A new multi-objective approach to optimize irrigation using a crop simulation model and weather history

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Abstract. Optimization of water consumption in agriculture is necessary to preserve freshwater reserves and reduce the environment's burden. Finding optimal irrigation and water resources for crops is necessary to increase the efficiency of water usage. Many optimization approaches maximize crop yield or profit but do not consider the impact on the environment. We propose a machine learning approach based on the crop simulation model WOFOST to assess the crop yield and water use efficiency. In our research, we use weather history to evaluate various weather scenarios. The application of multi-criteria optimization based on the non-dominated sorting genetic algorithm-II (NSGA-II) allows users to find the dates and volume of water for irrigation, maximizing the yield and reducing the total water consumption. In the study case, we compared the effectiveness of NSGA-II with Monte Carlo search and a real farmer's strategy. We showed a decrease in water consumption simultaneously with increased sugar-beet yield using the NSGA-II algorithm. Our approach yielded a higher potato crop than a farmer with a similar level of water consumption. The NSGA-II algorithm received an increase in yield for potato crops, but water use efficiency remained at the farmer's level. NSGA-II used water resources more efficiently than the Monte Carlo search and reduced water losses to the lower soil horizons.

Keywords: Water use efficiency · Machine learning · Multi-objective optimization· Sustainable agriculture

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1 Introduction

Global population growth leads to urbanization and intensification of food production. This intensification of food production causes an rise in water consumption, which yields a negative impact on the environment and may result in a reduction of freshwater quality [19]. The lack of availability of water resources is one of the main limiting factors in regions with low yields [16]. Efficient water resources for agricultural purposes is necessary to ensure food security and to reduce this environmental impact.

One can describe water resource efficiency as the amount of water spent to produce a certain amount of crop yield [18]. There are several factors that affect the efficiency of water resources usage [17], [22]. A part of the water is involved in plant growth, development, and transpiration, so this part is considered to be used efficiently. Another part of the water is not accessible to plant roots due to evaporation, migration with surface runoff, and deep percolation. So we can define water loss (part of irrigation water that cannot be transformed into economic gain) and efficiently used water (water that is transformed into yield). For irrigation agriculture, water use efficiency may vary from 13 to 18% of the water supplied [27]. Gleick estimates that approximately 63% of all water for irrigation is lost due to deep percolation and runoff [9]. Thus, it is necessary to reduce water loss for sustainable agriculture and for the conservation of water resources [11]. It is worth noting that the high level of water migration from the root zone can cause mineral fertilizers to percolate into the groundwater, which causes eutrophication and additional stress on the nearest water systems and their inhabitants [31]. It can also affect the migration of pesticides to groundwater [14], increasing environmental risks. Therefore, there is a need to minimize the amount of inaccessible water for the plant and deep percolation to reduce the impact of inefficient crop irrigation on the environment.

Conducting field experiments to find the best agricultural management practices is time-consuming, as it requires evaluating all possible combinations of agricultural practices. Crop simulation models are widely used to plan agricultural practices, such as planting and harvesting crops, fertilizing, and watering. Crop simulation models allow users to evaluate various agricultural activities and predict crop yields [7]. The most widespread used crop simulation models are the following: DNDC [8], APSIM [10], AGROTOOL [2], DSSAT [12], MONICA [20], AquaCrop [25], WOFOST [26], and others. These models have many differences in their ideology, utilized equations, choice of programming languages for the software implementations, the minimum set of input parameters, and spatial/temporal resolution.

Rapid computations allows users to supply optimization algorithms with a simulation model as an objective function and to improve agricultural practices automatically. A previous study's multi-objective differential evolution algorithm (MDEA) was applied to minimize water use and to maximize South African regions' income [1]. Yousefi et al. suggested that Multi-Objective Particle Swarm Optimization reduces the negative impacts of using treated water and it maximizes crop benefits [32]. In paper [21], the authors use multi-criteria optimization to maximize crop profit and reduce irrigation volume based on the CROPWAT model which showed the possibility of reducing irrigation volume by a quarter. García-Vila and Fereres used weather history and the AquaCrop model to optimize irrigation strategy on the farm-scale level in conditions of water scarcity [6]. Recently, research tested using DSSAT crop simulation system and the U-NSGA-III optimization algorithm to maximize crop yield and to minimize nitrogen leaching by selecting optimal irrigation water amounts and nitrogen fertilizers [15].

