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Effects of irrigation scheduling approaches on soil moisture and vegetable production in the Northeastern U.S.A.

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A R T I C L E I N F O

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A B S T R A C T

The Northeast United States is a temperate region that has historically experienced even rainfall distribution across the agricultural growing season. Due to climate change, seasonal precipitation and temperature dynamics are shifting, causing many farmers to rethink their approach to irrigation. Soil-water sensing technology, including tensiometers and granular matrix sensors, are often used by farmers to increase water use efficiency. However, adoption of these technologies is low in the Northeast. We conducted a field study to assess the potential of soil-water sensing hardware and software to improve crop outcomes in temperate agricultural regions such as the Northeast, and a survey to better understand farmer preferences for using soil moisture sensors and associated data. The survey involved two vegetable farmer industry associations, and focus groups at four agricultural conferences. We found a diversity of preferences among farmers when it comes to when and how they would like to access soil-water data. The cost of cloud-based data collection and storage is a barrier for some farmers, and they question the economic benefits of investing in these platforms. Additionally, we conducted field experiments in two locations across two growing seasons to investigate how using three irrigation strategies (feeling the soil, granular matrix sensors, and timers) affect soil-water conditions, leaching, and crop yield and quality. We found no significant effects of irrigation strategy on yield, though our results suggest other advantages in using soil moisture sensors. For example, the use of sensors increased the proportion of days during the growing season in which soil-water was in the optimal field capacity category. Therefore, using these sensors will reduce potential environmental risk associated with N contamination of groundwater.

1. Introduction

The northeast (NE) region of the U.S. has seen an 84 % increase in the number of farms in all sectors since 1992, with the farms tending to be small (38 ha average compared to 95 ha nationally) and highly diversified (Aguilar et al., 2015; USDA-NASS, 2012). In 2012, there were 26, 491 vegetable farms in the NE region totaling 163,000 ha, and reporting over 1B USD in annual sales (USDA-NASS, 2012). Efficient water use is an important component of sustainable vegetable production for several reasons. Applying the correct amount of water helps to maximize crop yield and quality, as well as reducing the risk of the leaching crop nutrients away from the root zone, which costs farmers money and can lead to high sediment loads which impair public waterways through eutrophication (Brooks et al., 2016; Imtiyaz et al., 2000) and groundwater

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contamination. Additionally, some growers find that water use efficiency is necessary if water resources are limited or if they purchase municipal water.

The NE region has long been considered to have abundant water resources. For vegetable producers, this has meant that access to water through rainfall, ground water, or surface reservoirs was generally sufficient for crop production. In recent years, however, the changing climate has challenged producers in two ways. First, heavy rain events, defined as the heaviest 1 % of daily rain events over an annual period (Melillo et al., 2014), have increased by 71 % in the NE region between 1958 and 2012 (Kunkel et al., 2013). In the NE region, this translates to rain events with more than 5–10 cm per day (Horton et al., 2011). This increase in heavy rain events is greater than in other regions in the United States (Walsh et al., 2014). Heavy rain events can lead to saturated soils, which can result in root anoxia and spread of root and foliar diseases (Volynchikova and Kim, 2022). Saturated soils can additionally lead to denitrification and potential emissions of nitrous oxide from anaerobic soils. Second, episodic drought is increasing in frequency and severity across the region, driven by higher temperatures, longer growing seasons, and longer dry periods between rainfalls (Sweet et al., 2017). Drought is not only a natural phenomenon, but an interaction between environmental conditions and demand placed on water resources by human activities (Wilhite and Buchanan-Smith, 2005). Excessive heat, which can exacerbate heat conditions, has been indicated as an overlooked stressor of plant water needs (Battisti and Naylor, 2009); crops require more water when ambient temperatures are high due to increased transpiration and potential heat stress.

Compared to vegetable growers in western states such as Arizona and California, NE vegetable growers apply much less irrigation water to crops, however it is likely that even NE growers will need to increase the amount of water they apply to crops in coming years as agricultural droughts increase in frequency and severity. There is evidence that this is already happening: for example, in 2016 vegetable producers in western New York experienced yield loss due to drought. Vegetable and fruit producers who irrigated their crops experienced losses of 19 % and 11 %, respectively, while those who did not irrigate reported 40 % and 47 % loss, respectively (Sweet et al., 2017). Similar losses occurred in Massachusetts, where 29,000 acres were affected by drought in the same year, leading to a request for a disaster declaration from the USDA (Campbell Nelson et al., 2017).

The shifting precipitation patterns present significant challenges to NE vegetable growers to ensure that crops receive sufficient water for production purposes, but not so much water as to lead to root anoxia and nutrient depletion. However, farmers are generally not knowledgeable about the degree to which their management practices are “water efficient” because they do not know their crop water needs, actual amounts of water applied, or the effect of water application on yield (Levidow et al., 2014). To achieve sustainable vegetable production systems, including resource conservation and farm profitability, it has been proposed that growers will need to move away from traditional methods of irrigation scheduling (i.e. observation of plant condition and/or feel of soil) and employ scheduling based on real-time soil moisture measurements. Increased use of localized soil monitoring can inform management decisions, consider local heterogeneity in a management unit, and provide information on the relationships between soil condition and plant growth (Viscarra Rossel and Bouma, 2016). Indeed, the development and widespread use of soil moisture sensing has been identified as an important priority in the ongoing work to further advance food and agricultural research (National Academies of Sciences Engineering and Medicine, 2018).

While there are a wide range of soil moisture sensing technologies available to help farmers achieve positive outcomes, tensiometers and granular matrix resistance sensors are particularly useful for farmer use due to their relative low cost and level of reliability (Heng, 2008). Advances in soil moisture sensing software and technology in recent years, accompanied by the introduction of new lower costs options, presents an opportunity to expand use of remote sensing systems to vegetable systems in the NE region of the U.S.

Although investing in these systems makes ecological and environmental sense, farmers are also concerned about the economic implications of these investments (Knox et al., 2012). It has been shown that, even in temperate climates like the NE region, precision irrigation has a positive economic benefit because of the way in which it supports yield, crop condition, and revenue during periods of periodic drought where water access may be constrained (Rey et al., 2016). A case study by the University of Vermont and the USDA Northeast Climate Hub (Knight and Hodgson, 2017) shows that even in years with plentiful rainfall, irrigation can have positive financial impacts on net returns. However, many growers in the NE may still be skeptical of the economic benefits of irrigation in general, and precision irrigation more specifically. Despite the benefits of soil moisture sensing technology in increasing water use efficiency and decreasing nutrient applications (National Academies of Sciences Engineering and Medicine, 2018), widespread adoption is not evident in the NE vegetable sector. Many NE vegetable growers irrigate as part of their management system, however in 2013, only 215 farms (out of 4098) in the New England Water Resource Region reported using soil moisture sensors (Schattman et al., 2018; USDA-NASS, 2014).

Our study has two objectives that will contribute to enhanced use and usability of precision irrigation in NE vegetable systems through an integrated field and social science investigation. First, a grower survey was used to get a better understanding of the current barriers that keep NE producers from investing in soil moisture sensing technology for irrigation management and determine what they need from the technology to enable them to use it effectively. We then conducted focus groups with commercial growers at four conferences where we introduced soil moisture sensor hardware and software, and collected farmer perspectives on the opportunities and challenges associated with these technologies. Second, a multi-year field study located in Maine and Vermont, U.S. was conducted to test the effects of three different irrigation decision approaches on soil moisture level, crop yield and quality, and subsurface N loss. The irrigation decision treatments were based on: 1) feel of the soil; 2) soil tensiometer readings; 3) daily timed irrigation, and 4) a control treatment that received no irrigation.

2. Material and methods

2.1. Grower survey and analysis

In 2017, we developed a survey instrument designed to assess whether farmers in the NE irrigated, approximately the proportion of their production areas that they irrigated, and how they decided when to apply water (and when to stop). Several of the survey questions were adapted from those used by the U.S. Department of Agriculture’s Economic Research Service (ERS), which conducts a national-scale irrigation survey approximately every five years. Five Extension personnel and one farmer tested the survey prior to deployment. IRB Exemption was secured through the University of Vermont (CHRBSS: 18-0199).

The survey was executed in UVM Lime, an online platform that allows for branching logic. The target participants were subscribers to the Vermont Vegetable and Berry Growers Association (VVGBA) listserv (608 subscribers in 2017, including an estimated 523 farmers) and subscribers to UMass VegNotes Newsletter (2786 subscribers, including an estimated 1906 farmers). The combined estimated number of farmers on both lists was 2167 individuals. Though we targeted farmers in Vermont and Massachusetts, some subscribers to the VVGBA listserv and the VegNotes Newsletter come from other NE states. We addressed potential overlap in subscribers to both lists by creating survey settings that placed cookies once respondents took the survey, disallowing duplicate submissions.

The survey was deployed three times between November 8, 2017 and January 11, 2018. These surveys were executed without incentives. In addition, we conducted an intercept survey with the same on-line survey instrument at the annual VVGBA members meeting in January, 2018. Participants in the intercept survey were incentivized with a free water test (value 8 USD). The survey was closed on February 6, 2018. We collected responses from 155 individuals (26 partial responses, 121 full responses). Using the AAPOR response rate approach 4, which accounts for both partial and full responses (AAPOR, 2016), we calculated that the response rate for VVGBA members was 10 %, the response rate for VegNotes subscribers was 1 %, and the combined response rate was 5 %. Because of low response rates, the results that we report from this survey should be interpreted with caution; they are indicative of survey respondents only, and should not be generalized to the greater population of vegetable producers in the NE. We present them in this manuscript to show our integrative approach to social and natural science. To do so, we derive methods and approaches from several disciplines. Low-inference descriptions such as verbatim quotes from participants helps to establish validity (Johnson, 1997), and we therefore include unedited responses to open-ended survey questions in our results. Analysis was conducted using IBM SPSS Statistics 24 (IBM, 2017).

