Automated river terrace detection and morphometry using digital elevation models

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Abstract

Fluvial terraces hold clues for inferring landscape history, including river response to climate, tectonics, base level change, and the intrinsic instability of meandering streams. Terrace geometry offers a potentially valuable avenue for distinguishing these genetic mechanisms, both in the field and in theoretical models. However, field mapping is time-consuming and terraces are inconsistently noted on geologic maps. Where terraces are mapped, the maps must be digitized and combined with digital elevation models (DEMs) to extract comprehensive morphologic information. Moreover, limited methods exist to quantitatively compare terraces generated in computer models. To address these shortcomings, we have developed a largely automated method to detect river terraces in DEMs. The algorithm utilizes slope and curvature criteria, as well as local elevation of landscape elements with respect to nearby channels, to distinguish terrace areas. Localizing these areas enables extraction of a variety of topographic metrics. The algorithm can identify terraces in a variety of physiographic environments, including along the Mattole River, California, and the LeSueur River, Minnesota. In addition to its utility as a mapping tool, the terrace detection algorithm allows rapid comparison of terraces using widely available topographic data, which may reveal underlying patterns in river terrace formation.

Motivation

Fill and strath terraces are ubiquitous in river systems worldwide in a variety of tectonic and climatic environments [1-2], and serve as rare surface archives of drainage basin history. While most commonly interpreted to record drainage basin response to climate change [1-2, and references therein], river terraces are also likely to form in response to changes in base level due tectonics [3-5] and sea level [4,6], and due to intrinsic properties of meander growth and stream migration [e.g., 7]. Although terraces may be vitally important for interpreting millennial-timescale watershed history, disentangling the potential drivers for their formation remains a formidable task. We posit that terrace geometry offers a potentially valuable avenue for distinguishing genetic mechanisms, both in the field and in theoretical models.

Terraces are difficult to map in the field and time-consuming and subjective to map manually using topographic data (Fig. 1). In the case of computer simulations, few tools currently exist to identify and compare river terraces made in different models. We are aware of one existing semi-automated terrace detection algorithm, which generates longitudinal profiles of terrace pixel detections [8]. While such profiles are commonly used to infer changes in river slope through time, particularly in tectonics studies, this can lead to spurious terrace correlation [4]. Moreover, extracting metrics inherent to individual terraces requires methods to group terrace pixels based on adjacency in three dimensions.

To address these shortcomings, we have developed a largely automated algorithm to detect and quantitatively characterize river terraces in digital elevation models, using a limited number of empirical thresholds. The new method reduces errors in measurements of terrace elevation with respect to the channel inherent to an existing method [8], and through a graphical interface, allows the user to interactively tune the detection algorithm.

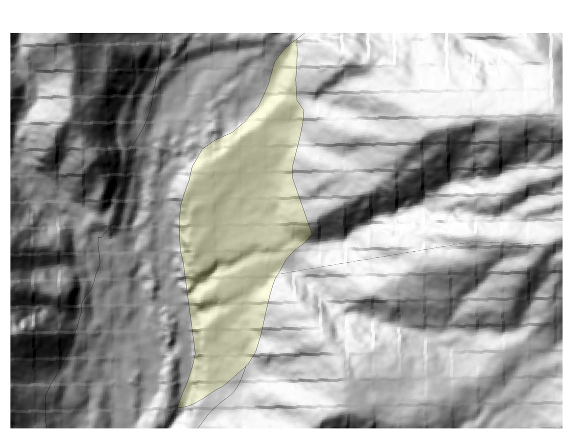

Figure 1. Fill terrace mapped along the North Fork San Gabriel River, California [9]. Mapped terrace includes portions of terrace riser and adjacent hillslope, which may introduce significant error to orientation calculations.

Algorithm

Using widely available National Elevation Dataset 1/3 arc second (~10 m in contental US) DEMs, preliminary tests have shown the algorithm to compare well with independently mapped terraces. Terraces are identified through the following process of elimination:

1. Crop DEM to study location and define stream centerline.
2. Identify regions with high density of pixels with high slope and curvature.
3. Assign each pixel a reference elevation corresponding to a nearby channel reach, using a steepest descent algorithm (Fig. 2).

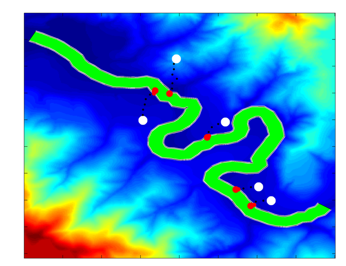

Figure 2. Illustration of steepest descent algorithm. Green polygon denotes buffer around Mattole River; warm colors indicate higher topography. Test points (white) are chosen, and a path of steepest descent is followed (black) until intersection with the channel buffer (green).

