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AI- and data-driven crop rotation planning

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ABSTRACT

Crop rotation planning is the process of deciding the types and the temporal succession of plants on agricultural areas to increase soil quality, crop yield, and pest/weed resistance. The data sources and modalities available for crop rotation planning are very diverse and the domain lacks solely data-driven approaches. In this paper we used literature- and NDVI-measurement-based successor crop suitability matrices and crop-specific attributes such as contribution margin and nitrogen demand as input for training an DQN-based reinforcement learning agent to generate crop rotation sequences. Practitioners and crop rotation experts validated the generated crop rotation sequences and concluded that most of the sequences are realistic, comply with existing crop rotation rule sets, and can be applied in practice.

1. Introduction

Crop rotation planning is the process of deciding the types and the temporal succession of crop plants on agricultural areas to increase soil productivity, crop yield, and pest/weed resistance. In conventional farming, crop rotation planning is becoming an increasingly important factor, while in organic farming it is an essential process. Particularly in the latter, choosing successor crops for various years is done by considering agronomic, environmental, ecological and economic factors.

The data sources and modalities available for analysis in the context of crop rotation planning are very diverse, ranging from structured, e.g. well-known sensors for temperature or humidity, which contribute continuous-like readings, to discrete data about timings and amounts of planting and cultivation, fertilization, or irrigation, to unstructured data provided e.g. by satellite imagery or other, similar remote sensing approaches. This demands a similar diverse approach to learning from this data, where hybrid approaches, integrating various techniques and angles, can be integrated to improve the performance of the final analysis tools. In the following we describe existing approaches to crop rotation planning.

The problem of selecting ideal crop rotation plans can be formulated as a combinatorial problem. In the combinatorial setting, the cost function of the crop rotation problem, is of linear nature, which means the combinatorial problem can be formulated as a linear program. Alfandari et al. (2015) did formulate it as a sub category, an integer programming problem. The main objective for finding an optimal crop sequence solution is profit. Other objectives such as sustainability should be of similar importance, especially in organic farming. Incorporating additional objectives, into the combinatorial optimization problem can be done in two ways. By regarding them in the cost function in the combinatorial problem setting, the achieved problem formulation is called multi-objective combinatorial optimization. Another approach is to implement the environmental and ecologic objectives and constraints into the algorithm, by disregarding states which do not meet these conditions, and by only using the single-objective combinatorial optimization for profit.

Pavón et al. (2009) compared three multi-objective evolutionary algorithms in the process of solving the multi-objective crop rotation optimization problem (Strength Pareto Evolutionary Algorithm 2, Non-dominated Sorting Genetic Algorithm and the micro-Genetic Algorithm). The work describes how a vector of integers can be used to describe the crop sequences. The objectives used were to minimize cost, maximize accumulation of nutrients in soils, maximize economic rise, promote diversification of crops in subsequent seasons.

Bachinger and Zander (2007) proposed a tool for evaluating crop rotations for organic farming systems in central Europe. It is a static-rule based planning tool (using Microsoft Access) at field level for farmers and advisers, i.e., ROTOR includes a database with all relevant crops separately defined with inputs and outputs, machinery and timing. The user enters a few crops and ROTOR designs possible crop rotations around them. It defines the field operations for each fruit type. Each

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crop can be cultivated in different ways, whereby the system defines the different cultivation methods by varying previous crops and types of cultivation, such as ploughing, reduced tillage, undersowing of crops, catch crops, organic fertilization, straw harvesting. The crop rotations in ROTOR describe a sequence of cultivation methods. The crop rotations are evaluated using the criteria: Yield, N discharge, N withdrawal, N balance, humus reproduction, weed risk. The user defines his location properties, including land, soil quality, precipitation/year together with the desired duration of the crop rotation (in years) and the planned crop types. In addition, production measures, such as fertilization, and straw harvesting, fodder use, share of legumes, as well as catch crops can be planned.

Adewumi and Chetty (2017) used local search meta-heuristic algorithms to find optimized solutions for the annual crop planning problem (i.e., finding the optimal just for a year and not several years). The authors compared the enhanced Best Performance Algorithm (eBPA) against two well-known local search meta-heuristic algorithms (Tabu Search and Simulated Annealing). Previous research of this authors included other algorithms in the field of swarm intelligence (cuckoo search, firefly algorithm and glowworm swarm optimization) (Chetty and Adewumi, 2014) or other local search meta-heuristic techniques (Best Performance Algorithm, Iterative Best Performance Algorithm and Largest Absolute Difference Algorithm) (Chetty and Adewumi, 2013).

von Lücken et al. (2021) considered a 7-objective crop rotation problem (including cost minimization, crop diversification, etc.). Five multi- and many-objective evolutionary algorithms with a comparison metric to find the Pareto optimal solutions were compared. The RVEA (Reference Vector Guided Evolutionary Algorithm) obtained the best values for metrics and instance used. Other algorithms, next to RVEA, that were studied include NSGA3 (Reference Point-Based non-dominated Sorting Genetic Algorithm III), MOEA/D (Multiobjective Evolutionary Algorithm with Decomposition), SPEA2 (Strength Pareto Evolutionary Algorithms 2) and NSGA2 (Non-Dominated Sorting Genetic Algorithm II).

