Dear Professor Kjeldsen,

Thank you for handling the review of our manuscript. We thank the two reviewers for their constructive comments and following on from our response to their reviews in the online discussion, we have conducted a major revision of the manuscript. Below is a point-by-point summary of the changes that have been made following the online discussion, as well as a copy of the revised manuscript showing the marked changes. We hope that this manuscript is now acceptable for publication in your journal.

Best regards

1

Murray Scown

Point-by-point changes:

- Further information regarding the study floodplains has been added to the study area section
- More detail of the DEMs used and how floodplains were delineated has been added to the methods section
- Further detail on the calculation of the indicators has been added to the methods section and Table 2
- The results section has been significantly shortened and rewritten in parts to make it less laborious
- Brief discussion on human impacts to hydrology has been added to the discussion section
- Discussion of tailoring window sizes for each floodplain individually based on floodplain width in future studies has been add to the discussion section
- Discussion of the present approach related to the meta-ecosystem approach has been included in the discussion section, along with mention of the complementarity of patch and surface metrics
- Discussion of the limitations due to the limited number of floodplains and lack of multiple regression approaches has been added to the discussion section
- The acronym SOC has been changed to SPO based on advice from another reviewer, due to the already established use of SOC as self-organized criticality
- Minor edits throughout the manuscript have been made

1 An index of floodplain surface complexity

2

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10 Abstract

Floodplain surface topography is an important component of floodplain ecosystems. It is the 11 primary physical template upon which ecosystem processes are acted out, and complexity in 12 13 this template can contribute is largely thought to contribute to the high biodiversity and productivity of floodplain ecosystems. There has been a limited appreciation of floodplain 14 15 surface complexity because of the traditional focus on temporal variability in floodplains as 16 well as limitations to quantifying spatial complexity. An index of floodplain surface complexity (FSC) is developed in this paper and applied to eight floodplains from different 17 geographic settings. The index is based on two key indicators of complexity; variability in 18 19 surface geometry (VSG) and the spatial organization of surface conditions (SOCSPO) and was 20 determined at three sampling scales. Relationships between these measures of spatial complexity and environmental drivers, namely; flow variability (mean daily discharge [Q], 21 22 the coefficient of variation of daily discharge $[Q_{CV}]$, the coefficient of variation of mean 23 annual discharge [Q_{CVAnn}], the coefficient of variation of maximum annual discharge 24 [Q_{CVMax}]), sediment yield (SY), valley slope (Vs), and floodplain width (Fpw) were 25 examined. FSC, VSG, and SOCSPO varied between the eight floodplains and this was dependent these differences depended upon sampling scale. All complexity values declined 26 27 with increasing Fpw in either a power, logarithmic, or exponential function. There was little change in surface complexity with floodplain widths greater than 10 km. VSG was 28 significantly related to SY and no significant relationships were determined between any of 29 30 the hydrological variables and floodplain surface complexity.

1 **1 Introduction**

2 The floodplain surface is an important component of floodplain ecosystems. It provides the 3 primary physical template (sensu Southwood, 1977) upon which ecosystem and evolutionary processes are acted out (Salo, 1990). Complexity of floodplain surfaces contributes to the 4 5 relative abundance of physical habitat (Hamilton et al., 2007), high biodiversity (Ward et al., 6 1999), and elevated levels of productivity (Thoms, 2003), as well as nonlinear ecosystem 7 responses to inundation (Murray et al., 2006; Thapa et al., 2015). The majority of floodplain 8 research has focused on temporal variations and in particular how hydrology drives floodplain 9 structure and function (Junk et al., 1989; Hughes, 1990; Bayley, 1995; Whited et al., 2007). 10 Such a focus has contributed to a limited appreciation of the spatial complexity of floodplain 11 surfaces.

12 There are two main components to the spatial complexity of floodplain surfaces (Scown et al., 2015a). The first component relates to the presence/absence, abundance, and diversity of 13 14 features or conditions present. This influences the number and range of distinct habitats and potential interactions between those habitats; both of which contribute to complexity (Levin, 15 16 1998; Phillips, 2003). The second component is concerned with the spatial organization of 17 features or conditions present within a floodplain surface. Spatial organization controls local 18 interactions and feedbacks between features, features and can emerge in the absence of any 19 global control (Hallet, 1990). It also affects the flux of matter and energy throughout systems 20 (Wiens, 2002). Any measurement of spatial complexity must incorporate both components; something that does not generally occur (Cadenasso et al., 2006). Studies of floodplain 21 22 surface complexity have been limited because they tend to only measure one of the components of spatial complexity (Scown et al., in press2015c). Moreover, many of the 23 24 measures of spatial complexity that have been proposed are based on categorical 'patch' data 25 (e.g., Papadimitriou, 2002). Such data have limitations because of the qualitative delineation of patch boundaries, loss of information within patches, and subsequent analyses of these data 26 being restricted to the initial minimum scale at which patches were initially defined 27 (McGarigal et al., 2009). Continuous numerical data have been used in some studies, and 28 single metrics of surface complexity have been developed, such as rugosity or fractal 29 dimension (see review by Kovalenko et al., 2012). These single-metric-based indices do not 30 31 fully encompass the multivariate nature of spatial complexity; thus, multiple indicators are 32 required to get the full measure of surface complexity (Dorner et al., 2002; Frost et al., 2005; 1 Tokeshi and Arakaki, 2012). While frameworks encompassing the multiple dimensions of 2 complexity have also been proposed (e.g., Cadenasso et al., 2006), they have not provided a 3 quantitative measure of spatial complexity (Scown<u>et al.</u>, 2015c). Quantitative measures of 4 floodplain spatial complexity are required in order to advance our understanding of the 5 influences of spatial complexity on these ecosystems and how it varies between floodplains.

6 New technologies are available for intensive data capture, such as light detection and ranging 7 (LiDAR), and the analysis of these data using geographic information systems (GIS) 8 overcomes many of the limitations that have inhibited the quantification of spatial 9 complexity. LiDAR provides high resolution, quantitative topographic data over large areas 10 for many landscapes including floodplains. These data are useful for measuring floodplain 11 surface complexity. LiDAR-derived digital elevation models (DEMs) of floodplain surfaces 12 can be used to measure the character and variability of surface features or conditions using a 13 suite of surface metrics (McGarigal et al., 2009) and moving window analyses (Bar Massada 14 and Radeloff, 2010; De Jager and Rohweder, 2012). The spatial organization of these features 15 or conditions can then be measured using spatial correlograms and geostatistical models (Rossi et al., 1992). These quantitative measurements of the two components of spatial 16 17 complexity can be incorporated into a single multivariate index. The advantages of using single indices that can be decomposed into sub-indices (e.g., for use in assessing ecosystem 18 19 health [Norris et al., 2007]) have been widely favoured in ecosystem research.

