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Using Field Scale Electrical Data to Understand Real-Time Agricultural Water Delivery

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USING FIELD SCALE ELECTRICAL DATA TO UNDERSTAND REAL-TIME AGRICULTURAL WATER DELIVERY

by

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Areas across the High Plains (Ogallala) Aquifer region are experiencing unsustainable groundwater level declines and impacts to streamflow due to increasing human influence, posing challenges for sustaining future agricultural economies and groundwater resources. State and local agencies manage water using groundwater models, which are not at the same temporal and spatial scale as water management on farms. Well-informed agricultural water usage cannot be achieved without reliable and cost-effective water use at farm scale. Water meters are expensive and rarely installed unless required by the state or other regulatory agency; however, most center pivots have their own power supply, which reports real-time electricity consumption. Thus, finding novel ways of measuring real-time water usage from center pivot irrigation provides essential information to farmers and watershed managers balancing economic, sustainability, and governance decisions. This study leverages data gathered across the food-energy-water nexus by translating electrical measurements gathered in 15-minute time intervals on 10 center pivot agricultural production wells in western Nebraska into estimates of water delivery. Water delivery estimated using an electrical run-time algorithm and ultrasonic flow tests is found to be within 6.60% when compared to water delivery measured taken independently with calibrated flow meters. Translating electrical measurements from wells is an accurate way to estimate water withdrawals relative to the

costs, but faces uncertainty arising from ultrasonic flow tests, field topography, and variable water delivery. Hydrologic modeling runs using the COHYST regulatory model for the Platte Basin demonstrated that errors in pumping on the scale of field-level estimated uncertainties can have a meaningful effect on estimated streamflow in the Platte River during peak pumping months, but that the model is constructed in a way that prevents assessment of the effects of the spatial distribution of pumping error. This novel data approach takes advantage of reliable and cost-effective data gathering across the rural electric smart grid to provide cost-effective food-energy-water solutions—supporting well-informed and economic use of water resources and models.

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CHAPTER 1. Introduction

1.1 Electrical Runtime Approach to Estimating Water Delivery

This study uses electricity measurements from irrigation center pivots in the Twin Platte Natural Resources District in western Nebraska to estimate the volume of water used for irrigation. Understanding water inputs in the context of the broader food-energy-water nexus provides a key area for researchers, policy makers, and water users to fill knowledge gaps that exist in understanding real time water usage at field scale. This project then tests the implications of field scale water withdrawal uncertainties at larger scales using a regional regulatory groundwater model.

This study uses an electrical runtime algorithm to estimate the amount of water used at 10 center pivots across the Twin Platte NRD. Each irrigation center pivot is assigned to an electrical smart meter by the public power provider which reports the total Kilowatt-hours (KHW) of energy used every 15 minutes. This approach uses the electrical record to determine the length of runtime of a center pivot. Figure 1 shows a representative irrigation event (a continuous set of individual power measurements, p_i, with no interruption), which is determined by a threshold value of 4 KWH to distinguish the occurrence of irrigation from non-irrigation related center pivot movement (or 25% of the typical electricity used during a 15 minute timer interval in our study area). Leading and trailing edges of an irrigation event are determined by the first and last occurrence of a continuous set of power measurements above this threshold value. Leading and trailing edges assigned a duration of time which is proportionate to the preceding or trailing interval's energy usage, while intervals between the leading and

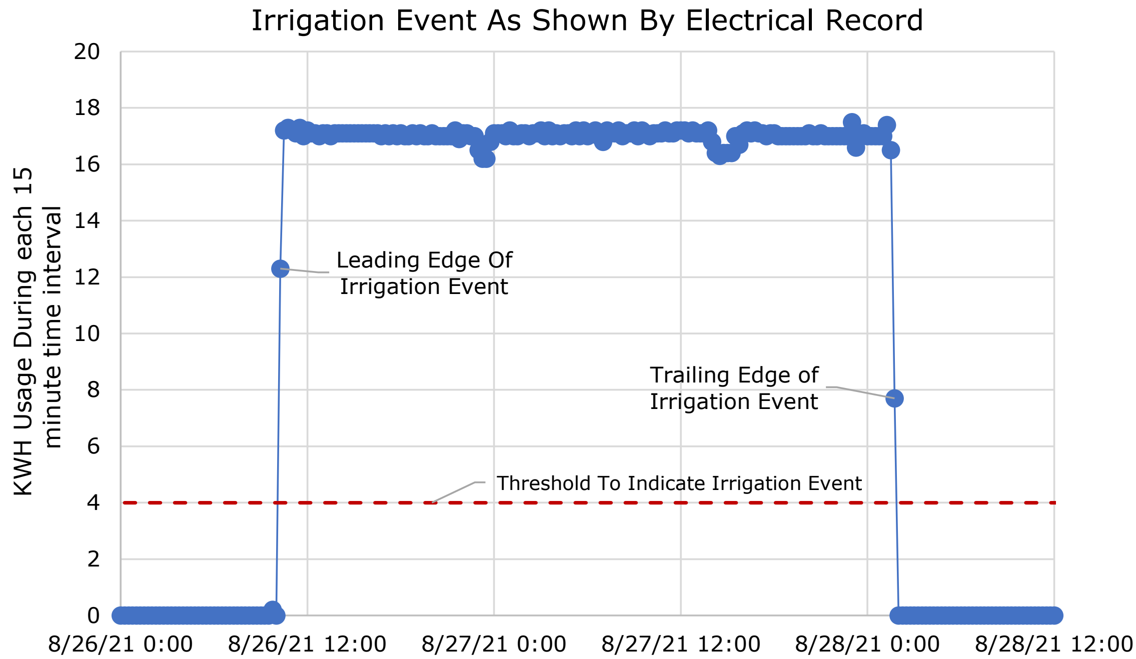

Figure 1. A representative irrigation event is shown for Well T4 during the end of August. An irrigation event is defined by a continuous set of power measurements, pi, which are above the threshold of 4 KWH. Leading and trailing edges are identified and assigned a time length which is proportional to the leading and trailing edge's power usage to the following or proceeding energy usage. Small dips in energy usage can be seen in the energy usage data, indicating the operation of end guns which will be discussed later. This study's approach uses the occurrence of energy usage at a center pivot to determine the length of time a center pivot is irrigating coupled with a flow rate determined by a vendor in an independent flow test to estimate the amount of water applied during irrigation.

trailing edges are identified as irrigating over the full 15 minute interval. Figure 2 shows electricity data measured over the course of a month of typical center pivot operations. The runtime of an irrigation center pivot is then coupled with a vendor ultrasonic flow test (a measure a well's flow rate) to estimate total water usage during each time interval of irrigation.

This study leverages the pre-existing rural electrical grid to translate electrical measurements into agricultural water usage estimates. Unlike direct measurements using flow meters, power usage is measured as a matter of course without the need to install expensive equipment (flow meters with telemetry) or travel to a field to take measurements (mechanical flow meters).

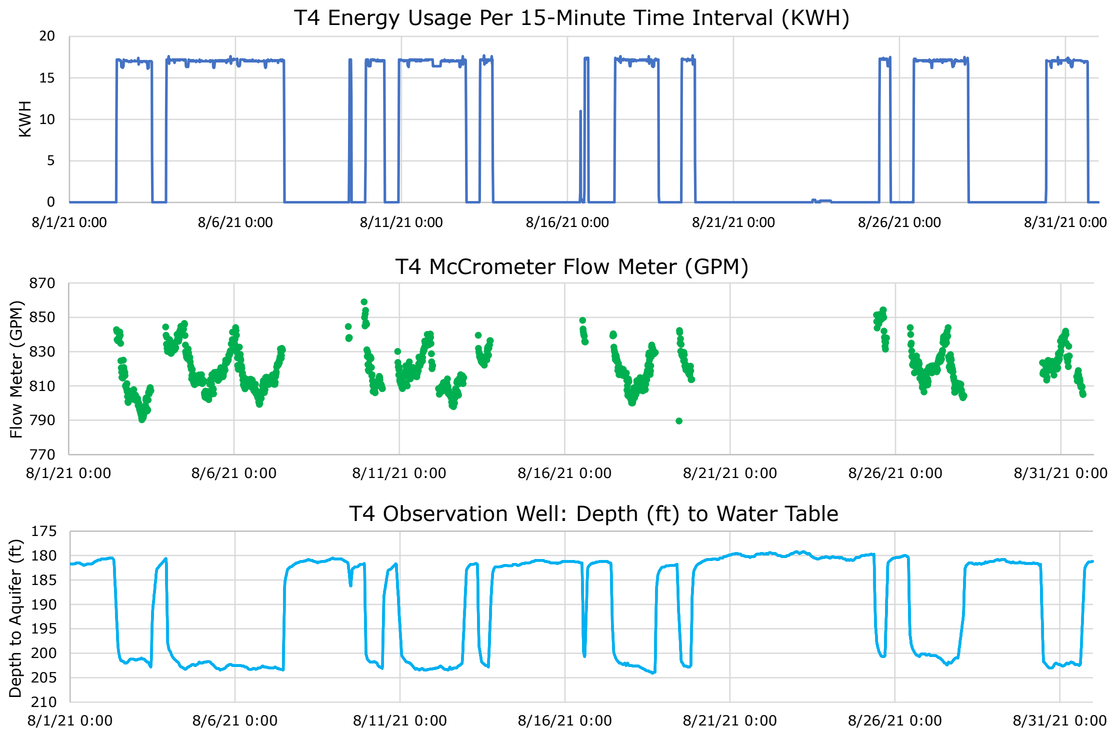

Figure 2. Data collected in the month of August for well T4. This study's primary data collection is power usage and vendor flow tests. Supporting data to assist in better understanding uncertainties are McCrometer Flow Meters which provide flow rates every 15 minutes and depth sensors which provide depth to aquifer levels every hour. Section 3.2.2 will discuss the characteristics displayed by these data such as center pivot end gun operations influencing energy usage and flow rates, as well as topography systematically impacting flow rates as a center pivot traverses a field.

This study installed 4 McCrometer McPropeller flow meters with telemetry (costing about $4219 each) to support this study's understanding of uncertainties related to the electrical runtime approach (see Section 2.3. Mechanical flow meters (which have no telemetry and require trips to the field to retrieve readings) are often used to gain accurate cumulative water delivery but cost about $2400 each. In contrast, the cost of a single ultrasonic flow test to use for this study's electrical runtime approach was $200 for Vendor A and $350 for Vendor B.

Just over 50% of irrigation pumps in Nebraska are powered by electricity, and this study hopes to utilize the preexisting and well maintained public power smart grid across rural Nebraska as a reliable source to gather information at

scale about agricultural water usage. The runtime of center pivots that do not utilize electricity smart meters is reported with cheaper telemetry devises by Growers' Information Services Coop (GiSC) and is outside of the scope of this study.

This study investigates the uncertainties of translating already existing electrical usage data into irrigation withdrawal estimates. To do this also have collected flow rates using McCrometer flow meters and taken aquifer measurements (Figure 2). Taken together, this study aims to leverage a cost effective way to estimate water delivery from electrical usage, supporting well-informed usage of water resources into the future. This study has five main objectives: (1) determine the reliability and accuracy of utilizing electrical data to estimate water delivery (Section 3.1.2); (2) determine the accuracy of using vendor ultrasonic flow tests to provide a cheap and broadly accurate estimate of flow rates for a well (Section 3.2.1); (3) investigate the feasibility of using the electrical runtime approach for by watershed managers within the context of regional modeling (Section 3.3); (4) discuss groundwater management and the added benefits of measuring water at field scale (Section 4.1); (5) discuss the benefits of utilizing a pre-existing infrastructure to estimate water usage (Section 3.2.5, Section 4.1).

1.2 Twin Platte Water Data Program

Conservation of groundwater in the Northern High Plains in Nebraska is managed by Natural Resources Districts (NRDs), which were set up in 1972 (Bleed and Babbitt, 2015; Evett et al., 2020). The NRD system is organized primarily around watershed boundaries and allows local communities to have control over local groundwater pumping polices under the auspices of the Nebraska Department of Natural Resources (Figure 3). Nebraska NRDs were set up with both groundwater and surfacewater under their purview to treat groundwater-surfacewater connections as a unified system. Understanding surfacewater-groundwater interactions is essential in effective agricultural water management since groundwater pumping can lead to streamflow reductions and harm to ecosystems when surfacewater-groundwater connections delink (Barlow and Leake, 2012; Li et al., 2016; Young et al., 2021).

Electricity data from irrigation center pivots are being used to provide farmers and watershed managers cost effective estimates of water usage across the Twin Platte NRD as part of the Twin Platte Water Data Program (GiSC, 2019; Nebraska Public Media, 2021). As of 2021, the Twin Platte Water Data Program has 90% adoption among growers across 320,000 acres in the Twin Platte NRD, which is located at the confluence of the North Platte and South Platte tributaries and containing Lake McConaughy and the cities of North Platte and Ogallala (Figure 3). The Twin Platte Water Data Program supports goals set by watershed managers and aids local farmers in making better informed water usage decisions by utilizing this study’s low cost electrical runtime approach to translate electrical data into water use estimates at field-scale.

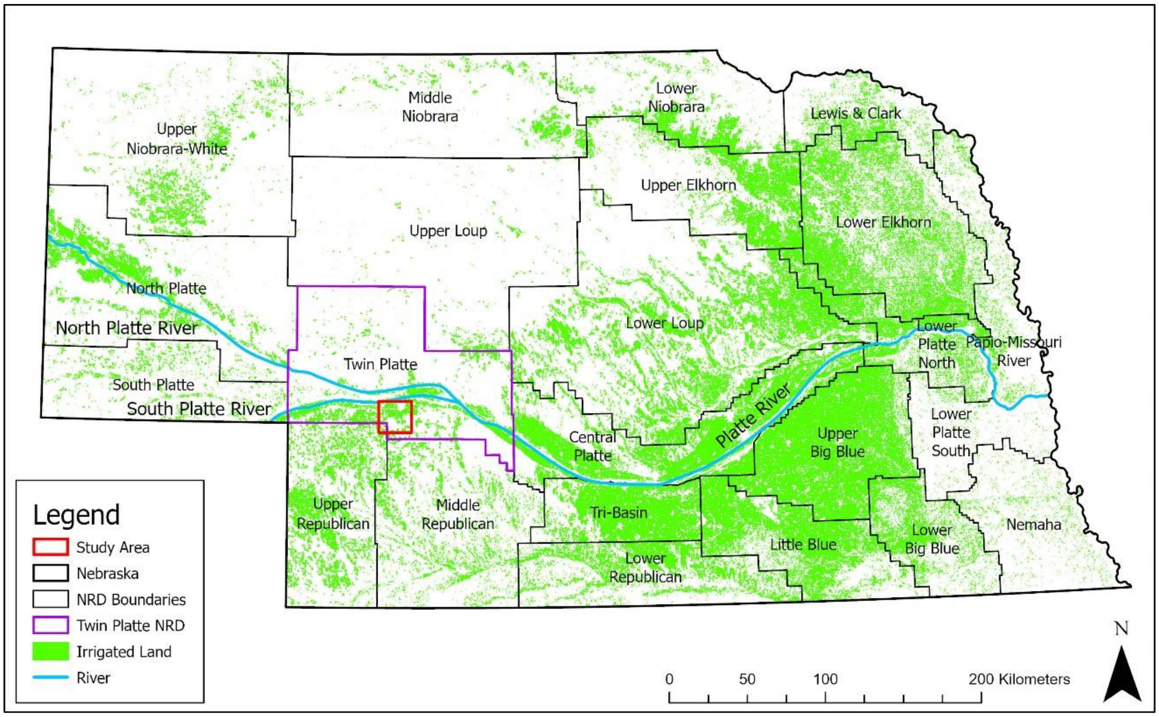

Figure 3. Natural Resources Districts (NRDs) that manage irrigation across Nebraska. The Twin Platte NRD is located where the North Platte River and South Platte River converge; the most of the irrigation is located in the southern half of the Natural Resources District. Irrigation Data from Deines et al. (2019) and Shrestha et al. (2019).

Farmers in Kansas that irrigate from the High Plains Aquifer are required to install flow meters and report annual groundwater consumption. Although this has yielded an excellent source of pumping data that is unique among High Plains Aquifer states, it has been expensive and is reported to be unpopular with farmers. Anecdotal accounts of Kansas farmers tampering with flow meters to purposely misrepresent aquifer withdrawals have been reported, despite steep penalties if caught (Bessire, 2021). Kansas pumping data are nevertheless the most complete publicly available source for irrigation withdrawals on the High Plains, but there are insufficient data to compare these withdrawals with electrical data at short timescales (McCarthy et al., 2020). This project provides a novel opportunity to translate real-time electrical usage into accurate water withdrawal estimates, an approach with a massive potential to be scaled up

across the High Plains.

Simple, accurate, and inexpensive measurement of water usage at the field scale can provide a key avenue for improving water users' decisionmaking. There are costs associated with the electricity needed to lift water from the saturated zone to the land surface and to operate a center pivot. If a farmer is applying more water than he or she realizes due to lack of real-time measurement, this inefficiency is a waste of money and energy as well as water. Since most of the power consumption of pumping wells is related to lift, electrical records have the potential to provide an accurate proxy for water withdrawal. However, this approach has not received widespread adoption been implemented for several reasons: (1) because of the difficulty of obtaining electrical records for wells; (2) the difficulties associated with sprinkler "end gun" operation (see Section 1.4) which prevents using a constant coefficient to translate electricity into withdrawal; and (3) the previous immaturity of smart grid (often called Internet of Things or IoT) technology. Reducing water usage for irrigated agriculture requires focusing on inputs within water-energy-food systems. Water users who can apply as little water as possible, but as much as necessary, to supply requirements of the crop to meet yield targets, can reduce costs while also advancing sustainability goals.

1.3 Agricultural Water Use

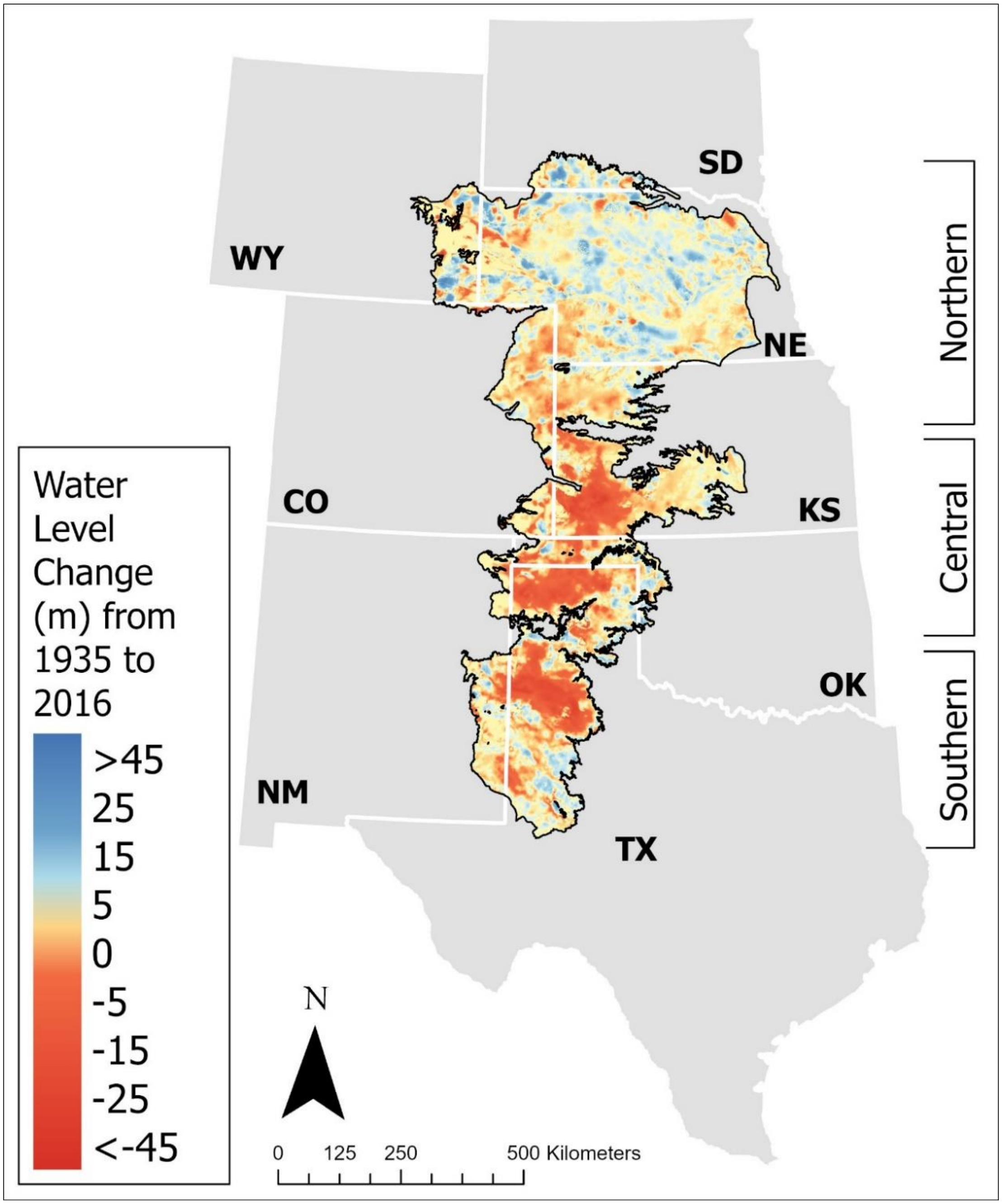

Figure 4. The High Plains Aquifer has been irrigated heavily for agriculture since 1935 with steep declines in the aquifer water level in the Central and Southern High Plains. The Northern High Plains in Nebraska have seen less declines and even water table increases in some areas. Adapted from (Haacker et al., 2016).

Groundwater decline and reductions to streamflow across the High Plains Aquifer are a result of intensive groundwater pumping for irrigated agriculture (Korus and Burbach, 2009; Scanlon et al., 2012; McGuire, 2013; Konikow, 2015;

Haacker et al., 2016; Steward and Allen, 2016; Whittemore et al., 2016). A quarter of the High Plains Aquifer currently has insufficient aquifer thickness (>/=9m of saturated thickness) to support irrigated agriculture, much of which is in the Central High Plains and Southern High Plains (Figure 4; (Richey et al., 2015; Haacker et al., 2016; Nozari et al., 2022).

In contrast to the steady groundwater declines that define much of the Southern High Plains Aquifer, the Northern High Plains have stable groundwater levels across most region (Figure 4). This study's focus on the Twin Platte Natural Resources District in western Nebraska provides a study in contrasts. Groundwater declines due to pumping remain unlikely, but future prospects for irrigation in the Northern High Plains may be threatened due to increased irrigation demand, changing regulatory and interstate water management agreements (Schlager and Heikkila, 2009), changing climate (Lauffenburger et al., 2018; Silva et al., 2019; Evett et al., 2020) and repeats of severe drought (Basara et al., 2013; Whittemore et al., 2016; Freire-González et al., 2017; NeDNR and TPNRD, 2019).

