

Improving River Flood Extent Delineation From Synthetic Aperture Radar Using Airborne Laser Altimetry

Article

Published Version

Mason, D. C. ORCID: <https://orcid.org/0000-0001-6092-6081>, Horritt, J. T., Dall'Amico, J. T., Scott, T. R. and Bates, P. D. (2007) Improving River Flood Extent Delineation From Synthetic Aperture Radar Using Airborne Laser Altimetry. IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 45 (12). pp. 3932-3943. ISSN 0196-2892 doi: <https://doi.org/10.1109/TGRS.2007.901032> Available at <https://centaur.reading.ac.uk/860/>

It is advisable to refer to the publisher's version if you intend to cite from the work. See [Guidance on citing](#).

To link to this article DOI: <http://dx.doi.org/DOI:10.1109/TGRS.2007.901032>

Publisher: IEEE Geoscience and Remote Sensing Society

Publisher statement: ©2007 IEEE. Personal use of this material is permitted. However, permission to reprint/republish this material for advertising or promotional purposes or for creating new collective works for resale or redistribution to servers or lists, or to reuse any copyrighted component of this work in other works must be obtained from the IEEE.

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in

the [End User Agreement](#).

www.reading.ac.uk/centaur

CentAUR

Central Archive at the University of Reading

Reading's research outputs online

Improving River Flood Extent Delineation From Synthetic Aperture Radar Using Airborne Laser Altimetry

David C. Mason, Matthew S. Horritt, Johanna T. Dall'Amico, Tania R. Scott, and Paul D. Bates

Abstract—Flood extent maps that are derived from synthetic aperture radar (SAR) images provide spatially distributed data for validating hydraulic models of river flood flow. The accuracy of such maps is reduced by a number of factors, including variation in backscatter from the different land cover types that are adjacent to the flood, changes in returns from the water surface that are caused by different meteorological conditions, and the presence of emergent vegetation. This paper describes how improved accuracy can be achieved by modifying an existing flood extent delineation algorithm to use airborne laser altimetry [light detection and ranging (lidar)] as well as SAR data. The lidar data provide an additional constraint that waterline heights should vary smoothly along the flooded reach. The method was tested on a SAR image of a flood for which contemporaneous aerial photography existed, together with lidar data of the unflooded reach. The waterline heights of the SAR flood extent that was conditioned on both SAR and lidar data matched the corresponding heights from the aerial photograph waterline significantly more closely than those from the SAR flood extent that was conditioned only on SAR data. For waterline heights in areas of low slope and vegetation, the root-mean-square error on the height differences reduced from 221.1 cm for the latter case to 55.5 cm for the former.

Index Terms—Data fusion, hydrology, lidar, snake.

I. INTRODUCTION

FLOOD extent maps that are derived from remotely sensed data are of considerable use in hydrology, providing spatially distributed data for validation of hydraulic models of river flood flow, for emergency flood relief management, and for development of spatially accurate hazard maps [1], [2]. The all-weather day–night capability of synthetic aperture radar (SAR) sensors gives these a considerable advantage for flood mapping over sensors operating at visible or infrared wavelengths, as the latter ones are unable to penetrate the cloud that often accompanies flood events. This advantage is tempered by the fact that a number of factors conspire to reduce the accuracy of flood maps that are derived from SAR imagery. These include the

substantial variation in backscatter from the different land cover types that are adjacent to the flood, the changes in returns from the water surface that are caused by different meteorological conditions, the presence of emergent vegetation, and the effects of man-made structures in urban areas. This paper describes a study to reduce inaccuracies from some of these sources in an existing flood extent delineation algorithm by using an additional data source, namely, airborne laser altimetry.

The simplest model of SAR backscatter from a river flood assumes that the water surface is smoother than the surrounding land and acts as a specular reflector, reflecting radiation away from a side-looking sensor, so that the water appears dark compared to the land. Two factors complicating the simple specular reflection model in practice are the effects of wind or rain roughening of the water surface, and emergent vegetation. The relationship between SAR backscatter and surface roughness that is caused by wind blowing over the oceans is well understood [3], and the effect may raise the backscatter from the water to similar or greater levels than the adjacent land [4], [5]. Wind roughening of a river flood surface can give rise to similar effects, but these can have substantial spatial variation, depending on the local topography, which determines the fetch for a given wind direction. The presence of emergent vegetation can give rise to multiple reflections between the water and the vegetation, leading to a substantial enhancement of backscatter, the magnitude of which is a function of radar wavelength, look angle, and polarization. The effect has been observed in a number of studies of flooded forest and marshland (e.g., [6]–[9]), and the increase in backscatter has been modeled mathematically in [10]. Enhanced backscatter from the water surface that is caused by wind roughening or emergent vegetation will also result in an increased level of noise due to the multiplicative nature of noise in SAR images.

A number of methods for the automated delineation of flood extent in SAR imagery of both fluvial and tidal environments have been developed [4], [5], [9], [11]–[21]. Several of these studies have illustrated the great potential of SAR sensors for synoptic observation of large flooding events. An automatic technique for delineating a fluvial flood using a statistical active contour model (or snake) that is applied to a SAR image to identify areas of homogeneous speckle statistics is described in [18] and [19]. This assumes that single-frequency single-polarization SAR intensities are available and was aimed at producing an observed flood extent against which to validate

Manuscript received October 9, 2006; revised March 26, 2007. This work was supported in part by the EPSRC-funded Flood Risk Management Research Consortium Grant GR/S76394/01.

D. C. Mason, J. T. Dall'Amico, and T. R. Scott are with the Natural Environment Research Council Environmental Systems Science Centre, University of Reading, RG6 6AH Reading, U.K.

M. S. Horritt is with Halcrow Group Ltd., W6 7BY London, U.K.

P. D. Bates is with the School of Geographical Sciences, University of Bristol, BS8 1SS Bristol, U.K.

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TGRS.2007.901032

86 a modeled flood extent. Due to the difficulties of imaging urban
 87 areas using SAR, its use is limited to large-area mapping of
 88 floods in rural areas. The SAR segmentation uses both local
 89 tone and texture measures, and is capable of accurate feature
 90 boundary representation. The method was applied to a flood
 91 that was imaged using the ERS-1 satellite SAR sensor and
 92 proven to be capable of identifying 75% of the flooded area
 93 correctly, with 70% of the waterline coinciding with ground
 94 data within 20 m. The main error in waterline position was
 95 found to be due to unflooded short vegetation that was adjacent
 96 to the flood giving similar radar returns to open water, causing
 97 an overestimation of flood extent. The loss of flood extent due
 98 to emergent vegetation was found to be a secondary source
 99 of error.

100 Further work on this topic [22], [23] found that, as a result of
 101 these error sources and the relatively large size of the European
 102 Remote Sensing Satellite (ERS) SAR pixel, the heights of the
 103 SAR waterline along a flooded reach could sometimes be in
 104 error by several meters (although, generally, it was much less)
 105 and could exhibit significant noise. One reason for this was that
 106 there was no constraint that the waterline heights should vary
 107 smoothly along the reach, whereas, in reality, the longitudinal
 108 slope of typical flood flows is low ($\sim 0.001\text{--}0.0001\text{ m} \cdot \text{m}^{-1}$),
 109 and changes in slope are very gradual. With this level of dif-
 110 ferences, the SAR image becomes much less useful for model
 111 flood extent validation than it could otherwise be.

112 Horritt *et al.* [19] point out that their flood extent map-
 113 ping procedure identifying the flood as a region of rela-
 114 tively homogeneous speckle statistics may be improved by
 115 the adoption of a model-based approach. In this vein, this
 116 paper describes the use of light detection and ranging (li-
 117 dar) data to modify the SAR waterline, so that it becomes
 118 more useful for validation. The snake algorithm [18], [19]
 119 is modified to look not only at SAR image space but also
 120 at lidar digital terrain model (DTM) and vegetation height
 121 maps, so that the snake can be conditioned to be smoothly
 122 varying in ground height as well as in SAR intensities and
 123 textures. This should reduce errors that are caused by un-
 124 flooded vegetation that is adjacent to the flood giving similar
 125 returns to open water and also errors due to the SAR pixel
 126 size. It could also help somewhat in reducing errors due to
 127 emergent vegetation. An additional benefit of producing a
 128 more smoothly varying waterline is that it may allow the
 129 development of improved performance measures for flood ex-
 130 tent validation based on patterns of height differences rather
 131 than on patterns of wet or dry pixels, as currently done [24].
 132 The algorithm specifically sets out to improve the vertical
 133 accuracy of the SAR waterline, although any improvement
 134 should also lead to improvement in the horizontal waterline
 135 accuracy due to their correlations that are contained within
 136 the DTM.

137 Used in this way, the lidar data may actually play a dual
 138 role in the modeling process, as lidar is often used to pa-
 139 rameterize the hydraulic model being validated, with the li-
 140 dar DTM providing the model bathymetry and possibly the
 141 vegetation heights being used to estimate bottom friction
 142 [22]. However, the use of lidar data in SAR waterline ex-
 143 traction as well as model parameterization does not under-

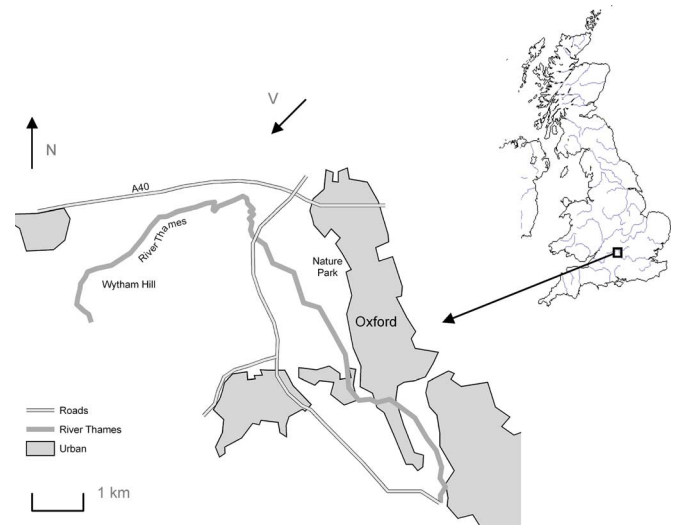


Fig. 1. Location of the test area.

mine the independence of the SAR waterline in the validation
 process.

II. TEST DATA SET

An ideal data set on which to validate the method would be
 from a flood for which both satellite SAR data and simultaneous
 aerial photography were available, so that the SAR snake
 waterlines that are conditioned without and with the lidar data
 could be compared with the waterline from the aerial pho-
 tographs. In addition, lidar data of the unflooded area should be
 available.

Biggin and Blyth [25] acquired oblique aerial photos of a
 flood on the Thames west of Oxford, U.K., on December 4,
 1992, at the same time (to within 2 h) as an ERS-1 SAR
 overpass of the area. The Thames is a low-relief slow-response
 catchment, and at this point along its course, the river discharge
 during a flood changes only very gradually, so that such timing
 differences are unimportant. The peak discharge for this event
 was measured at $76\text{ m}^3 \cdot \text{s}^{-1}$, which represents a $\sim 1\text{-in-5-year-}$
 recurrence interval flow. The ERS-1 SAR image was acquired
 approximately 36 h after the flood peak when the discharge had
 dropped to $73\text{ m}^3 \cdot \text{s}^{-1}$, indicating the very slow response of the
 catchment. At the time of overpass, there was no wind or rain in
 the area. The location of the test area is shown in Fig. 1, and an
 example of the aerial photography is shown in Fig. 2. The flood-
 plain over this reach is semirural, with the majority of fields
 being used at the time for pasture or having been ploughed.
 There are also several urban areas, and the region is crossed
 by a number of major roads and railways. The flood waterline
 was delineated by eye from the aerial photos and vectorized
 [19]. The waterline vectors were then georeferenced using an
 orthographic transform that is parameterized by a least squares
 method using 15–20 control points for each photograph. The
 error in the waterline position was assessed from waterline
 segments where the waterline was observed to lie alongside a
 hedgerow or field boundary that could be located on a 1 : 25 000
 scale map and was found to be less than 20 m.



Fig. 2. Example of the aerial photography in the upper section of the reach, looking southwest from the north of the region (the view direction is V in Fig. 1).

Lidar data at 1-m resolution were acquired for a section of this reach west of Oxford and approximately 12 km long by the Environment Agency of England and Wales (EA). The lidar was an Optech ALTM 2033 that was flown on a Cessna aircraft at 120 kn at a flying height of 900 m, with a laser firing rate of 33 kHz, a scanning frequency of 30 Hz, and a scanner half angle of 18°. The lidar heights were validated by the EA by comparing them with a set of global positioning system (GPS) heights of several flat unvegetated surfaces in the area. Based on a sample of 299 GPS readings, the lidar heights were found to have an rms error of 10.6 cm, which comprised a random error of 10.2 cm and a systematic error of 2.6 cm. Lidar height accuracy reduces on steeper slopes and in vegetated regions [26]. Lidar positional accuracy was about 0.4 m [27]. The postprocessed lidar DTM and vegetation height mask were obtained from the EA. These were degraded to 2-m pixel size to avoid too large a mismatch with the SAR pixel size of 12.5 m. Fig. 3 shows the lidar DTM with the high land of Wytham Hill in the west and the raised Oxford Nature Park in the east (see Fig. 1), both of which are relevant to this study. Fig. 3 also shows the aerial photo waterline overlain on the lidar DTM, with the waterline color representing its difference in height from the local mean waterline height (within 0.5-km distance). The presence of large sections of waterline having small differences (blue color) from the local mean height indicates that the aerial waterline height varies smoothly along the reach. The waterline includes instances of islands of higher ground that are surrounded by water. It is assumed here that all areas of water have been accurately mapped, so that the validation data are essentially error free.

III. FLOOD EXTENT EXTRACTION FROM SAR DATA

A. Algorithm Description

A detailed description of the algorithm to delineate a flood using an active contour model is given in [18], and only an overview is presented here. Active contour models or snakes are useful for converting incomplete or noisy edge maps into smooth continuous vector boundaries [5], [28]. The edge image space is searched using a dynamic curvilinear contour that is driven to be attracted to edge pixels using an energy minimization function, so that the contour can link together unconnected edge segments. The contour (snake) is represented in a piecewise linear fashion as a set of nodes (i.e., the coordinates of the snake points) that are linked by straight-line segments. Ivins and Porrill [29] developed a statistical snake that operates on the image itself rather than an edge image, dispensing with the need for a prior edge detection stage. Their technique involves estimating the local image mean intensity (tone) at a node using the pixels between this node and its adjacent nodes. This gives the advantage that noise due to SAR speckle is reduced by averaging pixel intensities along an edge while, at the same time, maintaining resolution that is perpendicular to the edge, giving accurate edge positioning. The local intensity variance (texture) is also calculated from these pixels, as this has proven to be a useful discriminator between different natural land cover types having similar mean intensities in SAR imagery.

The statistical snake is formulated as an energy minimization problem with the total snake energy $E(\mathbf{u}(s))$ given by

$$E(\mathbf{u}(s)) = E_{\text{tension}} + E_{\text{curvature}} - \iint G(I(x, y)) dx dy \quad (1)$$

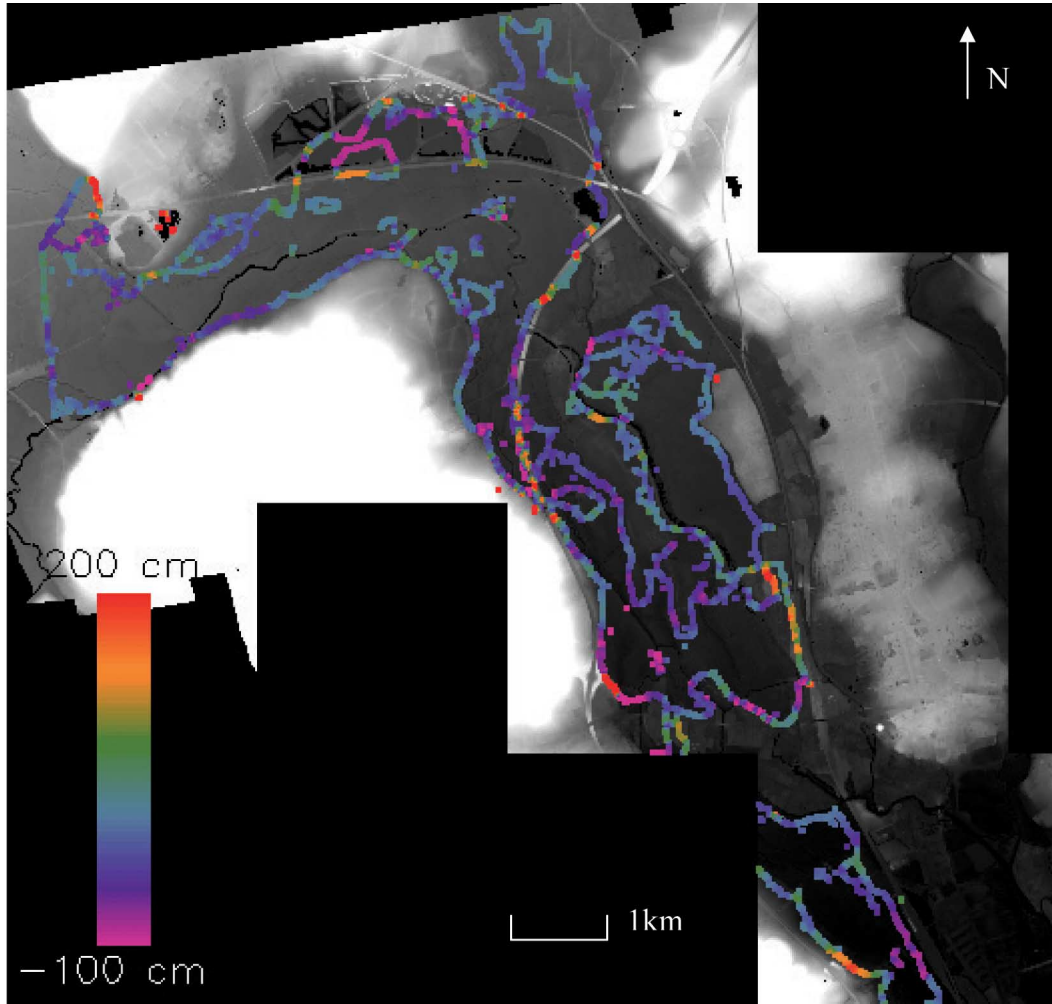


Fig. 3. Aerial photo waterline overlay on the lidar DTM. The colors represent the difference in height of the waterline from the local mean waterline height.

where $\mathbf{u}(s) = (x(s), y(s))$ describes the contour position (x, y) in the 2-D image space as a vector function of arc length parameter s . E_{tension} and $E_{\text{curvature}}$ are energies that are generated by the model's internal tension and stiffness constraints, which favor a smooth uncrenellated contour that is made up of evenly spaced nodes (see the following). G is a goodness function that assesses how well a set of image pixels $I(x, y)$ meets certain criteria. The total energy is minimized if the contour encloses a region of pixels that is homogeneous in tone and texture.

