

Mapping Hydromorphic Areas and Drainage Networks in Tropical Riparian Zones using Topographic Attributes

Henrique Marinho Leite Chaves ¹, Maria Tereza Leite Montalvão ², Maria Rita Souza
Fonseca ³, Eraldo Trondoli Matricardi⁴

¹ Forestry Dept., University of Brasilia

² The Nature Conservancy, Brasil

³ Dept. of Geography, University of Brasilia

⁴ Forestry Dept., University of Brasilia

¹Corresponding Author: Depto. de Eng. Florestal, Universidade de Brasília-UnB, Campus
Darcy Ribeiro, 70.910-900, Brasilia-DF Brazil hchaves@unb.br

Abstract

Riparian areas and channel networks are important landscape compartments, with key hydrological and ecologic functions. Hence, defining their spatial boundaries is an important step towards sustainable riparian management. In tropical countries, riparian areas are rarely mapped, although they represent a crucial component of local livelihoods and ecosystems. In this study, topographic attributes generated with a 30m SRTM DEM were used to delineate wet areas and stream networks of two small catchments in Central Brazil. The topographic attributes were the local slope, the slope curvature, and the Topographic Wetness Index-TWI, respectively. Threshold values of the selected topographic attributes were calibrated in the Santa Maria catchment, comparing the synthetic wet areas and drainage networks with corresponding reference (map) features, and validated in the nearby Santa Maria basin. Drainage network and wet area delineation accuracies were estimated with multi-criteria and confusion matrix methods. The drainage network delineation accuracy was 67.2% and 70.7%, and wet area prediction accuracy was 72.7% and 73.8%, for the Santa Maria and

Gama catchments, respectively. The delineation errors resulted from model incompleteness, DEM grid size and vertical inaccuracy, and from cartographic misrepresentation of the reference maps. The method performed equal or better than other studies in the literature, and could be used for preliminary mapping of riparian areas of tropical catchments.

Keywords: modelling, drainage network, riparian areas, delineation, catchment, GIS.

1. INTRODUCTION

Riparian zones play a fundamental role in the regulation of stream water quality, reducing sediment and nutrient loading (Laudon et al., 2016) through increased deposition and nutrient uptake (Tomer et al., 2009). Riparian areas also fulfil important ecologic functions in catchments (Johnson et al., 1999).

In the Cerrado biome in Central Brazil, gallery forests and grassy wetlands occur in riparian zones of valley bottoms, along stream channels (Skorupa et al., 2013), and are associated with the seasonal fluctuation of the water table (Eiten, 1972). Low-lying grasslands occur over hydric soils, and gallery forests cover well drained and hydromorphic soils (Oliveira Filho et al., 1989), forming the wet areas of river basins.

In tropical countries, data on riparian processes, functions, and values are scarce, even though riparian areas provide a crucial component of local livelihoods (Johnston et al., 2013). Therefore, defining the spatial boundaries between well drained/upslope and poorly drained/valley bottom areas is an important step towards riparian management (Acevedo et al., 2017). However, due to the high spatial variability of the soils and groundwater levels, soil and vegetation mapping in riparian zones is challenging (Skorupa et al., 2013), particularly when the original gallery forest was removed (Laudon et al., 2016).

Since shallow water tables in landscape bottoms are associated with hydric soils (Güntner et al., 2004; Laudon et al., 2016), gallery forests (Lenza et al., 2015; Oliveira Filho et al., 1989), and stream heads (Dunne, 1980; Hastings & Kampf, 2014), and because soil wetness is a

54 function of hillslope convergence (O'Loughlin, 1986), different topographic attributes that
55 predict soil wetness can be used to map riparian zones (Moore et al., 1988), particularly in
56 data-scarce locations, such as the tropics (Moore et al., 1991).

57 Most studies dealing with riparian area and drainage delineation were carried in temperate
58 regions. In an American catchment, Detty & McGuire (2010) found that the upslope area and
59 the topographic wetness index-TWI (Beven & Kirkby, 1979) were correlated with shallow
60 water table persistence. Burt & Butcher (1985) reported that the product of primary
61 topographic attributes, such as upslope area, slope gradient, and slope curvature, were good
62 predictors of soil wetness and water table depth. Buchanan et al. (2014) found that the TWI
63 was significantly correlated with soil wetness in agricultural fields in the USA, particularly
64 when high-resolution DEMs were used.

65 Güntner et al. (2004) used the upslope contributing area, the slope curvature, and the TWI to
66 predict the distribution of wetlands in a landscape in Sweden, utilizing geobotanical and
67 pedological criteria. They concluded that the upslope contributing area was the most
68 important explanatory factor in the prediction of saturated areas. The TWI and a model-
69 derived wetness index were utilized by Grabs et al. (2009) in the prediction of the spatial
70 distribution of saturated areas in Sweden, with the latter resulting in a higher accuracy
71 because of its dynamic nature.