4. Produce inundation maps for different floodplain levels above the local channel elevation (Fig. 3); user selects one.

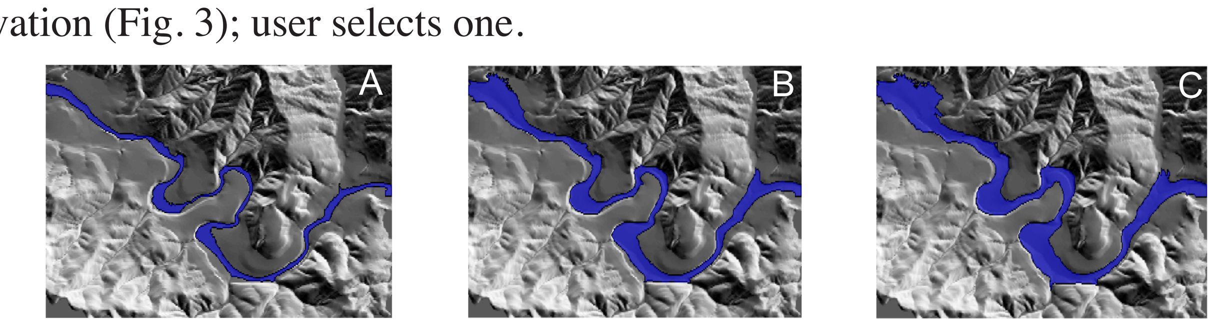

Figure 3. Modeled channel and floodplain along a portion of the Mattole River, California. Blue shaded areas correspond to pixels with elevations within the floodplain threshold, which equals the local channel elevation plus an additive constant. Local channel elevation for each pixel is determined using a path of steepest descent. **(A)** Floodplain 2 meters above local channel elevation; **(B)** 6 meters; **(C)** 10 meters.

5. Mask pixels that exceed slope or curvature thresholds, or do not exceed the local floodplain level (Fig. 4).

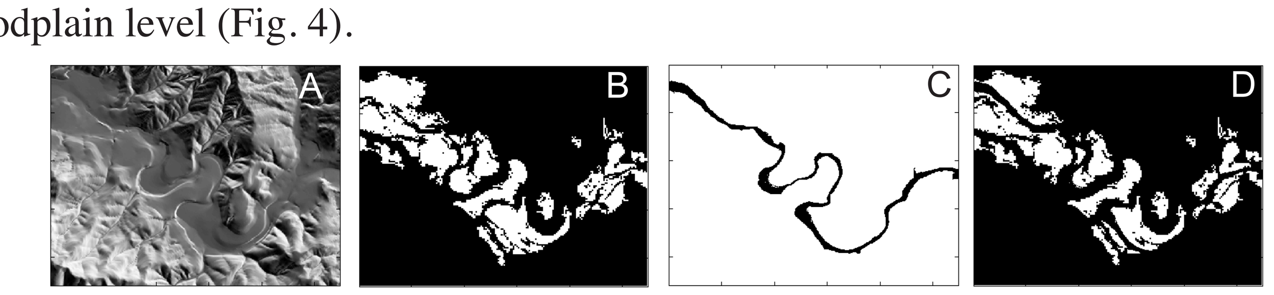

Figure 4. (A) Input topography; (B) Areas exceeding slope and curvature thresholds excluded (black); (C) Areas below local floodplain elevation excluded (black); (D) Remaining areas (white) treated as potential terraces.

6. Classify groups of pixels that exceed a critical area as terraces (Fig. 5).

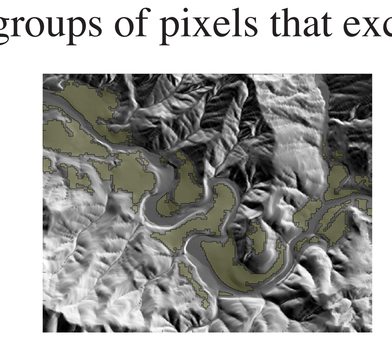

Figure 5. Terrace areas, shaded yellow, isolated from topography. Spurious detections can be removed manually using a graphical interface.

7. Extract morphologic information, including number of terraces, terrace area, mean elevation, slope and slope azimuth, width and length (approximated using a bounding ellipse), and surface roughness.

The terrace extraction algorithm functions most effectively in high-relief areas, where low terrace slope and curvature makes them distinct from surrounding hillslopes. In low-relief areas, utilizing a threshold elevation can aid in removing surrounding terrain (Fig. 6). False detections can be removed directly within the graphical user interface.

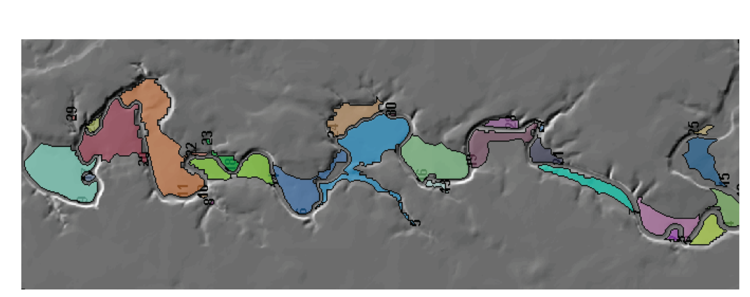

Figure 6. Detected terraces, LeSueur River, Minnesota. The surrounding low-relief areas caused false detections as terraces; however terrain flatness was exploited by filtering out all pixels above a threshold elevation. Despite river slope, the terraces are all inset below the surrounding plain.

