Comparative study of wet channel network extracted from LiDAR data under different climate conditions
Changjun Liu, Longfan Wang, Zhuohang Xin and Yu Li

ABSTRACT
Temporal streams are vitally important for hydrology and riverine ecosystems. The identification of wet channel networks and spatial and temporal dynamics is essential for effective management, conservation, and restoration of water resources. This study investigated the temporal dynamics of stream networks in five watersheds under different climate conditions and levels of human interferences, using a systematic method recently developed for extracting wet channel networks based on light detection and ranging elevation and intensity data. In this paper, thresholds of canopy height for masking densely vegetated areas and the ‘time of forward diffusion’ parameter for filtering digital elevation model are found to be greatly influential and differing among sites. The inflection point of the exceedance probability distribution of elevation differences in each watershed is suggested to be used as the canopy height threshold. A lower value for the ‘time of forward diffusion’ is suggested for watersheds with artificial channels. The properties of decomposed and composite probability distribution functions of intensity and the extracted intensity thresholds are found to vary significantly among regions. Finally, the wet channel density and its variation with climate for five watersheds are found to be reasonable and reliable according to results reported previously in other regions.

Key words | climate, human impact, LiDAR, temporal stream, valley network, wet channel network

INTRODUCTION
Temporary streams, which naturally cease to flow and dry up along their course are essential to the integrity of the entire water environment (Acuña et al. 2014). Intermittently flowing streams have been found to greatly support the majority of river networks (Fritz et al. 2013). A conservative estimate shows that intermittent streams constitute more than 30% of the total length and discharge of the global river network (Tooth 2000). Raymond et al. (2013) indicated that about 69% of first-order streams and rivers at latitudes below 60° are flowing intermittently. Temporary stream networks undergo cycles of expansion, contraction, and fragmentation (Stanley et al. 1997); therefore, their temporal and spatial dynamics are of key importance for watershed hydrology and riverine and riparian vegetation (Williams 2006; Zimmer et al. 2013). Temporary streams host a unique combination of aquatic, amphibious, and terrestrial assemblages as a result of their wet and dry phases (Steward et al. 2012). Wishart (2000) found that in a temporary stream in southern Africa, when the flow recovers, the inundated terrestrial biota and accumulated detritus serves as a major food source for newly colonizing aquatic species. The dynamics of temporary streams is also associated with the surface–subsurface water exchanges as shallow subsurface water may flow continuously beneath the riverbed (Camporese et al. 2010).

Nowadays, many water courses that were once perennial also undergo temporary flow regimes due to the changing climate or as a result of anthropogenic effects,
such as water extraction, land use change, and reservoir construction and operation (Zhang et al. 2013, 2014). Therefore, a better recognition and understanding of temporary streams can mitigate the likelihood of natural hazards from various sources and systems, such as flood, water contamination, and ecosystem degradation.

Information on temporary streams and channels is usually limited due to less availability of monitoring data and relative inaccessibility of the site. Airborne light detection and ranging (LiDAR) has become one of the most promising remote sensing techniques for topographic data acquisition due to the fine spatial resolution and high accuracy. A number of studies have addressed the feasibility of LiDAR in extracting flow directions (Orlandini & Moretti 2009), channel networks (Pelletier 2013; Clubb et al. 2014; Rapinel et al. 2015; Hooshyar et al. 2016), wetland extent (Zlinszky et al. 2012; Allen et al. 2013), and topographic depressions (Le & Kumar 2014). As an active remote sensing system, LiDAR has also been widely utilized to derive hydraulic parameters (e.g., roughness, friction) in flood modeling (Mason et al. 2005; Casas et al. 2006) and to model the forest canopy cover (Nelson et al. 1988; Smith et al. 2009), canopy structure and underlying terrain (Nilsson 1996; Suárez et al. 2005) in the field of forest management. One of the key facts provided by LiDAR data is the signal intensity, which measures the return pulse from obstacles by the LiDAR sensor. The LiDAR sensor emits near-infrared (NIR) laser pulses with a wavelength of 1,064 nm that are almost entirely absorbed by water but reflected by other land surfaces; thus, the amount of radiation reflected by the water surface towards the sensor is often too low to be detected (Höfle & Pfeifer 2007; Brzank et al. 2008). Taking advantage of LiDAR intensity characteristics, many studies have demonstrated the success of LiDAR systems in mapping various types of water surfaces including rivers, wetlands, ponds, and lakes. Brzank et al. (2008) proposed a point-based fuzzy classification method that calculates the membership weights of water for each laser point using elevation, intensity, and point density. Höfle et al. (2009) demonstrated a method integrating the geometrical and intensity information of LiDAR point cloud that allows a high degree of automation and accuracy of water surface mapping.

