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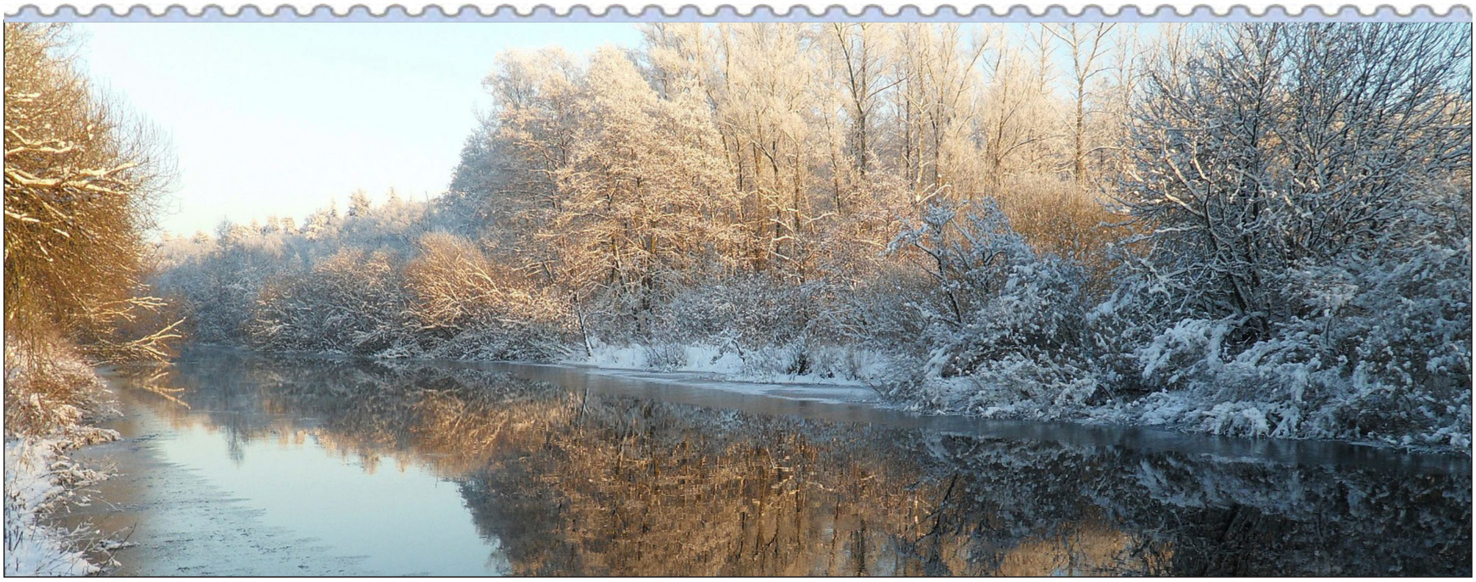

AIH is here to serve the profession and the members

- AIH is the only organization that certifies professionals in the fields of surface water and groundwater hydrology, and water quality both nationally and internationally.
- AIH provides educational training venues to the professionals in the field of hydrologic sciences.
- AIH speaks to lawmakers on behalf of you and the profession as an advocacy

Guest Editorial

Ron St. John, PHg; St. John – Mittelhauser & Associates, Inc.

"If a tree falls in the forest and nobody is there to hear it, does it make a sound? (and was it global warming, was it preventable or was it a natural disaster?)"

I have to say that in recent years I have been equally amused and appalled by the number of "natural disasters" that have been attributed to global warming. Now before I go any further on this topic, I should disclose the fact that I have suspiciously viewed the predictions of global warming modelers since the early 1990's when some modeling predictions forecast that much of coastal Florida was going to be inundated with oceanic water within the next 15 to 20 years. Additionally, after performing a significant amount of groundwater modeling during my 40-year career, I have come to embrace the modeling axiom "all models are wrong, some are just less wrong than others." Given all that, I recently committed to buying a fully electric vehicle that would serve as my daily driver (because in my opinion, the dangers of global warming far outweigh any skepticism I might have about its scale). However, this changed when I learned from the USEPA web site that I live in an area where I would have a larger carbon footprint with an electric car due to my electricity originating from coal-fired power plants.