20 A quantitative index of floodplain surface complexity is developed in this study and applied to eight floodplains from different geographic settings. The primary data source is a LiDAR-21 22 derived DEM for each floodplain. The character and variability of surface features and 23 conditions and their spatial organization are incorporated into a single quantitative index to 24 enable a comparison of surface complexity between floodplains. The different environmental settings of each floodplain provide an opportunity to determine the influence of 25 environmental controls on floodplain surface complexity. In addition, the index is measured 26 27 over three sampling scales (moving window sizes) to investigate the effects of scale on floodplain surface complexity. In this study we ask three questions: 1) Does the surface 28 complexity of the eight floodplains differ and is this consistent among sampling scales? 2) 29 Are the two components of spatial complexity related in floodplain surfaces? 3) What 30 31 environmental factors influence floodplain surface complexity?

1 2 Study area

2 Eight floodplain surfaces from different geographic settings were examined in this study (Fig. 3 1, Table 1). The Bidgee, Gwydir, Macquarie, Narran, and Yanga floodplains are all located within the Murray-Darling Basin in S.E. Australia; whereas the floodplain of the Woodforde 4 5 is located in central Australia approximately 150 km north of the town of Alice Springs. The 6 floodplain of the Shingwedzi is located in N.E. South Africa, in the northern regions of 7 Kruger National Park; and the floodplain of the Upper Mississippi is located within 8 navigation Pool 9 and forms the boundary of the states of Minnesota, Wisconsin and Iowa in 9 the USA. Details of the eight floodplains are provided in Table 1, and in summary, they differed in terms of their degree of valley confinement, climate, and position within the 10 stream network. Four floodplains (the Bidgee, Mississippi, Shingwedzi, and Woodforde) are 11 12 contained within relatively confined river valley troughs with floodplains width ranging between one and five kilometers. The remaining other four floodplains (the Gwydir, 13 Macquarie, Narran, and Yanga) are all contained within relatively unconfined river valleys 14 with floodplain widths up to 60 kilometers. The eight floodplains also differ in their 15 hydrology and geomorphology, exhibiting a variety of morphological features such as flood 16 channels, oxbows, natural levees, crevasse splays, and back swamps. Detailed descriptions of 17 18 each of the eight floodplains are provided by Scown et al. (2015a).

19

20 3 Methods

The Index of Floodplain Surface Complexity (FSC) developed for this study was calculated 21 from data extracted from LiDAR-derived digital elevation models (DEMs) for each 22 floodplain. Floodplain extents were delineated using multiple lines of evidence. This 23 24 delineation was based on examination of breaks of slope in the DEM, contours, changes in 25 vegetation from aerial photography, soil conditions from local soil conservation surveys, and floodwater extents derived from Landsat TM imagery. A buffer within this manually 26 delineated extent was also removed to ensure nothing other than what was deemed to be part 27 of the floodplain was included. Premanently inundated areas were also removed because 28 29 attaining accurate subsurface land elevations using LiDAR is difficult. Each DEM was then 30 detrended to remove the overall downstream slope. Details of the detrending procedures for each of the floodplains are provided by Scown et al. (2015a; 2015b). Each All-detrended 31

1 DEM wass were subsequently resampled to a 5×5 m² grid size using the cubic method in

2 ArcGIS 10.2 because this was the highestfinest resolution available for one of the floodplains.

The FSC index is comprised of two sub-indices, which record the two components of spatial 3 complexity; the variability in surface geometry (VSG) and the spatial organization of surface 4 5 conditions (SOCSPO). VSG is a composite of four surface metrics (Table 2), measured at 50 6 random sample locations throughout each of the floodplains, while SOCSPO is calculated 7 from spatial correlogram models of Moran's I over increasing lag distances for each of the 8 four surface metrics from 1000 random sample locations (Table 2). Specific detailsDetails of 9 the procedures for calculating each indicator are provided by Scown et al. (2015a). In 10 summary, the surface metrics are used to indicate increasing surface variability, while the spatial correlogram model parameters (range and nugget) are used to indicate increasing 11 'patchiness' or organization in the surface (Table 2). It is argued here, and elsewhere (Scown, 12 2015; Scown et al., 2015a), that increasing variability and spatial organization results in 13 increasing spatial complexity. All surface metrics were measured within sampling windows of 14 15 50 m, 200 m, and 1000 m radius. These window sizes were chosen based on the identification of scale thresholds between them by Scown et al. (2015b). This enabled us to determine the 16 17 analyses to be conducted across multiple sampling scales whether any effect of sampling scale 18 occurred.

19 The individual indicators were combined <u>and</u> weighted, using the standardized Euclidean 20 distance procedure, to calculate the overall *FSC* index. This index was used for an overall 21 assessment of floodplain surface complexity and the sub-indices of *VSG* and <u>SOCSPO</u> were 22 derived to provide specific interpretations of the two components of spatial complexity for 23 each floodplain surface. An example of *FSC* calculation is given in Equation (1), where I is 24 the overall index and *A*, *B*, *C*, ..., *N* are the <u>n</u> are the individual indicators of surface 25 complexity, the details of which are provided in Table 2.

$$I = 1 - \frac{\sqrt{(1-A)^2 + (1-B)^2 + (1-C)^2 + \dots + (1-N)^2}}{\sqrt{n}}$$
(1)

26

Calculating the *FSC* index required the *SOCSPO* indicators to have an additional weighting of 0.5, as there were twice as many as-indicators of *SOCSPO* compared to *VSG*. All indicators were range-standardized and scaled between 0 and 1, hence this index provides a relative measure among those floodplains studied. An index value approaching one indicates the floodplain surface is among the most spatially complex of all floodplains observed, while an index value approaching zero indicates the floodplain surface is among the least spatially complex. The approach used has been applied successfully in developing a <u>large scale n-index</u> of River Condition (Norris et al., 2007).

