TECHNICAL NOTE:

PROPOSING A LOW-TECH, AFFORDABLE, ACCURATE STREAM STAGE MONITORING SYSTEM

A. A. Royem, C. K. Mui, D. R. Fuka, M. T. Walter

ABSTRACT. *Streamflow data are essential for water resources planning and decision making and are routinely analyzed to determine the impacts of climate change on hydrology. Unfortunately, current stream gauges, largely the responsibility of the U.S. Geological Survey (USGS) in the U.S. and similar agencies worldwide, are expensive to install and operate and are being steadily decommissioned. Part of the solution to this problem is a low-cost stream gauging system that is simple enough to use by people with little or no formal training in environmental monitoring. In this article, a low-cost, digital camera-based stream stage monitoring system is proposed, described, and tested. As a proof-of-concept, a time series was generated by taking digital pictures of a staff gauge at 3 h intervals over several weeks at a current USGS gauging site. The image-based stage heights closely matched the USGS gauge values, although significant stage height errors were evident in a small percentage (<3%) of the images. We identified the problem as being caused by shadows and irregular lighting and proposed a protocol for eliminating these errant images. When the obviously problematic images were removed, the relative differences between the image-based stages and USGS stages were approximately 5%. The next step is to develop an on-line system for post-processing the images so that watershed networks, citizen science organizations, K-12 educational institutions, and others can engage in stream monitoring and make their data freely available. We also propose some possible next steps for determining stream cross-section and flow velocity using this low-cost camera- or image-based monitoring system.*

Keywords. *Citizen science, Digital camera, Low-tech, Monitoring, Stage, Streamflow.*

The journal *Nature* recently noted that a "dearth of data on water resources is holding up improved management practices" (Gilbert, 2010). The persistent and decades-long reduction in the stream discharge gauges of the U.S. Geological Survey (USGS) and similar agencies only serves to exacerbate this problem (Blankenship, 1998; Babitt and Groat, 1999; Stokstad, 1999; Carney, 2011). USGS stream discharge monitoring has been invaluable to the historically successful development of a wide variety of water management strategies and for testing our understanding of hydrological processes by providing observations against which to test models. Although there is a substantial historical USGS streamflow record, more than 100 years for some U.S. rivers, we cannot afford to diminish hydrological monitoring. Hydrologic changes in many areas will likely become more variable, potentially more severe (e.g., Barnett et al., 2005; Huntington, 2006), and more difficult to predict in the foreseeable future (Jackson et al., 2001; Revenga et al., 2005; Parry et al., 2007). With this lack of stationarity, past conditions are poor indicators of the future (e.g., Hayhoe et al., 2007; Milly et al., 2008). In addition, we need to recognize that most of the world has far fewer stream discharge measurements than the U.S.

It is tempting to rely heavily on models to help inform scientists and decision makers about likely or potential impacts of climate change on future water resources (e.g., Xu, 1999; Palmer et al., 2008). However, we cannot sidestep the continuing need to advance our fundamental understanding of environmental systems and improve our modeling of climate-related changes to the hydrologic cycle at scales relevant to decision making (e.g., Wagener et al., 2010). Such improvements necessitate continued, expanded, and long-term, environmental monitoring (e.g., Baedecker, 2011; Burt, 2012).

One critical challenge restricting more stream discharge observations is cost. The most commonly used technique for stream discharge monitoring is a gauge that continuously measures stream stage, which is subsequently correlated to periodic cross-sectional surveys of stream velocity. This general approach has remained virtually unchanged for a century or more (Rantz, 1982; Costa et al., 2006). Current costs are more than $30,000 to establish and install a gauge and at least $10,000 per year to maintain (Babitt and Groat,

Submitted for review in April 2012 as manuscript number SW 9731; approved for publication by the Soil & Water Division of ASABE in October 2012.

The authors are **A. Alisa Royem,** Graduate Student, Department of Natural Resources, **Christopher K. Mui,** Undergraduate Student, Department of Mechanical Engineering, **Daniel R. Fuka,** Graduate Student, and **M. Todd Walter,** Associate Professor, Department of Biological and Environmental Engineering, Cornell University, Ithaca, New York. **Corresponding author:** M. Todd Walter, Department of Biological and Environmental Engineering, Cornell University, Ithaca, NY 14853-5701; phone 607-255-2488; e-mail: mtw5@cornell.edu.

