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Quantitative measures for the local similarity of hydrological spatial patterns

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The task of assessing similarity between data sets is common in hydrological modelling. While this has been widely researched for temporal data sets, the similarity between spatial patterns has been largely ignored. This has been due to a lack of spatial pattern data. Today there is widespread use of distributed hydrological models and increasing availability of observed spatial patterns. These observed spatial patterns are useful for model calibration and optimisation, though at present there is limited use of the spatial information contained in them. This is mostly due to a lack of understanding in how to make optimal use of this information rich data. The work in this paper investigates some quantitative measures for judging the similarity between observed and simulated spatial patterns, with a particular emphasis on local similarity techniques. The different measures allow the user to assess different aspects of similarity, which can then be used together for automated model calibration and/or evaluation.

Introduction In hydrological modelling, assessing the similarity between data sets is an everyday task, regardless of whether the data is temporal or spatial. Many methods exist for doing this, but most were not developed specifically for hydrological data sets. As such, it is necessary to understand the methods and what their resulting measures actually represent. *Legates and McCabe* (1999) evaluate many methods used for assessing similarity between temporal data sets. Some methods are sensitive to matching extreme values, while others provide a test of fit but ignore absolute differences. It is concluded that relative, absolute, local and global measures should all be stated when assessing the similarity between data sets. Additionally, the use of specialised methods for particular types of hydrological data can provide more informative similarity measures. *Boyle et al.* (2000) present a method in which the hydrograph is divided into “process-related” components. Each component is then compared, providing a measure of similarity that can be directly related to the process. This requires prior knowledge about the phenomenon being compared and is more difficult for spatial data sets (herein referred to as spatial patterns).

There are many methods available for assessing similarity between spatial patterns. Together, these global and local methods can describe the similarity between the values in the spatial patterns. But as with most temporal measures, they mostly ignore the specific arrangement of the values (especially the global methods). As a result of this, most hydrologists rely on visual comparison for assessing similarity (*Grayson et al.*, 2002). Visual comparison can be thought of as a specialised method, as it incorporates knowledge about the hydrological phenomenon and other ancillary information. However, its weaknesses are that it is neither automated, objective, repeatable nor quantitative - all things that are important when assessing similarity between many data sets. This research aims to address some of these weaknesses by emulating parts of the visual comparison process computationally. There is no expectation that a computer algorithm will be able to emulate what the human brain does. However, the steps undertaken during visual comparison suggest many new avenues to pursue for developing specialised methods for assessing similarity. This paper discusses the background to similarity assessment and describes three different methods for assessing local similarity, including an example of their use.

Background A review of the literature on computer vision, image processing and pattern recognition has identified the major processes undertaken during visual comparison and methods that try to emulate them (*Wealands et al.*, 2004). A visual comparison involves both global and local similarity assessment (*Hagen*, 2003; *Hay et al.*, 2003). During local comparison, the image is viewed as a set of homogeneous regions, rather than individual pixels (*Hay et al.*, 2003). The visual comparison also focuses on particular features or parts of the spatial pattern, rather than treating every location equally (*Tompa et al.*, 2000). During this process, observations such as the similarity of shape, location and intensity are noted. Finally, the observed similarities and differences observed are explained and/or interpreted using extensive background knowledge (*Grayson et al.*, 2002). Thus, the procedure used during visual comparison can be described as "global similarity assessment, followed by local similarity assessment of regions in the spatial pattern using various measures, with a tolerance for minor differences and additional focus on more important parts of the spatial pattern".

Global methods for assessing similarity of spatial patterns are plentiful (see *Scheibe*, 1993). Basic statistics, geostatistics and landscape indices can all characterise certain features of the spatial pattern. These numerical summaries can then be compared to measure the similarity between spatial patterns. For local similarity, the most common method used is root mean squared error (RMSE), which provides a summary of the squared residuals. Local similarity methods are far more sensitive to differences between the spatial patterns than global methods, as they evaluate every location and use the spatial data in its complete form. At each location, a measure is calculated (e.g., the squared residual) to represent the similarity and this is stored in an intermediate spatial pattern. The intermediate spatial pattern is useful for closer inspection of the differences and is summarised to produce the resultant local similarity measure.