The users and institutions making individual agricultural water decisions at differing scales overlap in the food-energy-water nexus. Water is often the limiting input within food-energy-water systems, and conserving water resources for future productive and non-productive use requires careful consideration of both farm-level and regional water management within this nexus. Agricultural water management exists within environmental, economic and policy frameworks (Smidt et al., 2016; Haacker et al., 2019b), and the inherent connections within food-water-energy systems offer the opportunity for strategies leveraging overlapping institutions across each individual component

of these systems to inform each other across different scales (Smidt et al., 2016; D'Odorico et al., 2018; McCarthy et al., 2020). Repurposing the focus of institutions serving individual purposes within the food-energy-water nexus to a focus on the interconnected processes and overlapping infrastructures can lead to coordinated management and the translation of data across these systems (Cai et al., 2018).

This study contributes to the discussion about agricultural water management and security within food-energy-water systems by using a coupled energy-water approach to measuring irrigation withdrawal for agricultural purposes. I discuss water measurement using electrical runtime as a cheap and abundant dataset for use across large management regions or as an addition to any water measurement regime. Water resources cannot be effectively managed if the quantities of water usage are not measured. Effective water use measurement provides the requisite understanding of water usage in irrigated areas which is mandatory for effectively addressing aquifer depletion, streamflow depletion, and to ensure well informed and economic usage of water resources.

1.4 Irrigation Center Pivot Technology

1.4.1 Irrigation and the Water Balance

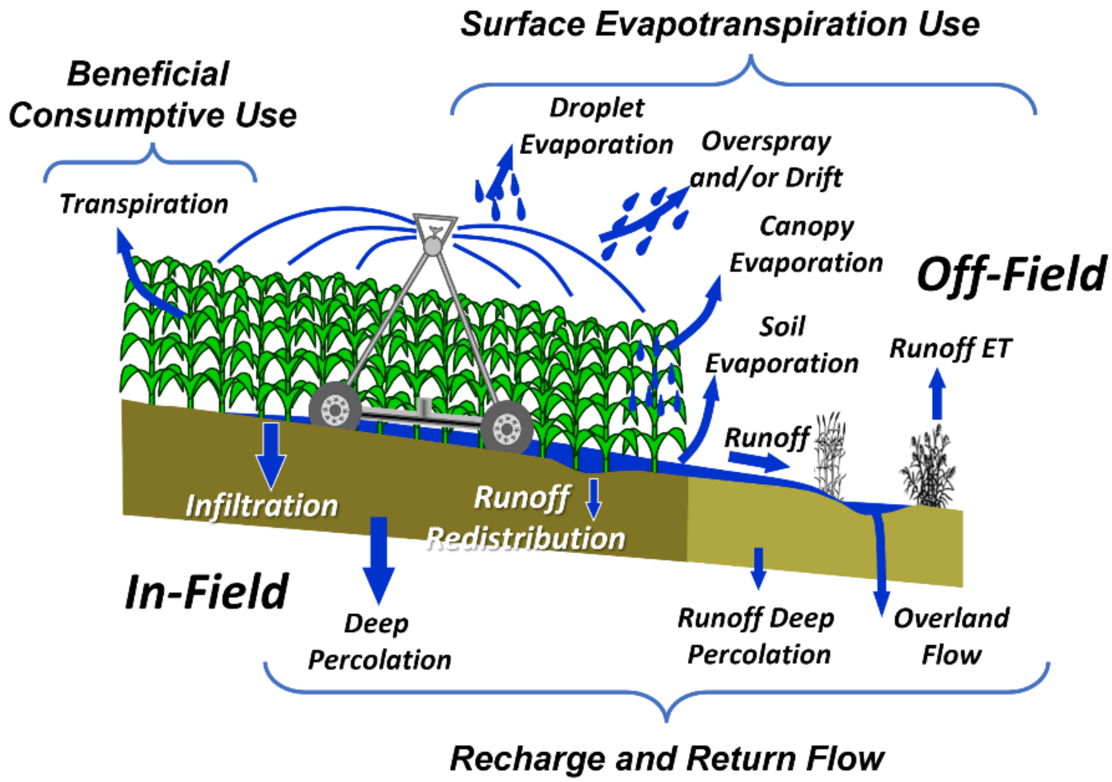

Figure 5. Irrigation Water Balance. Center Pivots are a fundamental part of the water balance in irrigated areas such as the High Plains Aquifer. Reproduced from (Martin et al., 2018).

Center pivot irrigation water usage is a central fixture within the agricultural water balance (Figure 5). To achieve an optimal crop yield during the growing season, the soil-water content must be maintained between saturation, above which leaching occurs, and a lower 'wilting point' where crops become stressed (USDA-NRCS, 1997). Crops can often be grown in a humid continental climate without the need for irrigation in years with adequate precipitation, but normal precipitation amounts in semi-arid regions such as the Twin Platte Natural Resources District require irrigation to maintain optimal soil-water content for corn and many other highly profitable crops. The pervasive usage of

irrigation across Nebraska and semi-arid climates has shifted the water balance towards a human dominated system (Abbott et al., 2019).

Determining the exact amount of irrigation to use and when to apply water, referred to as irrigation scheduling, requires forecasting to anticipate future water requirements as well as precise understanding of water application and the local water balance (Broner, 2005; Martin et al., 2018; Zhang et al., 2021). Improved irrigation scheduling requires accurate estimates of water delivery rates over different timescales and assists farmers while making irrigation decisions. Daily and weekly water usage informs farmers when they should schedule irrigation events and long-term estimates are needed to identify storage and conveyance system capacities (USDA-NRCS, 1997). Watershed managers use yearly figures of total water usage to help inform management needs. Establishing accurate water delivery estimates is important to farmers and watershed managers across a variety of contexts.

Expansion of irrigation began in the mid-1940s because of the development of the rural electricity grid, labor shortages and the development of new irrigation technologies (Dennehy et al., 2002; Edwards and Smith, 2018). Center pivot irrigation systems invented by Frank Zybach—who came up with the idea following an Irrigation Field Day in the summer of 1947—allowed for expansion of irrigated land in areas with topography unsuitable for gravity-fed irrigation practices (Evett et al., 2020). Improving irrigation efficiency now relies on improving pre-existing central pivot systems, such as the adoption of low-energy precision applications, low-energy spray applications (usually referred to as LEPA and LESA) (Colaizzi et al., 2009; Smidt et al., 2016), and improved irrigation scheduling (Martin et al., 2018; Zhang et al., 2021).

1.4.2 Pressure Regulation of Center Pivots

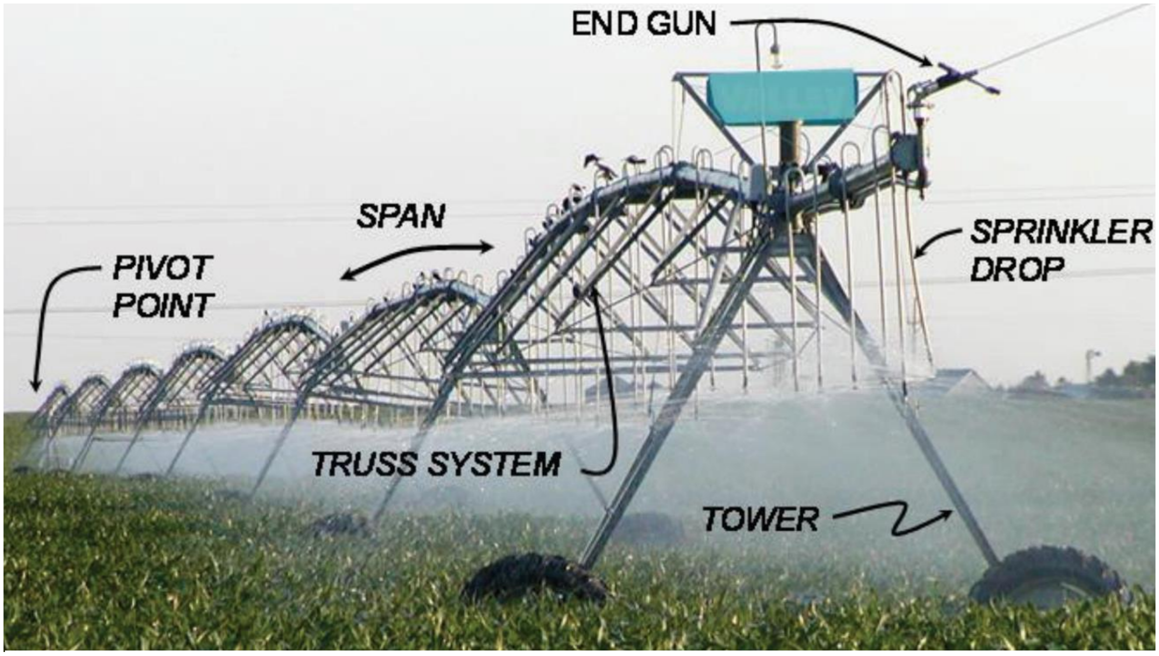

Figure 6. Center Pivot Lateral. An irrigation center pivot rotates around a field at the pivot point. The center pivot lateral extends outward across the field and supports the sprinkler systems. At the end of a center pivot there is an end gun which allows a center pivot to water the corners of a field. Reproduced from Martin et al. (2019).

Pressure regulated center pivots provide more or less constant water flow to irrigated cropland in the face of varying topography and aquifer water levels. Pressure along a center pivot lateral (see Figure 6 for a representative center pivot) is a function of the pivot lateral, elevation across the field, the sprinkler design, friction loss across the lateral, characteristics of the field, and interaction with the groundwater system (Martin et al., 2019). The effectiveness of pressure regulation of center pivots has led to widespread adoption of the technology, with 65% of irrigated area across the US utilizing pressure regulation systems and just under 90% of irrigated area in the High Plains utilizes pressure regulation technology (Evett et al., 2020). Effective use of pressure regulation can eliminate most nonuniformity in water distribution around the field that would result from topographic variability, though flow rates will still vary with

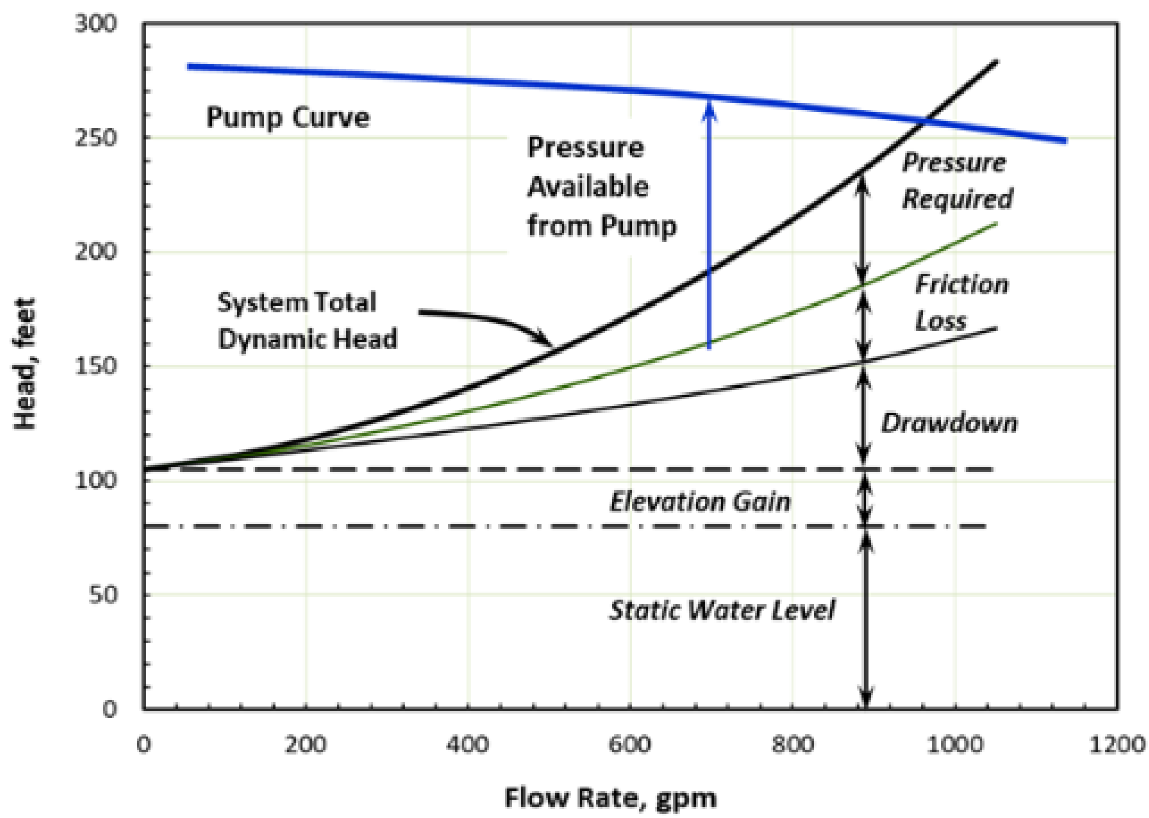

Figure 7. Total System Dynamic Head. The components typical of a center pivot and their contributions to the total system dynamic head. As a center pivot traverses around a field, the head will fluctuate due to the effectiveness of the pressurized system, elevation change, pump characteristics and aquifer drawdown during pumping. This change in head will result in a variable flow rate across time. Figure reproduced from Martin et al. (2019).

changes in head (Figure 7).

Pressure in the lateral will vary as a center pivot traverses hills in a field, which will affect the flow rate (Martin et al., 2018). Topographically lower points in a field will have more water delivery while higher topographical points in a field will experience decreased water delivery. Pressure regulated center pivots will reduce the amplitude of water variation delivered to crops around the field but cannot reduce all variation in water delivery during crop production. Relatively flat fields may not require the use of pressure regulation, but pressure regulation is generally recommended if discharge varies by more than 10% as a center pivot traverses around a field (Martin et al., 2018).

Center pivot irrigation systems often have end guns attached to the end of the pivot lateral to increase the area of a field that can be irrigated (Figure 6). The end gun has a large sprinkler that throws water onto the corners of the field as the pivot traverse the field. Often a booster pump is used on the end of the center pivot to increase the pressure needed to supply extra water for the end gun. This booster pump increases the pressure along the pivot lateral to draw more water for the end gun.

CHAPTER 2. Site Description and Methods

2.1 Site Description

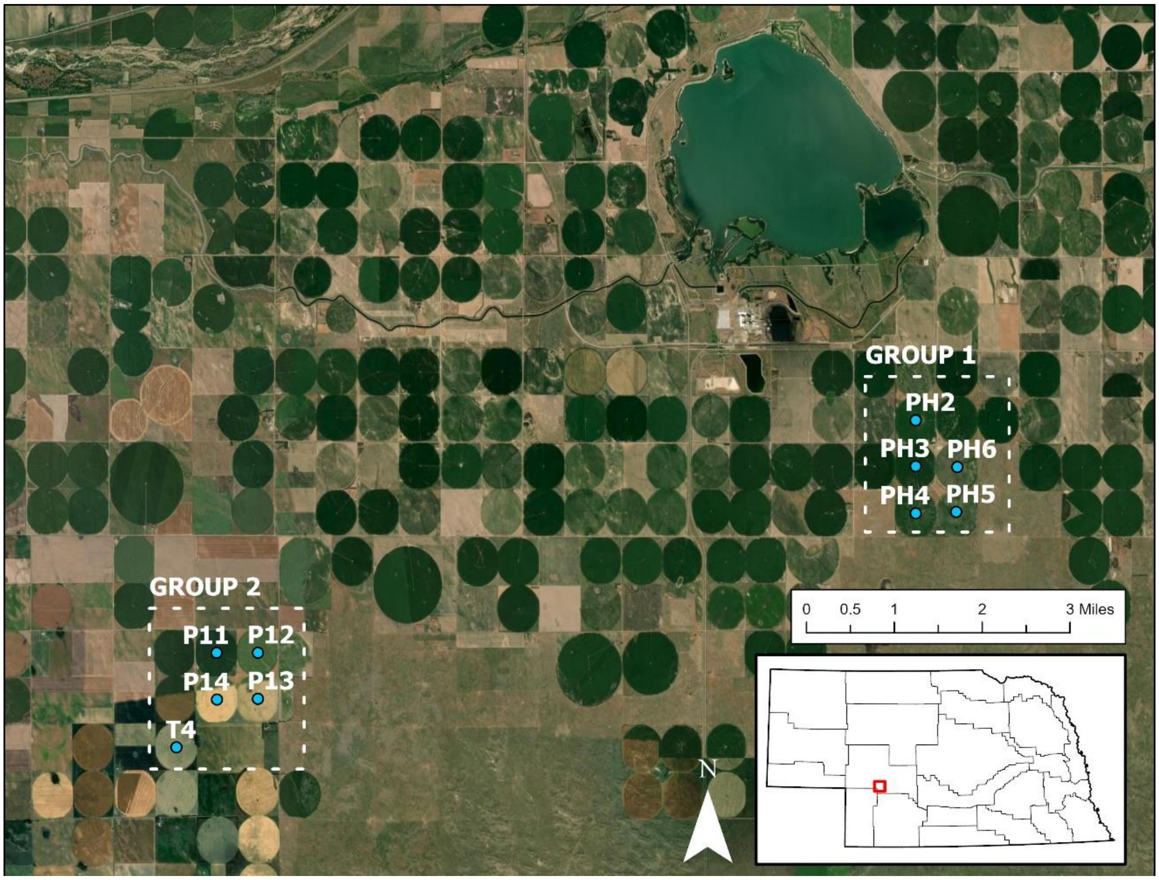

Figure 8. Center Pivot Well Locations used in this study. Ten center pivot wells are selected in the Twin Platte NRD to assess the feasibility of this study's novel approach to estimating real-time irrigation water delivery.

Ten center pivot irrigation wells in the Twin Platte Natural Resources District are selected to assess the uncertainties of this study's electrical runtime approach to estimating real-time irrigation water delivery. The Twin Platte NRD is located in western Nebraska where the North Platte and South Platte rivers converge (Figure 8). The Twin Platte NRD's agricultural water usage is primarily for corn, soybeans, and alfalfa, which are heavily irrigated (NeDNR and TPNRD, 2019). The ten wells selected in the Twin Platte NRD are part of Paulman Farms and receive power from the Midwest Electric Cooperative Corporation.

2.2 Data for Electrical Runtime Algorithm

2.2.1 Electricity Usage Data

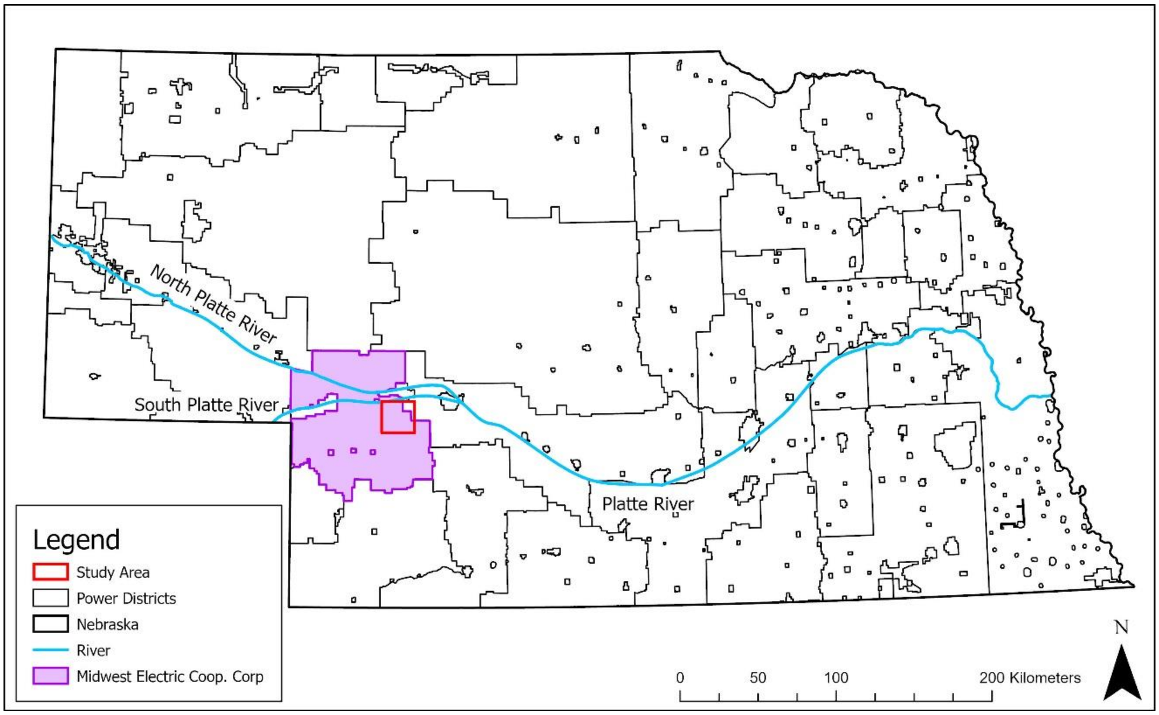

Figure 9. Nebraska Public Power Districts. Data from Midwest Electric is used for this study. Nebraska has an extensive network of public utility providers and smart meters across the various Public Power providers represents the largest network of IoT (Internet of Things) devices across rural Nebraska.

This study collects the electrical power consumption from the public power provider smart meters associated with each irrigation center pivot. Energy usage at each smart meter is reported as the total KHW of energy used each 15 minute time interval. This study then applies an algorithm to determine center pivot runtime.

Growers' Information Services Coop (GiSC) collected electrical usage data for each of the ten center pivots in 15 minute time intervals, leveraging data from Midwest Electric Cooperative Corporation's rural electric smart grid infrastructure (Figure 9). These data are collected over the 2020 and 2021 growing seasons and report the total energy usage during each 15 minute time

interval. Each irrigation center pivot is typically connected to a single electric smart meter, which allows for electrical records to be assigned to a specific center pivot. Since one meter is dedicated to each irrigation center pivot, the electrical record can be used as a track of operation time for each individual center pivot.

The runtime of an irrigation center pivot is then coupled with results from an annual flow test (a measure of a well's flow rate) performed by a local vendor using a calibrated ultrasonic flow meter, to estimate water usage of center pivots during each time interval. By calculating a center pivot's runtime and then multiplying runtime by the flow rate from a vendor ultrasonic flow test, this study translates the electrical record into an estimate for water volume as described in Section 2.4.

2.2.2 Vendor Ultrasonic Flow Tests

Ultrasonic flow tests are a way to determine the volume of flow through a pipe without having to permanently install a device to measure water flow rate. During an ultrasonic flow test, a vendor temporarily attaches a flow meter device which uses ultrasonic technology to measure the velocity of water moving through the center pivot pipe. Growers who do not have flow meters permanently installed on their wells due to higher costs and maintenance often contract vendors every year to every few years (depending on the stability of aquifer conditions, flow rates and the preference of a grower) to perform single ultrasonic flow tests (preferably when the end-gun is active) to understand the flow rates for his or her irrigation center pivots. Measuring a flow rate at a center pivot with a vendor ultrasonic flow tests is a $200 to $300 cost for farmers to accurately quantify an expected water delivery at a center pivot, far cheaper than permanently installing a $4000 device which will require upkeep. When ultrasonic flow meters are used correctly, accuracy ranges from +/- 1% to 5% of true water volume (Eisenhauer, 2008).

