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Development and Comparison of Approaches for Automated Mapping of Stream Channel Networks

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Accurate mapping of stream channel networks is important for measuring hydrologic parameters, for site planning in construction projects, and for use in hydrologic models. This article compares five existing and two new methods for extracting stream channel networks for use in topographic mapping. In order of increasing accuracy, these methods are: (1) blue lines on USGS 1:24,000 topographic maps (64.6 percent underrepresentation), (2) placing stream heads using a constant flow-accumulation area to mimic USGS blue lines (47.8 percent underrepresentation), (3) constant flow-accumulation area equal to the mean for identified channel heads (30.3 percent combined under- and overrepresentation), (4) variable flow-accumulation area estimated by multiple linear regression (28.9 percent combined under- and overrepresentation), (5) variable flow-accumulation area estimated by a slope-power relationship (23.6 percent combined under- and overrepresentation), (6) identifying stream cells using logistic regression (12.7 percent combined under- and overrepresentation), and (7) extracting stream channel head locations from digital orthophotoquads (DOQs) (nearly 100 percent accurate, but only applicable under ideal conditions). Methods 2–6 require 10 m resolution digital elevation models that can be acquired directly in many areas or can be derived from 1:24,000 hypsography where available; Methods 4 and 6 are new methods developed in this paper.

Using DOQs, while extremely accurate, is labor intensive and can be applied only in a small minority of locations where vegetation cover does not obscure channel head locations. We conclude that identifying stream cells using logistic regression has the broadest applicability because it can be implemented in an automated fashion using only DEMs while still achieving accuracies for mapping low-order streams that are far superior to existing USGS maps. *Key Words: stream channel mapping, stream channel heads, digital elevation models, hydrography, logistic regression.*

Problem Statement and Objectives

The identification and mapping of stream channel networks is important to applications in cartography, geomorphology, hydrology, and water resources management. For example, fluvial geomorphological studies often involve the measurement of quantitative basin characteristics such as drainage density and stream order from a drainage network. Basins with higher drainage density will tend to have a more peaked hydrograph than lower-density basins, have higher sediment production, and can present greater difficulties in development for agriculture or urbanization (Dunne and Leopold 1978). Definition of the permanent channel network aids watershed planners in targeting conservation and best management practices. For instance, the presence or absence of a stream channel influences the type of conservation programs (e.g., Conservation Reserve Program) and practices (e.g., grassed waterways, filter strips) that apply to an area (Lant, Kraft, and Gillman 1995). The presence of a first-order stream channel can increase the market value of a rural land parcel. Planning for construction of roads, buildings, and other projects can benefit from a more accurate mapping of ephemeral stream channels as well (Swisher 2002). Models such as AGNPS, SWAT, and BASINS utilize single-threshold flow-accumulation values to represent stream networks (Young et al. 1989, Arnold, Engel, and Srinivasan 1993). Analyses using these models are increasingly important in regulation of non-point source pollution under Total Maximum Daily Load (TMDL) requirements of the Clean Water Act (National Research Council 2001).

Unfortunately, present methods for mapping stream channel networks are inadequate. The most common existing channel representations in the United States are hydrographic "blue lines" found on 1:24,000 US Geological Survey (USGS) topographic maps. Similar topographic maps at the 1:25,000 scale are utilized by most western European countries (including the U.K., France, and Germany), and by Japan. However, Morisawa (1957) and Coates (1958) found that the blue lines on the USGS topographic maps grossly underestimated the streams found in the field. Mark (1983) and

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Montgomery and Foufoula-Georgiou (1993) also conclude that the printed blue lines do not represent a viable data source for many applications. The inaccuracies in the present published maps occur because stream channels are often difficult to detect and because cartographic generalizations and decision rules lead to inaccuracies in published drainage networks. For example, Drummond (1974) found that each agency surveyed in his study created its own set of decision rules and criteria for the inclusion and length of stream channels. Dunne and Leopold (1978) point out that limitations in the recognition of small channels make measures of drainage density dependent on map scale and the technique used for manually extending channels up topographic swales.

A better method is to use the location of actual stream channel heads to define starting points for topologically connected stream drainage networks. Mark (1983) is, to our knowledge, the first author to define the stream network mapping problem as a matter of identifying channel heads. Whereas Band (1986) asserts that channel networks are arbitrary and scale-dependent, other researchers have found that drainage channels are distinct fluvial geomorphologic features where overland flow on hillslopes crosses a threshold to create abrupt drainage channels (O'Callaghan and Mark 1984; Dietrich et al. 1993; Montgomery and Foufoula-Georgiou 1993; Tarboton and Ames, 2001). Dietrich et al. (1993) found that the channel head represents a shift in hydrologic process from mass wasting and diffusive flow to runoff-driven incision. Often, first-order channels are discontinuous, consisting of a well-defined channel head that gives rise to a distinct channel. This channel may, however, become less distinct over a section downstream of the channel head before being reinitiated in a continuous form from that point downstream. Montgomery and Dietrich (1989, 1907) define channel heads as "the farthest upslope location of a channel with well defined banks." This convention is followed here with the implication that short nonchanneled segments lying downstream of channeled segments are included in the mapped stream network. Our fieldwork, described below, also found that channel heads are clearly definable features on the landscape (Figure 1), but are also sometimes discontinuous in first-order reaches. Meeting the challenge of locating channel heads is thus the key to accurate mapping of stream networks. Even small errors in locating channel heads results in major errors in the total stream network length, stream order, and drainage density (Garbrecht and Martz 2000).

While geomorphic theories of channel initiation suffer from a lack of thorough fieldwork (Montgomery and Dietrich 1989), one or more of three processes are theorized to be at work. The most common is incision by overland flow where the shear stress of accumulated flow during high run-off periods exceeds the cohesive strength of surface materials, generally producing distinct and fairly stable channel heads where erosion exceeds accumulation of colluvium (Dietrich et al. 1993). However, these channel heads occasionally begin gradually making small errors possible in determining their location in the field (Montgomery and Dietrich 1989). The second process is seepage erosion where very distinct channel heads occur where subsurface pipeflow outlets to the surface in slowly retreating vertical walls. In steep topography, shallow landsliding is often the dominant process determining the location of channel heads.

Figure 1. A typical channel head identified in the study area.

