

Assessing field significance of kolmogorov-smirnov tests on spatially correlated precipitation data

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The original approach of Kolmogorov-Smirnov Test (KST) considered empirical distributions of local (i.e. point, pixel or grid cell) data series. So the question arises, how reliable is an integral analysis of spatially highly correlated KSTs. Are the result significant for the considered domain or are they just formed by chance (i.e. in terms of KST, is the portion of non-rejected Null-Hypothesis just significant or just emerged by coincidence) [Livezey and Chen, 1983]. This question can be answered assessing the field significance [Renard *et al.*, 2008]. When spatial (cross) correlation is negligible, the theory of binomial distribution can be used to identify it [Machiwal and Jha, 2012]. As this is obviously not the case with radar-derived precipitation data [Kronenberg *et al.*, 2012] the spatial correlation has to be considered. Field significance can be proofed by analysing the magnitude of individual p-values [Wilks, 2006]. This implies that field significance can be assessed of any hypothesis test employing p-values. However, it is so far mainly applied assessing spatial trend significance of climatological or hydrological variables [Khaliq *et al.*, 2009, Renard *et al.*, 2008]. In this work we use the concept of false detection rate (FDR) to analyse field significance of KST of different density functions fitted on radar-derived precipitation rates [Venture *et al.*, 2004].

- KST with FDR seems to perform more permissive than ordinary KSTs.
- The rejections through KST with FDR over different spatial scales show a similar curve behaviour like the ordinary KST.
- KST with FDR converges to the same level of rejection at larger spatial scales like the ordinary KST.

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