Recently, utilizing the intensity and elevation information derived from topographic LiDAR system, Hooshyar et al. (2015) developed a systematic approach for mapping the wet channel networks. The validation of their extracted wet channel is performed by establishing a power law relationship between the wetted channel length and streamflow, which yields a scaling exponent lying within the range reported from fieldwork in other regions. However, application of the method is limited to the headwater catchment in the Lake Tahoe area in the USA, where streams are typically narrower and shallower, and less influenced by human interference. Therefore, striving for a widely practical use of the method, this study has the goal of assessing the applicability of the proposed method in five watersheds with different site characteristics (i.e., different climate conditions and levels of human interference). The impacts of two parameters (the threshold of canopy height and the time of forward diffusion) as well as the properties of probability distribution function (PDF) of intensity (e.g., the modes of decomposed PDFs and composite PDFs) among the five watersheds are analyzed, and systematic methods are proposed to determine the values of the two parameters for individual watersheds. Finally, the results of generated wet channel densities are compared with the values reported in previous studies in other regions.

STUDY SITES AND DATA SOURCE

Study sites

This study is focused on five watersheds in China and the USA as shown in Figure 1, including Tantou and Taowan in Henan Province, China, Twin Creek and Shotgun Creek in Idaho, and Kauai in Hawaii. The basic information for these study watersheds is summarized in Table 1. The climate conditions for the watersheds are different in the three regions and the levels of human interference vary in the watersheds. Tantou watershed covers an area of 4.9 km² extending in a northwest to southeast direction. The area has a warm temperate continental monsoon climate with an annual mean air temperature of approximately 13.5 °C. January has the coldest mean monthly temperature at below 0 °C, and July is the warmest month with a mean air temperature of 25 °C. The catchment receives about 850 mm of precipitation annually, with 62% of precipitation occurring during the flood season from June to September.
The Taowan watershed covers an area of 17.8 km² and is located in close proximity to Tantou watershed; therefore, the climate in these two watersheds is similar. The Twin Creek and Shotgun Creek watersheds, with a continental climate, are located in the Clearwater National Forest in north central Idaho. The drainage areas

(Zhang et al. 2015). The Taowan watershed covers an area of 17.8 km² and is located in close proximity to Tantou watershed; therefore, the climate in these two watersheds is

![Figure 1](https://iwaponline.com/hr/article-pdf/49/4/1101/538018/nh0491101.pdf)

**Table 1** Summary of study site characteristics and LiDAR information

<table>
<thead>
<tr>
<th>Watershed</th>
<th>Tantou</th>
<th>Taowan</th>
<th>Twin Creek</th>
<th>Shotgun Creek</th>
<th>Kauai</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basin area (km²)</td>
<td>4.9</td>
<td>17.8</td>
<td>24.4</td>
<td>16.1</td>
<td>28.8</td>
</tr>
<tr>
<td>Climate</td>
<td>Warm temperate continental monsoon</td>
<td>Warm temperate continental monsoon</td>
<td>Continental</td>
<td>Continental</td>
<td>Oceanic</td>
</tr>
<tr>
<td>Annual precipitation (mm)</td>
<td>850</td>
<td>850</td>
<td>1,000</td>
<td>1,000</td>
<td>1,200–2,500</td>
</tr>
<tr>
<td>Level of human impact</td>
<td>Medium</td>
<td>Strong</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>LiDAR system</td>
<td>RIEGL VUX</td>
<td>RIEGL VUX</td>
<td>Optech Gemini</td>
<td>Optech Gemini</td>
<td>Optech Gemini</td>
</tr>
<tr>
<td>Data source</td>
<td>IWHR</td>
<td>IWHR</td>
<td>NCALM</td>
<td>NCALM</td>
<td>NCALM</td>
</tr>
<tr>
<td>Point spacing (m)</td>
<td>0.20–0.70</td>
<td>0.20–0.70</td>
<td>0.54</td>
<td>0.48</td>
<td>0.62</td>
</tr>
<tr>
<td>Scan angle</td>
<td>±60°</td>
<td>±60°</td>
<td>±21°</td>
<td>±21°</td>
<td>±18°</td>
</tr>
<tr>
<td>Flight altitude (m)</td>
<td>350</td>
<td>350</td>
<td>650</td>
<td>650</td>
<td>1,100</td>
</tr>
<tr>
<td>Elevation accuracy (m)</td>
<td>0.22</td>
<td>0.22</td>
<td>0.05–0.30</td>
<td>0.05–0.30</td>
<td>0.05–0.30</td>
</tr>
</tbody>
</table>
of the two watersheds are 24.4 km² and 16.1 km², respectively. The mean annual precipitation is 1,000 mm and is unevenly distributed throughout the year; the dry season is from June to September. The Kauai watershed covers an area of 28.8 km² and the climate is generally mild and humid throughout the year. It has an oceanic climate with an annual precipitation of 1,200 to 2,500 mm. The average temperature ranges from 22 °C in February and March to 26 °C in August and September.

