-1.

Zhuo, L., Mekonnen, M. M. and Hoekstra, A. Y. 2014. Sensitivity and uncertainty in crop water footprint accounting: a case study for the Yellow River basin. *Hydrol. Earth Syst. Sci.* **18:** 2219-2234.