5 Relationships between the two components of spatial complexity were also investigated VSG and <u>SOCSPO</u> at each sampling <u>scale</u>. In addition, relationships between VSG, <u>SOCSPO</u>, and 6 7 FSC and seven environmental variables were also investigated. The environmental variables 8 were mean daily discharge in ML/day (Q), CV daily discharge (Q_{CV}), CV mean annual 9 discharge (Q_{CVAnn}), CV maximum annual discharge (Q_{CVMax}), sediment yield in t/km²/y (SY), 10 average valley slope in m/m (Vs), and average floodplain width in km (Fpw). Detailed calculations of environmental variables are provided by Scown et al. (2015a). Each of these 11 environmental variables reflect an aspect of the flow, sediment, energy, and valley conditions, 12 which have previously been shown to influence floodplain surface morphology (Nanson and 13 Croke, 1992; Warner, 1992). Curve estimation between VSG, SOCSPO, and FSC and each 14 15 environmental variable at each sampling scale was conducted in SPSS-using linear regression. Q, SY, and Vs were normalized using a logarithmic transformation before analysis. 16

17

18 4 Results

19 4.1 Overall <u>fF</u>loodplain surface complexity (FSC)

20 Floodplain surface complexity, as measured by the FSC index, was highly variable among the eight floodplains and across sampling scales. The FSC index ranged from 0.12 for the 21 22 Gwydir, at the 50 m window size, to 0.72 for the Shingwedzi also at the 50 m window size. The Gwydir floodplain had the least complex of surfaces across all sampling scales (mean 23 24 FSC of 0.17), while the Shingwedzi floodplain had the most complex surface (mean FSC of 25 (0.69) across all scales (Fig. 2). This presumably reflects differences in the geomorphology of these two floodplains. The Shingwedzi floodplain is dissected by numerous channels and 26 27 gullies, which create highly organized patches of increased topographic relief, whereas the 28 Gwydir floodplain has a relatively flat, featureless surface over larger continuous areas and limited organization around any of the significant surface features. The effect of sampling 29 30 scale on FSC was not consistent across the eight floodplains (Fig. 2), indicating that comparisons among floodplains are scale-dependent. the scale at which floodplain surfaces 31

are most complex depends on the floodplain. For example, FSC values increased with 1 2 window size for the Gwydir and Narran floodplain surfaces became more complex with 3 increasing window size, but decreased for thewhereas the Shingwedzi, Macquarie, and 4 Mississippi floodplains became less complex. In the Bidgee, however, FSC was relatively 5 consistent across all window sizes, with an index range of only 0.02. FSC was most variable across window sizes for the Woodforde and Yanga floodplains. In particular, for the 6 7 Woodforde, FSC was 44 % lower at the 1000 m window size than at 200 m, while for Yanga 8 it was 65 % higher. This indicates that most floodplain surfaces become quantitatively more 9 or less complex at particular sampling scales.

10 In addition, the relative FSC among the eight floodplains differed across sampling window sizes. Rank order of FSC among the floodplains was consistent at the 50 m and 200 m 11 12 window sizes, with the Shingwedzi having the most complex floodplain surface, followed by 13 the Woodforde, Bidgee, Mississippi, Macquarie, Yanga, Narran, and Gwydir floodplains. 14 However, at the 1000 m window size, the Bidgee floodplain became the second most 15 complex, followed by the Yanga, Mississippi, Woodforde, Macquarie, Narran, and Gwydir floodplains. This indicates that the relative surface complexity among the eight floodplains is 16 17 consistent at small to intermediate window sizes, although the actual index scores may vary 18 slightly, but there is a reordering of relative surface complexity among the eight floodplains at 19 large sampling scales.

20 4.2 Variability in surface geometry (VSG)

21 The VSG index was also highly variable among the eight floodplains and across sampling scales . VSG ranged from 0.00 for the Gwydir floodplain when measured at the 50 m window 22 23 size, to 0.70 for the Shingwedzi also at the 50 m window size (Fig. 3). Again, Tthe Gwydir 24 floodplain consistently had the lowest values for this index over all window sizes (mean VSG 25 of 0.06), while the Shingwedzi floodplain consistently had the highest (mean VSG of 0.65). 26 This reflects the large differences in topographic relief and variability between these two 27 floodplains. The VSG score of 0.00 for the Gwydir floodplain at the 50 m window size 28 indicates that this floodplain had the lowest scores for all four indicators of variability in 29 surface geometry of the eight floodplains studied at this scale. **TSimilar to FSC**, the effect of 30 sampling scale on VSG was not consistent across floodplains (Fig. 3). VSG increased with sampling scale for the Narran floodplain, but decreased for the Shingwedzi, Bidgee, 31 32 Macquarie, and Woodforde floodplains. VSG was highest at the 50 m window size and lowest 1 at 200 m for the Mississippi and Yanga floodplains, while it was highest at 200 m and lowest 2 at 50 m for the Gwydir. This indicates that the scale at which surface geometry is most 3 variable depends on the floodplain. That is, surface geometry is most variable at small 4 sampling scales for some floodplains and at large sampling scales for others.

5 In addition, relative VSG among the eight floodplains was dependent upon sampling scale 6 (Fig. 3). At the 50 m window size, the Shingwedzi floodplain had the highest VSG, followed 7 by the Mississippi, Woodforde, Bidgee, Yanga, Macquarie, Narran, and Gwydir floodplains. 8 At the 200 m window size, the Woodforde floodplain increased to the second highest VSG, 9 and the Mississippi floodplain dropped to third, while all others remained consistent. At the 1000 m window size, the Mississippi floodplain again had the second highest VSG, followed 10 by the Bidgee, Yanga, Woodforde, Narran, Macquarie, and Gwydir floodplains. This 11 indicates that the relative variability in surface geometry among floodplains depends on the 12 13 sampling scale. That is, a particular floodplain can have a more variable surface geometry than another at one sampling scale, but less so at another sampling scale. 14

15 4.3 Spatial organisation of surface conditions (SOCSPO)