Montgomery and Dietrich (1989, 1917) emphasize "the significance of the channel head as a crucial linkage between hillslopes and channel networks" and point to "the need for greater understanding of the controls on channel initiation and channel head locations." Montgomery and Dietrich (1992) find that stream channels determine the limit of landscape dissection. Importantly, this creates a break in the fractal nature of drainage networks at scales less than the size needed to generate stream channels. They also found a hysteresis effect where expansion of channel heads and concave valleys toward drainage divides occurs much more quickly in response to changes in hydrologic circumstances that

increase runoff per unit area than does valley shortening away from drainage divides in response to a decrease in runoff. Thus the degree of dissection of many landscapes reflects the minimum drainage area needed to generate a channel that has obtained over recent geologic time. Their results "point to the need to focus on processes controlling the location of the channel head" (Montgomery and Dietrich 1992, 829) both for practical purposes and for understanding landscape evolution.

Geographic information systems (GIS), coupled with digital elevation models (DEMs), are proving to be valuable tools in the hydrologic sciences especially in terms of terrain-specific modeling. The past two decades have seen much work on the extraction of fluvial-geomorphic properties from DEMs including the automatic detection of drainage networks (e.g., Mark 1984; O'Callaghan and Mark 1983; Tarboton, Bras, and Rodrigues-Iturbe 1991; Fairfield and Leymarie 1991; Chorowicz et al. 1992; Tribe 1992; Dietrich et al. 1993). In a GIS, drainage network identification is generally founded on the concept of overland flow-accumulation as opposed to direct detection of the stream channels themselves. This is because DEM resolution has been, and continues to be, insufficient to directly detect the topographic signature of the relative topographic low associated with headwater streams. GIS-based automatic drainage network extraction techniques rely on broader-scale topographic properties to identify where channels are likely to be found in the landscape. Several authors have attempted to utilize DEMs to locate first-order stream channels and channel heads by proxy measures of the landscape; this article constitutes a continuation of those efforts.

The foundational work of O'Callaghan and Mark (1984) established the D8 algorithm for determining flow direction from DEMs and for measuring the source area for each cell in a manner that allows drainage networks to be identified using the threshold flow accumulation area method. Known problems of extracting drainage networks from DEMs are: (1) elevational "pits," subsequently resolved by Jensen and Dominique (1988), (2) water routing in flat topography, subsequently resolved by Garbrecht and Martz (1997), (3) "grid bias" in establishing flow direction, subsequently resolved by Tarboton (1997), and (4) imprecise lateral placement of higher-order meandering channels compared to surveyed or mapped channels, solved by a variety of techniques for "burning in" vector stream channels into the DEM (Hutchinson 1989; Maidment et al. 1996). Band (1986) also developed an algorithm using DEMs to locate drainage divides. However, accurately locating channel heads from DEMs remains unresolved. Garbrecht and Martz (2000) provide a comprehensive discussion on the topic of identifying sources of drainage networks based on DEMs and make the distinction between constant threshold flow-accumulation area methods and variable flow-accumulation area methods for the identification of channel sources. Tribe (1991, 1992) explored the possibility of locating channel heads by identifying valley heads as concave areas in DEMs. This work contributed sound methods for quantifying topographic concavity, but was ultimately unsuccessful in identifying channel heads in real landscapes (Martz and Garbrecht 1995). Dietrich et al. (1993) utilized a triangular irregular network (TIN) to identify areas of divergent, planar, and convergent flow in a steep watershed in Marin County, California. Their work was successful in differentiating areas in the watershed where landsliding versus overland flow is the dominant sediment transport mechanism, but they did not develop a generalizable stream network mapping algorithm. The work of Montgomery and Foufoula-Georgiou (1993) represents the best to date both for their examination of the geomorphic processes involved in channel initiation as discussed above and for their improvements in predicting, and thus mapping, channel heads and stream channel networks. Guided by hydrologic theory, they investigated the source-area–slope relationship in real landscapes and using a simple log regression model achieved an r^2 value of 0.68 where:

$$A_{cr} = 1790\,(\tan\theta)^{-1.84} \tag{1}$$

where A_{cr} is the "critical area" or upslope flow accumulation area giving rise to a channel, and $\tan\theta$ is the tangent (vertical distance divided by horizontal distance) of the slope at the channel head determined by field measurements. They achieved fairly good, but unquantified, correspondence between field-mapped and automated stream channels using a simple rule of $A_{cr} > 2000\ (\tan\theta)^{-2}$, and recommended the gathering of local field data to calibrate the model. They conclude, however, that "the extent of the contemporary channel network cannot be directly determined from drainage-area–slope relations extracted from DEMs. Field data, even if limited, on the drainage area-slope relation for channel heads is the best method for determining approximate values of parameters defining channel extent."

This article has two objectives. The first is to develop two procedures for mapping stream channel heads and networks from DEMs using (a) variable flow-accumulation area estimated by multiple regression and (b) identifying stream cells using logistic regression, Methods 6 and 7 below, which have not been used previously.

The second objective is to compare the performance of these two new methods and five existing methods for extracting stream channel heads and channel networks for use in topographic mapping. These methods are:

1. Extracting stream channel head locations from digital orthophotoquads (DOQs)
2. Existing blue lines on USGS 1:24,000 topographic maps
3. Placing stream heads using a constant flow-accumulation area to mimic USGS blue lines
4. Placing stream heads using the mean flow-accumulation area of identified channel heads
5. Placing stream heads using a slope raised to a power relationship as developed by Montgomery and Fouloula-Georgiou (1993)
6. Placing stream heads using a variable flow-accumulation area estimated by multiple linear regression
7. Identifying stream cells from digital elevation models (DEMs) using logistic regression

Methods 3 and 4 above are constant flow-accumulation area threshold methods, 5 and 6 are variable flow-accumulation area methods, and Method 7 uses flow-accumulation area as an independent variable in a model directly predicting the probability of a stream channel occurring in specific DEM cells.

Study Area

We used Tallgrass National Park and nearby areas in east central Kansas (Figure 2) as the primary study area for three reasons. First, stream channels in the area are easily mapped using DOQs, a rare occurrence made possible by the availability of DOQs in an area of primarily grass cover where stream channels are easily detected. Second, there is a variety of other geospatial data for the area, including 10-foot hypsography and detailed soils data. Third, the geology of the region is simple and homogenous, thereby minimizing the influence of geologic variability on surface hydrology, while providing topographic variation in slope, concavity, and aspect.