Among the five watersheds, Taowan suffers from strong anthropogenic impacts due to the high level of urbanization in the area, whereas the human impacts and urbanization are minimal in the other four watersheds.

**LiDAR and streamflow data**

Two sets of LiDAR data are utilized in this study, one for watersheds in China and the other for watersheds in the USA (Table 1). The LiDAR data for Tantou and Taowan watersheds were acquired using the RIEGL VUX LiDAR system and data were obtained from China Institute of Water Resources and Hydropower Research (IWHR) (Zhang et al. 2015). Each LiDAR return includes a spatial coordinate (X, Y, Z), intensity representing the strength of the reflected signal, and return number (first/last return). The LiDAR survey was carried out on October 25, 2014 with an approximate altitude of 350 m. The range of scan angle is ±60° and the vertical elevation accuracy is 0.22 m. The LiDAR cloud points are regularly distributed with the point space ranging from 0.2 to 0.7 m.

The LiDAR data for the Twin Creek, Shotgun Creek, and Kauai watersheds were provided by the National Center for Airborne Laser Mapping (NCALM) (http://www.opentopography.org), which is supported by the National Science Foundation (NSF). Data were acquired using an Optech ALTM Gemini LiDAR system at the altitude of 650 m for Twin Creek and Shotgun Creek watersheds and 1,100 m for Kauai watershed. The ranges of scan angle were ±21° and ±18°, respectively, and the vertical elevation accuracy ranged from 0.05 m to 0.30 m. The average spaces of LiDAR points for ground returns were 0.54 m, 0.48 m, and 0.62 m for Twin Creek, Shotgun Creek, and Kauai, respectively. The acquisition date covered 1 day for Twin Creek and Shotgun Creek watersheds, and 3 consecutive days for Kauai watershed. The ground returns of land surface and vegetation are utilized in this study and are further processed to derive the intensity map and digital elevation model (DEM) with a resolution of 1 m using ArcGIS 10.0 (ESRI, Redlands, CA).

Since there are no stream gages located inside the watersheds of Twin Creek, Shotgun Creek, and Kauai, the gages located 83 km (for Twin Creek and Shotgun Creek) and 6 km (for Kauai) downstream of the watersheds were utilized (Figure 1). Streamflow observations at the gages were obtained from the USGS National Water Information System. The hydrograph during the LiDAR acquisition dates are plotted in Figure 2. As shown in Figure 2(a), although the LiDAR acquisition date is during a hydrograph rising limb, it is, in a large time scale, at a recession period during the dry season. The hydrograph for Kauai shows that streamflow during the LiDAR acquisition period was dominated by base flow (Figure 2(b)). Therefore, all the three sites have a relatively low flow condition in which dry channels are expected. The streamflow condition at Tantou and Taowan are not available due to data limitation; however, precipitation occurred a few days prior to the LiDAR survey.

**METHODOLOGY**

The signal intensity of ground returns, normally represented by DN (digital number) units, is the main information that can be utilized to distinguish wet channels from dry ones. As water has a strong ability to absorb the light energy, the LiDAR intensity returned from water surface usually possesses lower values than that from a dry surface (Höfle et al. 2009). Figure 3 illustrates a LiDAR intensity map for the upper reach of the Shotgun watershed. The intensity value varies from 0 to 6,880 DN, from which, the wet channels can be visually identified by lower DN values. Based on the LiDAR intensity and elevation information generated from the LiDAR topographic system, Hooshyar et al. (2015) presented a systematic method that consists of six major steps for deriving wet channel networks. This methodology, originally applied to the headwater catchments in the USA, is tested herein for five watersheds to assess the adequacy and applicability for areas possessing different climate conditions and different levels of human impacts. The Shotgun watershed was selected to illustrate the procedures step by step.
Masking dense vegetation in intensity maps

LiDAR records the intensity of returned energy from each laser pulse, providing a record of the height distribution of the surface with different elevations illuminated by the laser pulse (Lefsky et al. 2002). The intensity maps of returns from the top of vegetation and the ground surface in Shotgun watershed are shown in Figure 4. It is noted that for vegetated areas, the intensity returned from the ground surface is relatively low and is comparable to that returned from the water surface due to energy absorption by vegetation. Therefore, to avoid erroneously classifying the ground surface under canopy as wet surface, it is essential to mask the densely vegetated areas from the intensity map.