Osman et al. (2015) proposed a machine learning approach to crop rotation modeling that can predict the crops most likely to be present in a given field using crop rotations from the past 3 to 5 years at the beginning of the agricultural season. The approach is able to learn from data and integrate expert knowledge represented as first-order logical rules. The authors' evaluation showed that the proposed approach is able to predict the crop type of each field before the beginning of the harvest season with an accuracy up to 60%, which is better than the results obtained with current approaches based on remote sensing images.

Pahmeyer et al. (2021) developed the web-based, open source decision support system 'Fruchtfolge' (German for 'crop rotation') which provides decision makers with crop management recommendations for each field based on a single farm optimization model. 'Fruchtfolge' includes big data related to farm, location and management characteristics and provides instant feedback on alternative management choices. The authors used the crop rotation matrix from the CropRota model (Schönhart et al., 2011) to generate yield-maximizing crop rotation sequences.

Zhang et al. (2019) proposed a machine learning framework for predicting field-level crop planting before the growing season using historical crop planting maps from the Cropland Data Layer (CDL), a satellite-based data set of land cover in the United States. The framework uses a multi-layer artificial neural network to learn the patterns of crop rotation from CDL time series and generate crop planting maps for future years. The paper evaluates the framework on the U.S. Corn Belt and shows that it can achieve high agreement with the future CDL and high correlation with the official crop acreage statistics.

Yaramasu et al. (2020) developed a novel system for predicting crop type maps before the growing season using deep neural networks and historical crop maps from the Cropland Data Layer (CDL), a satellite-based data set of land cover in the United States. The system consists of two modules: an encoder that learns the spatio-temporal patterns of crop rotation from CDL time series, and a decoder that generates crop type maps for future years. The paper tests the system on Nebraska data and shows that it can achieve high accuracy and outperform a Markov Chain based approach. The paper aims to provide early crop information for satellite-based agricultural applications and decision making.

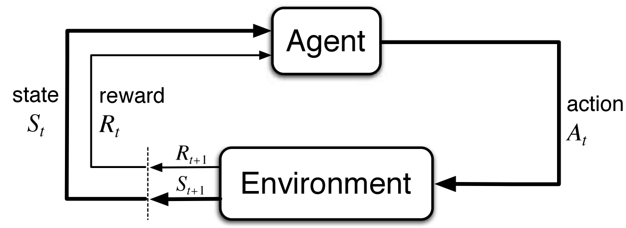

Fig. 1. Reinforcement learning entities and their interactions (Sutton and Barto, 2018).

Abernethy et al. (2023) proposed a novel method for preseason crop-type prediction using historical crop rotations from the Cropland Data Layer, a satellite-based data set of land cover in the United States. The method identifies groups of pixels with similar cropping history and summarizes them as polygons representing field boundaries, called crop sequence boundaries. These polygons reduce the computational cost and uncertainty of using all the Cropland Data Layer data for predictive modeling. The paper compares the polygon-based method with existing methods that use sampling and shows that it achieves the highest accuracy in most cases.

Compared to existing approaches the approach described in this paper is, to the best of our knowledge, the first one which uses reinforcement learning to train an agent which is capable of instantly generating realistic crop rotation sequences based on successor crop suitability matrices, soil nitrogen level, contribution margin, and cultivation breaks.

2. Algorithm and data

In organic farming, environmental and ecological objectives, are usually met by following heuristic rules. Especially successor crop suitability, like (Kolbe, 2006), is used to help reduce pest and weeds, and increase overall quality of the grown crops. As a subfield of artificial intelligence, reinforcement learning (RL) addresses the problem of automated learning of optimal decisions over time.

Fig. 1 shows entities in reinforcement learning and their interactions. The agent (learner and decision-maker) interacts with the environment (crops and their attributes in the crop rotation) which comprises everything outside the agent. The environment responds to actions conducted by the agent (selecting a specific crop after the current crop in the crop rotation) and presents new situations (new aggregated contribution margin, soil nitrogen level, etc.) to the agent. In some new situations the environment distributes rewards (yield) to the agent. The agent tries to maximize rewards (yield) over time (Sutton and Barto, 2018). In the reinforcement learning context combinatorial optimization problems may be formulated as a single player game: with states defined as the current solution, actions defined by adding or removing graph nodes or edges, and a reward (Drori et al., 2020).

The problem of crop rotation planning is suitable for reinforcement learning as we have an explicit transition and reward model: the revised and extended predecessor/successor crop suitability matrices by Kolbe (2006) (cf. Fig. 2) and by Fenz et al. (2023) (cf. Fig. 3). Both matrices describe which predecessor–successor crop combinations produce higher or lower yield based on long-term experiments (cf. Fig. 2) or

