



1 2	Title: X-BAND DUAL-POLARIZED RADAR QUANTITATIVE PRECIPITATION ESTIMATE ANALYSES IN THE MIDWESTERN UNITED STATES
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- 31 Furthermore, the R(Z,ZDR) and R(ZDR,KDP) algorithms were the only ones which reported NSE values
- 32 below 100%, whereas R(Z) and R(KDP) equations resulted in false precipitation amounts equal to or
- 33 greater than 65% of the total gauge recorded rainfall amounts. The results show promise in the utilization
- of the smaller, more cost-effective X-band radars in terms of quantitative precipitation estimation at
- ranges from 30 to 80 km from the radar.
- 36

37 Introduction

Since the late 20th Century, weather radars have been at the forefront of multiple studies to determine their accuracy in determining precipitation estimation (e.g., Kitchen and Jackson, 1993; Smith et al., 1996; Ryzhkov et al., 2003; Cunha et al., 2013; Simpson et al., 2016). Multiple researchers have reported accurate measurements in radar rainfall estimates when compared to terrestrial-based precipitation gauges (e.g., tipping buckets). This has several important implications for multi-disciplinary fields which rely on highly spatialized and temporal precipitation data, which can be obtained from radar estimates compared to the spatially inferior rain gauges.

45 Most studies in the US have utilized the National Weather Service (NWS) Next Generation 46 Radar (NEXRAD) system, comprised of Weather Surveillance Radar – 1988 Doppler (WSR-88D) series 47 instruments, operating at S-band (approximately, 10 - 11 cm) wavelength for their analyses. However, the cost of installation and maintenance of these instruments are much larger in comparison to the smaller, 48 lighter-weighted X-band radars, operating at, approximately, 3 cm wavelength (Matrosov 2010). Berne 49 50 and Krajewski (2013) have stated that, primarily due to the sparse coverage of the WSR-88D S-band radar system, smaller, more frequently-placed X-band radars are a viable option for remediating radar 51 52 rainfall errors that have been recorded at large distances (e.g., Smith et al., 1996; Ryzhkov et al., 2005; Simpson et al., 2016). Although long-term NWS studies have been conducted (Haylock et al., 2008; 53





54 Fairman et al., 2012; Goudenhoofdt and Delobbe 2012, 2016), the literature of multi-year studies of X-

55 band weather radars is not as abundant.

56 Matrosov et al. (2002) conducted a study analyzing 15 separate rainfall events during an eightweek field campaign in Virginia while utilizing the National Oceanic and Atmospheric Administration's 57 58 (NOAA) X-band dual-polarimetric radar. Several radar rainfall algorithms were implemented, including 59 combinations of the equivalent reflectivity (Z_e) , differential reflectivity (ZDR), and the specific 60 differential phase-shift (KDP), an R(KDP) equation, and two $R(Z_e)$ relations, over a region with three ground-truthed rain gauges. It was found that the combined polarimetric estimator (i.e., utilization of Ze, 61 62 KDP, and ZDR) resulted in the overall least standard deviation (22%), while the case-tuned $R(Z_e)$ relation 63 was slightly higher of 23%. It is noted that R(Ze) measurements are derived from a priori knowledge of 64 Z_{e} , KDP, and ZDR values, whereas the combined polarimetric estimator was not, implying the latter is 65 superior for real-time use. However, the performance of the combined polarimetric estimator works best 66 when rain rates exceeded 1.5 mm h^{-1} , while $R(Z_e)$ algorithms were superior at lighter rain rates. Results 67 from the R(KDP) algorithm reported an overall negative bias of 6-9% when compared to the gauge data, in addition to a standard deviation of 30%, primarily due to the sensitivity of KDP measurements while 68 69 utilizing X-band radars.

70 Expanding upon the literature of implemented R(KDP) algorithms through X-band radars, Wang 71 and Chandrasekar (2010) assessed the performance of three separate R(KDP) algorithms from the 72 Collaborative Adaptive Sensing of the Atmosphere (CASA) Engineering Research Center through the use 73 of the distributed collaborative adaptive sensing (DCAS) network. The DCAS network, essentially, 74 implements multiple radar networks within a relatively small spatial extent, all operating at different 75 volume coverage patterns (VCP's) such that high spatiotemporal resolution data is achieved in addition to 76 overall lower beam height over the area of interest (McLaughlin et al., 2009), mitigating effects that have been observed due to rain rate estimations at large ranges (Kitchen and Jackson, 1993; Ryzhkov et al., 77 78 2005; Simpson et al., 2016). The results indicated that through the use of several different R(KDP)