Back to global warming and natural disasters. In recent years, everything from California wild fires to the intensity of hurricane Harvey have been attributed to global warming. However, it does appear that other key factors can contribute to these "global warming" natural disasters; namely population

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Membership News - Meet Your AIH Peers (continued)

Metroplex, which has a current population of about 7 million and is projected to grow to about 14 million over the next 50 years. The area has an estimated 2020 dry-year demand of 1.5 million acre-feet (1,340 MGD) increasing to 2.7 million acre-feet (2,400 MGD) by 2070. Elements of the regional water plans are population and demand projections, analysis of existing water supplies, determining gaps in future water needs, evaluation (environmental, cost, quantity, feasibility, etc.) of various potential future water supplies (reuse, aquifer storage and recovery, new reservoirs, etc.), and recommendations of future supplies and strategies to meet water needs for the next 50 years.

Amy loves to bake, play golf with her husband, and hang out with her two teenage daughters. She's on the School Board of Trinity Christian Academy where her older daughter attends, and she's also active in her local church. Her favorite vacation spot is Banff, Alberta, Canada.

David Hansen
(East Bay Municipal Utility District, Oakland, CA)

David Hansen is a Hydrographer III at the East Bay Municipal Utility District (EBMUD) in Oakland, California. He received his B.A. (1999) from San Diego State University and his M.S. (2002) from The University of Southern California, where he focused on physical geography, coastal, and estuarine geomorphology. Dave was certified as a Hydrologic Technician, Surface Water Level III, by AIH in 2017. Dave is an EBMUD disaster first responder.

As part of his work at EBMUD, Dave collects and analyzes river, reservoir, groundwater, and meteorological data to document current conditions of the District's raw water resources. This data is then used to forecast future conditions of those resources. Dave also manages station maintenance, instrumentation, and data logger program upgrades. He performs data analysis and quality control and maintains station ratings and hydrological databases, and produces USGS annual water summaries, groundwater and river diversion reports, and compiles annual water production, gross consumption, and treated water loss audit reports in support of EBMUD's water rights and regulatory compliance. Dave also performs dam safety monitoring and reporting.

Prior to his position at EBMUD, Dave was an Associate and the Field Services Manager for Philip Williams & Associates, in San Francisco, where he performed project management, lead field teams tasked with the collection of pre-construction and post-construction monitoring data, and production of project deliverables for major environmental restoration projects in and around the San Francisco Bay and Northern California region.

In his spare time, he enjoys his family (wife and 3 kids), friends, and is active in his local Scout Troop. He also enjoys cooking, jogging, road cycling, camping, occasionally SCUBA, and home brewing. He takes pride in his delicious "blood orange witbier", India Pale Ales, and wheats.

Technical Paper 1

Assessment of Uncertainty in Doppler Radar Estimated Precipitation

By T.V. Hromadka II, Professor, Department of Engineering-Mathematics, United States Military Academy, West Point, NY
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Abstract
With Doppler radar data being used in various applications of hydrometeorology and engineering as well as weather forecasting, the importance of data accuracy and accuracy in precipitation estimates continues to increase in importance. In this article, five types of Doppler radar systems are evaluated and thousands of published data pairs of actual Doppler radar precipitation estimates versus rain gauge precipitation readings are examined. Using standard data normalization techniques, the data for both the radar estimated precipitation estimates and the rain gauge measured precipitation are normalized, and then multiple gauge sets and multiple radar sites of like type Doppler data sets are combined to produce populations of ordered pairs. The populations are then used to develop distributions of conditional estimates of gauge precipitation values given radar estimated precipitation values as obtained by the National Weather Service (NWS) data resources. The resulting distributions display a range of precipitation values associated with radar estimate precipitation values, and can be used in further assessment of Doppler radar estimated precipitation uncertainty in applications.