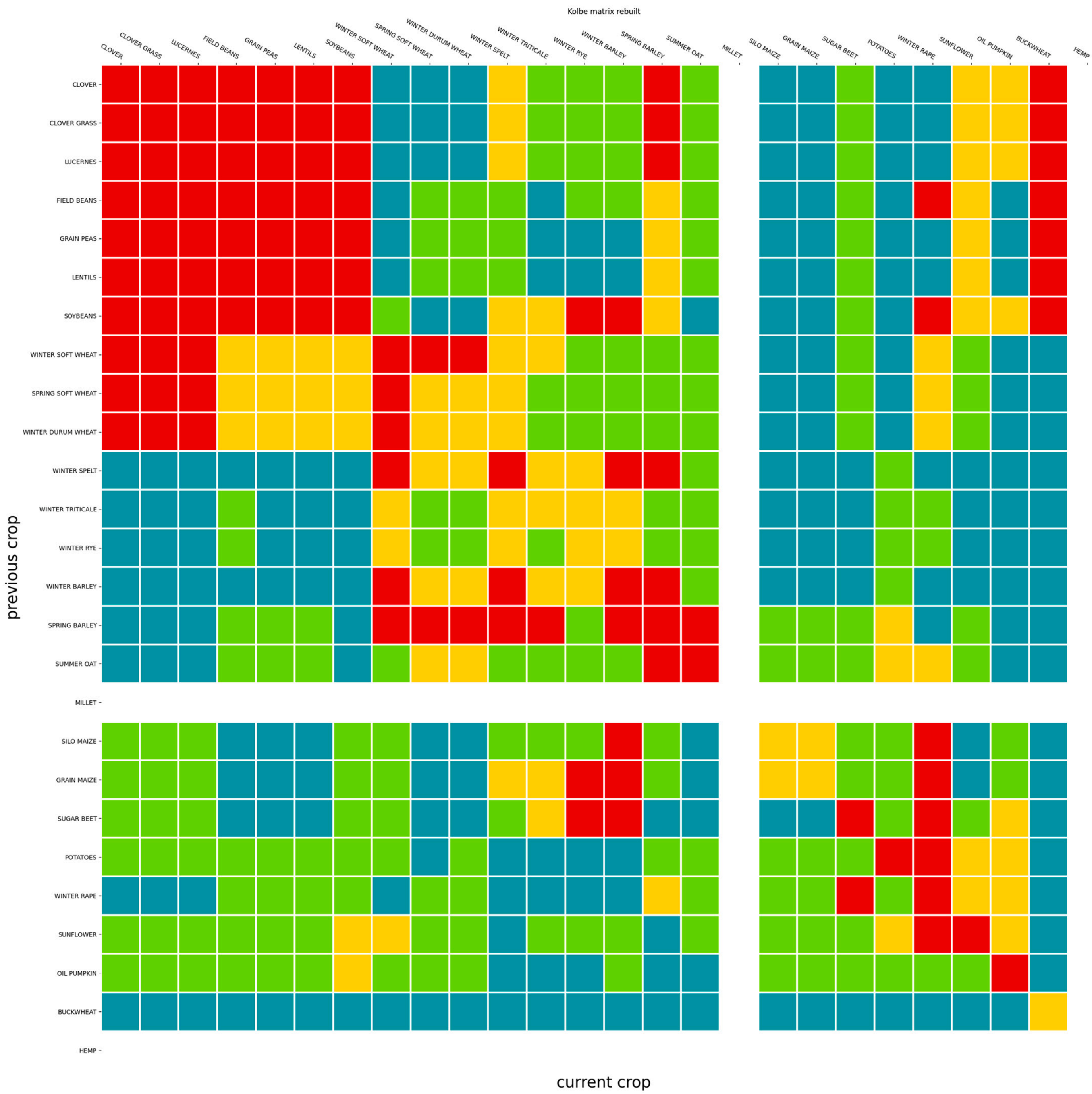

Fig. 2. Kolbe matrix (cf. Kolbe (2006)) extended by Wohlmuth, Friedel, Wagentristl, Surböck and mapped to discrete crops used in this project. Dark green: 120%–110% yield, light green: 110%–100% yield, yellow: 100%–90% yield, red: 90%–80% yield.

NDVI (Normalized Difference Vegetation Index) around harvesting time derived from satellite images as indicator for the yield (cf. Fig. 3[1]). Thus, both matrices can be used to generate long-term yield-enhancing crop rotation sequences.

Table 1 shows crop data (obtained from literature and experts) used at model training and the crop rotation sequence generation.

Based on Table 1 the following rules were used in the reward function defined in the environment of the reinforcement learning agent:

- During training the agent aims to maximize the reward within a crop rotation sequence of 5 and 7 steps (episode). If one of the following rules is violated during a transition from one step to another a negative reward (−2x the highest contribution margin in Table 1) will be added to the total reward of the episode.
- Each crop adds or removes nitrogen from soil during the crop rotation sequence. If nitrogen in soil drops below 0 a negative reward will be added.
- Only suitable successor crops should be planted after each crop, planting non suitable crop combinations will results in a negative reward. See Figs. 2 and 3 for the used successor crop suitability matrices.

[1] Please see Fenz et al. (2023) for further details on the matrix creation process.