79	algorithms from multiple different radars, radar Quantitative Precipitation Estimates (QPE) can be
80	improved significantly. Furthermore, the R(KDP) algorithms exhibited similar bias values (between -6
81	and 8 %) that were reported by Matrosov (2002) and Matrosov et al. (2010). However, the normalized
82	standard error (NSE) values ranged from, approximately, 16 to 54%, indicating that the overall error in
83	R(KDP) rain rate estimates were less than half of the total amount of rain observed for the study.
84	The overarching objective of the current study is to add to the relatively few articles on X-band
85	dual-polarization radar rain rate performance. Authors have proposed (e.g., Berne and Krajewski 2013)
86	that the capability of implementing more X-band radars in comparison to the relatively sparse and
87	expensive S-band WSR-88D NEXRAD system to enhance precipitation estimation is a viable option
88	(particularly over the inter-mountain West), especially for hydrologic analyses. However, others (e.g.,
89	McLaughlin et al., 2009) suggest the sheer number of radars to achieve such a difference in radar rain rate
90	estimation is impractical. Further justification for increasing, at least partially, the construction of X-band
91	weather radars is necessary through analyses of those that already exist.
92	The current study analyzes two year's of radar data from the newly-installed dual-polarimetric
93	MZZU X-band radar located in Central Missouri. Over 100 different algorithms were implemented to test
94	the performance of the radar while utilizing measurements of reflectivity (Z), differential reflectivity
95	(ZDR), and the specific differential phase shift (KDP). Rain rates were calculated based on combinations
96	of the aforementioned variables and compared to four separate tipping buckets, which served as ground-
97	truth. To determine the performance of all algorithms, multiple statistical analyses were conducted,
98	including the bias, mean absolute error, and normalized standard error. Additionally, several contingency
99	factors were calculated, such as the overall number of hits, misses, false alarms, and correct negatives.
100	Lastly, quantitative analyses, including the missed precipitation amount (MPA), false precipitation
101	amount (FPA), and overall error were computed to determine the performance of the 108 algorithms.
102	Analyses, such as the current study, are important for determining the accuracy and limitations of dual-
103	polarimetric radars such that their incorporation into hydrologic models may be correctly assessed (Ogden





- 104 et al., 1997; Vieux, 2004; Vieux et al., 2004; Vieux and Bedient, 2004; Gourley et al., 2010; Cunha et al.,
- 105 2015). Furthermore, studies analyzing the performance of X-band radars will allow further indications as
- 106 to whether they should be installed in regions devoid of optimal NWS WSR-88D coverage.
- 107
- 108 Data and methodology
- 109 Study location and gauge data

110 The dates analyzed ranged from August 2015 to August 2017 which, when accounting for radar

111 down time for maintenance and offline issues, yielded 608 days, or 14952 hours for analyses. The current

112 study was conducted in Boone County, located in Central Missouri (Figure 1), where the MZZU radar is

113 located at 38.906°N and 92.269°W. Several Missouri Mesonet rain gauges lie within the domain of the

114 MZZU radar, located in Versailles, Auxvasse, Williamsburg, and Vandalia, MO, located at,

approximately, 75-km, 30-km, 45-km, and 80-km from the radar, respectively.

116 Missouri is characterized as a continental type of climate, marked by relatively strong seasonality. 117 Furthermore, Missouri is subject to frequent changes in temperature, primarily due to its inland location 118 and its lack of proximity to any large lakes. All of Missouri experiences below-freezing temperatures on a 119 yearly-basis. The TE525 tipping bucket series performs optimally in temperature conditions between 0 120 and 50°C. Albeit no events recorded a daily maximum temperature above 50°C, 72 days in the cool season (e.g., January and February) recorded temperatures below 0°C. However, only 8 days that 121 122 exhibited sub-freezing average daily temperatures registered precipitation. Thus, less than 1% of the 123 entire data might be further unrepresentative of the actual precipitation. For this study, it was assumed 124 since the amount of precipitation recorded by the gauges during these events were below 5 mm in 125 precipitation, no significant errors would affect the overall statistics.

One tip from the fulcrum device registers 0.254 mm of precipitation, which is the minimum
resolution required for statistics to be analyzed between the radar and the tipping gauge. In spite of the





- 128 well-documented literature discussing the errors associated with tipping buckets (e.g., Ciach and
- 129 Krajewski, 1999a, 1999b; Habib and Krajewski 1999; Habib et al., 2001; Ciach 2002), the gauges are
- 130 well-maintained and well-documented in terms of instrumentation failure, clogging, or other
- 131 discrepancies with the devices. Therefore, they are assumed to be valid as ground-truth devices.
- 132
- 133 Radar discussion and data

The radar for the current study is part of the Missouri Experimental Project to Stimulate Competitive Research (EPSCoR) program, primarily aimed at enhancing Missouri's modelling capacity of weather and climate on plants and communities at the local, and regional scale. The X-band radar (MZZU) was installed in the Summer of 2015, in which data acquisition became possible by the Fall of 2015 near the South Farm Research Center, located in central Boone County, MO (Figure 1). The instrument is utilized, primarily, for research purposes, but is also quasi-operational. Specifics regarding the radar are detailed in Table 1.

141 Raw radar data were analyzed using the Weather Decision Support System - Integrated 142 Information (WDSS-II) program (Lakshmanan et al., 2007a) to assess reflectivity (Z) in addition to dual-143 polarized radar variables including differential reflectivity (ZDR) and specific differential phase shift 144 (KDP). Many different quality control techniques (e.g., Lakshmanan et al., 2007b, 2010, 2014) were 145 implemented to the weather radar data processing with WDSS-II. Three other variables were also generated based on a KDP-based smoothing field (Ryzhkov et al., 2003) for reflectivity, differential 146 reflectivity, and specific differential phase: DSMZ, DZDR, and DKDP, respectively. These were 147 analyzed to determine whether the additional KDP-smoothing fields tend to over- or underestimate QPE's 148 149 (Simpson et al., 2016).