72 In the prediction of saturated areas using soil information coupled with terrain data, Ali et al.
73 (2014) concluded that wetness indices worked well only when wet areas covered more than
74 30% of the catchment. In Taiwan, Chang & Lee (2008) found that the TWI was well
75 correlated with runoff generating areas. Using the TWI together with the slope gradient and
76 the slope curvature, Qin et al. (2011) predicted the spatial distribution of soil types and their
77 properties at fine scales.

78 Reviewing the application of primary and secondary topographic attributes in riparian
79 vegetation mapping, Franklin (1995) concluded that they are useful for interpolating
80 vegetation-environment correlations within a region. Kopecký & Čížková (2010) found an
81 important correlation between soil moisture, predicted by the TWI, and vegetation
82 composition. The latter also concluded that the choice of the flow routing algorithm had a
83 considerable effect on the index performance.

84 In eastern Brazil, Silva et al. (2019) used the slope, the valley bottom flatness, and the TWI to
85 map the soils of a riparian area, and concluded that mapping accuracy depended on the soil
86 drainage conditions. In the Brazilian savanna, Skorupa et al. (2013) found that the use of
87 gallery forests as a proxy for hydric soils overestimated the distribution of the latter, since
88 that type of vegetation also occurred on well-drained soils. This finding was corroborated by
89 Marimon et al. (2010), who concluded that gallery forests of Cerrado catchments were found
90 over both well and poorly drained soils, and that local slope and the distance from the stream
91 were useful attributes in riparian soil mapping.

92 Stream heads, on the other hand, are the boundaries between hillslopes and river channels
93 (Roth & La Barbera, 1997), and commonly occur at topographic convergences (hollows)
94 where enough runoff accumulates and exceeds an erosion threshold (Julian et al., 2012). In
95 steep terrains, land-sliding and seepage erosion are the dominant factors controlling channel
96 initiation (Montgomery & Dietrich, 1992), whereas in gentle slopes the main driving process
97 is overland flow (Gallon & Lindberg, 2014).

98 The ability to determine the location in the landscape where channels initiate is important for
99 understanding hydrologic and geomorphologic processes, and for managing headwater
100 streams (Henkle et al., 2011). However, because of the dense canopy of the gallery forests,
101 the conventional photogrammetric mapping of stream heads and the corresponding drainage

102 network is a subjective task, often resulting inaccurate hydrographic representations (Jaeger
 103 et al., 2007).
 104 Mapping channel heads in Oregon (USA), Montgomery and Dietrich (1992) confirmed the
 105 hypothesis that the channelization threshold is a distance just shorter than the hillslope length.
 106 In an earlier study, the same authors concluded that the location of channel heads on steep
 107 slopes is controlled by the subsurface flow-induced instability of the colluvial fill
 108 (Montgomery & Dietrich, 1989).
 109 Roth & La Barbera (1997) found that channel initiation in the landscape can be predicted by
 110 the square root of the contributing area times the slope gradient. Julian et al., (2012) reported
 111 that local slope, local plan curvature, and average profile curvature were good predictors of
 112 channel heads, but the predictive effectiveness depended on the type of catchment.
 113 Hastings & Kampf (2014) concluded that channel heads could be mapped using TWI
 114 threshold values. According to those authors, successful drainage network mapping should
 115 strike a reasonable balance between channel density, head-ward extent, and positional
 116 accuracy. Quinn et al. (1995) reported that the TWI threshold value for channel initiation
 117 ($TWI \geq 12$) was dependent on the DEM grid size.
 118 Kim & Lee (2004) integrated the TWI channel initiation threshold with a spatially distributed
 119 flow-apportioning algorithm, to delineate channel networks in Korea, and obtained
 120 reasonable results. McMaster (2002) used a critical support area to define channel initiation
 121 and drainage position, and concluded that the DEM routing method (D8 or D_{∞}) did not
 122 matter in steeper slopes, provided that the pixel size was smaller than the hillslope length.
 123 Ruhoff et al. (2011) utilized the TWI and different flow direction algorithms in six
 124 catchments in southern Brazil, and concluded that the single direction D8 algorithm
 125 concentrated runoff along the main channel, whereas the D_{∞} method dispersed it.

Considering that topographic attributes were used to map wet areas and drainage networks, particularly in temperate basins, and recognizing that tropical watersheds may require specific mapping strategies, the objective of this study was to use appropriate topographic attributes and thresholds to delineate wet areas and drainage networks of two small catchments in the Brazilian Cerrado, and to assess their mapping accuracy with unbiased methods.

2. MATERIALS AND METHODS

2.1 Study Catchments

Two small and hydrologic similar catchments of the Brazilian Cerrado biome, in central Brazil, were studied: The Santa Maria and the Gama river basins, situated 20 km apart (Figure 1). The former was used to calibrate the threshold values of the selected topographic attributes, and the latter was used to validate them. Table 1 presents the hydrologic characteristics of both catchments.

[Insert Figure 1]

[Insert Table 1]

Detailed (1:10,000) and semi-detailed (1:50,000) digital maps of hydrography, soils, and land-use were available for the Santa Maria (Figure 2) and Gama (Figure 3) basins, allowing the correlation of the selected topographic attributes with mapped (reference) features. However, since these reference maps were produced using aerial photogrammetry, they are subject to cartographic errors and misrepresentations (Jeager et al., 2007), and consequently were not taken as ground truth.