If the mean and variance of the intensities of the set of pixels that are immediately at either side of a particular snake node are measured, the knowledge of how these variables are distributed can be used to estimate the probability that these pixels match those that are already within the region that is enclosed by the contour. Horritt [18] relates G to the log of this probability, with the dependence on the measured sample mean μ' , for example, having the form

$$G(\mu') = 1 - n(\mu' - \mu)^2 / vk^2 \quad (2)$$

where μ and v are the mean and variance of the seed population that is already enclosed within the contour, respectively; n is

the sample size; and k is a parameter that can be adjusted to tune algorithm performance. G is then equal to 1 for a set of pixels with the expected mean but falls to zero if the mean differs by $k\sqrt{(v/n)}$ (i.e., k standard deviations) from the expected value. The parameter k is usually set at about 2 or 3 but may be increased further to allow for a level of statistical inhomogeneity in the region being segmented. The overall goodness function (with components that are based on both the measured mean and variance) is limited to a minimum value of -1 .

The roles of the tension and curvature constraints are to produce a contour of appropriate smoothness with evenly spaced nodes, by a consideration of the balance between image and curvature forces. Consider the situation that is shown in Fig. 4 for snake nodes at $\mathbf{u}_{i-1}$, $\mathbf{u}_i$, and $\mathbf{u}_{i+1}$ that are linked by unit vectors $\mathbf{v}_i$ and $\mathbf{v}_{i+1}$. The local curvature is $\Delta\theta/\Delta s$, where $\Delta\theta$ is the change of angle along arc length Δs . Horritt [18] gives the contribution to the total curvature energy as

$$\Delta E_{\text{curvature}} = \gamma(\Delta\theta/\Delta s)^2/\Delta s = \gamma|\mathbf{v}_{i+1} - \mathbf{v}_i|^2/a_i \quad (3)$$

where a_i is the distance between the midpoints of $\mathbf{v}_i$ and $\mathbf{v}_{i+1}$, and γ is a curvature energy weighting parameter. Equation (3)

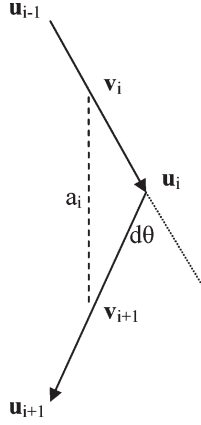


Fig. 4. Vectors for describing curvature and tension energies (after [18]).

278 is valid for small values of $\Delta\theta$. Similarly, the contribution to
279 the tension energy is given by

$$\Delta E_{\text{tension}} = \lambda (|\mathbf{u}_{i+1} - \mathbf{u}_i|^2 + |\mathbf{u}_i - \mathbf{u}_{i-1}|^2) \quad (4)$$

280 where λ is the tension energy weighting parameter. The mag-
281 nitudes of these energies can be adjusted using the weighting
282 parameters. Too large a value for the curvature parameter
283 will make the curvature term dominate the model energy and
284 produce an unrealistically smooth contour. Too large a value of
285 the tension parameter will favor a short contour and stifle the
286 growth of the snake.

287 The scheme that was used to minimize the energy is the
288 algorithm of Williams and Shah [28]. For each node at each
289 iteration, the change in energy dE is computed for moves to all
290 eight neighbors of the node

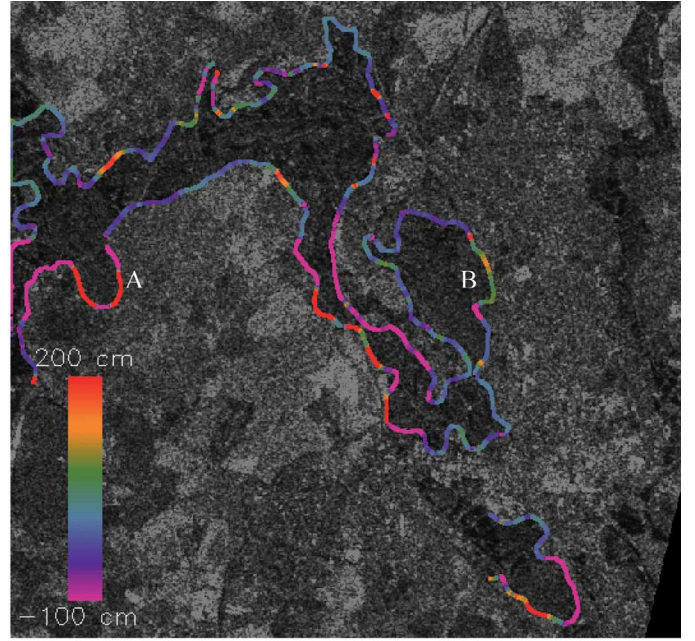
$$dE = -GdA + dE_{\text{tension}} + dE_{\text{curvature}}. \quad (5)$$

291 The lowest (most negative) dE is chosen. Obviously, dE is
292 equal to zero for no node movement. G is calculated along the
293 line segments linking the node with its two neighbors, and dA is
294 the local change in area. If G is positive, the snake is in a region
295 of homogeneous pixels, a positive dA is favored, and the snake
296 expands. If G is negative, the snake is in an inhomogeneous re-
297 gion, a negative dA is favored, and the snake retreats. The mean
298 and standard deviation of the seed population are calculated
299 from all pixels lying inside the contour every ten iterations.

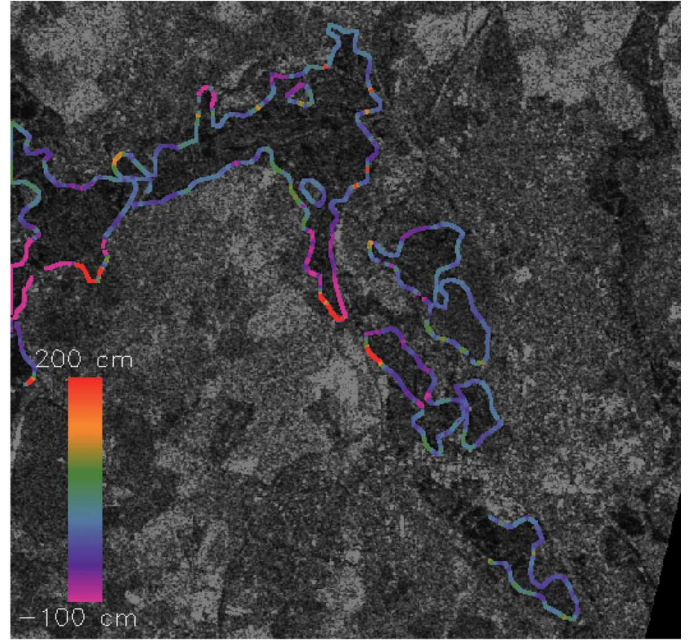
300 The flooded region may not be simply connected, as islands
301 and isolated water bodies may form holes and outliers. To cope
302 with this, the algorithm incorporates a method for dealing with
303 complex topology and snake self-intersection. As an example,
304 a snake may spawn a smaller subsnake within itself to represent
305 an island.

306 B. Implementation and Qualitative Assessment of Results

307 A personal computer (PC)-based implementation of the al-
308 gorithm (Psnake NT) was used in this paper [30]. Psnake NT
309 is a software package that is available to the hydrological
310 modeling community for the semiautomatic extraction of flood



(a)



(b)

Fig. 5. Waterline conditioned only on SAR data overlain on SAR data (a) for parameter $k = 3$ and (b) $k = 2$. The colors represent the difference in height of the waterline from the local mean waterline height.

4/C

extents from SAR data. Fig. 5 shows snake waterlines that are
311 generated using SAR data only, for the number of standard
312 deviations k of 3 and 2, overlain on SAR data. It has been found
313 by experiment that k is probably the most important parameter
314 controlling the snake [19]. Other parameter settings were a
315 minimum node spacing of 6 pixels, a maximum node spacing
316 of 12 pixels, curvature parameter γ of 68.3, tension parameter λ
317 of 0.1, a texture weight of 0.2, and iterations of 200. The snake
318 was seeded (i.e., initialized) manually as a narrow strip lying
319

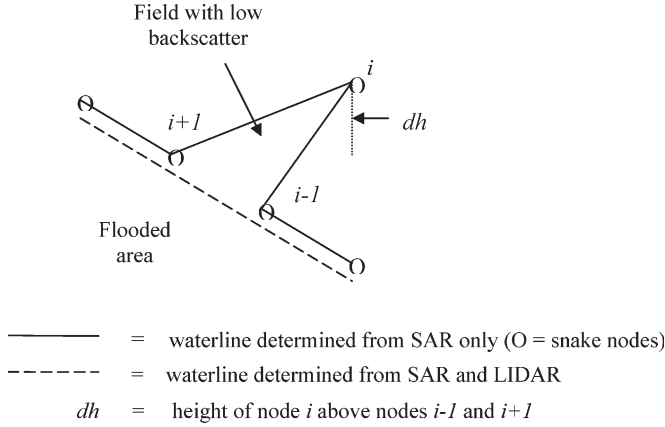


Fig. 6. Example error that might be corrected using lidar.

along the course of the unflooded river channel, ensuring that it contained only flooded pixels.

In Fig. 5, the snake shows a tendency to leak onto higher ground on Wytham Hill [point A in Fig. 5(a), see also Fig. 3]. This is likely to be due to the presence of vegetated fields, which correspond to areas of low SAR backscatter and are likely to be misclassified as flooded. While no ground reference data were acquired at the time of the flood, evidence for this comes from a recent aerial photograph that was obtained later than the SAR image. A further example of leakage of the snake onto higher ground is visible at point B in Fig. 5(a), where the snake has leaked onto the Oxford Nature Park, which is higher than the land toward the Thames yet again exhibits low SAR backscatter.

IV. FLOOD EXTENT EXTRACTION FROM SAR AND LIDAR DATA

A. Algorithm Modification

The snake algorithm was modified so that the snake was conditioned not only on the SAR image but also on the lidar DTM, so that it becomes smoothly varying in ground height as well as in SAR intensities and textures. The principle that was adopted was that the SAR image should still be the primary determinant of the flood extent. In most areas, the flood extent that was determined by the SAR will be correct within the SAR resolution, but where errors creep in the lidar can help to correct these.

The lidar DTM is able to provide a ground height at each pixel, so that each position $\mathbf{u}(x, y)$ becomes $\mathbf{u}(x, y, z)$. The modification involves using the lidar heights to measure curvatures and tensions at snake nodes in 3-D rather than 2-D space. Consider an instance where an unflooded field with low SAR backscatter is adjacent to a flood edge, such that the field is included in the SAR waterline determined by the snake (Fig. 6). As there will likely be a rise in height (dh) across the field that is perpendicular to the true flood edge, the error in the waterline will give rise to a significant component of curvature in the vertical plane, which will not be present in the waterline segments that are adjacent to the field. To be specific, in Psnake

NT, the contribution to the 3-D curvature energy at the snake node at $\mathbf{u}(x_i, y_i, z_i)$ from its two adjacent nodes is

$$\Delta E_{\text{curvature}} = \gamma |\mathbf{v}_{i+1} - \mathbf{v}_i|^2 / a_i = (c_{ix}^2 + c_{iy}^2 + c_{iz}^2) / a_i \quad (6)$$

where

$$\begin{aligned} c_{ix} &= (x_{i+1} - x_i) / d_{i+1} - (x_i - x_{i-1}) / d_i \\ c_{iy} &= (y_{i+1} - y_i) / d_{i+1} - (y_i - y_{i-1}) / d_i \\ c_{iz} &= (z_{i+1} - z_i) / d_{i+1} - (z_i - z_{i-1}) / d_i \\ d_i &= ((x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 + (z_i - z_{i-1})^2)^{0.5} \\ d_{i+1} &= ((x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2)^{0.5} \\ a_i &= \left(((x_{i+1} + x_i) / 2 - (x_i + x_{i-1}) / 2)^2 \right. \\ &\quad \left. + ((y_{i+1} + y_i) / 2 - (y_i + y_{i-1}) / 2)^2 \right. \\ &\quad \left. + ((z_{i+1} + z_i) / 2 - (z_i + z_{i-1}) / 2)^2 \right)^{0.5} \end{aligned}$$

and the suffixes refer to the node numbers in Fig. 6. To reduce the vertical curvature component c_{iz}^2 at node i in Fig. 6, the snake will try to contract to drag node i back to be collinear with nodes $i-1$ and $i+1$, which will also reduce c_{ix}^2 and c_{iy}^2 . The 3-D tension energy, which is proportional to $(d_{i+1}^2 + d_i^2)$, will also be reduced by this move.

A waterline error due to the presence of emergent vegetation at the edge of the flood might also have significant components of vertical curvature and tension that could be reduced by correcting the error. A complicating factor in this case is that the SAR and lidar forces might be acting against each other. In order to reduce the vertical curvature and tension by incorporating the area of enhanced backscatter into the flooded area, the inhomogeneity of the SAR returns in the flooded area would generally have to increase. Which force won out in a particular case would depend on their relative strengths. However, this effect is not the dominant source of error [19].

In order to take account of the fact that a change in height at a node should, in general, cause different changes in curvature and tension compared to the same magnitude change of node position in the xy plane, the lidar heights were scaled by weighting factor w_l with respect to the (x, y) coordinates.

The straightforward approach to combining the SAR and lidar data would be to use the existing algorithm with both data sets and simply calculate 3-D rather than 2-D curvature and tension energies. A possible objection to this might be that, if there were flooded mounds in the floodplain that are not visible to the SAR but visible to the lidar, these might retard the expansion of the snake and distort the eventual waterline. An alternative approach could be to use the algorithm with SAR data and 2-D curvatures and tensions only initially. Then, the snake iterations could continue using SAR and lidar data, and 3-D curvatures and tensions, causing the snake to adjust itself to correct errors where necessary. However, in cases where the waterline was significantly in error, it might be difficult to recover from these errors. For example, if the snake leaked onto higher ground, it might be impeded from returning to the true waterline position by a hollow in the higher ground. In practice, it turns out that the straightforward approach using

the existing algorithm and calculating 3-D curvatures and tensions works well enough.

The SAR data may have significantly lower resolution than the airborne lidar data, as in the present test data set comprising ERS satellite SAR data. In this case, it may be possible to correct the waterline position to sub-SAR pixel accuracy in a second pass of the algorithm. The idea would be to rescale the SAR image and the snake waterline from the first pass to the higher resolution of the lidar, and to continue iterating to try to move the snake nodes away from the centers of the enlarged SAR pixels to create a waterline varying more smoothly in height along its length. A constraint would be that a node should not be allowed to move outside its enlarged SAR pixel, as no further information could be extracted from the SAR image at this stage.

B. Implementation and Qualitative Assessment of Results

For the first pass of the modified algorithm, the lidar image was degraded to the same pixel size as the SAR image (12.5 m) by averaging the lidar heights within each SAR pixel. The parameter settings for this pass were the same as those for the snake that was conditioned on only the SAR data (other than for k and w_l). The initial value of lidar weight factor w_l was chosen by experiment to be 0.15. This took into account the fact that the leakage at Wytham Hill [at point A in Fig. 5(a)] occurs over a distance of about 0.5 km. Curvature at a node is calculated using the two adjacent nodes on either side of the central node, spanning four internode spacings. For an internode spacing of eight pixels, this corresponds to a distance of about 400 m, roughly matching that required. The w_l setting also reflected the facts that the lidar heights were expressed in millimeters and that a, for example, 1000-mm rise in the lidar height of the central node should give rise to a significant increase in 3-D curvature. Even though a node can only be moved horizontally by one SAR pixel at each iteration, this still amounts to a horizontal shift of 12.5 m, which is large compared to a 1-m vertical rise.