All six variables (Z, ZDR, KDP, DSMZ, DZDR, and DKDP) were converted from their native
polar grid to 256 x 256 1 km Cartesian grids, where the lowest radar elevation scans (0.5°) were used to





152	mitigate uncalculated effects from evaporation and wind drift. An average of 5-minute scans were used
153	for each of the variables, which were aggregated to hourly totals to be compared to the hourly tipping-
154	bucket accumulations. In spite of previous reports suggesting 5 minute to hourly aggregates can have
155	significant effects on QPE (Fabry et al., 1994), evidence has been presented that overestimation in
156	accumulations may not exceed 26% for a pixel size of 1 km (Shucksmith et al., 2011).
157	The latitude and longitude of each of the 15 gauges were matched with the radar pixel that
158	corresponds to the Cartesian grid value of the seven radar variables which were then implemented in rain
159	rate calculations. Three single-polarized $R(Z)$ algorithms were tested, including $R(Z)$ -Convective, $R(Z)$ -
160	Stratiform, and R(Z)-Tropical. The dual-polarized algorithms implemented are based from previous S-
161	and X-band research to more closely resemble the sensitivity of the radars on KDP estimates. Although,
162	theoretically, the relationship between R and Z for a well calibrated radar as controlled by the drop size
163	distribution should be independent of radar wavelength. However, as the phase shift of the wave is a
164	function of the ratio of wavelength to drop radius, the R(KDP) relationships are wavelength dependent.
165	The five R(Z,ZDR) S-band equations tested by Simpson et al. (2016) were implemented, whereas
166	six, three, and two X-band R(KDP) algorithms were adopted from Matrosov (2010), Wang and
167	Chandrasekar (2010), and Koffi et al. (2014) (Table 2). Additionally, two X-band R(Z,ZDR) and
168	R(ZDR,KDP) algorithms were adopted from Matrosov (2010) and Koffi et al. (2014), respectively. All
169	measures of Z, ZDR, and KDP were tested in addition to their KDP-smoothed derivatives, DSMZ,
170	DZDR, and DKDP. A rain rate echo classification variable (RREC) was also computed, which chooses
171	whether an R(Z), R(KDP), R(Z,ZDR), or R(ZDR, KDP) algorithm is implemented in estimating rain rates
172	based on the radar fields of Z, ZDR, and KDP (Kessinger et al., 2003). This echo classifier will provide
173	evidence as to whether a multi-parameter algorithm is superior to the single algorithms.
174	Furthermore, algorithms were grouped based on the variables implemented to estimate rain rates.
175	Collectively, three R(Z) algorithms were tested, R(Z)-Convective, R(Z)-Stratiform, and R(Z)-Tropical, in

addition to the DSMZ counterparts. Five separate R(Z,ZDR) equations were also implemented, including





- 177 five R(Z,DZDR), five R(DSMZ,ZDR), and the five R(DSMZ,DZDR) combinations. These 26 equations
- 178 encompass the S-band algorithms to be tested on the X-band radar, to determine how versatile the
- 179 equations are. Conversely, there were eleven R(KDP) X-band algorithms (and, thus, eleven R(DKDP)
- 180 equations), two R(Z,ZDR), and two R(ZDR,KDP) equations in addition to their DSMZ, DZDR, and
- 181 DKDP variables.

182 Statistical, contingency, and quantitative analyses

183 The results were split between three different categories: statistical, contingency, and quantitative. 184 The three statistics utilized included the bias, mean absolute error (MAE), and normalized standard error 185 (NSE). The NSE was chosen in place of the root-mean-square-error (RMSE) due to the ambiguity of the 186 measure (Willmott and Matsuura, 2005; Jerez et al., 2013). Contingency analyses included the number of 187 hits, misses, and false alarms. Accounting for the quantitative measure of precipitation due to the number 188 of misses and false alarms, the missed precipitation amount (MPA) and false precipitation amount (FPA) 189 were calculated. Additionally, the sum of precipitation is presented to render a long-term performance 190 (i.e., two year's) of the radar in comparison to the ground-truthed gauges.

191

192 Results and discussion

193From the four separate gauges, Auxvasse was the closest to the radar (approximately, 30 km)

194 while Vandalia was the furthest (80 km), with Versailles slightly closer at 75 km (Figure 1).

195 Williamsburg lies 45 km from the radar, placing it near the middle of the group of gauges in terms of

196 distance. The overall average amount of gauge recorded precipitation between the four sites was,

197 approximately, 1650 mm (Figure 2). Excluding the warm season (approximately from April –

198 September), the amount of gauge-recorded rainfall was similar across the four gauges. The large variance

in precipitation during the warm season were due, primarily, from several isolated convective cells which

were recorded at the certain gauges (e.g., Williamsburg), but missed at others (e.g., Versailles). The