Focus groups were conducted with growers at four regional conferences in 2019–2020 (prior to the COVID-19 pandemic). The conferences attended were the Pennsylvania Association for Sustainable Agriculture (PASA) annual conference, the Vermont Vegetable and Berry Growers Association (VVGBA) annual meeting, the bi-annual New England Vegetable and Fruit Conference, and the Maine Organic Farmers and Gardeners Association (MOFGA) Farmer to Farmer Conference. At all sessions, growers were offered monetary stipends and lunch for attending the special session. Focus group sessions were preceded by an educational presentation, followed by an open discussion about grower thoughts on using soil moisture sensors in their irrigation management systems. Attendees were asked to fill out pre- and post-workshop questionnaires to assess the effects of the event on their perceptions and willingness to invest in soil moisture monitoring systems. Outreach was conducted through conference organizers. Between the four focus groups there were 22 participants.

2.2. Field site locations and plot installation

This research was conducted at Rogers Farm, University of Maine, Old Town, ME (44.93° N, 68.70 W, 42 m) in 2021 and 2022 and the Horticultural Research and Education Center, University of Vermont, S. Burlington, VT (44.43° N, 73.21° W, 67 m) in 2019 and 2021. The soil at the Maine site was a Pushaw silt loam (fine-silty, mixed, semiactive, nonacid, frigid Aeric Epiaquept), and at the Vermont site it was an Adams Windsor loamy sand (Adams: sandy, isotic, frigid Typic Haplorthods; Windsor: mixed, mesic Typic Udipsamment) (USDA-NRCS, 2016). Selected soil physical and chemical parameters are shown in Table 1.

At both sites zero-tension lysimeters based on the Zotarelli et al. (2007) design were installed in a trench 60 cm deep to allow leachate sampling below the mature crop rooting zones. After installation the trenches were back filled with the excavated soil. Collected leachate was extracted through a sampling tube extending above the soil surface using a portable vacuum pump. Watermark model 200SS sensors (Irrometer Co., Riverside, CA) were installed at 30 cm and 60 cm depths on all twelve plots at both sites. The Maine site used a cellular-based IRROcloud IC-10, and the Vermont site used a WiFi-based IRROmesh (Irrometer Co., Riverside, CA) system for hourly data logging and archiving. Irrometer 200TS Watermark temperature sensors (Irrometer Co., Riverside, CA) were also installed in the plots for temperature self-compensation of the soil moisture sensor readings. Twelve raised bed plots were hand-built at both sites to incorporate the randomized block design of three treatments with three replicates. The plots were 8.64 m^2 at the Maine site with 0.6 m buffer borders on all sides and 4.46 m^2 in Vermont with 0.9 m buffer borders on all sides.

Table 1
Selected chemical and physical properties for Maine and Vermont soils in this study.

Soil parameter	Maine	Vermont
pH	5.7	6.6
Organic matter (%)	4.9	2.6
Sand (%)	17.6	88.9
Silt (%)	81.9[a]	6.4
Clay (%)		4.7
Soil texture class	Silt loam	Loamy sand

[a] Lab assessment combined silt and clay for Maine soils.

2.3. Irrigation system design and scheduling approaches

The irrigation source at both sites provided 103 kPa of water pressure to the system. The mainline was split into three header pipes for the separate irrigation treatments, each fitted with a timer and a flow meter. Within each irrigated plot, six lines of drip tape with 28 cm emitter spacing were installed. Water applications to the irrigated treatment plots were recorded weekly from the three flow meters installed in the treatment header pipes. Ambient precipitation was estimated using NOAA weather station data located at the Bangor International Airport (16.5 km from the Maine study site) and the Burlington International Airport (6.1 km from the Vermont study site). Daily evapotranspiration at both sites was modeled using the Climate Smart Farming Water Deficit Calculator (DeGaetano and Belcher, 2022).

Three irrigation scheduling methods plus a non-irrigated control treatment were investigated. All three treatments were developed based on preliminary survey data collected by our team (Schattman et al., 2018), specifically questions that investigated how farmers in the NE United States decided when to turn irrigation water on, and when to turn it off. Treatment 1 (i.e., 'Bradshaw Toe Drag') was based on the feel of the soil, assessed daily, to initiate irrigation when the soil was 'dry' (USDA-NRCS, 1998). Feeling the soil to make irrigation decisions is a common, traditional method used by growers in the NE (Schattman et al., 2018) and nationally (Hrozencik and Aillery, 2021). Treatment 2 irrigation was initiated when the soil tensiometer at 30 cm soil depth reached 20 kPa of water tension. The specific threshold was based on a rough estimation that would likely meet the needs of all three crops in our experiment, according to guidance published by the Irrometer Company (Riverside, CA). Treatment 3 was timer-based to apply irrigation daily. Many greenhouse growers use timers as a low-cost irrigation automation approach, especially in greenhouses. Treatment 4 was the control plot that did not receive irrigation. Irrigation volumes were all converted to depth units (i.e., cm) for the presentation of results. All treatments received ambient precipitation.

2.4. Vegetable crop planting and harvest

Fertility amendments were based on standard soil test results obtained with the Modified Morgan's (ammonium acetate, pH 4.8) extractant which is widely used in the NE U.S. (Wolf and Beegle, 1995). The soil test results for the macro- and micro-nutrients at both sites were in the medium to optimum range, with the exception of the P test value in Vermont which was in the high or excessive range. In Maine, 33 g m^{-2} of 10-10-10 fertilizer and 2440 g m^{-2} of lime was added at the start of the study in 2021 and no fertilizer was applied in 2022. In Vermont, 163 g m^{-2} of 8-2-2 dehydrated poultry manure and 33 g m^{-2} of K_2SO_4 was applied in 2019. In 2021, 244 g m^{-1} of 7-2-6 fertilizer was applied. Four seedlings each of 'Olympus F1' bell peppers (*Capsicum annuum*), 'Marketmore' cucumbers (*Cucumis sativus*), and 'Early Girl' tomatoes (*Solanum lycopersicum*) were planted in each plot using black plastic mulch at both sites. The seedlings were transplanted on June 3, 2021 and June 20, 2022 in Maine and May 29, 2019 and May 25, 2021 in Vermont. After reaching marketable stage, the crops were harvested twice each week and the count and weight recorded for each crop. The crops were also assessed for quality using a standard 1–5 grading scale for color uniformity, shape uniformity, gloss, firmness, and the presence/absence of defects (Mitcham et al., 1996). The final harvests were on October 10, 2021 and September 29, 2022 in Maine and were on October 7, 2019 and October 18, 2021 in Vermont.

In this study, we simulated a diversified cropping system by planting three crops in close proximity: tomato (*Solanum lycopersicum*), bell pepper (*Capsicum annuum*), and cucumber (*Cucumis sativus*). Through doing so, we sought to simulate the irrigation decision making of farmers in the Northeast United States. According to the United States Department of Agriculture, in 2012 the Northeast was home to 18,649 vegetable and 11,870 fruit operations, which together generated 2.3 billion USD in gross sales (USDA-NASS, 2014). Many of these farms are highly diversified; in fact this region has the highest degree of agricultural diversity of any in the country (Aguilar et al., 2015). Farmers often make irrigation decisions in “blocks’’ that encompass more than one type of crop or crop family. Crops are often rotated to break pest, weed, and disease cycles, and to allow for fallow periods or green manure production.

In addition, all three of the crops included in our study are grown in a variety of different ways in the Northeast. For example, tomatoes can be grown in the field or in greenhouses. Some tomato growers use grafted plants, with the desired cultivar top worked onto a highly productive and/or disease resistant rootstock (Benton Jones, 2007). All three crops are often (but not always) grown using black plastic mulch as a weed barrier. Some farmers in the region irrigate these crops, but many do not.

2.5. Soil N extraction and lysimeter solution analyses

To investigate the effect of irrigation treatments on available N dynamics, weekly soil cores between 15 and 30 cm depth were taken. The soils were extracted with 1 *M* KCl and analyzed using a flow-through analyzer with a Cd-reduction column to convert the nitrate to ammonium form. To monitor N loss from the crop rooting zone, the 60-cm soil depth lysimeter samples were collected weekly, volume recorded, and analyzed for nitrate content as above.

2.6. Statistical analysis

All statistical analysis was conducted using JMP© v. 16.0.0 (SAS Institute, Cary, NC). Each site-year was analyzed separately due to different soil and environmental conditions using ANOVA with the four treatments as the independent variable. Each of the dependent variable datasets was fit to the normal distribution in the quantile plot and the Shapiro-Wilk and Anderson-Darling goodness of fit test was used to evaluate whether the normal distribution assumption was valid by using a $P < 0.05$ threshold to indicate a poor normal fit. Non-normal data was transformed to approximate normal distribution with the Box-Cox transformation using optimized λ power parameter calculated by the boxcox function in MATLAB Release R2022b (Mathworks, Natick, MA) prior to ANOVA testing. Tukey’s HSD range test was used for means comparison when the ANOVA P-value was < 0.05. Trends in weekly data were fit using locally-weighted regression and smoothing scatterplots analysis as implemented by JMP© using quadratic local fitting (λ), tri-cubic weighting function, and a smoothness (α) value of 0.7.

3. Results and discussion

3.1. Farmer survey and focus groups

The majority of the 155 survey respondents reported growing vegetables (80 % of respondents), berries (50 %), cover crops (50 %), ornamentals (16 %), tree fruit (9 %), and livestock feed (9 %). Seventy-six percent of respondents reported producing products in two or more of the categories listed. Seventy-six percent of respondents were farm owners, while 39 % were farm managers and 6 % were farm staff. On average, respondents had 19 years of experience working on their current farm, with a standard deviation of 15 years. The majority of respondents were from Vermont (60 %) and Massachusetts (24 %).