However, most papers consider a single crop and optimize agricultural practice for a single year based on weather data, which may not be very useful given the lack of opportunity to predict the weather for the whole vegetation season in the future [23]. In most papers, the researchers also consider the optimization of continuous irrigation and fertilization parameters, such as water volume or fertilizer amount, but they do not consider the dates of the agricultural practices. We analyze how to combine crop simulation model WOFOST and multi-objective optimization to maximize crop yield and minimize water loss to address this gap.

We use the NASA POWER weather history and compute mean crop yield and mean water loss for the last 20 years to evaluate different weather scenarios [24]. We compare the performance of our approach based on the NSGA-II optimization algorithm [4] against the Monte Carlo search with the farmer's agriculture practice to assess the proposed solution.

2 Materials and methods

In this section, we describe the materials and methods that we use in our research.

2.1 Crop simulation model WOFOST

Crop simulation models (CSM) describe the dynamics of the atmosphere-soil-plants system's main processes that affect crop productivity. They can evaluate crop system productivity depending on weather, irrigation, and fertilizer application. Such models allow a user to avoid conducting long-term field experiments experiments and to select optimal agricultural practice. The rapid calculations of such models, about 0.5-2 seconds on a personal computer, allows a researcher to use such models in optimization problems as a function of the agricultural field productivity.

We utilize the WOrld FOod Studies (WOFOST) crop simulation model developed in Wageningen University to identify crops' productivity and irrigation water loss [30]. The WOFOST crop model describes dynamic growth processes, photosynthesis, transpiration, respiration, and biomass partitioning. We chose the WOFOST model because it is adapted and calibrated for European crops and environmental conditions. Figure 1 shows the experiment's scheme and the WOFSOT model application to optimize irrigation.

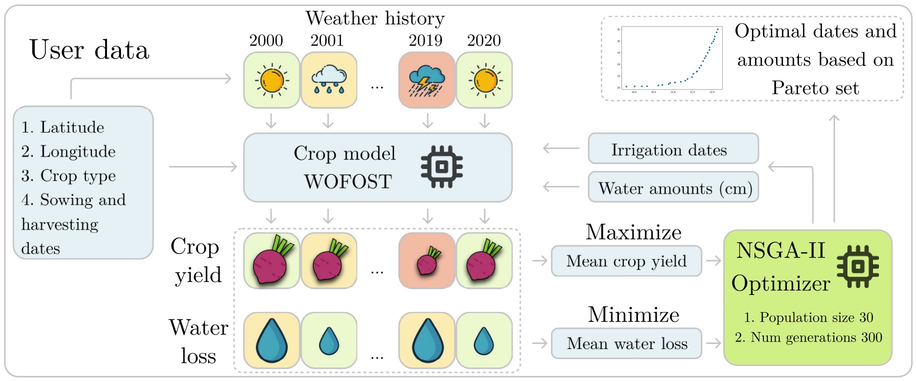


Fig. 1: Based on user data, we receive the weather history from NASA POWER. The optimizer generates dates and water amount for irrigation. Then we simulate the crop growth selected by a user for each of the weather history and get the yield and water loss for each year. The average yield values are passed to the optimizer and affect choosing the following combinations in the population. Finally, we select specific dates and water amount for irrigation from the Pareto front with the weighted sum method (see section 2.3)

The WOFOST crop model requires weather data for each day of the growing season to perform simulations. We received data from the NASA POWER database for the crop simulations [24]. The NASA Energy System provides weather data from 1983 to the present with a delay of three months. NASA POWER allows users to collect weather history data with daily time resolution and grid resolution of half a degree of arc of longitude by half a degree of arc of latitude. The WOFOST model requires several meteorological observations for each day, such as incoming global radiation (W/m^2), daily minimum temperature ($°C$), daily maximum temperature ($°C$), daily average vapor pressure (hPa), daily total precipitation (cm/day), daily average wind speed at an altitude of 2 m (m/sec). NASA's POWER data contains weather omissions for some dates that average 1-2% of all dates. We use the pandas' package *fillforward* method in python to fill data gaps.