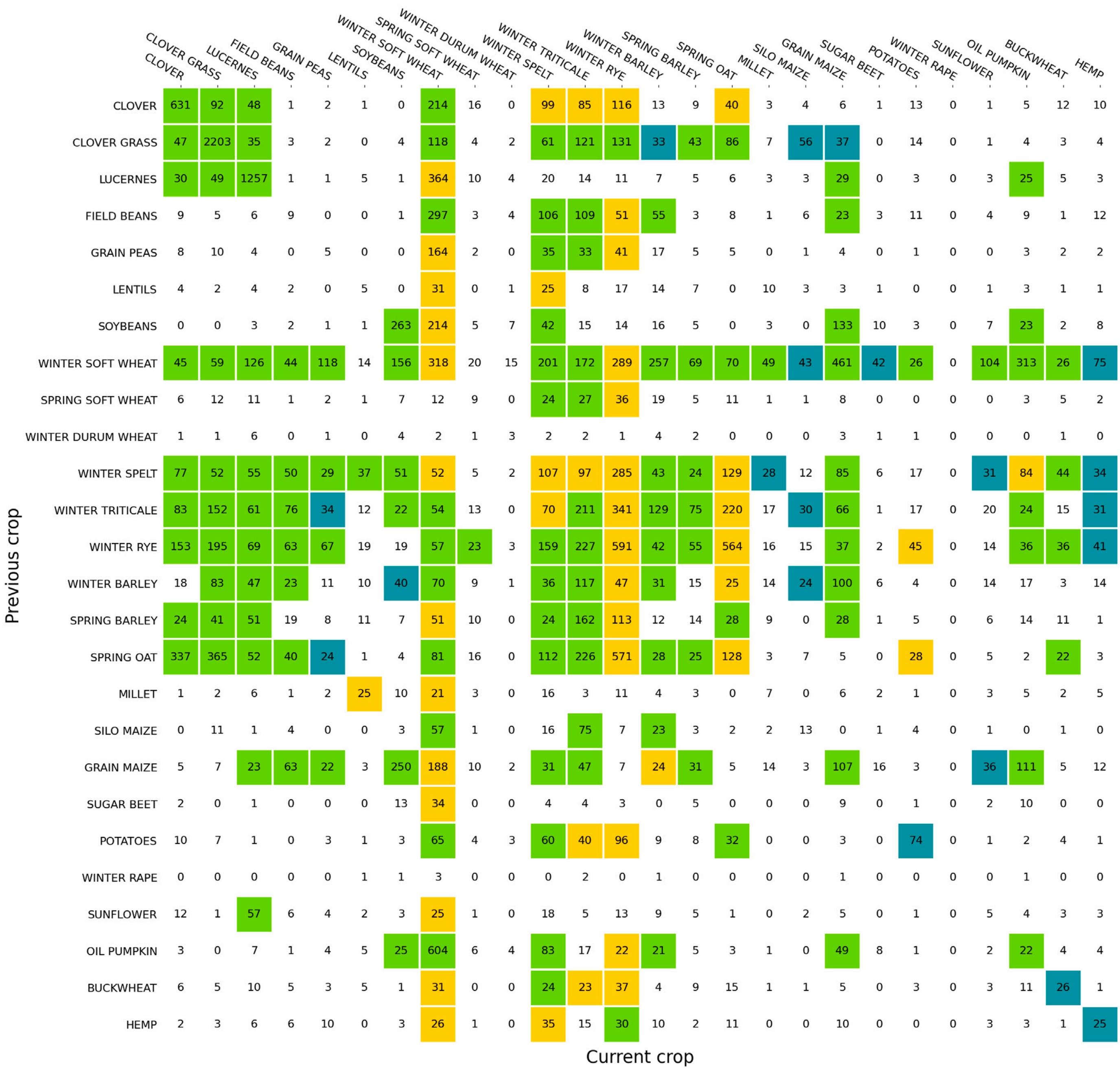

Fig. 3. Crop successor suitability matrix: measured NDVI (Normalized Difference Vegetation Index as indicator for the yield) effects for relevant crop combinations based on standardized NDVI values across all clusters. Dark green: 1.00–0.92 NDVI, light green: 0.92–0.84 NDVI, yellow: 0.84–0.75 NDVI, red: 0.75–0.67 NDVI, white: no or insufficient data available (data for less than 20 plots available). Cell numbers indicate the number of considered plots.

- If the same crop is planted earlier than indicated in the Recommended Break column a negative reward will be added.
- Crops which are classified as root crops are not allowed to be planted directly after each other. Otherwise a negative reward will be added.

3. Results

Based on (Mnih et al., 2015) and its Tensorflow/Keras implementation we developed a DQN-based crop rotation sequence generator which generates crop rotation sequences in line with the rules described above. DQNs (Deep Q Networks) learn control policies directly from sensory input using reinforcement learning. The environment for the reinforcement learning agent (DQNAgent) is defined as follows (cf. Fig. 4):

- Initialize the crop rotation sequence (episode) with a random crop from Table 1 and a soil nitrogen level of 200.
- The action space of the environment is defined by crops defined in Table 1 which can be planted after each other.
- When the agent observes the current environment it is able to observe the following facts: previously planted crop, currently planted crop, current nitrogen level in soil, current accumulated reward
- At each step nitrogen is added to the nitrogen level of the entire episode (cf. Column Nitrogen balance in Table 1)

Table 1
Crop data used in the training process. Nitrogen balance values are valid, when co-products remain on the field.