- 201 normalized standard error (NSE) was chosen as the statistic to assess the overall performance of each
 202 algorithm due to the (typical) non-Gaussian representation of precipitation (Kleiber et al., 2012; Alaya et
- 203 al., 2017).
- 204
- 205 Smoothed versus non-smoothed QPE
- 206 For the 26 S-band equations analyzed, the R(Z)-Convective had the lowest NSE at Auxvasse
- 207 (1.6), Williamsburg (1.51), and Versailles (1.59) whereas the R(Z)-Stratiform outperformed at the furthest
- 208 gauge, Vandalia (1.64) (Figure 3). A pattern of the R(DSMZ)-Tropical and then R(Z)-Tropical
- 209 performing the worst was exhibited, with the RREC performing worse than either the R(Z)- or R(DSMZ)-
- 210 Convective and Stratiform equations. Although there were no significant (p < 0.10) differences between
- 211 R(Z) and R(DSMZ), the difference between R(Z)-Tropical and R(DSMZ)-Tropical was significant (p <
- 212 0.10). These R(Z) algorithms in addition to the RREC performed best at 75 km from the radar, whereas 5
- km further (Vandalia) displayed the largest NSE values. This may be due, at least in part, to the fact that
- single gauges were utilized as ground truth, whereby any of the numerous errors associated with tipping
- bucket rain gauges (Ciach and Krajewski 1999a; Habib et al. 2001; Ciach 2002) occurred.
- 216 Due to the small impact of smoothing the ZDR field (i.e., DZDR) on QPE, neither the
- 217 R(Z,DZDR) nor R(DSMZ,DZDR) are reported. The addition of the DSMZ field was inferior for all
- 218 R(Z,ZDR) equations in terms of NSE. Two National Severe Storm Laboratory (NSSL) derived R(Z,ZDR)
- 219 equations (Ryzhkov et al., 2003) were superior compared to their R(DSMZ,ZDR) counter-parts. The
- 220 R(Z,ZDR) and R(DSMZ,ZDR) equation 2 recorded the largest NSE values (neither recording values less
- than 2.5) since the equation was derived from a sub-tropical environment (Brandes et al., 2002). The NSE
- values for the single- and dual-pol equations ranged from 1.6 to 2.5 and 1.6 to 4.3 at a distance of 30 km
- from the radar, respectively. The range in NSE values were least for the gauge at 75 km from MZZU (less
- 224 than 1.5 units).





225 Only the $R(Z,ZDR)^2$ and $R(DSMZ,ZDR)^2$ equations displayed a significant (p < 0.10) at each of 226 the four gauges, demonstrating the significant impact smoothed reflectivity has on QPE. The other significant difference in QPE was at the closest gauge between R(Z,ZDR)1 and R(DSMZ,ZDR)1. These 227 two algorithms were not derived by NSSL and, typically, performed the worst overall as the climatology 228 229 of precipitation in which these equations were derived (Bringi and Chandrasekar, 2001; Brandes et al., 230 2002) were more tropical compared to the continental properties at the NSSL. 231 232 **Statistical analyses** From the 68 algorithms overall, the best R(Z) equation was R(Z)-Convective, similar to the 233 findings of Simpson et al. (2016). However, R(Z,ZDR)4 outperformed R(Z,ZDR)5, which displayed the 234 235 lowest NSE in Simpson et al. (2016). Furthermore, the best R(KDP) algorithm was from Matrosov

236 (2010), while the best performing R(ZDR,KDP) equation was from Koffi et al., (2014), algorithms 6 and

11 from Table 2, respectively. These were chosen to be the best overall algorithms from each grouping ofequations due to their lowest MAE and NSE values (Table 3).

239 With Auxvasse being the closest gauge to the radar (30 km), this location registered the least bias 240 across all grouping of algorithms, excluding RREC. In fact, the R(Z,ZDR) equation showed no bias (0.0 mm), while R(KDP), R(ZDR,KDP), and RREC displayed slightly positive biases (0.3, 0.3, and 0.5 mm, 241 respectively). This is surprising since ZDR has not been calibrated for the MZZU radar, which has been 242 243 shown to significantly alter QPE (Hubbert and Bringi, 1995; Atlas, 2002; Illingworth, 2004; Williams et 244 al., 2005; Zrnic et al., 2010; Ice et al., 2013). Only the R(Z) equation registered a negative bias (-0.1 mm), 245 consistent with the fact that the conventional R(Z) algorithm is inappropriate for stratiform precipitation 246 (Klazura and Kelly, 1995; Seo et al., 2015). Interestingly, the RREC registered less bias as distance from the radar increased (0.5, 0.2, 0.2, and 0.1 mm for distances of 30, 45, 75, and 80 km, respectively) 247 248 whereas most other algorithms displayed an increase in magnitude as the distance from MZZU increased.





249	In general, Williamsburg, the second-furthest gauge from MZZU (45 km), registered the second-
250	best bias with the notable exception of the $R(Z)$ equation. For example, underestimation on the order of -
251	0.3 mm was recorded at Williamsburg for R(Z), while -0.2 mm and -0.4 mm were registered at Versailles
252	(75 km) and Vandalia 80 km), accordingly. Furthermore, Auxvasse was the only of the four gauges which
253	did not register a negative bias for R(Z,ZDR). The largest biases were recorded by R(KDP).
254	The mean absolute errors values recorded by the R(Z,ZDR) equation were 1.3, 1.4, 1.4, and 1.5
255	mm at distances of 30, 45, 75, and 80 km, respectively. Otherwise, the other four algorithms represented
256	increasing error with increasing range from MZZU, with the lowest MAE being R(ZDR,KDP) with 1.2
257	mm, and the largest being RREC (1.7 mm). This indicates that the RREC algorithms was incapable in
258	correctly determining the proper QPE algorithm based on the values of radar variables and near storm
259	environment surroundings.
260	At no locations for R(Z), R(KDP), or RREC did the normalized standard error fall below 100%.
261	Therefore, the two algorithms containing the differential reflectivity recorded NSE's less than 100%, in
262	particular at the two closest gauge locations. The R(ZDR,KDP) registered 84.7 and 93.1% at Auxvasse
263	and Williamsburg, whereas R(Z,ZDR) displayed NSE values of 89.2 and 99.0%, respectively.
264	Furthermore, these two algorithms calculated less NSE at the furthest location (Vandalia) than at the third
265	furthest location (Versailles), in spite of there being a 5 km difference in range between the two locations,
266	further demonstrating the impact of gauge errors on QPE (Sevruk, 2005; Rasmussen et al., 2012).
267	
268	Contingency analyses
269	To determine where the bulk of errors implicit within the bias, mean absolute error, and
270	normalized standard error originate from, contingency analyses were calculated, including hits, misses,
271	and false alarms.
272	The number of tips recorded at Auxvasse, Vandalia, Versailles, and Williamsburg were 810, 725,
273	762, and 855, accordingly (Figure 5). In terms of the number of hits, misses, and false alarms, an analysis