The WOFOST model accepts input data in a YAML file format containing necessary information about crop parameters, cultivar, soil conditions, and weather data in a CSV format. To assess the crop's productivity, we used the variable - total weight of storage organs (TWSO, t/ha). To estimate the volume of deep percolation water, we used the total amount of water lost to deeper soil (LOSST, cm). The WOFOST model has been used for more than 25 years and has various implementations in Fortran, python, and R. We used a python implementation of PCSE/WOFSOT model [4].

[4] https://github.com/ajwdewit/pcse

2.2 Multi-objective optimization

Notations and terms. In optimization problems, variables are changed to maximize or minimize the objective function. In agriculture, many tasks require finding the optimal solution, such as choosing irrigation dates and the amount of water to be watered, the amount of fertilizer application, and the date of application. Typically, the farmer tries to minimize their losses by avoiding inefficient use of fertilizers and water resources, fuel consumption, and to maximize their yield and crop quality.

However, in the real-world, minimizing one cost could immediately lead to maximization of another cost, which depends on the same set of variables. For example, one can use a massive amount of water or fertilizer to increase yield, but this can sometimes be barely profitable because of their water or fertilizer expenses. One way to deal with multiple objectives that could conflict with each other is through multi-objective optimization.

Suppose, we have T loss functions $\mathcal{L}^i(\boldsymbol{\theta}), \forall i = \overline{1,T}$:

$$\min_{\boldsymbol{\theta}} \boldsymbol{\mathcal{L}}(\boldsymbol{\theta}) = \min_{\boldsymbol{\theta}} \left(\mathcal{L}^1(\boldsymbol{\theta}), \ldots, \mathcal{L}^T(\boldsymbol{\theta})\right)^\top \tag{1}$$

In such a setting, we need to specify a way to compare a vector of objectives. The typical way to do this is by introducing the concept of Pareto dominance and Pareto optimality.

Definition 1 (Pareto optimality).

1. *A point $\boldsymbol{\theta}_1$ dominates $\boldsymbol{\theta}_2$ for a multi-objective optimization problem (1), if $\mathcal{L}^i(\boldsymbol{\theta}_1) \leq \mathcal{L}^i(\boldsymbol{\theta}_2) \, \forall i = \overline{1,T}$ and at least one inequality is strict.*
2. *A point $\boldsymbol{\theta}_*$ is called Pareto-optimal solution, if there is no other point $\boldsymbol{\theta}$ that dominates it.*

This article exploits multi-objective optimization to determine optimal irrigation dates and optimal water volume for irrigation to maximize crop yield and minimize water loss (water inaccessible to plants). In this setting we have $T = 2$ functions to minimize concurrently: $\mathcal{L}^1(\boldsymbol{\theta})$ - mean water loss for different weather scenarios, and $\mathcal{L}^2(\boldsymbol{\theta})$ - mean crop yield for different weather scenarios (taken with negative sign). The vector of parameters $\boldsymbol{\theta}$ contains irrigation dates and amounts of water, which is needed to be spent in the corresponding day. In our experiments we use 7 irrigation dates, therefore $\boldsymbol{\theta}$ is 14-dimensional vector.

Multi-objective optimization algorithms A lot of effective multi-objective optimization algorithms were developed [5], [13], [33]. However, due to the specific structure of the loss functions, which are the outputs of a WOFOST model, a function's value is the only information we have. Since no gradients or any other higher-order details are available, we are restricted to use zero-order algorithms. In this work, we compare the following approaches:

- **Monte Carlo optimizer.** We randomly generate $\boldsymbol{\theta}$ vectors and choose the best (in terms of Pareto optimization) point for our problems.

– **NSGA-II optimizer.** We use non-dominated sorting genetic algorithm (also known as NSGA-II) [4] method from PyMoo [3] package for Multi-objective optimization in python.

The experimental setup and optimization parameters are described in the section 2.6.

2.3 Choice of point from Pareto front

As a solution of problem (1) we typically have a set of Pareto optimal points, which is called *Pareto front*. The points cannot be compared directly between each other, since they all are optimal in some sense. At this stage, the best $\boldsymbol{\theta}$ needs to be chosen according to some prior information. There are several approaches that can be made for this choice [28, 29].