Crop (action space) Unit	Nitrogen balance [kg/ha]	Contribution margin (yield) [EUR/ha]	Rec. break [yrs]	Root crop 0/1: no/yes
CLOVER GRASS (perennial)	291	362	4	0
LUCERNE (perennial)	283	538	6	0
FIELD BEANS	59	137	5	0
GRAIN PEAS	29	4	6	0
LENTILS	−2	770	6	0
SOYBEANS	6	1097	4	0
WINTER SOFT WHEAT	−63	647	2	0
SPRING SOFT WHEAT	−46	429	2	0
WINTER DURUM WHEAT	−60	716	2	0
WINTER SPELT	−36	468	3	0
WINTER TRITICALE	−44	106	3	0
WINTER RYE	−30	31	2	0
WINTER FODDER BARLEY	−48	159	3	0
SPRING FODDER BARLEY	−41	96	2	0
SPRING OAT	−36	−40	5	0
MILLET	−36	318	2	0
SILO MAIZE	−116	1061	2	1
GRAIN MAIZE	−80	406	2	1
SUGAR BEET	−101	1328	4	1
POTATOES	−41	1974	4	1
WINTER RAPE	−46	83	6	0
SUNFLOWER	−50	474	6	1
OIL PUMPKIN	−10	1134	5	1
BUCKWHEAT	−31	922	1	0
HEMP	−22	896	1	0

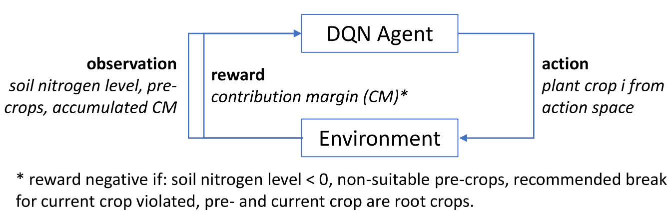

Fig. 4. DQN crop rotation generation framework.

- The reward is calculated and accumulated to the episode reward at each step as follows:
  - If the combination of previous and current crop is not suitable according to the successor crop suitability matrices the reward of the current step is set to a negative reward (see below). If the combination is suitable or very suitable the yield of the current crop (cf. Column Yield in Table 1) is multiplied by 1.1 or 1.2 and added to the accumulated episode reward.
  - The reward for the current step is set to a negative reward (two times the maximum yield in Table 1) if soil nitrogen level falls below 0, non-suitable crop combination, crop break rule violated, crop maximum occurrence rule violated, or row crop rule violated.

At the training phase the DQN Agent is initialized with

- three-layer sequential neural network (input and output layer take as input the current crop and provide the successor crop as output)
- sequential memory for experience replay
- EpsGreedyQPolicy as training and test policy
- disable double DQN
- 1000 warm up steps

At DQN training we use the Adam optimizer with a learning rate of 0.035 at 120.000 training steps. The average rewards during one exemplary DQN training run are shown in Fig. 5. As the first crop of the crop rotation sequence (episode) is chosen randomly, the average rewards vary over different training runs. Therefore, we saved the trained model's weights to a file if the model's performance was satisfactory after training (i.e., diverse and highly rewarding crop rotation sequences are produced by the model).

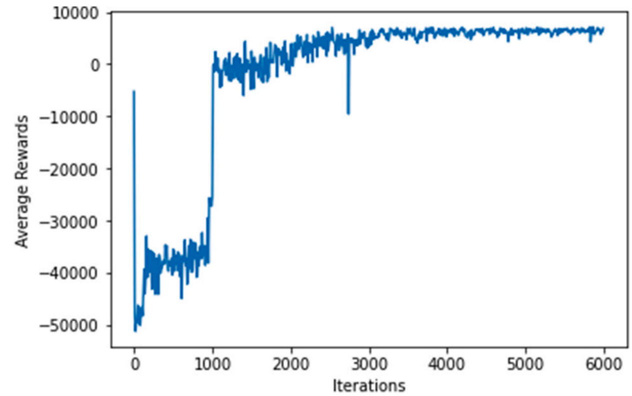

Fig. 5. Average rewards in one DQN training run.

Figs. 6 and 7 show the DQN testing debug output for the Kolbe-based and NDVI-measurement-based crop successor suitability matrices. The DQN environment renders detailed information for each step to check if rewards are distributed according to the intended rules described previously.

The trained model is executed 100 times with random start crops to produce crop rotation sequences of 10 steps. From these 100 sequences the details (i.e., the crops in the single steps) of the best sequences (in terms of reward) are shown to the user as possible and high rewarding crop rotation sequences. Figs. 8 and 9 show the exemplary top three sequences generated by the trained model using the Kolbe-based and NDVI-measurement-based crop successor suitability matrices.

Once the models are trained they allow for a fast generation of crop rotation sequences (compared to e.g., generation of sequences based on rules sets such as ontologies and genetic algorithms). As described in the next section we validated, together with practical and theoretical experts, crop rotation sequences generated by (i) the developed reinforcement learning approach using the Kolbe crop successor suitability matrix, and (ii) the developed reinforcement learning approach using the NDVI-measurement-based crop successor suitability matrix.

3.1. Validation

We validated the developed approach with relevant stakeholders to confirm its applicability in practice. Crop rotation exports and farmers, validated the generated crop rotation sequences with regard to their compliance to known rules from literature and practical experience. The evaluation results support the iterative optimization of the developed methods. In the following we list evaluation tasks for theoretical experts and the questionnaire for practical experts which was used during validation. Evaluation tasks for crop rotation expert:

1. Verification that crop rotation rules from literature are being followed in the generated crop rotation sequences (for Kolbe-based sequences)
2. Check crop rotation sequences for the practical suitability based on empirical knowledge of the theoretical expert (for Kolbe- and NDVI-based sequences)
3. What are the most prominent differences in crop rotation sequences produced by Kolbe- and NDVI-based matrices?