Respondents reported acreage in production (mean = 26 acres, median = 8 acres) and square feet in high tunnel production (mean = 7287 sq. ft., median = 2940 sq. ft.). We asked respondents to report the number of acres irrigated in 2017 (mean = 15 acres, median = 4 acres). The majority of respondents (90 %) reported irrigating either field acres or high tunnels/greenhouses in 2017. The majority of respondents who reported irrigating (94 %), reported using drip/trickle irrigation. In addition, 59 % reported using non-mobile overhead irrigation systems, and 28% reported using traveling overhead systems.

When asked how they decided when to irrigate, respondents were invited to select as many options as applied to them. The majority of farmers who responded to this question reported that they used crop condition (89 % of respondents) and/or the feel of the soil (83 %) as their cue to irrigate. This aligns with results from the most recent USDA Irrigation Survey (USDA-NASS, 2019) which reports that 78 % of U.S. growers who report irrigating use crop condition as their cue to irrigate, though a small proportion (only 40 %) of U.S. growers use the feel of the soil. Most respondents to our survey (93 %) reported that they did not measure the quantity of water used for irrigation in 2017. It should be noted that irrigation practices are influenced by the regulatory environment in which farmers operate, which may or may not limit the amount of ground or surface water farmers can use for irrigation, as well as reporting requirements (Schattman et al., 2021).

Farmers who attended the focus groups had a range of prior experiences with soil moisture sensors, from a general familiarity to no prior experience. When asked how they decided to initiate and stop irrigation, most (n = 9, or 69.23 % of the 13 participants who answered the pre- and post-workshop/focus group questionnaire) reported that they irrigated based on crop condition and the feel of the soil. This aligns with the survey results noted above. Most respondents (9 out of 13) had never used soil moisture sensors. Three participants had used soil moisture sensors in the past but had discontinued use because the sensors were "too complicated", "were defunct", or there was too much of a cost with "reinvesting on a new farm".

Two common themes that farmers discussed related to soil moisture sensors were: (a) preferences for various data delivery systems (in the field vs. in the cloud), and (b) frequency with which they wanted to view soil water tension data. Additionally, the pre- and post-focus group questionnaire revealed how farmers assessed their irrigation needs in a typical year, and whether their knowledge of soil moisture monitoring changed over the course of the workshop/focus group. Lastly, we asked how much they would be willing to invest in a soil moisture monitoring system, assuming different potential yield increases.

Through the focus group discussions, it became clear that farmers have different preferences for how to access data. Soil moisture data delivery systems include integrated tension gauges, handheld meters that provide point-in-time readings in the field, and dataloggers that record continuous data. Data loggers can be connected to cellular or wireless networks, allowing farmers to access data from a smart phone or computer. As one grower stated: "I don’t hate the idea of a reader on the (sensor), because I’d have to run back to the house to get on the computer and login, because I couldn’t do it through a phone. So, (a reader in the field would be) a quicker decision-making tool." Others indicated a preference for getting the information online. However, there is significant ongoing expense associated with cloud-based data, which some farmers indicated would be a barrier to them. One farmer noted: "I’m okay with the prices (for the sensors) as they are. It’s just that, if it were easier to get the data. it depends on if you’re going to get the software or not, honestly. That’s the expensive part." Another stated: "I think the big question is: When does this pay? What carrot yield bump would justify this expense? You’re getting fine carrots irrigation by feel (ing the soil) but would you get a $1000 more of your carrot crop by using this technology?" These quotes illustrate the *certainty equivalent*

(CE), a concept first introduced by Keeney and Raiffa (1976), which has been defined as the “amount of economic return that would have to be guaranteed in order for an individual to be indifferent towards a higher but less certain return” (Kelly et al., 2021, p. 3).

Focus group participants also discussed how frequently they wanted to use soil moisture data to inform irrigation decisions. Many indicated that they only wanted to check soil moisture sensors when they were able to irrigate. For some, this was once a week while for others it was every two or three days. Others indicated that their willingness to check sensors would be driven by weather. For high tunnel production, one farmer who grew tomatoes reported that checking soil moisture levels was a daily ritual, but that was not necessarily true for sensors that she installed in outdoor crops. Others indicated that having data that was collected on a shorter time step would be very useful to them as they tried to develop more sophisticated irrigation strategies. For example, one farmer stated:

> "I’m always curious about. water layering. turn it on for a little bit of time in the morning, and then once that’s sunk down, then turn it on again. in order to get the moisture lower. I’ve always been curious about what’s happening if I just water for ten minutes or what’s happening if I water for an hour."

These growers demonstrated an interest in better understanding the soil-water dynamics in their production areas, but were diverse in their preferences for how to access soil moisture data and how often they wished to access it.

Farmer participants were asked to report their level of agreement with several statements associated with on-farm water management before the workshop/focus group, and again after the session was complete. Participants reported that the workshop portion of the session increased their familiarity with soil moisture hardware and software, increased the likelihood that they perceived soil moisture sensor information as relevant to their farm operations, and increased their willingness to invest in soil moisture technology (Table 2). As a result of participating in the workshops and focus groups, farmers reported that their knowledge about soil moisture sensors had increased (4.5 average level of agreement, with 5 = strong agreement and 1 = strong disagreement). Participants also indicated that they would use soil moisture sensors in the future (mean response = 4.5) and that their confidence in using soil moisture sensors had increased (mean response = 4.0). Though attendees at the workshop were a self-selected group (i.e., they were there because they were interested in the topic of soil moisture sensing, and therefore may be more disposed to adopt this technology than the average farmer), these results show that NE growers often do not have as much information as they desire related to this well-established approach to irrigation scheduling.

Table 2
Focus group participants level of agreement to statements presented on pre- and post-workshop questionnaires. 5 = strongly agree; 1 = strongly disagree.

Statement	Average level of agreement	
	PRE	POST
My current irrigation system allows me to successfully meet the water needs of my crops.	2.6	2.1
I am concerned about the effects of precipitation (rainfall and snow) on my crops’ ability to access to nutrients.	3.6	3.7
Fertilizer efficacy plays a role in my decisions about when to irrigate.	2.7	3.5
My irrigation system is efficient.	1.8	1.9
I wish to enhance irrigation efficiency on my farm.	4.4	4.5
I am familiar with soil moisture sensor hardware (sensors).	2.0	3.6
I am familiar with soil moisture sensor software (for reading data output).	1.5	2.9
Soil-moisture sensors provide information that is relevant to irrigation-related decisions that I make on my farm.	2.0	3.3
Considering what I know about crop water needs, I am willing to invest in soil moisture sensing technology.	3.5	3.8
I have concerns about managing soil moisture hardware in the field.	3.3	3.2
I am confident in my ability to interpret data generated by soil moisture sensing software.	3.3	3.5

We asked participants how much they would be willing to invest in soil moisture monitoring, if they could achieve 10 %, 20 %, 30 %, or 40 % increased yield (Fig. 1). Several farmers reported that they would be willing to invest less than $500 for only a 10 % increase in yield (8 out of 13 respondents), but willingness to invest greater sums was contingent upon higher rates of yield improvement. For example, 5 respondents would consider investing more than $2000 if the return was a 40 % increase in yield, but only 2 farmers would consider investing that sum for a 30 % increase in yield. Only one respondent indicated that they would spend over $2000 for a yield improvement of 20 %, and no one was willing to invest this much money for a 10 % yield improvement.

Though the research literature is rich in assessments of different soil moisture assessment technologies, studies concerning farmers’ perceptions of these technologies are few. Understanding farmers’ preferences and questions about this technology is a critical step in making soil moisture monitoring a more accessible approach for irrigation scheduling. However, a recent study conducted with Nebraskan corn producers found that, while farmers tend to over or underestimate soil-water content, precise soil moisture information is not required for farmers to make good irrigation decisions. The authors propose that a better approach is for agricultural advisors to provide growers with recommendations based on crop-water models and optimization techniques (Kelly et al., 2021).

This suggests that investing in on-farm soil moisture sensors and online data platforms may not be necessary for farmers to improve their bottom lines, however working closely with agricultural advisors who have the expertise to make irrigation recommendations on a regular basis is a worthwhile activity. It is worth noting that irrigation approaches likely need to be adjusted several times over the course of a growing season, in response to weather forecasts (Kelly et al., 2023), meaning agricultural advisors who assist growers with irrigation scheduling should revisit and revise recommendations several times within a single growing season. Building upon the work that Kelly and colleagues have completed in Nebraska, the field trial component of our study explored whether soil moisture sensing could improve crop outcomes in diversified vegetable production in the Northeast.

3.2. Local climatic conditions and evapotranspiration

Irrigation scheduling, in any form, aims to maintain soil moisture levels that adequately meet plant water demands. A simplified water balance model consists of precipitation (PR) and irrigation (IRR) as inputs to the soil system and evaporation, plant transpiration (traditionally combined into a single term, evapotranspiration (ET)), surface

Fig. 1. Amount (USD) that focus group farmers would invest in soil moisture sensor technology (hardware and software) at different levels of potential yield increase.

runoff (SR), and deep percolation (DP) as outputs (Hillel, 2004). Thus, the net irrigation requirement (NIR), often termed soil water deficit, can be calculated as:

$$NIR = DP + SR + ET - PR \quad (1)$$

The variables DP and SR are difficult to estimate, and typically the sum of DP and SR is much less than ET, so that they can be set to zero and Eq. (1) can be simplified to:

$$NIR = ET - PR \quad (2)$$

Conceptually, Eq. (2) shows that irrigation can be scheduled by knowing PR, an easily measured parameter, and ET. The ET parameter is a function of a set of conditions that include crop type, soil texture, temperature, wind, humidity, and solar radiation. Recently, online tools have become available to obtain real-time modeled ET values providing producers with information to make sound irrigation management decisions (DeGaetano and Belcher, 2022).