The original snake seed that was used contained only pixels south of the A40 road west of Oxford (Fig. 1), and it was found on the first pass that, with the 3-D curvature constraint, the snake would not expand into the flooded areas north of the embanked road, even though this was, on average, only 1.5 m higher than the fields surrounding it. In practice, floodwater from the Thames flows under the A40 onto the lower land to the north through culverts that are spaced at about 250-m intervals. To overcome this difficulty, additional snake seed pixels were inserted to the north of the A40, which were then able to expand into the northernmost part of the flooded region. The same snake seed was used for all snakes that were generated, whether they were conditioned using the lidar data or not.

The second pass took place at higher resolution, i.e., at the 2-m pixel spacing of the lidar data. The input to this pass was the snake output from the first pass, with the node coordinates scaled up by 6.25 to match the change in resolution. The SAR image was interpolated from 12.5 to 2 m using nearest neighbor interpolation. The number of iterations was set to 3,

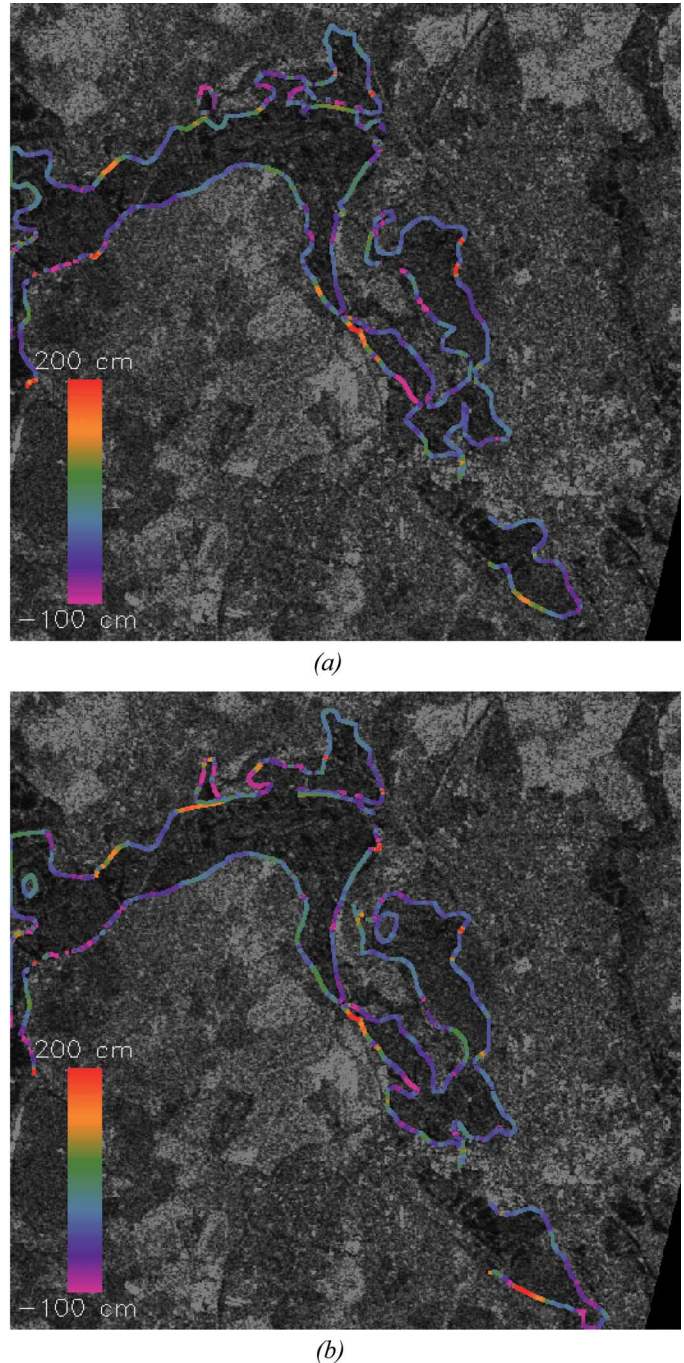


Fig. 7. Waterline conditioned on SAR and lidar data overlain on SAR data (a) for parameter $k = 3$ and $w_l = 0.15$, and (b) for $k = 4$ and $w_l = 0.15$. The colors represent the difference in height of the waterline from the local mean waterline height.

4/C

to ensure that the snake nodes would not move outside the SAR pixels within which they had stabilized after the first pass. The minimum and maximum node spacings were also upscaled to 37 and 74 pixels, respectively, ensuring similar 3-D curvatures to those on the first pass.

Fig. 7 shows snake waterlines that were conditioned on both SAR and lidar data, for k values of 3 and 4 and lidar weight $w_l = 0.15$, overlain on 12.5-m SAR data. It is clear that the tendency for the snake to leak to higher ground at Wytham Hill and at the Oxford Nature Park has been much reduced (see

also Fig. 3). A further benefit is that the snake appears to be more stable to parameter changes. For example, in Fig. 5, the snake that was conditioned only on SAR data shows substantial change when k is raised from 2 to 3, whereas in Fig. 7, the snake that was conditioned on SAR and lidar shows less change when k is raised from 3 to 4. This finding is born out more rigorously in the quantitative analysis described in the next section.

The main errors in waterline position that were corrected using the lidar data are due to the unflooded short vegetation that is adjacent to the flood giving similar returns to open water. The ability of the algorithm to correct loss of flood extent due to emergent vegetation is hardly tested using this data set, as this has few significant examples. The most obvious instances are emergent hedges between adjacent flooded fields, but these are generally of insufficient area to stop the snake subsuming them into its interior, even if conditioned only on SAR data.

V. PARAMETER OPTIMIZATION AND QUANTITATIVE COMPARISON OF METHODS

The snake parameters were optimized using a quantitative measurement of algorithm performance. The snake and aerial photo waterlines were first heighted by superimposing them on the lidar DTM. The snake waterline is defined only at the snake nodes. Only nodes on low slopes and in areas of short vegetation in the lidar vegetation height map were selected for heighting, as these are the ones that are likely to be heighted most accurately. The lower the slope, the smaller the node height error for a given error in its position. No requirements were made that selected nodes should have a strong SAR edge [indicated by a low G value (2)] associated with them, as this would reject nodes at the boundaries between the flood and an unflooded field giving low SAR backscatter, or between a region of emergent vegetation at the flood edge and an adjacent unflooded land (both giving high SAR backscatter).

For each snake node that was selected, the aerial photo height to associate with the snake height was found by finding the height of the closest aerial photograph waterline point. This was found by applying a distance-with-destination transform to the aerial photo waterline image. The distance-with-destination transform is a form of distance transform that stores, for each pixel in the transform image, its distance to the nearest waterline point and also the direction from which the minimum distance was propagated. This allows backtracking from a pixel to find its nearest waterline point [31]. Corroborating the finding of [19], the average separation distance was about 50 m, although this value was strongly influenced by a small number of pairs having large separations, and the average separation of 70% of the pairs having separations of less than 50 m was only 20 m. However, the pairs with large separation were not rejected, as they included examples where, e.g., the SAR waterline was displaced from the aerial photo waterline by a complete field width due to misclassification of the field as flooded. The anticipation was that these events would be less common when the snake was conditioned on the SAR and lidar data than on the SAR data alone.

Parameters were optimized by minimizing the sum of the squared height differences between the snake nodes and their

corresponding aerial photo waterline points. To ensure that adjacent pairs of heights were largely uncorrelated, the pairs that were selected so far were thinned further, so that no pair was closer than 200 m to another. This distance was estimated by constructing a correlogram from the set of pairs [32] and was the distance at which the average correlation between adjacent pairs became less than 0.2. From the remaining pairs, the mean and standard deviations of the snake and aerial photograph waterline heights were calculated, as was the rms error of the height differences, with this being the variable to minimize in the parameter optimization. The mean height difference and the standard deviation of the differences were also calculated, and this allowed a paired t-test to be performed to test whether the differences were significantly nonzero. The paired t-test is used to exploit the fact that, while corresponding SAR and aerial photograph waterline heights will be correlated due to the gradual drop in height along the reach, the height differences at corresponding nodes will be uncorrelated due to the thinning process, as required by the paired test.

Only the most important parameters were investigated in the optimization procedure. For the snake that was conditioned on only SAR data, the parameter that was optimized was k . For the snake that was conditioned on SAR and lidar data, k and w_l were optimized.

Table I(a) shows the results of varying k for the snake that was conditioned on only the SAR data. The minimum rms error is 221.1 cm, which was obtained for $k = 2.0$. The associated high t value implies that there is a significant height difference at the 5% level between the snake and aerial photo waterlines. The corresponding snake is shown in Fig. 5(b). Higher values of k give significantly larger rms errors, and the high t values that were coupled with positive mean height differences imply that, for all these k values, the snake waterline heights are significantly higher than those of the aerial photograph.

Table I(b) shows the results of varying k for the snake that was conditioned on SAR and lidar data, with w_l held constant at 0.15. The minimum rms error is 55.5 cm, which was obtained for $k = 3.0$. The associated t value is not significantly nonzero, so that there is no significant difference between the snake and aerial photo waterline heights. The corresponding snake is shown in Fig. 7(a).

Table I(c) shows the results of varying w_l for the snake that was conditioned on SAR and lidar data, with k held constant at 3.0. The minimum rms error is obtained at $w_l = 0.15$. Over the ranges of k and w_l that were investigated, none of the t values are significantly nonzero, implying greater robustness to parameter changes than the case for the snake that was conditioned on only SAR data.

Table II gives the frequency tables of the absolute differences of the paired heights for the parameter sets giving the minimum rms errors for the snake that was conditioned on only the SAR data and the snake that was conditioned on SAR and lidar data. It can be seen that the increase in the rms error in the case of the snake that was conditioned only on SAR data is due almost entirely to the large number of pairs having height differences of greater than 300 cm. This is also apparent in Fig. 8, where the paired height differences for the two cases are plotted as a

TABLE I

RESULTS OF (a) VARYING k FOR THE SNAKE CONDITIONED ON ONLY THE SAR DATA, (b) VARYING k FOR THE SNAKE CONDITIONED ON SAR AND LIDAR DATA, WITH w_l HELD CONSTANT AT 0.15, AND (c) VARYING w_l FOR THE SNAKE CONDITIONED ON SAR AND LIDAR DATA, WITH k HELD CONSTANT AT 3.0

k	Number of height pairs	R.m.s. error in height (cm)	Mean height difference (cm)	t_0	Probability $t > t_0 $ (one-sided test)	Relative height standard deviation (cm)
1.5	165	238.8	31.6	1.7	0.04	105.3
2.0	200	221.1	33.7	2.2	0.02	136.2
2.5	197	381.3	65.4	2.4	0.01	263.1
3.0	195	331.4	64.5	2.8	0.004	314.4
4.0	206	317.5	70.7	3.3	0.0005	379.1

(a)

k	Number of height pairs	R.m.s. error in height (cm)	Mean height difference (cm)	t_0	Probability $t > t_0 $	Relative height standard deviation (cm)
2.8	195	57.8	-1.5	-0.4	0.35	43.5
3.0	191	55.5	-4.3	-1.0	0.15	42.6
3.2	190	86.6	-3.1	-0.5	0.30	52.6
3.5	195	120.8	5.2	0.6	0.28	65.4
4.0	195	63.7	4.5	1.0	0.15	48.9

(b)

w_l	Number of height pairs	R.m.s. error in height (cm)	Mean height difference (cm)	t_0	Probability $t > t_0 $	Relative height standard deviation (cm)
0.10	187	90.2	-0.1	-0.1	0.46	47.4
0.14	196	61.0	5.4	1.2	0.10	43.0
0.15	191	55.5	-4.3	-1.0	0.15	42.6
0.16	191	55.8	0.7	0.2	0.42	43.5
0.20	195	81.5	-9.0	-1.5	0.07	54.7

(c)

580 function of distance downstream. The main effect of the lidar
581 data is to correct errors in the sections of waterline containing
582 these outliers, when the snake is conditioned on both SAR and
583 lidar.

584 The effect of the second pass of the algorithm in correcting
585 the waterline position to sub-SAR pixel accuracy was also
586 assessed. For the parameter set giving the minimum rms error
587 for the snake that was conditioned on SAR and lidar data
588 ($k = 3.0$ and $w_l = 0.15$), the algorithm was run for only the
589 first pass. The minimum rms error was 58.1 cm, which is
590 only slightly higher than the 55.5 cm that was achieved when
591 both passes were employed. There was slightly more difference
592 when k was raised to 4.0 and when the rms error increased to
593 70.8 from 63.7. This indicates that the main reduction in error is
594 being generated in the first pass and that the second gives only
595 a second-order improvement. This may be partly because only
596 snake nodes on low slopes have been selected, and thus, height
597 differences across the SAR pixel, due to its size, will be small.

TABLE II

FREQUENCY TABLES OF THE ABSOLUTE DIFFERENCES OF PAIRED HEIGHTS FOR THE PARAMETER SETS GIVING THE MINIMUM RMS ERRORS FOR THE SNAKE CONDITIONED ON ONLY THE SAR DATA AND THE SNAKE CONDITIONED ON SAR AND LIDAR DATA

	0-49cm	50-99cm	100-149cm	150-199cm	200-249cm	250-299cm	300-499cm	>=500cm
Snake conditioned on SAR data ($k = 2.0$)	155	20	9	3	3	1	3	6
Snake conditioned on SAR and LiDAR data ($k = 3.0$, $w_l = 0.15$)	154	20	9	5	2	1	0	0

VI. DISCUSSION

598

The method may be applied to the validation of the flood 599 models of other river reaches, with the only prerequisites 600 additional to the usual data required to set up a hydraulic 601 model (e.g., an inflow hydrograph and river channel cross- 602 sectional data) being the availability of SAR imagery of the 603 river in flood and reasonably contemporaneous lidar data of 604 the unflooded reach. It would be relatively straightforward to 605 make the procedure operational. Lidar data are now often used 606 to parameterize the hydraulic model, making it more likely that 607 they would also be available to improve the SAR waterline. 608 It would be straightforward to implement the modified algo- 609 rithm within the Psnake NT software package. For this catch- 610 ment, the algorithm processing time was less than 1 min on a 611 Pentium IV personal computer. 612

The emphasis in the foregoing has been on ERS satellite 613 SAR data because of the availability of simultaneous ERS SAR 614 and aerial photography of the 1992 Oxford flood. While ERS 615 SAR data have poorer resolution than airborne lidar data, the 616 technique should also be applicable in cases where the SAR 617 resolution is similar to that of the lidar (e.g., airborne SAR), 618 in which case a second pass of the algorithm would certainly 619 be unnecessary. The algorithm of [18] and [19] has been used 620 to delineate flood extents in airborne SAR imagery [33], [34]. 621 However, given the increasing number of satellite SAR sensors 622 flying or planned and the difficulty of flying aircraft in poor 623 weather often accompanying floods, satellite SARs are likely 624 to remain to be a major source of SAR data for flood mapping 625 in the future. While the ERS SAR sensor has single VV polar- 626 ization and a fixed 23° viewing angle, the advent of later sensors 627 with higher resolutions, multiple polarizations, and variable 628 viewing angles (e.g., RADARSAT and Envisat Advanced SAR) 629 has allowed improved flood delineation (e.g., [15]). The high- 630 resolution satellite SAR sensors due for launch shortly (e.g., 631 RADARSAT-2, TerraSAR, and the Cosmo-Skymed constella- 632 tion) will have resolutions that match or almost match that of 633 airborne lidar. 634

Production of a more smoothly varying waterline may allow 635 the development of improved performance measures for flood 636 extent validation based on patterns of height differences be- 637 tween observed and modeled waterlines rather than on patterns 638 of wet or dry pixels, as currently done. Aronica *et al.* [24] 639

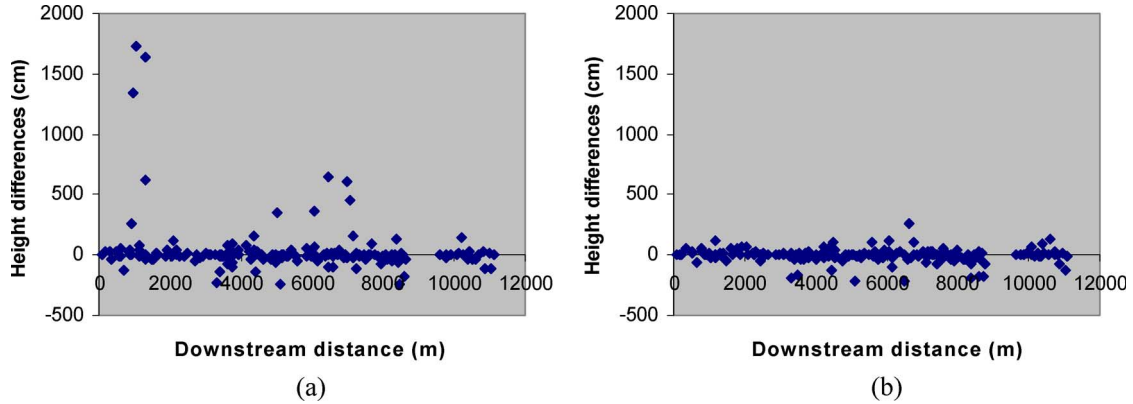


Fig. 8. Paired height differences versus distance downstream for the parameter sets giving the minimum rms errors for the snake that was conditioned on (a) SAR data and (b) SAR and lidar data.