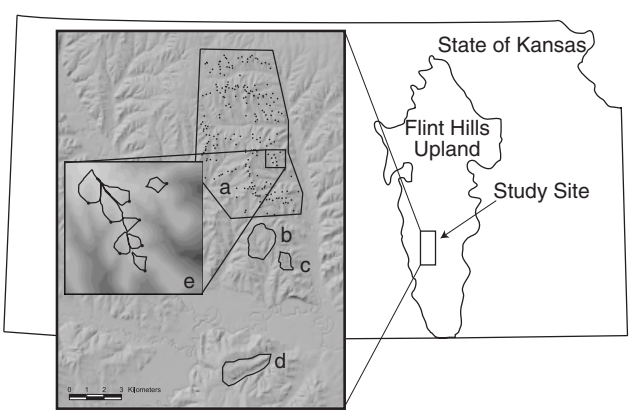

Figure 2. The primary study area in Tallgrass National Park, Kansas, overlaid on a digital elevation model: (a) the location of channel heads within the calibration area for the multiple linear regression model, (b) the calibration area for the logistic regression model, (c) the verification watershed for all methods, (d) the area used to compare DOQ-derived with field data, and (e) a selection of upslope flow-accumulation areas.

The Tallgrass study site falls within the Osage Plains section of the Central Lowlands province (Fenneman and Johnson 1946). The maximum elevation in the study site is 580 m, with local relief up to 80 m. The site is underlain by lower Permian limestones and shales; the limestone layers possess cherty deposits that are more resistant to erosion than the shale and are responsible for areas of relatively steep slopes. Soils are developed in weathered bedrock and losses are typically less than 0.5 m on the uplands (Neill 1974). Similar to the rest of the Great Plains, the Flint Hills temperatures vary widely between seasons. The annual average daily maximum temperature is 20.2°C and the average daily low temperature is 6.5°C. Average annual precipitation in the region is 81.7 cm of which 17.8 cm is runoff (Gebert, Graczyk, and Krug 1987).

Methods

For this study, a hydrologically corrected 10 m DEM was developed using topographic and hydrographic data from USGS 1:24,000 topographic maps in digital line graph form. While 30 m DEMs are now available for the entire contiguous United States, 10 m DEMs, which are not hydrologically corrected, are currently being developed and are available for portions of the country (U.S. Geological Survey 2003). The hydrological correction of the DEM was performed using TOPOGRID in ARC/INFO (Hutchinson 1989). TOPOGRID is based on an interpolation algorithm that uses a combination of point elevation, hypsography, and hydrography data to produce a hydrologically corrected DEM. The program requires that all stream arcs in the hydrograph are facing in the direction of flow. An Arc Macro Language (AML) script utilizing elevation differences was used to flip 90 percent of the arcs to the downstream direction; the remainder were flipped manually. The resulting DEMs are superior to existing USGS DEMs because they allow for enforcement, or "burning in," of known channel meander patterns (i.e., artificially lowering the elevations of known stream channel locations using another data source), and the elimination of inconsistencies in stream

topology (i.e., ensuring that the stream network generated has no breaks because of depressions and/or disconnected stream segments).

Using these improved DEMs as the primary source of data, methods of locating channel heads and delineating connected drainage channel networks were developed for each of the seven methods as described below.

1. Stream networks derived from channel heads located using DOQs. To test the practicality of collecting stream channel head locations using DOQ images, twenty channel heads were located with a differential GPS on a field visit in May 2000 to Chase County Lake Park, approximately 8 km south of the Tallgrass National Park (Figure 2). The mean distance between the GPS-derived and DOQ-derived channel head locations was found to be 14.52 meters, within the margin of error of the raster dataset used in the study. This high level of accuracy represents one result of the study. However, it simultaneously provides sound evidence that DOQ-derived channel heads can serve in this unique study area as ground truth for use in evaluating the accuracy of the other six methods for stream channel mapping evaluated in this study.

Given this preliminary result, we used DOQ-derived channel head locations as surrogates for actual channel head locations in order to measure the accuracy of the remaining methods. From the DOQ images, 224 channel head locations were identified and recorded using on-screen digitizing techniques. Among these, 204 were used to calibrate the multiple regression model for Methods 6 and 20 were used as ground truth for the validation site.

2. Mapping stream networks using existing USGS hydrography. Blue lines appearing on the 1:24,000-scale USGS quadrangle for this area were compared with the DOQ-derived stream channel network. Consistent with earlier studies cited above, this analysis showed that blue lines capture only 34.1 percent of measured stream channel length.

3. Placing stream heads using a constant flow-accumulation area from DEMs to mimic USGS blue lines. The D8 method proposed by O'Callaghan and Mark (1984) is by far the most widely used method for the extraction of drainage patterns from DEMs. Using a flow-direction surface, it is possible to compute attributes such as the cumulative number of upstream cells for each cell in a grid. The output of the flow-accumulation algorithm is a continuous grid in which each cell's value is the number of cells flowing into that cell. Thus, a cell that is located at a watershed divide would have a flow-accumulation value of zero, and the cell located at the outlet of the basin would have a value of the sum of all of the cells in the basin. The drainage network can then be mapped by selecting a flow-accumulation area threshold for the placement of channel heads. All cells with a flow-accumulation area greater than this threshold are classified as part of the drainage network. This drainage network identification approach is simple and directly generates connected networks (Martz and Garbrecht 1995).

The primary limitation in using the single-accumulation-threshold method is selection of the minimum flow-accumulation area that gives rise to a stream channel. Selection of different flow-accumulation areas produces radically different drainage networks in terms of total stream channel length, stream order, and drainage density (Figure 3). In this method, a trial-and-error process is used to choose a flow-accumulation area threshold that produces a stream network that matches the length of blue lines through visual inspection.

4. Placing stream heads using a constant flow-accumulation area to maximize accuracy. Given blue lines' substantial underrepresentation of stream channels, one alternative to mimicking blue lines is to find the flow-accumulation threshold that produces a stream network

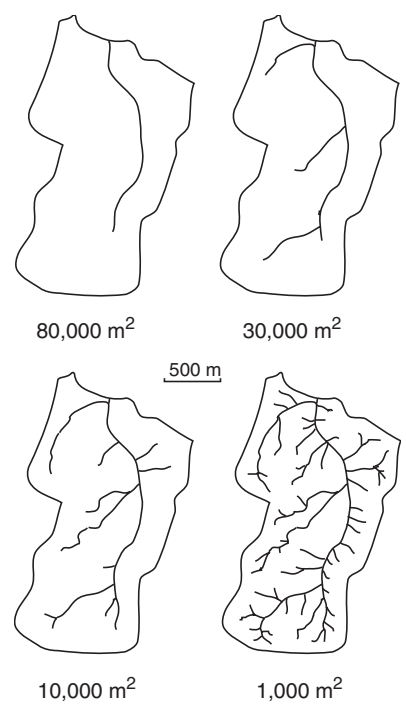

Figure 3. The effect of threshold upslope flow-accumulation area on the channel network.

that best corresponds with actual stream channels. This, of course, is applicable only in locations where the upslope flow-accumulation area of a sample of channel heads has been estimated by field measurements. We used the mean flow-accumulation area among 204 channel heads (17,495 m^2) as this constant upslope flow accumulation threshold. A channel network was then derived from these channel head locations.