Because ET is a function of atmospheric conditions, it is highly variable on daily, weekly, and annual time-steps, and therefore irrigation requirements are highly dependent on short-term weather history. Considerable differences in PR were observed among the four site-years (Fig. 2). The total PR was more variable at the Maine field site with 49.5 cm in 2021 and 29.9 cm in 2022, while the Vermont site received 34.5 cm in 2019 and 42.1 cm in 2021. Patterns of PR were also different with Maine-2021 receiving high PR amounts in the early and late stages of the growing season (Fig. 2A). ET was more consistent with average ET being 30.8 ± 0.7 cm in Maine and 35.3 ± 4.1 cm for Vermont. For the growing season, the NIR was − 19.2 cm for Maine 2021, 1.4 cm for Maine 2022, 3.8 for Vermont 2019, and − 9.7 cm for Vermont 2021

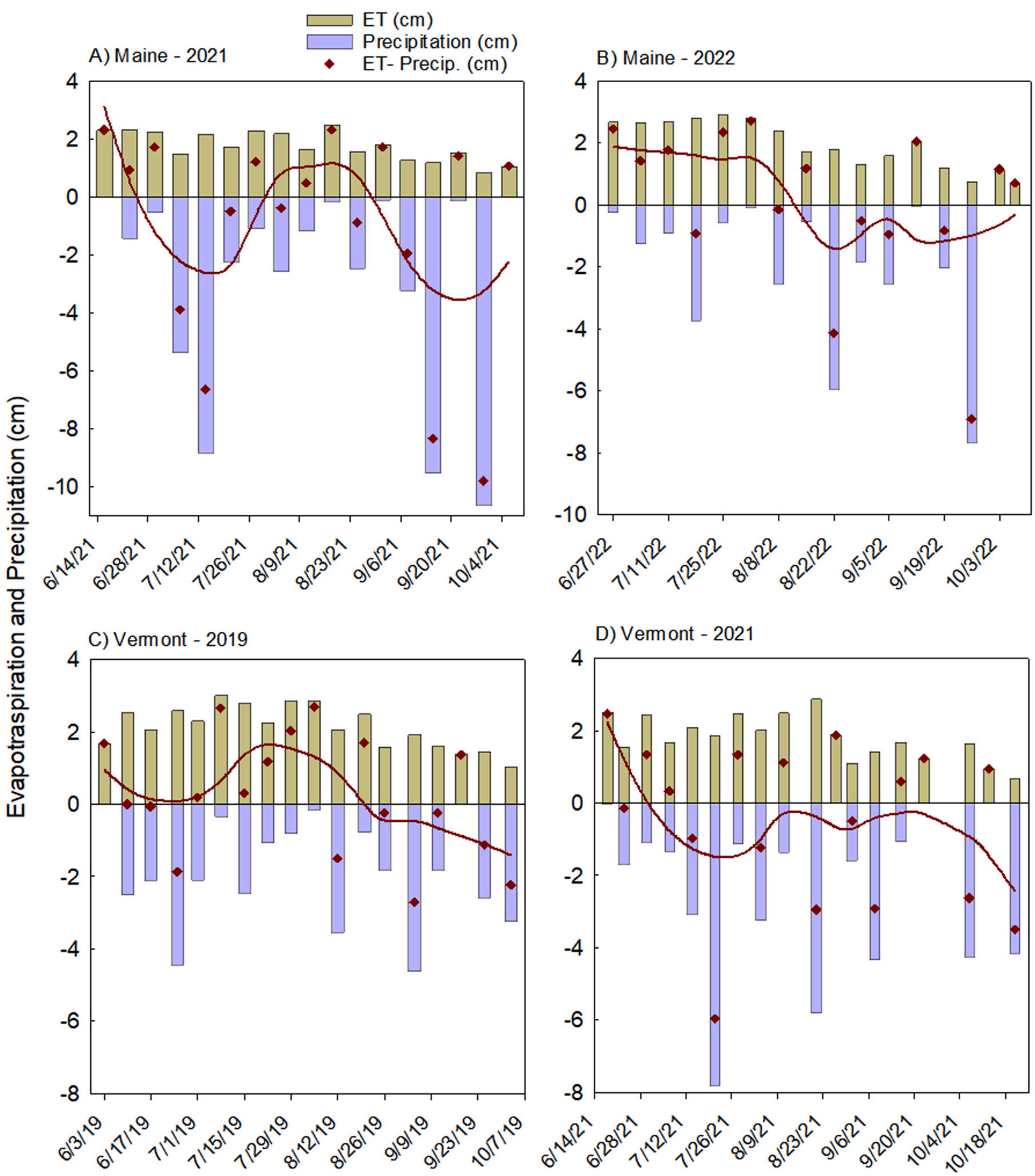

Fig. 2. Modeled evapotranspiration and measured precipitation for the four site-years: A) Maine 2021, B) Maine 2022, C) Vermont 2019, and D) Vermont. 2021. When the red fitted line crosses into positive values, this indicates a moisture deficit.

where negative values indicate surplus water status.

NIR trends during the growing season are shown by the fitted regression lines and indicate that NIR can be positive within weekly time steps despite the total season NIR being negative. There were nine weekly sampling periods that in each of the four site-year studies had positive NIR indicating a need for irrigation (Fig. 2). There were temporal differences in when irrigation was indicated, with Maine 2021 and Vermont 2019 needing irrigation early- and mid-season, Maine 2022 showing consistent irrigation need for the first half of the growing season, and Vermont 2021 showing irrigation need for the early phase of the growing season.

3.3. Irrigation volume and timing

The irrigation quantity for the three scheduling methods and the precipitation data are shown in a cumulative plot for the four site years (Fig. 3). The timing of irrigation events between the feel and sensor methods were similar as evident by the coinciding step increases in the histogram, suggesting that the timing of events within these treatments was similar. In years with more precipitation (Maine 2021 and Vermont 2021), both of the informed scheduling methods (feel and sensor) had long periods without irrigation. This conserved water resources, and was likely driven by the buildup of soil moisture through rain events. The irrigation quantity applied using a daily timer scheduling method was much higher than the feel or sensor methods, and likely resulted in surplus water being applied to the plots. The total irrigation and precipitation applied by the three scheduling approaches for the four site years are shown in Table 3. The feel and sensor treatment means were not significantly different using the Tukey's HSD test, suggesting that both approaches led to similar quantities of irrigation.

3.4. Soil moisture levels during growing season

The daily soil moisture level averaged between midnight and 5 AM at 30 and 60 cm depths of each treatment replication are shown for Maine 2021 and Maine 2022 studies in Fig. 4 and for Vermont 2019 and

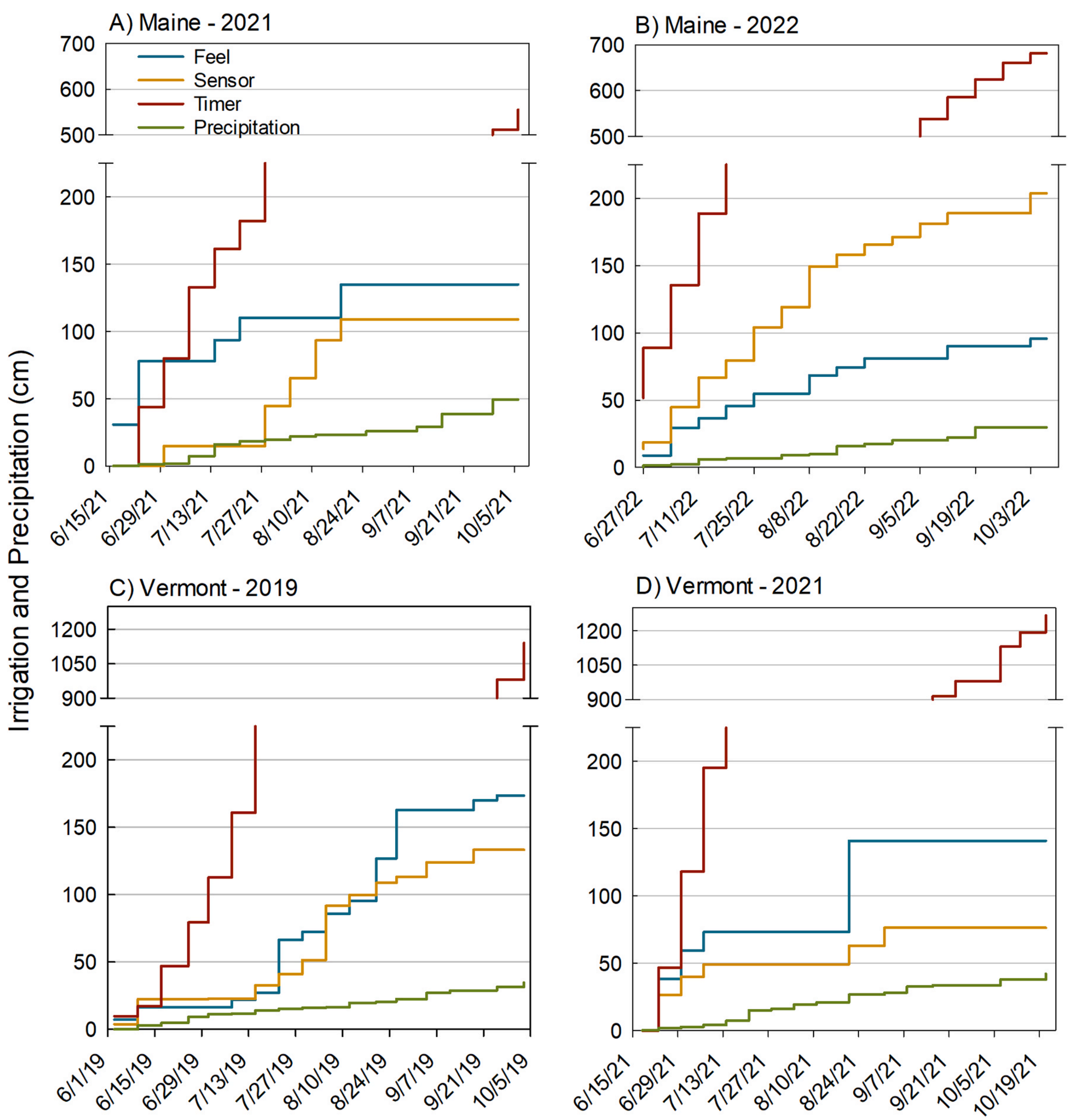

Fig. 3. Cumulative histogram of irrigation applied for the feel, sensor, timer irrigation scheduling methods and ambient precipitation for the four site-years: A) Maine 2021, B) Maine 2022, C) Vermont 2019, and D) Vermont. 2021.