640 describe current performance measures based on binary pat-
641 terns. One measure representative of these is

$$F^{(2)} = (A_{\text{obs}} \cap A_{\text{mod}}) / (A_{\text{obs}} \cup A_{\text{mod}}) \quad (7)$$

642 where A_{obs} and A_{mod} represent the set of pixels that are ob-
643 served to be inundated and predicted as inundated, respectively.
644 $F^{(2)}$ is equal to 1 when observed and predicted areas coincide
645 exactly and equal to 0 when no overlap between predicted and
646 observed areas exists. A performance measure based on height
647 differences might have several advantages over one such as
648 $F^{(2)}$ based on binary pattern data. First, as the distribution of
649 t is known, it is possible to estimate the probability $P(t > |t_0|)$
650 of obtaining a t value that is greater than the absolute value
651 of that measured (t_0), whereas $F^{(2)}$ is simply a weight factor.
652 Second, the height difference measure between two model
653 runs with different parameter settings might turn out to be
654 more sensitive than $F^{(2)}$, because a small change in mean
655 height might cause a large change in $P(t > |t_0|)$ yet only a
656 small change in $F^{(2)}$. Third, the sign of the t value identifies
657 whether an overprediction or an underprediction has occurred,
658 whereas $F^{(2)}$ may give similar values for overprediction and
659 underprediction.

660 In this case, the parameters of the snake that was generated
661 using SAR and lidar have been optimized using the aerial
662 photo waterline, but this will not be available in the more usual
663 situation in which the snake is being used to validate a model
664 waterline. It is interesting that, for those nodes in areas of low
665 slope and low vegetation, the standard deviation of their heights
666 relative to their local mean height (within an 0.5-km distance)
667 is a minimum at the same parameter setting at which the rms
668 error of height differences between snake and aerial photo
669 waterlines is minimized [Table I(b) and (c)]. This presumably
670 reflects the fact that the snake is most smoothly varying when
671 the relative height standard deviation is minimized, and it may
672 be possible to use this measure as a surrogate for optimizing the
673 snake parameters when using the snake to validate a modeled
674 flood extent. However, a more likely scenario is that a single
675 optimum parameter set would not be sought in this situation. In
676 flood model validation, emphasis is now placed on associating
677 uncertainties with model flood extents, by deriving flood extent

probability maps showing the probability of each pixel being
678 flooded, given a flood event of the given magnitude. It has
679 been found that, for a particular event, many different sets
680 of model parameters may give flood extents that match the
681 observed extent to a greater or lesser degree. Such equifinality
682 has been well documented and has resulted in the development
683 of the generalized likelihood uncertainty estimation (GLUE)
684 technique, whereby many model runs are carried out, spanning
685 the likely ranges of model parameters [35]. A flood extent
686 probability map is obtained by performing a weighted average
687 of the binary-valued modeled flood extents (with the value for
688 a pixel being 1 for flooded and 0 for not flooded), with each
689 model flood extent being weighted according to its performance
690 measure relative to an observed flood extent. As previously
691 mentioned, the performance measure could be based on pat-
692 terns of height differences between observed and modeled
693 waterlines rather than on patterns of wet or dry pixels. To date,
694 the GLUE methodology has been mainly used to assess flood
695 extent uncertainty due to model parameter errors (see, e.g., [21]
696 and [36]). However, it seems a natural future step to try to
697 extend the method to cope with uncertainty in both model and
698 snake algorithm parameters [36]. Some method of limiting the
699 number of model runs that are required would probably need to
700 be employed (e.g., Gaussian emulation [37]), although some
701 reduction might result from using an improved performance
702 measure based on height differences. 703

VII. CONCLUSION

704 An algorithm has been developed for the automatic
705 extraction of flood extent using a snake that was generated
706 from combined SAR and lidar data, and the resulting waterline
707 compared to that generated using SAR data alone. From the re-
708 sulting snakes, sets of nodes in areas of low slope and low veg-
709 etation have been extracted, followed by further thinning. After
710 optimization of parameters, the heights of the resulting node set
711 from the snake that was conditioned on SAR and lidar matched
712 the corresponding node heights from the aerial photo waterline
713 significantly more closely than those from the snake that was
714 conditioned solely on SAR data. The conclusion is that, for
715 the variety of situations that are present in this particular
716

717 data set, the use of the lidar data has resulted in an observed
718 waterline that varies more smoothly along the reach and is a
719 better match to our best estimate of the true waterline heights.

720 ACKNOWLEDGMENT

721 The authors would like to thank the EA for the provision
722 of lidar data, CEH Wallingford for the SAR and photographic
723 data, and the referees for their improvements to this paper.

724 REFERENCES

725 [1] P. D. Bates, M. S. Horritt, C. N. Smith, and D. C. Mason, "Integrating
726 remote sensing observations of flood hydrology and hydraulic modeling,"
727 *Hydrol. Process.*, vol. 11, no. 14, pp. 1777–1795, 1997.
728 [2] L. C. Smith, "Satellite remote sensing of river inundation area, stage
729 and discharge: A review," *Hydrol. Process.*, vol. 11, no. 10, pp. 1427–
730 1439, 1997.
731 [3] F. T. Ulaby, R. K. Moore, and A. K. Fung, *Microwave Remote Sensing*,
732 vol. 3. Norwood, MA: Artech House, 1986.
733 [4] J.-S. Lee and I. Jurkevich, "Coastline detection and tracing in SAR
734 images," *IEEE Trans. Geosci. Remote Sens.*, vol. 28, no. 4, pp. 662–668,
735 Jul. 1990.
736 [5] D. C. Mason and I. J. Davenport, "Accurate and efficient determination of
737 the shoreline in ERS-1 SAR images," *IEEE Trans. Geosci. Remote Sens.*,
738 vol. 34, no. 5, pp. 1243–1253, Sep. 1996.
739 [6] J. A. Richards, P. W. Woodgate, and A. K. Skidmore, "An explanation of
740 enhanced radar backscattering from flooded forests," *Int. J. Remote Sens.*,
741 vol. 8, no. 7, pp. 1093–1100, 1987.
742 [7] F. M. Henderson, "Environmental factors and the detection of open sur-
743 face water using X-band radar imagery," *Int. J. Remote Sens.*, vol. 16,
744 no. 13, pp. 2423–2437, 1995.
745 [8] S. I. Solomon, "Methodological considerations for the use of ERS-1 SAR
746 imagery for the delineation of river networks in tropical forest areas," in
747 *Proc. 1st ERS-1 Symp.*, Frascati, Italy, Jun. 26–27, 1995, pp. 595–600.
748 [9] M. S. Horritt, D. C. Mason, D. M. Cobby, I. J. Davenport, and P. D. Bates,
749 "Waterline mapping in flooded vegetation from airborne SAR imagery,"
750 *Remote Sens. Environ.*, vol. 85, no. 3, pp. 271–281, May 2003.
751 [10] Y. Wang, L. L. Hess, S. Filoso, and J. M. Melack, "Understanding the
752 radar backscattering from flooded and non-flooded Amazonian forests:
753 Results from canopy backscatter modelling," *Remote Sens. Environ.*,
754 vol. 54, no. 3, pp. 324–332, Dec. 1995.
755 [11] M. Badji and S. Dautrebande, "Characterisation of flood inundated areas
756 and delineation of poor drainage soil using ERS-1 SAR imagery," *Hydrol.*
757 *Process.*, vol. 11, no. 10, pp. 1441–1450, 1995.
758 [12] M. L. Imhoff, C. Vermillion, M. H. Story, A. M. Choudhury, A. Gafoor,
759 and F. Pocllyn, "Monsoon flood boundary delineation and damage assess-
760 ment using space borne imaging radar and Landsat data," *Photogramm.*
761 *Eng. Remote Sens.*, vol. 53, no. 4, pp. 405–413, 1987.
762 [13] H. Liu and K. C. Jezek, "Automated extraction of coastline from satellite
763 imagery by integrating Canny edge detection and locally adaptive thresh-
764 olding method," *Int. J. Remote Sens.*, vol. 25, no. 5, pp. 937–958, 2004.
765 [14] A. Niedermeier, E. Romaneessen, and S. Lehner, "Detection of coastlines
766 in SAR images using wavelet methods," *IEEE Trans. Geosci. Remote*
767 *Sens.*, vol. 38, no. 5, pp. 2270–2281, Sep. 2000.
768 [15] Y. Yu and S. T. Acton, "Automated delineation of coastline from polarim-
769 etric SAR imagery," *Int. J. Remote Sens.*, vol. 25, no. 17, pp. 3423–3438,
770 Sep. 2004.
771 [16] P. A. Brivio, R. Colombo, M. Maggi, and R. Tomasoni, "Integration of
772 remote sensing data and GIS for accurate mapping of flooded areas," *Int.*
773 *J. Remote Sens.*, vol. 23, no. 3, pp. 429–441, Feb. 2002.
774 [17] G. Nico, M. Pappalepore, G. Pasquariello, A. Refice, and
775 S. Samarelli, "Comparison of SAR amplitude vs. coherence flood
776 detection methods—A GIS application," *Int. J. Remote Sens.*, vol. 21,
777 no. 8, pp. 1619–1631, May 2000.
778 [18] M. S. Horritt, "A statistical active contour model for SAR image segmen-
779 tation," *Image Vis. Comput.*, vol. 17, no. 3/4, pp. 213–224, Mar. 1999.
780 [19] M. S. Horritt, D. C. Mason, and A. J. Luckman, "Flood boundary de-
781 lineation from synthetic aperture radar imagery using a statistical active
782 contour model," *Int. J. Remote Sens.*, vol. 22, no. 13, pp. 2489–2507,
783 Sep. 2001.
784 [20] G. Schumann, R. Hostache, C. Puech, L. Hoffmann, P. Matgen,
785 F. Pappenberger, and L. Pfister, "High-resolution 3D flood information

from radar imagery for flood hazard management," *IEEE Trans. Geosci.*
786 *Remote Sens.*, vol. 45, no. 6, pp. 1715–1725, Jun. 2007. 787
788 [21] F. Pappenberger, K. Beven, M. Horritt, and S. Blazkova, "Uncertainty in
789 the calibration of effective roughness parameters in HEC-RAS using inun-
790 dation and downstream level observations," *J. Hydrol.*, vol. 302, no. 1–4,
791 pp. 46–69, 2005. 792
793 [22] D. C. Mason, D. M. Cobby, M. S. Horritt, and P. D. Bates, "Flood-
794 plain friction parameterization in two-dimensional river flood models
795 using vegetation heights derived from airborne scanning laser altimetry,"
796 *Hydrol. Process.*, vol. 17, no. 9, pp. 1711–1732, 2003. 797
798 [23] D. M. Cobby, D. C. Mason, M. S. Horritt, and P. D. Bates, "Two-
799 dimensional hydraulic flood modelling using a finite element mesh de-
800 composed according to vegetation and topographic features derived from
801 airborne scanning laser altimetry," *Hydrol. Process.*, vol. 17, no. 10,
802 pp. 1979–2000, 2003. 803
804 [24] G. Aronica, P. D. Bates, and M. S. Horritt, "Assessing the uncertainty in
805 distributed model predictions using observed binary pattern information
806 within GLUE," *Hydrol. Process.*, vol. 16, no. 10, pp. 2001–2016, 2002. 807
808 [25] D. S. Biggin and K. Blyth, "A comparison of ERS-1 satellite radar and
809 aerial photography for river flood mapping," *J. Chart. Inst. Water Eng.*
810 *Manag.*, vol. 10, pp. 1777–1795, 1996. 811
812 [26] L. M. G. Pereira and L. L. F. Janssen, "Suitability of laser data for DEM
813 generation: A case study in the context of road planning and design,"
814 *ISPRS J. Photogramm. Remote Sens.*, vol. 54, no. 4, pp. 244–253, 1999. 815
816 [27] I. J. Davenport, N. Holden, and R. J. Gurney, "Characterizing errors
817 in airborne laser altimetry data to extract soil roughness," *IEEE Trans.*
818 *Geosci. Remote Sens.*, vol. 42, no. 10, pp. 2130–2141, Oct. 2004. 819
820 [28] D. J. Williams and M. Shah, "A fast algorithm for active contours and
821 curvature estimation," *CVGIP, Image Underst.*, vol. 55, no. 1, pp. 14–26,
822 Jan. 1992. 823
824 [29] J. Ivins and J. Porrill, "Statistical snakes: Active region models," in
825 *Proc. 5th Brit. Mach. Vis. Conf.*, York, U.K., Sep. 1994, vol. 1 and 2,
826 pp. 377–386. 827
828 [30] M. S. Horritt, "Psnake NT user manual," Univ. Bristol, Bristol, U.K.,
829 2002. School of Geographical Sciences Report. 830
831 [31] D. C. Mason, T. R. Scott, and H.-J. Wang, "Extraction of tidal channel
832 networks from airborne lidar data," *ISPRS J. Photogramm. Remote Sens.*,
833 vol. 61, no. 2, pp. 67–83, 2006. 834
835 [32] C. V. Deutsch and A. Journel, *GSLIB: Geostatistical Software Library and*
836 *Users's Guide*. New York: Oxford Univ. Press, 1992, p. 41. 837
838 [33] P. D. Bates, M. Wilson, M. S. Horritt, D. C. Mason, N. Holden, and
839 A. Currie, "Reach scale floodplain inundation dynamics observed using
840 airborne SAR imagery," *J. Hydrol.*, vol. 328, no. 1/2, pp. 306–318, 2006. 841
842 [34] S. Neelz, G. Pender, I. Villanueva, M. D. Wilson, N. G. Wright,
843 P. D. Bates, D. C. Mason, and C. Witlow, "Using remotely sensed
844 data to support flood modelling," *Proc. Inst. Civil Eng.*, vol. 159, no. 1,
845 pp. 35–44, 2006. 846
847 [35] K. J. Beven and A. M. Binley, "The future of distributed models: Model
848 calibration and predictive uncertainty," *Hydrol. Process.*, vol. 6, no. 3,
849 pp. 279–298, 1992. 850
851 [36] M. S. Horritt, "A methodology for the validation of uncertain flood inun-
852 dation models," *J. Hydrol.*, vol. 326, no. 1–4, pp. 153–165, 2006. 853
854 [37] J. E. Oakley and A. O'Hagan, "Probabilistic sensitivity analysis of com-
855 plex models: A Bayesian approach," *J. R. Stat. Soc., Series B*, vol. 66,
856 no. 3, pp. 751–769, Aug. 2004. 857



David C. Mason received the B.Sc. and Ph.D. de- 841
grees in physics from the University of London, 842
London, U.K., in 1963 and 1968, respectively. 843
He was with the U.K. Medical Research Coun- 844
cil and Plessey Electronic Systems Research. Since 845
1984, he has been with the Natural Environment 846
Research Council Environmental Systems Science 847
Centre, University of Reading, Reading, U.K., carry- 848
ing out research on the automated extraction of infor- 849
mation from remotely sensed data and linking these 850
data to environmental models. His current research 851
interests include using remotely sensed data for validation and parameterization 852
of river flood models and assimilation into coastal morphodynamic models. 853



Matthew S. Horritt received the Ph.D. degree from the University of Reading, Reading, U.K., in 1998.

He was with the University of Leeds, Leeds, U.K., and the Department of Civil Engineering, University of Bristol, Bristol, U.K., as a Postdoctoral Research Fellow and a Lecturer in civil engineering, respectively. He is currently a Specialist Modeler with Halcrow Group Ltd., London, U.K. His research interests are flood inundation models, remote sensing of floods and floodplain topography, and model validation.



Tania R. Scott received the B.Sc. degree in 1975 astronomy from the University of Canterbury, Christchurch, New Zealand, in 1992 and the Ph.D. degree in astronomy from the University of Cambridge, Cambridge, U.K., in 1998.

She was with the U.K. Met Office, where she developed meteorological products for the aviation industry to address safety and environmental issues. She is currently with the Natural Environment Research Council (NERC) Environmental Systems Science Centre, University of Reading, Reading, U.K., where she is interested in using remote sensing data in aid of environmental modeling. Her current project is to apply data assimilation techniques to coastal area morphodynamic modeling, which is funded under the NERC program Flood Risk from Extreme Events.



Johanna T. Dall'Amico is currently working toward the B.Sc. degree in mathematics at the University of Reading, Reading, U.K., and a Diploma in geography and remote sensing at Ludwig-Maximilian University of Munich, Munich, Germany.

She is a Visiting Student at the Natural Environment Research Council Environmental Systems Science Centre, University of Reading, where she works on remote sensing applications for fluvial flood models.