Figures 3b and 4b show the Pareto front with all of the points being Pareto-optimal. One could consider the full spectrum of proposed solutions, but it may be convenient to select only a particular one. A farmer might want to know how to save money with a proposed approach or how to deal with strictly limited water resources.

We propose an inclusive way to address this problem. After the optimization procedure we have a set of m possible solutions $\{\boldsymbol{\theta}_j\}_{j=1}^m$ with corresponding loss functions values $\left\{\mathcal{L}^1(\boldsymbol{\theta}_j)\right\}_{j=1}^m$ and $\left\{\mathcal{L}^2(\boldsymbol{\theta}_j)\right\}_{j=1}^m$. We normalize the values of each objective function to zero mean and unit variance, denoting it as $\left\{\hat{\mathcal{L}}^1(\boldsymbol{\theta}_j)\right\}_{j=1}^m$ and $\left\{\hat{\mathcal{L}}^2(\boldsymbol{\theta}_j)\right\}_{j=1}^m$. This step allows users to deal with the objectives of different scales. After standardization, we select a point with minimal sum of the normalized loss value functions.

$$\min_{j \in (1,\dots,m)} \hat{\mathcal{L}}^1(\boldsymbol{\theta}_j) + \hat{\mathcal{L}}^2(\boldsymbol{\theta}_j) \tag{2}$$

In this approach, we treat each objective equally. The results from this choice are presented on the Figures 3b and 4b. However, the approach could be easily transformed to a weighted choice when you multiply objectives in the problem (2) to some coefficients, which could be interpreted as important. Note that it would be better to use some a-priori information to determine a specific choice of the irrigation dates and amounts of water among the Pareto set in each particular case.

For clarity we mean this specific method of choosing point from Pareto front, while we compare methods between each other. In all figures by "Ours" we mean a single point from Pareto front, produced by NSGA-II method, selected using the routine described above, just as well as for the Monte Carlo method. Since, the way of comparison is not unique, we also present the entire set of intermediate points for each method.

2.4 Weather averaging

The irrigation schedule is affected by uncertain weather factors. For example, precipitation affects the choice of irrigation dates. Since we cannot predict the weather for an entire growing season ahead, we cannot know the irrigation schedule's optimal dates in advance. However, we can consider weather history over the past few decades as various possible weather scenarios. We can assume that the weather next year may be similar to the past decades' weather scenarios. We can also assume that we can find the irrigation dates and irrigation volume for a particular location that will increase crop yield on average for various weather scenarios and minimize average water loss. For example, we can take the last 20-30 years and consider the weather as different climate scenarios for a given geographical region.

The general plan of the experiment is presented in Figure 1. The user specifies geographic coordinates of crop and planning of agricultural management practices, such as planting and harvesting crop dates, dates and amounts of irrigation, dates of fertilizer application, and fertilizer amounts. We use NASA's POWER data to receive weather data for recent years based on based on their geographical coordinates. At the next step, we initialize the NSGA-II optimizer to search for optimal irrigation dates and water volumes. For calculations, we use irrigation dates as discrete integer values ranging from the planting date (day 0) to the harvesting date, usually in the range of 120-150 days. We use water volume values between 0 and 150 mm of water per hectare. The optimizer offers solutions in the form of a combination of irrigation dates and water volumes, which we add to the input data for the WOFOST model. After using these inputs, we run simulations for each year for the last 20 years of available weather. For each year, we compute the crop yield value and the volume of lost water. Then the obtained values for 20 years are averaged and returned to the optimizer. Based on these two target values, the optimizer offers new combinations of irrigation dates and water volume. As the number of iterations increases, the values progress towards to optimal solutions. As a result, we receive a Pareto-set of optimal combinations of irrigation dates and water volumes. The specific choice of the solution is described in section 2.3.