Introduction
Weather radar technology and the associated precipitation quantification algorithms are maturing towards reliably predicting hydro meteorological events. In the last century, the radar technology evolved from WR 66, WSR 57, C Band, WSR-88D (Doppler) to the current Dual Polarization Doppler. While each update improved the rainfall estimates by addressing limitations of the previous, the first major generational development came with the installation of NEXRAD network, also called WSR-88D radars, which is the corner stone in modern weather technology. The WSR-88D is an offshoot of the advances made in Doppler signal processing theory, scientific knowledge of precipi-

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tation characteristics, hardware capabilities, and visualization tools. The advances made in better understanding the science behind precipitation events has led to further upgrades of the WSR-88D radars to Dual Polarization Radars. The dual polarimetry allows for data quality enhancements. While WSR-88D radars transmit and receive radio waves along a single horizontal polarization, Dual Polarization radars transmit and receive radio signals across both horizontal and vertical polarizations to enable better precipitation estimates and differentiate between heavy rain, hail, snow, and sleet. By 2013, all 159 Doppler radars in United States had been upgraded to Dual Polarization.

Methods

Doppler technology relies on synthesizing the signal information that the radars receive back from the atmosphere. The post processing of the received signals requires using various relationships between several parameters and statistical regression equations to arrive at an rainfall estimate. By such regression data fits, estimates of precipitation quantities are possible and subsequently used for study purposes. The accuracy of such Doppler radar estimated precipitation is quantified by the frequency distribution of actual comparative gauge data versus the statistical fits. An indication of the estimation error is displayed by comparison of the frequency distribution of the source data against the regression equation predictors.

Table 1 summarizes the Radar data characteristics for the five radar types that were analyzed. Based on the published graphs/ tables from the cited references, the radar and gauge precipitation values were compiled for each radar type. While the analysis was done for all five radar types, the results are presented only for the Doppler radar. The statistical analysis was performed using Seaborn (https://seaborn.pydata.org/), a Python data visualization library based on matplotlib. The software provides a high-level interface for drawing attractive and informative statistical graphics.

The raw input data file consisted of two columns of rainfall data (Gauge and Radar). The Gauge column included rainfall values (mm) as measured by recording gauge and the Radar column included radar estimated values (mm). Concatenating the two columns created an ordered pair, resulting in 8846 ordered pairs for the Doppler data file. The data in the two columns were normalized and analysis using Seaborn software was done on the normalized data.

Results

Visualizing the data of the two variables along the spectrum can offer many insights into their distribution trends. In the following graphs, we fit a probability density function (PDF) to the data that corresponds to the data's density of a continuous random variable. Doing this will help one to interpret a value at any given point or sample within the sample space, i.e. the set of possible values taken via the random variable, and link the sample to a relative likelihood that the value of the random variable would equal that of the sample. In other words, the PDF here is used to specify the probability of the random variable that lies within the specified range of values. Figure 1 shows the spectrum of the normalized Doppler Gauge and radar together with the probability density plot. The seaborn.jointplot () function (Appendix 1) which creates a multi-panel figure that shows both the bivariate (or joint) relationship between the two variables, was used to generate the figure.