5. Placing stream heads using a slope-power relationship. In order to implement the Montgomery and Foufoula-Georgiou (1993) method, where the natural logs of variable flow-accumulation area thresholds are calculated using slope raised to a power as determined through regression analysis, we calculated the natural log of the tangent of the slope angle for each channel head. This was used as the independent variable in a simple linear regression explaining the natural log of drainage area. The results are highly significant and explain nearly half of the variation in the natural log of drainage areas giving rise to channel heads (Table 1). The resulting equation, after back-calculating for natural logs is:

$$A_{cr} = 2649.7\,(\tan\theta)^{-0.9576} \qquad (2)$$

Our equation is similar to that calibrated by Montgomery and Foufoula-Georgiou (1993), but shows a smaller coefficient reflecting less sensitivity of critical drainage area to slope and a somewhat lower R^2. This perhaps reflects that our local slopes were calculated using our hydrologically corrected DEM data rather than the more accurate field measured local slopes used by Montgomery and Foufoula-Georgiou (1993) and the generally steeper topography in their coastal Oregon study area as compared to the Flint Hills.

6. Placing stream heads using a variable flow-accumulation area estimated by multiple linear regression. In an attempt to improve the predictive accuracy of existing methods, we developed a variable flow-accumulation threshold method for the identification of channel sources, where the flow-accumulation area of stream heads is determined to be a function of independent variables that can be derived from DEMs. This was done using a multiple linear regression model. Other variables, such as land use and climate, also influence overland flow, and thus the existence of stream channels, but were not included in this study so that we could focus on stream channel mapping based on DEM data alone. To a certain extent, concavity, as an effect as well as a cause of stream channels, serves as a surrogate for variables not obtainable from DEMs. The relationship among these factors is shown in Figure 4.

Table 1. Results of Regression of Critical Source Area on Slope-Power

Variable	Regression Coefficient	Student's t	Prob > t
Intercept	7.882	64.88	< .0001
Natural log of tan θ	− 0.9576	− 13.85	< .0001

$N = 204$; $R^2 = 0.486$; Adj. $R^2 = 0.483$; $F = 191.7$ (Prob > $F = 0.0001$).

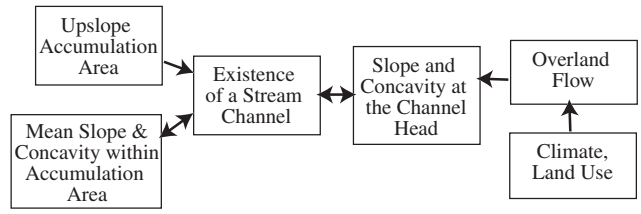

Figure 4. Causal relationships between the existence of a channel and variables measurable from a DEM: upslope source area, slope, and concavity.

The existence of stream channels is determined by the shear stress of overland flow relative to the cohesive strength of surface materials. The latter is locally variable and very difficult to measure even in the field, and thereby, it introduces an element of error into the process of predicting the location of channel heads. Shear stress of overland flow, however, is determined by local gradient and the quantity of overland flow, which is, in turn, determined by the flow-accumulation area and the climatic, geologic, topographic, and land use conditions within it. Stream channels arise in concave areas on the landscape and then reinforce this measurable valley-shaped concavity through erosion (Montgomery and Foufoula-Georgiou, 1993). Concavity is thus both a cause and an effect of stream channels, and, by providing information beyond that included in slope and flow-accumulation area, serves as a useful predictive variable for determining the location of stream channels and their heads.

Extraction of landscape parameters, such as slope and concavity, at each grid cell location is a simple matter in a standard raster GIS software package. However, we are also interested in the explanatory effect of slope and concavity variables over the entire upslope flow-accumulation area. In order to make these calculations, a new script was written in Avenue to create new grid layers whose individual grid values are generated by computing the upstream average of other grid layers. Inputs to this script include a flow-accumulation grid layer and any other raster layer thought to have an influence on downstream flow properties, such as slope curvature, but other hydrologic predictors such as land

Table 2. Dependent and Independent Variables Used in Regression Models Predicting the Occurrence of Stream Channels

Variable	Mean	Std. Dev.
Existence of a stream channel (0/1)	0.0310	NA
Flow-accumulation area (m^2)	17,495	15,157
Measured at Channel Heads		
Slope (degrees)	12.25	5.76
Profile curvature	0.300	0.657
Plan curvature	− 1.859	0.870
Measured for Flow-Accumulation Areas		
Slope (degrees)	10.29	4.63
Profile curvature	− 0.195	0.171
Plan curvature	− 0.164	0.142

use or cover type could be used. The script works by: (1) identifying the flow-accumulation area upslope of each cell, one by one, (2) using the accumulation area to average the additional layers (e.g., slope, plan, and profile), (3) recording these average values to a temporary file, and (4) creating new grids, one for each hydrologic predictor, that record the average value of the parameter over the contributing area at each cell location. Once all of the significant independent variables are encoded to raster grid representations, the mechanics involved in extracting independent variables from GIS data include use of the point on grid overlay capability available in the GIS. In the case of the linear regression model creation, the DOQ-derived channel head points are overlaid onto the grids and the corresponding values from the grids are appended to the points' attribute table as new fields. Each row in the point attribute table represents a single channel head, and the columns contain such information as average slope over the flow-accumulation area, curvature at the channel head, and so on for all the raster layers (Table 2). Topographic variables used in this article include slope, plan curvature, and profile curvature (Figure 5). Aspect was also calculated but was not found to have a significant relationship to stream channels.

The statistical relationship between channel head flow-accumulation area and four key independent variables (slope at channel head, average slope in the flow-accumulation area, average upstream plan curvature, average upstream profile curvature) is log-linear and homoscedastic (Figure 6a–d). Bivariate correlations between dependent and independent variables are also higher when the natural log of channel head flow-accumulation area rather than channel head flow-accumulation area is used as the dependent variable (Table 3). We used the natural log of flow-accumulation area as the dependent variable in the regression model to maintain homoscedasticity and maximize model fit. However, given that the concavity variables take both positive and negative forms, it was not possible to use a model form similar to the slope-power relation described above with these additional independent variables.