[Insert Figure 2]

[Insert Figure 3]

Both catchments have gentle slopes, well drained (Oxisols) and poorly drained (Entisols) soils, and are covered with different gradations of savanna vegetation (Unesco, 2002). In the

upslope areas, open savanna vegetation occurs over well-drained soils. In valley bottoms, gallery forests cover poorly and well-drained soils, and grassy marshes occur over hydric soils. There are two types of valley bottoms in the catchments studied: *V-type* bottoms, where gallery forests predominate, and *U-type* bottoms, where marshy flats are dominant. Figure 4 shows these features in both catchments.

[Insert Figure 4]

2.2. Topographic Attributes

Considering the objective of the study, the selection of topographic attributes favoured the aspects of simplicity and data availability, requiring only the 30m-DEM as input. After a thorough search in the literature, the chosen attributes for the wet area delineation were the local slope and the slope curvature. The Topographic Wetness Index-TWI was selected for the delineation the drainage networks.

In the case of the local slope, flatter areas are associated with hydric soils (Marimon et al., 2010). In the case of slope curvature, negative values are associated with areas of flow accumulation (Moore et al., 1991).

The topographic wetness index-WTI, on the other hand, is an integrated indicator of concentrated flow paths (Beven & Kirkby, 1979; O'Loughlin, 1986), and more suitable for drainage delineation. The TWI is given by (Beven & Kirby, 1979):

$$TWI = \ln (\alpha / \tan \beta) \quad (1)$$

where: α = the upslope contributing area per unit contour length (m), reflecting the tendency of the site to receive upslope water, and β = the local slope gradient (radians), indicating the tendency of the site to drain/retain water. In equation 1, soil transmissivity was assumed to be constant throughout the catchment (Schneiderman et al., 2007). When the slope β in equation 1 was smaller than 0.001, a constant value of 0.001 was added, to avoid a division by zero (O'Neill et al., 1997).

176 Considering that the D_{∞} flow routing algorithm tends to disperse water in gentle slopes,
 177 creating a feathering effect in the synthetic drainage network (Hastings & Kampf, 2014), the
 178 D8 flow direction routine (Jenson & Domingue, 1988), which concentrates runoff along a
 179 channel (Ruhoff et al., 2011), was selected for the TWI computation.

180 The DEM used in the calculation of the topographic attributes was the 1-arc-second, 30m
 181 SRTM-Topodata (Valeriano et al., 2009). All spatial calculations of the three topographic
 182 attributes, including their intermediary coverages (flow direction, filling, and flow
 183 accumulation), were performed with the *ArcGIS 10.6.1® Spatial Analyst* software.

184 **2.3. Drainage Network Delineation**

185 Different simulated drainage networks were obtained with the TWI in the Santa Maria
 186 (calibration) basin, testing different channel initiation threshold values (Hastings & Kampf,
 187 2014; Kim & Lee, 2004). The synthetic stream networks were compared to the reference
 188 (map) hydrography. Following the recommendation of Quin et al. (1995), the calibrated
 189 (optimal) TWI threshold in Santa Maria catchment was obtained by the balance of two
 190 mapping criteria: i) the drainage network accuracy; and ii) the channel initiation accuracy,
 191 namely:

$$192 \quad TWI_o = \frac{(B_p/T_p) + (O_1/T_1)}{2} \quad (2)$$

193 where: TWI_o = optimal threshold value; B_p = number of TWI pixels falling inside a 150-m
 194 buffer, built around the reference drainage network (Russell et al., 1997); T_p = the total
 195 number of pixels of the TWI drainage network in the basin; O_1 = number of first order
 196 streams of the reference map identified by TWI pixels; and T_1 = total number of first order
 197 streams of the reference drainage network.

198 The left term in the numerator of equation 2 represents the drainage delineation accuracy, and
 199 the right term indicates the channel initiation accuracy. The calibrated TWI threshold in the

Santa Maria catchment, obtained by the maximization of equation 2, was subsequently applied to the TWI in the Gama basin, to validate the methodology. Finally, the TWI prediction accuracy of both basins were compared with the accuracies of other drainage delineation studies, in the literature.

2.4. Wet Area Delineation

Following the recommendation of Marimon et al. (2010), the reference wet areas of both catchments were obtained by merging the features of ‘gallery forests’ and ‘grassy marshes’ of their corresponding land-use maps. Considering that wet areas in the landscape are associated with flats and hollows (Marimon et al., 2010; Skorupa et al., 2013) (see Figure 4), the combination of local slope and slope curvature was used to delineate them (Burt & Butcher, 1985; McMaster, 2002; Rinderer et al., 2014), with appropriate thresholds:

$$S_c \leq k_1 \quad \text{and} \quad S_l \leq k_2 \quad (3)$$

where: S_c = slope curvature; S_l = local slope, both obtained with the GIS, using the 30m DEM; and k_1 and k_2 are calibrated threshold values. In equation 3, the constant k_1 is negative, since convergent landscape features, such as hollows and concave slopes, were sought. The value of k_2 , on the other hand, is small and positive, to assess valley flats.