Besides the intensity returns, the LiDAR data also provide elevations at different surfaces. In this study, a pixel is marked as densely vegetated if the elevation of canopy surface ($h_c$) is strongly higher than that of the ground surface ($h_g$). For this, a threshold factor $h_t$, representing the canopy height, is introduced to map the densely vegetated areas. Therefore, a pixel is marked as densely vegetated and is omitted from the intensity map if the condition in Equation (1) is satisfied:

$$h_c \geq h_g + h_t$$  \hspace{1cm} (1)

Note that $h_t$ varies with study regions considering the local canopy characteristics. A threshold value of 2 m was applied by Hooshyar et al. (2015). Considering the local canopy characteristics and its subsequent effects on wet pixel identification, $h_t$ is set to 3 m for Tantou, Taowan, Twin Creek, and Shotgun Creek watersheds, and 4 m for Kauai watershed. The impacts of $h_t$ are discussed further in the section ‘Results and discussion’. The identified densely vegetated areas using Equation (1) and the intensity map after masking out these areas are shown in Figure 5.

Extracting valley extent and network

Since wet channels lie within topographically convergent regions referred to as valley, it is more accurate and efficient
to first extract the valley extent from the entire watershed to constrain the potential areas of wet channel. Howard (1994) has proven that valley is associated with positive tangential curvature, whereas ridge has negative tangential curvature. Therefore, the tangential curvature is calculated based on the DEM following two steps: (1) the DEM was smoothed to reduce noise and eliminate insignificant features using a Perona–Malik filter (Perona & Malik 1990; Passalacqua & Foufoula-Georgiou 2015); (2) tangential curvature (κ) was computed using the following equation (Mitasova & Hofierka 1995; Hooshyar et al. 2016):

\[
\kappa = \frac{-Z_{xx}Z_y^2 - 2Z_{xy}Z_xZ_y + Z_{yy}Z_x^2}{(Z_x^2 + Z_y^2)^{3/2}} \sqrt{1 + Z_x^2 + Z_y^2}
\]

where \(Z_x\) and \(Z_{xx}\) (\(Z_y\) and \(Z_{yy}\)) represent the first and second derivative of elevation (\(z\)) with respect to \(x\) (or \(y\)). \(Z_{xy}\) is the first derivative of \(z_x\) with respect to \(y\).

In the first step of DEM smoothing, a parameter referred to as ‘time of forward diffusion’ and denoted by \(T_F\) was employed, which is the number of iterations for the numerical representation of derivatives for smoothing (Hooshyar et al. 2016). In this study, \(T_F\) was set to 50 for Tantou, Twin Creek, Shotgun Creek, and Kauai watersheds, and 2 for Taowan watershed. The impacts of \(T_F\) are discussed in the section ‘Results and discussion’. The tangential curvature map derived from a DEM is shown in Figure 6(a). Further, the valley extent is generated by imposing a relatively small curvature threshold (\(\kappa_v\)) to the curvature map.
The intensity return within the identified valley extent with the absolute value of curvature greater than or equal to \( \kappa_v = 0.025 \text{ m}^{-1} \) is shown in Figure 6(b). The final valley network is generated by eliminating the first-order valley segments with length less than 25 m.

Decomposing composite PDF of intensity

The signal intensity varies with land surface characteristics, and the variation can be represented by the PDF of intensity. Assuming the intensity from a single type of surface follows a Gaussian distribution, the composite PDF of intensity can be decomposed into several modes of Gaussian distributions, which can be represented by a Gaussian mixture model (GMM). GMM with \( N \) modes is given in Equation (3) (Rasmussen 1999):

\[
f(x|\mu_1, \ldots, \mu_N, \sigma_1, \ldots, \sigma_N, W_1, \ldots, W_N) = \sum_{i=1}^{N} w_i \times \mathcal{N}(x|\mu_i, \sigma_i)
\]  

where \( f \) is the Gaussian mixture distribution, \( \mathcal{N}(\mu_i, \sigma_i) \) is an individual Gaussian distribution for mode \( i \) with a mean of \( \mu_i \) and standard deviation of \( \sigma_i \), \( w_i \) is the weight or proportion of each mode that sums to unity for all values of \( i \).

As demonstrated by Hooshyar et al. (2015), three modes are considered for identifying a wet channel, two of which represent wet and dry surfaces, and one that represents transition areas. To estimate the mean, standard deviation, and weight corresponding to each mode in Equation (3) an expectation–maximization (EM) algorithm that alternates between the subsequent expectation (E-step) and maximization (M-step) steps is utilized (Moon 1996). The E-step creates an expectation function of the log-likelihood evaluated using the current estimate of the parameters, and the M-step computes parameters maximizing the expected log-likelihood based on the former E-step. In this study, the number of iterations and tolerance of the EM algorithm are set to \( 1.5 \times 10^4 \) and \( 1.0 \times 10^{-8} \), respectively. The PDF of intensity of each single mode for Shotgun watershed is illustrated in Figure 7.