Table 3
Cumulative quantity of irrigation applied in cm units and precipitation during the growing season in the four field site-year studies. The control treatment received only ambient precipitation, but no irrigation. Treatment means with different letters are significantly different using the Tukey's HSD test.

Site - Year	Control (cm)	Feel of soil (cm)	Sensors (cm)	Timers (cm)
Maine - 2021	49.5	135	109	555
Maine - 2022	29.9	95	204	681
Vermont - 2019	34.5	174	133	1140
Vermont - 2021	42.1	141	76.4	1267
Treatment Mean (p = 0.005)		136 B	131 B	910 A

Vermont 2021 in Fig. 5. In the heat maps, the blue color scale reflects lower soil matric potential (more moistness) and the red color scale reflects higher matric potential (more dryness). There are several trends observable from these heat maps. First, with the possible exception of the Maine 2021 results, the sensor plots generally had more consistent days in the color-scale blue region than the feel plots, suggesting that the use of soil moisture sensors for irrigation scheduling results in more consistency in the desired range of soil moisture than the traditional feel method.

Second, the individual replications within a treatment were more variable for the Maine field site than for the Vermont site, highlighting the high degree of spatial heterogeneity of soil physical characteristics that affect soil-water-plant relationships. The greater variability for the Maine site is likely to be related to its silt loam soil texture, compared to loamy sand at the Vermont site. Moreover, the Maine soil has 88 % more organic matter than the Vermont soil (Table 1). Loam soils have a wide range in pore size, providing many meso- and micro-sized pores to retain water (O'Geen). Increasing organic matter content increases soil

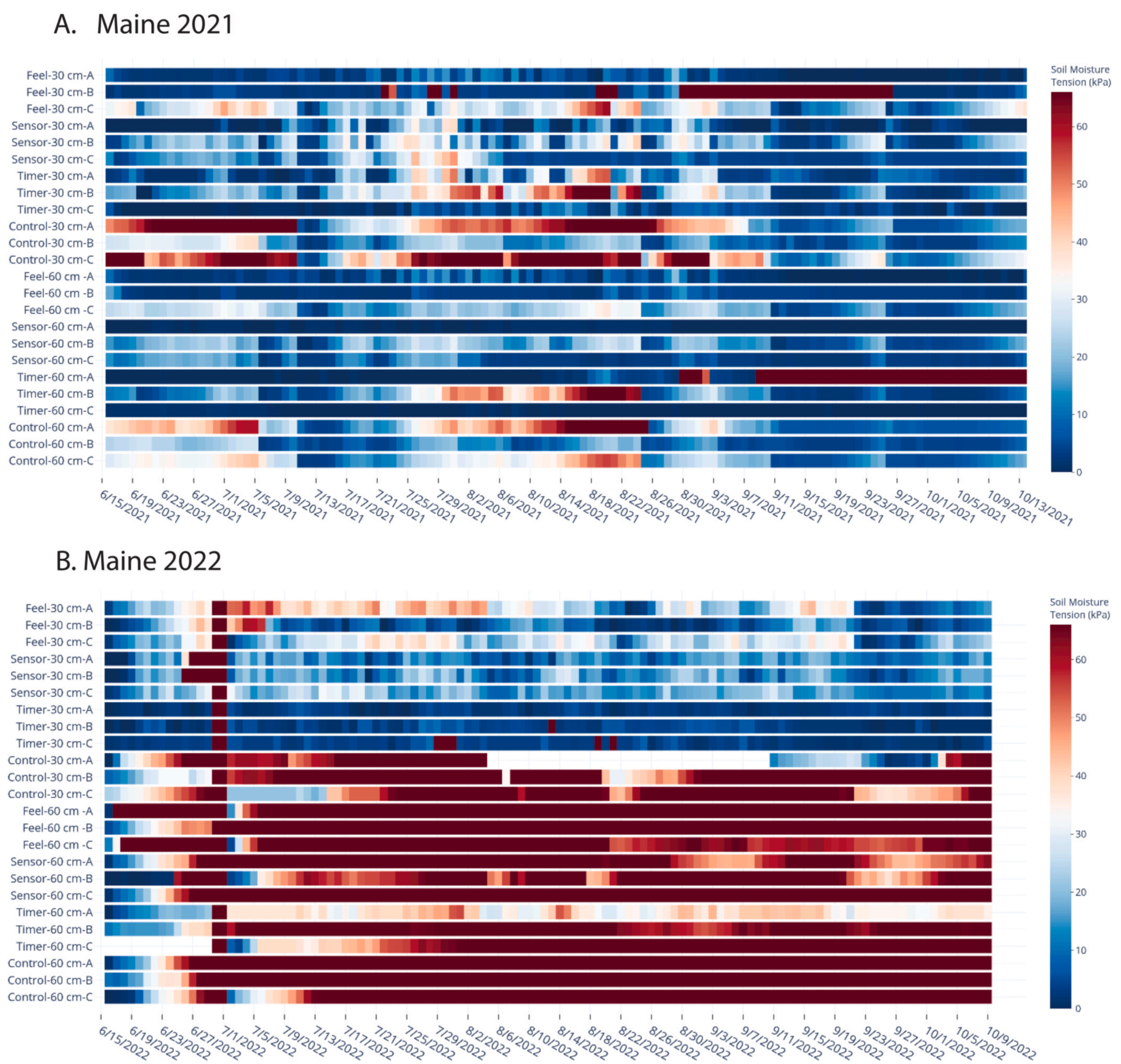

Fig. 4. Daily soil moisture sensor readings for the Maine 2021 and 2022 studies. The daily readings are the average of the hourly readings from midnight to 5 AM. Row labels refer to the experimental "cues to irrigate" (*feel* = feel of soil; *sensor* = Watermark model 200SS sensors; *control* = no irrigation; *timer* = automatic timers); depth of sensor placement (30 cm or 60 cm); and replication (A–C).

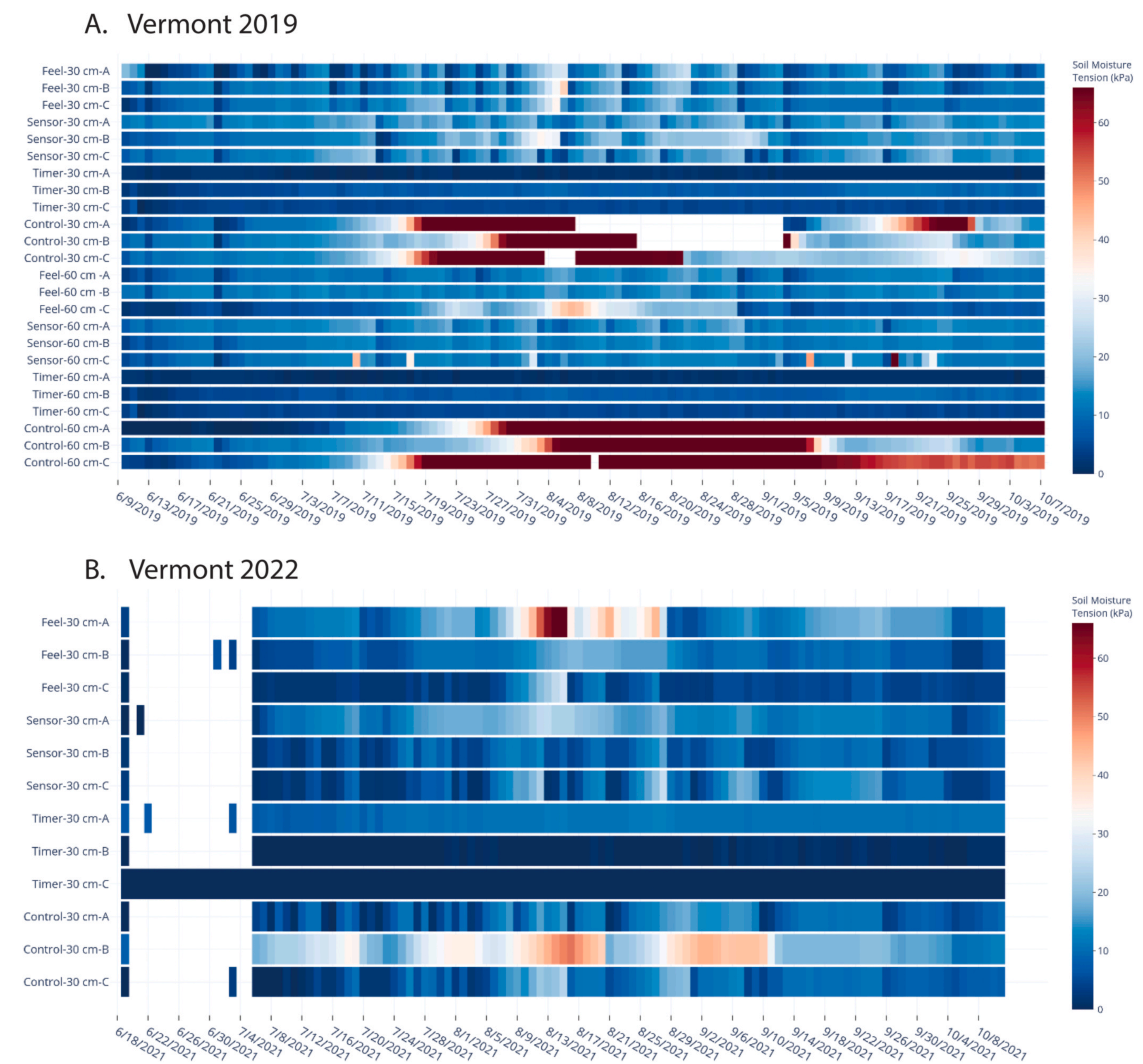

Fig. 5. Daily soil moisture sensor readings for Vermont 2019 and 2021 studies. The daily readings are the average of the hourly readings from midnight to 5 AM. Row labels refer to the experimental "cues to irrigate" (*feel* = feel of soil; *sensor* = Watermark model 200SS sensors; *control* = no irrigation; *timer* = automatic timers); depth of sensor placement (30 cm or 60 cm); and replication (A–C). Only 30 cm soil depth data was available for the 2021 study.

aggregation, which also increases water retention (Lal, 2020). In contrast, sandier soils have large macro-pores that results in rapid downward water flow. The more tortuous flow paths of soils with higher organic matter contents and finer textures are likely to create localized areas of water retention in the Maine soils which may lead to the higher degree of variability observed.