Ultrasonic flow tests were performed during the 2019 and 2021 growing seasons to provide calibrated measurements of water delivery. These flow tests were performed to estimate the volumetric flow rate of water a particular center pivot delivers during normal operations, typically with the end-guns turned on, to provide a representative water volume during the center pivot’s operation. Flow tests were performed by two independent flow test vendors (referred to herein as Vendor A and Vendor B) who have experience with irrigation data collections, and both used similar Fuji ultrasonic flow meters that had up-to-date calibration certificates. All ten wells were assessed by Vendor A in the fall of

2019. During the 2021 growing season, eight wells were tested by Vendor A (PH2, PH5, P11, T4, PH6, P12, P13, P14) on September 16 and four of the wells were tested twice by Vendor B (PH2, PH5, P11, and T4), first on July 29 and again on September 22.

2.3 Flow Meters and Water Levels

Well	Electrical Data	Flow Meter	Water Level Data
PH2	Full Growing Season	7/2/2021 - End Growing Season	NA
P11	Full Growing Season	7/2/2021 - End Growing Season	NA
PH5	8/4/2021 - End Growing Season	7/2/2021 - 8/18/2021	6/2/2021 - End Growing Season
T4	Full Growing Season	7/2/2021 - End Growing Season	5/31/2021 - End Growing Season 8/25/2021 - 9/30/2021 (monitoring well)
P12	Full Growing Season	NA	5/29/2021 - End Growing Season
PH4	Full Growing Season	NA	NA
PH3	Full Growing Season	NA	NA
PH6	Full Growing Season	NA	NA
P13	Full Growing Season	NA	NA
P14	Full Growing Season	NA	NA

Table 1. Study Data Collection. Water Balance Alliance (NEWBA) and Growers' Information Services Coop (GiSC) collected electrical data with the support of Midwest Electric Public Power and installed flow meters to measure flow rates at center pivots and installed depth sensors to gather data about the water level in the aquifer. Taken together, these datasets aim to put together a full picture of irrigation at 10 study wells and support an assessment of this study's electrical runtime algorithm approach to estimating water delivery.

To test the accuracy of this study's electrical runtime approach, representatives of the Growers' Information Services Coop (GiSC) and Nebraska Water Balance Alliance (NEWBA) installed McCrometer flow meters on 4 center pivot production wells to measure flow rates, 3 observation wells to measure depth to water table immediately at the well and an observation well to measure depth to water table further removed from the wells in this study's study area. These data are summarized in Table 1 and explained in greater detail in this section.

2.3.1 Aquifer Water Levels

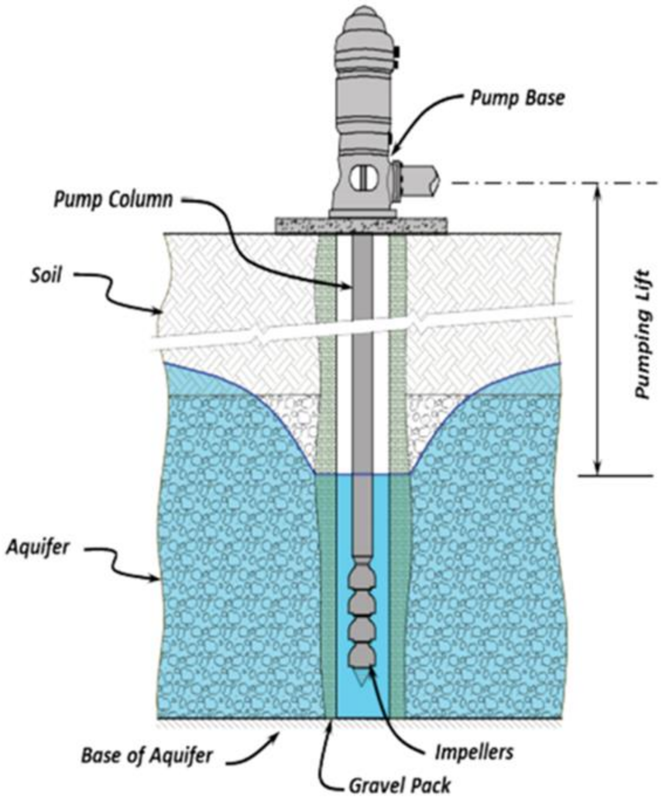

Figure 10. Example of Cone of Depression. Observation wells immediately adjacent (50 to 100 feet) to the pump which measure depth to aquifer will measure the greatest decrease in drawdown because of pumping. Monitoring wells which measure depth to aquifer farther removed from the well (a quarter mile in this study).

Aquifer levels were taken at three observation wells and one monitoring well with pressure sensors that provide estimates of water depth. Observation wells were placed adjacent (50 to 100 feet away) to the pumps and capture the steep cones of depression which formed around the pumps. This drawdown can result in 20 feet or more of aquifer decline once irrigation pumping begins and a cone of depression forms, increasing the total lift required by the pump (see Figure 10). Aquifer water levels were recorded from pressure transducers deployed in observation wells at PH5, T4 and P12 (see Figure 8). Observation well data were captured hourly beginning June 2021 and the data captures the steep section within the cone of depression around each pump.

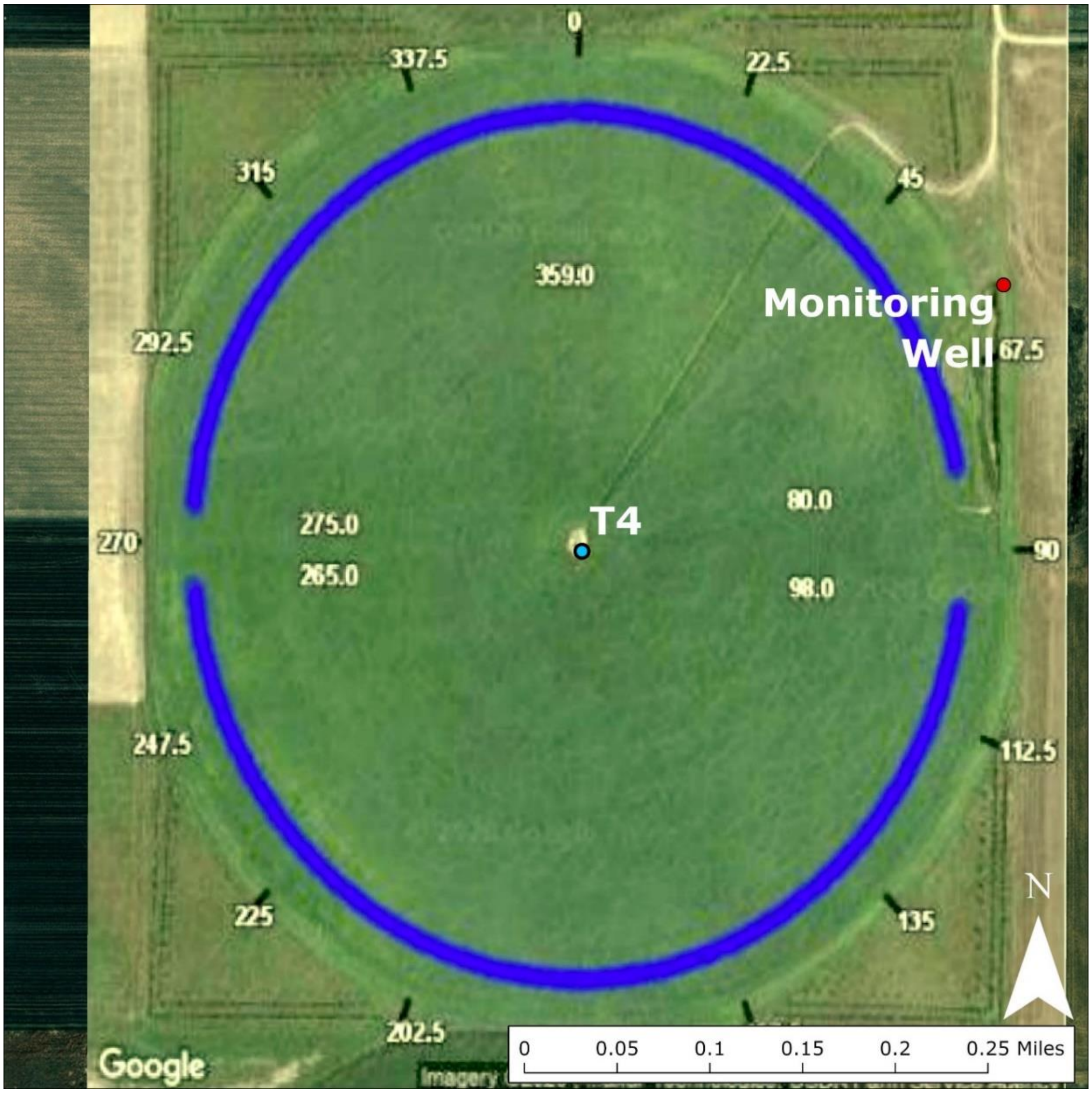

Figure 11. The T4 monitoring well was installed just over a quarter mile from the field center where the irrigation well is located. An observation well was installed at T4 immediately adjacent to the pump.

An additional monitoring well was placed at the edge the T4 field, just over a quarter of a mile away from the well pump (Figure 11). The monitoring well at T4 captured data in September 2021 and is intended to capture aquifer dynamics further outside the steep sections of cone of depression. Monitoring wells inform understanding of aquifer dynamics and drawdown across the growing season in an area of the aquifer less impacted by drawdown due to active pumping.

2.3.2 McCrometer Flow Meters

McCrometer flow meters are installed on four study wells (PH2, PH5, P11 and T4) to provide independent and internally consistent measurements of flow rates over time. The flow meter is a McCrometer McPropeller 8-inch flow meter with specified accuracy of +/-2%. Flow rates were collected as instantaneous values every 15 minutes beginning July 2, 2021, and these data represent most of the irrigation events in the 2021 growing season. This dataset provides an important internally consistent set of measurements of water delivery through time—a resolution not captured by individual vendor ultrasonic flow test readings. This is also a common setup for wells that do have flow meters installed; while this is uncommon due to the expense of installing, maintaining, and interpreting data, and flow meter data are not reported to state and local agencies without an existing regulatory framework to require these data, they are representative of the gold standard for water withdrawal information. Growers' Information Services Coop (GiSC) collected the McCrometer flow meter data in 15 minute time intervals beginning July 2, 2021.

2.4 Analysis of field scale data

2.4.1 Electrical Runtime Algorithm

This study uses electrical usage data collected by Midwest Electric's smart energy grid coupled with vendor ultrasonic flow tests to estimate water usage over the growing season. This novel approach uses the electrical record to provide the duration in time of center pivot operation during each interval of electrical usage recording (which is 15 minutes for Midwest Electric) and the vendor flow test to provide the flow rate, which together produce the volume of water delivered over each time interval:

$$W_i = ac_iF_{cal}\Delta t_i \tag{1}$$

where W_i is the volume of water delivered over each interval, *a* is a constant that depends on units, c_i is a dimensionless end gun correction factor applied to each irrigation event (discussed in Section 2.4.2), F_{cal} is the calibrated ultrasonic flow meter rate established by the vendor, and Δt_i is the duration of irrigation usage per time interval the center pivot is operating. An example dataset of a representative irrigation event is shown in Table 2. Water delivery over the entire growing season is computed by the sum of the water delivery for each time interval:

$$W_{est} = \sum_{Season} W_i = \sum_{Season} a\, c_iF_{cal}\Delta t_i \tag{2}$$

where *W* is the total water delivery over the growing season. Consult the appendices for implementation of the electrical runtime approach in R Code.

The beginning of an irrigation event (a continuous set of individual power measurements, p_i, with no interruption) is determined with a threshold value of 4 KWH (or 25% of the typical electricity used during a 15 minute timer interval in my study area). This threshold value is set as a minimum value by which to

DateTime	F_{cal}: Vendor Flow Rate (GPM)	Energy Usage (KWH)	ΔT: Irrigation Runtime (minutes)	KWH Bound	End Gun On or Off	c: End Gun Correction Value	W_i: Volume of Water Delivered
7/5/21 9:30		0	0				0
7/5/21 9:45		0	0				0
7/5/21 10:00	818	10.6	10.1	16.15	On	0.985	8140
7/5/21 10:15	818	15.8	15	16.15	Off	0.985	12089
7/5/21 10:30	818	15.8	15	16.15	Off	0.985	12089
7/5/21 10:45	818	15.8	15	16.15	Off	0.985	12089
7/5/21 11:00	818	15.8	15	16.15	Off	0.985	12089
7/5/21 11:15	818	15.8	15	16.15	Off	0.985	12089
7/5/21 11:30	818	16.1	15	16.15	Off	0.985	12089
7/5/21 11:45	818	16.5	15	16.15	On	0.985	12089
7/5/21 12:00	818	16.4	15	16.15	On	0.985	12089
7/5/21 12:15	818	16.5	15	16.15	On	0.985	12089
7/5/21 12:30	818	16.4	15	16.15	On	0.985	12089
7/5/21 12:45	818	16.8	15	16.15	On	0.985	12089
7/5/21 13:00	818	15.9	15	16.15	Off	0.985	12089
7/5/21 13:15	818	16.5	15	16.15	On	0.985	12089
7/5/21 13:30	818	16.4	15	16.15	On	0.985	12089
7/5/21 13:45	818	16.4	15	16.15	On	0.985	12089
7/5/21 14:00	818	16.4	15	16.15	On	0.985	12089
7/5/21 14:15	818	16.5	15	16.15	On	0.985	12089
7/5/21 14:30	818	16.6	15	16.15	On	0.985	12089
7/5/21 14:45	818	16.5	15	16.15	On	0.985	12089
7/5/21 15:00	818	16.4	15	16.15	On	0.985	12089
7/5/21 15:15	818	16.6	15	16.15	On	0.985	12089
7/5/21 15:30	818	16.5	15	16.15	On	0.985	12089
7/5/21 15:45	818	16.5	15	16.15	On	0.985	12089
7/5/21 16:00	818	16.5	15	16.15	On	0.985	12089
7/5/21 16:15	818	16	15	16.15	Off	0.985	12089
7/5/21 16:30	818	15.8	15	16.15	Off	0.985	12089
7/5/21 16:45	818	15.8	15	16.15	Off	0.985	12089
7/5/21 17:00	818	15.9	15	16.15	Off	0.985	12089
7/5/21 17:15	818	15.8	15	16.15	Off	0.985	12089
7/5/21 17:30	818	11.2	10.6	16.15	On	0.985	8543
7/5/21 17:45		0	0				0

Table 2. Example dataset from July 5, 2021 from well T4. Using the vendor flowrate of 818 GPM, energy usage converted to runtime, and an end gun correction value, an estimate of water delivery during each 15 minute interval using Equation (1). Put simply, flowrate multiplied by time and multiplied by an end gun correction equals our estimated volume of water each interval.

identify an irrigation event is occurring, and leading and trailing edges are determined by the first occurrence of an interval in the electrical record above the threshold value. Leading and trailing edges are then assigned a duration of

time which is proportional to the proceeding or trailing interval's energy usage.

Occasionally the electrical smart meters fail to send energy usage data. When this occurs, the algorithm gap-fills over missing data intervals. When a missing electrical datum is either preceded and followed by a value lower than twice the threshold value (8 KWH, or 50% of the typical energy used during 15 minutes of irrigation), the missing datum is gap-filled with 0 electrical usage values. When the missing electrical datum is both preceded and followed by values higher than twice the threshold value, the missing intervals are gap-filled based on the higher of the preceding and trailing reported energy usage (see Section 3.2.5 for a discussion on reliability of data telemetry). This higher value is chosen with the assumption that the end gun is typically on and that the primary function of the electrical usage is to create a duration of time of center pivot operation.

2.4.2 End Gun Correction Algorithm

The end gun correction factor, c, is used to estimate water delivery while the end-gun is off. Since vendor ultrasonic flow tests are typically conducted while the end-gun is on, this value would overestimate water delivery during time intervals where the end-guns are turned off. This correction factor must be determined within each irrigation event. I assume as a preliminary assumption that water delivered by the end gun is proportional to power consumed by the end gun, which allows for a correction to be made based on vendor flow tests with the end gun on (see Section 3.2.2 for further discussion).

The correction factor is calculated by identifying the median of the ten highest electrical power values, p_{ui}, between the leading and trailing edges of each irrigation event, and the median of the ten lowest electrical power values,

p_{li}. The average of the upper and lower medians is then used to provide a test criterion to separate electrical power values, p_i, from each 15-minute interval of an irrigation event into an upper grouping, P_U, with end gun on, or a lower grouping, P_L, with end gun off. Each individual irrigation interval is then assigned either to the upper group, P_U, if the value is above the average, or to the lower group, P_L, if the value is below the average. The mean of the upper collection P_U is then computed, as well as the mean of the lower collection P_L.

An end gun correction factor, c_i, is applied to each 15 minute irrigation interval within the continuous irrigation events based on the mean P_U and mean P_L values and given the number intervals identified with the upper group, n_U, and the number intervals identified with the lower group, n_L. This correction factor is shown below:

$$c_i = 1 - \frac{n_l}{n_l + n_u}\left(1 - \frac{\overline{P_l}}{\overline{P_u}}\right) \tag{3}$$

The end gun correction factor, c_i, is typically 0.95 to 1 as end guns often are responsible for a 2-5% increase in water delivery depending on the exact characteristics of the end gun, booster pump and pivot lateral location within the field.

2.4.3 Comparing Electrical Runtime Volumes to McCrometer Flow

Seasonal water delivery estimates computed according to this study’s electrical runtime approach (Equation 2) were compared to integrated water deliveries measured by the McCrometer flow meters over the same time intervals. McCrometer McPropeller flow meters report instantaneous flow readings every 15 to 16 minutes. To convert flow meter readings directly to comparable measured electricity intervals, this study performed constant

interpolation of McCrometer flow meter readings and resampled to fit the middle of each 15 minute electrical record interval. Constant interpolation was chosen to reduce noise during resampling, since a center pivot does not move substantially during a 15 minute timeframe. This resampled dataset was matched to the electrical runtime using the same method as discussed in Section 2.4.1 as part of Equation (1) and to provide a measured flow rate during each 15 minute interval. McCrometer flow rates are gap-filled using constant interpolation when one or two flow meter intervals failed to report, while larger time gaps are not gap-filled to avoid introducing excess uncertainty.

Calculation of water volume during each interval using the resampled McCrometer flow rates uses an equation identical to Equation (1) except that *F* is now the McCrometer flow meter, F_{mcfm}, and no end gun correction factor is required as flow rates are measured at the center pivot:

$$W_i = aF_{mcfm}\Delta t_i \tag{4}$$

The sum of each individual water volume is then summed across the growing season in the same method as Equation (2):

$$W_{meas} = \sum_{Season} W_i = \sum_{Season} a\, F_{mcfm}\Delta t_i \tag{5}$$

The McCrometer flow meters are compared to the vendor flow tests by selecting the intervals of overlapping data between McCrometer readings and data where electrical readings are present. While the electric record provides reliable data, errors do occur in data reporting. McCrometer flow meters have occasional data loss. Due to this limitation of using IoT devices, water deliveries using electrical run times and vendor flow tests calculated with Equation (2) are compared with water deliveries using McCrometer flow rates calculated with Equation (5) only when results from both data streams are available.

2.5 Analysis of data within regional context

2.5.1 Integrated Groundwater Modeling

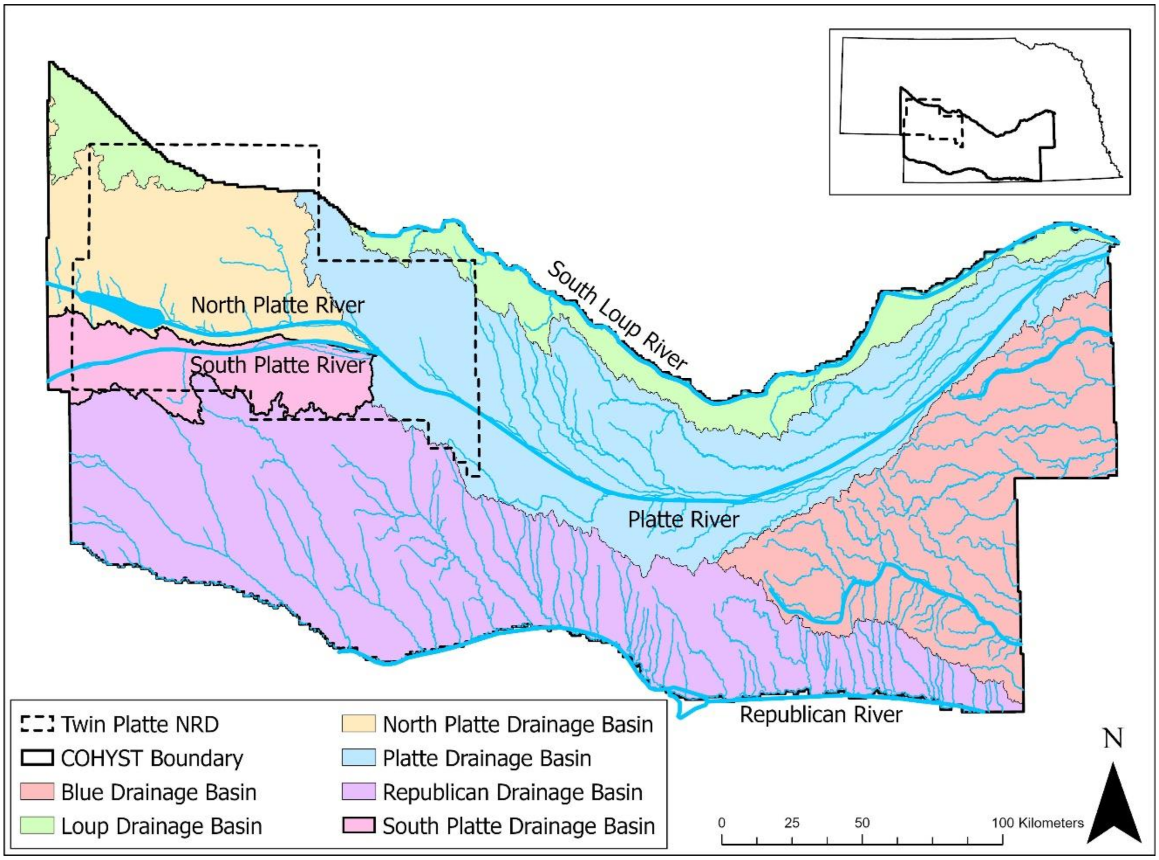

Figure 12. COHYST Subregional Drainage Basins. The COoperative HYdrological Study (COHYST) regional regulatory groundwater model area is bound by the South Loup River to the north and the Republican River to the South with the Platte River drainage basin as the central focus of the model. This study will focus on effects to baseflow in the South Platte River Basin, which lies primarily within the Twin Platte Natural Resources District.