Preliminary results and ongoing work

We are testing and improving the terrace detection algorithm in several locations, spanning environments with a large range of relief, rock type, and channel lateral and vertical erosion rates. Moreover, sites span a variety of tectonic settings, from the Texas Gulf coastal plain which experiences slow, progressive uplift, to terraces made in more active tectonic settings such as coastal California. In ongoing work at these sites, we endeavor to identify the primary drivers of terrace morphology. Figure 7 shows an example of orientation data gleaned from terraces along the LeSueur River. While most terraces dip west or east, comparison to valley trend shows that almost all terraces dip orthogonal to the valley axis. Because terraces in the region appear to have been abandoned by a series of migrating knickpoints following sudden baselevel fall [10], vertical erosion would be expected to have occurred in distinct phases. This would leave flat-topped terraces with steep risers. Our preliminary findings instead suggest that enough vertical erosion occurred during lateral bevelling of the terrace tread to result in a tread sloping perpendicular to the valley. In continuing work, we will investigate a variety of other metrics and compare results between sites where potential controlling factors (e.g., average rock uplift rate) can be constrained.

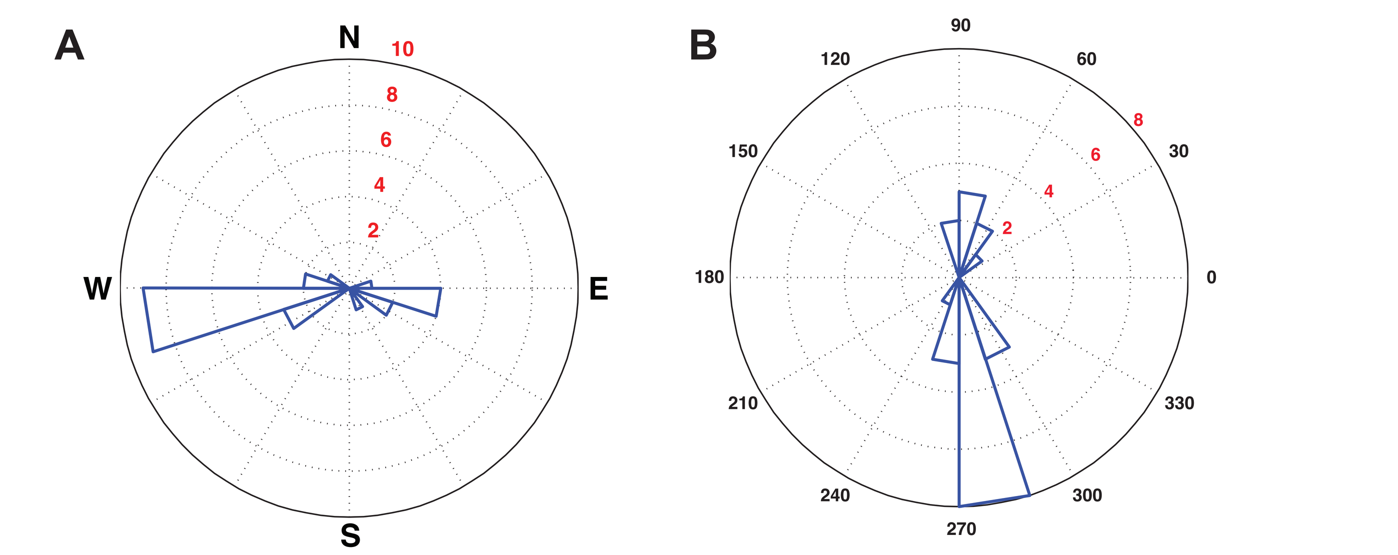

Figure 7. Terrace orientations along the reach of the LeSueur River shown in Fig. 6. **(A)** Dip direction. **(B)** Angle between terrace dip direction and the local, downstream-oriented valley centerline vector. The majority of terraces dip orthogonal to the valley trend (90 and 270 degrees).

Conclusions

- **Limited tools exist for automated terrace detection and morphometry.**
- **New algorithm identifies terraces with enhanced precision and reduced subjectivity using widely available topographic data.**
- **Algorithm works in areas of high and low relief, and can extract a variety of metrics related to terrace size, frequency, and orientation.**
- **Different forcing mechanisms may produce distinct geometries; once these links are known, the inverse problem could aid in distinguishing drivers of terrace abandonment and elucidate watershed responses to climatic and tectonic controls.**

References

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