Some observations about the flow of the irrigated water down to the 60-cm depth can be made from the soil water tension values shown in Figs. 4A, B, 5A and B. The Maine 2021 and Vermont 2019 data shows the deeper 60-cm soil water tension values mirroring those of the corresponding 30-cm sensor values. In contrast, the Maine 2022 results shows that soil was very dry, particularly at 60-cm, from late-July to the end of the study regardless of treatment. This different pattern may be due to the 66 % greater precipitation in 2021 than in 2022 (Table 3). The sum of the modeled positive weekly ET values for Maine (Fig. 2) was 7.6 cm in 2021 and 15.8 cm in 2022 indicating higher rates of soil water transfer from the soil to the atmosphere. These factors likely led to the transfer of soil water from the 60-cm soil depth to the shallower 30-cm region where it would become available for evapotranspiration. Alternatively, roots may have extended deeper into the soil profile during the drier year, leading to drier soils.

The 30-cm daily soil moisture tension values binned into four range categories: 0–5 kPa, saturation; 5–20 kPa, field capacity; 20–60 kPa, moderately dry; and 60 +, stressfully dry (Harrison, 2012) are shown in Fig. 6. A higher proportion of the readings were in the optimal field capacity category for the sensor plots as compared to the feel plots for all four site years. With the exception of the Maine 2021 data, the timer treatment led to soils being in the saturated class in more than 84 % of days, showing that daily timed irrigation in this study led to over-irrigation. Not surprisingly, the non-irrigated control was the most

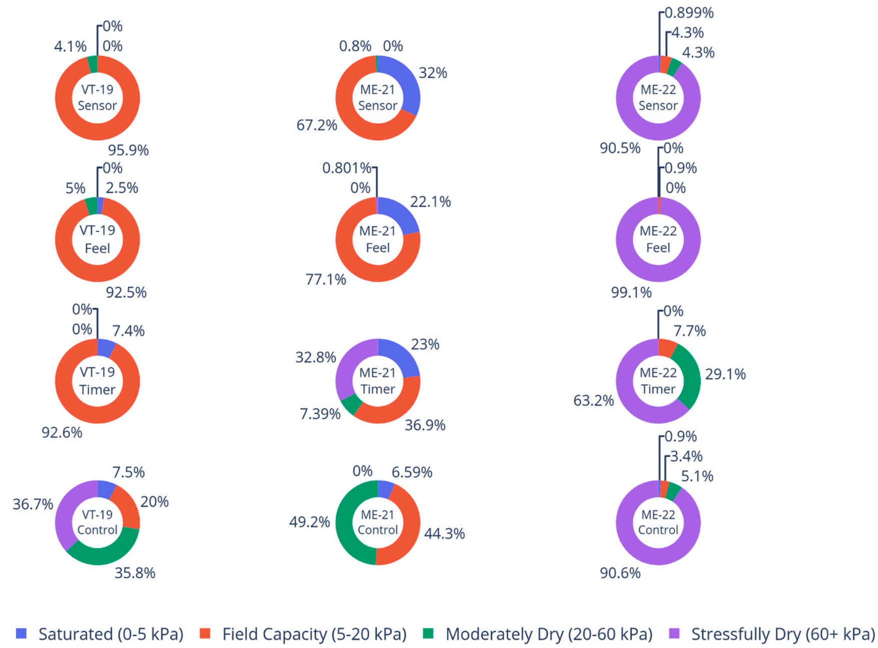

Fig. 6. Proportion of soil moisture level readings at 30 cm depth into four categories: saturated (0–5 kPa), field capacity (5–20 kPa), moderately dry (20–60 kPa), and stressfully dry (60 + kPa).

variable with both Maine study years having moderately-dry and stressfully-dry as the dominant category. In both years in Vermont, optimal field capacity was the dominant category (Fig. 6). The 60-cm sensor data was collected in Maine for both years, and in Vermont in 2019. The 60-cm sensor data for the Vermont 2021 study were not collected. The 30- and 60-cm values for Vermont 2019 were qualitatively similar which is likely due to high sand content (89 %) of the soil allowing for rapid transport through the soil. The much drier 60-cm soils for Maine 2021 than in Maine 2021 evident in Fig. 4 is supported with 63–99 % of the days in the stressful category.

3.5. Leachate volume

The volume of water collected by the lysimeter at 60-cm depth expressed directly in cm units and as a percentage of the sum of precipitation and irrigation inputs is shown in Table 4. The leachate volume in Maine was consistently low with values between a trace and 1.1 cm of water. There was greater leachate in Vermont, with the range between a trace and 14.1 cm of water which reflects the high sand content (Table 1) allowing for greater percolation of water through the soil profile. Expressed as a percentage of the sum of precipitation and/or irrigation inputs, the Maine values were all less than 1 % and Vermont values ranged between 0 % and 1.9 %. These low values for both sites support the use of the simplified Eq. (2) that ignores the deep percolation term because it is often negligible compared to the ET term in estimating the required irrigation quantity.

3.6. Nitrogen transport in deep percolation

The nitrate anion is both readily available to crops and highly mobile and subject to leaching loss. The deep percolation loss of nitrate-N in plots was estimated by scaling the area of the lysimeter to the field plot area and is shown for the Maine 2021, Vermont 2019 and 2021 studies (Table 4). The average NO_3^--N concentration was low in the Maine 2021 study resulting in the average transport of 3.6 mg of NO_3^--N to the deeper soil depths. This loss is insignificant in comparison to the 28.5 g of N applied to each treatment plot. The two Vermont years had contrasting results with the NO_3^--N concentration of the leachate high in 2019 and low in 2021 leading to 3700 and 213 mg of NO_3^--N lost in deep percolation, respectively (Table 5). The NO_3^--N concentration of the leachate was highly variable with a range between 8 and 34 mg NO_3^--N L^{-1} in 2019 compared to a much more consistent and narrower range of 0.17–0.36 mg NO_3^--N L^{-1} in 2021. This difference is likely related to the use of poultry manure in 2019 which added 58 g of N to each plot and synthetic fertilizer in 2021 which added 76 g of N. Surprisingly, the NO_3^--N concentration in the leachate was higher in the year that poultry manure was used although only 30–60 % of the total N in poultry manure is probably mineralized to plant available inorganic-N (Sims, 1986; Bitzer and Sims, 1988). It is important to note that NO_3^--N in leachate is driven not only by fertilizer applications and irrigation, but

Table 4
The number of weeks with lysimeter samples (sample count), total volume of leachate, and the leachate volume as a percentage of sum of precipitation and irrigation inputs for the four irrigation treatments at the Maine and Vermont study sites. PR = precipitation; IRR = irrigation.

	Maine – 2021			Maine – 2022			Vermont – 2019			Vermont – 2021		
Treatment	Sample Count	Total Leachate Volume (cm)	% of PR + IRR	Sample Count	Total Leachate Volume (cm)	% of PR + IRR	Sample Count	Total Leachate Volume (cm)	% of PR + IRR	Sample Count	Total Leachate Volume (cm)	% of PR +IRR
Feel of soil	5	0.9	0.5 %	2	0.3	0.2 %	5	1.1	0.5 %	0	0	0 %
Sensor	5	0.9	0.6 %	1	0.2	0.1 %	1	Trace	–	16	2.2	1.9 %
Timer	5	1.1	0.2 %	2	0.4	0.1 %	17	14.1	1.2 %	16	8.7	0.7 %
Control	4	0.4	0.8 %	1	Trace	–	0	0	0 %	14	4.7	11.2 %

Table 5
Average N concentration and total N content of lysimeter samples for the four treatments at the Maine – 2021, Vermont – 2019, and Vermont - 2021.

Treatment	Maine – 2021		Vermont – 2019		Vermont – 2021	
	Average N (mg L^{-1})	Total N (mg)	Average N (mg L^{-1})	Total N (mg)	Average N (mg L^{-1})	Total N (mg)
Feel of soil	0.04	3.8	19.7	868	-	-
Sensor	0.05	3.8	33.6	12	0.36	100
Timer	0.06	5.1	8.0	10,220	0.34	431
Control	0.05	1.5	-	-	0.17	109
Average	0.05	3.6	20.4	3700	0.29	213

also precipitation.

Mass balance of N was not possible in these studies because the loss of nitrate through reduction to gaseous N_2O and N_2 by the denitrification process is unknown, and because crop uptake (leaf tissue samples) was not measured. Denitrification occurs under anaerobic conditions such as water saturated soils with low soil oxygen levels (Weil and Brady, 2016). The NO_3^--N content of leachate in the poultry manure-amended year (Vermont 2019) had the lowest concentration in the timer treatment samples which would be consistent with denitrification loss because the soil in the treatment was saturated 84 % of days in the surface to 30 cm soil depth. Our results suggest that the risks of adverse impacts of transport of leachate NO_3^--N down to groundwater is low with the use of inorganic fertilizer with average leachate concentrations less than 0.29 mg NO_3^--N L^{-1} (Table 4). There may be higher risks with the use of manure as a nutrient source with average leachate concentrations of 20.4 mg NO_3^--N L^{-1}.