This portion of the study aims to explore the scaled effects of uncertainties in pumping data and assess potential implications to agricultural water management. This study applies findings from the electrical runtime approach at field scales by using the COoperative HYdrological Study (COHYST) regional regulatory groundwater model (see COHYST model region in Figure 12). COHYST is an integrated model developed by the Nebraska Department of Natural Resources (Cannia et al., 2006; NeDNR, 2017) which was used to

simulate the effects of uncertainty about pumping as quantified at the field scale in the South Platte Drainage Basin in the Twin Platte NRD (Figure 12). The COHYST model incudes a groundwater flow model using the U.S. Geological Survey MODFLOW 2005 software (Harbaugh, 2005), a surfacewater model using the modeling software STELLA Version 10.1.2 by isee systems and a crop growth model using CROPSIM and FORTRAN code. This project performed COHYST model simulations by utilizing the Groundwater Evaluation Toolbox (Olsson Associates, 2022), which has a cloud implementation of the COHYST 2010 regulatory model.

The importance of agricultural water management on the High Plains Aquifer has prompted efforts to develop modeling tools such as COHYST to inform water resource vulnerability to address agricultural water management in Nebraska and help inform water managers' decisionmaking within the Platte River drainage basin in central Nebraska (NeDNR, 2017). Ultimately, understanding sources of uncertainty in our electrical runtime approach will help with estimating irreducible uncertainties. Quantifying uncertainty using our electrical runtime approach is important if modeling applications are to be employed using this study's low cost water usage estimates, such as the Nebraska Department of Natural Resources' "10/50 Rule" (Li et al., 2016) which prohibits wells that deplete streamflow by 10% or more of their annual withdrawal after 50 years of pumping.

2.5.2 Estimating Baseflow Effects from Pumping Uncertainty

While aquifer depletion threatens many aquifers—including portions of the High Plains Aquifer (Haacker et al., 2016; Gleeson et al., 2020)—this study primarily seeks to use COHYST to look at the impact to stream depletion as a

management concern in the Twin Platte NRD and the Platte River Valley. Since aquifer levels in the Northern High Plains have adequate thickness to support irrigated agriculture, impacts to streamflow are a primary management concern across Nebraska and in the Twin Platte NRD specifically.

COHYST uses a 'rules-driven' approach while calculating impacts to baseflow. Due to this aspect of the model construction, results tend to be linearized following built-in subwatershed rules (NeDNR, 2017). COHYST uses operational rules for determining the impact to baseflow from groundwater pumping which are calibrated based on historical results (the 1985-2010 time-period) within each subwatershed component. In practice the surface operations model often does not get used for official management scenarios due to the linear effects resulting from model construction, but this study used COHYST as a preliminary attempt to provide a worst case scenario estimate of bias associated with uncertainty related to estimating water delivery at field scale.

This study used the well flow rates provided by the State of Nebraska for active registered wells designated for irrigation within the South Platte Drainage Basin where the study wells are located (NeDNR, n.d.). I selected wells associated with fields larger than 100 acres with pump rates greater than 550 gallons per minute in irrigated areas identified in recent literature using satellite remote imagery classification (Deines et al., 2019). In total, 1139 wells were selected within the South Platte Drainage basin (Figure 13). Pump rates were combined within each COHYST grid cell and then each grid cell was randomly assigned an uncertainty value for each roughly half mile by half mile grid cell. Irrigation length in each cell was set to a cumulative duration of 30 days of pumping. Five model simulations were run using this study's selected data such

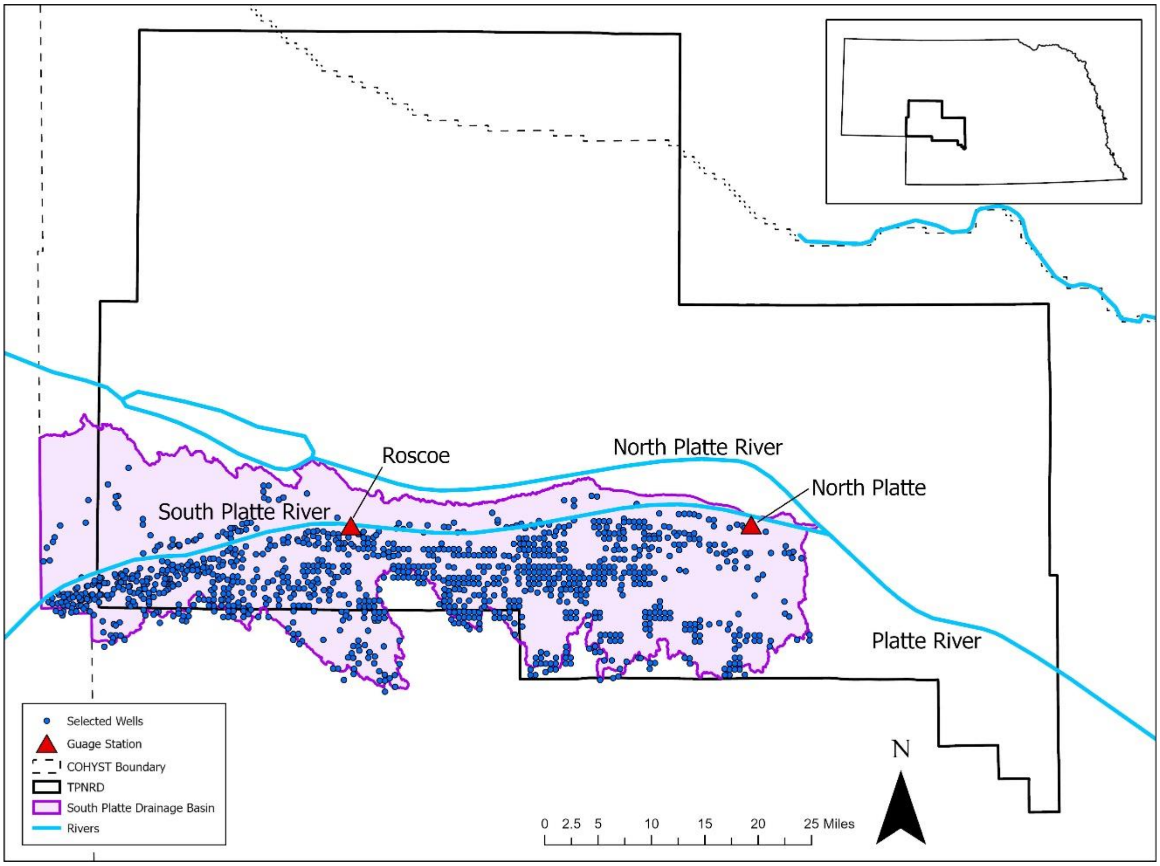

Figure 13. Wells selected based on irrigation data and well characteristics for use in COHYST model simulations. COHYST model runs show impact to baseflow to the South Platte River from Roscoe to North Platte.

that each run had uncertainty values across all of the wells averaging 2%, 4%, 5%, 6% and 8%:

- run 1) 0% to 16% uncertainty applied to each grid cell (averaging 8%);
- run 2) 0% to 12% uncertainty applied to each grid cell (averaging 6%);
- run 3) 0% to 10% uncertainty applied to each grid cell (averaging 5%);
- run 4) 0% to 8% uncertainty applied to each grid cell (averaging 4%);
- run 5) 0% to 4% uncertainty applied to each grid cell (averaging 2%).

The baseline COHYST model was used to compare with model runs to mimic bias in this study’s electrical runtime approach. Impact to baseflow is estimated by the COHYST model along the Roscoe to North Platte reach. Historical discharge

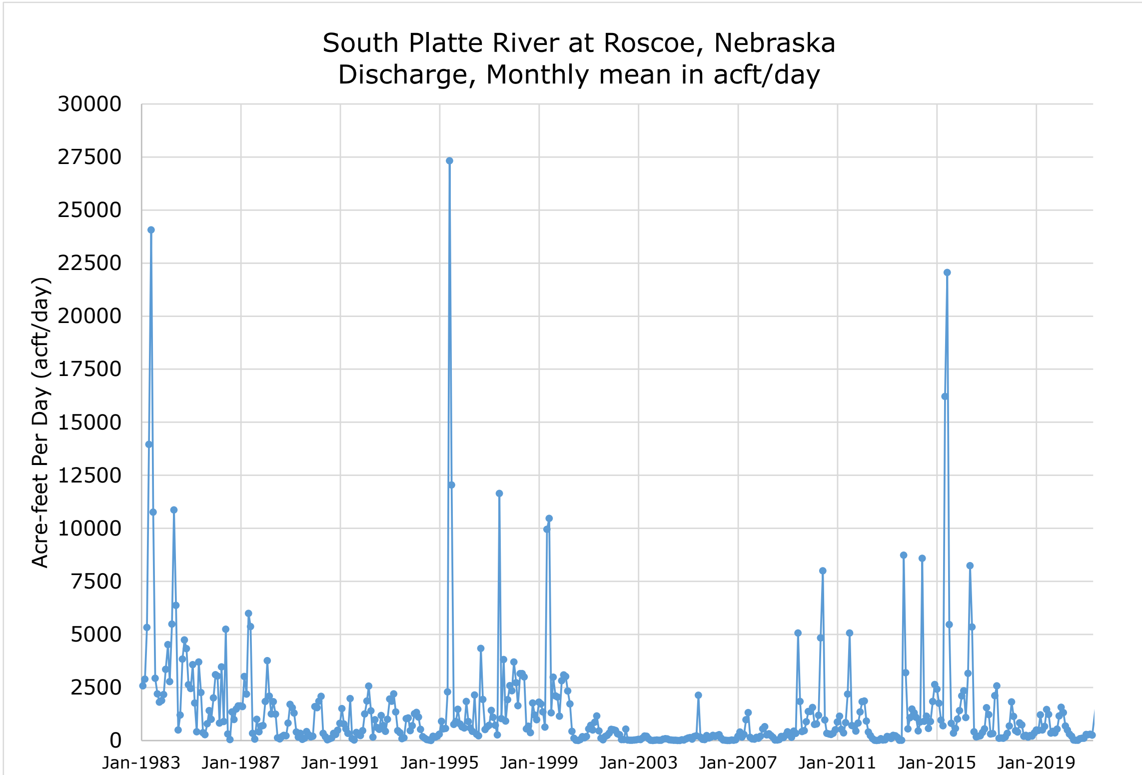

Figure 14. Observed monthly mean discharge (in acre-feet per day) at Roscoe, Nebraska. Discharge often peaks in the South Platte River in June due to melting snowpacks upstream. August through September often represent the lowest streamflow amounts following seasonal agricultural pumping and upstream weather conditions.

rates at Roscoe Nebraska are shown in Figure 14 (USGS, 2022).

This study's methodology assumes that the COHYST model's baseline results are the expected baseflow quantities from Roscoe to North Platte along the South Platte River (see Figure 15) and that all uncertainties in pumping applied within each grid cell will result in excess pumping above baseline leading to decrease in streamflow. This approach provides a worst case scenario where were uncertainty due to this study's electrical runtime approach always underestimates water usage compared to measured water usage. In practice our electrical runtime approach will both overestimate and underestimate water usage at field scale (see Table 4 for a later discussion on results).

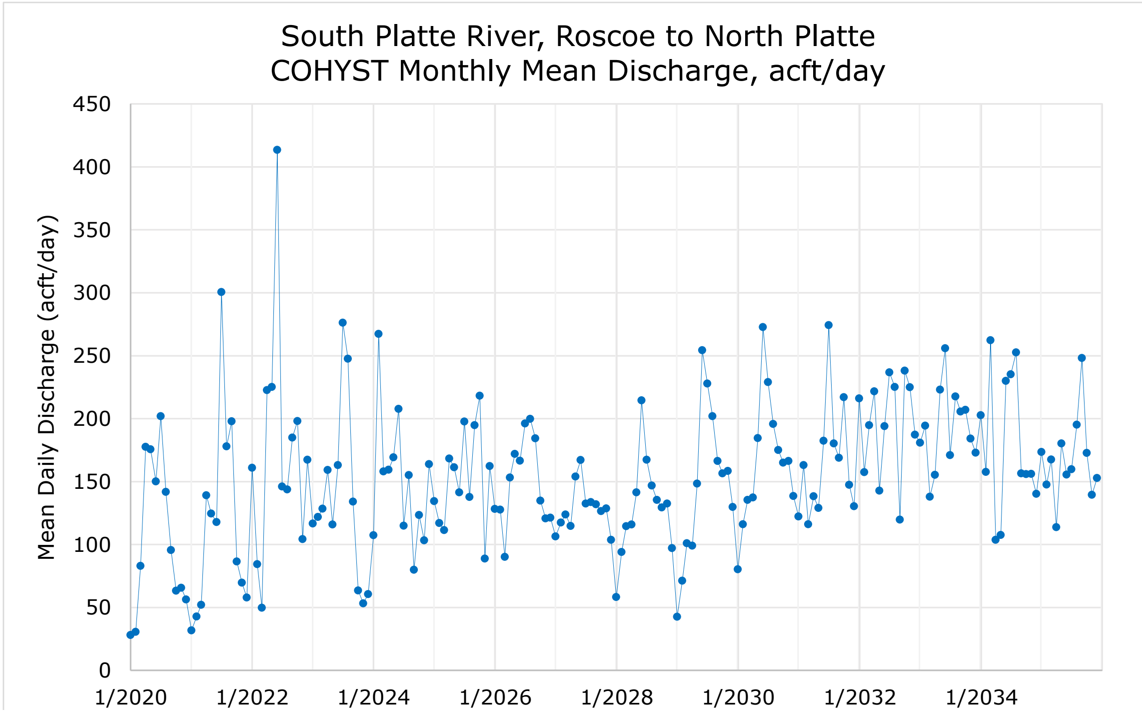

Figure 15. COHYST monthly mean discharge for the Roscoe, Nebraska to North Platte, Nebraska reach. This model data is used as the baseline data for this study.

This model simulation bias towards a worst case scenario approach is due in part to underlying COHYST model construction and how net pumping calculations are performed by COHYST. The COHYST model is constructed in a way that prevents assessment of the effects of the spatial distribution of pumping error, and as a result adjacent positive and negative pumping will functionally cancel each other out during the linear interpolation conducted by the model rules. Due to the limitations of model construction, the results discussed in Section 3.3 represent expected upper bounds based on our electrical runtime approach's uncertainties with estimating measuring water volume at field scale.

CHAPTER 3. Results and Discussion

3.1 Field Scale Results

3.1.1 Vendor Flow Test Results

					By Vendor					McCrometer Only					
Well name	End gun	Vendor	Date	time (CDT)	Vendor Flow rate (GPM)	Vendor mean	Vendor SD	Vendor CV (%)	n	McCrometer Flow Rate (GPM)	McCrometer mean	McCrometer SD	McCrometer CV (%)	n	Vendor/McCrometer
PH5	on	A	Falll 2019	-----	789	796	7	0.8	2	-----	-----	-----	-----		-----
PH5	on	A	9/16/21	11:50	802					786	785	8	1.0	3	1.020
PH5	on	B	7/29/21	8:43	736	757	21	2.7	2	774					0.951
PH5	on	B	9/22/21	9:46	777					794					0.979
T4	on	A	Fall 2019	-----	858	850	8	0.9	2	-----	-----	-----	-----		-----
T4	on	A	9/16/21	12:42	842					839	823	18	2.2	3	1.004
T4	on	B	7/29/21	10:24	750	777	27	3.4	2	798					0.940
T4	on	B	9/22/21	12:00	803					833					0.964
P11	on	A	Fall 2019	-----	723	721	2	0.3	2	-----	-----	-----	-----		-----
P11	on	A	9/16/21	1:56	719					718	700	23	3.3	3	1.001
P11	on	B	7/29/21	12:05	661	677	16	2.4	2	668					0.990
P11	on	B	9/22/21	10:53	693					715					0.969
P12	on	A	Fall 2019	-----	708	-----	-----	-----	-----	-----	-----	-----	-----		-----
P12	on	A	9/16/21	1:11	518					498	468	-----	-----		1.040
P12	on	B	7/29/21	11:19	472	-----	-----	-----	-----	490					0.963
P12	?	B	9/22/21	12:41	418					415					1.007
PH2	on	A	Fall 2019	-----	743	753	10	1.3	2	-----	-----	-----	-----		-----
PH2	off	A	9/16/21	10:27	763					815	835	23	2.8	3	0.936
PH2	on	B	7/29/21	9:25	818	791	27	3.4	2	868					0.942
PH2	off	B	9/22/21	9:08	764					823					0.928

Table 3. Vendor Ultrasonic Flow Test Results.

Results from flow tests performed by Vendor A and Vendor B are listed in Table 3 and the comparison between vendor results and instantaneous flow meter readings are shown in Figure 16. Well P12 experienced well degradation between the flow tests in 2019 and 2021 and will not be considered further within this study, as it is not representative. Comparing Vendor A's flow test results conducted two years apart, variability was 1.3% or lower for the ultrasonic flow tests performed in fall 2019 and summer 2021 for wells PH2, PH5, P11 and T4. The two flow tests conducted by Vendor B just under two months apart within the 2021 growing season for wells PH2, PH5, P11 and T4 showed a variability of 3.4% or less. These wells operated normally in both the 2019 and 2021 growing seasons. Absent well degradation, the flow test results

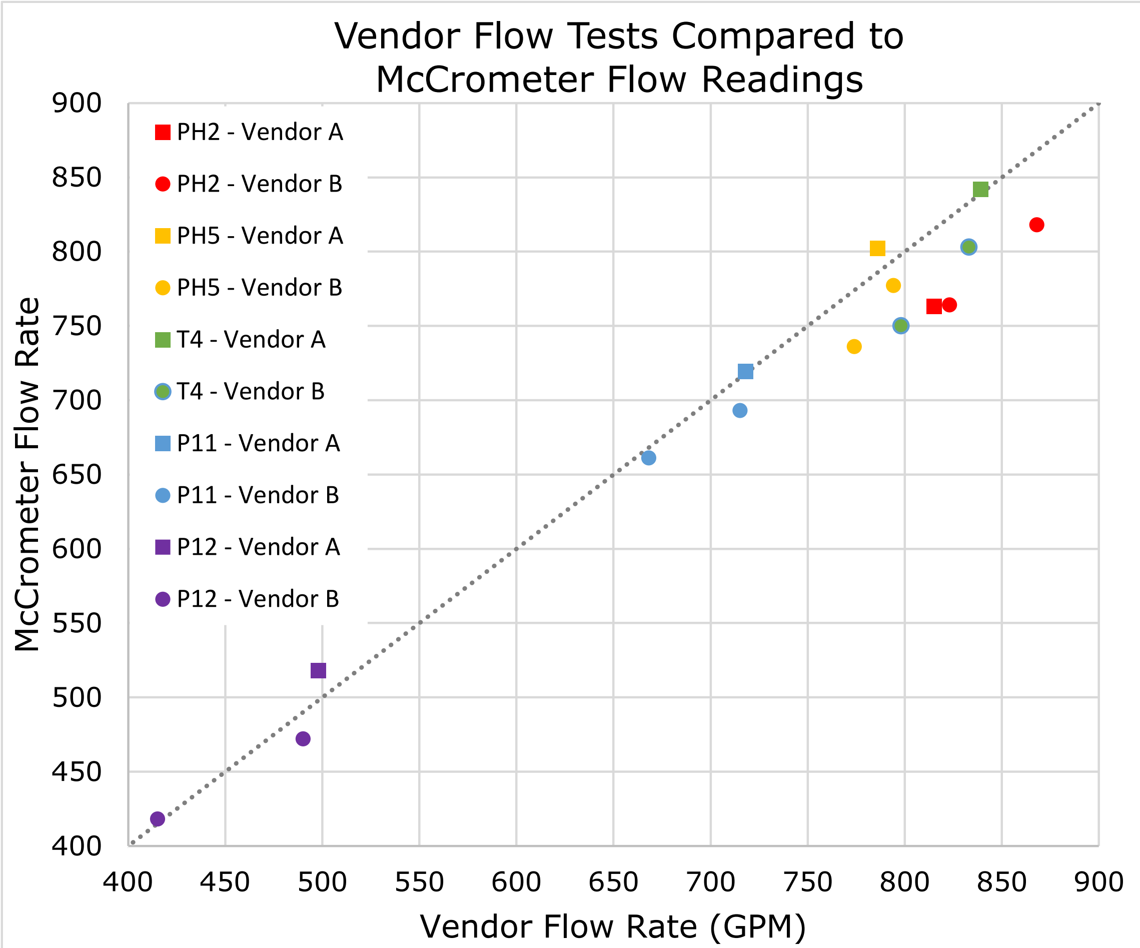

Figure 16. Comparison between vendor ultrasonic flow tests readings and instantaneous flow meter readings.

between the 2019 and 2021 growing seasons are in reasonable agreement.

Vendor A and Vendor B both performed flow tests for wells PH2, PH5, P11 and T4 about one week apart in August 2021. Simultaneously the McCrometer flow meter readings were also recorded to allow for an internally consistent reading to be compared to the instantaneous flow tests results. Vendor A's results are higher than Vendor B for PH5, T4 and P11, but not PH2, while measurements made by Vendor B are lower when compared to the McCrometer measurements than are measurements made by Vendor A. No irrigation was conducted between these tests, providing analogous conditions and center pivot locations within the field during both vendor tests.

While conditions remained similar during the tests (no irrigation or center pivot movement occurred between flow tests) on 9/16 and 9/22, comparing the internally consistent flow meter results conducted during both vendor flow tests showed that McCrometer values fluctuated by three to eight gallons per minute depending on the well, far less than large fluctuations which result due to center pivot rotation. The McCrometer flow meters can provide important internally consistent readings, but do not represent true water delivery as their absolute accuracy cannot be determined. For example, the McCrometer flow meter for PH2 was always 5% higher or more than the vendor flow rates, showing that while well PH2's McCrometer rates are internally consistent they may also be systematically higher than true flow rates. These challenges with verification of 'gold standard' data illustrate the inherent difficulties faced by farmers and natural resource managers in determining local to regional pumping quantities.

3.1.2 Seasonal Cumulative Water Volume Results

	T4			PH2			PH5			P11		
	ac-ft	inches	% dev inches	ac-ft	inches	% dev inches	ac-ft	inches	% dev inches	ac-ft	inches	% dev inches
Flow Meters:	116.3	10.36	0%	107.7	9.85	0.0%	30.2	2.69	0%	107.5	9.57	0%
Vendor B1:	106.3	9.48	-8.53%	103.2	9.44	-4.18%	28.8	2.56	-4.74%	105.0	9.36	-2.26%
Vendor B2:	113.9	10.15	-2.07%	96.4	8.81	-10.5%	30.4	2.71	0.56%	110.1	9.81	2.47%
Vendor A1:	121.7	10.85	4.64%	93.7	8.57	-13.0%	30.9	2.75	2.11%	114.9	10.23	6.91%
Vendor A2:	119.4	10.64	2.69%	96.2	8.80	-10.6%	31.4	2.79	3.80%	114.3	10.18	6.32%
Average Deviation (%) Between Flow Meter Volumes and Vendor Volumes:			-0.82%			-9.57%			0.43%			3.36%
Days of Irrigation for Comparison:			32.3			28.9			8.9			36.5
Power Usage (KWH):			52664.7			46,481			12,186			57,408
acres:			134.6			131.2			134.8			134.7
Mean (in)			10.30			9.09			2.70			9.83
SD (in)			0.47			0.47			0.08			0.34
n			5			5			5			5
95% CI (in)			0.59			0.59			0.10			0.42

Table 4. Comparing McCrometer and Electrical Runtime Results. Measured cumulative volumes using flow meter values were calculated using Equation (5) and estimated volume of gallons using the electrical runtime approach were calculated using Equation (2). The average deviation between cumulative flow meter volumes and cumulative vendor results for all four wells was -6.60%.