2.5 Case study

To assess the method's performance, we have chosen agricultural fields in the Moscow region, Russia (Figure 2). The fields are located on the Oka River banks in the floodplain. The soil was characterized as Sandy loam with the following characteristics: bulk density - 1.4 g/cm$\hat{3}$, clay content - 13.9%, silt content - 13.1%, sand content - 73%, surface hardness - 0,87 MPa and subsurface hardness - 3.81 MPa. In these fields, farmers grow vegetable crops such as beets, potatoes, onions, and carrots. For the experiment, we chose sugar-beet (*Beta vulgaris*) and potato (*Solánum tuberósum*). We received information from farmers about sowing and harvesting operations and the proposed irrigation operations for sugar-beet and potatoes fields for the 2019 year. Irrigation was done seven times

Fig. 2: Map of the investigated region. We marked the experimental fields with potato and sugar-beet near the Oka river with color.

per season (June 10 and 20, July 1, 10, 20 and 29, August 15) for both crops with a water amount of 2 cm/ha. Sometimes farmers have to shift the dates by 1-2 days due to weather and other conditions. We took this into account and conducted ten simulations randomly changing the dates of watering, planting and harvesting for part of the experiment with farmer data. During the season, farmers, on average, contribute 190 kg/ha of nitrogen fertilizers for both crops.

2.6 Numerical experiments setup

We performed all of our numerical simulations on the Google Cloud platform (4 vCPUs, 4 GB memory). The average time of a WOFOST model run takes 10 s for 20 different weather scenarios. For the NSGA-II algorithm, we used 300 generations and a population size of 30 for each generation, so the algorithm performs 9000 estimations of computing crop yield and water loss. To maintain equality, we ran the Monte Carlo search with the number of iterations of 9000. The whole optimization procedure took around 25 hours for the single run. We conducted 10 runs with different random initializations and calculated mean and standard deviations for the reported metrics.

3 Results and discussion

In this section, we describe the results and compare the performance of our approach against Monte Carlo search. We ran the NSGA-II and the Monte Carlo search algorithms ten times with random initialization to evaluate their performance. As it was discussed above in section 2.3, we compare the performance of the methods with respect to the specific choice of the point from Pareto front. Thus, we received ten values of yield and water loss for potato and sugar beet and calculated the mean and standard deviation of loss functions. We ran the calculation ten times with a random date deviation of 1-2 days for the farmer's irrigation scheme to calculate the mean and standard deviation. The tables 1, 2 below contains mean values as well as standard deviations for the selected parameters.

	Yield (t/ha)	Water loss (cm)
`Farmer`	12.74 ± 0.03	$\mathbf{23.99 \pm 0.21}$
`Monte Carlo`	13.95 ± 0.18	35.54 ± 2.26
`Ours`	$\mathbf{14.11 \pm 0.09}$	26.84 ± 1.40

Table 1: Potato

	Yield (t/ha)	Water loss (cm)
`Farmer`	11.97 ± 0.1	31.73 ± 0.17
`Monte Carlo`	$\mathbf{12.17 \pm 0.03}$	42.38 ± 2.97
`Ours`	12.16 ± 0.03	$\mathbf{28.22 \pm 0.98}$

Table 2: Sugar-beet

The results presented in table 1 with potatoes experiments show that the NSGA-II algorithm consistently achieves higher yields than Monte Carlo. Results of experiments with sugar beet presented in the table 2 show that the Monte Carlo and NSGA-II produced approximately the same crop yield level. However, the NSGA-II algorithm chose strategies with significantly lower water loss.