1999). Balancing the number of possible gauging sites for maximum usefulness with budgetary and personnel constraints has been a continual challenge (e.g., Leopold, 1994).

One avenue for expanding environmental monitoring is citizen-based observation networks, many of which have been very successful, such as tracking ornithological patterns over time (e.g., Lepage and Francis, 2002) and monitoring weather (e.g., Moon et al., 2009). Two key challenges in citizen-based stream monitoring are (1) making the monitoring affordable and (2) ensuring that meaningful data are achievable without extensive training. To meet these challenges in the case of stream discharge monitoring, a simple, reliable gauge needs to be developed that can be easily deployed and provide accurate stream discharge estimates. If a time series of stream stage can be recorded, discharge could be approximated using the traditional rating-curve approach, if there is access to expertise for making measurements of flow velocity and stream cross-section. However, even without this expertise, reasonable, albeit less precise, estimates could be made, for example, using open-channel flow equations (fig. 1). We believe that this sacrifice in precision could potentially be offset by a large number of observations, similar to the underpinning philosophy of remote sensing.

In this article, we describe a simple, low-tech stream gauging system that uses a photographic time series to measure stage height in a stream. Digital photographs can offer not only an accurate measure of stage height but also provide other qualitative information that may be useful, e.g., weather conditions, snow, debris or animals in the stream, etc. This idea is admittedly simple, but an extensive search using the ISI Web of Science and various combinations of obviously relevant terms (e.g., camera, digital image, image analysis, water level, stream stage, etc.) produced no published work on this idea. A Google search revealed a similar, although somewhat more complicated, effort at North Carolina State University (Birgand et al., 2009; www.gaugecam.com/). It appears that this effort is concurrent with our own, with initial off-campus presentations of the respective systems in 2010 (Gilmore et al., 2010; Royem et al., 2010). The product website for the NCSU system (www.gaugecam.com/product/publications/, accessed 16 Oct. 2012) shows a paper "to be submitted" to the *Journal of Hydrology*. A colleague forwarded two relevant papers (Takagi et al., 1998; Kim et al., 2011) that did not appear in our on-line searches. Kim et al. (2011) used sequences of video images to identify the waterline by determining where differences between images were influenced by reflections on water ripples relative to the more static, staff portion of the image. Takagi et al. (1998) used the refraction of the staff to identify the waterline. The NCSU system appears to also detect the waterline, although the exact method used is not clear from their product website (www.gaugecam.com/product/overview/). Kim et al. (2011) listed references to several conference presentations for which we were unable to obtain more detailed information. However, the titles of these citations suggested that similar waterline-detection approaches were being explored, and most appeared to use video or other relatively high-speed, image capture techniques (Tsunashima et al., 2000; Takagi et al., 2001; Iwahashi and Udomsiri, 2007; Kim et al., 2007). The method presented here is much simpler and uses a simple graphical user interface to train the post-processing software to segregate the staff from the rest of the image.

Stage Gauge Description

The proposed stage gauge consists of two elements: the monitoring hardware and the post-processing software. The hardware includes a digital camera that can be programmed to automatically capture images at prescribed intervals and a stage staff that can be easily detected from the background (e.g., painted a unique, uniform color). The digital camera must be weatherproof or contained in a weatherproof shell and be securely positioned with a clear view of the staff. The staff needs to be securely installed in the stream channel. Figure 2 shows a schematic of the setup used in our proof-of-concept test. The software post-processes the images to: (1) identify the staff gauge, (2) re-

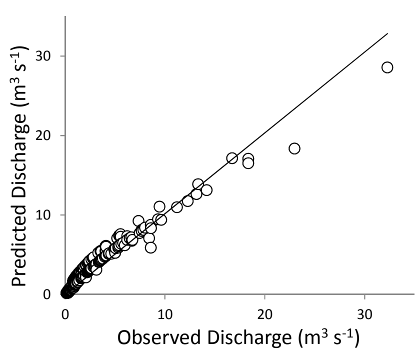

Figure 1. USGS reported discharge (observed) vs. discharge predicted using Manning's equation and the USGS reported stage (predicted) for Sixmile Creek near Ithaca, New York (USGS ID 04233300, 21 June 2010 to 21 June 2011). The channel was approximated as rectangular in cross-section. The width was measured with a tape measure (4.6 m, 15 ft), the slope was approximated from Google Maps (0.02), and the roughness coefficient was the mean tabulated value for a winding channel with some weeds, pools, and stones (0.045; Chow, 1959). The slope of the regression line is 1.02 (R^2 = 0.93).

