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Building Databases to Calibrate Alfalfa Crop Models: Paving the Way for an Advanced Yield Forecasting Tool

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ABSTRACT. *Escalating pressure on water resources in the western U.S. has led alfalfa (Medicago sativa L.) producers in this region to adopt irrigation practices falling below the crop's optimal evapotranspiration levels. This has resulted in deficit irrigation and diminished yields. This study is part of a project that aims to develop an alfalfa hay Yield Forecasting Tool (YFT) that can be used to estimate the effects on yield of different irrigation management decisions. The YFT will utilize weather, soil characteristics, crop agronomics, crop management, and crop development indicators for this purpose. In the future, the YFT will be integrated into a Decision Support System that will be designed to recommend irrigation management decisions that can minimize yield losses caused by insufficient irrigation. This study aims to build comprehensive databases with varying levels of data completeness that can be used to train and test alfalfa crop growth models and machine learning algorithms that will be embedded in the YFT for robust alfalfa yield forecasting. The databases were created using 210 crop years of data from historical and ongoing field experiments in the Texas High Plains and Northern Nevada. Managing extensive information from diverse experimental domains with varying data completeness necessitates comprehensive databases for training different crop growth models and machine learning algorithms. This study will describe the generation of such databases.*

Keywords. *Alfalfa, crop growth mode, machine learning, yield forecasting, irrigation scheduling.*

Introduction

Alfalfa, scientifically known as *Medicago sativa* L., is a perennial, C-3, forage legume known for its nutritional value, versatility, and agronomic benefits (Barness et al., 2003; McDonald et al., 2021). Originating in Iran and Central Asia, alfalfa has been cultivated for centuries. Its introduction to the U.S. was first recorded in Utah (Brough et al., 1997), and it is now the third most economically important crop in the country (USDA-NASS, 2023). Alfalfa is widely cultivated across the U.S., covering approximately 15.6 million acres, with an average productivity rate of 3.2 tons per acre (National Forage Review, 2023). However, the increasing cultivation of this dietary feeding crop has faced significant challenges, particularly in regions with limited water resources. Arid and semiarid areas, characterized by hot summers and cold winters, are particularly affected. The mounting pressure on water resources is forcing alfalfa hay producers in these regions to irrigate without meeting the full evapotranspiration (ET) needs of the alfalfa crop, threatening the yield and hence the livelihood of communities in the same region (Klocke et al., 2013; Sammis, 1981; Sheaffer et at, 1988).

Alfalfa's economic importance and relatively large water footprint in the western U.S. (National Forage Review, 2023) are motivating researchers to develop Deficit Irrigation (DI) management strategies that can help farmers reduce water consumption while minimizing yield reduction loss. Thus, our long-term goal is to develop a Smart Deficit Irrigation Scheduling Method (SDISM) that will use an optimization method and an alfalfa hay Yield Forecasting Tool (YFT) to identify irrigation management decisions that optimize alfalfa hay yield without exceeding a limited seasonal water budget. The optimization method will use the YFT to estimate the alfalfa yield from various potential irrigation management scenarios. We expect the SDISM to help alfalfa producers make informed decisions throughout the irrigation season by recommending how much and when to irrigate to achieve an alfalfa hay yield that is as large as possible within a given seasonal water budget.

The alfalfa YFT will incorporate an alfalfa crop growth model or a machine learning algorithm to consistently estimate alfalfa hay yield with accuracy. The specific objective of this study is to generate a dataset to calibrate and evaluate data-intensive alfalfa crop growth models, such as the CROPGRO-Perennial Forage Model (PFM) and the Agricultural Production Systems sIMulator (APSIM), as well as machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM) and eXtreme Gradient Boosting (XGBoost). The best performing crop growth model and/or machine learning algorithm will be embedded in the alfalfa YFT to predict the effects that different irrigation amounts will have on seasonal alfalfa hay yield. Previously, Quintero et al. (2023) used a machine learning approach to estimate alfalfa hay yield in Northern Nevada and found that water and extreme temperatures are the most important weather components affecting yield. However, the study also emphasized that more data is needed to accurately represent the effects of different biotic and abiotic factors on crop yield.

To execute this project, preliminary datasets were derived from five different experiments conducted in Northern Nevada and the Texas High Plains. These regions are situated in semiarid areas of the western U.S., where water resources face varying degrees of pressure. Nevada is the most arid state in the country, and alfalfa is its most important crop, accounting for almost half of the irrigated agricultural land in the state (Nevada Agricultural Statistics Bulletin, 2023). Crops grown in Northern Nevada, where the University of Nevada, Reno (UNR) campus is located, experience high consumptive water use, which in combination with negligible precipitation during its growing season makes this region an ideal test bed for DI management strategies for alfalfa grown in arid and semi-arid areas. Similar environmental conditions exist in the semi-arid Texas High Plains, where alfalfa production is expected to increase to meet the demand of the growing regional dairy industry (Quintero et al., 2023). These preliminary datasets will serve as a foundation for developing and testing the alfalfa Yield Forecasting Tool (YFT) and Smart Deficit Irrigation Scheduling Method (SDISM).