Questionnaire for practical experts (e.g., farmers):

```
Previous crop: 12 Oil squash         Current crop: 6 Soy beans             Suitability: 1  Crop counter: 1/-1    Row crop: 1-1    Soil: 6 = 206    Reward: -5290
Previous crop: 6 Soy beans           Current crop: 7 Winter barley         Suitability: 1  Crop counter: 1/-1    Row crop: 1-0    Soil: -48 = 158 Reward: 174.9
Previous crop: 7 Winter barley       Current crop: 6 Soy beans             Suitability: 2  Crop counter: 2/-1    Row crop: 0-1    Soil: 6 = 164    Reward: 1316.3999999999999
Previous crop: 6 Soy beans           Current crop: 11 Summer oat           Suitability: 2  Crop counter: 1/-1    Row crop: 1-0    Soil: -36 = 128 Reward: -48.0
Previous crop: 11 Summer oat         Current crop: 1 Field peas            Suitability: 1  Crop counter: 1/-1    Row crop: 0-0    Soil: 18 = 146   Reward: 4.4
Previous crop: 1 Field peas          Current crop: 5 Potato                Suitability: 2  Crop counter: 1/2     Row crop: 0-1    Soil: -41 = 105 Reward: 2368.7999999999997
Previous crop: 5 Potato              Current crop: 7 Winter barley         Suitability: 2  Crop counter: 2/-1    Row crop: 1-0    Soil: -48 = 57   Reward: 190.79999999999998
Previous crop: 7 Winter barley       Current crop: 6 Soy beans             Suitability: 2  Crop counter: 3/-1    Row crop: 0-1    Soil: 6 = 63     Reward: 1316.3999999999999
Previous crop: 6 Soy beans           Current crop: 7 Winter barley         Suitability: 1  Crop counter: 3/-1    Row crop: 1-0    Soil: -48 = 15   Reward: 174.9
Previous crop: 7 Winter barley       Current crop: 6 Soy beans             Suitability: 2  Crop counter: 4/-1    Row crop: 0-1    Soil: 6 = 21     Reward: 1316.3999999999999
Episode 2: reward: 1525.000, steps: 10
Previous crop: 3 Maize               Current crop: 0 Lucerne (2 years)     Suitability: 1  Crop counter: 1/2     Row crop: 1-0    Soil: 283 = 483 Reward: 591.8000000000001
Previous crop: 0 Lucerne (2 years)   Current crop: 5 Potato                Suitability: 2  Crop counter: 1/2     Row crop: 0-1    Soil: -41 = 442 Reward: 2368.7999999999997
Previous crop: 5 Potato              Current crop: 10 Winter spelt         Suitability: 2  Crop counter: 1/-1    Row crop: 1-0    Soil: -36 = 406 Reward: 561.6
Previous crop: 10 Winter spelt       Current crop: 6 Soy beans             Suitability: 2  Crop counter: 1/-1    Row crop: 0-1    Soil: 6 = 412    Reward: 1316.3999999999999
Previous crop: 6 Soy beans           Current crop: 7 Winter barley         Suitability: 1  Crop counter: 1/-1    Row crop: 1-0    Soil: -48 = 364 Reward: 174.9
Previous crop: 7 Winter barley       Current crop: 6 Soy beans             Suitability: 2  Crop counter: 2/-1    Row crop: 0-1    Soil: 6 = 370    Reward: 1316.3999999999999
Previous crop: 6 Soy beans           Current crop: 7 Winter barley         Suitability: 1  Crop counter: 2/-1    Row crop: 1-0    Soil: -48 = 322 Reward: 174.9
Previous crop: 7 Winter barley       Current crop: 6 Soy beans             Suitability: 2  Crop counter: 3/-1    Row crop: 0-1    Soil: 6 = 328    Reward: 1316.3999999999999
Previous crop: 6 Soy beans           Current crop: 7 Winter barley         Suitability: 1  Crop counter: 3/-1    Row crop: 1-0    Soil: -48 = 280 Reward: 174.9
Previous crop: 7 Winter barley       Current crop: 11 Summer oat           Suitability: 1  Crop counter: 1/-1    Row crop: 0-0    Soil: -36 = 244 Reward: -44.0
Episode 3: reward: 7952.100, steps: 10
Previous crop: 4 Sunflower           Current crop: 1 Field peas            Suitability: 1  Crop counter: 1/-1    Row crop: 1-0    Soil: 18 = 218   Reward: 4.4
Previous crop: 1 Field peas          Current crop: 11 Summer oat           Suitability: 1  Crop counter: 1/-1    Row crop: 0-0    Soil: -36 = 182 Reward: -44.0
Previous crop: 11 Summer oat         Current crop: 10 Winter spelt         Suitability: 1  Crop counter: 1/-1    Row crop: 0-0    Soil: -36 = 146 Reward: 514.8000000000001
Previous crop: 10 Winter spelt       Current crop: 1 Field peas            Suitability: 2  Crop counter: 2/-1    Row crop: 0-0    Soil: 18 = 164   Reward: 4.8
Previous crop: 1 Field peas          Current crop: 10 Winter spelt         Suitability: 1  Crop counter: 2/-1    Row crop: 0-0    Soil: -36 = 128 Reward: 514.8000000000001
Previous crop: 10 Winter spelt       Current crop: 11 Summer oat           Suitability: 1  Crop counter: 2/-1    Row crop: 0-0    Soil: -36 = 92   Reward: -44.0
Previous crop: 11 Summer oat         Current crop: 8 Winter rye            Suitability: 1  Crop counter: 1/-1    Row crop: 0-0    Soil: -30 = 62   Reward: 34.1
Previous crop: 8 Winter rye          Current crop: 6 Soy beans             Suitability: 2  Crop counter: 1/-1    Row crop: 0-1    Soil: 6 = 68     Reward: 1316.3999999999999
Previous crop: 6 Soy beans           Current crop: 11 Summer oat           Suitability: 2  Crop counter: 3/-1    Row crop: 1-0    Soil: -36 = 32   Reward: -48.0
Previous crop: 11 Summer oat         Current crop: 1 Field peas            Suitability: 1  Crop counter: 3/-1    Row crop: 0-0    Soil: 18 = 50    Reward: 4.4
Episode 4: reward: 2257.700, steps: 10
```