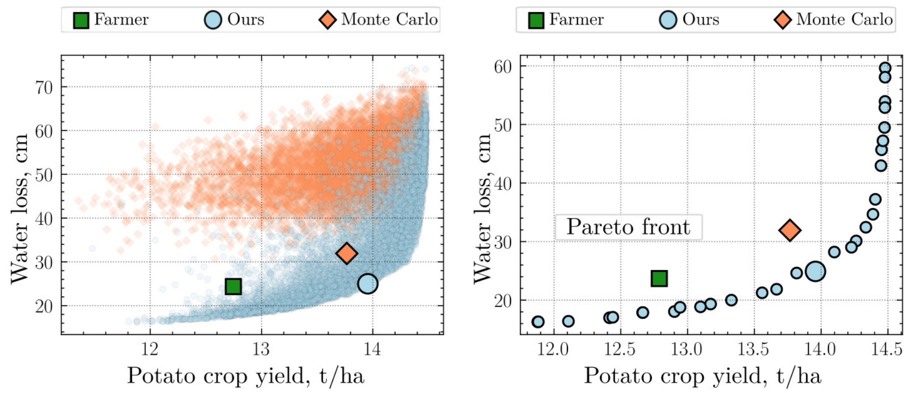
3.1 Potato crop

Figure 3 compare our approach based on NSGA-II to the Monte Carlo search for the potato crop. Scatter-plot 3a demonstrates the objective values received by NSGA-II, Monte Carlo search, and values achieved by a farmer's strategy for the single run. Scatter-plot 3b shows Pareto front achieved by NSGA-II and optimal solution selected by a weighted-sum method. We considered the importance of crop yield and water loss equally to select the optimal solution. Using the same approach, we selected the optimal solution from the objective values generated by the Monte Carlo search. Additionally, we plotted objective values based on farmer strategy.

These numerical experiments on optimizing potato irrigation based on weather history are shown in Figure 3. Points from both NSGA-II and the Monte Carlo search algorithms are approaching a limit of the yield of approximately 14.5 t/ha. We can assume that this is the maximum yield under the given conditions of soil, weather, and agricultural practices. In the seasonal water loss minimization problem, the NSGA-II algorithm is superior to the Monte Carlo search. Most of the water loss values are lower than the values obtained by the Monte Carlo search on the graph. It is interesting to mention that there are points from the NSGA-II Pareto front, which dominate a farmer's choice, while this property is not valid for the Monte Carlo Pareto front.

In the experiment to optimize potato irrigation, our approach achieved a mean potato yield of 14.11 t/ha, which is 9.7% higher than the farmer's solution with 12.74 t/ha. The Monte Carlo search achieved a yield of 13.95 t/ha, which is 8.6% percent higher than the farmer's.

On the other hand, farmer irrigated the field more efficiently (23.99 cm) than our approach (26.84 cm) and the Monte Carlo search (35.54 cm). However, our method only increased the mean water loss by 10%, whereas the Monte Carlo search by as much as 33%.



(a) All solutions

(b) Pareto front

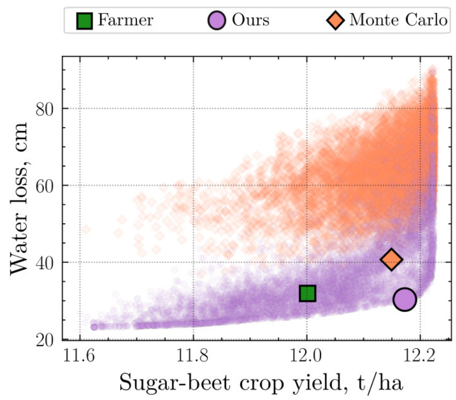
Fig. 3: NSGA-II performs better at searching for strategies with low water loss. Objective values selected by weighted-sum methods denoted by the larger icons show our method's advantage over the Monte Carlo search and the farmer's strategy for crop yield objective. The inflection on the line of objectives values achieved by NSGA-II shows that the increase in irrigation associated with water loss does not increase productivity.

The plot also shows the Pareto front, where we can identify the inflection when the yield values of the order of 14.5 t/ha and water loss of 30 cm are reached. Therefore, we can conclude that a further increase in irrigation does not increase potato yield.

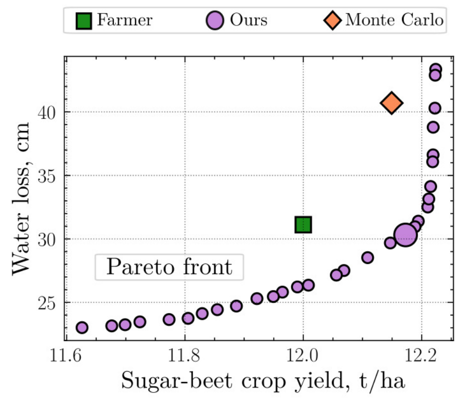
3.2 Sugar-beet crop

The values of the algorithm solutions for optimizing sugar-beet irrigation are shown in Figure 4. Figure 4a represents all the objective function values obtained by our algorithm, Monte Carlo's search and the farmer strategy for the single run. Figure 4b represents the Pareto front of our solution and the values selected based on our method's weighted sum method, Monte Carlo, and the farmer's value. The maximal yield obtained for both algorithms was about 12.15 t/ha. For the sugar-beet, the inflection on the Pareto front is more pronounced.