The local slope and slope curvature maps of the Santa Maria and Gama catchments are shown in Figures 5 and 6, respectively. To assess the accuracy of the wet areas delineated by equation 3, 10 linear transects (Ågren et al., 2014) were randomly laid across riparian areas of both catchments (Figure 5).

[Insert Figure 5]

[Insert Figure 6]

Subsequently, the 10 gridded transects shown in Figure 5 were intersected with the predicted and reference wet areas of both basins, and a confusion matrix was obtained. The wet area prediction accuracy (A_c) was given by (Ågren et al., 2014):

$$A_c = \frac{(T_p + T_n)}{(T_p + T_n + F_p + F_n)} \quad (4)$$

where: T_p = number of true positive pixels in the transects; T_n = number of true negative pixels; F_p = number of false positive pixels; and F_n = number of false negative pixels. A ‘true positive’ pixel was obtained when a predicted wet area in the transect lines correctly intersected a reference wet area. Conversely, a ‘true negative’ pixel occurred when a dry area was correctly predicted. A ‘false-positive’ (Type I error) was obtained when a predicted wet area in the transect was actually dry. Finally, a ‘false-negative’ (Type II error) occurred when a predicted dry area was actually wet.

In the calibration phase, carried in the Santa Maria catchment, the thresholds k_1 and k_2 which maximized equation 4 were obtained by trial and error. The calibrated values of k_1 and k_2 were then applied to the validation (Gama) catchment, and its prediction accuracy was calculated using equation 4. Finally, the wet area delineation accuracy of both basins was compared with those of similar studies in the literature.

3. RESULTS

3.1. Drainage Network Delineation

The calibrated value of TWI in the Santa Maria basin was 15, balancing stream initiation and channel delineation accuracies. Quinn et al. (1995) found a TWI threshold of 12 for a perennial drainage network in England. Moore et al. (1988) found that ephemeral gullies heads in an Australian catchment occurred when $TWI \geq 7$.

The predicted and reference drainage networks of the calibration and validation catchments are presented in Figure 7. As expected, the synthetic drainage networks were concentrated flow paths, since the D8 single-direction routing algorithm was used (Ruhoff et al., 2011).

[Insert Figure 7]

Figure 7 indicates that there is a relatively good agreement between the simulated and reference channel networks, particularly in the Santa Maria catchment. Despite the small offsets observed in the Gama basin, there was a good overall drainage delineation accuracy in both catchments, namely 67.2% and 70.7% for the Santa Maria and Gama basins, respectively (Table 2).

[Insert Table 2]

3.2. Wet Area Delineation

The calibrated values of slope curvature (S_c) and local slope (S_l) in the Santa Maria basin were -0.05 and 0.01, respectively, and the simulated and reference wet areas of the Santa Maria and Gama catchments are presented in Figure 8. Table 3 shows the confusion matrix and overall wet area delineation accuracies for both catchments.

[Insert Figure 8]

[Insert Table 3]

According to Table 3, the overall wet area delineation accuracy in the Santa Maria and Gama catchments were 72.7% and 73.8%, respectively. The predicted wet areas in both catchments were concentrated in the valley bottoms, although scattered pixels occurred in well-drained upslope areas.

4. DISCUSSION

4.1. Drainage Network Delineation

According to Table 2, channel delineation (accuracies of 78.9% and 77.5%) was better predicted than channel initiation (accuracies of 44.4% and 63.9%), in the Santa Maria and Gama basins, respectively. Figure 7 also indicates that higher order channels were better delineated than first order streams.

Nevertheless, the overall drainage network prediction accuracies in Table 2 were higher than similar studies in the literature. Julian et al. (2012) found that stream mapping accuracy using $\ln(\alpha)$ in the USA varied between 30% and 55%, depending on the geology. In Algeria, Dewitte et al. (2015) obtained a Spearman correlation of 0.5 between the predicted and observed gully heads, using the TWI.

The homogeneous geology and gentle topography of the Santa Maria and Gama catchments, with corresponding dendritic drainage patterns (Figures 2 and 3), may have contributed to the good drainage mapping accuracy. The discrepancies observed between predicted and reference drainage networks have resulted from a combination of model (TWI) error and cartographic misrepresentation of the reference maps (Kim & Lee, 2004). Additionally, the large DEM grid size (Capoane et al., 2015; Quinn et al., 1995) and DEM vertical error, the latter resulting from the SRTM radar inability to penetrate dense riparian vegetation (Orlandi et al., 2019), may have reduced the accuracies in Table 2.

Channel initiation was overestimated by the TWI with respect to the reference network because many simulated first order channels corresponded to temporary streams and ravines, which were not identified in the photogrammetry-based reference maps (Jaeger et al., 2017).