274	of variance (ANOVA) table was constructed to determine whether any significant differences exist
275	between the five algorithms. Results indicate that, with 99% confidence, the number of hits between the
276	five algorithms, in addition to the number of misses and false alarms did not differ significantly from one
277	algorithm to the next. Therefore, the results of contingency analyses will be conducted utilizing the
278	R(ZDR,KDP) algorithm to reduce redundancies.
279	The number of hits were 688, 603, 647, and 736 at Auxvasse, Vandalia, Versailles, and
280	Williamsburg, respectively, indicating that 85, 83, 85, and 86% of the precipitation events were correctly
281	assessed by the radar. With 122, 122, 115, and 119 misses, only 15, 17, 15, and 14% of rainfall events
282	were missed. However, the occurrences of false alarms were similar to the number of hits and, for
283	Vandalia, exceeded the number of gauge tips. For example, Auxvasse, Williamsburg, Versailles, and
284	Vandalia registered 7 more, 4 more, 9 less, and 135 more false alarms than the number of hits. Therefore,
285	it may be concluded that the bulk of the errors in the QPE's were, primarily, due to false alarms.
286	In spite of the prevalent occurrences of the number of false alarms, the correlation coefficient
287	values between the gauge recorded and radar estimated precipitation were as large as 0.70, particularly for
288	the R(Z)-Convective and RREC algorithms (Figure 6). Furthermore, these two algorithms had the same
289	R^2 values for all of the four stations of 0.7, 0.68, 0.56, and 0.5 for Auxvasse, Williamsburg, Versailles,
290	and Vandalia, respectively. The R(KDP) equation had similar values with the exception of Auxvasse,
291	which was 0.69 (0.01 less).
292	The ZDR-containing algorithms have been shown to be superior to the other three equations in
293	terms of NSE (Table 3), yet produced the, overall, lowest R^2 values. Therefore, the added benefit of dual-
294	polarized parameters may be limited to certain types of hydrometeors (Cunha et al., 2015). The best
295	values were 0.63 and 0.62 at Auxvasse for R(Z,ZDR) and R(ZDR,KDP), respectively, while the lowest
296	values were 0.43 and 0.41 at Vandalia, accordingly. The reason for the findings may be due to the fact
297	that the R(Z,ZDR) and R(ZDR,KDP) algorithms showed more spread in the correlation data, particularly
298	at Auxvasse. Although the RREC displayed spread in the data as well, the magnitudes of error were,





- typically, contained below 15 mm as estimated by the radar. Furthermore, the radar tended to
- 300 underestimate precipitation for R(Z) and RREC, but showed larger radar estimated precipitation for
- 301 R(KDP) and R(ZDR,KDP), correlating with the bias values described earlier (Table 3).
- 302

303 **Quantitative analyses**

The quantitative analyses are the amount of precipitation associated with each miss, false alarm, or due to error overall. Additionally, the overall accumulation of precipitation over the course of the study is presented to determine whether the errors cancel out over longer time periods.

- is presented to determine whether the errors cancer out over longer time periods.
- 307 Although it was found that 15, 17, 15, and 14% of rainfall events were missed, this accounted for
- 308 6.5, 5.6, 11.0, and 11.6% of the error relative to the gauge for the R(Z)-Convective equation (Table 4).
- 309 This indicates that, on average, most of the missed precipitation events were for values less than 1.0 mm.
- 310 This may be due, at least in part, to the fact that tipping buckets are incapable of measuring the beginning
- of a precipitation event, or, very light rainfall periods (Ciach, 2002). For algorithms that did not contain
- 312 ZDR, the furthest location (Vandalia) typically registered the largest MPA values, in addition to
- 313 contributing the most amount of MPA compared to the gauge accumulated total for any of the four
- 314 locations. The largest MPA for R(Z) was at Vandalia (180.8 mm), which was 11.6 of the total gauge
- amount, where QPE's estimated at Williamsburg only recorded 99.4 mm of MPA (5.6% of total).
- 316 Although Williamsburg (second-furthest gauge) recorded the least amount of MPA for R(Z), R(KDP) and
- 317 RREC, the closest gauge (Auxvasse) registered the least amount of missed precipitation for R(Z,ZDR)
- 318 (101.1 mm) and R(ZDR,KDP) (105.1 mm). Overall, the R(Z,ZDR) algorithm registered the least amount
- 319 of missed precipitation overall at Auxvasse.
- 320 Conversely, the R(KDP) equation was calculated to have the lowest MPA (95.6) at Williamsburg,
- 321 with R(Z) and RREC both recording 98.7 mm. This accounted for 5.4 and 5.6% of the total gauge
- 322 recorded rainfall amount (1769.3 mm), while R(Z,ZDR) and R(ZDR,KDP)'s MPA percentages were 9.9
- and 11.3%, accordingly. Therefore, algorithms containing ZDR tend to underestimate the rain rate at