The comparison between the cumulative water volumes calculated using Equation (2) (our electrical runtime approach) and Equation (5) McCrometer flow rates) are show in Table 4. The average deviations between the flow meter cumulative volume and vendor cumulative volumes were -0.82% for T4, -9.57% for PH2, 0.43% for PH5 and 3.36% for P11. The average deviation between cumulative flow meter volumes and cumulative vendor results for all four wells was -6.60%. Results from T4 for each 15-minute time interval over the 2021 growing season are shown in Figure 17.

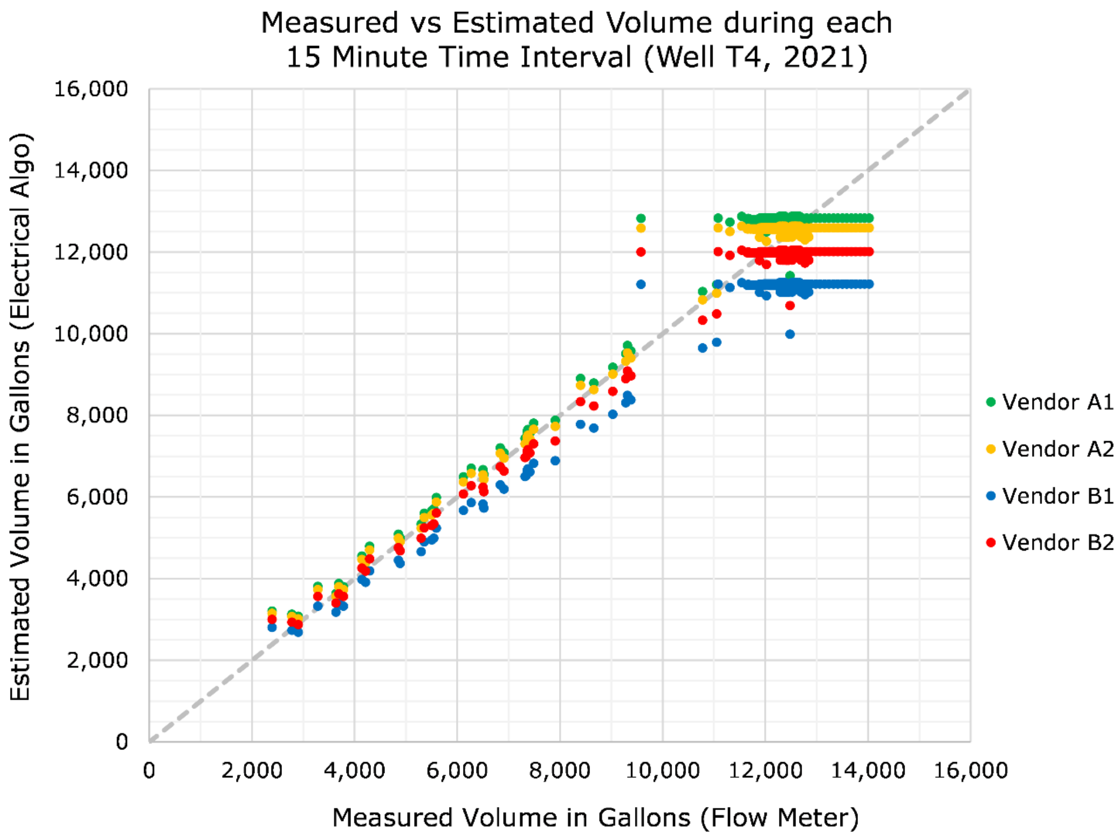

Figure 17. Observed flow meter results compared to predicted electrical runtime algorithm (Electrical Algo for short) results for each 15 minute interval over the growing season where electrical usage data and flow meter data were both present. Measured volume using flow meter values were calculated using Equation (4) and estimated volume of gallons using the electrical runtime approach were calculated using Equation (1). Vendor A1 results represent a flow test performed in 2019 and Vendor A2, B1 and B2 represent flow tests performed in 2021 (see Table 3 for flow test results)

3.2 Field Scale Uncertainty

While utilizing the electrical usage as a means of determining center pivot operation is extremely precise and reliable, determining precise flow rates while the center pivot is in operation remains the fundamental question in measuring water delivery to crops regardless of method. Vendor ultrasonic flow tests show great variability in our approach as shown by our preliminary results shown in Table 4 and Figure 17, which introduce several key sources of uncertainty in the flow rate measurements: (1) the reproducibility of flow tests across time, the reproducibility of flow tests between vendors and the absolute uncertainty of flow test measurements, (2) variations in actual flow rates due to aquifer level, (3) variations in actual flow rates due to topography, and (4) variations in actual flow rates due to end gun operations. Reliability of reporting electrical data and further economic cost considerations of this study's electrical runtime approach will also be discussed.

3.2.1 Uncertainty Due to Flow Tests

Fundamentally, this study's accuracy to estimating water delivery over the growing season depends on the accuracy of a flow test to provide a representative flow rate across time. Equation (1) shows that accurate flow tests, which establish F_{cal}, are a fundamental requirement of this study's approach to measuring water delivery with the electrical runtime method. Inconsistent measurement of water delivery in flow tests by different vendors and across time can introduce important sources of uncertainty.

An uncertainty associated with using electrical runtime and vendor flow tests to estimate water delivery is how well flow tests represent actual water

delivery over time. Many irrigation wells across Nebraska have been in production for decades. While precise comparison of flow test across time is challenging because of the center pivot's location in the field (affecting topography and end gun operations) and aquifer conditions, flow tests at PH5, T4, P11, and PH2 showed good agreement between 2019 and 2021 flow tests given all other sources of uncertainty affecting actual flow rates. In contrast, well P12 experienced degradation between the flow tests in 2019 and 2021 and saw a sharp decrease in well flow rates over the 2 year period. Aging irrigation infrastructure will occur at some wells and attempts to scale our approach across larger study areas will inevitably include wells experiencing flow issues not shown in just the electrical record.

Figure 18 illustrates the electrical record for Well PH2—which shows a systematic change in energy usage patterns in the middle of July, likely due to grower decisions. Measured McCrometer flow rates did not change, but without ground measurements of water delivery it would be hard to make definitive statements of the impacts of changing energy usage on flow rates. Changes during the growing season because of grower decisionmaking could introduce uncertainty in our electrical runtime approach if a decision was made which impacted flow rates. Though in this case (Figure 18), no uncertainty was introduced as there was no change to runtime, measured water delivery or estimated water delivery. Growers respond to conditions on the ground in real time, but knowledge of any changes to irrigation or mechanical adjustments to a center pivot cannot be known without having knowledge of the decisions.

The repeatability of flow tests between different vendors and the absolute accuracy of flow test measurements are large sources of uncertainty in our

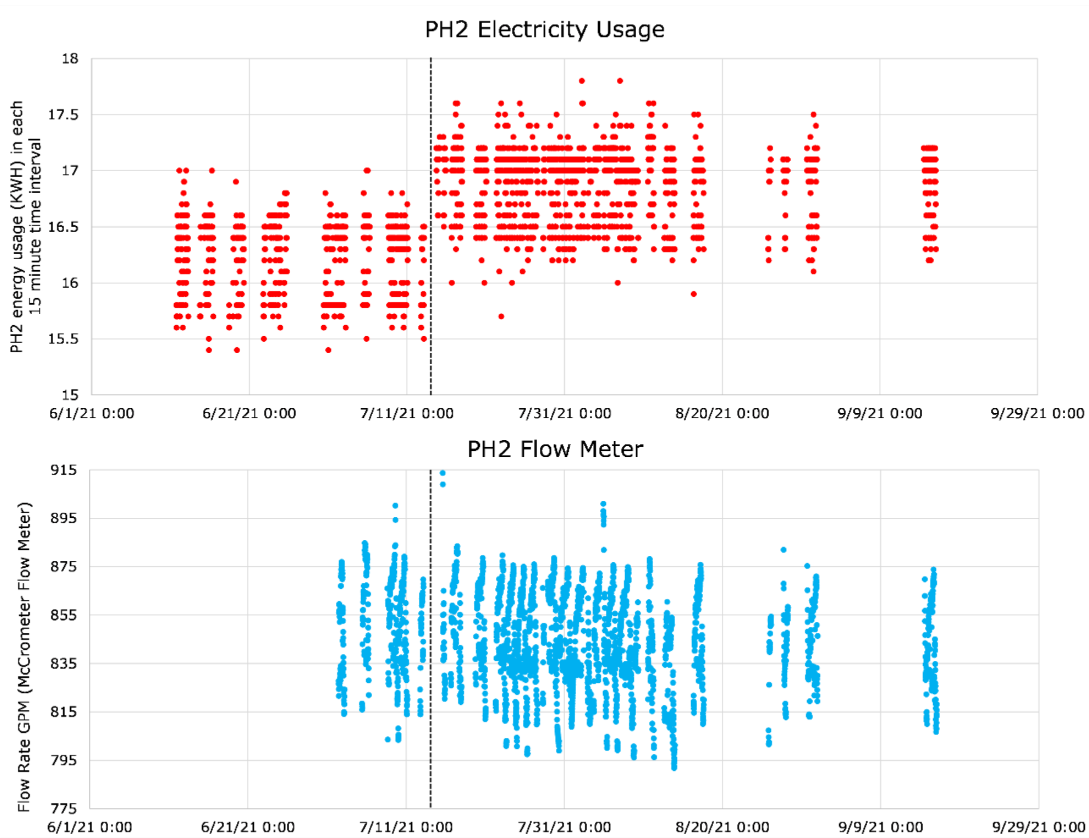

Figure 18. Energy usage over the growing season for well PH2. On July 14, 2021, a systematic change occurred in the electrical usage, likely due to a change in center pivot operations or an adjustment of machine parts. While the measured McCrometer rates did not show any change in flow rates, this occurrence provides an example of uncertainty which exists in our electrical runtime approach when flow rate measurements cannot by verified in real time. Grower decisionmaking is localized and attempts to understand irrigation patterns at scale with our approach cannot easily determine the exact cause of local behavioral changes.

approach, but also an area with the most potential to reduce uncertainty in this study’s electrical runtime approach. Well flow rate changes across time and irrigation changes due to farmer decisionmaking are outside the control of our study. In practice, vendor ultrasonic flow tests can be conducted by growers as inexpensive alternatives to installing flow meters, but norms and protocols for ensuring consistent measurements between different vendors often are not established. While ultrasonic flow meters accuracy ranges from +/- 1% to 5% of true water volume when installed correctly (Eisenhauer, 2008), human error can occur during the normal course of vendor flow tests in the field.

3.2.2 Uncertainty Due to Aquifer Level

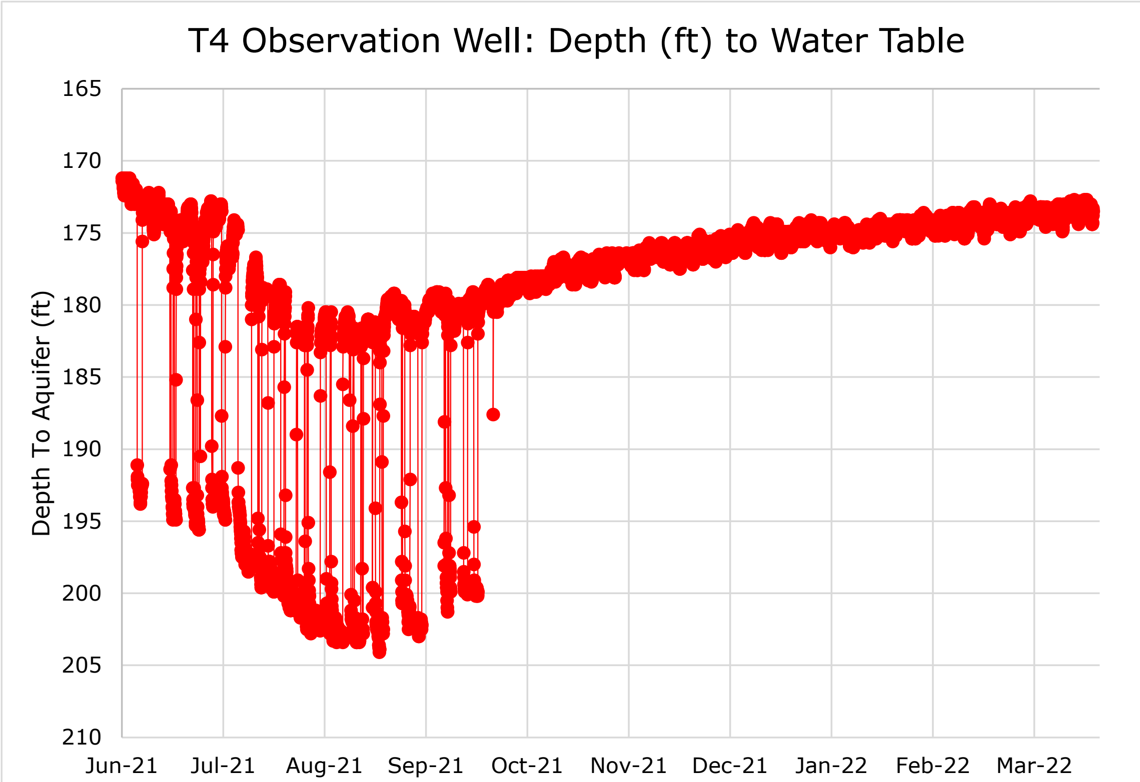

Figure 19. Observation Well at T4. The observation well at T4 captures aquifer dynamics immediately adjacent to the field pump from June 2021 through March 2022. Steep declines in the aquifer can be seen resulting from active pumping forming steep cones of depression around the well, with fast rebounds once pumping stops. During times of no pumping, there can be seen a just over 10 foot decrease in the aquifer table from beginning of measurement to the lowest point in August, with the aquifer's water level rebounding steadily following the end of the growing season.

Drawdown in the water table over the course of the growing season introduces uncertainty as the lift required to pump water increases. In the Twin Platte NRD, the aquifer remains relatively stable over the growing season. Well T4 saw just over 10 feet of drawdown over the growing season at the observation well (Figure 19). As such, drawdown was likely a smaller contributor to changes in pump rate over the growing season as compared to topography which changes by 30 feet from high point in the field to low point. In areas with less stable aquifer water levels than in the Twin Platte NRD, the total system dynamic head (see Figure 7) will fluctuate more over the growing season.

<u>3.2.3 Uncertainty Due to Field Topography</u>

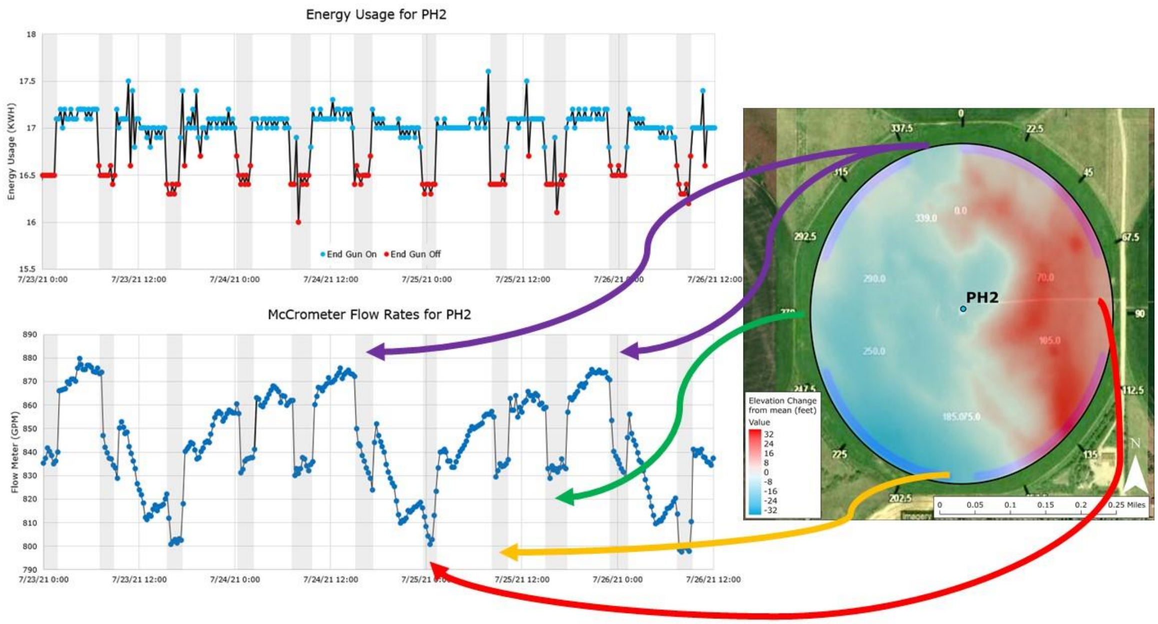

Figure 20. Flow Rates shown varying with topography for PH2. Periods where the end gun is off are highighted in grey, and resulting decreases in power usage and flow rates can be seen. Over a change of just over 60 feet of elevation at PH2, flow rates measured by the McCrometer flow meter can be seen change by nearly 75 GPM (just under 9% of the PH2 average flow rate of 845 GPM).

Flow rates fluctuate systematically with changes in topography as the pivot traverses around the field. This can be seen in Figure 20, where over a period of three and a half days, flow rates measured by the McCrometer flow meter fluctuate with the center pivot's traverse around the field. Over a change of just over 60 feet of elevation at PH2, flow rates measured by the McCrometer flow meter can be seen change by nearly 75 GPM (just under 9% of the PH2 average flow rate of 845 GPM). Flow rates can also be seen changing systematically with end gun operations (end gun off periods shown in grey), which will be discussed in later in this section.

PH2 had the largest changes in elevation of the study wells that had McCrometer flow meters installed (Figure 21), with a total change of 60 feet from highest point in the field to lowest. P11 had a total change of 38 feet, PH5

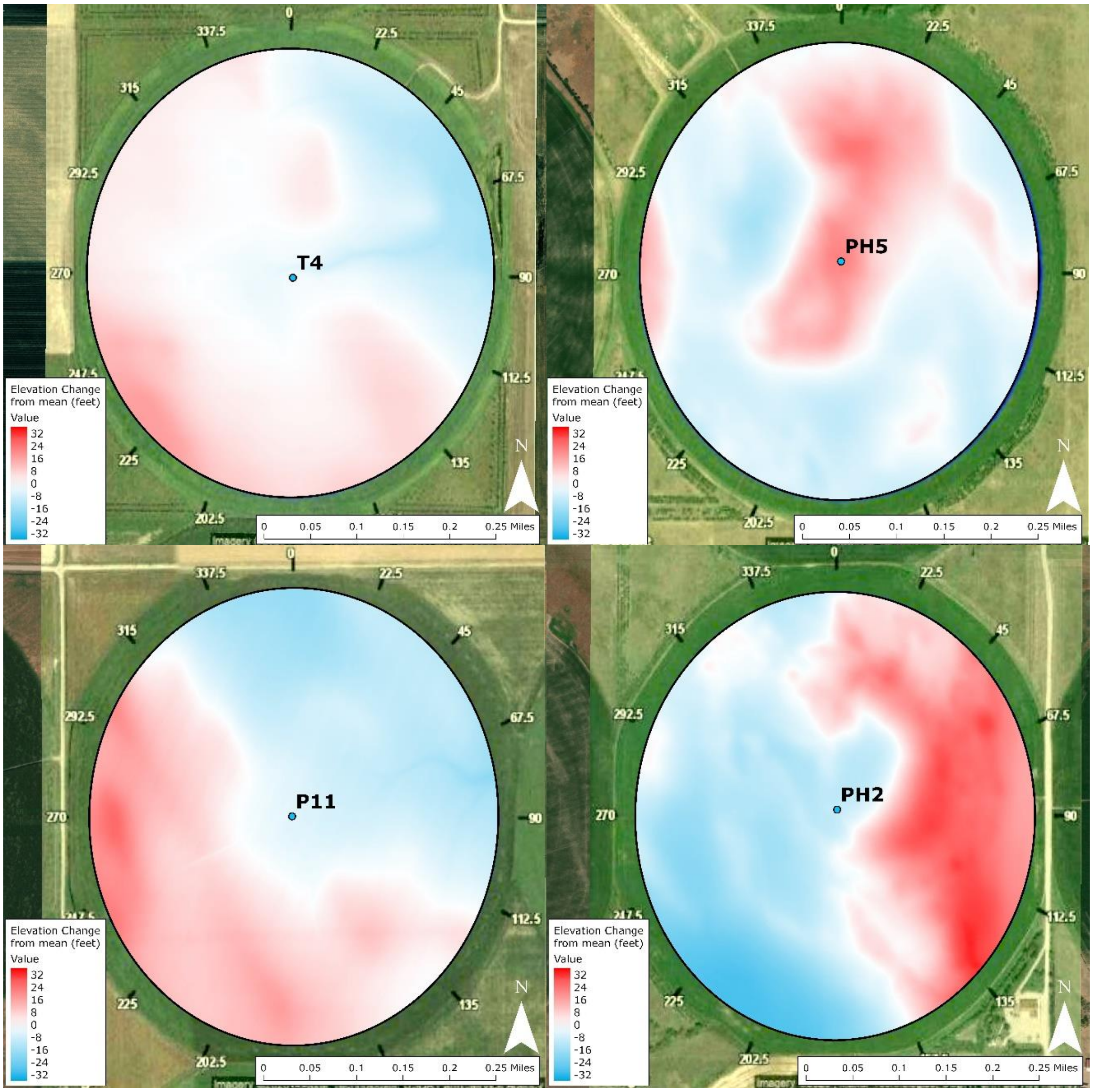

Figure 21. Topography for Fields PH2, PH5, P11, T4. P11 had a total change of 38 feet, PH5 had a change of 36 feet and T4 had the least elevation change with 30 feet. Flow rates vary systematically with topography, with decreased flow rates at higher topographical points due to increased lift.

had a change of 36 feet, and T4 had the least elevation change with 30 feet. PH2 had large changes in flow rates measured by McCrometer flow meters as shown in Figure 22, which fluctuated around 75 GPM (just under 9% of the PH2 average flow rate of 845 GPM) while electrical usage fluctuated less than 0.5KWH per 15 minute interval due to topography (just under 3% of the average electrical usage). PH2 had the largest changes in flow rates due to topography.