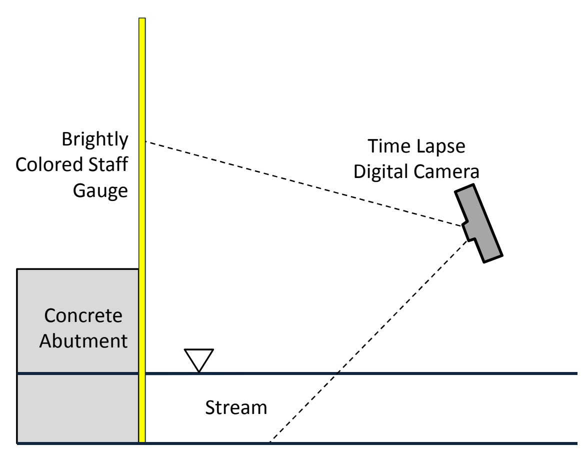

Figure 2. Schematic view of stream gauge hardware. In our proof-of-concept, we attached our staff gauge to a concrete abutment, but any secure attachment would work.

late the staff in the image to an actual river stage height, and (3) convert the images into a stage time series. We developed a proof-of-concept post-processing algorithm and programmed it in MATLAB (R2008a, MathWorks, Inc., Natick, Mass.).

Identifying the Staff Gauge

The proposed gauging system requires that the staff gauge be distinguishable from the background in the images. We do this by training the program to recognize the staff in the images by its unique color. To do this, the user choses a calibration image, preferably an image taken at low flows so that a large portion of the staff is out of the water. When the user selects the calibration image file, our program launches a graphical user interface (GUI) that allows the user to draw a polygon on the image seen on the screen with the computer mouse; the area inside this polygon is the region of interest (ROI) (fig. 3a). The ROI should ideally be a small area at the top of the staff gauge that is visible in all of the images to be processed. Each pixel is characterized by the amount of red (R), green (G), and blue (B) that defines the pixel's color. To simplify our analysis, our program transforms the image from the red-green-blue (RGB) color space to luminosity (l^*) and chromaticity (a^*b^*), where a^* indicates a color's position between magenta and green, and b^* indicates a color's position between yellow and blue. By doing this, we can characterize each pixel by two parameters, i.e., its values of a^* and b^*, instead of three parameters, i.e., R, G, and B. Conceptually, we have reduced our image to two dimensions in which each pixel can be plotted on a graph by coordinates (a^*, b^*). Mean values for a^* and b^* are calculated for the group of pixels in the ROI (ROI_a and ROI_b, respectively). All pixels in the image that are sufficiently similar to ROI_a and ROI_b are considered part of the staff. We do this by calculating the difference (Ω) between (a^*, b^*) for each pixel relative (ROI_a, ROI_b):

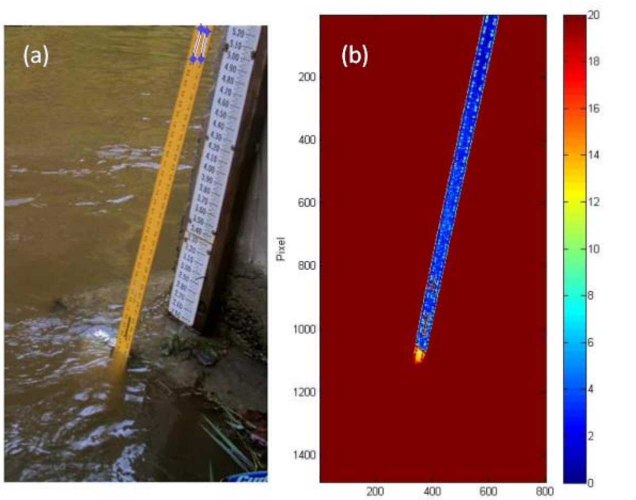

Figure 3. (a) Calibration image with the ROI shown as a blue box at the top of the staff gauge and (b) color distance in *a*b space displayed as a color map where blue indicates areas in the image similar to the color of the ROI and maroon indicates areas very different from the ROI. Note the ambiguity for the portion of the staff below the water line. The white staff gauge was the property of the USGS.**