After extracting the decomposed PDFs, two thresholds that are critical for further wet channel extraction are obtained: (1) \( I_w \) represents the intensity at the intersect of the wet and transition PDFs; (2) \( I_d \) represents the intensity at the intersect of the transition and dry PDFs.

Detecting edges

As water surfaces have lower intensity values than their surrounding surface, the edges at the border of wet channels are visually detectable, as shown in Figure 8(a). Here, the edges are detected using the Canny method (Canny 1986) based on the gradient of intensity returns. The intensity map is firstly smoothed using the Perona–Malik filter to
remove the noise and calculate the gradient of the image (Perona & Malik 1990), and then the magnitude and direction of the gradient are computed using Equations (4) and (5):

\[ d_l = \sqrt{I_x^2 + I_y^2} \]  

(4)

\[ \theta = \tan^{-1} \frac{I_y}{I_x} \]  

(5)

where \( I_x \) and \( I_y \) are the local intensity gradients in the horizontal and vertical directions. The local maximums of gradient are identified and marked as potential edges. The lower (\( d_{l_{\text{min}}} \)) and upper (\( d_{l_{\text{max}}} \)) gradient thresholds are defined to eliminate weak edges from the potential edges. Potential edge pixels with gradient larger than \( d_{l_{\text{max}}} \) are retained and marked as strong edges, while those with gradient less \( d_{l_{\text{max}}} \) are deleted if either of the two conditions is satisfied: (1) pixels with gradient between \( d_{l_{\text{min}}} \) and \( d_{l_{\text{max}}} \) if they are not connected to a strong edge; (2) pixels with gradient less than \( d_{l_{\text{min}}} \). The edges in the upper Shotgun watershed are detected by setting \( d_{l_{\text{min}}} \) and \( d_{l_{\text{max}}} \) to 60 DN and 80 DN, respectively (Figure 8(b)).

### Identifying wet pixels

The wet pixels are identified based on the decomposed intensity PDFs and the detected edges in the prior steps. Any pixel that satisfies either of the following two criteria is marked as wet: (1) pixels with intensity less than or equal to \( I_w \); (2) pixels with intensity higher than \( I_w \) and less than \( I_d \), and edges are detected within 1 m. The result of identified wet pixels for partial Shotgun watershed is shown in Figure 9.

### Generating wet channel network

The wet channel network is extracted based on the valley network delineated from the DEM and the wet pixels identified from the intensity returns, as explained above. However, Hooshyar et al. (2015) found that the valley network does not always overlie the wet pixels, leading to a disconnection of the wet channel network. With regard to this issue, three rules were applied for extracting wet
channels: (1) any valley pixel that has a wet pixel within 1 m is marked as wet; (2) for any 400 m long valley section starting from point p heading to downstream, if at least 50% of the section’s length is classified as wet, the point p is considered as a part of the wet channel network; (3) any first-order wet channel that has less than 20% of its length initially identified as wet pixels is eliminated. The resulting wet channel network is further processed manually to connect the segments which are isolated due to missing intensity data. An example of the valley network and the connected wet channel in the Shotgun watershed is shown in Figure 10.

RESULTS AND DISCUSSION

Threshold for canopy height

As stated above, the vegetated areas may be erroneously classified as wet surface since the intensity under canopy is comparable to that from water surface. In the ‘Methodology’ section, a threshold value \( h_t \) was introduced to mask out the densely vegetated areas based on the DEM and digital surface model. The threshold values are determined mainly with two considerations: (1) it should represent the minimum canopy height of densely vegetated areas; (2) the wet pixels can be properly identified in the further step after removing the densely vegetated pixels. The effects of canopy height thresholds on the PDFs of intensity were investigated taking the Kauai watershed as an example (Figure 11). Threshold values of 3 m, 4 m, 4.5 m, and 5 m were selected, since the year-round warmth, sunshine, and frequent passing showers have formed huge arrays of shrubs, vines, and high trees in the region, leading to relatively higher vegetation height. The wet and dry intensity thresholds extracted from the decomposed PDFs under different \( h_t \) are summarized in Table 2.