NSGA-II and the Monte Carlo achieved approximately the same yield values for sugar-beet. The mean crop yield value was 12.17 t/ha for both algorithms that 1.6% higher than the result of the farmer's strategy with 12.00 t/ha. However, our method (28.22 cm) reduced water loss by 11%, while the Monte Carlo search (42.38) strategy increased water loss by 33.5%.



(a) All solutions

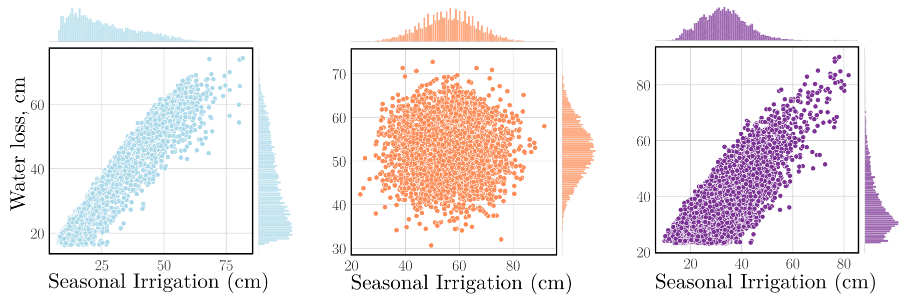


(b) Pareto front

Fig. 4: NSGA-II performs better at searching for strategies with low water loss. Objective values selected by weighted-sum methods denoted with the larger icons show our method's superiority over the Monte Carlo search and the farmer's strategy for crop yield and water loss. The inflection on the line of objectives values achieved by NSGA-II shows that the increase in irrigation, associated with water loss, does not increase productivity.

One of the multi-criteria optimization tasks is to reduce seasonal water losses. We compared the distribution of mean values of total irrigated water and the distribution of deep percolation water losses over 20 years of weather scenarios for all solutions produced by NSGA-II and Monte Carlo search for the single run. Results were obtained based on our approach and on the Monte Carlo search for sugar-beet and potato. The scatter-plots in Figure 5 illustrate the mean water loss dependence over 20 years of weather scenarios based on the total seasonal irrigation. Figure 5b demonstrates a scatter-plot for the Monte Carlo search. The scatter-plots in Figure 5 show the mean water loss dependence over 20 years of weather scenarios on the mean of total seasonal irrigation over 20 years of weather scenarios. Because of the random selection of irrigation water values, total seasonal irrigation and water loss have a normal distribution.

Figures 5a and 5c illustrate the result of the optimizer's performance, which shifts the seasonal water loss values' distribution to smaller values as water loss minimization undergoes. For both crops, seasonal water irrigation distribution and decreases the seasonal water loss values are similar. Because of the optimizer, these distributions are shifted towards smaller values. However, we can note differences in the distributions for potato and sugar-beet. The distribution of sugar-beet irrigation water has not moved as much to the lower values as for potatoes. However, the distribution of sugar-beet water losses has shifted significantly to the lower values. Such differences may be related to different plant physiology and root system features defined in the crop model.



(a) NSGA-II Potato (b) Monte Carlo search (c) NSGA-II sugar-beet

Fig. 5: Scatter-plots and distributions of values for water loss (cm) and total irrigation amount (cm) for our method and Monte Carlo search. NSGA-II attempts to minimize water loss and water volume for irrigation and generates agricultural practices that decrease water loss in front of the Monte Carlo search. The distributions of objective values for NSGA-II are shifted to low values, which is positive for agricultural purposes.

4 Conclusions

Multi-objective irrigation optimization based on crop model WOFOST and evolutionary algorithm NSGA-II has demonstrated its efficiency in finding the optimal irrigation strategy. We have shown the effectiveness of using the approach on the case study example with sugar-beet and potato crops. The results with potatoes experiments show that the NSGA-II algorithm consistently achieves higher yields. In experiments with sugar-beet, the Monte Carlo and NSGA-II produced approximately the same level of yield. However, the NSGA-II algorithm chose strategies with significantly lower water loss. Based on our numerical experiments, we see the advantage of using evolutionary multi-objective optimization over the Monte Carlo search. The use of the algorithm reduces seasonal water loss and increases crop yield based on long-term weather data. The source code and the results are available in our GitHub repository[1].

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