$$\Omega_i = \sqrt{\left(a_i^* - \mathrm{ROI}_a\right)^2 + \left(b_i^* - \mathrm{ROI}_b\right)^2} \tag{1}$$

where i indicates the ith pixel in the image. If Ω_i is lower than a user-defined threshold, i.e., the color segmentation bias, then the pixel in question is considered a close enough match to the gauge color and is considered part of the gauge (fig. 3b). We found that thresholds could be determined with a little trial and error. Users with some programming skill may want to sample the staff portion of several images to determine the range of a^* and b^* in their set of images. In our program, the user can specify cropping amounts for the images to reduce the number of pixels that need to be evaluated. Note that the location of the ROI is defined for one image, and that location is repeatedly used in all the rest of the images. The values ROI_a and ROI_b are determined for each image independently.

Relating the Staff Image to River Stage Height

The calibration image used to define the ROI, as described in the previous section, can also be used to develop a relationship between "pixel-length" and stage. The program user clicks first on the upper right corner of the image of the staff, i.e., the pixel located at (x_A, y_A), and then on several other points farther down the gauge on the right edge of the staff gauge where the physical lengths are marked; the program will display the pixel-lengths for each selected point. The pixel-length is the number of pixels that define a line in the image between the upper right corner, (x_A, y_A), and the subsequently selected points. Although this step could be generalized in the code, we found it simple to convert the pixel-lengths into stage heights in a spreadsheet with a best-fit function that relates the two; this function is then coded into our MATLAB program. By selecting several points along the entire staff to develop this relationship, the function will automatically account for any distortion from the camera optics or due to an oblique angle between the camera and the staff.

Converting Images into a Stage Time Series

Once the calibration is complete, i.e., the ROI has been identified and a relationship between the image and actual stream stage is determined, the program loops through all the images. For each image, it identifies the staff-pixels based on the ROI color in that image. All images are converted to a binary matrix of the same dimensions as the cropped image, indicating the location where colors are within an acceptable range of similarity to the ROI color, i.e., pixels associated with the staff gauge. Pixels outside of the accepted range are designated as the background of the image (fig. 4). The pixel-length is calculated as the longest length between the upper right staff gauge pixel, at (x_A, y_A), to another acceptable staff pixel along the line defined by the points selected to relate the image to an actual stage height. Using the relationship developed in the previous section, this pixel length is converted into a stage height.

Pixel Filtering

The color segmentation may not fully separate the staff

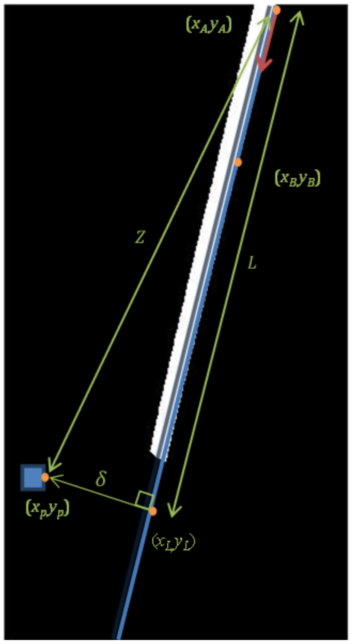

Figure 4. Binary output of color segmentation with labeled solution space restriction geometry.

gauge portion of the image from the background because some objects may create image artifacts with a similar color as the staff gauge (leaves, reflections, etc.). From the calibration, the program knows the general area in the image where staff pixels must be. We use a solution space restriction filter to discard extraneous pixels using the following procedure. Consider an acceptable staff color match pixel located at position (x_p, y_p) in an image (fig. 4). The user, during calibration of pixel-length to stage, inputs the locations of several points along the edge of the staff, e.g., (x_A, y_A) and (x_B, y_B) in figure 4. All acceptable pixels must lie along the line defined by these points or within an acceptable lateral distance defined by a distance cutoff value, e.g., the width of the staff. The point (x_L, y_L) is the intersection of the shortest path length line from (x_p, y_p) to the vector $\overline{AB}$ defined by (x_A, y_A) and (x_B, y_B) (fig. 4). Points (x_A, y_A), (x_p, y_p), and (x_L, y_L) define the right triangle $Z\delta L$ (fig. 4). The vectors $\overline{AP}$ and $\overline{AB}$ and the angle between (θ) them are given by:

$$\overline{AP} = \left(x_p - x_A\right)\hat{i} + \left(y_p - y_A\right)\hat{j} \quad (2a)$$

$$\overline{AB} = \left(x_B - x_A\right)\hat{i} + \left(y_B - y_A\right)\hat{j} \quad (2b)$$

$$\theta = arccos\left(\frac{\overline{AB}\cdot\overline{AP}}{\left|\overline{AB}\right|\left|\overline{AP}\right|}\right) \quad (3)$$

where $\hat{i}$ and $\hat{j}$ are orthogonal unit vectors parallel to the image's width and height. The parameters L and δ can be found by simple trigonometry:

$$L = Z\cos\left(\theta\right) \quad (4a)$$

$$\delta = L\tan\left(\theta\right) \quad (4b)$$

When the value of δ is less than the distance cutoff, the pixel is acceptably close to the gauge, and the value L is saved as a possible solution.

Proof-of-Concept Test

To test our stage gauge concept, we set up our hardware at the USGS gauge station at Fall Creek in Ithaca, New York (USGS ID 04234000, 42° 27′ 12″ N, 76° 28′ 23″ W). A bright yellow, steel, 1 m long ruler was glued (Gorilla Glue) to the concrete abutment at the base of the gauge station to create a staff gauge (fig. 3a). A CuddeBackPro digital camera (Non Typical, Inc., Park Falls, Wisc., ~$150), with automatic flash and housed in a watertight plastic case, was mounted on an aluminum tripod. The camera was operated in time-lapse mode, taking a digital photograph once every 3 h and storing the information on a 1 GB compact flash memory card. Figure 2 shows a schematic view of the setup. Images were collected from 30 August to 6 October 2010, during which time streamflows ranged from 3.5 to 72 $m^3 s^{-1}$. For reference, 3.5 $m^3 s^{-1}$ is approximately equal to the median daily flow rate, and a daily flow rate of 72 $m^3 s^{-1}$ is equaled or exceeded about 2% of the time. The MATLAB post-processing program described earlier was used to convert the images into a time series of stage heights.

The proposed gauge system showed reasonably good agreement (relative difference = 16%) with the reported USGS stage heights (fig. 5). The greatest deviations from USGS values occurred on 3 October at 1:00 p.m. and 3:00 p.m. (labeled outliers in figure 5 and representing 2.7% of the images). These problem images were due to irregular lighting due to shadows cast by nearby trees (fig. 6). This irregular lighting "spoofed" the color segmentation part of the post-processing calibration procedure. We anticipate that these problems images could be eliminated with a filtering procedure that, for example, disregarded any images that resulted in an increase or decrease in stage above a user-defined threshold. Although we anticipated problems for night images because of poor flash conditions, we did not observe any. We also did not observe problems with reflections or separat-

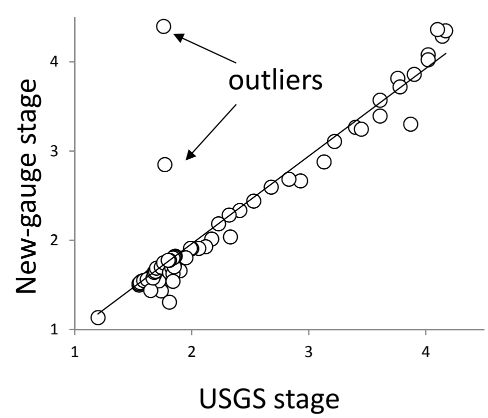

Figure 5. Comparison between the USGS stage and the stage determined with the proposed gauging system. The slope of the regression line is 0.98 (R^2 = 0.83), and the relative difference is 16%. When the two outliers are removed, the slope is 1.02 (R^2 = 0.98), and the relative difference is 5%.