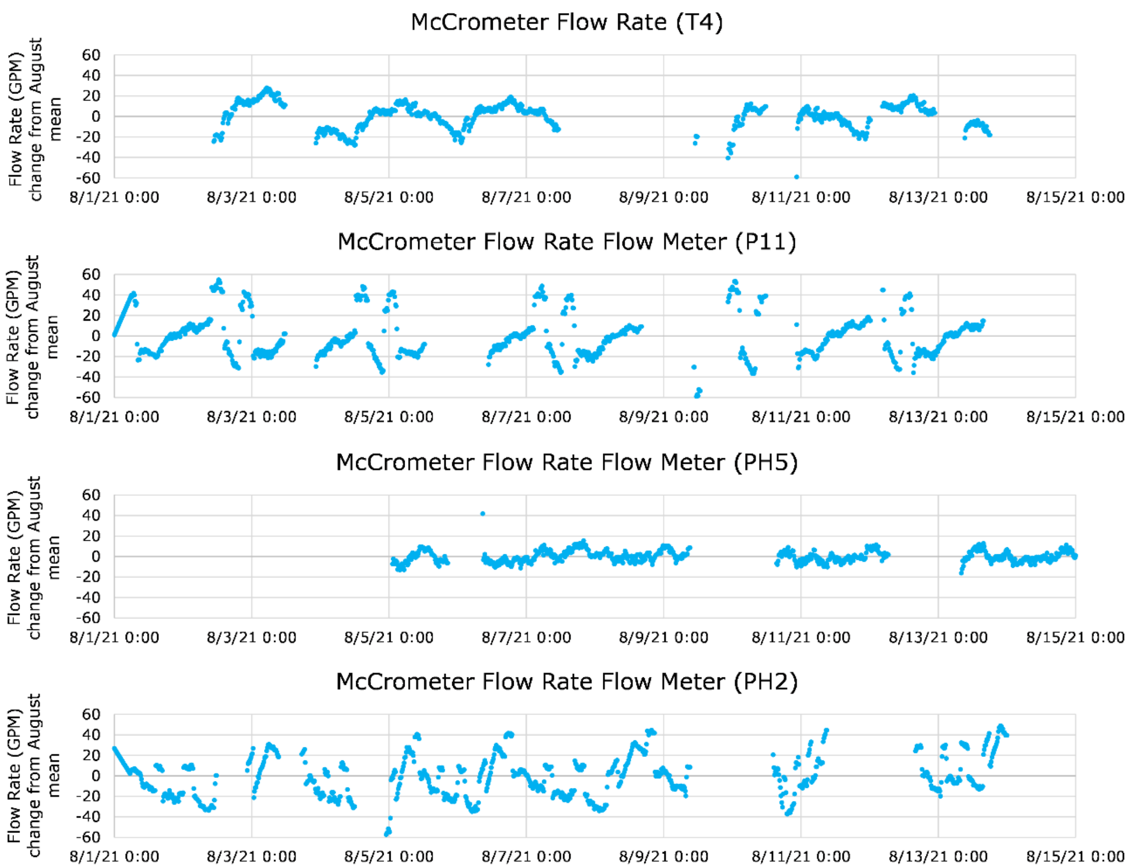

Figure 22. Flow rate change from average in August for wells PH2, PH5, P11 and T4.

P11 (which had 38 feet of topographical change from low to high point on the field) had flow rates that fluctuated nearly 50 GPM (just under 8% of average flow rates of 667 GPM).

T4 has less elevation change than PH2 and P11 and, as expected, had less fluctuations in flow rates. PH5, however, showed very little fluctuation in flow rates despite having more topographical change than T4 and nearly as much as P11. This suggests pressure regulation may be more effective at PH5 and demonstrates that elevation is not the sole determinant how much flow rates will change as the pivot traverses the field.

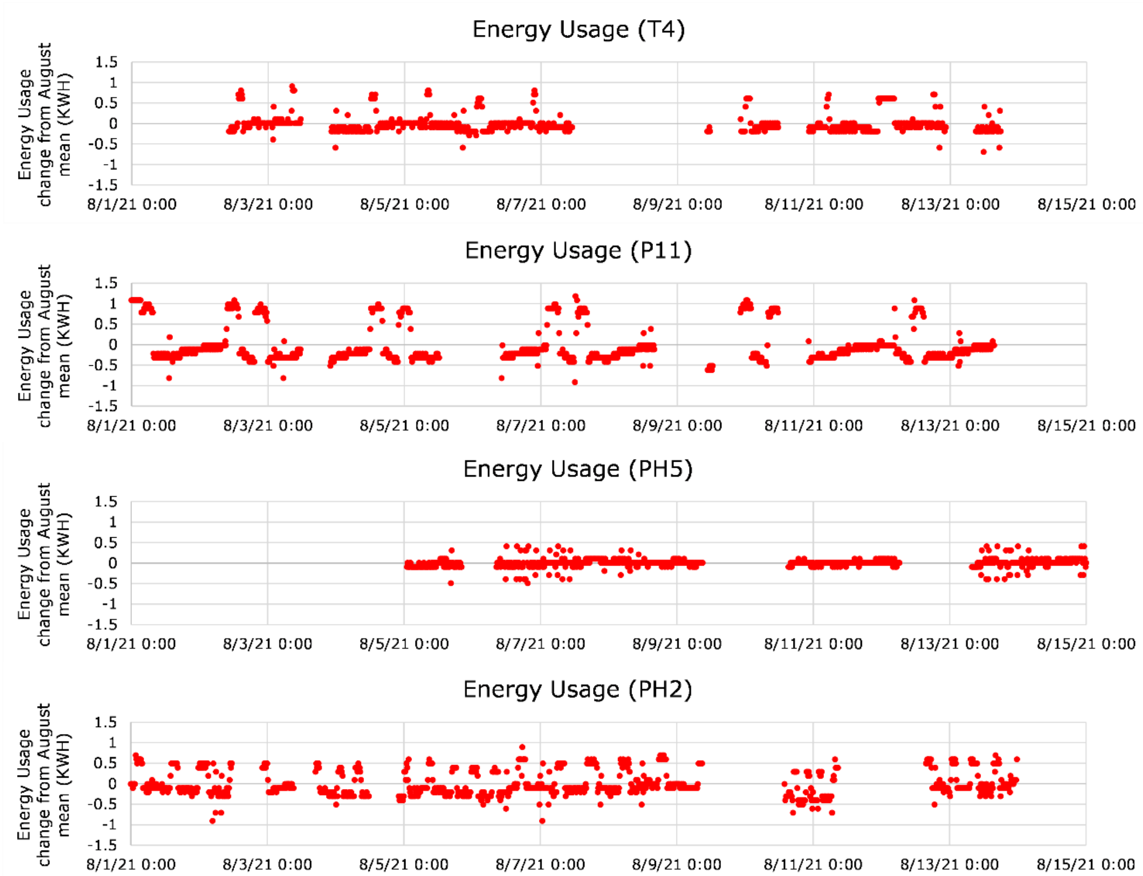

Figure 23. Energy Usage change from average in August for PH2, PH5, P11 and T4.

3.2.4 Uncertainty Due to End Guns

Well	Electrical Runtime: End Gun On	Field Mapping: End Gun (#1) On	Field Mapping: End Gun (#2) On	End Gun Correction Factor
PH3	50.0%	90.3%	43.1%	0.918
P11	75.8%	77.8%	NA	0.987
P13	72.5%	74.4%	NA	0.980
P14	77.5%	78.9%	NA	0.986
T4	87.5%	92.2%	NA	0.996
PH2	70.0%	70.6%	NA	0.990
PH4	64.5%	94.4%	NA	0.993
PH5	75.8%	100.0%	NA	0.997
PH6	85.6%	82.8%	NA	0.989
P12	73.2%	74.2%	NA	0.975

Table 5. End Gun usage comparing electrical runtime results to field mapping.

Our preliminary approach to estimating the percentage of time an end gun is operating shows the strong agreement between estimated end gun operation based on our end gun correction algorithm (Equation 3) as compared to the estimated percentage of time the end gun is operating based on end gun mapping (Table 5). The noticeable exception to this strong agreement occurs when the end gun is expected to be on 90% of the time or more based on field diagrams (PH4 and PH5) and wells with multiple end guns (PH3).

In the case of the end guns being on 90% of the time or more, the calculated rate of end gun operations shown by the electrical runtime data greatly underestimates the amount the end gun is used as shown by field mapping since the differences between the highest and lowest electrical power consumption values used to construct Equation (5) are driven by factors other than end gun operation. Cases where the end gun is primarily on (or off) will produce a correction factor near 1 because the difference between the upper and

	Power Usage		Flow Meter	
	End Gun Turned On Mean % Change	End Gun Turned Off Mean % Change	End Gun Turned On Mean % Change	End Gun Turned Off Mean % Change
P11	4.29%	-4.08%	8.63%	-7.75%
PH2	2.92%	-3.63%	3.84%	-3.57%
T4	3.03%	-3.72%	1.41%	-2.26%
PH5*	NA	NA	NA	NA

* Well PH5 has an end gun which is always on

Table 6. The average change in power usage and flow rates with a change in end gun operations.

lower groupings will be small. For example, PH5 had an end gun correction of 0.997, which was the smallest end gun correction factor in our study wells and the only well with the end guns on 100% of the time. PH4 had end guns on 94% of the time based on end gun mapping, and while the electrical runtime algorithm underestimated end gun usage (64.5%), the end gun correction factor was near unity (0.993), so its quantitative impact was small.

Multiple end guns (such as with PH3) pose another source of uncertainty in estimated water use related to end gun operations. While a typical center pivot may have one end gun that increases flow by 3% to 5%, center pivots with two end guns can impact our approach to differentiating end gun status based on upper and lower groupings of energy usage (see Equation 3). More detailed studies of wells with multiple end guns are needed to better understand end gun dynamics and the feasibility of our approach when multiple end guns.

A key assumption made in our end gun correction algorithm is the power usage and flow rates will change proportionally to each other with end gun operations. In practice, this ratio likely changes between center pivots. This constitutes a large area of future work, as shown by the results from wells P11, PH2 and T4.

<u>3.2.5 Reliability of Data Telemetry</u>

	2020 Electrical Data Intervals			2021 Electrical Data Intervals			2021 Flow Meter Data Intervals		
Well	Errors	Total	% Error	Errors	Total	% Error	Errors	Total	% Error
T4	228	16,320	1.40%	335	14,016	2.39%	519	11,745	4.42%
PH2	324	16,320	1.99%	55	14,016	0.39%	695	11,809	5.89%
PH3	316	16,320	1.94%	1,749	14,016	12.48%	NA	NA	NA
PH4	NA	NA	NA	51	14,016	0.36%	NA	NA	NA
PH5	332	16,320	2.03%	7,745	14,016	55.26%	268	4554*	5.88%
PH6	456	16,320	2.79%	105	14,016	0.75%	NA	NA	NA
P11	NA	NA	NA	374	14,016	2.67%	712	11,790	6.04%
P12	NA	NA	NA	356	14,016	2.54%	NA	NA	NA
P13	NA	NA	NA	319	14,016	2.28%	NA	NA	NA
P14	287	16320	1.76%	331	14,016	2.36%	NA	NA	NA

* PH5's Flow Meter ceased operating on 8/18/2021 and requires repair

Table 7. Number of errors in the datasets for the 2020 electrical data, 2021 electrical data and 2021 flow meter data.

Well PH5 2021 ceased data transmission for a substantial length of time from May 15 to August 4 due to a smart meter requiring maintenance by the power provider. Of the 7745 errors messages for PH5 in 2021, 7740 of these errors occurred during this period from May 15 to August 4 where maintenance was required. Well PH3 during the 2021 growing season experienced intermittent data loss throughout the entire growing season for unknown reasons. When operating normally, electrical data is likely transmitted around 98% of the time while this study's McCrometer flow meters reported around 94% of the time.

The example between the electrical data for PH5 during the 2021 growing season and the McCrometer flow meter installed at PH5 highlights a key benefit of using infrastructure already maintained for a different purpose. The electrical smart meter for PH5 was fixed by the power company to support their infrastructure, while the flow meter installed for our study will require contracting repair and incurring additional costs to regain telemetry.

3.3 Regional Scale Results

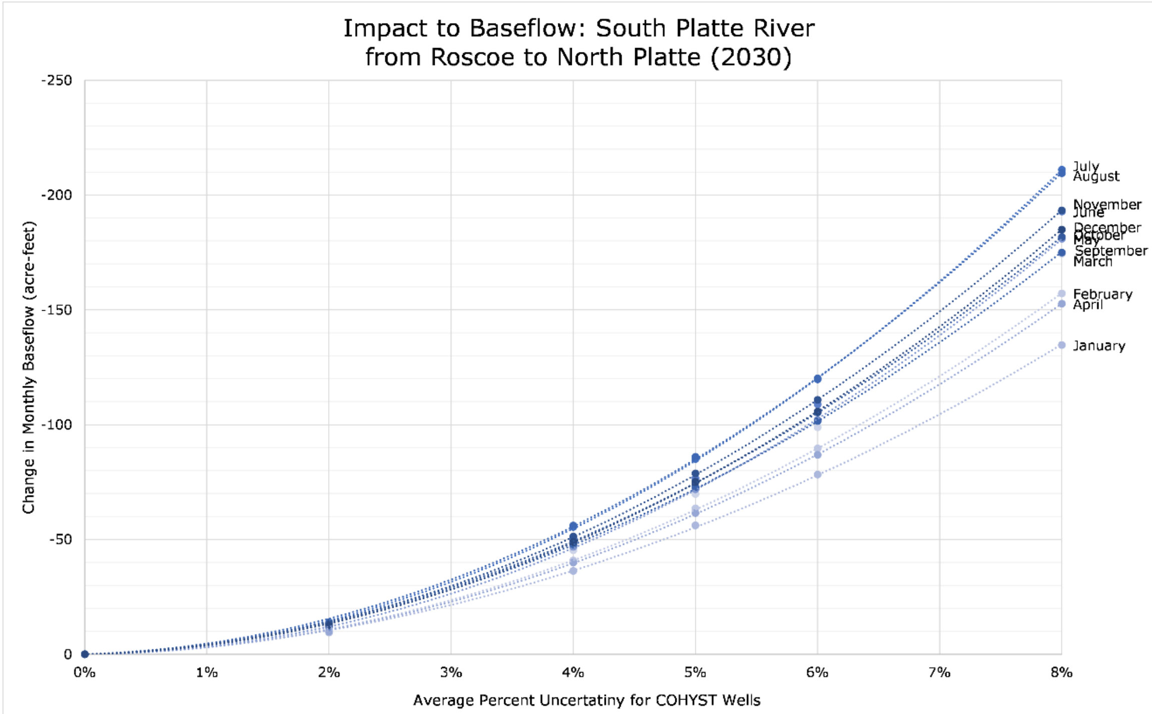

Figure 24. Impact to Baseflow above Baseline from Roscoe, Nebraska to North Platte, Nebraska by monthly total for the year 2030. Highest totals can been seen during peak pumping months of July and August.

Results from the COHYST model runs are shown in Figure 24 and represent the impact to baseflow of the South Platte River above baseline COHYST streamflow predations from Roscoe to North Platte in 2030. In our worst case modeling where the average uncertainty has an 8% bias in excess pumping, there would be a reduction of just over 200 acre-feet in total monthly streamflow during summer months compared to a baseline expectation (Figure 24). Excess pumping in this worst case scenario would result in a 3 foot decline in the water table in the month of January 2030 at the point of largest drawdown, which will likely not have substantial impacts on farmers' ability to irrigate in this region (Figure 25). Our most likely scenario where the average uncertainty has a 6.60% bias (see Table 4) in additional pumping, there would be a reduction of monthly baseflow of 120 acre-feet in peak summer months as

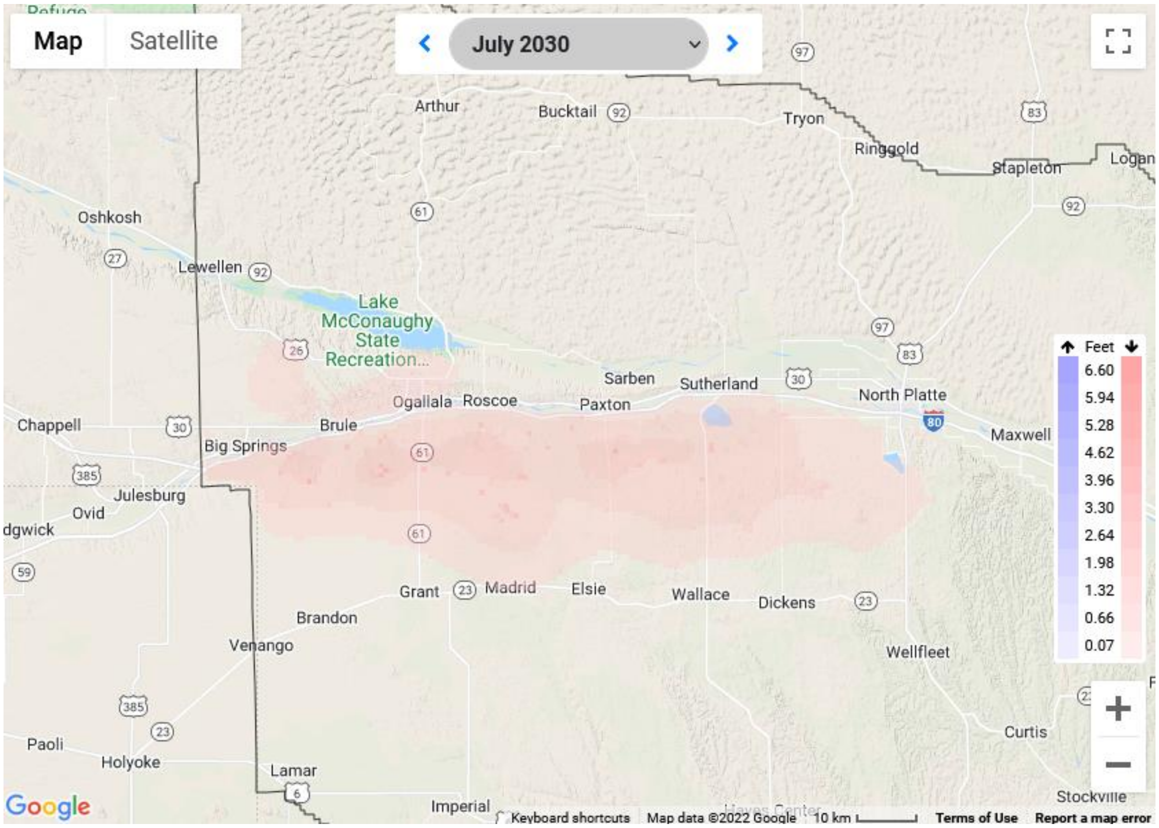

Figure 25. Aquifer table decline in extreme scenario. Average decline is typically less than 3 feet decrease across most of the South Platte Drainage Basin during peak pumping months.

compared to the monthly baseline. The model cannot resolve whether this reduction in streamflow would occur during high- or low-flow events, or whether it would be distributed across the month.

Streamflow depletion does increase as this study increases pumping bias at each well, but low levels of bias have a relatively small impact on baseflow compared with monthly normal values. Improving precision in our ability to estimate water delivery using vendor flow tests and improving our understanding of the uncertainties in this approach can bring down our uncertainties regarding externalities to streamflow. Future work in reducing our uncertainties with estimating water delivery at field scale and understanding how both error and bias in our results might impact our basinwide results is an important step in bridging local decision-making across larger scales.

CHAPTER 4. Conclusions and Broader Implications

4.1 Broader implications of this work

Management of groundwater resources remains in an incipient phase in relation to surfacewater management. Groundwater management policies may not work as expected, such as when improved irrigation efficiency results in the movement towards more water intensive crops (Smidt et al., 2016). Despite management challenges and the decentralized decisionmaking of individual water users, aquifer depletion and significant streamflow reductions are not inevitable. Careful management and innovation approaches are considered to limit depletion rates (Haacker et al., 2019a) and can result in reduced water usage and maintaining of agricultural economies.

Nearly all approaches to managing groundwater resources exist within a comanagement spectrum between complete control by state management agencies and user-centric governance of water resources (Molle and Closas, 2020), with various different approaches within this continuum having been considered. Groundwater pumping fees as a price-intervention has shown success in reducing pumping rates as farmers decrease water extraction for irrigation in some areas (Smith et al., 2017; Rouhi Rad et al., 2020). Both price interventions and farmer adaptation to changing local aquifer conditions can also lead to the movement away from high water crops to low water crops (Nelson, 2012; Hornbeck and Keskin, 2014; Smith, 2018). Water trading can provide a potential water management approach by shifting water usage across time and space to better allocate water usage (Anderson and Hill, 1975; Palazzo and Brozović, 2014; Young and Brozović, 2019).

There is no perfect form of governance despite successful governance in

some areas, and different policies can work within some water resource contexts and fail in others (Ostrom, 1990; Meinzen-Dick, 2007). This water management dilemma often needs to be tailored and adapted to specific attributes of any individual water resource system. Well-informed agricultural water usage by farmers and effective management decisions across different water resource systems cannot be achieved without reliable measurement of the inputs within food-energy-water systems (Scanlon et al., 2017).

Management of groundwater in the High Plains Aquifer is already a focus for water users, though short-term and long-term incentives have yet to align in a sustainable way over parts of the aquifer. All new agricultural management approaches must consider local heterogeneity. When considering each possible management strategy based on local water resource characteristics, a fundamental question is whether there is enough data to make well-considered management decisions and effectively evaluate changes in management. Without effective measurement of water use at field scale, well informed water usage will remain at a nascent stage.

4.2 Suggestions for future work and implementation

Pursuing and improving upon conservation and measurement techniques by approaching growers, private sector partners, and irrigation companies, is a likely successful approach to advancing water sustainability goals and promoting well-informed water usage decision-making. Focus on trying to reduce input costs for growers can crowd-in water sustainability norms while ensuring local agricultural economies and farm profits can be maintained. While no single measurement approach may provide all necessary information for local growers and watershed managers, approaching conservation by providing growers with improved ways to measurement water use and focusing on reducing input costs can provide new paths for effective water conservation.

Supporting improved measurement techniques such as this study's electrical runtime approach require future study and building upon this study's promising preliminary findings. Further understanding of how to measure representative instantaneous ultrasonic flow tests will need to be explored as well as the development of norms to create trust in the accuracy of flow rate measurement. Creating norms and protocols for vendor ultrasonic flow tests likely provides a reasonable path to reducing uncertainties and creating consistent measuring practices across wells. Additionally, for watershed managers looking at basinwide water withdrawals, it is necessary to understand the effects of bias and error that might result in incorrect measurements.

If measurement practices are going to be successfully expanded across larger scales, reducing uncertainties will be essential as water volumes become more important in making management and business decisions. Tightening in the uncertainties of measuring water delivery using the electrical runtime

approach requires replication in areas with larger changes in topography (McDougall, 2015) and areas with declining water table elevations (Mieno et al., 2021).

4.3 Conclusions

This study seeks to find a low-cost approach of measuring real-time water delivery to crops which can support farmers and watershed managers balancing economic, sustainability, and governance decisions through resource usage measurement. The techniques in this study uniquely capture the temporal aspect of irrigation and demonstrate the advantages of utilizing the electrical dataset for water measurement. Many methods for measuring water volume exists, but often rely on flow meters which require maintenance and cooperation with local growers to adopt the technology. In contrast, this method's primary advantage over other systems—which require widescale installation of measurement devices—is to leverage pre-existing methods which already exist at scale.