4.2. Wet Area Delineation

Although the overall wet area delineation accuracies of the Santa Maria and Gama catchments were acceptable (72.7% and 73.8%, respectively), wet areas were incorrectly assigned to the basins' upslope zones (Figures 2 and 3). This may have resulted from model error, large DEM grid size (Buchanan et al., 2014), and DEM vertical inaccuracy (Orlandi et al., 2019), affecting the overall mapping accuracy. Additionally, since the land-use feature 'gallery forest' was taken as a reference wet area, its occurrence over both well and poorly drained soils (Marimon et al., 2010) may have contributed to reduce the wet area delineation accuracy, as recognized by Skorupa et al. (2013).

In the literature, wet area mapping using topographic attributes gave mixed results. Ågren et al. (2014) obtained an accuracy of 85.2% in Sweden, using a combination of TWI and a depth-to-water index. Buchanan et al., (2014) reported a R^2 of 0.61 between the TWI and wet areas in the USA, and Russell et al. (1997) obtained a mapping accuracy of 73% in California. Considering that those studies used higher spatial resolution maps and secondary topographic attributes, the simplicity and robustness of the methods used in this study are encouraging, and allow their utilization in the mapping of drainage networks and wet areas of data-scarce tropical catchments.

5. CONCLUSIONS

Topographic attributes were used to delineate drainage networks and wet areas in two small catchments of the Cerrado biome, in Central Brazil. The selected attributes were the TWI, and the local slope and the slope curvature, respectively. A 30-m SRTM DEM was used as input, and hydrographic and land-use maps were used as references. Calibrated threshold values were obtained for the three topographic attributes in the Santa Maria catchment, and subsequently validated in the Gama basin, using balanced multi-criteria methods.

The accuracies obtained for the simulated drainage networks (67.2% and 70.7%) and wet areas (72.7% and 73.8%) in the Santa Maria and Gama catchments, respectively, were equivalent or higher than those of similar studies in the literature, and the delineation errors were associated with DEM grid size, DEM vertical inaccuracy, and with reference map bias. Due to its simplicity and robustness, the method could be used in the mapping of drainage networks and wet areas of tropical catchments.

ACKNOWLEDGEMENTS

This research was an initiative of the GRAPHIC/UNESCO Project in Latin America and the Caribbean, and of The Nature Conservancy-Brazil, and carried at the Watershed Management Laboratory of the School of Technology of University of Brasilia.

322

323 REFERENCES

- 324 Acevedo, J.A., Escobar-Martínez, J.F., Massone, H., Booman, G., Quiroz-Londoño, O.M.,
325 Cañón-Barriga, C.C., Montoya-Jaramillo, L.J., Palomino-Ángel, S. (2017). Identificación de
326 áreas de humedal en el contexto del desarrollo agrícola usando teledetección y SIG. *DYNA*,
327 84, 186–194. <https://doi.org/10.15446/dyna.v84n201.58600>
- 328 Ågren, A.M., Lidberg, W., Strömberg, M., Ogilvie, J., Arp, P.A. (2014). Evaluating digital
329 terrain indices for soil wetness mapping-a Swedish case study. *Hydrol. Earth Syst. Sci.*, 18,
330 3623–3634. <https://doi.org/10.5194/hess-18-3623-2014>
- 331 Ali, G., Birkel C., Tetzlaff, D., Soulsby, C., McDonnell, J.J., Tarolli, P. (2014). A comparison
332 of wetness indices for the prediction of observed connected saturated areas under contrasting
333 conditions. *Earth Surf. Process. Landforms*, 39, 399–413. <https://doi.org/10.1002/esp.3506>
- 334 Aspinall, R.J., Pearson, D.M. (1995). Describing and managing uncertainty of categorical
335 maps in GIS, in Fisher, P. (Ed.): *Innovations in GIS 2*, London: Taylor & Francis, 71-83
- 336 Beven, K.J., Kirkby, M.J. (1979). A physically based, variable contributing area model of
337 basin hydrology. *Hydrol. Sci. Bull.*, 24, 43–69. <https://doi.org/10.1080/02626667909491834>
- 338 Buchanan, B.P., Fleming, M., Schneider, R.L., Richards, B.K., Archibald, J., Qiu Z., Walter,
339 M.T. (2014). Evaluating topographic wetness indices across central New York agricultural
340 landscapes. *Hydrol. Earth Syst. Sci.*, 18, 3279–3299. [https://doi.org/10.5194/hess-18-3279-](https://doi.org/10.5194/hess-18-3279-2014)
341 2014
- 342 Burt, T.P., Butcher, D.P. (1985). Topographic controls of soil moisture distributions. *J. Soil*
343 *Sci.*, 36, 469–486. <https://doi.org/10.1111/j.1365-2389.1985.tb00351.x>
- 344 Capoane, V., Tiecher, T., Rasche Alvarez, J.W.R., Pellegrini, A., Schaefer, G.L., Santos,
345 L.J.C., Santos, D.R. (2015). Influência da resolução do modelo digital de elevação na

346 determinação do índice topográfico de umidade e na capacidade de predição dos teores
 347 carbono orgânico do solo. *Geo UERJ*, 0, 144–155. (in Portuguese)
 348 <https://doi.org/10.12957/geouerj.2015.13452>