The multiple linear regression model explaining the variance in the natural log of flow-accumulation areas is significant at 0.0001 and explains 62 percent of the variance (Table 4). Consistent with theory and previous research, the greater the slope at the channel head, the smaller the flow-accumulation area needed to generate a channel. The positive coefficient for the average profile curvature demonstrates that valley-shaped areas that are concave along the flow line require smaller contributing areas to generate a stream. The positive coefficient on the average slope in the flow-accumulation area shows that the steeper the flow-accumulation area, the larger it must be to generate a stream channel, a counter-intuitive result. Given that the bivariate relationship between accumulation area and average slope is negative (Table 3), we can infer that this is due to multicollinearity between average slope in the flow-accumulation area and slope at the channel head ($r = 0.40$). Each of these predictor variables can be derived from DEMs alone using the methods described above. Model parameters were estimated using Jump In 4 (SAS Institute 2000).

Identifying stream cells using the linear regression model involves applying the above described regression model to each cell in a raster grid representation of a given study site (Figure 7a). Each independent variable

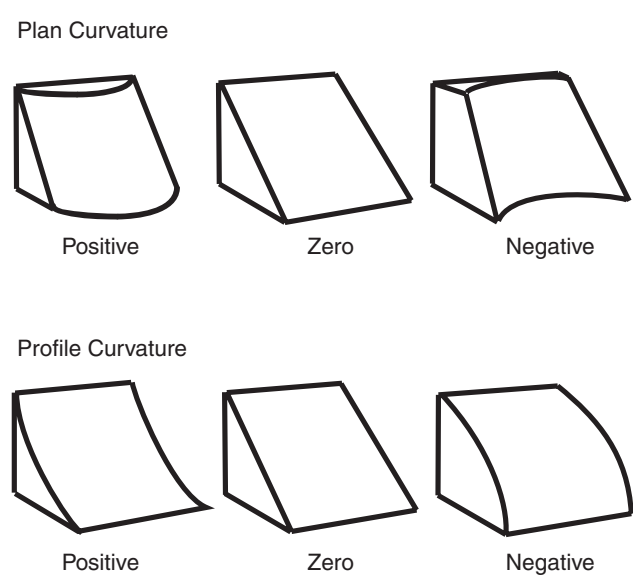

Figure 5. Diagrammatic illustration of plan and profile curvature (Plan+0 − ; Profile+0 −).

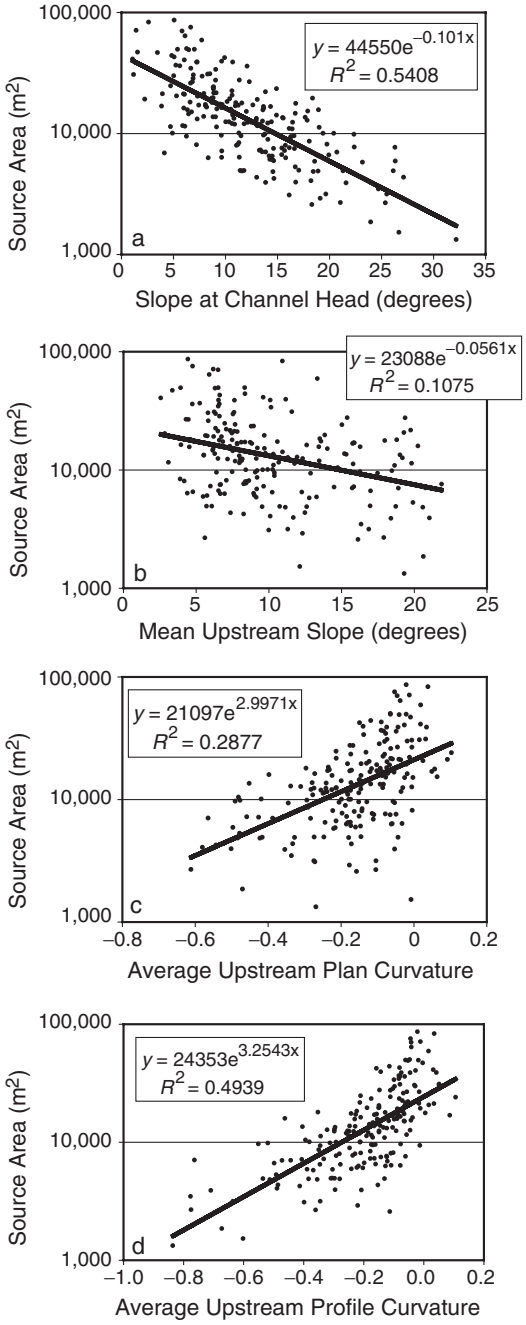

Figure 6. Semi-logarithmic scatterplots of flow-accumulation area vs. independent variables: (a) slope at channel head, (b) average slope in flow-accumulation area, (c) average upstream plan curvature, (d) average upstream profile curvature.

(e.g., slope, average upstream profile curvature, and average upstream slope) exists as raster grids derived originally from the study site DEM. Since the dependent variable in the multiple regression model is the minimum contributing area necessary to initiate a channel, the application of the model over the raster surfaces results in a new raster surface that represents, at each cell location, the amount of area required to give rise to a channel. This resulting layer is then overlaid and subtracted, cell by cell, from the computed D8-based flow-accumulation grid to find cell locations where the necessary area is exceeded by the actual contributing area. If the actual area exceeds the necessary area, the cell is classified as a channel; if necessary area exceeds actual, it is classified as nonstream channel.

7. Identifying stream cells using logistic regression. An alternative analytical approach is for each raster cell in the DEM to be coded as either a channel or a nonchannel and to find those independent variables, of which upslope flow-accumulation area is one, that best predict channel cells. This was done using a logistic regression (logit) model with channel/nonchannel as the 1/0 dependent variable. This requires calculating independent variable values for each raster cell rather than each channel head, a somewhat computationally demanding task.

To build the calibration data table for logistic regression, each of the raster surfaces was converted from a grid to a point file. Physical parameters were sampled at each raster cell in the study site rather than at each channel head location. For this reason, the calibration area for the logit model is much smaller than for the multiple regression model, yet it still contains 19,088 observations. This output table possesses a row for each raster cell in the study site and a column for each of the variables of interest and is ready to be imported into a statistical software package.

The logistic regression model predicting the probability that a cell contains a stream performed very well; Pseudo R-Square U (uncertainty coefficient) is 0.909 and Chi-Square is a very high 5391 (Table 5). The explanatory variables are similar to those in the multiple regression model, except that the natural log of flow-accumulation area, the dependent variable in the regression model, is a highly significant independent variable in the logistic regression model. Consistent with hydrologic theory, the coefficients on slope and accumulation area are positive, indicating that as these values rise, the probability of the cell containing a stream channel also rises. Also, whereas profile curvature was significant in the regression model, the highly collinear ($r = 0.83$) plan curvature is more significant in the logit model. The negative coefficient indicates that the concavity characteristic of valley cross sections is associated with streams. Average slope in the flow-accumulation area has a positive coefficient in this model, consistent with hydrologic theory and the bilinear relationship (Table 5).