In order to be useful for a SDISM that can be used in a wide range of conditions, the YFT should be able to provide an accurate estimation of alfalfa yield using as few data inputs as possible, while prioritizing the use of data that is readily available. Crop growth models and machine learning algorithms will be thus compared using a two-tiered approach, where these computational tools will be evaluated based on the accuracy that they can achieve when they have access to limited (but readily available) data and when they have access to more detailed (but not readily available) data. In this study, we thus compiled two databases using data from historical and ongoing experiments, totaling 210 crop years that were captured in 20 spreadsheets. The first dataset contained data that were considered to be accessible to most crop managers in the western U.S., such as weather data, irrigation amounts and application dates, harvesting dates, and alfalfa hay yield from each harvest. The second dataset contained data that were not typically available to most crop managers in the western U.S. This dataset consisted of all the information from the first database, plus a set of indicators of crop development.

Through the creation of two datasets with different levels of data completeness, our objective is to evaluate the reliability and consistency of crop growth models and machine learning algorithms in predicting alfalfa yield under constrained data availability. This comparative analysis would enable us to pinpoint the most accurate and robust approach for alfalfa yield estimation, thereby improving agricultural decision-making and management practices.

Dataset Description

Introduction to Experimental Designs

The two databases were generated using data from two historical and three ongoing experiments. The first historical source consists of a series of experiments conducted in UNR's Newlands Agricultural Research Center in Fallon, NV, spanning from 1973 to 1978 and 1981 to 1982. The objective was to measure weekly ET of alfalfa cultivated on three large non-weighing lysimeters with three different water table depths: (i) a fluctuating water table matching the field water table depth, (ii) a static water table at a depth of 1.219 m (4 ft), and (iii) a static water table at a depth of 1.829 m (6 ft). The experiment was planted in 1972 with the alfalfa variety "Washoe" (Guitjens, 1974). This experiment provides a total of 24 crop years (3 lysimeters × 8 years) of data.

The second historical experiment took place at the USDA-ARS Conservation and Production Research Laboratory (CPRL) in Bushland, TX from 1996 to 1999. It aimed to measure the ET of alfalfa cultivated on two large weighing lysimeters. Alfalfa was irrigated using a linear move sprinkler irrigation system, applying full irrigation (FI) for the first three years and Deficit Irrigation (DI) in the final year. This experiment was planted in 1995 with the alfalfa variety "Pioneer 5454" and provided 8 crop years (2 lysimeters × 4 years) of data (Evett et al., 2016). This dataset is available to the public through the Ag Data Commons online repository (Evett et al., 2022a).

Transitioning to ongoing experiments, the first experiment aims to evaluate the response of two alfalfa varieties to FI, mild DI (80% of FI), and moderate DI (60% of FI) at the UNR Valley Road Field Laboratory (VRFL) in Reno, NV. The experiment was planted in the fall of 2020 with two alfalfa varieties: "Ladak II" (Great Basin Seed), marketed as drought tolerant, and "Stratica" (CROPLAN), marketed as producing high forage yield. Experimental plots measuring 9.14 m × 1.52 m (30 ft × 5 ft) were irrigated with a drip irrigation system. This experiment was carried out over three growing seasons from 2021 to 2023, yielding a total of 54 crop years (18 plots × 3 years) (Cholula et al., 2022).

The second ongoing experiment, conducted at the CPRL in Bushland, TX, evaluates alfalfa's response to FI, and mild DI (70% of FI) with different fertilizer and manure treatments. The experiment was planted in 2022 with the alfalfa variety "RR 6 Shot Plus" (CROPLAN). Plots were irrigated with a center pivot irrigation system equipped with a commercial variable rate irrigation (VRI) system. Each treatment plot, measuring 9.14 m × 9.14 m (30 ft × 30 ft), contains a neutron access tube centered within the plot. Over two years (seasons 2022 to 2023), this experiment provides 64 crop years of data (32 plots × 2 years).

Lastly, the third ongoing experiment is being conducted at the UNR VRFL in Reno, NV using a linear move VRI system. Alfalfa varieties "6516R" (Nexgrow) and "Ladak II" were planted in the spring of 2022. Experimental plots were assigned one of the following irrigation treatments: (i) FI, (ii) mild constant DI (80% of FI), (iii) moderate constant DI (60% of FI), (iv) mild regulated DI (matching 80% of FI), and (v) moderate regulated DI (matching 60% of FI). A FI treatment was applied to all plots during the 2022 growing season to ensure good stand establishment. Irrigation treatments were initiated in the 2023 growing season, and this experiment provides 60 crop years of data (30 plots × 2 years).