Fig. 6. DQN testing debug output with Kolbe-based crop successor suitability matrix.

```
Previous crop: 19 WINTER RAPE         Current crop: 15 SUNFLOWER            Suitability: -1 Crop counter: 1/-1    Row crop: 0-1    Soil: -50 = 150 Reward: -2030
Previous crop: 15 SUNFLOWER           Current crop: 9 LUCERNES              Suitability: 1  Crop counter: 1/3     Row crop: 1-0    Soil: 283 = 433 Reward: 591.8000000000001
Previous crop: 9 LUCERNES             Current crop: 4 POTATOES              Suitability: -1 Crop counter: 1/-1    Row crop: 0-1    Soil: -41 = 392 Reward: -2030
Previous crop: 4 POTATOES             Current crop: 22 WINTER SOFT WHEAT    Suitability: 1  Crop counter: 1/-1    Row crop: 1-0    Soil: -46 = 346 Reward: 471.90000000000003
Previous crop: 22 WINTER SOFT WHEAT   Current crop: 24 OIL PUMPKIN          Suitability: 1  Crop counter: 1/-1    Row crop: 0-1    Soil: -10 = 336 Reward: 1247.4
Previous crop: 24 OIL PUMPKIN         Current crop: 16 WINTER SPELT         Suitability: 1  Crop counter: 1/-1    Row crop: 1-0    Soil: -36 = 300 Reward: 514.8000000000001
Previous crop: 16 WINTER SPELT        Current crop: 15 SUNFLOWER            Suitability: 2  Crop counter: 2/-1    Row crop: 0-1    Soil: -50 = 250 Reward: 568.8
Previous crop: 15 SUNFLOWER           Current crop: 9 LUCERNES              Suitability: 1  Crop counter: 2/3     Row crop: 1-0    Soil: 283 = 533 Reward: 591.8000000000001
Previous crop: 9 LUCERNES             Current crop: 22 WINTER SOFT WHEAT    Suitability: 1  Crop counter: 2/-1    Row crop: 0-0    Soil: -46 = 487 Reward: 471.90000000000003
Previous crop: 22 WINTER SOFT WHEAT   Current crop: 24 OIL PUMPKIN          Suitability: 1  Crop counter: 2/-1    Row crop: 0-1    Soil: -10 = 477 Reward: 1247.4
Episode 1: reward: 1645.800, steps: 10
Previous crop: 5 CLOVER               Current crop: 22 WINTER SOFT WHEAT    Suitability: 1  Crop counter: 1/-1    Row crop: 0-0    Soil: -46 = 154 Reward: 471.90000000000003
Previous crop: 22 WINTER SOFT WHEAT   Current crop: 24 OIL PUMPKIN          Suitability: 1  Crop counter: 1/-1    Row crop: 0-1    Soil: -10 = 144 Reward: 1247.4
Previous crop: 24 OIL PUMPKIN         Current crop: 16 WINTER SPELT         Suitability: 1  Crop counter: 1/-1    Row crop: 1-0    Soil: -36 = 108 Reward: 514.8000000000001
Previous crop: 16 WINTER SPELT        Current crop: 15 SUNFLOWER            Suitability: 2  Crop counter: 1/-1    Row crop: 0-1    Soil: -50 = 58   Reward: 568.8
Previous crop: 15 SUNFLOWER           Current crop: 9 LUCERNES              Suitability: 1  Crop counter: 1/3     Row crop: 1-0    Soil: 283 = 341 Reward: 591.8000000000001
Previous crop: 9 LUCERNES             Current crop: 22 WINTER SOFT WHEAT    Suitability: 1  Crop counter: 2/-1    Row crop: 0-0    Soil: -46 = 295 Reward: 471.90000000000003
Previous crop: 22 WINTER SOFT WHEAT   Current crop: 24 OIL PUMPKIN          Suitability: 1  Crop counter: 2/-1    Row crop: 0-1    Soil: -10 = 285 Reward: 1247.4
Previous crop: 24 OIL PUMPKIN         Current crop: 16 WINTER SPELT         Suitability: 1  Crop counter: 2/-1    Row crop: 1-0    Soil: -36 = 249 Reward: 514.8000000000001
Previous crop: 16 WINTER SPELT        Current crop: 15 SUNFLOWER            Suitability: 2  Crop counter: 2/-1    Row crop: 0-1    Soil: -50 = 199 Reward: 568.8
Previous crop: 15 SUNFLOWER           Current crop: 9 LUCERNES              Suitability: 1  Crop counter: 2/3     Row crop: 1-0    Soil: 283 = 482 Reward: -2030
Episode 2: reward: 4167.600, steps: 10
Previous crop: 6 CLOVER GRASS         Current crop: 22 WINTER SOFT WHEAT    Suitability: 1  Crop counter: 1/-1    Row crop: 0-0    Soil: -46 = 154 Reward: 471.90000000000003
Previous crop: 22 WINTER SOFT WHEAT   Current crop: 24 OIL PUMPKIN          Suitability: 1  Crop counter: 1/-1    Row crop: 0-1    Soil: -10 = 144 Reward: 1247.4
Previous crop: 24 OIL PUMPKIN         Current crop: 16 WINTER SPELT         Suitability: 1  Crop counter: 1/-1    Row crop: 1-0    Soil: -36 = 108 Reward: 514.8000000000001
Previous crop: 16 WINTER SPELT        Current crop: 15 SUNFLOWER            Suitability: 2  Crop counter: 1/-1    Row crop: 0-1    Soil: -50 = 58   Reward: 568.8
Previous crop: 15 SUNFLOWER           Current crop: 9 LUCERNES              Suitability: 1  Crop counter: 1/3     Row crop: 1-0    Soil: 283 = 341 Reward: 591.8000000000001
Previous crop: 9 LUCERNES             Current crop: 22 WINTER SOFT WHEAT    Suitability: 1  Crop counter: 2/-1    Row crop: 0-0    Soil: -46 = 295 Reward: 471.90000000000003
Previous crop: 22 WINTER SOFT WHEAT   Current crop: 24 OIL PUMPKIN          Suitability: 1  Crop counter: 2/-1    Row crop: 0-1    Soil: -10 = 285 Reward: 1247.4
Previous crop: 24 OIL PUMPKIN         Current crop: 16 WINTER SPELT         Suitability: 1  Crop counter: 2/-1    Row crop: 1-0    Soil: -36 = 249 Reward: 514.8000000000001
Previous crop: 16 WINTER SPELT        Current crop: 15 SUNFLOWER            Suitability: 2  Crop counter: 2/-1    Row crop: 0-1    Soil: -50 = 199 Reward: 568.8
Previous crop: 15 SUNFLOWER           Current crop: 9 LUCERNES              Suitability: 1  Crop counter: 2/3     Row crop: 1-0    Soil: 283 = 482 Reward: -2030
```