Figure 6. Image “spoofing” caused by shadows and irregular lighting.

ing the staff from the background, which other researchers have found challenging (e.g., Kim et al., 2011), probably because we chose a non-white, uniquely colored staff.

Discussion and Conclusions

Having demonstrated the feasibility of a stream gauging system that costs only a few hundred dollars (ours cost ~$200 including batteries, tripod, staff, glue, etc.), in contrast to tens of thousands of dollars for a traditional USGS gauge, we think the somewhat diminished precision is acceptable. It should be noted that much of the cost of USGS stream gauging is for labor and that the actual cost of the equipment is estimated at 10% to 20% of the total cost (Norris, 2010); Campbell Scientific supplied a quote for a basic stage gauge of $3000 to $3500 (personal contact with salesman, 6 July 2012). We are implicitly assuming that labor costs are not relevant for the intended users of our proposed stream gauging system. The contrast in cost is less extreme when comparing our proposed system to one that uses a pressure transducer, acoustic sensor, or capacitance probe (approximately $500 to $1000), as is commonly adopted by researchers. However, the intuitiveness of the camera-based system relative to a pressure transducer-based system makes it more accessible to a broad range of people who may be interested in stream monitoring, including inexperienced users such as primary school students.

We would like to emphasize that the system presented here is meant as a proof-of-concept designed for a do-it-yourself environmental monitor and that there are many ways to modify or alter the concept. We think our approach provides a good balance between measurement precision and simplicity. By contrast, image-based stream gauges that use potentially subtle indicators of a waterline in an image (e.g., Kim et al., 2011) may be more precise, but are substantially more complicated. Although the use of MATLAB in our proof-of-concept could introduce substantial extra cost if one needed to obtain a license for the software, an executable program can be developed that does not require a MATLAB license. The code is easily transferrable to any modern programming language. We have recently written the same program functionality in R, a freely downloadable programming language (http://cran.r-project.org/). These codes are available from the corresponding author.

The next step is to develop an internet-based environment in which citizen stream monitors can upload images for post-processing and where the subsequent numerical stream data can be archived for open access. To translate the stage into flow rate, monitors could, of course, develop rating curves themselves and make the stage-discharge function available as part of the post-processing. Although admittedly crude, simple measurements of channel width, slope, and Manning’s roughness coefficient could be supplied or perhaps determined remotely to make discharge estimates like those shown in figure 1. It may also be possible to modify the camera-based gauging system described here to estimate channel width and flow velocity. The latter could perhaps be achieved using particle tracking velocimetry (PTV; e.g., Tang et al., 2008) of ambient materials in the streams. We are also considering a similar system that uses Quick Response (QR) codes on the staff that could be more directly processed without the potential problems of reflections, shadows, etc.

Other hydrologists are experimenting with ways to crowd-source hydrologic data (e.g., Lowry, 2012). Low-cost, easy-to-use stream monitoring has good potential to facilitate this by providing a system accessible to K-12 students and teachers, to watershed network and citizen scientists, and to researchers. If the crowd-sourcing evolved a dense enough network of near-real-time observations, there are a number of opportunities to use the information in decision support systems. For example, emergency response teams could access real-time information on flooded stream segments, which could be used to optimize travel routes. Additionally, real-time streamflow data could be used as part of a forecast system to predict likely storm runoff source areas that should be avoided during agricultural activities that could potentially contribute NPS pollution (e.g., Agnew et al., 2006).

Acknowledgements

The primary funding for this project was from the Cornell Engineering Learning Initiative’s Undergraduate Research Grant program. We also thank Dr. Steve Lyon of Stockholm University (who suggested the QR idea) and Dr. John Selker of Oregon State University for their early reviews of the manuscript and valuable suggestions. We would also like to acknowledge Lauren McPhillips (doctoral candidate at Cornell University) and Terence Schwarz (Alaska Department of Natural Resources) for their early work on digital-image-based monitoring of snow depth (e.g., McPhillips, 2007) and stream discharge. We are grateful to Lauren McPhillips and Brian Buchanan (doctoral candidate at Cornell University) for proofreading our final submission. Lastly, we want to thank Dr. James Zollweg (SUNY Brockport), two anonymous reviewers, and the ASABE associate editor for their valuable suggestions during the review process.