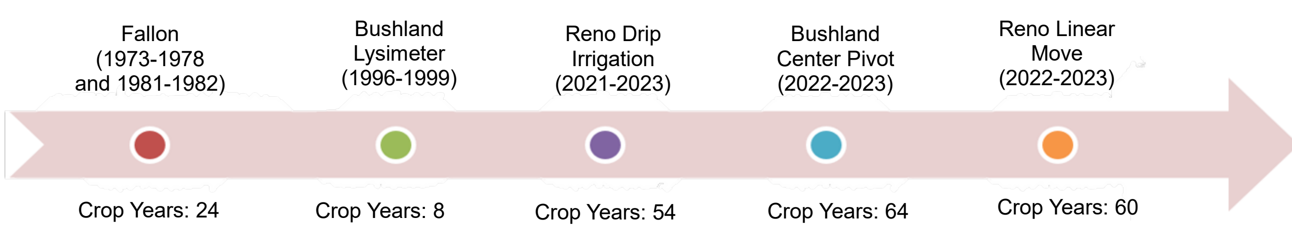

Figure 1: Data from five experiments conducted in Northern Nevada and the Texas High Plains were used to generate two databases with different degrees of data completeness. The number of crop years contributed from each experiment is included below a circle representing each experiment in a timeline.

Level 1 Dataset – Data available to most crop managers

The first dataset, containing information that is accessible to most crop managers in the western U.S., will encompass weather data, irrigation amounts and application dates, harvesting dates, and alfalfa hay yield from each harvest.

Weather Data

Throughout the growing season, daily and hourly weather data were gathered from different weather stations near experimental fields. For Bushland's experiments, the source of weather data was research weather stations adjacent to the lysimeters (Evett et al., 2018). These data are available in the online repository of the USDA ARS NAL Ag Data Commons

(Evett et al., 2022b). For the Reno experiments, the source was a weather station located at the VRFL, at approximately 250 m from the field where the experimental plots were located. Data reported by this weather station is available through the Western Regional Climate Center's website (WRCC, 2024). The following meteorological parameters were included in the Level 1 Dataset when available for an experiment:

1. Total Solar Radiation (expressed in kW-hr/m2)
2. Average Wind Speed (measured in m/s)
3. Average Air Temperature (recorded in degrees Celsius)
4. Total Precipitation (measured in millimeters)
5. Relative Humidity (expressed as a percentage)

Soil Data

Soil information includes general site and surface information as well as soil profile characteristics. These data can be obtained from the USDA-NRCS's Web Soil Survey (NRCS, 2024) and/or by testing soil samples in a laboratory. The following site and soil information were included in the Level 1 Dataset when available for an experiment:

1. Location of experimental site
   - Latitude
   - Longitude
   - Elevation
2. Soil Surface information
   - Soil Series
   - Soil Classification
   - Soil Color
3. Soil Profile data for each soil horizon
   - Sand, Silt, and clay (%)
   - Soil Texture
   - Filed Capacity, Permanent Wilting Point, and Available Water Capacity
4. Soil Chemical Properties (According to soil analysis report)
   - Organic Matter (%)
   - Individual Macronutrients (ppm)
   - Individual Micronutrients (ppm)
   - Soil pH
   - Cation Exchange Capacity (meq/100g)
   - Percent Cation Saturation
   - Soluble Salts (mmhos/cm)

Soil-Water Data

Time Domain Reflectometers (TDRs) and Neutron Probes were used to measure soil water content levels across different experiments (Table 1). These devices enabled the measurement of volumetric water content (%) at various depths within the soil profile.

Table 1: Individual experimental details of soil water sensing systems used to estimate soil water content.

Experiment	Soil water sensing device	Frequency of soil water content data collection
Fallon (1973-1981)	Neutron Probe (model 4302, Troxler, Research Triangle Park, NC)	Weekly
Bushland Lysimeter (1996-1999)	Neutron Probe (model 503DR1.5, Campbell Pacific Nuclear, Martinez, CA)	Weekly
Reno Drip Irrigation (2021-2023)	TDRs (model 315H, Acclima, Meridian ID)	Hourly
Bushland Center Pivot (2022-2023)	Neutron Probe (model 503DR1.5, Campbell Pacific Nuclear, Martinez, CA)	Weekly
Reno Linear Move (2022-2023)	TDRs (model 315H, Acclima, Meridian ID)	Hourly

Irrigation Management

Distinct irrigation systems were employed for each experiment, as outlined in Table 2. Each experiment encompasses a diverse range of irrigation treatments, spanning from full irrigation (full replenishment of soil water depletion to field capacity within the root zone) to constant and regulated deficit irrigation methodologies. Additionally, the Level 1 dataset included the date of each irrigation event and the irrigation amount applied (in mm) to individual plots. This record of irrigation management data enables the comparison of different water management strategies employed across the experiments, which can be considered by the alfalfa crop growth models and machine learning algorithms.