324 Williamsburg such that values less than 0.25 mm were registered and, ultimately, assumed no

325 precipitation to be present. Larger magnitudes of ZDR were thus estimated by the radar, lowering the

326 overall QPE for both R(Z,ZDR) and R(ZDR,KDP).

327 Due to the fact Versailles and Vandalia were 75 and 80 km from the MZZU radar, their

328 differences in overall error were dependent upon the algorithm chosen. For example, similar to the

329 instances when R(Z), R(KDP), and RREC were lower in MPA and the MPA percentage at Williamsburg

than Auxvasse, these algorithms were more accurate at Versailles than Vandalia. This result demonstrates

that the algorithms containing ZDR were superior at close (Auxvasse) and further (Vandalia) ranges from

the MZZU radar, whereas the other three equations were best at intermediate distances (i.e., between 30

333 and 75 km).

As noted in the contingency analyses section, the number of false alarms outnumbered the counts 334 335 of misses by more than six times, mirroring the number of hits, overall. Therefore, the false precipitation amount (FPA) is, unsurprisingly, approximately six times the MPA, particularly for the algorithms that 336 337 did not contain ZDR. Conversely, R(Z,ZDR) and R(ZDR,KDP) recorded, approximately, twice the 338 amount of FPA as MPA. For example, the FPA for R(Z,ZDR) at the gauge locations at increasing 339 distances from the radar were 265.1, 295.8, 417.1, and 382.9 mm, whereas the MPA were 101.1, 175.5, 340 224.1, and 204.3 mm, respectively. This indicates that no MPA for R(Z,ZDR) was more than 15% of total 341 precipitation measured at the gauge locations, whereas FPA did not exceed 27% (but was no lower than 15%). However, R(ZDR,KDP) displayed the lowest FPA, overall, at each locations such that it did not 342 343 exceed 375 mm (373.1 mm at Versailles) nor did it register any less than 230 mm (233.7 mm at 344 Auxvasse).

At all locations, the R(Z), R(KDP), and RREC overestimated the amount of total radar estimated QPE compared to the gauge recorded rainfall (Figure 7). Furthermore, the FPA tend to exceed the overall gauge recorded rainfall amount for these algorithms as well (Table 4). The only algorithm which had a lower total accumulation of radar estimated QPE than the gauge recorded amount of rainfall was





R(ZDR,KDP) at both Williamsburg and Vandalia. However, R(Z,ZDR) had more similar values (within 20 mm) at Vandalia than P(ZDR KDP) than at Williamsburg

350 20 mm) at Vandalia than R(ZDR,KDP) than at Williamsburg.

351 The total precipitation error is the quantitative value of all errors in the QPE. In other words, it is the quantitative value of precipitation analyzed by the normalized standard error, and follows a similar 352 353 pattern. The TPE for all locations analyzed by the R(KDP) equation did was not lower than 2000 mm 354 (Table 4). Conversely, none of the ZDR-containing equations had a TPE larger than 1800 mm, but the 355 only locations where the TPE was less than the gauge accumulated precipitation amount were at Auxvasse and Williamsburg for both R(Z,ZDR) and R(ZDR,KDP). For these two algorithms, less than 356 357 40% of the total error were due to either MPA or FPA, whereas the FPA resulted in the bulk of error for 358 the other 3 algorithms. This indicates that most of the errors, when utilizing ZDR, were due to errors by 359 hits.

360 The sum of precipitation (Figure 7) represents the amount of precipitation that would result if the direct accumulation of radar estimated QPE were conducted, such that missed precipitation were not 361 362 included and false alarms were accounted for. Essentially, it acts as a long-term performance of the QPE 363 from each algorithm at each site. From the quantitative analyses, it is seen that the ZDR-containing 364 algorithms R(Z,ZDR) and R(ZDR,KDP) not only displayed the overall lowest MAE and NSE, but are 365 more accurate with their overall accumulation of precipitation with respect to time (Figure 7). In other 366 words, in spite of the relatively large FPA and MPA across all algorithms at each location, the ZDRcontaining equations cancelled the FPA, MPA, and overall MAE over time, resulting in accurate gauge-367 368 accumulation precipitation amounts represented as the closeness in values to the gauge recorded rainfall and total sum of precipitation black and magenta contours in Figure 7, accordingly). 369