More specialized methods involve additional processing both before and during the calculation of similarity measures. For example, preprocessing can involve smoothing or aggregation to change the scale of the spatial patterns. These adjusted spatial patterns are then used for computing the similarity measure. Alternatively, each location can be compared against neighbouring locations in the other spatial pattern, with the most similar measure from the whole neighbourhood used to represent the similarity for that location. Both these examples illustrate how a minor modification can alter a standard method, thus making it more specialised.

Local comparison methods The aim of local comparison methods is to emulate the major features of detailed visual comparison, so that these can be quantified and automated. Three methods used to produce local similarity measures are (1) fuzzy comparison, (2) importance maps and (3) image segmentation.

Fuzzy comparison is a method used for tolerating shifts and differences during the calculation of the similarity measure. This allows the user to specify weights for locational matching (i.e., what amount of displacement is acceptable) and value matching (i.e., what amount of error is considered acceptable). The method processes each location in the spatial pattern, computing a similarity value between the respective location and its neighbouring locations in the second spatial pattern (more details in *Hagen*, 2003; *Wealands et al.*, 2004). From the nine similarity values (range of 0 to 1) computed, the highest level of similarity is retained. Figure 2.1i) shows two different sets of residual and location weights that have been used to calculate the fuzzy similarity between observed and simulated soil moisture data. The more tolerant residual weights