Table 3. Correlation Matrix for Variables Used in the Multiple Regression and Logistic Regression Methods (Data from the Linear Regression Calibration Site; See Figure 2a)

Variable/Pearson's *R*	1	2	3	4	5
1. Flow-accumulation area					
2. Natural log of flow-accumulation area	0.88				
3. Slope at the channel head (degrees)	−0.60	−0.73			
4. Average slope over the flow-accumulation area (degrees)	−0.27	−0.32	0.40		
5. Average plan curvature over the flow-accumulation area	0.48	0.54	−0.45	−0.45	
6. Average profile curvature over the flow-accumulation area	0.54	0.70	−0.67	−0.50	0.83

$N = 204$.

Figure 7 diagrams the process by which the model parameters are used to create a GIS raster grid of stream channels. For the multiple linear regression model, all grid cells with flow-accumulation areas equal to or greater than the area determined by the multiple regression equation are classified as stream channels. For the logistic regression model, the model parameters, transformed by the logit equation as shown in Figure 7(b), generate a probability score between 0 and 1 of containing a stream channel for each raster cell. This data layer can be used to generate stream channels by designating any threshold probability or any range of probabilities as stream channels or probable stream channels. We simply designated all cells with a probability of greater than 0.5 as streams. However, the probability distribution of these scores is highly bimodal, demonstrating a robustness to the method and insensitivity to the choice of threshold probability (Figure 8).

Converting the model-designated channel raster cells into a topologically correct vector drainage network was completed by tracing the downstream cost path of each channel-designated cell to the outlet. This is similar to the raindrop tool in a standard GIS package where the downstream path is traced from a chosen point on the landscape to the lowest point in the basin; the path is recorded to a vector line file. Each channel-designated raster cell seeds a vector-downstream path; however, many cells' paths end up overlapping. Because overlapping channels are redundant, a final step of simplifying overlapping vectors into a single vector eliminates the redundancy and effectively records only the head-most channel-designated raster cells as the sources for the channel network. The vectors in the resulting channel network are oriented in the downstream direction and are fully connected.

Results

In order to compare how closely stream channel networks generated by each of the methods discussed mimic reality, a 604,320 m^2 validation watershed was chosen where all twenty of the stream channel heads were clear on the DOQ images (Figure 2). A stream channel network was mapped using this quasi ground-truth (Figure 9a) as a basis from which to measure the performance of the other methods studied (Table 6, column a). For example, the USGS 1:24,000 quadrangle was found to underrepresent total stream length and drainage density by 64 percent (Figure 9b) and identified the basin as first-rather than third-order (Table 6, column b). These results are consistent with the literature cited above.

Placing stream heads at a constant flow-accumulation area (50,000 m^2) in order to mimic blue lines (Figure 9c) resulted in specifying the basin as second-order rather than third and underestimating stream length and drainage density by 48 percent (Table 6, column c). Nevertheless, this is an improvement over existing blue lines.

Table 4. Results of Multiple Linear Regression with the Natural Log of the Flow-Accumulation Area above 204 Channel Heads as the Dependent Variable

Variable	Regression Coefficient	Student's t	Prob > t
Intercept	10.513	104.18	<.0001
Slope at the channel head (degrees)	−0.0664	−8.29	<.0001
Average profile curvature over the upslope flow-accumulation area	1.958	6.82	<.0001
Average slope over the upslope flow-accumulation area (degrees)	0.0145	1.68	0.0943

$N = 204$; $R^2 = 0.625$; Adjusted $R^2 = 0.619$; $F = 110.89$ (<.0001).

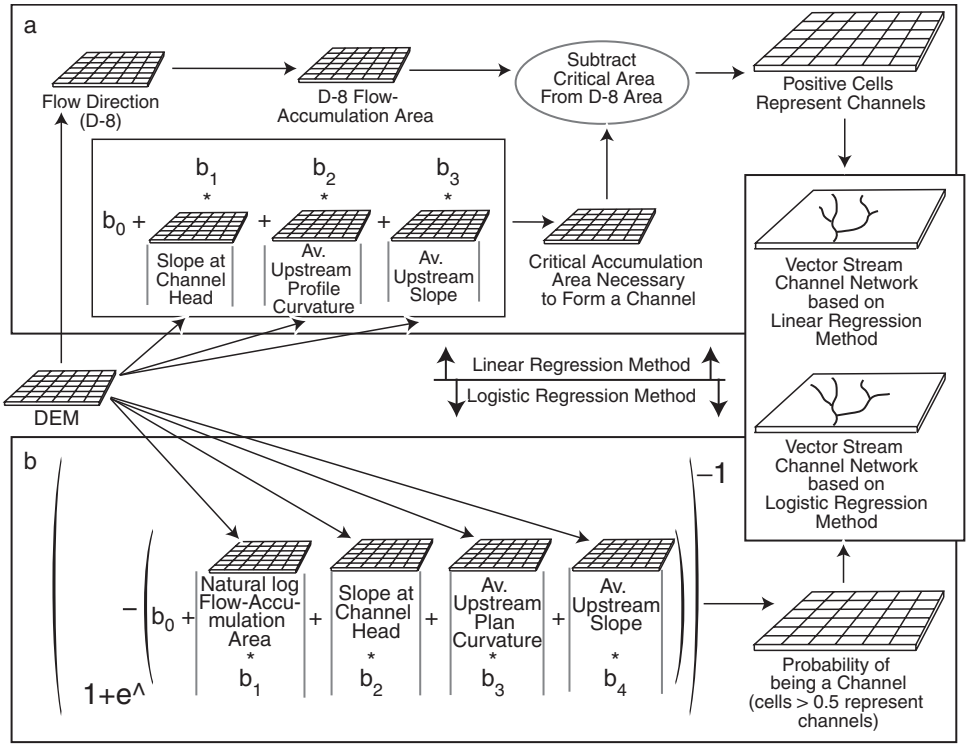

Figure 7. Diagram of statistical and spatial analysis procedures used to construct channel source approximation models: (a) multiple linear regression, (b) logistic regression.