I conclude that (1) electrical data already being collected commercially are widely available, reliable and highly scalable and can provide an additional dataset to any water measurement approach; (2) vendor ultrasonic flow tests can provide a cheap and broadly accurate estimate of flow rates for a well, but further research on the accuracy of flow tests and development of proper protocols should be investigated to reduce uncertainties; (3) using this study's method of coupling the electrical runtime and vendor ultrasonic flow tests can provide an uncomplicated and inexpensive way of measuring water usage for growers and watershed managers and can be used independently at scale or layered on top of other water measurement methods to enhance water management and well-informed water resource usage; (4) accurate and precise knowledge of water usage can align farmer's incentives with environmental concerns if management is considered thoughtfully; (5) incorporation of measurement techniques into already existing systems and frameworks as well

as coupling data across food-energy-water systems can drive adoption of improved technology and data utilization practices.

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Appendices

Tidying Electrical Data—R Code

```
########################################
##### Tidy Raw Electrical Datasets #####
########################################

## Script to take SQL format for electrical data and convert to tidy fo
rm
## This script has no assumptions and does no calculations
## This script merely tidys the electrical data. See https://bookdown.o
rg/roy_schumacher/r4ds/

if(!require(tidyverse)){install.packages('tidyverse', dependencies = TR
UE)}## debian based linux requires dependencies for tidyverse: ~$ sudo
apt-get install r-cran-tidyverse
if(!require(here)){install.packages('here', dependencies = TRUE)}

library(tidyverse)
library(here)
here::i_am(".RData")

##############################
##### Paths, inputs, etc #####
##############################

path_to_raw_elec_data         = here("_data", "raw-data-electrical.csv"
)
save_location_2020_elec_tidy  = here("_data_tidy", "tidy_electrical_202
0.csv")
save_location_2021_elec_tidy  = here("_data_tidy", "tidy_electrical_202
1.csv")

############################
###### Tidy Elec Data ######
############################

### Inserting the Raw Electrical Data CSV from ### -SQL- ###
df_raw <- read.csv(path_to_raw_elec_data,stringsAsFactors = TRUE, check
.names=FALSE)
colnames(df_raw)[1] <- "DAY"
colnames(df_raw)[2] <- "WellID"

## "%Y-%m-%d" OR  "%m/%d/%y" Date may change depending on format of exc
el during export process
df_raw$DAY <- as.POSIXct(strptime(df_raw$DAY, format="%m/%d/%y"))


## Certain error codes will be set to 0 automatically
df_raw[2:ncol(df_raw)][df_raw[2:ncol(df_raw)] == "NULL"] <- 0
df_raw[2:ncol(df_raw)][df_raw[2:ncol(df_raw)] == "262272"] <- 0
```

```
## Lots of duplicates in the data due to telemetry. All data which are
reported twice are removed
df_raw <- df_raw %>% distinct(df_raw, across(everything()), .keep_all =
TRUE)

#Pivot LONGER! tidy the data: one row for each individual electrical re
ading
df_stack <- df_raw %>% pivot_longer(cols = 3:98,names_to = "TIME",value
s_to = "rawVAL")
df_stack$DateTime <- as.POSIXct(strptime(as.character(paste(df_stack$DA
Y, df_stack$TIME)), format = "%Y-%m-%d %H:%M:%S", tz = "America/Denver"
))
df_stack <- df_stack[order(df_stack$DateTime), ]
row.names(df_stack) <- NULL

### Separate out by the 2020 growing season and 2021 growing season
df_elec_20 <- df_stack[df_stack$DAY >= "2020-05-15" & df_stack$DAY <= "
2020-10-31" , ]
df_elec_20 <- df_elec_20 %>% pivot_wider(names_from = WellID, values_fr
om = rawVAL)
df_elec_20 <- select(df_elec_20, -c(DAY, TIME))

df_elec_21 <- df_stack[df_stack$DAY >= "2021-05-01" & df_stack$DAY <= "
2021-10-31", ]
df_elec_21 <- df_elec_21 %>% pivot_wider(names_from = WellID, values_fr
om = rawVAL)
df_elec_21 <- select(df_elec_21, -c(DAY, TIME))

################
##### save #####
################

write.csv(df_elec_20, save_location_2020_elec_tidy, row.names = TRUE)
write.csv(df_elec_21, save_location_2021_elec_tidy, row.names = TRUE)
```

Tidy and Interpolate Aquifer Level Readings—R Code

```
###############################################
##### Tidy + Interpolate Water Level Data #####
###############################################

## debian based linux requires dependencies for tidyverse: ~$ sudo apt-
get install r-cran-tidyverse
if(!require(tidyverse)){install.packages('tidyverse')}#if(!require(lubr
idate)){install.packages('lubridate')}
## debian based linux requires dependencies for imputeTS: ~$ sudo apt-g
et install libjpeg62-turbo-dev r-cran-forecast libcurl4-openssl-dev lib
ssl-dev libxml2-dev icu-doc libssl-doc libpng-dev libpng-tools
if(!require(imputeTS)){install.packages('imputeTS')}
if(!require(here)){install.packages('here', dependencies = TRUE)}

library(tidyverse)
library(imputeTS)
library(here)
options(scipen = 999)

##############################
##### Paths, inputs, etc #####
##############################

### All dates are being standardized to "America/Denver" time regardles
s of geographical location

## T4 is used here as an example
WaterLevel <- "T4_2in"
WellCode <- "T4"

path_to_water_level_data  = here("_data", str_c(WaterLevel,"_WL.csv"))
save_location_WL_interp   = here("_data_tidy",str_c("tidy_",WaterLevel,
"_WL_Interp.csv"))

### All dates are being standardized to tzStandardize time regardless o
f geographical location
tzCollected    = "America/Chicago"
tzStandardize  = "America/Denver"

###############################
###### Tidy WATER LEVELS ######
###############################

df_WL <- read.csv(path_to_water_level_data,stringsAsFactors = TRUE, che
ck.names=FALSE)
colnames(df_WL)[1] <- "DateTime"
colnames(df_WL)[2] <- "WL"
df_WL$DateTime <- as.POSIXct(strptime(df_WL$DateTime, format = "%m/%d/%
```

```
y %H:%M", tz = tzStandardize))

####################################
##### INTERPOLATE WATER LEVELS #####
####################################

day_first <- as.POSIXct(str_sub((first(df_WL$DateTime)), start = 1L, en
d = 10L), format = "%Y-%m-%d", tz=tzStandardize)
day_last  <- as.POSIXct(str_sub((last(df_WL$DateTime)), start = 1L, end
= 10L), format = "%Y-%m-%d", tz=tzStandardize)
df_interpolation <- data.frame(seq(day_first, day_last, by = 15*60))
colnames(df_interpolation)[1] <- "DateTime"

## Interpolation here used constant interpolation.
interpolated_data <- approxfun(x=df_WL$DateTime,y=df_WL$WL,method="cons
tant")
df_interpolation$WL <- round((interpolated_data(as.numeric(df_interpola
tion$DateTime + (7.5*60)))) ,digits = 1)

################
##### save #####
################

colnames(df_interpolation)[1] <- str_c("DateTime")
colnames(df_interpolation)[2] <- str_c(WaterLevel,"_WL")
write.csv(df_interpolation, save_location_WL_interp, row.names = TRUE)
```

Tidy and Interpolate Flow Meter Readings—R Code

```
##############################################
##### Tidy + Interpolate Flow Meter Data #####
##############################################

if(!require(tidyverse)){install.packages('tidyverse')}
## debian based linux requires dependencies for tidyverse: ~$ sudo apt-
get install r-cran-tidyverse
if(!require(here)){install.packages('here', dependencies = TRUE)}

library(tidyverse)
library(here)
here::i_am(".RData")

options(scipen = 999)

##############################
##### Paths, inputs, etc #####
##############################

WellCode <- "T4"

# Importing the well characteristics
path_to_flow_meter_data    = here("_data", str_c(WellCode,"_Flow.csv"))
save_location_flow_meters = here("_data_tidy", str_c("tidy_",WellCode,"
_Flow_Interp.csv"))

### All dates are being standardized to tzStandardize time regardless o
f geographical location
tzCollected     = "America/Chicago"
tzStandardize   = "America/Denver"

#############################
###### Tidy Flow Meter ######
#############################

df_tidy_flow <- read.csv(path_to_flow_meter_data,stringsAsFactors = TRU
E, check.names=FALSE)
colnames(df_tidy_flow)[3] <- str_c("Flow")

df_tidy_flow$Date <- as.POSIXct(strptime(df_tidy_flow$Date, format="%m/
%d/%y"))
df_tidy_flow$Time <- str_sub((as.POSIXct(strptime(df_tidy_flow$Time, fo
rmat="%r"))), -8)

df_tidy_flow$DateTime <- as.POSIXct(strptime(as.character(paste(df_tidy
_flow$Date, df_tidy_flow$Time)), format = "%Y-%m-%d %H:%M:%S", tzCollec
ted))
df_tidy_flow$DateTime <- as.POSIXct(format(df_tidy_flow$DateTime, tz=tz
```

```
Standardize))

# There is a 15 minute (15*60 seconds) lag in data reporting from AdCon
, per private communication
df_tidy_flow$DateTime <- df_tidy_flow$DateTime - 15*60

## Set 0 to NA
df_tidy_flow$Flow[df_tidy_flow$Flow == 0] <- NA

## ASSUMPTION. we are just setting all of the values preceeding large t
ime series gaps to NA.
## The reason for this is we assume some type of error
## values preceeding large gaps often fall outside of the expected flow
range and often are anomyalous readings.
#48 implies you missed 2 intervals of reporting. we exclude all leading
values preceeding gaps of 3 or more time intervals.
df_tidy_flow$Flow[(lead(df_tidy_flow$DateTime) - df_tidy_flow$DateTime)
> 48] <- NA

###################################
##### INTERPOLATE FLOW METERS #####
###################################

day_first <- as.POSIXct(str_sub((first(df_tidy_flow$DateTime)), start =
1L, end = 10L), format = "%Y-%m-%d", tz=tzStandardize)
day_last  <- as.POSIXct(str_sub((last(df_tidy_flow$DateTime)), start =
1L, end = 10L), format = "%Y-%m-%d", tz=tzStandardize)
df_interpolation <- data.frame(seq(day_first, day_last, by = 15*60))
colnames(df_interpolation)[1] <- "DateTime"

interpolated_data <- approxfun(x=df_tidy_flow$DateTime,y=df_tidy_flow$F
low,na.rm=F,method="constant") #method="linear"

## set a midpoint (+7.5minutes) for each 15 minute interval and extract
interpolated_data to those points
df_interpolation$Flow <- round(((interpolated_data(as.numeric(df_interp
olation$DateTime + (7.5*60))))) ,digits = 1)

################
##### save #####
################

colnames(df_interpolation)[2] <- str_c(WellCode,"_Flow")
write.csv(df_interpolation, save_location_flow_meters, row.names = TRUE
)
```

Electrical Runtime Algorithm—R Code

```
########################################
##### Electrical Runtime Algorithm #####
########################################

if(!require(tidyverse)){install.packages('tidyverse', dependencies = TR
UE)}
## debian based systems requires dependencies for tidyverse: ~$ sudo ap
t-get install r-cran-tidyverse
if(!require(imputeTS)){install.packages('imputeTS', dependencies = TRUE
)}
## debian based systems requires dependencies for imputeTS: ~$ sudo apt
-get install libjpeg62-turbo-dev r-cran-forecast libcurl4-openssl-dev l
ibssl-dev libxml2-dev icu-doc libssl-doc libpng-dev libpng-tools
if(!require(here)){install.packages('here', dependencies = TRUE)}

library(tidyverse)
library(imputeTS)
library(here)
here::i_am(".RData")

##############################
##### Paths, inputs, etc #####
##############################

#### Set the Well Code for this script. Can be changed to different wel
l by code

### All wells: PH2, PH3, PH4, PH5, PH6, P11, P12, P13, P14, T4
### 2020 wells: P12, PH2, PH4, PH5, PH6, T4
### 2021 wells: PH2, PH3, PH4, PH5, PH6, T4, P11, P12, P13, P14
### Flow meters: T4, PH5, PH2, P11
### Water Level: T4, PH5, P12
### All years: 2020, 2021

WellCode <- "T4"
YEAR <- "2021"

path_to_well_characteristics = here("wells", "Well_Characteristics.csv"
)
path_to_compiled_elec_data   = here("_data_tidy", str_c("compiled_data_
",YEAR,".csv"))
save_location_well_output    = here("_output_algo", str_c("ElecAlgo_",W
ellCode,"_",YEAR,".csv"))
save_location_ie_output      = here("_output_algo", "associated_files",
str_c("ieSummary_",WellCode,"_",YEAR,".csv"))

# Importing the well characteristics
WellInfo <- read.csv(path_to_well_characteristics, stringsAsFactors = T
```

```
RUE, row.names = "Code")
#flow rates are in volume gallons per minute (GPM)
gpm_S1   = as.numeric(WellInfo[WellCode,"GPM_S1"])
gpm_S2   = as.numeric(WellInfo[WellCode,"GPM_S2"])
gpm_D1   = as.numeric(WellInfo[WellCode,"GPM_D1"])
gpm_D2   = as.numeric(WellInfo[WellCode,"GPM_D2"])
multiple = as.numeric(WellInfo[WellCode,"multiple"])
convert_gal_to_acft = 0.0000030689
convert_gal_to_acin = 0.0000368266
threshold = 4
threshold_raw = as.numeric(WellInfo[WellCode,"TH_raw_val"])
ACRES = as.numeric(WellInfo[WellCode,"acres"])


##########################
###### Elec Runtime ######
##########################

# Import the Raw data from the CSV
raw_data <- read.csv(path_to_compiled_elec_data, stringsAsFactors = TRU
E)
raw_data <- raw_data %>% distinct(DateTime, .keep_all = TRUE)
raw_data$DateTime <- as.POSIXct(strptime(raw_data$DateTime, format = "%
Y-%m-%d %H:%M:%S", tz = "MST")) #"%m/%d/%y %H:%M"

### BEGIN ALGO--create a setting up collumns date + raw values electric
al
df_well <- data.frame(raw_data$DateTime,as.numeric(unlist(raw_data[Well
Code])))
colnames(df_well)[1] <- "DateTime"
colnames(df_well)[2] <- "raw_val"

# ADD the flow meter data (PH2, PH5, P11 and T4) if applicable
# ADD the observation well + monitoring well if applicable
# No calculations are performed, this is merely pulling in the data
ifelse(WellCode == 'PH2' & YEAR == '2021', df_well <- df_well %>% add_c
olumn(flow_meter = raw_data$PH2_Flow), ifelse(WellCode == 'PH5' & YEAR
== '2021',  df_well <- df_well %>% add_column(flow_meter = raw_data$PH5
_Flow), ifelse(WellCode == 'P11' & YEAR == '2021', df_well <- df_well %
>% add_column(flow_meter = raw_data$P11_Flow), ifelse(WellCode == 'T4'
& YEAR == '2021', df_well <- df_well %>% add_column(flow_meter = raw_da
ta$T4_Flow), df_well$flow_meter <- NaN))))

ifelse(WellCode =='PH5'& YEAR=='2021', df_well <- df_well %>% add_colum
n(observation_well = raw_data$PH5_WL), ifelse(WellCode =='T4' & YEAR=='
2021', df_well <- df_well %>% add_column(observation_well = raw_data$T4
_2in_WL), ifelse(WellCode =='P12'& YEAR=='2021', df_well <- df_well %>%
add_column(observation_well = raw_data$P12_WL), df_well$observation_wel
l <- NaN)))
```

```
ifelse(WellCode =='T4' & YEAR=='2021', df_well <- df_well %>% add_colum
n(monitoring_well = raw_data$T4_4in_WL), df_well$monitoring_well <- NaN
)

### Correct for the error code 16383
### Column raw_val_corrected has been added.
### If the error code 16383 is proceeded by values lower than the thres
hold, raw_val set to be 0
### If the error code 16383 is leaded AND trailed by a value 2 times th
e threshold, the higher raw value of the leading and trailing values is
applied to the list of error codes.
### This higher value is chosen with the assumption that the end gun is
typically on, and since this algo uses electricity as a runtime, interp
olation is not needed
### If neither of the criteria solve the error code, raw_val set to be
0
df_well$raw_val_corrected <- df_well$raw_val
df_well$raw_val_corrected[df_well$raw_val_corrected == 16383] <- NA
df_well$raw_val_corrected <- ifelse(df_well$raw_val==16383 & imputeTS::
na_locf(df_well$raw_val_corrected) < threshold_raw, 0, df_well$raw_val_
corrected)
df_well$raw_val_corrected <- ifelse(df_well$raw_val==16383 & imputeTS::
na_locf(df_well$raw_val_corrected) > (2*threshold_raw) & imputeTS::na_l
ocf(df_well$raw_val_corrected, option = "nocb") > (2*threshold_raw), pm
ax(imputeTS::na_locf(df_well$raw_val_corrected), imputeTS::na_locf(df_w
ell$raw_val_corrected, option = "nocb")), df_well$raw_val_corrected)
df_well$raw_val_corrected[is.na(df_well$raw_val_corrected)] <- 0

#### KWH column --> KWH = (multiple/1000) * raw_val , rounded to the te
ns digit. the (multiple/1000) is values given by the electrical company
to convert meter values to KWH
df_well$KWH <- round((multiple/1000) * df_well$raw_val_corrected, digit
s = 1)

### Create a code for each irrigation event to determine the leading ed
ge, trailing edge and full irrigation event conditions. Codes:
# 1: leading edge of irrigation event; 2: irrigation event; 3: trailing
edge of irrigation event
df_well$irr_code <- ifelse(df_well$KWH >= threshold  & lag(df_well$KWH)
>= threshold  & lead(df_well$KWH) >= threshold , 2,
                    ifelse(df_well$KWH >= threshold  & lead(df_well$KWH
) >= threshold , 1,
                    ifelse(df_well$KWH >= threshold  & lag(df_well$KWH)
>= threshold , 3, NA)))

### Number each irrigation event (ie) and create the interval number wi
thin each irrigation event
df_well <- df_well %>% mutate(ie = ifelse(df_well$irr_code == 1, row_nu
mber(df_well$irr_code), NA)) %>% fill(ie,.direction = "down")
df_well$ie <- ifelse(is.na(df_well$irr_code),NA, df_well$ie)
```

```
df_well <- df_well %>% group_by(ie) %>% mutate(ie_count = row_number(ie
))

### Create a new dataframe to summarize each irrigation event
df_ie <- data.frame(aggregate(ie_count ~ ie, df_well, FUN = max))
colnames(df_ie)[length(colnames(df_ie))]<-"ie_intervals"

### Add the Irrigation Length column to the main data frame
df_well <- merge(df_well, (merge(df_well, df_ie, by='ie', all=TRUE, sor
t=T,incomparables = NULL)[, c('DateTime','ie_intervals')]), by='DateTim
e', sort=T,all=TRUE, incomparables = NULL)

### Here are the three calculations made based on the implied irrigatio
n state code (1,2 or 3)
#1:   equation           ---  irr_timeConA <- ifelse(df_well$irr_code =
= 1, ifelse(df_well$KWH/lead(df_well$KWH)*15>15,15,df_well$KWH/lead(df_
well$KWH)*15), 0)
#2:   equals 15 minutes  ---  irr_timeConB <- ifelse(df_well$irr_code =
= 2, 15, 0)
#3:   equation           ---  irr_timeConC <- ifelse(df_well$irr_code =
= 3, ifelse(df_well$KWH/lag(df_well$KWH)*15>15,15,df_well$KWH/lag(df_we
ll$KWH)*15), 0)
# Then we take the maximum value of these three conditions, which will
either be 15 minutes for a full interval (case 2) or either the lead ed
ge (case 1) or trailing edge (case 3) of the interval
df_well$irr_time <- round(pmax(ifelse(df_well$irr_code == 1, ifelse(df_
well$KWH/lead(df_well$KWH)*15>15,15,df_well$KWH/lead(df_well$KWH)*15),
0), ifelse(df_well$irr_code == 2, 15, 0), ifelse(df_well$irr_code == 3,
ifelse(df_well$KWH/lag(df_well$KWH)*15>15,15,df_well$KWH/lag(df_well$KW
H)*15), 0)),digits=1)
df_well$irr_time[is.na(df_well$irr_time)] <- 0

##############################
##### End-Gun Correction #####
##############################

### Make a KWH column EXCLUDING the leading and trailing edge for end g
un analysis
df_well$KWH_exclude <- ifelse(df_well$irr_code == 2 & df_well$ie_interv
als >= 3, df_well$KWH, 0)
df_well$KWH_exclude[is.na(df_well$KWH_exclude)] <- 0

### Here, we are choosing the median value of the highest 10 and lowest
10 KWH (excluding the leading and trailing edges) values in each ie
## Set Up Functions
medLowfunction = function(x) {
  if (length(x) == 1)
    return(x)
  return(sort(x, decreasing = FALSE)[5])}
df_ie$low_KWH_for_eg <- pull(aggregate(KWH_exclude ~ ie, df_well, FUN =
```

```
medLowfunction))
#df_ie$low_KWH_for_eg[is.na(df_ie$low_KWH_for_eg)] <- 0
df_ie$low_KWH_for_eg[df_ie$ie_intervals < 13] <- threshold

medHIGHfunction =  function(x) {
  if (length(x) == 1)
    return(x)
  return(sort(x, decreasing = TRUE)[5])}
df_ie$high_KWH_for_eg <- pull(aggregate(KWH_exclude ~ ie, df_well, FUN
= medHIGHfunction))
#df_ie$high_KWH_for_eg[is.na(df_ie$high_KWH_for_eg)] <- 0
df_ie$high_KWH_for_eg[df_ie$ie_intervals < 13] <- threshold

### MERGE IN THE low_KWH_for_eg + high_KWH_for_eg column
df_well <- merge(df_well, (merge(df_well, df_ie, by='ie', all=TRUE, sor
t=T,incomparables = NULL)[, c('DateTime','low_KWH_for_eg')]), by='DateT
ime', sort=T,all=TRUE, incomparables = NULL)
df_well <- merge(df_well, (merge(df_well, df_ie, by='ie', all=TRUE, sor
t=T,incomparables = NULL)[, c('DateTime','high_KWH_for_eg')]), by='Date
Time', sort=T,all=TRUE, incomparables = NULL)
df_well$low_KWH_for_eg[is.na(df_well$low_KWH_for_eg)] <- 0
df_well$high_KWH_for_eg[is.na(df_well$high_KWH_for_eg)] <- 0

### Set Bounds for End Gun on / End Gun off
df_well$bound_KWH_for_eg <- (((df_well$high_KWH_for_eg)-(df_well$low_KW
H_for_eg))/2)+(df_well$low_KWH_for_eg)

### Determine if End Gun On or End Gun Off
### "eg" is "end gun"
df_well$eg_code <- ifelse(df_well$KWH > threshold & df_well$irr_code ==
2, ifelse( df_well$KWH >= df_well$bound_KWH_for_eg, 1,0 ),NA)
df_well$eg_on   <- ifelse(df_well$eg_code == 1, df_well$KWH, NA)
df_well$eg_off  <- ifelse(df_well$eg_code == 0, df_well$KWH, NA)

### Mean KWH for when the end gun is on and end gun is off
df_ie$eg_off_KWH_mean <- round(pull(slice(df_well %>% group_by(ie) %>%
summarise(eg_off_KWH_mean = mean(eg_off,na.rm=T)), 1:(n()-1))[, c('eg_o
ff_KWH_mean')]),digits=2)
df_ie$KWH_mean <-  round(pull(slice(df_well %>% group_by(ie) %>% summar
ise(KWH_mean = mean(KWH,na.rm=T)), 1:(n()-1))[, c('KWH_mean')]),digits=
2)
df_ie$eg_on_KWH_mean = round(pull(slice(df_well %>% group_by(ie) %>% su
mmarise(eg_on_KWH_mean = mean(eg_on,na.rm=T)), 1:(n()-1))[, c('eg_on_KW
H_mean')]),digits=2)

### ie_count number of segments with end gun on vs off!
df_well$eg_on[(df_well$irr_code == 1 | df_well$irr_code == 3)] <- 0
df_ie$eg_on_count <- pull(aggregate(eg_on ~ ie, df_well, FUN = length))
df_ie$eg_off_count <- df_ie$ie_intervals - df_ie$eg_on_count
```