Alfalfa Harvesting dates and hay yield for each harvest

The harvesting dates of alfalfa, along with the corresponding dry hay yield (in Mg/ha) for each plot, were included in the Level 1 dataset. Dry hay yield will be the main variable to be forecasted by the crop growth models and machine learning algorithms.

Table 2: Availability and collection intervals of weather, crop, and crop management data included in two datasets that will be used to train and evaluate crop growth models and machine learning algorithms. Superscripted numbers following the name of parameters in the first column indicate if the parameter is readily available to most crop managers[1] (and thus the parameter is included in the Level 1 dataset) or not readily available to most crop managers[2] (and thus the parameter is only included in the Level 2 dataset).

Location	Fallon	Bushland	Reno	Bushland	Reno
Years	1973-1978 and 1981-1982	1996-1999	2021-2023	2022-2023	2022-2023
Irrigation System	Flood	Linear move	Drip	Center pivot	Linear move
Crop years	24	8	54	64	60
Weather data W collection interval (if available)					
Air temp.1	Daily	15 min	1 h	1 h	1 h
Rel. Hum.1	Weekly	15 min	1 h	1 h	1 h
Solar irrad.1	N/A	15 min	1 h	1 h	1 h
Wind speed1	Weekly	15 min	1 h	1 h	1 h
Precipitation1	Daily	15 min	1 h	1 h	1 h
Crop development data C collection interval (if available)					
LAI2	N/A	Biweekly	Biweekly	N/A	Biweekly
Plant height2	N/A	Biweekly	Biweekly	Monthly	Biweekly
Biomass2	N/A	Biweekly	Biweekly	N/A	Biweekly
Growth stage2	N/A	Biweekly	N/A	N/A	N/A
ET2	Weekly	Daily	N/A	N/A	N/A
Hay yield1	4 cuts/yr	4 cuts/yr	4 cuts/yr	4 cuts/yr	4 cuts/yr
Crop management M data collection interval (if available)					
Irrigation schedule1	Variable	Variable	Variable	Variable	Variable
Soil water1	Weekly	Weekly	Hourly	Weekly	Hourly
Harvesting days1	4 cuts/yr	4 cuts/yr	4 cuts/yr	4 cuts/yr	4 cuts/yr

Level 2 Dataset- Data not available to most crop managers

The second dataset contains all the information from the first dataset, plus additional information not typically available to most crop managers, such as Leaf Area Index (LAI), plant height (cm), fresh biomass (Mg/ha), growth stage, and ET (mm). The inclusion of this additional information will allow us to determine if these parameters have a significant impact on alfalfa yield.

Crop development indicators

Agronomic indicators of crop development provide valuable insights into the development and progression of the alfalfa crop over time (Yang et al., 2024). Measurements of plant height, LAI, and growth stage were available for the Bushland Lysimeter, Reno Drip, and Reno Linear Move experiments but not for the Fallon Lysimeter and Bushland Center Pivot experiments (Table 2). This lack of data was due to various factors, such as experimental design constraints or logistical challenges. Despite this limitation, the available data could offer significant information for analysis.

Evapotranspiration

Evapotranspiration data (mm) included in the Level 2 dataset were recorded weekly throughout the duration of each growth season for the Fallon Lysimeter experiment (1973-1981), and daily for the Bushland Lysimeter experiment (1996-1999) (Table 2). Adding this parameter to the Level 2 dataset could improve crop growth models and machine learning algorithms by better accounting for water losses resulting from the combined effects of soil evaporation and plant transpiration processes. The availability of ET data for these two experiments could facilitate in-depth analysis and interpretation of the water dynamics within experimental plots, aiding in understanding the crop water requirements and growth performance over time.

Biomass

The Level 2 dataset included fresh and dry biomass data (Mg/ha) collected on a biweekly basis for the Reno Drip (2021-2023) and Bushland center pivot (1996-1999) experiments. These data could offer insights into the biomass accumulation and productivity of alfalfa over time, aiding in the assessment of their overall health and vigor throughout the growing season.

Conclusion

A comprehensive two-tier database has been constructed, comprised of 20 spreadsheets (one per growing season of each experiment), containing data from five experiments conducted in Northern Nevada and the Texas High Plains and totaling 210 crop years. This database lays the foundation for a forthcoming study aimed at identifying a computational tool—among alfalfa crop growth models and machine learning algorithms—that could accurately forecast alfalfa yield under diverse irrigation management conditions using limited data inputs.

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