Using a constant flow-accumulation area equal to the mean flow-accumulation area of channel heads found in the calibration site (17,495 m^2) resulted in substantially better performance (Figure 9d). The basin was correctly identified as third-order and drainage density was overestimated by only 5.6 percent. While these aggregate measures are fairly accurate, this method misses 12.2 percent of actual stream miles and incorrectly identifies a somewhat larger length of error streams, resulting in a total of 974 missed or incorrectly included stream meters—30.3 percent of the DOQ-measured stream length in the validation watershed (3216 m).

The Montgomery and Foufoula-Georgiou (1993) slope-power method resulted in a nearly perfect estimate of drainage density (Table 6, column e), but this was achieved serendipitously with a near perfect balance of false streams and missed streams (Figure 9e) that resulted in 23.6 percent total error stream miles. This is a substantial improvement over constant flow-accumulation area threshold methods and represents the best of the preexisting, DEM-based methods for mapping streams.

Relative to a constant flow-accumulation area approach, the variable flow-accumulation method reduced the length of both missed streams and incorrectly included streams (Figure 9f). However, it did not exceed the performance of the slope-power method. The total length of error streams is 28.9 percent, a slight improvement over the constant flow-accumulation area approach, but a greater error rate than the slope-power method. It also resulted in an overestimate of drainage density of 11.7 percent, a greater error than the constant flow-accumulation area approach (Table 6, column f).

Identifying stream and nonstream cells through logistic regression performed very well (Figure 9g). Drainage density was estimated within 1 percent of the

Table 5. Results of Logistic Regression Using Presence of a Stream Channel as the Dependent Variable

Variable	Regression Coefficient	Chi Square	Prob > Chi Square
Intercept	− 56.674	273.02	< .0001
Natural log of flow-accumulation area (m^2)	3.567	285.59	< .0001
Average plan curvature over the upslope flow-accumulation area	− 14.798	77.23	< .0001
Slope at the channel head (degrees)	0.213	63.65	< .0001
Average slope over the upslope flow-accumulation area (degrees)	0.0776	5.28	0.0216

N = 19,088; R Square (U) 0.909; Chi Square = 5391.1; Prob > Chi Square < .0001.

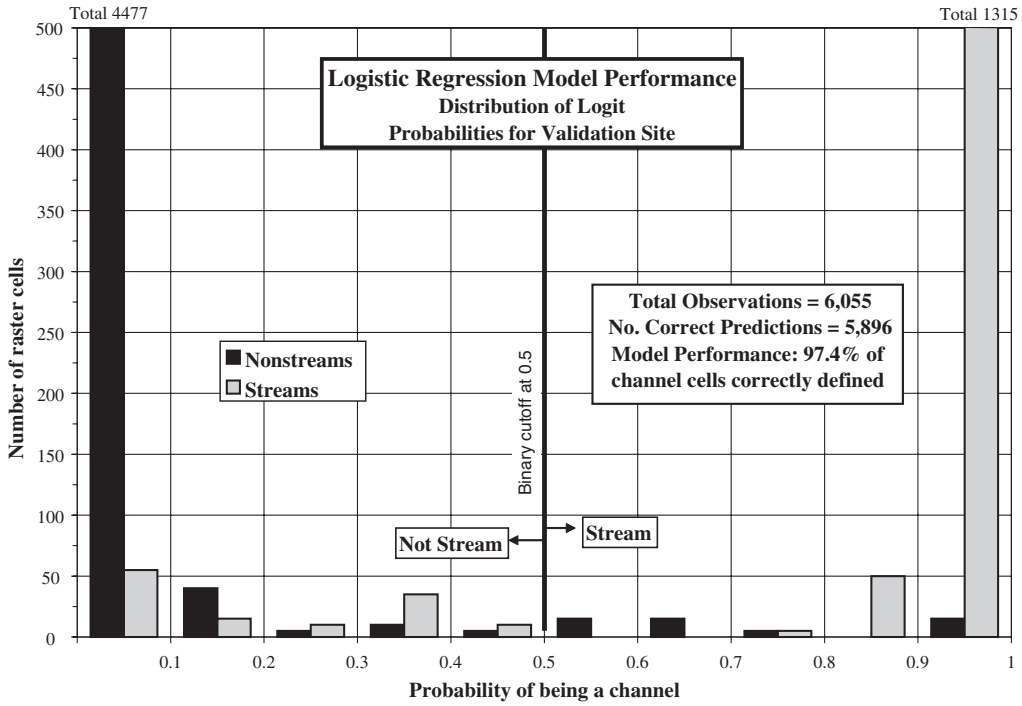

Figure 8. Distribution of probabilities of grid cells containing a stream channel estimated by logistic regression.

actual measure (Table 6, column g). The length of actual streams missed is least of all the DEM-derived methods, and the length of nonstreams incorrectly identified as streams is by far the lowest, leading to a total of 410 meters of error streams, which is only 12.7 percent of the length of actual stream channels in the validation watershed. Thus, this method mapped DOQ-derived stream channels most accurately of the DEM-based methods studied.

The close statistical fit between streams mapped using logistic regression (Figure 9g) and the DOQ-derived ground truth (Figure 9a) also provides an opportunity to interpret the geomorphic processes giving rise to stream channels. The relative explanatory power of variables shown in Table 5 shows that the area draining to a DEM cell is the dominant factor in determining the probability that a stream channel will occur, but also that other topographic factors are very important. Plan curvature over the upslope flow-accumulation area is very significant, indicating that concave topography captures water flow, but also that stream channel erosion resulting from this concentration of water flow creates concave topography in a positive feedback process, as suggested in Figure 4, that reinforces a stable location for first-order

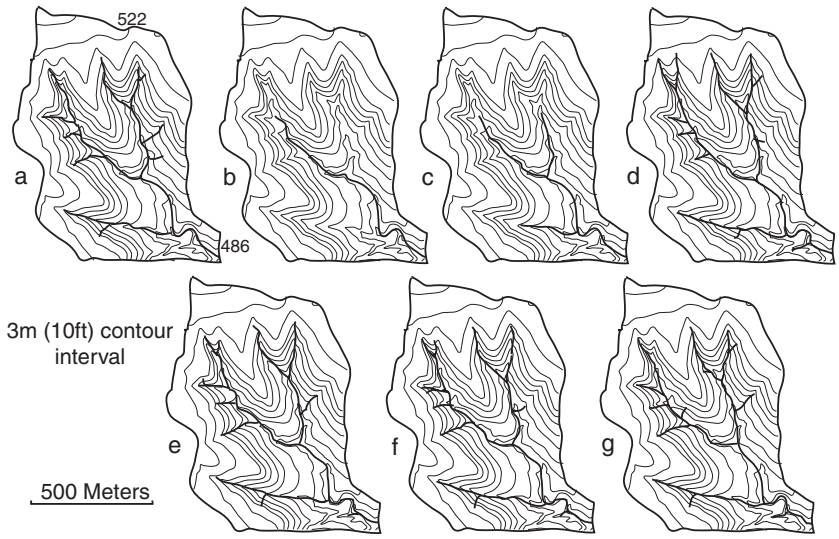

Figure 9. Spatial comparison of stream networks overlaid on topographic contours using (a) field-verified DOQ-derived data (ground truth), (b) USGS blue lines, (c) constant flow-accumulation area to mimic USGS blue lines, (d) constant flow-accumulation area to maximize accuracy, (e) slope-power regression on flow-accumulation area, (f) variable flow-accumulation area estimated using multiple regression analysis, and (g) variable flow-accumulation area estimated using logistic regression analysis.