It is found that when \( h_t \) equals to 3 m, a large portion of the total PDF of intensity is occupied by the transition and dry modes (Figure 11(a)), and these two modes are not clearly distinguished. The reason is that more pixels are regarded as dense vegetation and those that have a lower
intensity are removed when the threshold is small. However, when \( h_t = 4 \) m, 4.5 m, and 5.0 m, the properties of PDFs are similar and they all shift to the lower intensity range compared with \( h_t = 3 \) m (Figure 11(b)–11(d)). In addition, when \( h_t \) is greater than 4 m, \( I_w \) and \( I_d \) do not change with \( h_t \) (Table 2), although the properties of PDFs vary slightly in terms of the peak values of each mode. The properties of PDFs and the extracted \( I_w \) and \( I_d \) values are not sensitive to the threshold when the threshold value is greater than 4 m. The impacts of the \( h_t \) value on the results of wet pixel extraction were also investigated. As shown in Figure 12(a), the distribution of wet pixel is more scattered compared with the other three values of \( h_t \) and many wet pixels are detected on the hillslope. As discussed above, a smaller canopy threshold (e.g., \( h_t = 3 \) m) will eliminate many lower intensity pixels, leading to a shift of PDFs towards higher intensity range, as well as a larger \( I_w \) (=17 DN) intensity threshold. Thus, compared with Figure 12(b)–12(d), the scattered wet pixels distributed on the hillslope are mostly those that have an intensity ranging from 12 DN to 17 DN.

When \( h_t \) is set as 4 m, 4.5 m and 5 m, the wet pixels are more connected and concentrated onto the valley extent (Figure 12(b)–12(d)). Given a relatively smaller \( I_w \) (=12 DN), the scattered wet pixels on the hillslope in Figure 12(a) are eliminated. There are no apparent distinctions on the spatial distributions of wet pixels among these three thresholds; the total number of wet pixels increased slightly with the increase of \( h_t \) due to the fact that less pixels were removed when a higher value of canopy height threshold was used. Since the final wet channels are

![Figure 11](https://iwaponline.com/hr/article-pdf/49/4/1101/538018/nh0491101.pdf)

**Table 2** | Wet and dry thresholds under different vegetation conditions

<table>
<thead>
<tr>
<th>Canopy height threshold ( h_t ) (m)</th>
<th>3.0</th>
<th>4.0</th>
<th>4.5</th>
<th>5.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I_w ) (DN)</td>
<td>17</td>
<td>12</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>( I_d ) (DN)</td>
<td>66</td>
<td>33</td>
<td>33</td>
<td>33</td>
</tr>
</tbody>
</table>
generated by overlaying the identified wet pixels onto the existing valley network, the increased wet pixels will not greatly affect the final wet channel extraction.

To better understand canopy height characteristics in the study area, the PDFs of elevation difference between the top of the canopy and the ground surface are plotted in Figure 13 for the five watersheds. To eliminate the noise in the data, the data with an elevation difference within the range of 1.5 m and 10 m were selected. All the figure panels show an inflection point, at which there is a transition for the slope of the curve. The transition point can be used as the threshold, since it indicates a general condition of the canopy height in the area. Therefore, in this study considering the local canopy characteristics and the PDFs of canopy height, a threshold value of 3 m is given for Tantou, Taowan, Twin Creek, and Shotgun Creek watersheds, and 4 m for Kauai watershed.

**Parameter for DEM filtering**

To extract the valley network, Perona–Malik filter was applied in this study to smooth the DEM, which employs a parameter referred to as time of forward diffusion, $T_F$. Higher values of $T_F$ produce rougher contours at channels and ridges, but reduce more noise and eliminate more insignificant features. After several trials of different values of $T_F$, it was found that in the watersheds of Tantou, Twin Creek, Shotgun Creek, and Kauai a value of 50, which was also suggested by Sangireddy *et al.* (2016) and Hooshyar *et al.* (2016), is appropriate in reducing...
Figure 13 | PDF of elevation difference between the top of the canopy and the ground surface, and the identified inflection point of each curve for (a) Tantou, (b) Taowan, (c) Twin Creek, (d) Shotgun Creek, and (e) Kauai watersheds.
the noise while simultaneously enhancing the local geomorphic features. This is because that in the areas with none or less human interference, the valleys are naturally formed in the convergent topography in the landscape and the edges can be easily detected. However, in the watershed like Taowan which suffers from considerable human activities and has many artificial channels, the value of 50 is found to result in an over-smoothing of the sharp edges. The hillshade images for partial Taowan under different values of DEM filtering parameter ($T_F$) were compared. The hillshade without DEM smoothing is shown in Figure 14(a), and the images with $T_F = 2$, 10, and 50 are shown in Figure 14(b)–14(d), respectively. The geomorphic features can be clearly seen without DEM filtering, including artificial channels and agricultural land.

With the increase of $T_F$ values, the images become more smoothed and the edges become obscure. Further results on the extracted valley network based on smoothed DEM with different $T_F$ values are shown in Figure 15. It is clear that the extracted valley network in Figure 15(a) ($T_F = 2$) most closely matches the real situation. When $T_F = 10$ and 50 (Figure 15(b) and 15(c)), valleys that do not really exist are generated as DEM getting smoother; this is further verified through the total valley length of 168 km, 202 km, and 203 km in Taowan watershed under $T_F = 2$, 10, and 50, respectively. Therefore, for the areas that have considerable human interference, a smaller $T_F$ is suggested for extracting the valley network since the over-smoothing of DEM obscures the edges of artificial channels.