References

Agnew, L. J., S. Lyon, P. Gérard-Marchant, V. B. Collins, A. J. Lembo, T. S. Steenhuis, and M. T. Walter. 2006. Identifying

hydrologically sensitive areas: Bridging science and application. *J. Environ. Mgmt.* 78(1): 64-76.
Babitt, B., and C. G. Groat. 1999. Streamflow information for the next century. USGS Open-File Report 99-456. Reston, Va.: U.S. Geological Survey.
Baedecker, M. J. 2011. The fellows speak: The need for reliable data in hydrologic investigations. *AGU Hydrology Section Newsletter* (Dec.): 5-8. Available at: http://hydrology.agu.org/pdf/AGUHydro-201112.pdf. Accessed 30 July 2012.
Barnett, T. P., J. C. Adam, and D. P. Lettenmaier. 2005. Potential impacts of a warming climate on water availability in snow-dominated regions. *Nature* 438(7066): 303-309.
Birgand, F., T. Gilmore, K. Chapman, and A. Brown. 2009. GaugeCam. Available at: www.gaugecam.com/. Accessed 29 June 2011.
Blankenship, K. 1998. Loss of stream gauges worries scientists. *Chesapeake Bay Journal* 7(10). Available at: www.bayjournal.com/article/loss_of_stream_gauges_worries_scientists_. Accessed 9 September 2012.
Burt, T. 2012. The value of long time series in hydrological research. *AGU Hydrology Section Newsletter* (July): 5-8. Available at: http://hydrology.agu.org/pdf/AGUHydro-201207.pdf. Accessed 30 July 2012.
Carney, K. 2011. Funding could threaten river gauges. *Sioux City Journal* (posted on-line 21 March 2011). Available at: www.siouxcityjournal.com/news/local/article_66386aae-557a-57e3-b9fa-142e89344273.html. Accessed 23 June 2011.
Chow, V. T. 1959. *Open Channel Hydraulics*. New York, N.Y.: McGraw-Hill, Inc.
Costa, J. E., R. T. Cheng, F. P. Haeni, N. Melcher, K. R. Spicer, E. Hayes, W. Plant, K. Hayes, C. Teague, and D. Barrick. 2006. Use of radars to monitor stream discharge by noncontact methods. *Water Resources Res.* 42: W07422.
Hayhoe, K., C. P. Wake, T. G. Huntington, L. Luo, M. D. Schwartz, J. Sheffield, E. Wood, B. Anderson, J. Bradbury, A. DeGaetano, T. J. Troy, and D. Wolfe. 2007. Past and future changes in climate and hydrological indicators in the U.S. northeast. *Climate Dynamics* 28(4): 381-407.
Huntington, T. G. 2006. Evidence for intensification of the global water cycle: Review and synthesis. *J. Hydrol.* 319(1-4): 83-95.
Gilbert, N. 2010. A dearth of data on water resources is holding up improved management practices. *Nature* (published online 4 Oct. 2010) doi: 10.1038/news.2010.490.
Gilmore, T. E., F. Birgand., K. Chapman, and A. Brown. 2010. Providing real-time hydrologic data using webcams. Poster presented at the National Academy of Engineering Grand Challenge Regional Summit, Raleigh, North Carolina.
Iwahashi, M., and S. Udomsiri. 2007. Water level detection from video with FIR filtering. In *Proc. 16th Intl. Conf. Computer Communication and Networks*, 826-831. Piscataway, N.J.: IEEE.
Jackson, R. B., S. R. Carpenter, C. N. Dahm, D. M. McKnight, R. J. Naiman, S. L. Postel, and S. W. Running. 2001. Water in a changing world. *Ecol. Applic.* 11(4): 1027-1045.
Kim, K. J., N. K. Lee, Y. J. Han, and H. S. Hahn. 2007. Remote detection and monitoring of a water level using narrow band channel. In *Proc. 6th WSEAS Intl. Conf. Signal Processing, Robotics and Automation (ISPRA '07)*, 16-19. World Scientific and Engineering Academy and Society.
Kim, K. J., Y. J. Han, and H. S. Hahn. 2011. Embedded implementation of image-based water-level measurement system. *IET Computer Vision* 5(2): 125-133.
Leopold, L. B. 1994. *A View of the River.* Cambridge, Mass.: Harvard University Press.