3.7. Crop available N dynamics

The availability of NO_3^--N to crops is a key factor in determining productive yields. We used the 1 M KCl extractable N tests to monitor the trends in extractable NO_3^--N throughout the growing season (Fig. 7). The data was normalized to the initial extractable concentration at the time of transplanting the seedlings to highlight the changes during the season. The color-coded local kernel smoothing lines shows the treatment averages from three field studies (Maine 2021, Vermont 2019, Vermont 2021). Note that in 2022 in Maine there was only one NO_3^--N value in a lysimeter sample, therefore this site-year has been excluded from this part of the analysis. The feel treatment line reached a minimum of 0.25 at week 13 and ended at 0.26 at the end of the growing season at week 17. The sensor treatment line reached a minimum of 0.39 at week 12 and increased slightly to 0.43 at week 17. The timer line reached a minimum of 0.21 at 12 weeks and rose slightly to 0.29 at week 17. In contrast to the irrigated treatments where the extractable N was less than at the time of transplanting, the control treatment line reached a minimum of 0.54 at week 13 and recovered to 1.02 at the end of growing season. This recovery was likely driven by organic matter decomposition followed by nitrification in a moist environment. It is also likely that mineralization was occurring in all plots, but N was leached out of irrigated treatments. It is interesting to note that the rank ordering of minimum values mirrored the inverse ordering of total irrigation quantities (Table 3) suggesting that irrigation treatment was a factor in the declining extractable N during the growing season. Thus, the fate of the added N is likely to be some combination of crop uptake, NO_3^--N leaching loss, and denitrification.

3.8. Vegetable yield and quality

The individual total yields for the cucumber, pepper, and tomato crops harvested in the four field studies are shown in Fig. 8. There were no significant irrigation treatment differences in yield across all 12 crop-site-year combinations. The lack of an irrigation effect was surprising since the non-irrigated control plots had surface-30 cm soil moisture levels that were either moderately-dry or stressfully-dry 24–98 % of the days (Fig. 5). Across the four site-year studies, peppers were the most consistent in yield production with an average yield of 4.03 kg/m^2 and a coefficient of variation (average/standard deviation) of 9.6 %, tomatoes were intermediate in consistency with a yield of 18.7 kg/m^2 kg and a coefficient of variation of 28 %, and cucumber yield was highly variable with an average of 20.00 kg/m^2 and a coefficient of variation of 96 %.

It should be noted that vegetable crop yields vary based on climate, crop variety and genotype, fertilizer applications, and other factors. Pepper yields documented in our study were generally comparable to those documented in research, which range between 2.1 and 3.5 kg/m^2 (Sezen et al., 2006). Tomato yields in our study were higher than those documented in other research, which range between 60.0 and 110.0 tons/ha (6 and 11 kg/m^2) (Warner et al., 2004). However, it is difficult to compare the outcomes of a wide range of tomato production approaches including grafted versus ungrafted, field versus greenhouse, and many different approaches for trellising (Benton Jones, 2007). Lastly, cucumber yields in our study were much higher than yields

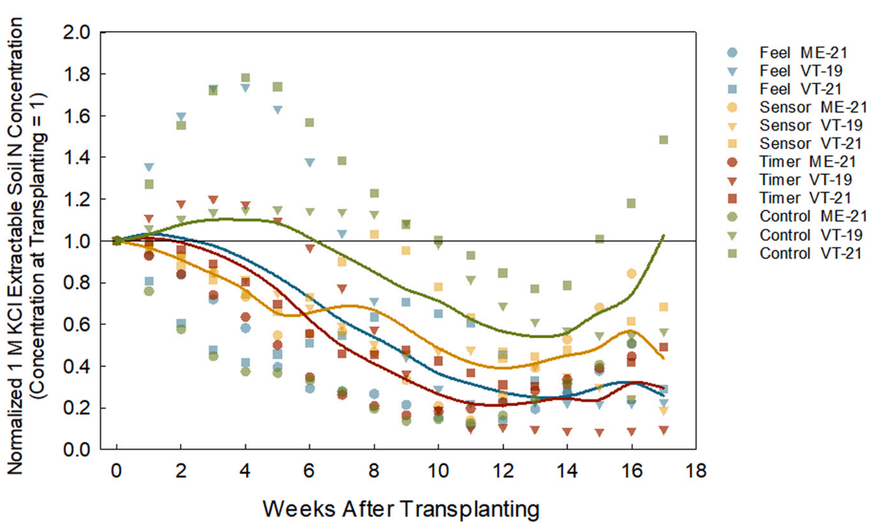

Fig. 7. Weekly 1 M KCl extractable N concentration of the feel, sensor, timer, and control treatment plots over the growing season at the four site years. The data points were normalized with respect to N concentration by setting the concentration at the time of transplanting to 1 and time was with respect to date of transplanting. The LOWESS regression fitting of the treatment response averaged over the four site years are shown.

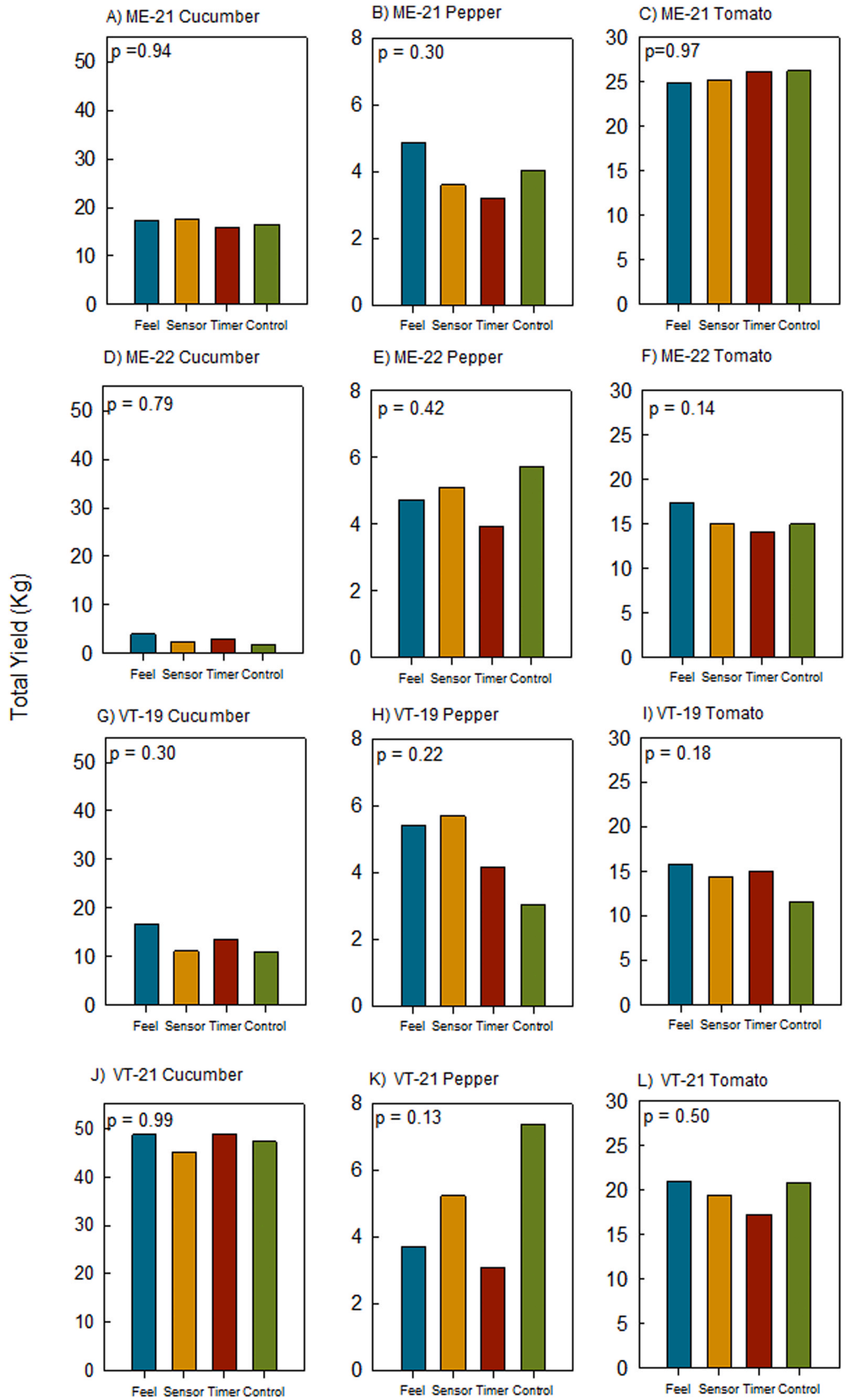

Fig. 8. Total yield of the cucumber, pepper, and tomato crops are shown for Maine 2021 (A–C), Maine 2022 (D–F), Vermont 2019 (G–I), and Vermont 2021 (J–L).

documented in other studies, which range between 15 and 76 tons/ha (1.5 and 7.6 kg/m^2) (Rahil and Qanadillo, 2015; Şimşek et al., 2005). Planting density has been shown to have a significant effect on cucumber yield (Ngouajio et al., 2006), which likely influenced our results.

Similar to the yield results, there were no significant effect of treatment on the vegetable quality assessment parameters for the two Maine field studies (Table 6). For tomato, there was a significant treatment effect on the quality index for color, shape, defect, and firmness in the VT-19 study (Table 7). The timer treatment scored significantly better for the shape, defect, and firmness indices than the control treatment suggesting that the low soil moisture levels in the control affected the quality of the harvested tomatoes. The color index of the control tomatoes was significantly higher than those of the feel treatment tomatoes.