370

371 Conclusions





- 372 The current study analyzed two years' worth of X-band dual-polarimetric quantitative
- 373 precipitation estimates (QPE) from Central Missouri. Four separate terrestrial-based precipitation gauges
- 374 (i.e., tipping buckets) served as ground-truth. Over 50 algorithms were tested, of which the analyses of the
- 375 five best from each grouping of algorithms from R(Z), R(Z,ZDR), R(KDP), R(ZDR,KDP), and echo
- 376 classifiers, were reported. Statistical, contingency, and overall quantitative analyses were reported to
- 377 determine not only the best performing algorithms overall, but to determine the course of the error.
- 378 The best equations were determined to be the R(Z)-Convective algorithm, an NSSL-derived
- 379 R(Z,ZDR) equation from Ryzhkov et al., (2003, 2005), an R(KDP) equation from Matrosov (2010), an
- 380 R(ZDR,KDP) equation from Koffi et al. (2014), and the rain rate echo classifier. Algorithms containing
- 381 reflectivity typically exhibited negative biases, of which, the R(Z,ZDR) had the lowest bias values,
- overall. Conversely, the KDP-containing algorithms showed positive biases, with the R(KDP) being the
- 383 largest, overall.

384 Overall, the R(Z,ZDR) and R(ZDR,KDP) equations performed the best. This was evidenced as 385 these algorithms having the lowest MAE and NSE at nearly every gauge location. Furthermore, these 386 were the only equations which exhibited NSE values below 100 %, particularly at the two closest gauge 387 locations (30 and 45 km from the radar). However, these equations had the overall lowest correlation coefficient (R^2) values in comparison to the other algorithms. It is theorized that these low R^2 values were 388 due, primarily, from an overall larger spread in the QPE's from these particular equations. The R(Z), 389 R(KDP), and RREC algorithms exhibited correlation values as large as 0.70 at the closest gauge location, 390 391 while values as low as 0.5 were reported at the furthest location (Vandalia, 80 km). A typical reduction in R^2 values were observed as range from the radar increased. 392

The majority of the error from the QPE's at each location were due to false alarms, potentially due to evaporation (Kumjian and Ryzhkov, 2010; Martinaitis et al., 2017). In some instances, particularly for R(Z), R(KDP), and RREC, the false precipitation amounts were up to 65% of the total of the gauge accumulated rainfall amounts. Conversely, the ZDR-containing equations displayed not only the lowest





- 397 missed and false precipitation amounts, but the overall accumulation of precipitation from these two
- 398 equations were most similar to the accumulated gauge rainfall amounts, thus indicating the robust
- 399 performance of the utilization of ZDR in QPE estimates.
- 400 The results presented display the accuracy of X-band QPE estimates. It is noted that, however, no
- 401 equations were derived and tested for the current study. The results of the performance of the radar may
- 402 be improved by not only comparing results to disdrometer data, but also from combinations of the
- 403 algorithms at specific rain rates, much like the overall Joint Polarization (Ryzhkov et al., 2005;
- 404 Giangrande and Ryzhkov 2008) and CSU-CHILL (Cifelli et al., 2011) algorithms. The promising results,
- 405 particularly through the implementation of the differential reflectivity, further the considerations as to
- 406 installing the devices as permanent, cost-effective solutions to the WSR-88D NEXRAD system,
- 407 especially in regions where a gap in the radar coverage exists.
- 408

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570 Figures





Figure 1. Study location including to the four gauges utilized for the current study. From left-to-right,
the gauges are Versailles, Auxvasse, Williamsburg, and Vandalia, MO. The MZZU X-band radar is

575	plotted in	addition to	25-, 5	0-, 75-,	and 100)-km rang	e rings.
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Figure 2. Accumulated gauge-recorded precipitation from the beginning to the end of the study for thefour-separate terrestrial-based tipping buckets.







Figure 3. Performance of the 3 R(Z) and 3 R(DSMZ), RREC, 5 R(Z,ZDR) and 5 R(DSMZ,ZDR) S-band
equations at each of the four gauge locations.









Figure 4. Performance of the 11 R(KDP), 2 R(Z,ZDR), 2 R(DSMZ,ZDR), 2 R(ZDR,KDP), and 2
R(ZDR,DKDP) X-band algorithms at each of the four gauge locations.







Figure 5. Contingency analyses at each of the four gauges utilized for the current study

651 utilizing the R(ZDR,KDP) equation, including the accumulated number of tipping bucket

- 652 tips, hits, misses, and false alarms.



















709	Tables
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711 Table 1. MZZU X-band radar characteristics.

Variable	Value
Location (x,y)	38.906°N, -92.269°W
Altitude Above Ground Level	308 m
Dual Pulse Repetition Frequency	5:4 Stagger: 2,000 Hz – 124 kts
Radar Type	EWR Solid State: Parabolic prime focus
	composite reflector (Dish mounted radome cover)
Peak Power	1 kW standard
Frequency	9.35 GHz ± 50 MHz (User Selectable)
Pulse Width	1 – 80 µs
Diameter	1.82 m
Beamwidth	1.27°
Gain	42 dB
Sensitivity	(80 µs at 50 km range): -1.5 dBZ
Elevation Angle	-5° to 120°