Paul D. Bates received the Ph.D. degree from the University of Bristol, Bristol, U.K., in 1993, with support from a Natural Environmental Research Council studentship.

Subsequently, he has been with at the University of Bristol as a Postdoctoral Researcher and Lecturer, and has been a Full Professor since 2003. He is currently the Director of the Hydrology Research Group, School of Geographical Sciences, University of Bristol. He has been a Visiting Scientist at Princeton University, Laboratoire National D'Hydraulique, Paris, and the EU Joint Research Centre, Ispra, Italy. His research interests include the development and analysis of numerical models for predicting river flood flows, principally using data derived from remote sensing sources, spatial prediction, risk, and uncertainty. He is the Editor-in-Chief of the *International Journal of River Basin Management*.

Improving River Flood Extent Delineation From Synthetic Aperture Radar Using Airborne Laser Altimetry

David C. Mason, Matthew S. Horritt, Johanna T. Dall'Amico, Tania R. Scott, and Paul D. Bates

Abstract—Flood extent maps that are derived from synthetic aperture radar (SAR) images provide spatially distributed data for validating hydraulic models of river flood flow. The accuracy of such maps is reduced by a number of factors, including variation in backscatter from the different land cover types that are adjacent to the flood, changes in returns from the water surface that are caused by different meteorological conditions, and the presence of emergent vegetation. This paper describes how improved accuracy can be achieved by modifying an existing flood extent delineation algorithm to use airborne laser altimetry [light detection and ranging (lidar)] as well as SAR data. The lidar data provide an additional constraint that waterline heights should vary smoothly along the flooded reach. The method was tested on a SAR image of a flood for which contemporaneous aerial photography existed, together with lidar data of the unflooded reach. The waterline heights of the SAR flood extent that was conditioned on both SAR and lidar data matched the corresponding heights from the aerial photograph waterline significantly more closely than those from the SAR flood extent that was conditioned only on SAR data. For waterline heights in areas of low slope and vegetation, the root-mean-square error on the height differences reduced from 221.1 cm for the latter case to 55.5 cm for the former.

Index Terms—Data fusion, hydrology, lidar, snake.

I. INTRODUCTION

FLOOD extent maps that are derived from remotely sensed data are of considerable use in hydrology, providing spatially distributed data for validation of hydraulic models of river flood flow, for emergency flood relief management, and for development of spatially accurate hazard maps [1], [2]. The all-weather day–night capability of synthetic aperture radar (SAR) sensors gives these a considerable advantage for flood mapping over sensors operating at visible or infrared wavelengths, as the latter ones are unable to penetrate the cloud that often accompanies flood events. This advantage is tempered by the fact that a number of factors conspire to reduce the accuracy of flood maps that are derived from SAR imagery. These include the

substantial variation in backscatter from the different land cover types that are adjacent to the flood, the changes in returns from the water surface that are caused by different meteorological conditions, the presence of emergent vegetation, and the effects of man-made structures in urban areas. This paper describes a study to reduce inaccuracies from some of these sources in an existing flood extent delineation algorithm by using an additional data source, namely, airborne laser altimetry.

The simplest model of SAR backscatter from a river flood assumes that the water surface is smoother than the surrounding land and acts as a specular reflector, reflecting radiation away from a side-looking sensor, so that the water appears dark compared to the land. Two factors complicating the simple specular reflection model in practice are the effects of wind or rain roughening of the water surface, and emergent vegetation. The relationship between SAR backscatter and surface roughness that is caused by wind blowing over the oceans is well understood [3], and the effect may raise the backscatter from the water to similar or greater levels than the adjacent land [4], [5]. Wind roughening of a river flood surface can give rise to similar effects, but these can have substantial spatial variation, depending on the local topography, which determines the fetch for a given wind direction. The presence of emergent vegetation can give rise to multiple reflections between the water and the vegetation, leading to a substantial enhancement of backscatter, the magnitude of which is a function of radar wavelength, look angle, and polarization. The effect has been observed in a number of studies of flooded forest and marshland (e.g., [6]–[9]), and the increase in backscatter has been modeled mathematically in [10]. Enhanced backscatter from the water surface that is caused by wind roughening or emergent vegetation will also result in an increased level of noise due to the multiplicative nature of noise in SAR images.

A number of methods for the automated delineation of flood extent in SAR imagery of both fluvial and tidal environments have been developed [4], [5], [9], [11]–[21]. Several of these studies have illustrated the great potential of SAR sensors for synoptic observation of large flooding events. An automatic technique for delineating a fluvial flood using a statistical active contour model (or snake) that is applied to a SAR image to identify areas of homogeneous speckle statistics is described in [18] and [19]. This assumes that single-frequency single-polarization SAR intensities are available and was aimed at producing an observed flood extent against which to validate

Manuscript received October 9, 2006; revised March 26, 2007. This work was supported in part by the EPSRC-funded Flood Risk Management Research Consortium Grant GR/S76394/01.

D. C. Mason, J. T. Dall'Amico, and T. R. Scott are with the Natural Environment Research Council Environmental Systems Science Centre, University of Reading, RG6 6AH Reading, U.K.

M. S. Horritt is with Halcrow Group Ltd., W6 7BY London, U.K.

P. D. Bates is with the School of Geographical Sciences, University of Bristol, BS8 1SS Bristol, U.K.

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TGRS.2007.901032

86 a modeled flood extent. Due to the difficulties of imaging urban
 87 areas using SAR, its use is limited to large-area mapping of
 88 floods in rural areas. The SAR segmentation uses both local
 89 tone and texture measures, and is capable of accurate feature
 90 boundary representation. The method was applied to a flood
 91 that was imaged using the ERS-1 satellite SAR sensor and
 92 proven to be capable of identifying 75% of the flooded area
 93 correctly, with 70% of the waterline coinciding with ground
 94 data within 20 m. The main error in waterline position was
 95 found to be due to unflooded short vegetation that was adjacent
 96 to the flood giving similar radar returns to open water, causing
 97 an overestimation of flood extent. The loss of flood extent due
 98 to emergent vegetation was found to be a secondary source
 99 of error.

100 Further work on this topic [22], [23] found that, as a result of
 101 these error sources and the relatively large size of the European
 102 Remote Sensing Satellite (ERS) SAR pixel, the heights of the
 103 SAR waterline along a flooded reach could sometimes be in
 104 error by several meters (although, generally, it was much less)
 105 and could exhibit significant noise. One reason for this was that
 106 there was no constraint that the waterline heights should vary
 107 smoothly along the reach, whereas, in reality, the longitudinal
 108 slope of typical flood flows is low ($\sim 0.001\text{--}0.0001\text{ m} \cdot \text{m}^{-1}$),
 109 and changes in slope are very gradual. With this level of dif-
 110 ferences, the SAR image becomes much less useful for model
 111 flood extent validation than it could otherwise be.

112 Horritt *et al.* [19] point out that their flood extent map-
 113 ping procedure identifying the flood as a region of rela-
 114 tively homogeneous speckle statistics may be improved by
 115 the adoption of a model-based approach. In this vein, this
 116 paper describes the use of light detection and ranging (li-
 117 dar) data to modify the SAR waterline, so that it becomes
 118 more useful for validation. The snake algorithm [18], [19]
 119 is modified to look not only at SAR image space but also
 120 at lidar digital terrain model (DTM) and vegetation height
 121 maps, so that the snake can be conditioned to be smoothly
 122 varying in ground height as well as in SAR intensities and
 123 textures. This should reduce errors that are caused by un-
 124 flooded vegetation that is adjacent to the flood giving similar
 125 returns to open water and also errors due to the SAR pixel
 126 size. It could also help somewhat in reducing errors due to
 127 emergent vegetation. An additional benefit of producing a
 128 more smoothly varying waterline is that it may allow the
 129 development of improved performance measures for flood ex-
 130 tent validation based on patterns of height differences rather
 131 than on patterns of wet or dry pixels, as currently done [24].
 132 The algorithm specifically sets out to improve the vertical
 133 accuracy of the SAR waterline, although any improvement
 134 should also lead to improvement in the horizontal waterline
 135 accuracy due to their correlations that are contained within
 136 the DTM.

137 Used in this way, the lidar data may actually play a dual
 138 role in the modeling process, as lidar is often used to pa-
 139 rameterize the hydraulic model being validated, with the li-
 140 dar DTM providing the model bathymetry and possibly the
 141 vegetation heights being used to estimate bottom friction
 142 [22]. However, the use of lidar data in SAR waterline ex-
 143 traction as well as model parameterization does not under-

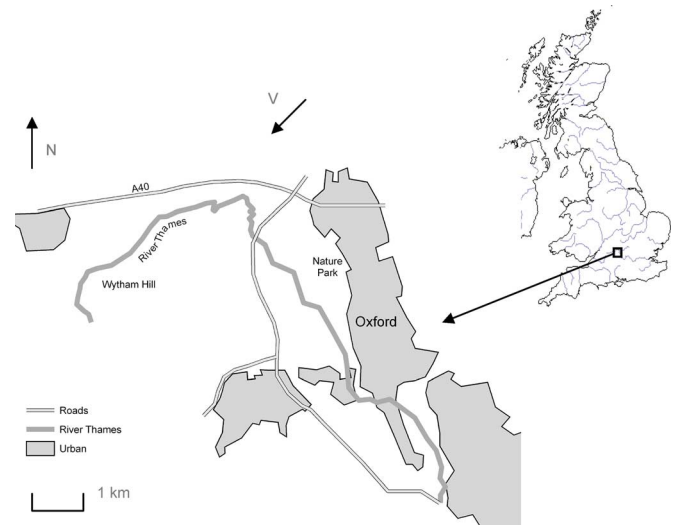


Fig. 1. Location of the test area.

mine the independence of the SAR waterline in the validation
 process.

II. TEST DATA SET

An ideal data set on which to validate the method would be
 from a flood for which both satellite SAR data and simultaneous
 aerial photography were available, so that the SAR snake
 waterlines that are conditioned without and with the lidar data
 could be compared with the waterline from the aerial pho-
 tographs. In addition, lidar data of the unflooded area should be
 available.

Biggin and Blyth [25] acquired oblique aerial photos of a
 flood on the Thames west of Oxford, U.K., on December 4,
 1992, at the same time (to within 2 h) as an ERS-1 SAR
 overpass of the area. The Thames is a low-relief slow-response
 catchment, and at this point along its course, the river discharge
 during a flood changes only very gradually, so that such timing
 differences are unimportant. The peak discharge for this event
 was measured at $76\text{ m}^3 \cdot \text{s}^{-1}$, which represents a $\sim 1\text{-in-5-year-}$
 recurrence interval flow. The ERS-1 SAR image was acquired
 approximately 36 h after the flood peak when the discharge had
 dropped to $73\text{ m}^3 \cdot \text{s}^{-1}$, indicating the very slow response of the
 catchment. At the time of overpass, there was no wind or rain in
 the area. The location of the test area is shown in Fig. 1, and an
 example of the aerial photography is shown in Fig. 2. The flood-
 plain over this reach is semirural, with the majority of fields
 being used at the time for pasture or having been ploughed.
 There are also several urban areas, and the region is crossed
 by a number of major roads and railways. The flood waterline
 was delineated by eye from the aerial photos and vectorized
 [19]. The waterline vectors were then georeferenced using an
 orthographic transform that is parameterized by a least squares
 method using 15–20 control points for each photograph. The
 error in the waterline position was assessed from waterline
 segments where the waterline was observed to lie alongside a
 hedgerow or field boundary that could be located on a 1 : 25 000
 scale map and was found to be less than 20 m.



Fig. 2. Example of the aerial photography in the upper section of the reach, looking southwest from the north of the region (the view direction is V in Fig. 1).

Lidar data at 1-m resolution were acquired for a section of this reach west of Oxford and approximately 12 km long by the Environment Agency of England and Wales (EA). The lidar was an Optech ALTM 2033 that was flown on a Cessna aircraft at 120 kn at a flying height of 900 m, with a laser firing rate of 33 kHz, a scanning frequency of 30 Hz, and a scanner half angle of 18°. The lidar heights were validated by the EA by comparing them with a set of global positioning system (GPS) heights of several flat unvegetated surfaces in the area. Based on a sample of 299 GPS readings, the lidar heights were found to have an rms error of 10.6 cm, which comprised a random error of 10.2 cm and a systematic error of 2.6 cm. Lidar height accuracy reduces on steeper slopes and in vegetated regions [26]. Lidar positional accuracy was about 0.4 m [27]. The postprocessed lidar DTM and vegetation height mask were obtained from the EA. These were degraded to 2-m pixel size to avoid too large a mismatch with the SAR pixel size of 12.5 m. Fig. 3 shows the lidar DTM with the high land of Wytham Hill in the west and the raised Oxford Nature Park in the east (see Fig. 1), both of which are relevant to this study. Fig. 3 also shows the aerial photo waterline overlain on the lidar DTM, with the waterline color representing its difference in height from the local mean waterline height (within 0.5-km distance). The presence of large sections of waterline having small differences (blue color) from the local mean height indicates that the aerial waterline height varies smoothly along the reach. The waterline includes instances of islands of higher ground that are surrounded by water. It is assumed here that all areas of water have been accurately mapped, so that the validation data are essentially error free.

III. FLOOD EXTENT EXTRACTION FROM SAR DATA

A. Algorithm Description

A detailed description of the algorithm to delineate a flood using an active contour model is given in [18], and only an overview is presented here. Active contour models or snakes are useful for converting incomplete or noisy edge maps into smooth continuous vector boundaries [5], [28]. The edge image space is searched using a dynamic curvilinear contour that is driven to be attracted to edge pixels using an energy minimization function, so that the contour can link together unconnected edge segments. The contour (snake) is represented in a piecewise linear fashion as a set of nodes (i.e., the coordinates of the snake points) that are linked by straight-line segments. Ivins and Porrill [29] developed a statistical snake that operates on the image itself rather than an edge image, dispensing with the need for a prior edge detection stage. Their technique involves estimating the local image mean intensity (tone) at a node using the pixels between this node and its adjacent nodes. This gives the advantage that noise due to SAR speckle is reduced by averaging pixel intensities along an edge while, at the same time, maintaining resolution that is perpendicular to the edge, giving accurate edge positioning. The local intensity variance (texture) is also calculated from these pixels, as this has proven to be a useful discriminator between different natural land cover types having similar mean intensities in SAR imagery.

The statistical snake is formulated as an energy minimization problem with the total snake energy $E(u(s))$ given by

$$E(u(s)) = E_{\text{tension}} + E_{\text{curvature}} - \iint G(I(x, y)) dx dy \quad (1)$$

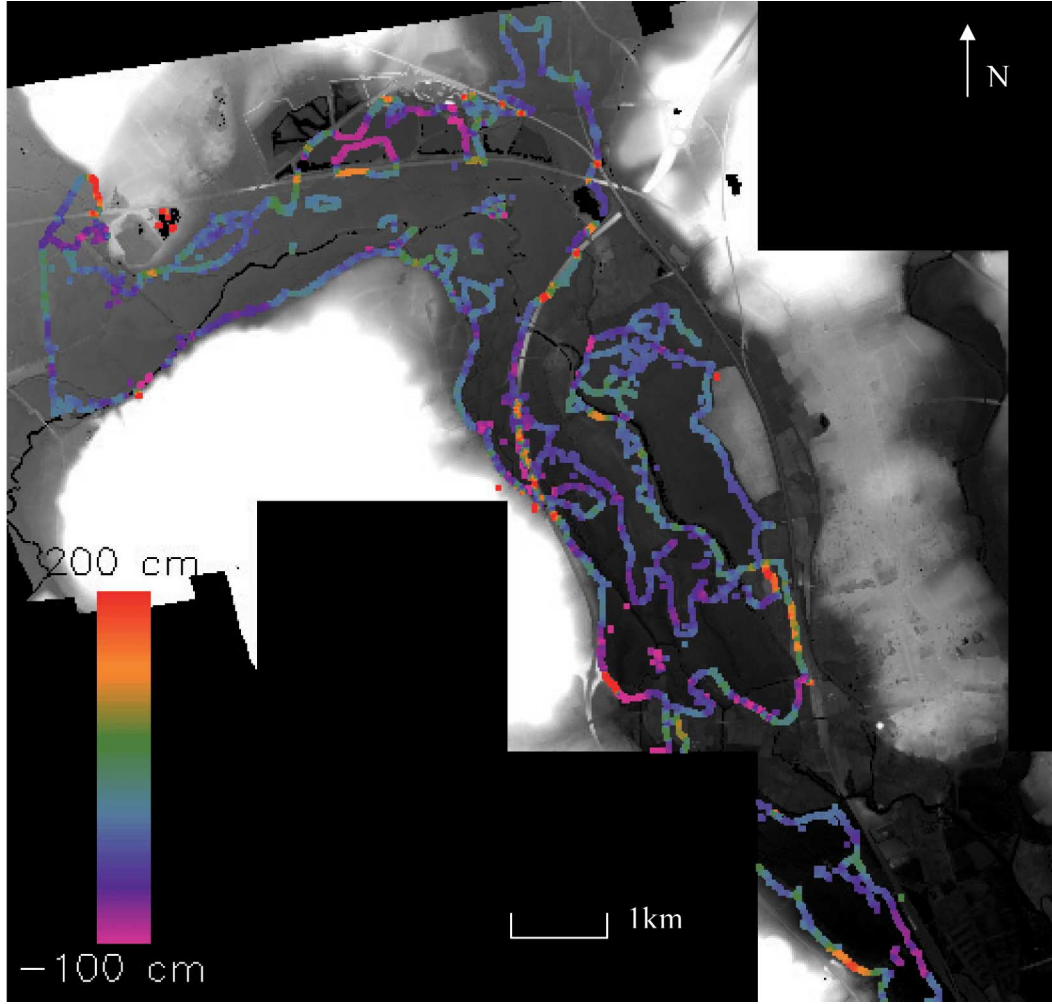


Fig. 3. Aerial photo waterline overlay on the lidar DTM. The colors represent the difference in height of the waterline from the local mean waterline height.

where $\mathbf{u}(s) = (x(s), y(s))$ describes the contour position (x, y) in the 2-D image space as a vector function of arc length parameter s . E_{tension} and $E_{\text{curvature}}$ are energies that are generated by the model's internal tension and stiffness constraints, which favor a smooth uncrenellated contour that is made up of evenly spaced nodes (see the following). G is a goodness function that assesses how well a set of image pixels $I(x, y)$ meets certain criteria. The total energy is minimized if the contour encloses a region of pixels that is homogeneous in tone and texture.