Lepage, D., and C. M. Francis. 2002. Do feeder counts reliably indicate bird population changes? 21 years of winter bird counts in Ontario, Canada. *Condor* 104(2): 255-270.
Lowry, C. 2012. Using crowdsourcing in hydrologic measurements: Crowd hydrology. Paper No. 175-4. Presented at the GSA Annual Meeting, Charlotte, North Carolina. Boulder, Colo.: Geological Society of America. Available at: gsa.confex.com/gsa/2012AM/finalprogram/abstract_211400.htm . Accessed 13 September 2012.
McPhillips, L. E. 2007. Snow distribution patterns at land cover boundaries in Tompkins County, New York. Senior honors research thesis. Ithaca, N.Y.: Cornell University, College of Agriculture and Life Sciences.
Milly P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer. 2008. Stationarity is dead: Whither water management? *Science* 319(5863): 573-574.
Moon, J. T. III, P. E. Guinan, D. J. Snider, and A. R. Lupo. 2009. CoCoRaHs in Missouri: Four years later, the importance of observations. *Trans. Missouri Acad. Sci.* 43: 8-19.
Norris, M. J. 2010. U.S. Geological Survey stream gauge operation and maintenance cost evaluation. Fact Sheet 2010-3025. Reston, Va.: U.S. Geological Survey.
Palmer, M. A., C. Reidy, C. Nilsson, M. Florke, J. Alcamo, P. S. Lake, and N. Bond. 2008. Climate change and the world's river basins: Anticipating response options. *Frontiers Ecol. Environ.* 6(2): 81-89.
Parry, M. L., O. F. Canziani, J. P. Palutikof, P. J. van der Linden, and C. E. Hanson, eds. 2007. *Climate Change 2007: Impacts, Adaptation and Vulnerability*. Contribution of Working Group II to the 4th assessment report of the Intergovernmental Panel on Climate Change. Cambridge, U.K.: Cambridge University Press.
Rantz, S. E. 1982. *Measurement and Computation of Streamflow: Vol. 1. Measurement of Stage and Discharge*. USGS Water Supply Paper 2175. Reston, Va.: U.S. Geological Survey.
Revenga, C., I. Campbell, R. Abell, P. de Villiers, and M. Bryer. 2005. Prospects for monitoring freshwater ecosystems towards the 2010 targets. *Phil. Trans. Royal Soc. London B* 360(1454): 397-413.
Royem, A. A., C. K. Mui, and M. T. Walter. 2010. Low-cost stream gaging through analysis of stage height using digital photography. Presented at the 2010 AGU Fall Meeting (Abstract No. H51D-0930). Washington, D.C.: American Geophysical Union.
Stokstad, E. 1999. Scarcity of rain, stream gages threatens forecasts. *Science* 285(5431): 1199-1200.
Takagi, Y., A. Tsujikawa, M. Takato, T. Saito, and M. Kaida. 1998. Development of a non-contact liquid level measuring system using image processing. *Water Sci. Tech.* 37(12): 381-387.
Takagi, Y., T. Yoneoka, H. Mori, M. Yoda, A. Tsujikawa, and T. Saito. 2001. Development of a water level measuring system using image processing. In *Proc. 1st IWA Conf. Instrumentation, Control and Automation*, 309-316. London, U.K.: International Water Association.
Tang, H. W., C. Chen, H. Chen, and J. T. Huang. 2008. An improved PTV system for large-scale physical river model. *J. Hydrodynamics* 20(6): 669-678.
Tsunashima, N., M. Shiohara, S. Sasaki, and J. Tanahashi. 2000. Water level measurement using image processing. *IPSJ Trans. Computer Vision and Image Media* 121(15): 111-117. Tokyo, Japan: Information Processing Society of Japan.
Wagener, T., M. Sivapalan, P. A. Troch, B. L. McGlynn, C. J. Harman, H. V. Gupta, P. Kumar, P. S. C. Rao, N. B. Basu, and J. S. Wilson. 2010. The future of hydrology: An evolving science for a changing world. *Water Resources Res.* 46: W05301.
Xu, Chong-yu. 1999. Climate change and hydrologic models: A review of existing gaps and recent research developments. *Water Resources Mgmt.* 13(5): 369-382.