The <u>SOCSPO</u> index was also highly variable among the eight floodplains and across sampling 16 17 scales . SOCSPO ranged from 0.19 for the Gwydir floodplain when measured at the 200 m window size, to 0.89 for the Woodforde floodplain when measured at the 200 m window size 18 19 (Fig. 4). Unlike FSC and VSG, there was no consistency as to which floodplain had the highest and lowest SOCSPO across sampling scales. This indicates that no floodplain has 20 21 consistently the highest or lowest degree of spatial organization of surface conditions among 22 the eight floodplains studied. The effect of sampling scale on SOCSPO was not-also 23 inconsistent across floodplains (Fig. 4). For five of the eight floodplains, SOCSPO was lowest 24 at the 200 m window size and highest at 1000 m. For the Mississippi and Woodforde 25 floodplains, the opposite was observed, with SOCSPO being highest at 200 m and lowest at 26 1000 m. The Bidgee floodplain was the only floodplain for which SOCSPO increased consistently across all sampling scales. This indicates that the degree of spatial organization 27 28 of surface conditions is highest at large sampling scales for most floodplains, but at intermediate scales for some. The Shingwedzi floodplain had the most consistent SOCSPO 29 30 across all window sizes, with an index range of only 0.03, indicating little change in the spatial organization of surface conditions across sampling scales for this floodplain. 31 Conversely, SOCSPO was highly variable across window sizes for the Yanga, Woodforde, 32

and Gwydir floodplains. *SOCSPO* was 178 % higher at the 1000 m window size than at 200 m for the Gwydir floodplain and 138 % higher for the Yanga floodplain, while for the Woodforde floodplain it was 61 % lower. This indicates a significant change in the spatial organization of these floodplain surfaces between these two sampling scales. The results also showed that floodplain and window size have a greater combined effect on *SPO* among the eight floodplains than on relative *FSC* and *VSG* (Figs. 2, 3, and 4).

7 In addition, relative SOCSPO among the eight floodplains was highly dependent upon 8 sampling scale (Fig. 4). The Shingewedzi floodplain had the highest SOCSPO of all 9 floodplains at the 50 m window size, and the second highest at 200 m and 1000 m. The Woodforde floodplain had the second highest SOCSPO at 50 m and the highest at 200 m, but 10 11 dropped to second lowest at 1000 m. The Bidgee floodplain had the third highest SOCSPO at 12 all window sizes. The Yanga floodplain had the third lowest SOCSPO at 50 m and 200 m, but 13 the highest at 1000 m. The Gwydir floodplain had the second lowest SOCSPO at 50 m, the 14 lowest at 200 m, and the fourth highest at 1000 m. The Macquarie and Mississippi floodplains 15 always had either the fourth, fifth, or sixth highest SOCSPO. The Narran floodplain always had a SOCSPO in the lowest two floodplains. This indicates that the relative degree of spatial 16 17 organization of surface conditions among floodplains depends on the sampling scale. That is, 18 a particular floodplain can have a more highly organized surface than another at one sampling 19 scale, but less so at another sampling scale. It also indicates that floodplain and window size have a greater combined effect on relative SOCSPO among the eight floodplains than on 20 21 relative FSC and VSG.

22 4.4 Relationship between VSG and <u>SOCSPO</u>

SOCSPO values were, on average, 17 % higher than the VSG values. The greatest difference between SOCSPO and VSG was 0.51 for the Woodforde floodplain, at the 200 m window size, followed by 0.47 for the Bidgee and Yanga floodplains at the 1000 m window size (Figs. 3 and 4). The Mississippi floodplain was the only floodplain where SOCSPO was lower than the VSG, with an average difference of -0.03. This comparison between SOCSPO and VSG values, suggests surface conditions across the eight floodplains are generally more highly spatially organized than they are geometrically variable.

Average variance of <u>SOCSPO</u> across sampling scales within a floodplain (0.0212) was almost six times higher than that of *VSG* (0.0037). However, the average <u>SOCSPO</u> variance was dominated by a limited number of floodplains; notably the Gwydir, Woodforde, and Yanga floodplains (Fig. 4). Four of the five other floodplains had a less variable *SOCSPO* across sampling scales compared to their *VSG*; with the exception being the Bidgee floodplain. These results of *SOCSPO* variance across sampling scales indicates that, on average, the spatial organization of surface conditions is much more sensitive to sampling scale than the variability of surface geometry.

7 Significant linear relationships between VSG and SOCSPO were recorded at the 50 m and 200 8 m window sizes only (Table 3). Overall, SOCSPO increased with VSG (Fig. 5) and this 9 positive relationship was strongest at the 50 m window size, with more than 61 % of the variance in SOCSPO explained by VSG, reducing to 56 % at the 200 m window size, and less 10 11 than 8 % at 1000 m window size. The y-intercept of each regression line was greater than 0.1 12 at all window sizes, while the slope was less than one at 50 m and 1000 m, but greater than 13 one at 200 m (Table 3). This indicates provides further indication that SOCSPO is generally 14 higher than VSG in these eight floodplains., and that this difference increases as index values 15 increase when measured at the 200 m window size. However, at the 50 m window size, the 16 two indices tend to converge as their values increase.

4.5 Relationships between floodplain surface complexity and environmental variables

19 Floodplain width (Fpw) was the only environmental variable statistically related to any of the 20 three indices of spatial complexity (p < 0.05). This variable was significantly related to FSC 21 and VSG over all window sizes, and to SOCSPO over all but the 1000 m window size (Table 22 4). The decrease in all three complexity indices with increasing Fpw was best explained by either a power, logarithmic, or exponential function (Table 4). In terms of the decrease in FSC 23 24 with increasing Fpw, this was best explained by a power function at all window sizes (Fig. 6a), indicating FSC undergoes rapid decline with increases in Fpw, approaching an asymptote 25 26 at approximately 10 km in Fpw. The modelled change in FSC with increasing Fpw was almost identical between the 50 m and 200 m window sizes. At the 1000 m window size, FSC 27 28 was generally lower compared to that at 50 m and 200 m windows sizes in narrow 29 floodplains, before approaching a higher asymptote at larger Fpw. This indicates that broad 30 floodplains generally have higher FSC when measured at larger sampling scales, whereas narrow floodplains generally have higher FSC when measured at smaller sampling scales. 31

1 Decreases in VSG with increasing Fpw are-was best explained by a logarithmic function at the 2 50 m window size, a power function at the 200 m window size, and an exponential function at 1000 m (Fig. 6b). These models indicate a more rapid initial decline in VSG with increasing 3 Fpw at the 200 m window size than at the 50m and 1000 m window sizes. This is followed by 4 5 approach to a higher asymptote at the 200 m window size above Fpw of approximately 10 km, whereas modelled VSG continues to decline between Fpw of 10 km and 25 km at the 50 6 7 m and 1000 m window sizes. This indicates that Fpw has a greater effect on VSG in wider 8 floodplains when measured at small and large sampling scales than it does at intermediate 9 scales. The relationship was strongest at the 200 m window size, with more than 80 % of the 10 variance in VSG being explained by Fpw.