If the mean and variance of the intensities of the set of pixels that are immediately at either side of a particular snake node are measured, the knowledge of how these variables are distributed can be used to estimate the probability that these pixels match those that are already within the region that is enclosed by the contour. Horritt [18] relates G to the log of this probability, with the dependence on the measured sample mean μ' , for example, having the form

$$G(\mu') = 1 - n(\mu' - \mu)^2 / vk^2 \quad (2)$$

where μ and v are the mean and variance of the seed population that is already enclosed within the contour, respectively; n is

the sample size; and k is a parameter that can be adjusted to tune algorithm performance. G is then equal to 1 for a set of pixels with the expected mean but falls to zero if the mean differs by $k\sqrt{(v/n)}$ (i.e., k standard deviations) from the expected value. The parameter k is usually set at about 2 or 3 but may be increased further to allow for a level of statistical inhomogeneity in the region being segmented. The overall goodness function (with components that are based on both the measured mean and variance) is limited to a minimum value of -1 .

The roles of the tension and curvature constraints are to produce a contour of appropriate smoothness with evenly spaced nodes, by a consideration of the balance between image and curvature forces. Consider the situation that is shown in Fig. 4 for snake nodes at $\mathbf{u}_{i-1}$, $\mathbf{u}_i$, and $\mathbf{u}_{i+1}$ that are linked by unit vectors $\mathbf{v}_i$ and $\mathbf{v}_{i+1}$. The local curvature is $\Delta\theta/\Delta s$, where $\Delta\theta$ is the change of angle along arc length Δs . Horritt [18] gives the contribution to the total curvature energy as

$$\Delta E_{\text{curvature}} = \gamma(\Delta\theta/\Delta s)^2/\Delta s = \gamma|\mathbf{v}_{i+1} - \mathbf{v}_i|^2/a_i \quad (3)$$

where a_i is the distance between the midpoints of $\mathbf{v}_i$ and $\mathbf{v}_{i+1}$, and γ is a curvature energy weighting parameter. Equation (3)

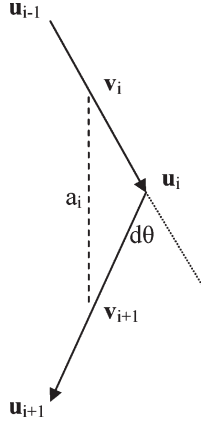


Fig. 4. Vectors for describing curvature and tension energies (after [18]).

278 is valid for small values of $\Delta\theta$. Similarly, the contribution to
279 the tension energy is given by

$$\Delta E_{\text{tension}} = \lambda (|\mathbf{u}_{i+1} - \mathbf{u}_i|^2 + |\mathbf{u}_i - \mathbf{u}_{i-1}|^2) \quad (4)$$

280 where λ is the tension energy weighting parameter. The mag-
281 nitudes of these energies can be adjusted using the weighting
282 parameters. Too large a value for the curvature parameter
283 will make the curvature term dominate the model energy and
284 produce an unrealistically smooth contour. Too large a value of
285 the tension parameter will favor a short contour and stifle the
286 growth of the snake.

287 The scheme that was used to minimize the energy is the
288 algorithm of Williams and Shah [28]. For each node at each
289 iteration, the change in energy dE is computed for moves to all
290 eight neighbors of the node

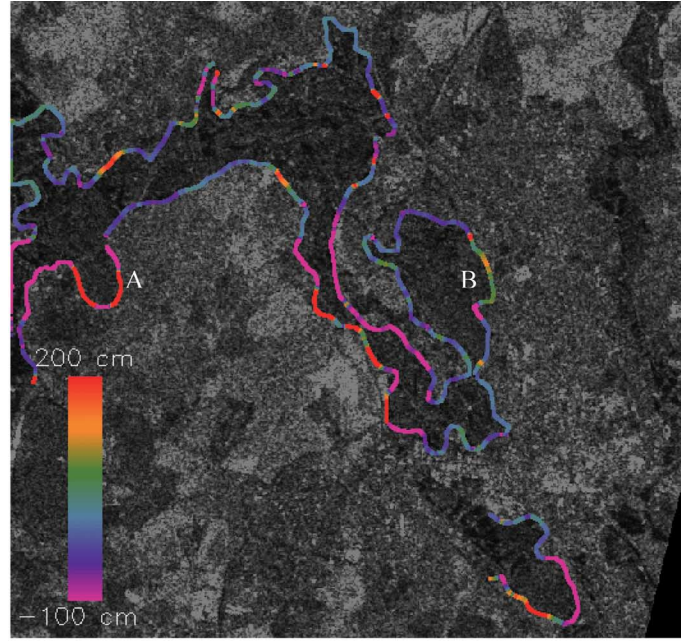
$$dE = -GdA + dE_{\text{tension}} + dE_{\text{curvature}}. \quad (5)$$

291 The lowest (most negative) dE is chosen. Obviously, dE is
292 equal to zero for no node movement. G is calculated along the
293 line segments linking the node with its two neighbors, and dA is
294 the local change in area. If G is positive, the snake is in a region
295 of homogeneous pixels, a positive dA is favored, and the snake
296 expands. If G is negative, the snake is in an inhomogeneous re-
297 gion, a negative dA is favored, and the snake retreats. The mean
298 and standard deviation of the seed population are calculated
299 from all pixels lying inside the contour every ten iterations.

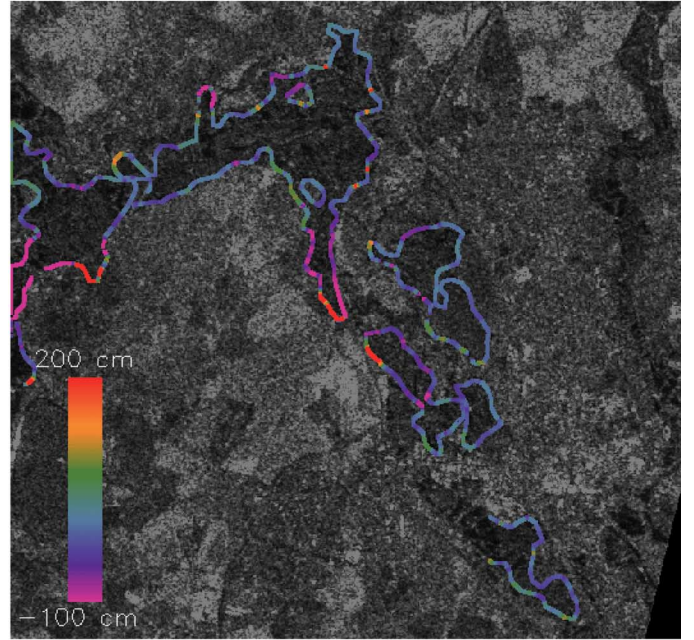
300 The flooded region may not be simply connected, as islands
301 and isolated water bodies may form holes and outliers. To cope
302 with this, the algorithm incorporates a method for dealing with
303 complex topology and snake self-intersection. As an example,
304 a snake may spawn a smaller subsnake within itself to represent
305 an island.

306 B. Implementation and Qualitative Assessment of Results

307 A personal computer (PC)-based implementation of the al-
308 gorithm (Psnake NT) was used in this paper [30]. Psnake NT
309 is a software package that is available to the hydrological
310 modeling community for the semiautomatic extraction of flood



(a)



(b)

Fig. 5. Waterline conditioned only on SAR data overlain on SAR data (a) for parameter $k = 3$ and (b) $k = 2$. The colors represent the difference in height of the waterline from the local mean waterline height.

4/C

extents from SAR data. Fig. 5 shows snake waterlines that are
311 generated using SAR data only, for the number of standard
312 deviations k of 3 and 2, overlain on SAR data. It has been found
313 by experiment that k is probably the most important parameter
314 controlling the snake [19]. Other parameter settings were a
315 minimum node spacing of 6 pixels, a maximum node spacing
316 of 12 pixels, curvature parameter γ of 68.3, tension parameter λ
317 of 0.1, a texture weight of 0.2, and iterations of 200. The snake
318 was seeded (i.e., initialized) manually as a narrow strip lying
319

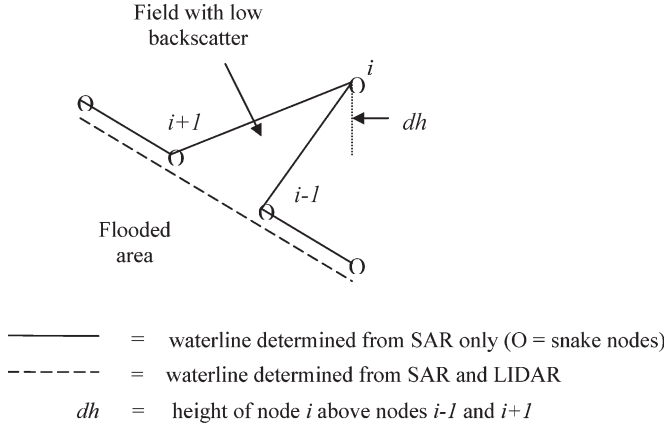


Fig. 6. Example error that might be corrected using lidar.

along the course of the unflooded river channel, ensuring that it contained only flooded pixels.

In Fig. 5, the snake shows a tendency to leak onto higher ground on Wytham Hill [point A in Fig. 5(a), see also Fig. 3]. This is likely to be due to the presence of vegetated fields, which correspond to areas of low SAR backscatter and are likely to be misclassified as flooded. While no ground reference data were acquired at the time of the flood, evidence for this comes from a recent aerial photograph that was obtained later than the SAR image. A further example of leakage of the snake onto higher ground is visible at point B in Fig. 5(a), where the snake has leaked onto the Oxford Nature Park, which is higher than the land toward the Thames yet again exhibits low SAR backscatter.

IV. FLOOD EXTENT EXTRACTION FROM SAR AND LIDAR DATA

A. Algorithm Modification

The snake algorithm was modified so that the snake was conditioned not only on the SAR image but also on the lidar DTM, so that it becomes smoothly varying in ground height as well as in SAR intensities and textures. The principle that was adopted was that the SAR image should still be the primary determinant of the flood extent. In most areas, the flood extent that was determined by the SAR will be correct within the SAR resolution, but where errors creep in the lidar can help to correct these.

The lidar DTM is able to provide a ground height at each pixel, so that each position $\mathbf{u}(x, y)$ becomes $\mathbf{u}(x, y, z)$. The modification involves using the lidar heights to measure curvatures and tensions at snake nodes in 3-D rather than 2-D space. Consider an instance where an unflooded field with low SAR backscatter is adjacent to a flood edge, such that the field is included in the SAR waterline determined by the snake (Fig. 6). As there will likely be a rise in height (dh) across the field that is perpendicular to the true flood edge, the error in the waterline will give rise to a significant component of curvature in the vertical plane, which will not be present in the waterline segments that are adjacent to the field. To be specific, in Psnake

NT, the contribution to the 3-D curvature energy at the snake node at $\mathbf{u}(x_i, y_i, z_i)$ from its two adjacent nodes is

$$\Delta E_{\text{curvature}} = \gamma |\mathbf{v}_{i+1} - \mathbf{v}_i|^2 / a_i = (c_{ix}^2 + c_{iy}^2 + c_{iz}^2) / a_i \quad (6)$$

where

$$\begin{aligned} c_{ix} &= (x_{i+1} - x_i) / d_{i+1} - (x_i - x_{i-1}) / d_i \\ c_{iy} &= (y_{i+1} - y_i) / d_{i+1} - (y_i - y_{i-1}) / d_i \\ c_{iz} &= (z_{i+1} - z_i) / d_{i+1} - (z_i - z_{i-1}) / d_i \\ d_i &= ((x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 + (z_i - z_{i-1})^2)^{0.5} \\ d_{i+1} &= ((x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2)^{0.5} \\ a_i &= \left(((x_{i+1} + x_i) / 2 - (x_i + x_{i-1}) / 2)^2 \right. \\ &\quad \left. + ((y_{i+1} + y_i) / 2 - (y_i + y_{i-1}) / 2)^2 \right. \\ &\quad \left. + ((z_{i+1} + z_i) / 2 - (z_i + z_{i-1}) / 2)^2 \right)^{0.5} \end{aligned}$$

and the suffixes refer to the node numbers in Fig. 6. To reduce the vertical curvature component c_{iz}^2 at node i in Fig. 6, the snake will try to contract to drag node i back to be collinear with nodes $i-1$ and $i+1$, which will also reduce c_{ix}^2 and c_{iy}^2 . The 3-D tension energy, which is proportional to $(d_{i+1}^2 + d_i^2)$, will also be reduced by this move.

A waterline error due to the presence of emergent vegetation at the edge of the flood might also have significant components of vertical curvature and tension that could be reduced by correcting the error. A complicating factor in this case is that the SAR and lidar forces might be acting against each other. In order to reduce the vertical curvature and tension by incorporating the area of enhanced backscatter into the flooded area, the inhomogeneity of the SAR returns in the flooded area would generally have to increase. Which force won out in a particular case would depend on their relative strengths. However, this effect is not the dominant source of error [19].

In order to take account of the fact that a change in height at a node should, in general, cause different changes in curvature and tension compared to the same magnitude change of node position in the xy plane, the lidar heights were scaled by weighting factor w_l with respect to the (x, y) coordinates.

The straightforward approach to combining the SAR and lidar data would be to use the existing algorithm with both data sets and simply calculate 3-D rather than 2-D curvature and tension energies. A possible objection to this might be that, if there were flooded mounds in the floodplain that are not visible to the SAR but visible to the lidar, these might retard the expansion of the snake and distort the eventual waterline. An alternative approach could be to use the algorithm with SAR data and 2-D curvatures and tensions only initially. Then, the snake iterations could continue using SAR and lidar data, and 3-D curvatures and tensions, causing the snake to adjust itself to correct errors where necessary. However, in cases where the waterline was significantly in error, it might be difficult to recover from these errors. For example, if the snake leaked onto higher ground, it might be impeded from returning to the true waterline position by a hollow in the higher ground. In practice, it turns out that the straightforward approach using

the existing algorithm and calculating 3-D curvatures and tensions works well enough.

The SAR data may have significantly lower resolution than the airborne lidar data, as in the present test data set comprising ERS satellite SAR data. In this case, it may be possible to correct the waterline position to sub-SAR pixel accuracy in a second pass of the algorithm. The idea would be to rescale the SAR image and the snake waterline from the first pass to the higher resolution of the lidar, and to continue iterating to try to move the snake nodes away from the centers of the enlarged SAR pixels to create a waterline varying more smoothly in height along its length. A constraint would be that a node should not be allowed to move outside its enlarged SAR pixel, as no further information could be extracted from the SAR image at this stage.

B. Implementation and Qualitative Assessment of Results

For the first pass of the modified algorithm, the lidar image was degraded to the same pixel size as the SAR image (12.5 m) by averaging the lidar heights within each SAR pixel. The parameter settings for this pass were the same as those for the snake that was conditioned on only the SAR data (other than for k and w_l). The initial value of lidar weight factor w_l was chosen by experiment to be 0.15. This took into account the fact that the leakage at Wytham Hill [at point A in Fig. 5(a)] occurs over a distance of about 0.5 km. Curvature at a node is calculated using the two adjacent nodes on either side of the central node, spanning four internode spacings. For an internode spacing of eight pixels, this corresponds to a distance of about 400 m, roughly matching that required. The w_l setting also reflected the facts that the lidar heights were expressed in millimeters and that a, for example, 1000-mm rise in the lidar height of the central node should give rise to a significant increase in 3-D curvature. Even though a node can only be moved horizontally by one SAR pixel at each iteration, this still amounts to a horizontal shift of 12.5 m, which is large compared to a 1-m vertical rise.