349 Chang, C.H., Lee, K.T. (2008). Analysis of geomorphologic and hydrological characteristics in
 350 watershed saturated areas using topographic-index threshold and geomorphology-based
 351 runoff model. *Hydrol. Process.*, 22, 802–812. <https://doi.org/10.1002/hyp.6638>

352 Detty, J.M., McGuire, K.J. (2010). Topographic controls on shallow groundwater dynamics:
 353 Implications of hydrologic connectivity between hillslopes and riparian zones in a till
 354 mantled catchment. *Hydrol. Process.*, 24, 2222–2236. <https://doi.org/10.1002/hyp.7656>

355 Dewitte, O., Daoudi, M., Bosco, C., Van Den Eeckhaut, M. (2015). Predicting the
 356 susceptibility to gully initiation in data-poor regions. *Geomorphology*, 228, 101–115.
 357 <https://doi.org/10.1016/j.geomorph.2014.08.010>

358 Dunne, T. (1980). Formation and controls of channel networks. *Progress in Physical*
 359 *Geography*. <https://doi.org/10.1177/030913338000400204>

360 Eiten, G. (1972). The Cerrado Vegetation of Brazil. *Bot. Rev.*, 38, 201–341.
 361 <https://doi.org/10.1017/CBO9781107415324.004>

362 Franklin, J. (1995). Predictive vegetation mapping: Geographic modelling of biospatial
 363 patterns in relation to environmental gradients. *Prog. Phys. Geogr.*, 19, 474–499.
 364 <https://doi.org/10.1177/030913339501900403>

365 Gallon, E., Lindberg, S. (2014). Where does the stream begin? Stream initiation under
 366 variable wetness conditions in a boreal landscape. *Självständigt Arb.* 34p.

367 Grabs, T., Seibert, J., Bishop, K., Laudon, H. (2009). Modeling spatial patterns of saturated
 368 areas: A comparison of the topographic wetness index and a dynamic distributed model. *J.*
 369 *Hydrol.*, 373, 15–23. <https://doi.org/10.1016/j.jhydrol.2009.03.031>

370 Güntner, A., Seibert, J., Uhlenbrook, S. (2004). Modeling spatial patterns of saturated areas:
 371 An evaluation of different terrain indices. *Water Resour. Res.*, 40, 1–19.
 372 <https://doi.org/10.1029/2003WR002864>

373 Hastings, B.E., Kampf, S.K. (2014). Evaluation of digital channel network derivation
 374 methods in a glaciated subalpine catchment. *Earth Surf. Process. Landforms*, 39, 1790–1802.
 375 <https://doi.org/10.1002/esp.3566>

376 Henkle, J.E., Wohl, E., Beckman, N. (2011). Locations of channel heads in the semiarid
 377 Colorado Front Range, USA. *Geomorphology*, 129, 309–319.
 378 <https://doi.org/10.1016/j.geomorph.2011.02.026>

379 Jaeger, K.L., Montgomery, D.R., Bolton, S. (2007). Channel and perennial flow initiation in
 380 headwater streams: Management implications of variability in source-area size. *Environ.*
 381 *Manage.*, 40, 775–786. <https://doi.org/10.1007/s00267-005-0311-2>

382 Jenson, S.K., Domingue, J.O. (1988). Extracting Topographic Structure from Digital
 383 Elevation Data for Geographic Information System Analysis. *Photogrammetric Engineering*
 384 *and Remote Sensing*, 54 (11): 1593–1600.

385 Johnson, M.A., Saraiva, P.M., Coelho, D. (1999). The role of gallery forests in the
 386 distribution of cerrado mammals. *Rev. Bras. Biol.*, 59, 421–427.
 387 <https://doi.org/10.1590/s0034-71081999000300006>

388 Johnston, R., Cools, J., Liersch, S., Morardet, S., Murgue, C., Mahieu, M., Zsuffa, I.,
 389 Uyttendaele, G.P. (2013). WETwin: A structured approach to evaluating wetland
 390 management options in data-poor contexts. *Environ. Sci. Policy* 34, 3–17.
 391 <https://doi.org/10.1016/j.envsci.2012.12.006>

392 Julian, J.P., Elmore, A.J., Guinn, S.M. (2012). Channel head locations in forested watersheds
 393 across the mid-Atlantic United States: A physiographic analysis. *Geomorphology*, 177–178,

394 194–203. <https://doi.org/10.1016/j.geomorph.2012.07.029>

395 Kim, S., Lee, H. (2004). A digital elevation analysis: A spatially distributed flow
 396 apportioning algorithm. *Hydrol. Process.*, 18, 1777–1794. <https://doi.org/10.1002/hyp.1446>

397 Kopecký, M., Čížková, Š. (2010). Using topographic wetness index in vegetation ecology:
 398 Does the algorithm matter? *Appl. Veg. Sci.*, 13, 450–459. <https://doi.org/10.1111/j.1654->
 399 109X.2010.01083.x