Figure 14 | Hillshade images based on DEM smoothed with different settings of $T_F$: (a) without smoothing, (b) $T_F = 2$, (c) $T_F = 10$, (d) $T_F = 50$. 
As discussed above, the intensity thresholds, derived by decomposing the overall PDF of intensity into several individual Gaussian distributions, are essential for further differentiating wet and dry pixels. The PDFs of intensity along with the extracted modes (i.e., wet, transition, and dry) for four watersheds (Shotgun is shown in Figure 7) are shown in Figure 16. The wet ($I_w$) and dry ($I_d$) thresholds for the study watersheds are summarized in Table 3. The thresholds vary significantly among sites due to the differences in LiDAR sensor, scan angle, altitude change, atmospheric condition, and soil moisture. In Tantou watershed, the composite PDF presents a tardy increase at the lower intensity range, followed by a sharp increase when the intensity is larger than 600 DN (Figure 16(a)). This could be attributed to the precipitation that occurred a few days prior to the LiDAR survey, which increased the soil moisture and contributed to the formation of transition areas. The Twin Creek and Shotgun Creek watersheds are located in the same climate zone and are flown with the same LiDAR system, thus they have a similar property of decomposed PDF of intensity of wet, transition, and dry modes (Figures 16(c) and 7, respectively). The wet thresholds are both identified as 29 DN, and the dry thresholds are 97 DN and 88 DN, respectively. The composite PDFs tend to shift to the larger intensity range, indicating a relatively dry condition in the areas. In the Kauai watershed, the wet and transition surfaces occupy a relatively larger proportion of the total area, and the composite PDF shows a more rapid
increase rate at lower intensity range (Figure 16(d)). These may be due to the relatively larger annual precipitation as well as the mild and humid climate all year round in the region.

As stated above, three modes corresponding to the surface types of wet, transition, and dry, are considered appropriate for watersheds less influenced by human activities. This is also true for the five watersheds predominantly covered by forest and shrub areas around Lake Tahoe, as reported by Hooshyar et al. (2015). However, in the Taowan watershed presented here, only two types of ground surface, wet and dry modes, are generated through the decomposing process (Figure 16(b)). This is probably due to the strong human activities in the area that further result in a complexity of land cover, low soil moisture, and minimal transition areas. In this case, \( I_w \) is defined as the intensity at the intersection of the wet and dry PDFs.

### Wet channel network

The methodology discussed above is employed to extract wet channel networks for the five watersheds, as presented in Figure 17. The associated valley length, wet channel length as well as valley density and wet channel density that are defined as the ratio of valley length and wetted channel length to total drainage area, respectively, are

### Table 3  
The wet \( (I_w) \) and dry \( (I_d) \) thresholds, valley length, wet channel length, valley density, and wet channel density for the five watersheds

<table>
<thead>
<tr>
<th>Watershed</th>
<th>Tantou</th>
<th>Taowan</th>
<th>Twin Creek</th>
<th>Shotgun Creek</th>
<th>Kauai</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I_w ) (DN)</td>
<td>611</td>
<td>480</td>
<td>29</td>
<td>29</td>
<td>12</td>
</tr>
<tr>
<td>( I_d ) (DN)</td>
<td>1,075</td>
<td>–</td>
<td>97</td>
<td>88</td>
<td>33</td>
</tr>
<tr>
<td>Valley length (km)</td>
<td>67.8</td>
<td>168.3</td>
<td>192.3</td>
<td>85.3</td>
<td>203.2</td>
</tr>
<tr>
<td>Wet channel length (km)</td>
<td>11.3</td>
<td>36.3</td>
<td>20.0</td>
<td>16.3</td>
<td>72.4</td>
</tr>
<tr>
<td>Valley density (km/km²)</td>
<td>13.8</td>
<td>9.4</td>
<td>7.9</td>
<td>5.3</td>
<td>7.0</td>
</tr>
<tr>
<td>Wet channel density (km/km²)</td>
<td>2.3</td>
<td>2.0</td>
<td>0.8</td>
<td>1.0</td>
<td>2.5</td>
</tr>
</tbody>
</table>
summarized in Table 3. The valley density varies among sites due to geologic and topographic characteristics of the watersheds. The total wet channel length for Tantou and Taowan watersheds are 11.3 km and 36.3 km, respectively. The wet channel density in Tantou is 2.3 km/km², which is higher than that in Taowan of 2.0 km/km². Since these
two watersheds have a similar climate condition and the LiDAR surveys were conducted using the same system on October 25, 2014, the small discrepancy in wet channel density is due to the different levels of human impact, i.e., Tantou watershed is less influenced by human activities so that the natural condition (e.g., canopy cover) beneficial to the formation of wet channels is largely maintained. In addition, precipitation occurred a few days prior to the LiDAR surveys at Tantou and Taowan watersheds, resulting in relatively larger wetted channel density in these two watersheds although the mean annual precipitation is low.