The original snake seed that was used contained only pixels south of the A40 road west of Oxford (Fig. 1), and it was found on the first pass that, with the 3-D curvature constraint, the snake would not expand into the flooded areas north of the embanked road, even though this was, on average, only 1.5 m higher than the fields surrounding it. In practice, floodwater from the Thames flows under the A40 onto the lower land to the north through culverts that are spaced at about 250-m intervals. To overcome this difficulty, additional snake seed pixels were inserted to the north of the A40, which were then able to expand into the northernmost part of the flooded region. The same snake seed was used for all snakes that were generated, whether they were conditioned using the lidar data or not.

The second pass took place at higher resolution, i.e., at the 2-m pixel spacing of the lidar data. The input to this pass was the snake output from the first pass, with the node coordinates scaled up by 6.25 to match the change in resolution. The SAR image was interpolated from 12.5 to 2 m using nearest neighbor interpolation. The number of iterations was set to 3,

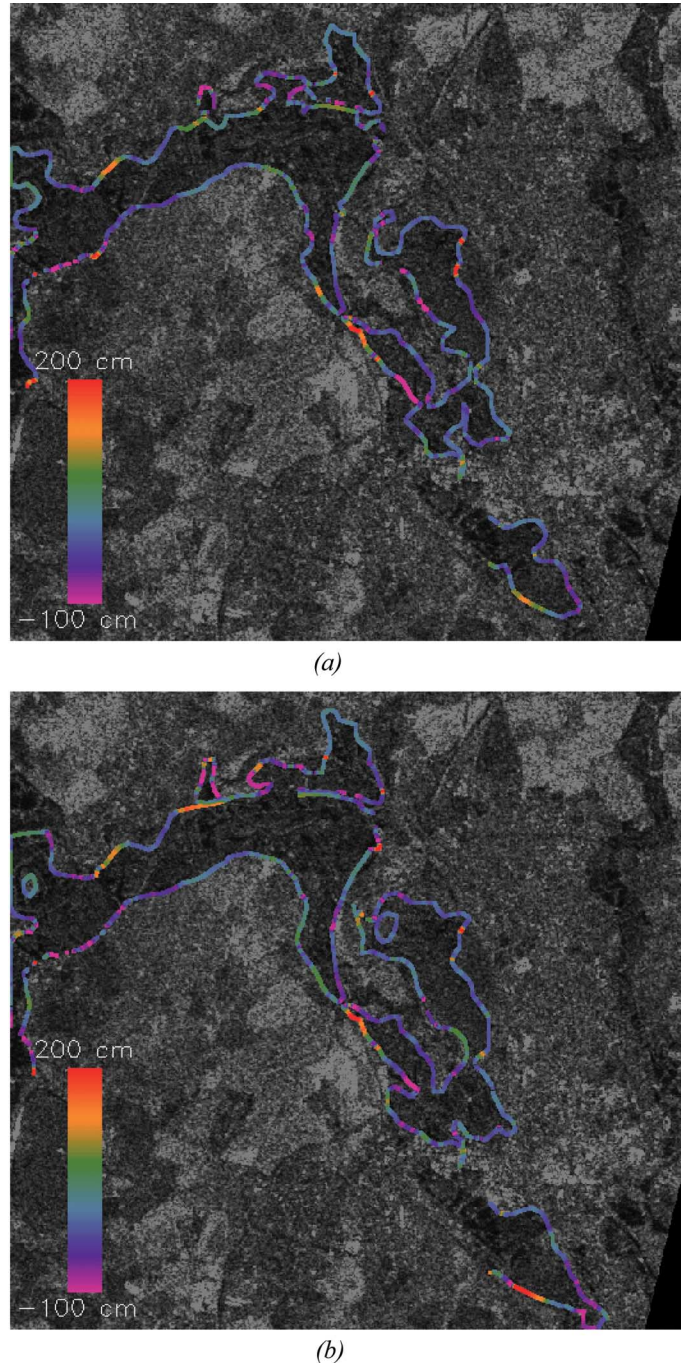


Fig. 7. Waterline conditioned on SAR and lidar data overlain on SAR data (a) for parameter $k = 3$ and $w_l = 0.15$, and (b) for $k = 4$ and $w_l = 0.15$. The colors represent the difference in height of the waterline from the local mean waterline height.

4/C

to ensure that the snake nodes would not move outside the SAR pixels within which they had stabilized after the first pass. The minimum and maximum node spacings were also upscaled to 37 and 74 pixels, respectively, ensuring similar 3-D curvatures to those on the first pass.

Fig. 7 shows snake waterlines that were conditioned on both SAR and lidar data, for k values of 3 and 4 and lidar weight $w_l = 0.15$, overlain on 12.5-m SAR data. It is clear that the tendency for the snake to leak to higher ground at Wytham Hill and at the Oxford Nature Park has been much reduced (see

also Fig. 3). A further benefit is that the snake appears to be more stable to parameter changes. For example, in Fig. 5, the snake that was conditioned only on SAR data shows substantial change when k is raised from 2 to 3, whereas in Fig. 7, the snake that was conditioned on SAR and lidar shows less change when k is raised from 3 to 4. This finding is born out more rigorously in the quantitative analysis described in the next section.

The main errors in waterline position that were corrected using the lidar data are due to the unflooded short vegetation that is adjacent to the flood giving similar returns to open water. The ability of the algorithm to correct loss of flood extent due to emergent vegetation is hardly tested using this data set, as this has few significant examples. The most obvious instances are emergent hedges between adjacent flooded fields, but these are generally of insufficient area to stop the snake subsuming them into its interior, even if conditioned only on SAR data.

V. PARAMETER OPTIMIZATION AND QUANTITATIVE COMPARISON OF METHODS

The snake parameters were optimized using a quantitative measurement of algorithm performance. The snake and aerial photo waterlines were first heighted by superimposing them on the lidar DTM. The snake waterline is defined only at the snake nodes. Only nodes on low slopes and in areas of short vegetation in the lidar vegetation height map were selected for heighting, as these are the ones that are likely to be heighted most accurately. The lower the slope, the smaller the node height error for a given error in its position. No requirements were made that selected nodes should have a strong SAR edge [indicated by a low G value (2)] associated with them, as this would reject nodes at the boundaries between the flood and an unflooded field giving low SAR backscatter, or between a region of emergent vegetation at the flood edge and an adjacent unflooded land (both giving high SAR backscatter).

For each snake node that was selected, the aerial photo height to associate with the snake height was found by finding the height of the closest aerial photograph waterline point. This was found by applying a distance-with-destination transform to the aerial photo waterline image. The distance-with-destination transform is a form of distance transform that stores, for each pixel in the transform image, its distance to the nearest waterline point and also the direction from which the minimum distance was propagated. This allows backtracking from a pixel to find its nearest waterline point [31]. Corroborating the finding of [19], the average separation distance was about 50 m, although this value was strongly influenced by a small number of pairs having large separations, and the average separation of 70% of the pairs having separations of less than 50 m was only 20 m. However, the pairs with large separation were not rejected, as they included examples where, e.g., the SAR waterline was displaced from the aerial photo waterline by a complete field width due to misclassification of the field as flooded. The anticipation was that these events would be less common when the snake was conditioned on the SAR and lidar data than on the SAR data alone.

Parameters were optimized by minimizing the sum of the squared height differences between the snake nodes and their

corresponding aerial photo waterline points. To ensure that adjacent pairs of heights were largely uncorrelated, the pairs that were selected so far were thinned further, so that no pair was closer than 200 m to another. This distance was estimated by constructing a correlogram from the set of pairs [32] and was the distance at which the average correlation between adjacent pairs became less than 0.2. From the remaining pairs, the mean and standard deviations of the snake and aerial photograph waterline heights were calculated, as was the rms error of the height differences, with this being the variable to minimize in the parameter optimization. The mean height difference and the standard deviation of the differences were also calculated, and this allowed a paired t-test to be performed to test whether the differences were significantly nonzero. The paired t-test is used to exploit the fact that, while corresponding SAR and aerial photograph waterline heights will be correlated due to the gradual drop in height along the reach, the height differences at corresponding nodes will be uncorrelated due to the thinning process, as required by the paired test.

Only the most important parameters were investigated in the optimization procedure. For the snake that was conditioned on only SAR data, the parameter that was optimized was k . For the snake that was conditioned on SAR and lidar data, k and w_l were optimized.

Table I(a) shows the results of varying k for the snake that was conditioned on only the SAR data. The minimum rms error is 221.1 cm, which was obtained for $k = 2.0$. The associated high t value implies that there is a significant height difference at the 5% level between the snake and aerial photo waterlines. The corresponding snake is shown in Fig. 5(b). Higher values of k give significantly larger rms errors, and the high t values that were coupled with positive mean height differences imply that, for all these k values, the snake waterline heights are significantly higher than those of the aerial photograph.

Table I(b) shows the results of varying k for the snake that was conditioned on SAR and lidar data, with w_l held constant at 0.15. The minimum rms error is 55.5 cm, which was obtained for $k = 3.0$. The associated t value is not significantly nonzero, so that there is no significant difference between the snake and aerial photo waterline heights. The corresponding snake is shown in Fig. 7(a).

Table I(c) shows the results of varying w_l for the snake that was conditioned on SAR and lidar data, with k held constant at 3.0. The minimum rms error is obtained at $w_l = 0.15$. Over the ranges of k and w_l that were investigated, none of the t values are significantly nonzero, implying greater robustness to parameter changes than the case for the snake that was conditioned on only SAR data.

Table II gives the frequency tables of the absolute differences of the paired heights for the parameter sets giving the minimum rms errors for the snake that was conditioned on only the SAR data and the snake that was conditioned on SAR and lidar data. It can be seen that the increase in the rms error in the case of the snake that was conditioned only on SAR data is due almost entirely to the large number of pairs having height differences of greater than 300 cm. This is also apparent in Fig. 8, where the paired height differences for the two cases are plotted as a

TABLE I

RESULTS OF (a) VARYING k FOR THE SNAKE CONDITIONED ON ONLY THE SAR DATA, (b) VARYING k FOR THE SNAKE CONDITIONED ON SAR AND LIDAR DATA, WITH w_l HELD CONSTANT AT 0.15, AND (c) VARYING w_l FOR THE SNAKE CONDITIONED ON SAR AND LIDAR DATA, WITH k HELD CONSTANT AT 3.0

k	Number of height pairs	R.m.s. error in height (cm)	Mean height difference (cm)	t_0	Probability $t > t_0 $ (one-sided test)	Relative height standard deviation (cm)
1.5	165	238.8	31.6	1.7	0.04	105.3
2.0	200	221.1	33.7	2.2	0.02	136.2
2.5	197	381.3	65.4	2.4	0.01	263.1
3.0	195	331.4	64.5	2.8	0.004	314.4
4.0	206	317.5	70.7	3.3	0.0005	379.1

(a)

k	Number of height pairs	R.m.s. error in height (cm)	Mean height difference (cm)	t_0	Probability $t > t_0 $	Relative height standard deviation (cm)
2.8	195	57.8	-1.5	-0.4	0.35	43.5
3.0	191	55.5	-4.3	-1.0	0.15	42.6
3.2	190	86.6	-3.1	-0.5	0.30	52.6
3.5	195	120.8	5.2	0.6	0.28	65.4
4.0	195	63.7	4.5	1.0	0.15	48.9

(b)

w_l	Number of height pairs	R.m.s. error in height (cm)	Mean height difference (cm)	t_0	Probability $t > t_0 $	Relative height standard deviation (cm)
0.10	187	90.2	-0.1	-0.1	0.46	47.4
0.14	196	61.0	5.4	1.2	0.10	43.0
0.15	191	55.5	-4.3	-1.0	0.15	42.6
0.16	191	55.8	0.7	0.2	0.42	43.5
0.20	195	81.5	-9.0	-1.5	0.07	54.7

(c)

580 function of distance downstream. The main effect of the lidar
581 data is to correct errors in the sections of waterline containing
582 these outliers, when the snake is conditioned on both SAR and
583 lidar.

584 The effect of the second pass of the algorithm in correcting
585 the waterline position to sub-SAR pixel accuracy was also
586 assessed. For the parameter set giving the minimum rms error
587 for the snake that was conditioned on SAR and lidar data
588 ($k = 3.0$ and $w_l = 0.15$), the algorithm was run for only the
589 first pass. The minimum rms error was 58.1 cm, which is
590 only slightly higher than the 55.5 cm that was achieved when
591 both passes were employed. There was slightly more difference
592 when k was raised to 4.0 and when the rms error increased to
593 70.8 from 63.7. This indicates that the main reduction in error is
594 being generated in the first pass and that the second gives only
595 a second-order improvement. This may be partly because only
596 snake nodes on low slopes have been selected, and thus, height
597 differences across the SAR pixel, due to its size, will be small.

TABLE II

FREQUENCY TABLES OF THE ABSOLUTE DIFFERENCES OF PAIRED HEIGHTS FOR THE PARAMETER SETS GIVING THE MINIMUM RMS ERRORS FOR THE SNAKE CONDITIONED ON ONLY THE SAR DATA AND THE SNAKE CONDITIONED ON SAR AND LIDAR DATA

	0-49cm	50-99cm	100-149cm	150-199cm	200-249cm	250-299cm	300-499cm	>=500cm
Snake conditioned on SAR data ($k = 2.0$)	155	20	9	3	3	1	3	6
Snake conditioned on SAR and LiDAR data ($k = 3.0$, $w_l = 0.15$)	154	20	9	5	2	1	0	0

VI. DISCUSSION

598

The method may be applied to the validation of the flood 599 models of other river reaches, with the only prerequisites 600 additional to the usual data required to set up a hydraulic 601 model (e.g., an inflow hydrograph and river channel cross- 602 sectional data) being the availability of SAR imagery of the 603 river in flood and reasonably contemporaneous lidar data of 604 the unflooded reach. It would be relatively straightforward to 605 make the procedure operational. Lidar data are now often used 606 to parameterize the hydraulic model, making it more likely that 607 they would also be available to improve the SAR waterline. 608 It would be straightforward to implement the modified algo- 609 rithm within the Psnake NT software package. For this catch- 610 ment, the algorithm processing time was less than 1 min on a 611 Pentium IV personal computer. 612

The emphasis in the foregoing has been on ERS satellite 613 SAR data because of the availability of simultaneous ERS SAR 614 and aerial photography of the 1992 Oxford flood. While ERS 615 SAR data have poorer resolution than airborne lidar data, the 616 technique should also be applicable in cases where the SAR 617 resolution is similar to that of the lidar (e.g., airborne SAR), 618 in which case a second pass of the algorithm would certainly 619 be unnecessary. The algorithm of [18] and [19] has been used 620 to delineate flood extents in airborne SAR imagery [33], [34]. 621 However, given the increasing number of satellite SAR sensors 622 flying or planned and the difficulty of flying aircraft in poor 623 weather often accompanying floods, satellite SARs are likely 624 to remain to be a major source of SAR data for flood mapping 625 in the future. While the ERS SAR sensor has single VV polar- 626 ization and a fixed 23° viewing angle, the advent of later sensors 627 with higher resolutions, multiple polarizations, and variable 628 viewing angles (e.g., RADARSAT and Envisat Advanced SAR) 629 has allowed improved flood delineation (e.g., [15]). The high- 630 resolution satellite SAR sensors due for launch shortly (e.g., 631 RADARSAT-2, TerraSAR, and the Cosmo-Skymed constella- 632 tion) will have resolutions that match or almost match that of 633 airborne lidar. 634

Production of a more smoothly varying waterline may allow 635 the development of improved performance measures for flood 636 extent validation based on patterns of height differences be- 637 tween observed and modeled waterlines rather than on patterns 638 of wet or dry pixels, as currently done. Aronica *et al.* [24] 639

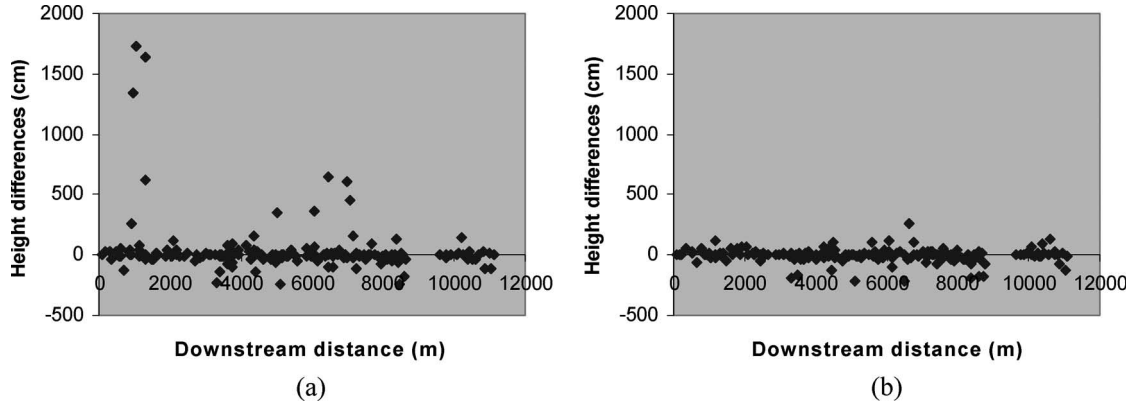


Fig. 8. Paired height differences versus distance downstream for the parameter sets giving the minimum rms errors for the snake that was conditioned on (a) SAR data and (b) SAR and lidar data.