400 Laudon, H., Kuglerová, L., Sponseller, M.F., Nordin, A., Bishop, K., Lundmark, T., Egnell,
 401 G., Anneli, A. (2016). The role of biogeochemical hotspots, landscape heterogeneity, and
 402 hydrological connectivity for minimizing forestry effects on water quality. *K.*
 403 *VetenskapsAkademien*, 45, S152–S162. <https://doi.org/10.1007/s13280-015-0751-8>

404 Lenza, E., Santos, J.O., Maracahipes-Santos, L. (2015). Species composition, diversity, and
 405 vegetation structure in a gallery forest-cerrado sensu stricto transition zone in eastern Mato
 406 Grosso, Brazil. *Acta Bot. Brasilica*, 29, 327–338. <https://doi.org/10.1590/0102->
 407 33062014abb3697

408 Marimon, B.S., Felfili, J.M., Lima, S., Duarte, W.G., Marimon-Júnior, B.H. (2010).
 409 Environmental determinants for natural regeneration of gallery forest at the
 410 Cerrado/Amazonia boundaries in Brazil. *Acta Amaz.*, 40, 107–118.
 411 <https://doi.org/10.1590/s0044-59672010000100014>

412 McMaster, K.J.(2002). Effects of digital elevation model resolution on derived stream
 413 network positions. *Water Resour. Res.*, 38, 13-1-13–8. <https://doi.org/10.1029/2000wr000150>

414 Montgomery, D.R., Dietrich, W.E. (1989) Source areas, drainage density, and channel
 415 initiation. *Water Res. Res.*, 25, 1907-1918.

416 Montgomery, D.R., Dietrich, W.E. (1992). Channel initiation and the problem of landscape
 417 scale. *Science*, 255, 826–830. <https://doi.org/10.1126/science.255.5046.826>

418 Moore, I.D., Burch, G.J., Mackenzie, D.H. (1988). Topographic Effects on the Distribution of
 419 Surface Soil Water and the Location of Ephemeral Gullies. *Trans. Am. Soc. Agric. Eng.*, 31,
 420 1098–1107. <https://doi.org/10.13031/2013.30829>

421 Moore, I.D., Grayson, R.B., Ladson, A.R. (1991). Digital terrain modelling: A review of
 422 hydrological, geomorphological, and biological applications. *Hydrol. Process.*, 5, 3–30.
 423 <https://doi.org/10.1002/hyp.3360050103>

424 O’Loughlin, E.M.O. (1986). Natural Catchments by Topographic Analysis Net drainage
 425 Flux. *Water Resour.*, 22, 794–804.

426 O’Neill, M.P., Schmidt, J.C., Dobrowolski, J.P., Hawkins, C.P., Neale, C.M.U. (1997).
 427 Identifying sites for riparian wetland restoration: Application of a model to the Upper
 428 Arkansas River Basin. *Restor. Ecol.*, 5, 85–102. [https://doi.org/10.1111/j.1526-](https://doi.org/10.1111/j.1526-100X.1997.00085.x)
 429 [100X.1997.00085.x](https://doi.org/10.1111/j.1526-100X.1997.00085.x)

430 Oliveira Filho, A.T., Shepherd, G.J., Martins, F.R., Stubblebine, W.H. (1989).
 431 Environmental factors affecting physiognomic and floristic variation in an area of cerrado in
 432 central brazil. *J. Trop. Ecol.*, 5, 413–431. <https://doi.org/10.1017/S0266467400003862>

433 Orlandi, A.G., Carvalho Júnior, O.A., Guimarães, R.F., Souza Bias, E., Corrêa, D.C., Gomes,
 434 R.A.T. (2019). Vertical accuracy assessment of the processed SRTM data for the Brazilian
 435 territory. *Bol. Ciencias Geod.*, 25, 1–14. <https://doi.org/10.1590/s1982-21702019000400021>

436 Qin, C.Z., Zhu, A.X., Pei, T., Li, B.L., Scholten, T., Behrens, T., Zhou, C.H. (2011). An
 437 approach to computing topographic wetness index based on maximum downslope gradient.
 438 *Precis. Agric.*, 12, 32–43. <https://doi.org/10.1007/s11119-009-9152-y>

439 Quinn, P.F., Beven, K.J., Lamb, R. (1995). The $\ln(a/\tan\beta)$ index: How to calculate it and
 440 how to use it within the topmodel framework. *Hydrol. Process.*, 9, 161–182.
 441 <https://doi.org/10.1002/hyp.3360090204>