11 The decrease in SOCSPO with increasing Fpw was best explained by a logarithmic function 12 at the 50 m and 200 m window sizes (Fig. 6c). The modelled decline in SOCSPO was initially 13 more rapid at the 50 m window size than at 200 m, before approaching a higher asymptote at narrower Fpw. This indicates that Fpw has more of an effect on SOCSPO in wider floodplains 14 15 when measured at the 200 m window size than at 50 m. The relationship was strongest at the 200 m window size, with more than 77 % of the variance in SOCSPO being explained by 16 17 Fpw. This was reduced to 71 % at the 50 m window size. There was no significant 18 relationship between Fpw and SOCSPO at the 1000 m window size (Fig. 6c). This suggests 19 that Fpw exerts little or no control over the spatial organization of surface conditions when 20 measured at large sampling scales.

A weak statistical relationship was recorded between *SY* and *VSG*. The <u>An</u> increase in *VSG* with increasing SY was observed at the 200 m window size ($r^2 = 0.44$; p = 0.07). The relatively lower level of significance of this result was attributable to the Gwydir having a high SY but a very low *VSG*. When the Gwydir floodplain was removed from the analysis, there was a significant and strong linear relationship between log-transformed SY and *VSG* across all window sizes for the remaining seven floodplains (Table 5, Fig. 7). This relationship was almost identical across all window sizes.

28

29 **5 Discussion**

The Euclidean Index of floodplain surface complexity (FSC) used in this study is comprised of the two key components of spatial complexity; the character and variability of features or conditions, and their spatial organization. This index appears to discriminate between

floodplains with distinctly different geomorphological features. The multivariate nature of the 1 2 index, comprised of 12 indicators of surface complexity (Table 2), has advantages over 3 univariate indices that have been applied to measure floodplain surface complexity. Univariate indices fail to incorporate both aspects of surface structure, which contribute to 4 5 surface complexity (Dorner et al., 2002; Frost et al., 2005; Tokeshi and Arakaki, 2012). Having a single, multivariate-based index is also favorable rather than multiple individual 6 7 indicators of floodplain surface complexity, as it allows a quantitative measure that can be 8 compared for multiple riverine landscapes. Norris et al. (2007) provide a comparable example 9 of such an application in their assessment of river condition. It is important to note that, the 10 standardization of indicator scores from 0 to 1 is necessary for the Euclidean Index equation 11 (Norris et al., 2007), as the FSC index is a relative index of floodplain surface complexity 12 across a group of floodplains all of which were all-included in the standardization of the 13 indicators. This is appropriate for examining relationships between floodplain surface complexity and environmental controls, given adequate replication over a range of floodplain 14 settings is achieved. However, it should not be used to compare against indices of other 15 studies, unless all floodplains being compared are included in the calculation of the index. 16

17 The results of this research demonstrate: floodplain surface complexity to be highly variable 18 among the eight floodplains studied,; and, floodplain width to exert a significant 'top-down' control (sensu Thorp et al., 2008) on differences in floodplain surface complexity. These 19 results clearly support geomorphological and ecological thinking that "...the valley rules the 20 stream...", as argued first by Hynes (1975) and strongly supported since (e.g., Schumm, 1977; 21 22 Miller, 1995; Panin et al., 1999; Thoms et al., 2000). In this case, the valley rules the 23 floodplain surface complexity, at least in terms of the 'top-down' influences investigated here. The influence of floodplain width on floodplain surface complexity decreases significantly 24 25 once widths are greater than 10 km. Above 10 km, little change in the index of floodplain 26 surface complexity was recorded. This is likely due to the dissipation of flood energy in wide 27 floodplains, limiting the construction of large topographic features, which contribute to surface complexity. However, subtle topographic features in wide floodplains are also 28 29 importance surface features (Fagan and Nanson, 2004), which may have been overlooked in 30 this index. In narrower, confined settings, where widths are less than 10 km, floodplain construction may be the result primarily of vertical processes (e.g., accretion/incision) leading 31 32 to more prominent topographic features that exhibit a higher degree of spatial organization 33 and thus increased surface complexity (Nanson and Croke, 1992). Such complexity can lead to the concentration of flood energies in particular areas, promoting episodic catastrophic stripping (Nanson, 1986). The narrowest floodplain examined in this study was, on average, 1.5 km in width and the results presented in this study may not be consistent in floodplains narrower than this. In particular, there is a loss of surface complexity when floodplains are contained between artificial levees or embankments (Florsheim and Mount, 2002; Gurnell and Petts, 2002), so floodplain surface complexity should not be considered to increase indefinitely in floodplains approaching a width of 0 km.

Valley trough or floodplain width has been identified as a primary controller of floodplain 8 9 pattern and process in several previous studies. Spatial patterns of flow depth, velocity, and 10 shear stress in overbank flows were found by (Miller, (1995) to all be influenced by valley 11 width and this influence was particularly noticeable at locations of valley widening or 12 narrowing. Similarly, Thoms et al. (2000) found that valley width had a significant effect on 13 sediment textural character and associated heavy metal concentrations within different morphological units of the Hawkesbury River Valley, New South Wales. In particular, they 14 15 found higher proportions of silt and clay, and lower proportions of sand and gravel, in wide 16 floodplain sections compared to narrow floodplains. The results of this present research 17 support the findings that floodplain width is an important controlled controller of floodplain 18 pattern and process.

19 The effect of floodplain width was relatively consistent across all three indices examined. 20 This suggests that floodplain width has a similar effect on the variability of floodplain surface geometry, the degree of spatial organization, and overall floodplain surface complexity. This 21 22 likely explains the significant positive linear relationship between the variability of surface 23 geometry and the spatial organization of surface conditions sub-indices. This relationship 24 likely occurs because environmental conditions, particularly related to floodplain width, which promote higher variability in floodplain surfaces, also cause a high degree of spatial 25 organization. Reinforcing feedbacks between these two components of spatial complexity 26 27 may also exist. That is, high variability of surface geometry promotes a high degree of spatial 28 organization, and vice versa. Positive feedback is common in complex systems (Levin, 1998; 29 Phillips, 2003), and feedbacks between hydrology, geomorphology, and biology in 30 floodplains may play a part in this (Hughes, 1997).