640 describe current performance measures based on binary pat-
641 terns. One measure representative of these is

$$F^{(2)} = (A_{\text{obs}} \cap A_{\text{mod}}) / (A_{\text{obs}} \cup A_{\text{mod}}) \quad (7)$$

642 where A_{obs} and A_{mod} represent the set of pixels that are ob-
643 served to be inundated and predicted as inundated, respectively.
644 $F^{(2)}$ is equal to 1 when observed and predicted areas coincide
645 exactly and equal to 0 when no overlap between predicted and
646 observed areas exists. A performance measure based on height
647 differences might have several advantages over one such as
648 $F^{(2)}$ based on binary pattern data. First, as the distribution of
649 t is known, it is possible to estimate the probability $P(t > |t_0|)$
650 of obtaining a t value that is greater than the absolute value
651 of that measured (t_0), whereas $F^{(2)}$ is simply a weight factor.
652 Second, the height difference measure between two model
653 runs with different parameter settings might turn out to be
654 more sensitive than $F^{(2)}$, because a small change in mean
655 height might cause a large change in $P(t > |t_0|)$ yet only a
656 small change in $F^{(2)}$. Third, the sign of the t value identifies
657 whether an overprediction or an underprediction has occurred,
658 whereas $F^{(2)}$ may give similar values for overprediction and
659 underprediction.

660 In this case, the parameters of the snake that was generated
661 using SAR and lidar have been optimized using the aerial
662 photo waterline, but this will not be available in the more usual
663 situation in which the snake is being used to validate a model
664 waterline. It is interesting that, for those nodes in areas of low
665 slope and low vegetation, the standard deviation of their heights
666 relative to their local mean height (within an 0.5-km distance)
667 is a minimum at the same parameter setting at which the rms
668 error of height differences between snake and aerial photo
669 waterlines is minimized [Table I(b) and (c)]. This presumably
670 reflects the fact that the snake is most smoothly varying when
671 the relative height standard deviation is minimized, and it may
672 be possible to use this measure as a surrogate for optimizing the
673 snake parameters when using the snake to validate a modeled
674 flood extent. However, a more likely scenario is that a single
675 optimum parameter set would not be sought in this situation. In
676 flood model validation, emphasis is now placed on associating
677 uncertainties with model flood extents, by deriving flood extent

probability maps showing the probability of each pixel being
678 flooded, given a flood event of the given magnitude. It has
679 been found that, for a particular event, many different sets
680 of model parameters may give flood extents that match the
681 observed extent to a greater or lesser degree. Such equifinality
682 has been well documented and has resulted in the development
683 of the generalized likelihood uncertainty estimation (GLUE)
684 technique, whereby many model runs are carried out, spanning
685 the likely ranges of model parameters [35]. A flood extent
686 probability map is obtained by performing a weighted average
687 of the binary-valued modeled flood extents (with the value for
688 a pixel being 1 for flooded and 0 for not flooded), with each
689 model flood extent being weighted according to its performance
690 measure relative to an observed flood extent. As previously
691 mentioned, the performance measure could be based on pat-
692 terns of height differences between observed and modeled
693 waterlines rather than on patterns of wet or dry pixels. To date,
694 the GLUE methodology has been mainly used to assess flood
695 extent uncertainty due to model parameter errors (see, e.g., [21]
696 and [36]). However, it seems a natural future step to try to
697 extend the method to cope with uncertainty in both model and
698 snake algorithm parameters [36]. Some method of limiting the
699 number of model runs that are required would probably need to
700 be employed (e.g., Gaussian emulation [37]), although some
701 reduction might result from using an improved performance
702 measure based on height differences. 703

VII. CONCLUSION

704 An algorithm has been developed for the automatic
705 extraction of flood extent using a snake that was generated
706 from combined SAR and lidar data, and the resulting waterline
707 compared to that generated using SAR data alone. From the re-
708 sulting snakes, sets of nodes in areas of low slope and low veg-
709 etation have been extracted, followed by further thinning. After
710 optimization of parameters, the heights of the resulting node set
711 from the snake that was conditioned on SAR and lidar matched
712 the corresponding node heights from the aerial photo waterline
713 significantly more closely than those from the snake that was
714 conditioned solely on SAR data. The conclusion is that, for
715 the variety of situations that are present in this particular
716

717 data set, the use of the lidar data has resulted in an observed
718 waterline that varies more smoothly along the reach and is a
719 better match to our best estimate of the true waterline heights.

720 ACKNOWLEDGMENT

721 The authors would like to thank the EA for the provision
722 of lidar data, CEH Wallingford for the SAR and photographic
723 data, and the referees for their improvements to this paper.

724 REFERENCES

725 [1] P. D. Bates, M. S. Horritt, C. N. Smith, and D. C. Mason, "Integrating
726 remote sensing observations of flood hydrology and hydraulic modeling,"
727 *Hydrol. Process.*, vol. 11, no. 14, pp. 1777–1795, 1997.
728 [2] L. C. Smith, "Satellite remote sensing of river inundation area, stage
729 and discharge: A review," *Hydrol. Process.*, vol. 11, no. 10, pp. 1427–
730 1439, 1997.
731 [3] F. T. Ulaby, R. K. Moore, and A. K. Fung, *Microwave Remote Sensing*,
732 vol. 3. Norwood, MA: Artech House, 1986.
733 [4] J.-S. Lee and I. Jurkevich, "Coastline detection and tracing in SAR
734 images," *IEEE Trans. Geosci. Remote Sens.*, vol. 28, no. 4, pp. 662–668,
735 Jul. 1990.
736 [5] D. C. Mason and I. J. Davenport, "Accurate and efficient determination of
737 the shoreline in ERS-1 SAR images," *IEEE Trans. Geosci. Remote Sens.*,
738 vol. 34, no. 5, pp. 1243–1253, Sep. 1996.
739 [6] J. A. Richards, P. W. Woodgate, and A. K. Skidmore, "An explanation of
740 enhanced radar backscattering from flooded forests," *Int. J. Remote Sens.*,
741 vol. 8, no. 7, pp. 1093–1100, 1987.
742 [7] F. M. Henderson, "Environmental factors and the detection of open sur-
743 face water using X-band radar imagery," *Int. J. Remote Sens.*, vol. 16,
744 no. 13, pp. 2423–2437, 1995.
745 [8] S. I. Solomon, "Methodological considerations for the use of ERS-1 SAR
746 imagery for the delineation of river networks in tropical forest areas," in
747 *Proc. 1st ERS-1 Symp.*, Frascati, Italy, Jun. 26–27, 1995, pp. 595–600.
748 [9] M. S. Horritt, D. C. Mason, D. M. Cobby, I. J. Davenport, and P. D. Bates,
749 "Waterline mapping in flooded vegetation from airborne SAR imagery,"
750 *Remote Sens. Environ.*, vol. 85, no. 3, pp. 271–281, May 2003.
751 [10] Y. Wang, L. L. Hess, S. Filoso, and J. M. Melack, "Understanding the
752 radar backscattering from flooded and non-flooded Amazonian forests:
753 Results from canopy backscatter modelling," *Remote Sens. Environ.*,
754 vol. 54, no. 3, pp. 324–332, Dec. 1995.
755 [11] M. Badji and S. Dautrebande, "Characterisation of flood inundated areas
756 and delineation of poor drainage soil using ERS-1 SAR imagery," *Hydrol.*
757 *Process.*, vol. 11, no. 10, pp. 1441–1450, 1995.
758 [12] M. L. Imhoff, C. Vermillion, M. H. Story, A. M. Choudhury, A. Gafoor,
759 and F. Pocllyn, "Monsoon flood boundary delineation and damage assess-
760 ment using space borne imaging radar and Landsat data," *Photogramm.*
761 *Eng. Remote Sens.*, vol. 53, no. 4, pp. 405–413, 1987.
762 [13] H. Liu and K. C. Jezek, "Automated extraction of coastline from satellite
763 imagery by integrating Canny edge detection and locally adaptive thresh-
764 olding method," *Int. J. Remote Sens.*, vol. 25, no. 5, pp. 937–958, 2004.
765 [14] A. Niedermeier, E. Romaneessen, and S. Lehner, "Detection of coastlines
766 in SAR images using wavelet methods," *IEEE Trans. Geosci. Remote*
767 *Sens.*, vol. 38, no. 5, pp. 2270–2281, Sep. 2000.
768 [15] Y. Yu and S. T. Acton, "Automated delineation of coastline from polarim-
769 etric SAR imagery," *Int. J. Remote Sens.*, vol. 25, no. 17, pp. 3423–3438,
770 Sep. 2004.
771 [16] P. A. Brivio, R. Colombo, M. Maggi, and R. Tomasoni, "Integration of
772 remote sensing data and GIS for accurate mapping of flooded areas," *Int.*
773 *J. Remote Sens.*, vol. 23, no. 3, pp. 429–441, Feb. 2002.
774 [17] G. Nico, M. Pappalepore, G. Pasquariello, A. Refice, and
775 S. Samarelli, "Comparison of SAR amplitude vs. coherence flood
776 detection methods—A GIS application," *Int. J. Remote Sens.*, vol. 21,
777 no. 8, pp. 1619–1631, May 2000.
778 [18] M. S. Horritt, "A statistical active contour model for SAR image segmen-
779 tation," *Image Vis. Comput.*, vol. 17, no. 3/4, pp. 213–224, Mar. 1999.
780 [19] M. S. Horritt, D. C. Mason, and A. J. Luckman, "Flood boundary de-
781 lineation from synthetic aperture radar imagery using a statistical active
782 contour model," *Int. J. Remote Sens.*, vol. 22, no. 13, pp. 2489–2507,
783 Sep. 2001.
784 [20] G. Schumann, R. Hostache, C. Puech, L. Hoffmann, P. Matgen,
785 F. Pappenberger, and L. Pfister, "High-resolution 3D flood information

from radar imagery for flood hazard management," *IEEE Trans. Geosci.*
786 *Remote Sens.*, vol. 45, no. 6, pp. 1715–1725, Jun. 2007. 787
788 [21] F. Pappenberger, K. Beven, M. Horritt, and S. Blazkova, "Uncertainty in
789 the calibration of effective roughness parameters in HEC-RAS using inun-
790 dation and downstream level observations," *J. Hydrol.*, vol. 302, no. 1–4,
791 pp. 46–69, 2005. 792
793 [22] D. C. Mason, D. M. Cobby, M. S. Horritt, and P. D. Bates, "Flood-
794 plain friction parameterization in two-dimensional river flood models
795 using vegetation heights derived from airborne scanning laser altimetry,"
796 *Hydrol. Process.*, vol. 17, no. 9, pp. 1711–1732, 2003. 797
798 [23] D. M. Cobby, D. C. Mason, M. S. Horritt, and P. D. Bates, "Two-
799 dimensional hydraulic flood modelling using a finite element mesh de-
800 composed according to vegetation and topographic features derived from
801 airborne scanning laser altimetry," *Hydrol. Process.*, vol. 17, no. 10,
802 pp. 1979–2000, 2003. 803
804 [24] G. Aronica, P. D. Bates, and M. S. Horritt, "Assessing the uncertainty in
805 distributed model predictions using observed binary pattern information
806 within GLUE," *Hydrol. Process.*, vol. 16, no. 10, pp. 2001–2016, 2002. 807
808 [25] D. S. Biggin and K. Blyth, "A comparison of ERS-1 satellite radar and
809 aerial photography for river flood mapping," *J. Chart. Inst. Water Eng.*
810 *Manag.*, vol. 10, pp. 1777–1795, 1996. 811
812 [26] L. M. G. Pereira and L. L. F. Janssen, "Suitability of laser data for DEM
813 generation: A case study in the context of road planning and design,"
814 *ISPRS J. Photogramm. Remote Sens.*, vol. 54, no. 4, pp. 244–253, 1999. 815
816 [27] I. J. Davenport, N. Holden, and R. J. Gurney, "Characterizing errors
817 in airborne laser altimetry data to extract soil roughness," *IEEE Trans.*
818 *Geosci. Remote Sens.*, vol. 42, no. 10, pp. 2130–2141, Oct. 2004. 819
820 [28] D. J. Williams and M. Shah, "A fast algorithm for active contours and
821 curvature estimation," *CVGIP, Image Underst.*, vol. 55, no. 1, pp. 14–26,
822 Jan. 1992. 823
824 [29] J. Ivins and J. Porrill, "Statistical snakes: Active region models," in
825 *Proc. 5th Brit. Mach. Vis. Conf.*, York, U.K., Sep. 1994, vol. 1 and 2,
826 pp. 377–386. 827
828 [30] M. S. Horritt, "Psnake NT user manual," Univ. Bristol, Bristol, U.K.,
829 2002. School of Geographical Sciences Report. 830
831 [31] D. C. Mason, T. R. Scott, and H.-J. Wang, "Extraction of tidal channel
832 networks from airborne lidar data," *ISPRS J. Photogramm. Remote Sens.*,
833 vol. 61, no. 2, pp. 67–83, 2006. 834
835 [32] C. V. Deutsch and A. Journel, *GSLIB: Geostatistical Software Library and*
836 *Users's Guide*. New York: Oxford Univ. Press, 1992, p. 41. 837
838 [33] P. D. Bates, M. Wilson, M. S. Horritt, D. C. Mason, N. Holden, and
839 A. Currie, "Reach scale floodplain inundation dynamics observed using
840 airborne SAR imagery," *J. Hydrol.*, vol. 328, no. 1/2, pp. 306–318, 2006. 841
842 [34] S. Neelz, G. Pender, I. Villanueva, M. D. Wilson, N. G. Wright,
843 P. D. Bates, D. C. Mason, and C. Witlow, "Using remotely sensed
844 data to support flood modelling," *Proc. Inst. Civil Eng.*, vol. 159, no. 1,
845 pp. 35–44, 2006. 846
847 [35] K. J. Beven and A. M. Binley, "The future of distributed models: Model
848 calibration and predictive uncertainty," *Hydrol. Process.*, vol. 6, no. 3,
849 pp. 279–298, 1992. 850
851 [36] M. S. Horritt, "A methodology for the validation of uncertain flood inun-
852 dation models," *J. Hydrol.*, vol. 326, no. 1–4, pp. 153–165, 2006. 853
854 [37] J. E. Oakley and A. O'Hagan, "Probabilistic sensitivity analysis of com-
855 plex models: A Bayesian approach," *J. R. Stat. Soc., Series B*, vol. 66,
856 no. 3, pp. 751–769, Aug. 2004. 857



David C. Mason received the B.Sc. and Ph.D. de- 841
grees in physics from the University of London, 842
London, U.K., in 1963 and 1968, respectively. 843
He was with the U.K. Medical Research Coun- 844
cil and Plessey Electronic Systems Research. Since 845
1984, he has been with the Natural Environment 846
Research Council Environmental Systems Science 847
Centre, University of Reading, Reading, U.K., carry- 848
ing out research on the automated extraction of infor- 849
mation from remotely sensed data and linking these 850
data to environmental models. His current research 851
interests include using remotely sensed data for validation and parameterization 852
of river flood models and assimilation into coastal morphodynamic models. 853



Matthew S. Horritt received the Ph.D. degree from the University of Reading, Reading, U.K., in 1998.

He was with the University of Leeds, Leeds, U.K., and the Department of Civil Engineering, University of Bristol, Bristol, U.K., as a Postdoctoral Research Fellow and a Lecturer in civil engineering, respectively. He is currently a Specialist Modeler with Halcrow Group Ltd., London, U.K. His research interests are flood inundation models, remote sensing of floods and floodplain topography, and model validation.



Tania R. Scott received the B.Sc. degree in 1975 astronomy from the University of Canterbury, Christchurch, New Zealand, in 1992 and the Ph.D. degree in astronomy from the University of Cambridge, Cambridge, U.K., in 1998.

She was with the U.K. Met Office, where she developed meteorological products for the aviation industry to address safety and environmental issues. She is currently with the Natural Environment Research Council (NERC) Environmental Systems Science Centre, University of Reading, Reading, U.K., where she is interested in using remote sensing data in aid of environmental modeling. Her current project is to apply data assimilation techniques to coastal area morphodynamic modeling, which is funded under the NERC program Flood Risk from Extreme Events.



Johanna T. Dall'Amico is currently working toward the B.Sc. degree in mathematics at the University of Reading, Reading, U.K., and a Diploma in geography and remote sensing at Ludwig-Maximilian University of Munich, Munich, Germany.

She is a Visiting Student at the Natural Environment Research Council Environmental Systems Science Centre, University of Reading, where she works on remote sensing applications for fluvial flood models.



Paul D. Bates received the Ph.D. degree from the University of Bristol, Bristol, U.K., in 1993, with support from a Natural Environmental Research Council studentship.

Subsequently, he has been with at the University of Bristol as a Postdoctoral Researcher and Lecturer, and has been a Full Professor since 2003. He is currently the Director of the Hydrology Research Group, School of Geographical Sciences, University of Bristol. He has been a Visiting Scientist at Princeton University, Laboratoire National D'Hydraulique, Paris, and the EU Joint Research Centre, Ispra, Italy. His research interests include the development and analysis of numerical models for predicting river flood flows, principally using data derived from remote sensing sources, spatial prediction, risk, and uncertainty. He is the Editor-in-Chief of the *International Journal of River Basin Management*.