Two watersheds, Twin Creek and Shotgun Creek, are in close proximity with similar climate conditions. The wet channel density is calculated at 0.8 km/km² and 1.0 km/km², respectively, which are smaller compared with the other three watersheds. This indicated a dry condition during the data acquisition dates in the dry season (June to September) of the year when the soil moisture is low. The Kauai watershed has the largest wetted channel density of 2.5 km/km² among all watersheds, and nearly half of the extracted valley is covered with wet surface (Figure 17(e)). This can be attributed to the relatively larger annual precipitation and the mild and humid climate all year round.

The generated wet channel density for five study watersheds ranges from 0.8 to 2.5 km/km², which is comparable to the results previously reported by Hooshyar et al. (2015). Results in watersheds with different climate conditions in this study indicate that generally wet channel density increases with increasing rainfall amount. This is in accordance with the results from Wang & Wu (2013), that the stream density is inversely proportional to the climate aridity index defined as the ratio of potential evaporation to precipitation. Therefore, the wet channel extraction method developed by Hooshyar et al. (2015) appears to be applicable to various watersheds that possess different characteristics in terms of the local climate conditions and levels of human impact.

CONCLUSIONS

Temporary streams that naturally and periodically cease to flow along their course are vitally important for stream hydrology and biotic health. As such, a better recognition and understanding of wet channel networks is essential for ecological management and conservation. Based on the LiDAR elevation and intensity data, this study investigated the temporal dynamics of stream networks using a systematic method for extracting the wet channel network in five watersheds considering different climate conditions and levels of human interferences.

In this paper, the variations of canopy height threshold ($h_i$) and time of forward diffusion ($T_F$) among watersheds were assessed. The effects of canopy height threshold on wet intensity threshold ($I_w$) and wet pixels were analyzed. It was found that $I_w$ and wet pixel distributions are not sensitive to the threshold $h_i$ when it is greater than a certain value. The inflection point of the exceedance probability distribution of elevation differences in each watershed is suggested to be used as the canopy height threshold. As well, the impacts of $T_F$ on DEM filtering and valley network extractions were investigated in the Taowan watershed where considerable human interference exists. A lower $T_F$ value (=2) is suggested for the Taowan watershed since the edges of artificial channels can be clearly detected when DEM is reasonably smoothed.

The results generated at each step during the processes of wet channel extractions for five watersheds were compared and analyzed. Generally, the composite intensity PDF can be decomposed into three modes, referred to as wet, transition, and dry modes; whereas for Taowan watershed, only wet and dry modes could be generated, indicating a minimum effect from transition zones in the area. In addition, properties of the composite PDFs and the decomposed individual PDFs of intensity behave differently among the three regions (Taowan and Tantou, Twin Creek and Shotgun Creek, and Kauai) due to the differences in climate conditions, levels of human impact, and LiDAR acquisition systems. Finally, the generated wet channel density and the change in density with climate conditions were found to be reasonable and reliable according to results reported previously in other regions.

The comparative analysis conducted in this study emphasized the applicability of the proposed method using different LiDAR systems and parameter settings (e.g., point density, scan angle and altitude, canopy height, time of forward diffusion), and more importantly, it has provided
valuable insights for understanding the temporal dynamics of stream networks in various watersheds considering different climate and human interference conditions.

ACKNOWLEDGEMENTS

This research was supported by the Special Public Welfare Research Fund of Ministry of Water Resources of China (Grant No. 201401014-2), the National Natural Science Foundation of China (Grant No. 51279021), and the projects of Application of remote sensing on water and soil conservation in Beijing and its demonstration (Z161100001116102), Key technology on dynamic soil conservation in Beijing and its demonstration projects of Application of remote sensing on water and foundation of China (Grant No. 51279021), and the National Natural Science Research Fund of Ministry of Water Resources of China (Grant No. 201401014-2), the National Natural Science Foundation of Ministry of Water Resources of China (Grant No. Z161100001116102), Key technology on dynamic warming of flash flood in Henan Province (China) and its application (HNSW-SHZH-2015-06), Study on infiltration mechanisms of special underlying surface in coalmine goaf in Shanxi Province (China) and application of runoff generation and concentration theory (ZNGZ2015-008_2), and Research on spatio-temporal variable source runoff model and its mechanism (JZ0145B2017).

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First received 4 November 2016; accepted in revised form 30 April 2017. Available online 8 June 2017.