The textural character of floodplain sediments and local energy conditions during inundation
has been postulated as important controls of floodplain morphology (Nanson and Croke,

1992). These two drivers would also be expected to influence floodplain surface complexity. 1 2 In this study, sediment yield was found to have a weak effect on the variability in surface geometry, although relationships were not significant. This may be because estimates of 3 contemporary sediment yield were used in this study, whereas and historical sediment yields 4 5 are relatively more important (Panin et al., 1999). Substantial anthropogenic increases in sediment loads have been reported for the Gwydir floodplain (De Rose et al., 2003). Removal 6 7 of this floodplain from our analyses, resulted in a significant increase in variability in surface 8 geometry with increasing sediment yield across the seven remaining floodplains. This result 9 suggests that sediment yield may exert 'top-down' control on the variability of floodplain 10 surface geometry, although recent anthropogenic changes in sediment yields (Prosser et al., 11 2001), particularly increased erosion in the catchment due to land use changes, may have 12 delayed 'lag' effects on floodplain surfaces which have not yet been observed. Valley slope 13 was used in this study as a surrogate for stream energy, and this was not found to have any 14 effect on overall floodplain surface complexity. More accurate measures of energy conditions 15 such as specific stream power (Nanson and Croke, 1992) may reveal any effects of energy conditions on floodplain surface complexity, if they exist, more clearly. It is also likely that 16 17 variable flood energy conditions within each floodplain have an effect on localized surface 18 complexity. For example, Fagan and Nanson (2004) found distinct differences in floodplain 19 surface channel patterns among high, intermediate, and low energy areas of the semi-arid 20 Cooper Creek in Australia. They also found the energy of flood flows to be largely controlled 21 by floodplain width.

22 Hydrology has been widely considered the main determinant of floodplain ecosystem pattern 23 and process (Junk et al., 1989; Hughes, 1990; Bayley, 1995; Whited et al., 2007). However, the research presented in this paper indicates that this may not be the case for floodplain 24 25 surface complexity. None of the four hydrological variables measured here had a significant 26 effect on floodplain surface complexity. This suggests that, although hydrology is largely 27 important in driving floodplain ecosystem processes, floodplain width and sediment 28 conditions appear to exert more control over the complexity of floodplain surfaces. This is 29 important given that floodplain research and restoration is often focused on hydrology, 30 particularly connectivity (e.g., Thoms, 2003; Thoms et al., 2005); whereas valley trough, sediment, and energy conditions may be more important in structuring and maintaining the 31 32 physical template upon which hydrology acts as an ecosystem driver (Salo, 1990). Loss of 33 floodplain surface complexity due to changes in sediment yield and or ealibercalibre, or hydrology and should not be overlooked (Thoms, 2003). It is important to note, however, that
some most of the eight floodplains studied have experienced anthropogenic alterations to their
hydrology. Thus, hydrological parameters based on contemporary data may not reflect the
nature of the flow regime that was influential in establishing current surface conditions;
lagged effects of altered hydrology on surface complexity may occur in the future (sensu
Thoms, 2006).
Riverine landscapes and their floodplains are hierarchically organized ecosystems (Dollar et

confinement between artificial levees, may be as ecologically important as changes to

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9 al., 2007; Thorp et al., 2008), being composed of discrete levels of organization distinguished 10 by different process rates (O'Neill et al., 1989). Each level of organization, or holon, has a 11 spatial and temporal scale over which processes occur and patterns emerge (Holling, 1992). 12 The different sampling scales used in this research reflect different spatial scales over which 13 patterns occur. The results indicate that the scale at which patterns in floodplain surfaces are 14 most complex depends on the floodplain setting. In particular, wide, unconfined floodplains 15 appear to have higher floodplain surface complexity when measured at larger sampling scales, whereas narrow, confined floodplains have so at smaller sampling scales. Thus, the scale at 16 17 which floodplain surface complexity is maximized likely relates to the width of the 18 floodplain. Selecting different window sizes tailored to each floodplain individually relative 19 to floodplain width should be the focus of future research. This may reveal consistent effects 20 of scale ion floodplain surfaces.

These results suggest that Thus, the scale of processes that maximize complexity, and 21 22 potentially biodiversity and productivity (Tockner and Ward, 1999), in floodplains differ 23 between different valley settings. This has implications for understanding and managing the 24 complexity of floodplain ecosystems. Floodplain processes, which operate over certain 25 temporal scales, elicit a response over relative spatial scales (Salo, 1990; Hughes, 1997). Consequently, managing processes at the appropriate scale to achieve desired outcomes is 26 important (Parsons and Thoms, 2007). This has already been recognized for managing 27 floodplain hydrology to maintain biodiversity (Amoros and Bornette, 2002) and these results 28 29 indicate it is also important for managing the processes that maintain floodplain surface complexity. The effects of scale were also inconsistent among the three indices, indicating 30 31 that particular component of floodplain surface complexity may respond to processes at 32 different scales.

Recent approaches to examining and understanding ecosystem complexity and the emergent 1 2 properties that arise from interactions within the systems emphasise the importance of 3 heterogeneity, connectivity, and contingency within the landscape (Loreau et al., 2003; 4 Cadenasso et al., 2006). We have presented an index of floodplain surface complexity within 5 such a framework that incorporates measures of variability and spatial organization. These two components of spatial complexity are directly associated with heterogeneity and 6 7 connectivity (Wiens, 2002), although no direct measure of historical contingency is given in 8 this spatial approach. Metrics and indicators used to measure properties of landscape and 9 ecosystem complexity in the past have largely been based on discrete units and the familiar 10 concept of 'patches' (Forman and Godron, 1981). The surface metrics employed in this study 11 are conceptually equivalent to certain patch metrics and a comprehensive comparison of surface and patch metrics is provided by McGarigal et al. (2009). Thus, the approach 12 13 presented in this study should be considered complimentary to other ecosystem complexity 14 frameworks, such as the meta-ecosystem approach (Loreau et al., 2003), which are based on 15 patches.