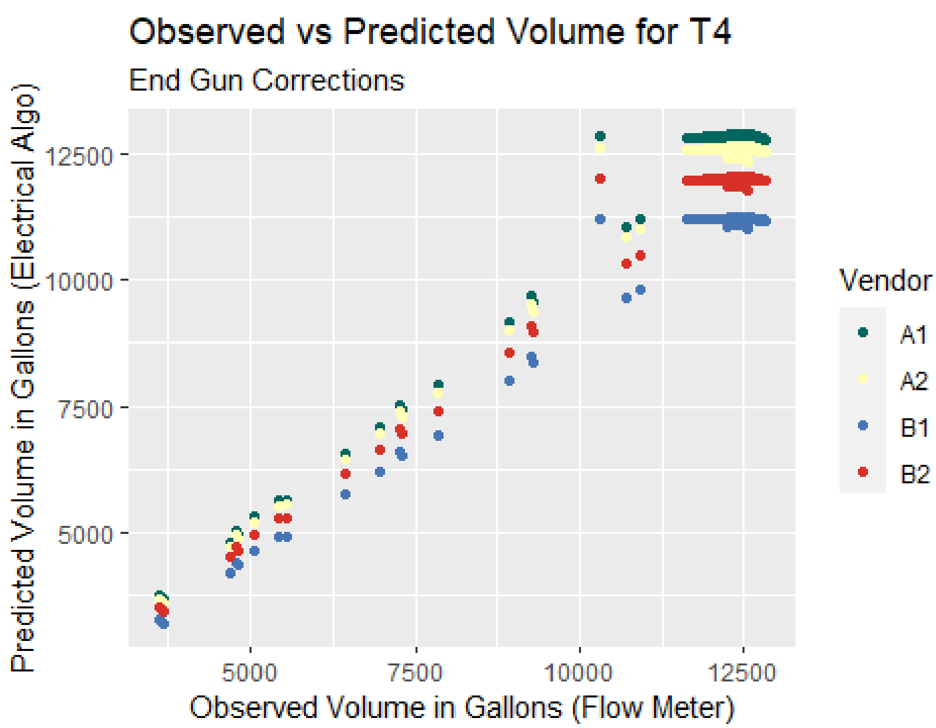
```
### CACLULATE FRACTIONAL DELIVERY AND MERGE INTO MAIN data.frame
df_ie$fractional_delivery <- (1 -(1-(df_ie$eg_off_KWH_mean /   df_ie$eg
_on_KWH_mean)) * (df_ie$eg_off_count /  (df_ie$eg_off_count + df_ie$eg_
on_count)))
df_ie$fractional_delivery[df_ie$fractional_delivery == "NaN"] <- 1
df_well <- merge(df_well, (merge(df_well, df_ie, by='ie', all=TRUE, sor
t=T,incomparables = NULL)[, c('DateTime','fractional_delivery')]), by='
DateTime', sort=T,all=TRUE, incomparables = NULL)
df_well$high_KWH_for_eg[is.na(df_well$high_KWH_for_eg)] <- 0

################################
##### Compute Final Values #####
################################

df_well$gal_flow_meter    <- ifelse(df_well$flow_meter == "NaN", NA,df_
well$flow_meter) * df_well$irr_time
df_well$acft_flow_meter   <- df_well$gal_flow_meter * (convert_gal_to_a
cft)
df_well$inches_flow_meter <- df_well$gal_flow_meter * (convert_gal_to_a
cin / ACRES)

df_well$gal_algo_D1 <-  df_well$irr_time * gpm_D1 * df_well$fractional_
delivery
df_well$acft_algo_D1   <-  df_well$gal_algo_D1 * (convert_gal_to_acft)
df_well$inches_algo_D1 <-  df_well$gal_algo_D1 * (convert_gal_to_acin /
ACRES)

df_well$gal_algo_D2 <-  df_well$irr_time * gpm_D2 * df_well$fractional_
delivery
df_well$acft_algo_D2   <-  df_well$gal_algo_D2 * (convert_gal_to_acft)
df_well$inches_algo_D2 <-  df_well$gal_algo_D2 * (convert_gal_to_acin /
ACRES)

df_well$gal_algo_S1 <-  df_well$irr_time * gpm_S1 * df_well$fractional_
delivery
df_well$acft_algo_S1   <-  df_well$gal_algo_S1 * (convert_gal_to_acft)
df_well$inches_algo_S1 <-  df_well$gal_algo_S1 * (convert_gal_to_acin /
ACRES)

df_well$gal_algo_S2 <-  df_well$irr_time * gpm_S2 * df_well$fractional_
delivery
df_well$acft_algo_S2   <-  df_well$gal_algo_S2 * (convert_gal_to_acft)
df_well$inches_algo_S2 <-  df_well$gal_algo_S2 * (convert_gal_to_acin /
ACRES)

################
##### save #####
################

## MAKE THINGS EASIER TO READ: No ANALYSIS RUN IN THIS BLOCK
```

```
## we have decided to arbitrarily assign "NaN" to all data points where
that data stream was not collected
## "NA" is assigned for values where the data is being collected, but f
or whatever reason, there is no value (ex: flow meter decided to take a
5 hour break from transmitting data back to home)
df_well$low_KWH_for_eg[df_well$low_KWH_for_eg == 0] <- NA
df_well$high_KWH_for_eg[df_well$high_KWH_for_eg == 0] <- NA
df_well$bound_KWH_for_eg[df_well$bound_KWH_for_eg == 0] <- NA
df_ie[df_ie == 0] <- NA
df_well$gal_flow_meter[df_well$flow_meter == "NaN"] <- NaN
df_well$gal_flow_meter <- ifelse(is.na(df_well$flow_meter),NA, df_well$
gal_flow_meter)
df_well$acft_flow_meter[df_well$flow_meter == "NaN"] <- NaN
df_well$acft_flow_meter <- ifelse(is.na(df_well$flow_meter),NA, df_well
$acft_flow_meter)
df_well$gal_algo_D1[is.na(gpm_D1)] <- NaN
df_well$acft_algo_D1[is.na(gpm_D1)] <- NaN
df_well$gal_algo_S1[is.na(gpm_S1)] <- NaN
df_well$acft_algo_S1[is.na(gpm_S1)] <- NaN
df_well$gal_algo_D2[is.na(gpm_D2)] <- NaN
df_well$acft_algo_D2[is.na(gpm_D2)] <- NaN
df_well$gal_algo_S2[is.na(gpm_S2)] <- NaN
df_well$acft_algo_S2[is.na(gpm_S2)] <- NaN

#### Export and save
write.csv(df_well, save_location_well_output, row.names = TRUE)
write.csv(df_ie, save_location_ie_output, row.names = TRUE)
```

Comparing Measured Water Volume to Estimated Water Volume—R Code

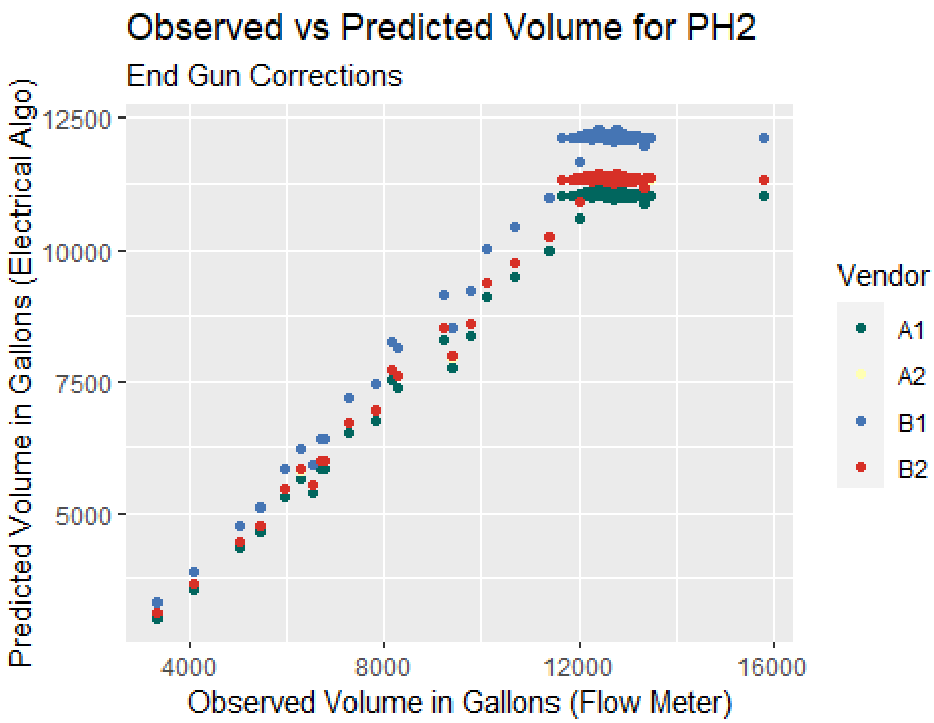
```
################################################
##### Flowmeter and elec algo comparison #####
################################################

if(!require(tidyverse)){install.packages('tidyverse', dependencies = TR
UE)}
## debian based systems requires dependencies for tidyverse: ~$ sudo ap
t-get install r-cran-tidyverse
if(!require(here)){install.packages('here', dependencies = TRUE)}

library(tidyverse)
library(here)
here::i_am(".RData")
options(scipen=999)  # scientific notation

##############################
##### Paths, inputs, etc #####
##############################

### Flow meters: T4, PH5, PH2, P11
path_to_well_characteristics = here("wells", "Well_Characteristics.csv"
)
path_to_T4_data = here("_output_algo","ElecAlgo_T4_2021.csv")
path_to_PH2_data = here("_output_algo","ElecAlgo_PH2_2021.csv")
path_to_PH5_data = here("_output_algo","ElecAlgo_PH5_2021.csv")
path_to_P11_data = here("_output_algo","ElecAlgo_P11_2021.csv")
save_location_df_sums = here("_output_algo","_flow_vs_algo_Sums.csv")
save_location_df_sums_algo = here("_output_algo","_flow_vs_algo_Sums_wh
ole_season.csv")

WellInfo <- read.csv(path_to_well_characteristics, stringsAsFactors = T
RUE, row.names = "Code")
df_T4  <- read.csv(path_to_T4_data, stringsAsFactors = TRUE)
df_PH2 <- read.csv(path_to_PH2_data, stringsAsFactors = TRUE)
df_PH5 <- read.csv(path_to_PH5_data, stringsAsFactors = TRUE)
df_P11 <- read.csv(path_to_P11_data, stringsAsFactors = TRUE)

###########################
###########################
###### T4 comparison ######
###########################
###########################

WellCode = "T4"
df <- df_T4 %>% filter(flow_meter>0) %>% filter(irr_time>0)

df$DateTime <- as.POSIXct(strptime(df$DateTime, format = "%Y-%m-%d %H:%
M:%S", tz = "MST")) #"%m/%d/%y %H:%M"
```

```
df$KWH_exclude[df$KWH_exclude == 0] <- NA

###### Plot of Observed vs Predicted ######
ob_vs_pred_T4 <- ggplot(df, aes(x=gal_flow_meter)) +
  geom_point(aes(y=gal_algo_S1,colour = "A1")) +
  geom_point(aes(y=gal_algo_S2,colour = "A2")) +
  geom_point(aes(y=gal_algo_D1,colour = "B1")) +
  geom_point(aes(y=gal_algo_D2,colour = "B2")) +

  scale_color_manual(name = "Vendor",values = c("A1"="#01665e","A2"="#f
fffb3","B1"="#4575b4","B2"="#d73027"))+
  labs(title= str_c("Observed vs Predicted Volume for ", WellCode),
       subtitle="End Gun Corrections",
       x="Observed Volume in Gallons (Flow Meter)",
       y="Predicted Volume in Gallons (Electrical Algo)",
       caption = "")
plot(ob_vs_pred_T4)
```



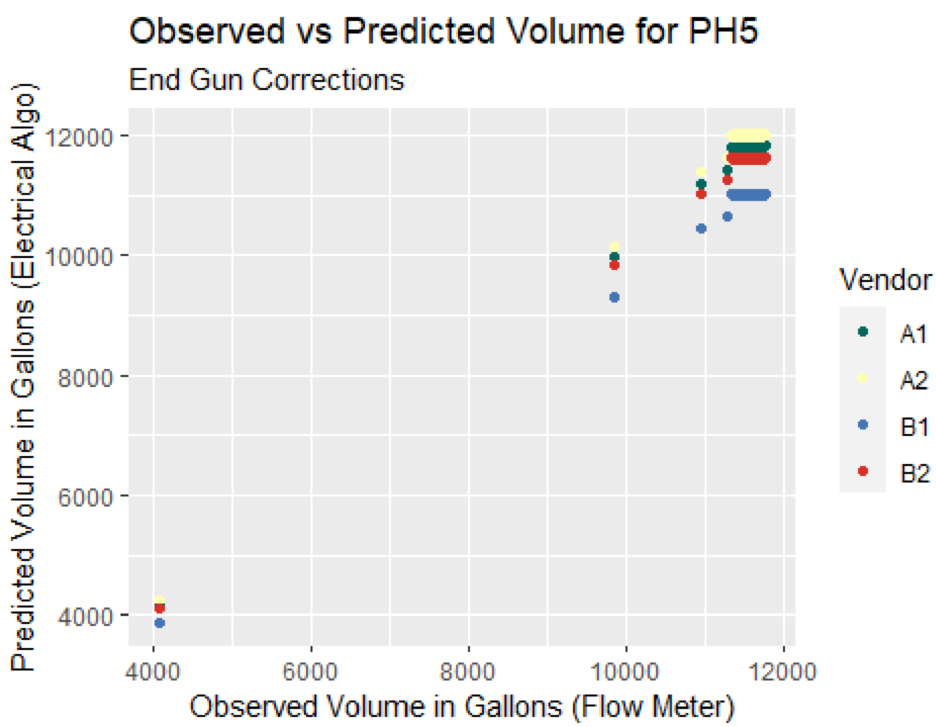

```
sum(df$acft_flow_meter,na.rm = T)

## [1] 116.2608

sum(df$acft_algo_D1,na.rm = T)

## [1] 106.3415

sum(df$acft_algo_D2,na.rm = T)
```

```
## [1] 113.8563

sum(df$acft_algo_S1,na.rm = T)

## [1] 121.6546

sum(df$acft_algo_S2,na.rm = T)

## [1] 119.386

############################
############################
###### PH2 comparison ######
############################
############################

WellCode = "PH2"
df <- df_PH2 %>% filter(flow_meter>0) %>% filter(irr_time>0)

df$DateTime <- as.POSIXct(strptime(df$DateTime, format = "%Y-%m-%d %H:%
M:%S", tz = "MST")) #"%m/%d/%y %H:%M"
df$KWH_exclude[df$KWH_exclude == 0] <- NA

###### Plot of Observed vs Predicted ######
ob_vs_pred_PH2 <- ggplot(df, aes(x=gal_flow_meter)) +
  geom_point(aes(y=gal_algo_S1,colour = "A1")) +
  geom_point(aes(y=gal_algo_S2,colour = "A2")) +
  geom_point(aes(y=gal_algo_D1,colour = "B1")) +
  geom_point(aes(y=gal_algo_D2,colour = "B2")) +

  scale_color_manual(name = "Vendor",values = c("A1"="#01665e","A2"="#f
fffb3","B1"="#4575b4","B2"="#d73027"))+
  labs(title= str_c("Observed vs Predicted Volume for ", WellCode),
       subtitle="End Gun Corrections",
       x="Observed Volume in Gallons (Flow Meter)",
       y="Predicted Volume in Gallons (Electrical Algo)",
       caption = "")
plot(ob_vs_pred_PH2)
```



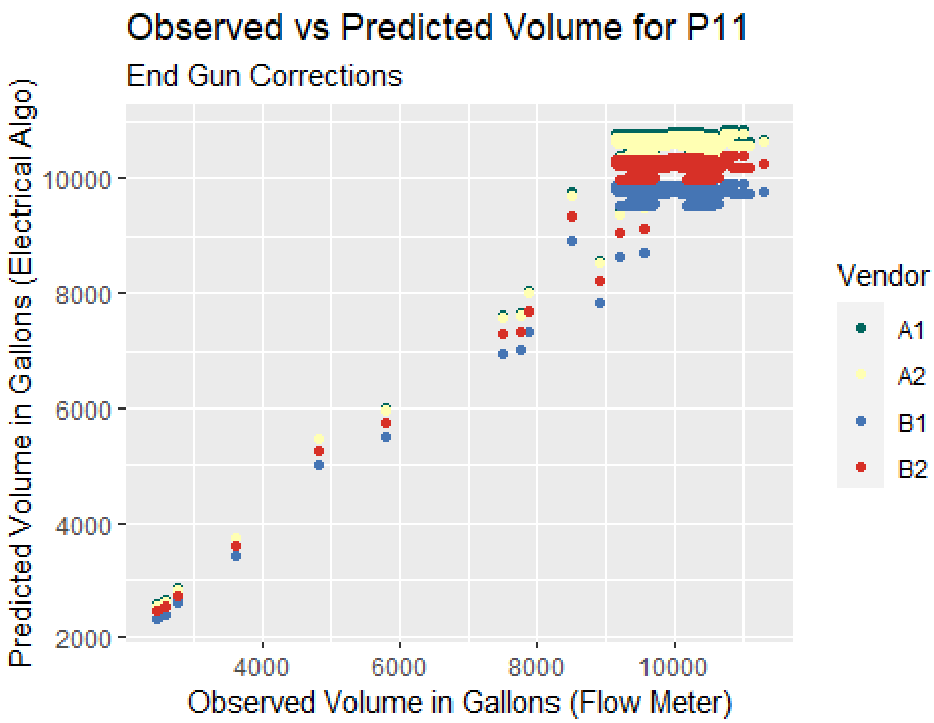

```
sum(df$acft_flow_meter,na.rm = T)

## [1] 107.6927

sum(df$acft_algo_D1,na.rm = T)

## [1] 103.1862

sum(df$acft_algo_D2,na.rm = T)

## [1] 96.37439

sum(df$acft_algo_S1,na.rm = T)

## [1] 93.72536

sum(df$acft_algo_S2,na.rm = T)

## [1] 96.24825

############################
############################
###### PH5 comparison ######
############################
############################

WellCode = "PH5"
df <- df_PH5 %>% filter(flow_meter>0) %>% filter(irr_time>0)
```

```
df$DateTime <- as.POSIXct(strptime(df$DateTime, format = "%Y-%m-%d %H:%
M:%S", tz = "MST")) #"%m/%d/%y %H:%M"
df$KWH_exclude[df$KWH_exclude == 0] <- NA

###### Plot of Observed vs Predicted ######
ob_vs_pred_PH5 <- ggplot(df, aes(x=gal_flow_meter)) +
  geom_point(aes(y=gal_algo_S1,colour = "A1")) +
  geom_point(aes(y=gal_algo_S2,colour = "A2")) +
  geom_point(aes(y=gal_algo_D1,colour = "B1")) +
  geom_point(aes(y=gal_algo_D2,colour = "B2")) +

  scale_color_manual(name = "Vendor",values = c("A1"="#01665e","A2"="#f
fffb3","B1"="#4575b4","B2"="#d73027"))+
  labs(title= str_c("Observed vs Predicted Volume for ", WellCode),
       subtitle="End Gun Corrections",
       x="Observed Volume in Gallons (Flow Meter)",
       y="Predicted Volume in Gallons (Electrical Algo)",
       caption = "")
plot(ob_vs_pred_PH5)
```




```
sum(df$acft_flow_meter,na.rm = T)

## [1] 30.22756

sum(df$acft_algo_D1,na.rm = T)

## [1] 28.79355
```

```r
sum(df$acft_algo_D2,na.rm = T)

## [1] 30.39754

sum(df$acft_algo_S1,na.rm = T)

## [1] 30.867

sum(df$acft_algo_S2,na.rm = T)

## [1] 31.37559

############################
############################
###### P11 comparison ######
############################
############################

WellCode = "P11"
df <- df_P11 %>% filter(flow_meter>0) %>% filter(irr_time>0)

df$DateTime <- as.POSIXct(strptime(df$DateTime, format = "%Y-%m-%d %H:%
M:%S", tz = "MST")) #"%m/%d/%y %H:%M"
df$KWH_exclude[df$KWH_exclude == 0] <- NA

###### Plot of Observed vs Predicted ######
ob_vs_pred_P11 <- ggplot(df, aes(x=gal_flow_meter)) +
  geom_point(aes(y=gal_algo_S1,colour = "A1")) +
  geom_point(aes(y=gal_algo_S2,colour = "A2")) +
  geom_point(aes(y=gal_algo_D1,colour = "B1")) +
  geom_point(aes(y=gal_algo_D2,colour = "B2")) +

  scale_color_manual(name = "Vendor",values = c("A1"="#01665e","A2"="#f
fffb3","B1"="#4575b4","B2"="#d73027"))+
  labs(title= str_c("Observed vs Predicted Volume for ", WellCode),
       subtitle="End Gun Corrections",
       x="Observed Volume in Gallons (Flow Meter)",
       y="Predicted Volume in Gallons (Electrical Algo)",
       caption = "")
plot(ob_vs_pred_P11)
```




```
sum(df$acft_flow_meter,na.rm = T)

## [1] 107.4761

sum(df$acft_algo_D1,na.rm = T)

## [1] 105.0464

sum(df$acft_algo_D2,na.rm = T)

## [1] 110.1319

sum(df$acft_algo_S1,na.rm = T)

## [1] 114.8995

sum(df$acft_algo_S2,na.rm = T)

## [1] 114.2638
```