Table 6. Hydrologic Parameters Derived from Each of the Stream Channel Network Estimation Methods (Values Derived from the Verification Watershed Site; See Figure 2c)

Hydrologic Predictor	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Total stream length (m)	3,216	1,140	1,680	3,403	3,210	3,590	3,239
Stream order	3	1	2	3	3	3	3
Drainage density (km/km^2)	5.32	1.89	2.78	5.63	5.31	5.94	5.36
(% error)	(0)	(−64)	(−48)	(+5.6)	(−0.2)	(+11.7)	(+0.75)
Actual stream cells correctly	270	86	143	237	250	251	256
identified (%)	(100)	(31.9)	(53.0)	(87.8)	(93.0)	(93.0)	(94.8)
Actual stream cells incorrectly	0	184	127	33	23	19	14
identified (%)	(0)	(68.1)	(47.0)	(12.2)	(8.1)	(7.0)	(5.2)
Nonstream cells correctly	5,785	5,601	5,658	5,731	5,737	5,735	5,768
identified (%)	(100)	(97.0)	(97.8)	(99.1)	(99.2)	(99.1)	(99.7)
Nonstream cells incorrectly	0	184	127	54	45	50	17
identified (%)	(0)	(3.2)	(2.2)	(0.9)	(0.8)	(0.9)	(0.3)
Total length of error streams (m)	0	2,109	1,481	974	758	929	410
(%)	(0)	(65.6)	(46.1)	(30.3)	(23.6)	(28.9)	(12.7)
Computer time required (minutes)	45	4	8	5	7	7	11

Methods
(a) DOQ-Derived Network
(b) USGS Hydrography
(c) Flow-Accumulation to Mimic USGS Hydrography
(d) Constant Flow-Accumulation Area
(e) Variable Flow-Accumulation Identified by Slope-Power Relationship
(f) Variable Flow-Accumulation Estimated by Multiple Linear Regression
(g) Stream Cells Identified by Logistic Regression

streams. At only slightly less explanatory power is slope at the channel head. As fluvial landscapes evolve, stream channels grow in length, penetrating relatively flat interfluves through erosion until they reach a point where upslope flow-accumulation area is inadequate to support a stream channel. In an incised plateau topography such as the Flint Hills, the topographic transition from the higher-elevation interfluves to the lower, base-level controlled, elevations within stream valleys creates a high slope at channel heads. Average slope is statistically significant because the proportion of precipitation that occurs as surface runoff is positively correlated with slope on all landscapes, but has less explanatory power. These results provide insight into the process of stream channel evolution and provide an excellent approach to the mapping of stream channels, but do not differentiate among the processes of incision by overland flow and erosion at pipeflow outlets (landsliding does not occur in this moderate-gradient landscape) as identified by Montgomery and Dietrich (1989).

Discussion and Conclusions

This article compares five existing methods and introduces two new methods for improved mapping of stream channel networks for use in hydrographic data layers in digital and traditional topographic mapping. It was found that existing USGS blue lines greatly underrepresent stream channel networks. Of five methods based on models using widely available DEM data, identifying stream cells using a logistic regression model estimated DOQ-derived stream channel networks most accurately.

Which of the methods described should be used to generate USGS hydrography data layers? Improved performance is accomplished at a cost of increased computer processing time (Table 6, bottom row). While the DOQ method does produce very accurate stream channel networks, it possesses two drawbacks. First, digitizing makes this method labor intensive. More importantly, it is severely limited to regions where DOQs are available and channel heads are visible on them. DOQs are not available for all areas, and woody vegetation in the headwaters obscures the channel sources in the DOQ images in most locations, particularly in the eastern portion of the United States. In arid climates, the low contrast of desert sands makes differentiating channel sources from hillslopes difficult, thus reducing the geographic areas where this method is applicable. As discussed above, our study site was, in fact, chosen as one of the few areas where DOQ data could be used as a source of ground truth for comparison to more widely applicable and less time-consuming methods based on DEM data. Therefore, while DOQs proved very accurate

as a source of ground truth in this study, a method other than DOQs is needed to map stream networks in the vast majority of cases.

Based on this study, the variable flow-accumulation method estimated by logistic regression is the best solution where DEM data are available. While the proposed methodology requires hydrologically corrected DEMs and considerable computer processing time, it produces quite accurate stream channel head locations and, therefore, stream network parameters such as drainage density. The total length of error streams was only 12.7 percent, only half the error rate of the next best DEM-based method. It therefore represents a means to greatly improve the accuracy of USGS blue lines and hydrographic representations on similar topographic maps over large regions in a straightforward manner. Given that existing blue lines were shown to make only errors of omission, not commission, in identifying streams, and given their superior depiction of meander patterns in higher-order streams, these blue lines could be used with the logistic regression method used to identify and locate low-order streams. One potentially significant use of these methods is to derive topographic channels from worldwide 1-arc-second DEMs (with approximately 30 m cell resolution) created as a result of the Shuttle Radar Topography Mission in 2000. Therefore, this method is quite accurate and widely applicable, and it is becoming even more so as the availability and quality of DEM data improves. However, elevation errors in the Shuttle DEM may negatively affect the accuracy of stream mapping by this and other DEM-based methods.

The primary question left unanswered is the generalizability of the specific variables and coefficients shown in Table 5. While the coefficients shown can be directly applied in other areas, accuracy would likely be improved by recalibrating the model using a sample of channel heads identified through local fieldwork. Further calibration and validation work to examine the change in significant independent variables and model coefficients in different climatic, land use, and topographic contexts would further improve the accuracy of the method for regions outside the Flint Hills study site used here. Ecoregions (Bailey 1983; Omernik 1987) would likely form a suitable geographic basis to explore the variability in these models.

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