***Figure 1* – Spectrum of the normalized Doppler radar and Gauge values with the probability density plot**

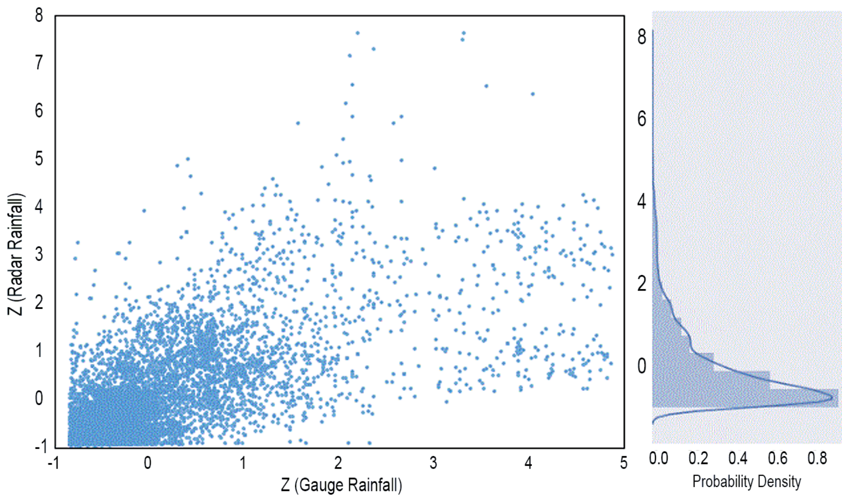

***Table 1* – Summary of Radar data characteristics**

Radar Type	Paper ID*	# of ordered pairs (N)	Radar Data		Gauge Data	
			Mean	SD	Mean	SD
WSR 57	3,12	123	5.3	2.7	5.4	3.3
WR 66	1	173	11.1	8.2	11.6	9.6
C-Band Doppler	5	1010	1.6	1.8	2.8	2.6
Doppler	2,6,7,8,9,10,11,13, 14,15	8846	20.9	22.8	23.8	28.1
Dual Polarization	4,13,14	1588	44	39.9	42.6	45.2

*see **References** for corresponding paper

The Doppler radar data are analyzed by taking "cross-sections" of the data with respect to the independent variable, Doppler radar Estimated Rainfall (given in terms of "standard deviation" units (Figures 2 and 3). The data are presented in "standard deviation" units for both the Doppler radar Estimated Precipitation (independent variable) and the Rain Gauge Measured Precipitation (dependent

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variable). Then, the data are graphically described on a selected cross-section interval also called as 'range' basis.

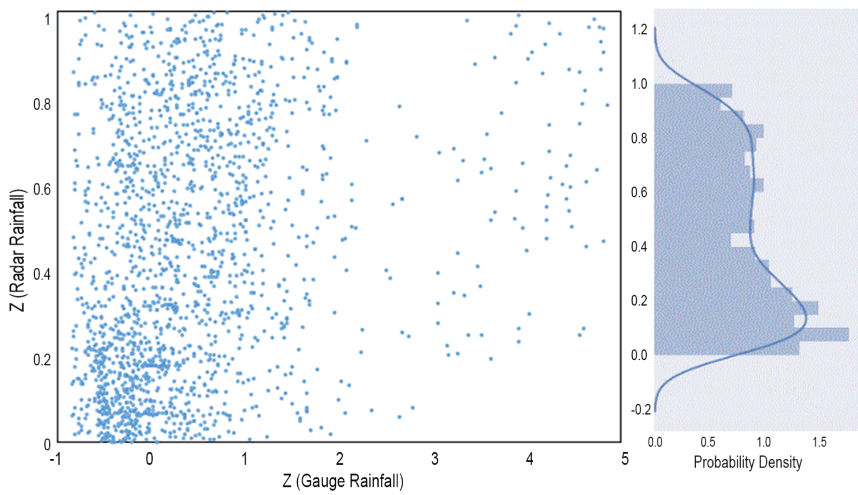

Figure 2 – **Spectrum of the normalized Doppler radar (Range is 0 to 1) and Gauge Values**

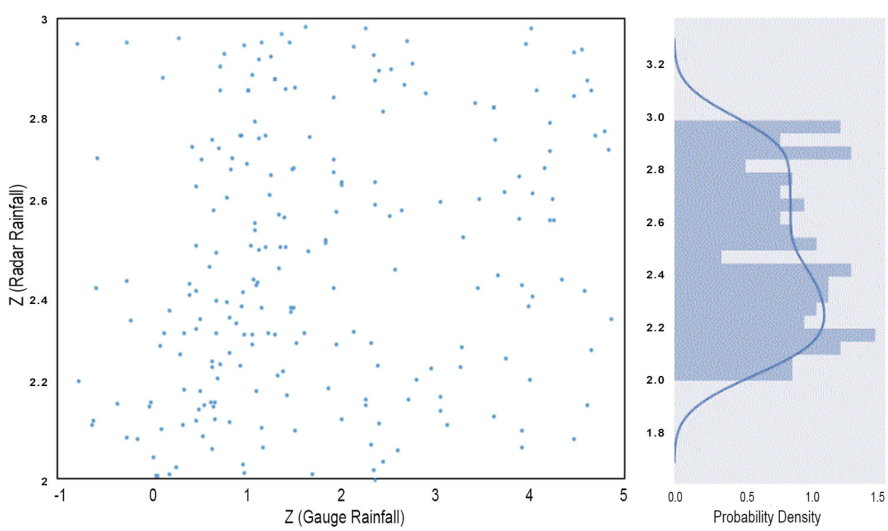

Figure 3 – **Spectrum of the normalized Doppler radar (Range is 2 to 3) and Gauge values**