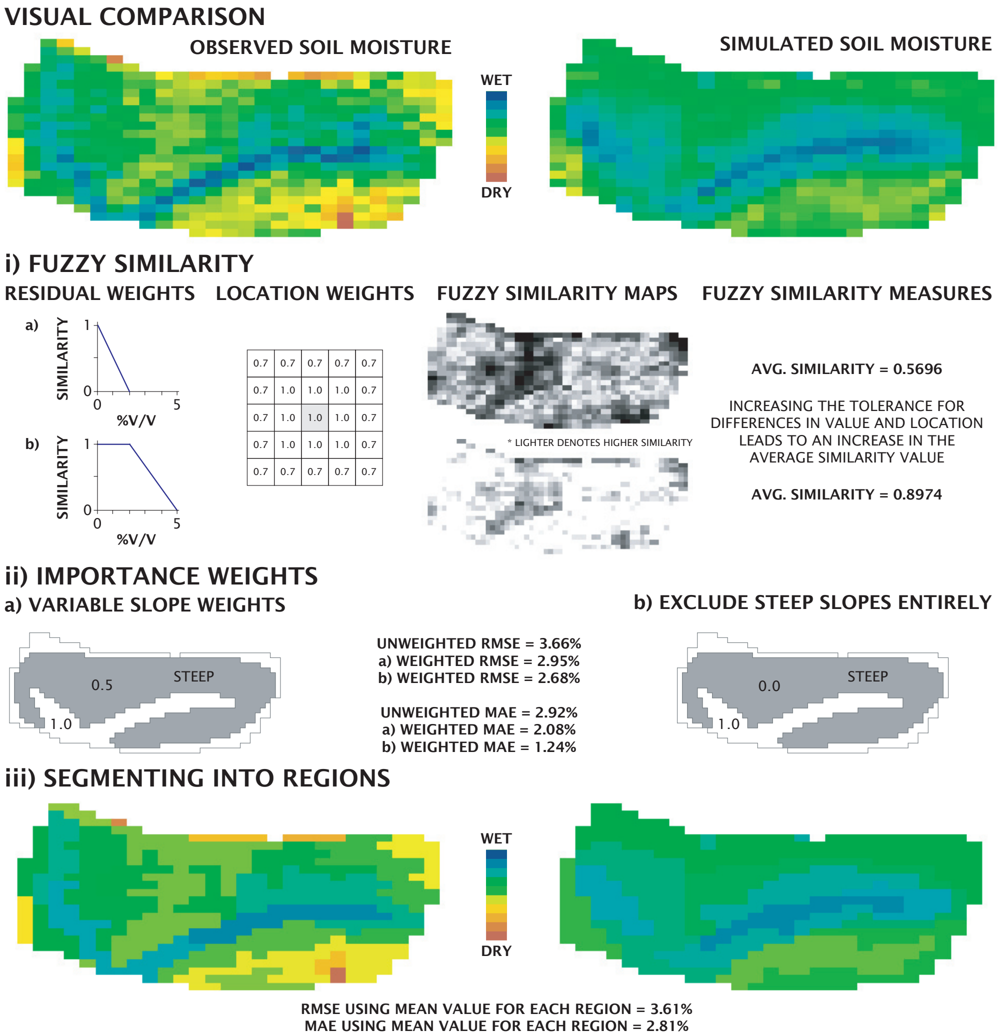

Figure 2.1: Example illustrating three specialized methods for assessing local similarity. The methods aim to emulate some aspects of visual comparison, including i) tolerance for differences in values and locations; ii) focus on certain parts of the spatial pattern more than others; and iii) comparison of regions rather than pixels.

(b) produce a higher overall similarity value than the more limiting weights (a). When multiple sets of observed and simulated spatial patterns are compared, this method can help reveal similar spatial patterns that are not detected by standard local similarity methods due to shifts or minor differences.

Weighting spatial patterns before computing similarity measures is a way of focusing on the "important areas". Visual comparison does this automatically as a result of both visual cues (e.g., bright spots) and background knowledge (e.g., focusing only on areas the user knows are gullies). While there is literature on what draws visual attention in an image, these findings are often related to the type of image. However, it has been recognised that features occurring infrequently in images (e.g., extreme values) are of high perceptual importance (*Tompa et al.*, 2000). This can be used to produce perceptually weighted spatial patterns, in which the infrequent values are given higher weights than those that are common. Due to the weightings, calculation of the standard RMSE measure will lead to a larger residual where the infrequent values do not match (see

Wealands et al., 2004, for examples). Weighting can also be applied to limit the areas in which the similarity measure is computed. If the user is only interested in the similarity of certain areas (e.g., north facing slopes), then a weighting that either enhances or separates these areas will focus the meaning of the similarity measure accordingly. Figure 2.1ii) shows the differences between standard RMSE calculations when using different slope weights to focus the comparison. By using the weights to limit the influence of slopes greater than 10 degrees (a), the similarity measure is focused more on similarity in flatter areas. If the weights exclude the steeper areas entirely (b), then a measure that is only related to flat areas is produced.

Segmentation is the process of breaking up an image into regions using a set of rules. The simplest approach to segmentation is thresholding, where a value is chosen to separate an image into two regions. During visual comparison, spatial patterns are viewed as regions rather than pixels (*Hay et al.*, 2003), with the regions detected at varying scales. Emulating this computationally is a difficult task. Using a multiresolution segmentation technique from image processing (*Baatz and Schäpe*, 2000), the spatial patterns of soil moisture have been segmented into homogeneous regions in figure 2.1iii). Using the mean values for each region, an RMSE measure has been calculated between the segmented spatial patterns. This value is less than the RMSE calculated between the original spatial patterns due to the removal of “noise” via averaging within regions. This method seeks to emulate the region detection process that is done visually, by simplifying the spatial pattern prior to comparison. It may be particularly useful for detecting similarity between noisy data sets, in which the noise precludes the use of standard methods like RMSE.

Discussion This research has investigated multiple methods for assessing different aspects of local similarity between spatial patterns. Methods have been sourced from other disciplines and adapted to work with spatial patterns common in hydrology. These methods focus on emulating aspects of visual comparison. It is widely recognised that no single method for assessing similarity can capture everything, but by using multiple methods together a strong test of spatial pattern similarity can be made. Further work with the methods described above will identify their particular benefit for assessing similarity in different contexts.

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