These result show that the cucumber, pepper, and tomato crops used in this study showed resilience to a wide range of irrigation water applied and soil moisture levels found occurring during the growing season without any yield reductions, and for the most part, without many impacts on quality. This may be in part due to the field studies taking place in relatively high precipitation years during the growing season. The monthly precipitation values at the two sites in their respective years are shown along with the past 20-year average in Fig. 9. There was 28 % and 15 % greater precipitation in 2021 and 2022, respectively, in Maine as compared to the 20-year average. In Vermont, there was 8 % and 20 % greater precipitation than the average in 2019 and 2021, respectively. The irrigation treatments may increase vegetable yields when precipitation is below average during the growing season.

4. Conclusion

A survey of Vermont and Massachusetts vegetable and small fruit growers in 2017, and four focus groups with farmers in 2019 and early 2020 demonstrate that many growers are interested in refining their irrigation scheduling approach, but many do not have experience with the soil moisture sensing tools currently on the market. More commonly, vegetable and small fruit farmers in the Northeast used observable crop condition and the tactile dryness of soil to determine when to initiate and desist irrigation. Soil moisture sensor technology that measures plant available water is an approach that farmers are interested in, but they have varied preferences for how they wish to access soil moisture data (locally versus remotely) and how often they wish to use that data to make irrigation decisions. We present initial findings that farmer willingness to invest in soil moisture sensors and software increases as potential yield gain also increases, though this type of choice experiment should be conducted with a larger sample size in the future.

Field experiments were conducted in Maine and Vermont, U.S.A. for two growing seasons to investigate how using the feel method, soil moisture sensors, and timers to schedule irrigation affects soil moisture levels, leaching, and crop yield and quality. The three scheduling methods were compared to a non-irrigated control treatment. Although there were no significant effects of irrigation scheduling method on yield of the vegetable crops, some results suggested advantages to the use of soil moisture sensors to schedule irrigation. The use of sensors increased the proportion of days during the growing season in the optimal field capacity category as compared to the other scheduling methods. The effects of soil-water consistency on crop development and yield is an understudied topic, and deserves further attention. Additionally, the field trials were conducted in years where above average precipitation was recorded at both study sites, and it is still possible that use of sensors could improve crop yields and quality in drier conditions. The use of sensors resulted in less irrigation applied compared to the feel method in three of the four field studies. Nitrate leaching in soils, especially sandy textured soils, is a concern with potential to contaminate groundwater sources and is a direct economic cost as N is lost for crop uptake. The depletion of extractable soil N occurred to the greatest extent for the timer method and the least extent with the sensor method suggesting that over-irrigation may lead to the loss of NO_3-N from the rooting soil zone. Minimizing unnecessary water use is important giving increasingly variable water availability in the Northeast, and the potential for regulatory changes that may require farmers to monitor or limit their water use. Overall, the results from these field studies show that the use of soil moisture sensors to initiate irrigation will result in soils having optimal soil moisture levels on more days and reduce potential environmental risk associated with N contamination of groundwater sources.

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Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Rachel E. Schattman reports financial support was provided by Northeast Sustainable Agriculture Research & Education. Rachel E. Schattman reports financial support was provided by US Department of Agriculture.

Table 6
Vegetable color, gloss, shape, defect, and firmness quality indices for the four irrigation cue treatments at the Maine study sites.

Crop	Treatment	Maine 2021					Maine 2022				
		Color	Gloss	Shape	Defect	Firmness	Color	Gloss	Shape	Defect	Firmness
Cucumber	Feel of soil	2.9	1.7	2.4	3.0	4.2	1.9	1.8	1.5	2.1	4.8
Cucumber	Sensor	3.1	1.7	2.2	3.1	3.9	3.5	1.3	4.3	2.5	5.0
Cucumber	Timer	2.8	1.9	2.1	3.1	3.9	2.9	1.5	2.4	2.5	5.0
Cucumber	Control	2.7	2.1	2.1	2.9	4.3	2.3	1.5	3.0	3.1	5.0
	Prob > F	0.74	0.16	0.52	0.56	0.31	0.59	0.67	0.06	0.33	0.08
Pepper	Feel of soil	1.8	3.6	3.3	1.7	4.0	1.8	3.7	3.2	1.8	4.1
Pepper	Sensor	1.8	3.8	3.1	2.1	4.2	2.0	3.8	3.6	2.1	4.2
Pepper	Timer	1.7	3.5	2.8	1.6	4.1	2.0	3.6	3.2	1.5	4.3
Pepper	Control	1.8	3.6	3.1	1.9	4.2	2.0	3.7	3.3	1.7	4.0
	Prob > F	0.99	0.45	0.38	0.51	0.66	0.82	0.60	0.21	0.18	0.88
Tomato	Feel of soil	2.3	3.0	3.5	2.7	3.7	1.8	3.7	3.2	1.8	4.1
Tomato	Sensor	2.7	3.1	3.4	2.7	3.8	2.0	3.8	3.6	2.1	4.2
Tomato	Timer	2.8	3.0	3.7	2.7	3.8	2.0	3.6	3.2	1.5	4.3
Tomato	Control	2.9	3.1	3.5	2.8	3.8	2.0	3.7	3.3	1.7	4.0
	Prob > F	0.20	0.95	0.40	0.87	0.95	0.83	0.60	0.21	0.18	0.88

Table 7
Vegetable color, gloss, shape, defect, and firmness quality indices for the four irrigation cue treatments at the Vermont study sites.

Crop	Treatment	Vermont 2019					Vermont 2021				
		Color	Gloss	Shape	Defect	Firmness	Color	Gloss	Shape	Defect	Firmness
Cucumber	Feel of soil	2.3	1.1	3.2	2.3	4.0	1.8	3.8	3.3	2.2	4.6
Cucumber	Sensor	2.2	1.0	3.1	2.4	4.2	2.0	3.0	2.8	2.2	4.0
Cucumber	Timer	2.2	1.0	3.2	2.0	4.0	2.0	3.5	3.2	2.3	4.4
Cucumber	Control	2.4	1.1	3.2	2.0	4.1	1.7	3.5	3.2	1.9	4.3
	Prob > F	0.66	0.42	0.99	0.37	0.67	0.44	0.06	0.31	0.36	0.21
Pepper	Feel of soil	1.9	3.3	3.3	2.4	3.8	1.3	2.2	2.1	1.4	2.5
Pepper	Sensor	1.6	3.3	3.6	2.1	3.8	1.2	2.6	2.3	1.4	2.8
Pepper	Timer	2.0	3.2	3.3	2.6	3.9	1.4	2.3	2.0	1.5	2.5
Pepper	Control	1.9	3.0	3.4	2.6	3.6	1.6	3.0	2.6	1.6	3.0
	Prob > F	0.52	0.11	0.75	0.43	0.21	0.25	0.25	0.47	0.84	0.46
Tomato	Feel of soil	2.8 B	3.2	3.3 A	3.4 AB	3.5 AB	2.9	3.4	3.3	2.8	3.8
Tomato	Sensor	3.3 AB	3.2	3.3 A	3.2 AB	3.4 AB	2.9	3.5	3.4	2.9	3.7
Tomato	Timer	2.9 AB	3.2	3.3 A	2.9 B	3.6 A	2.7	3.4	3.2	2.6	3.7
Tomato	Control	3.5 A	2.7	2.4 B	4.3 A	3.0 B	2.7	3.5	3.3	2.6	3.8
	Prob > F	0.03	0.06	0.01	0.03	0.04	0.69	0.86	0.81	0.71	0.95

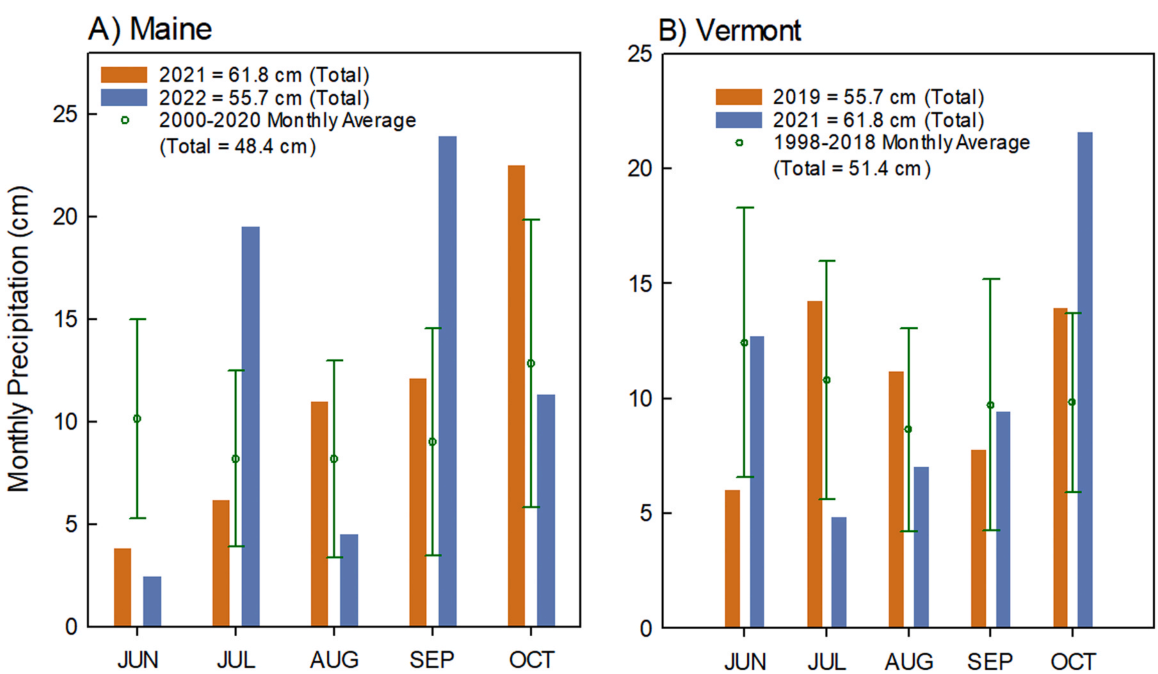

Fig. 9. Monthly precipitation data for four site years and the past 20-year monthly averages at the Maine and Vermont site.

Data Availability

Data will be made available on request.

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