The resulting frequency-distribution of the data, located within a selected neighborhood of the selected cross section independent variable value, provide the backdrop for development of a conditional frequency-distribution, given the selected value for the independent variable. As such, a result, a frequency-distribution of dependent values corresponding to the selected independent variable value is developed based entirely on the measured data. Therefore, for any selected value of Doppler radar Estimated Precipitation, an outcome of a frequency-distribution of dependent variable precipitation can be determined. Using the frequency distributions defined by the normalized data analysis conducted for this study, Radar estimated precipitation may be encapsulated into a probabilistic distribution of likely values that can then be cascaded into other uses such as estimation of uncertainty in runoff predictions.

Conclusions

The assessment of uncertainty associated with modern Doppler-Radar measurements of precipitation have several important sources of uncertainty. For example, variable Z-R relationships, radar miscalibration, clutter, attenuation, and an inaccurate understanding of the physics behind precipitation along with instrumentation related factors can all contribute to uncertainty. Additionally, uncertainty exists in the operation of the Radar type as well as mathematical prediction equations as applied to the collected data under investigation.

In the current research work, an attempt is made to quantify the uncertainty in the published data by use of statistical distributions fitted to the data pairs of Radar estimated precipitation versus precipitation gauge estimated precipitation. The analysis indicates that additional research is needed to better describe such uncertainty trends in order to cascade the resulting distributions into application models such as rainfall-runoff models. ■

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Appendix 1

The two columns in the input data file (Doppler) are labeled as Gauge and Radar. The python code, written for the analysis and visualization of the data as presented in Figure 1 is given below.

t = sns.jointplot (Ddoppler.Gauge, Doppler.Radar, space=0.2, size=10, ratio=2, kind="reg", marginal_kws=dict(bins=20));

```
plt.setp(t.ax_marg_x.get_yticklabels(), visible=True)
plt.setp(t.ax_marg_x.get_xticklabels(), visible=True)
plt.setp(t.ax_marg_x.set_xlabel('Probability Density'))
plt.setp(t.ax_marg_y.get_xticklabels(), visible=True)
plt.setp(t.ax_marg_y.get_yticklabels(), visible=True)
plt.setp(t.ax_marg_y.set_xlabel('Probability Density'))
```

Technical Paper 2

Hydrodynamic Modeling to Support the Design of a U-Shaped Weir in Central Florida

By Shabbir Ahmed, Civil Engineer, Hydrologic Modeling Section, U. S. Army Corps of Engineers (USACE), Jacksonville, FL
Russ Weeks, Chief, Hydrologic Modeling Section, USACE, Jacksonville, FL

Abstract

A numerical modeling analysis was performed to evaluate the hydraulic performance of a U-shaped weir. This weir was designated the S-69 structure to be constructed as part of the Kissimmee River Restoration (KRR) Project in Central Florida. An Adaptive Hydraulics (AdH) model code developed by the U. S. Army Corps of Engineers (USACE) Engineer Research and Development Center was used to represent the U-shaped weir and the hydraulic features in the Kissimmee River floodplain upstream and downstream of the weir. The AdH model was used to evaluate the effects of different weir configurations (length and weir crest elevation) on water stages and velocities both upstream and downstream of the weir under a variety of flow conditions. The weir was analyzed for different flow events under the future full-restoration condition, during construction sequencing, and with a bypass channel to divert some flow around the weir site during construction. The modeling analysis for 100-year fully restored condition is presented in this paper.

Introduction

The Kissimmee River historically flowed in a 1-2 mile wide floodplain along a 103-mile meandering river course from Lake Kissimmee downstream to Lake Okeechobee. During the wet season, the river would often overtop its bank and inundate the adjacent riverine floodplain for periods ranging from days to several months. This prolonged floodplain inundation, while natural, impacted the ability of local landowners to farm and graze cattle in the floodplain,

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