442 Rinderer, M., Meerveld, H.J., van Seibert, J. (2014). Topographic controls on shallow
 443 groundwater levels in a steep, prealpine catchment: When are the TWI assumptions valid?
 444 *Water Resour. Res.*, 50, 6067–6080. <https://doi.org/10.1002/2013WR015009>.
 445 Roth, G., La Barbera, P. (1997). Morphological characterization of channel initiation. *Phys.*
 446 *Chem. Earth*, 22, 329–332. [https://doi.org/10.1016/S0079-1946\(97\)00153-5](https://doi.org/10.1016/S0079-1946(97)00153-5)
 447 Ruhoff, A.L., Castro, N.M.R., Risso, A. (2011). Numerical Modelling of the Topographic
 448 Wetness Index: An Analysis at Different Scales. *Int. J. Geosci.*, 2, 476–483.
 449 <https://doi.org/10.4236/ijg.2011.24050>
 450 Russell, G.D., Hawkins, C.P., O'Neill, M.P. (1997). The role of GIS in selecting sites for
 451 riparian restoration based on hydrology and land use. *Restor. Ecol.*, 5, 56–68. <https://doi.org/10.1111/j.1526-100X.1997.00056.x>
 452 10.1111/j.1526-100X.1997.00056.x
 453 Schneiderman, E.M., Steenhuis, T.S., Thongs, D.J., Easton, Z.M., Zion, M.S., Neal, A.L.,
 454 Mendoza, G.F., Walter, M.T. (2007). Incorporating variable source area hydrology into a
 455 curve-number-based watershed model. *Hydrol. Process.*, 21, 3420–3430.
 456 <https://doi.org/10.1002/hyp.6556>
 457 Silva, B., Silva, M., Avalos, F., Menezes, M., Curi, N. (2019). Digital soil mapping including
 458 additional point sampling in Posses ecosystem services pilot watershed, southeastern Brazil.
 459 *Sci. Rep.*, 9, 1–12. <https://doi.org/10.1038/s41598-019-52011-0>
 460 Skorupa, A.L.A., Fay, M., Zinn, Y.L., Scheuber, M. (2013). Assessing hydric soils in a
 461 gallery forest in the Brazilian Cerrado. *Soil Use Manag.*, 29, 119–129.
 462 <https://doi.org/10.1111/sum.12023>
 463 Tomer, M.D., Dosskey, M.G., Burkart, M.R., James, D.E., Helmers, M.J., Eisenhauer, D.E.
 464 (2009). Methods to prioritize placement of riparian buffers for improved water quality.
 465 *Agrofor. Syst.*, 75, 17–25. <https://doi.org/10.1007/s10457-008-9134-5>

466 Unesco (2002). *Vegetation of the Federal District: Time and space*. 2.ed. Brasília, 70 p. (in
467 Portuguese)

468 Valeriano, M., Rossetti, D., Albuquerque, P.C.G. (2009). *Topodata: Development of the first*
469 *geomorphometric data base at the national level*. Bibdigital.Sid.Inpe.Br, 5499–5506

470

471

472

473 Table 1. Main hydrologic characteristics of the Santa Maria and Gama catchments.

Catchment	A (km ²)	H_{min} (m)	H_{max} (m)	S (%)	D_d (km ⁻¹)	C_r	O	P (mm)	Q (mm)
Santa Maria (C)	368.8	1,012	1,307	5.04	0.45	0.48	4	1,400	335
Gama (V)	144.7	1,012	1,263	6.73	0.58	0.44	4	1,460	326

474 A = basin area; H_{min} = minimum altitude; H_{max} = maximum altitude; S = mean basin slope; D_d = drainage density;
475 C_r = Miller's circularity ratio; O = Strahler's basin order; P = mean annual precipitation; Q = mean annual runoff;
476 C = calibration catchment; V = validation catchment.

477

478
479

480

481
482

Table 2. Drainage network mapping accuracy of the Santa Maria (calibration) and Gama (validation) catchments, using the TWI.

Catchment	Network Delineation Accuracy (%)	Channel Initiation Accuracy (%)	Overall Accuracy (%)
Santa Maria	78.9	44.4	67.2
Gama	77.5	63.9	70.7

483
484
485

486
487

Table 3. Confusion matrices and overall wet area delineation accuracy of the Santa Maria and Gama catchments.

Catchment		Santa Maria		Gama		
		<i>Ref. Wet Area</i>		<i>Ref. Wet Area</i>		
		<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>	
<i>Predicted Wet Area</i>	<i>No</i>	1406	83	<i>No</i>	911	80
	<i>Yes</i>	510	172	<i>Yes</i>	292	137
Accuracy		72.7%		73.8%		

FIGURE CAPTIONS

Figure 1. Location of the Santa Maria and Gama catchments, in Central Brazil.

Figure 2. Elevation, hydrography, soils, and vegetation of the Santa Maria catchment.

Figure 3. Elevation, hydrography, soils, and vegetation of the Gama catchment.

Figure 4. Typical topographic profiles of the Santa Maria (A & B) and Gama (C & D) catchments. A, C are U-type bottoms, and B, D are V-type valleys.

Figure 5. Local slope of the Santa Maria (left) and Gama (right) catchments, and the transects used to assess wet area delineation accuracy.

Figure 6. Slope curvatures of the Santa Maria (left) and Gama (right) catchments.

Figure 7. Predicted (TWI-based) and reference drainage networks of the Santa Maria (left) and Gama (right) catchments. The insets show both networks in higher detail.

Figure 8. Predicted and reference wet areas of the Santa Maria (left) and Gama (right) catchments. The insets show the predicted and reference wet areas in higher detail.