The-In terms of the origin and implications of floodplain surface complexity, this research 16 17 presented focuses on 'top-down' environmental drivers of floodplain surface complexity. 'Bottom-up' feedbacks from the floodplain ecosystem are also likely to affect surface 18 19 complexity. For example, vegetation establishment on deposited floodplain sediments is known to produce a positive feedback loop in which more sediment is trapped and semi-20 21 permanent morphological features such as islands develop (Nanson and Beach, 1977; Hupp 22 and Osterkamp, 1996). Such feedbacks are likely to influence floodplain surface complexity, 23 particularly in floodplains dominated by such features (Gurnell and Petts, 2002; Stanford et al., 2005). 'Bottom-up' influences on floodplain surface complexity are difficult to quantify 24 25 and were not examined in this study. Future research into the influence of vegetation type and 26 density on floodplain surface complexity, particularly in relation to its hydraulic roughness, 27 may provide valuable insights into 'bottom-up' controls on floodplain surface complexity. 28 Such data are also available through LiDAR (Straatsma and Baptist, 2008). Effects of 29 floodplain surface complexity on biodiversity and productivity should also be examined in future research. The floodplain surface provides the primary geomorphic template upon which 30 31 ecosystem and evolutionary processes are acted out (Salo, 1990) and it would be expected 32 that increased surface complexity would promote the range of physical habitats required to 33 maintain floodplain biodiversity (Hamilton et al., 2007).

| 1 | The inclusion of other humid-floodplains, from different regions, in future studies of this |
|----|---|
| 2 | nature, along with more arid, sub-tropical, and continental locations, would is essential to |
| 3 | further determine whether the trends observed in this study extend beyond the eight |
| 4 | floodplains investigated here. This study was limited to eight floodplains because of due to |
| 5 | data availability. As high-resolution LiDAR data across many more floodplains are made |
| 6 | available to researchers, other more sophisticated analyses such as multiple regression will be |
| 7 | possible in studies such as this. Multiple regression would enable the interactive effects of |
| 8 | environmental variables to be elucidated, whereas this study was limited to relatively simple |
| 9 | linear regression because of due to the sample size of only eight floodplains. |
| 10 | |
| 11 | Acknowledgements |
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| 13 | Upper Midwest Environmental Sciences Center, without which this research would not have |
| 14 | been possible. Any use of trade, product, or firm names is for descriptive purposes only and |
| 15 | does not imply endorsement by the U.S. Government. |
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- 12

| 5 | 6 6 1 | e | |
|-----------------|----------------|---------------------|------------------------|
| Floodplain name | Valley setting | Climate | Stream network setting |
| Bidgee | Confined | Semi-arid/temperate | Lowland continuous |
| Gwydir | Unconfined | Semi-arid/temperate | Lowland terminal |
| Macquarie | Unconfined | Semi-arid/temperate | Lowland continuous |
| Mississippi | Confined | Continental | Upland continuous |
| Narran | Unconfined | Semi-arid | Lowland terminal |
| Shingwedzi | Confined | Sub-tropical | Upland continuous |
| Woodforde | Confined | Arid | Headwaters continuous |
| Yanga | Unconfined | Semi-arid/temperate | Lowland continuous |

1 Table 1. Summary of the geographical and climatic settings of the eight study floodplains.

Table 2. Summary of the indicators used to calculate the index of Floodplain Surface Complexity (*FSC*). Averages and standard deviations of the surface metrics (left columns) are calculated from 50 random sample locations throughout each floodplain. The nugget and range from the Moran's I spatial correlograms (right columns) are extracted from the exponential isotropic models fit to these. See Scown et al. (2015a) for detailed calculation procedures.

| Indicators of variability | | Indicators of spatial organisation | | |
|---|---|--|---|--|
| in surfa | ace geometry | of surface conditions | | |
| Average standard deviation of surface heights | Indicates variability in surface elevation within an area | Spatial correlogram exponential isotropic model nugget (×4 metrics) | Indicates strength of spatial organisation | |
| Average coefficient of variation of surface heights | Indicates variability in surface elevation relative to the mean elevation within an area | Inverse of the spatial correlogram exponential isotropic model range (×4 metrics) | Indicates patchiness or fragmentation in spatial organisation | |
| Standard deviation of skewness of surface heights | Indicates variability in erosional and depositional features within an area | | | |
| Average standard deviation of surface curvature | Indicates how convoluted the surface is | | | |

1 Table 3. Results from regression analyses of <u>SOCSPO</u> against VSG at each of the three

2 window sizes.

| | Best model | F | d.f. | р | r ² |
|--------|--------------------|-------|------|------|----------------|
| 50 m | y = 0.703x + 0.223 | 9.676 | 1, 7 | 0.02 | 0.61 |
| 200 m | y = 1.135x + 0.120 | 7.627 | 1, 7 | 0.03 | 0.56 |
| 1000 m | y = 0.329x + 0.429 | 0.472 | 1, 7 | 0.52 | 0.07 |

1 Table 4. Results from regression analyses of *FSC*, *VSG*, and *SOCSPO* against Fpw at each of

2 the three window sizes.

| | Best model | F | d.f. | р | r ² |
|----------|----------------------------|--------|------|-------|----------------|
| 50 m | $y = 0.765 x^{-0.414}$ | 10.344 | 1,7 | 0.02 | 0.63 |
| 200 m | $y = 0.762x^{-0.420}$ | 25.523 | 1, 7 | 0.00 | 0.81 |
| 1000 m | $y = 0.549x^{-0.213}$ | 5.871 | 1, 7 | 0.05 | 0.50 |
| 50 m | $y = -0.151 \ln x + 0.630$ | 9.642 | 1, 7 | 0.02 | 0.62 |
| SA 200 m | $y = 0.627 x^{-0.418}$ | 26.319 | 1,7 | 0.00 | 0.81 |
| 1000 m | $y = 0.472e^{-0.064x}$ | 13.574 | 1, 7 | 0.01 | 0.69 |
| 50 m | $y = -0.145 \ln x + 0.737$ | 14.515 | 1, 7 | 0.01 | 0.71 |
| 200 m | $y = -0.204 \ln x + 0.866$ | 20.586 | 1,7 | 0.00 | 0.77 |
| 1000 m | | 0.570 | 1, 7 | 0.48* | 0.09 |

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1 Table 5. Results from regression analyses of VSG against $\log_{10}(SY) + 1$ at each of the three

| | Best model | F | d.f. | р | r^2 |
|--------|--------------------|--------|------|------|-------|
| 50 m | y = 0.183x + 0.088 | 50.497 | 1,6 | 0.00 | 0.91 |
| 200 m | y = 0.158x + 0.084 | 18.179 | 1,6 | 0.00 | 0.78 |
| 1000 m | y = 0.142x + 0.088 | 36.076 | 1,6 | 0.00 | 0.88 |

2 window sizes with Gwydir removed.