713 Table 2. List of X-band polarimetric algorithms used for radar rainfall estimates.

Algorithm number	0	h		Deferences
Algorithm number	ä	D	С	References
1	17.0	0.73	-	Matrosov (2010)
2	16.5	0.71	-	Matrosov (2010)
3	16.6	0.82	-	Matrosov (2010)
4	14.4	0.71	-	Matrosov (2010)
5	16.4	0.80	-	Matrosov (2010)
6	14.9	0.79	-	Matrosov (2010)
7	47.3	0.79	-	WC (2010)
8	18.2	0.79	-	WC (2010)
9	19.6	0.82	-	WC (2010)
10	13.6	0.83	-	Koffi et al. (2014)
11	21.0	0.57	-	Koffi et al. (2014)
$R(Z,ZDR) = aZ^b ZDR^c$				
Algorithm number				References
1	0.0039	1.07	-5.97	Matrosov (2010)
2	0.0056	1.02	-5.60	Matrosov (2010)
$R(ZDR, KDP) = aZDR^{b}KDP^{c}$				
Algorithm number				References
1	15.1	-0.29	0.94	Koffi et al. (2014)
2	20.9	-0.05	0.59	Koffi et al. (2014)

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- Table 3. Statistical analyses for the MZZU radar and the best algorithms from each grouping of
- 718 equations with their respective distance from the radar.

Algorithm	Auxvasse 30 km	Williamsburg 45 km	Versailles 75 km	Vandalia 80 km
R(Z)	Bias: -0.1	Bias: -0.3	Bias: -0.2	Bias: -0.4
	MAE: 1.3	MAE: 1.4	MAE: 1.4	MAE: 1.5
	NSE: 102.6	NSE: 107.8	NSE: 119.9	NSE: 134.6
R(Z,ZDR)	Bias: 0.0	Bias: -0.2	Bias: -0.3	Bias: -0.2
	MAE: 1.3	MAE: 1.6	MAE: 1.6	MAE: 1.5
	NSE: 89.2	NSE: 99.0	NSE: 110.5	NSE: 106.9
R(KDP)	Bias: 0.3	Bias: 0.4	Bias: 0.5	Bias: 0.6
	MAE: 1.3	MAE: 1.3	MAE: 1.5	MAE: 1.6
	NSE: 119.1	NSE: 126.1	NSE: 142.5	NSE: 158.6
R(ZDR,KDP)	Bias: 0.3	Bias: 0.3	Bias: 0.5	Bias: 0.5
	MAE: 1.2	MAE: 1.3	MAE: 1.4	MAE: 1.5
	NSE: 84.7	NSE: 93.1	NSE: 104.7	NSE: 101.8
RREC	Bias: 0.5	Bias: 0.2	Bias: 0.2	Bias: 0.1
	MAE: 1.6	MAE: 1.7	MAE: 1.7	MAE: 1.7
	NSE: 103.1	NSE: 108.1	NSE: 120.0	NSE: 135.1





738	Table 4. Quantitative analyses, including the missed precipitation amount (MPA), false
739	precipitation amount (FPA), and total precipitation error (TPE). Percent indicates the relative
740	error due to either MPA or FPA relative to the gauge accumulated precipitation amount (Gauge
741	Precip row).

	Auxvasse	Williamsburg	Versailles	Vandalia
Gauge Precip	1695.7	1769.3	1583.7	1557.4
R(Z)	MPA: 110.3	MPA: 99.4	MPA: 174.4	MPA: 180.8
	Percent: 6.5	Percent: 5.6	Percent: 11.0	Percent: 11.6
	FPA: 634.0	FPA: 633.9	FPA: 674.23	FPA: 811.3
	Percent: 37.4	Percent: 35.8	Percent: 42.6	Percent: 52.1
	TPE: 1739.6	TPE: 1906.7	TPE: 1899.3	TPE: 2096.9
R(Z,ZDR)	MPA: 101.1	MPA: 175.5	MPA: 224.1	MPA: 204.3
	Percent: 6.0	Percent: 9.9	Percent: 14.2	Percent: 13.1
	FPA: 265.1	FPA: 295.8	FPA: 417.1	FPA: 382.9
	Percent: 15.6	Percent: 16.7	Percent: 26.3	Percent: 24.6
	TPE: 1512.0	TPE: 1751.0	TPE: 1750.2	TPE: 1664.3
R(KDP)	MPA: 107.6	MPA: 95.6	MPA: 172.1	MPA: 171.9
	Percent: 6.3	Percent: 5.4	Percent: 10.9	Percent: 11.0
	FPA: 794.7	FPA: 797.7	FPA: 840.6	FPA: 1012.1
	Percent: 46.9	Percent: 45.1	Percent: 53.1	Percent: 65.0
	TPE: 2020.3	TPE: 2230.6	TPE: 2256.6	TPE: 2470.4
R(ZDR,KDP)	MPA: 105.1	MPA: 200.4	MPA: 268.8	MPA: 224.4
	Percent: 6.2	Percent: 11.3	Percent: 17.0	Percent: 14.4
	FPA: 233.7	FPA: 254.2	FPA: 373.1	FPA: 321.8
	Percent: 13.8	Percent: 14.4	Percent: 23.6	Percent: 20.7
	TPE: 1436.5	TPE: 1647.1	TPE: 1657.3	TPE: 1586.0
RREC	MPA: 109.3	MPA: 98.7	MPA: 174.2	MPA: 180.8
	Percent: 6.4	Percent: 5.6	Percent: 11.0	Percent: 11.6





FPA: 635.2	FPA: 635.2	FPA: 674.2	FPA: 811.3
Percent: 37.5	Percent: 35.9	Percent: 42.6	Percent: 52.1
TPE: 1748.0	TPE: 1912.7	TPE: 1899.9	TPE: 2103.6



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