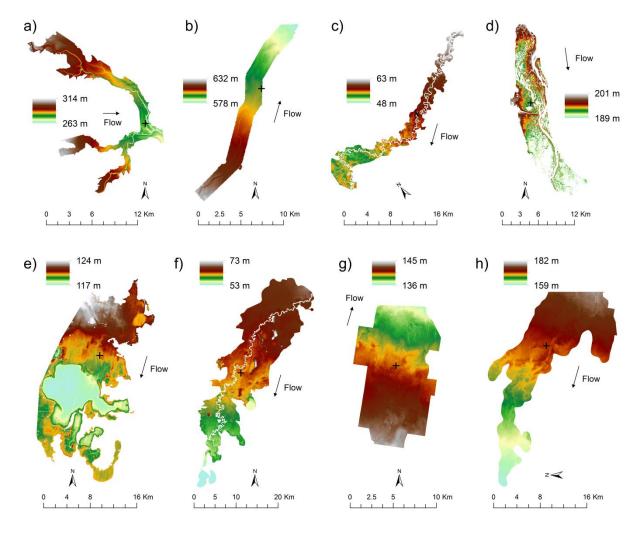
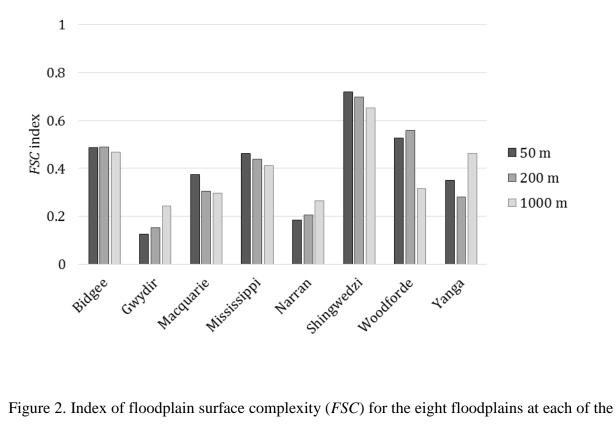
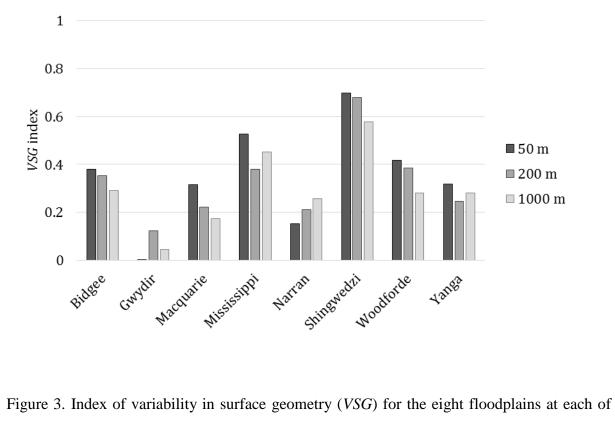


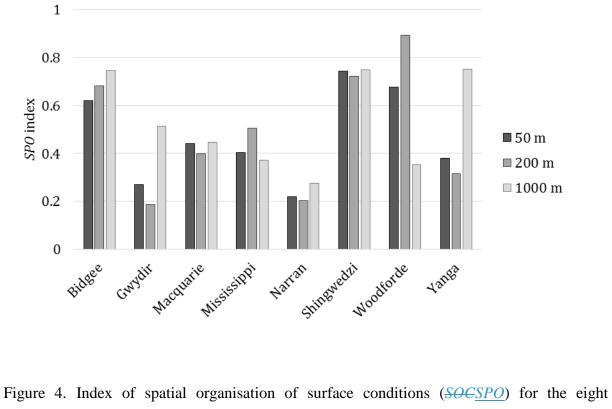
Figure 1. Digital elevation models displaying the floodplain surface in meters above sea level
for each study site (crosses indicate coordinates listed): a) Shingwedzi (31°24'E, 23°05'S); b)
Woodforde (133°20'E, 22°21'S); c) Bidgee (143°24'E, 34°42'S); d) Mississippi (91°15'W,
43°29'N); e) Narran (147°23'E, 29°48'S); f) Yanga (143°42'E, 34°30'S); g) Macquarie
(147°33'E, 30°41'S); h) Gwydir (149°20'E, 29°16'S).



- 4 three window sizes.



- 4 the three window sizes.



4 floodplains at each of the three window sizes.

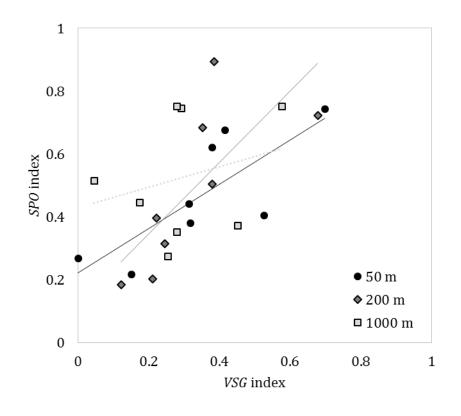


Figure 5. Linear relationships between variability in surface geometry (*VSG*) and spatial organisation of surface conditions (SOCSPO) at each of the three window sizes.

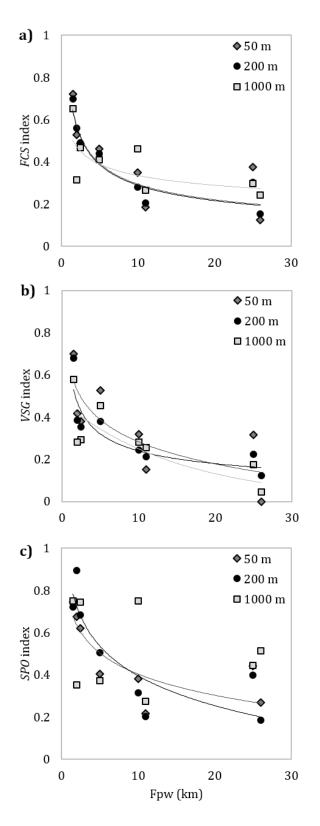


Figure 6. Power relationships between floodplain width (Fpw) and a) floodplain surface
complexity (*FSC*), b) variability of surface geometry (*VSG*), and c) spatial organisation of
surface conditions (*SOCSPO*) at each of the three window sizes.

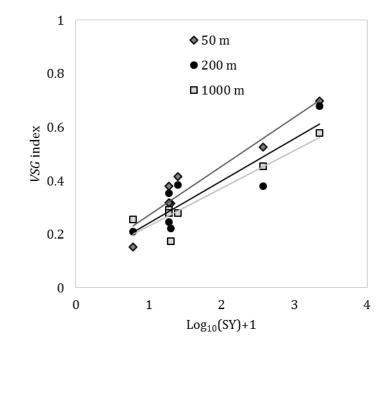


Figure 7. Linear relationships between log-transformed SY and variability of surface
geometry (*VSG*) at each of the three window sizes with Gwydir removed.