Fig. 7. DQN testing debug output with NDVI-measurement-based crop successor suitability matrix.

1. General questions about crop rotation design
   (a) What are the main factors influencing your crop selection at the crop rotation planing?
   (b) How many crop rotations do you have on the farm?
   (c) How often do you change your crop rotation(s)?
   (d) How do you plan your crop rotation?
2. Input data questions
   (a) Does the required input data reflect operational reality?
   (b) Is the range of crops sufficient?
   (c) What crops are missing to reflect your farm operations?
3. Output data questions
   (a) How realistic and applicable are the generated crop rotation sequences?
   (b) Which rotations do you think are not realistic? And why not?
   (c) Can you find familiar crop rotation in the selection?
   (d) Does the output have the potential to encourage you to rethink your current crop rotations?
   (e) Are there any other comments, hints or suggestions for improvement that you would like to share with us?

The following sequences, generated by the developed approach, were used at the validation with one crop rotation expert and two farmers. Each sequence (episode) is referenced by a unique number, the total reward in terms of contribution margin, and the contribution margin after each step (grown crop). AI- and Kolbe-based crop rotation sequences are based on the crop successor suitability matrix shown in Fig. 2, AI- and measured NDVI-based crop rotation sequences are based on the crop successor suitability matrix shown in Fig. 3.

5-step AI- and Kolbe-based crop rotation sequences

Episode: 51 Reward: 4707
POTATOES 1974 CLOVER GRASS 398 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361 SPRING BARLEY 115

Episode: 45 Reward: 3692
BUCKWHEAT 922 SPRING BARLEY 115 CLOVER 434 WINTER DURUM

```
Epsiode: 5 Reward; 8655.199999999999
   Lucerne (2 years)   591.8000000000001
   Potato              2368.7999999999997
   Winter triticale    127.19999999999999
   Soy beans           1316.3999999999999
   Summer oat          -48.0
   Soy beans           1316.3999999999999
   Winter barley       174.9
   Soy beans           1316.3999999999999
   Winter barley       174.9
   Soy beans           1316.3999999999999
Epsiode: 53 Reward; 6107.299999999999
   Summer oat          -44.0
   Winter rye          34.1
   Soy beans           1316.3999999999999
   Summer oat          -48.0
   Lucerne (2 years)   645.6
   Potato              2368.7999999999997
   Winter spelt        561.6
   Soy beans           1316.3999999999999
   Summer oat          -48.0
   Field peas          4.4
Epsiode: 47 Reward; 6088.999999999999
   Field peas          4.4
   Potato              2368.7999999999997
   Field peas          4.4
   Winter triticale    127.19999999999999
   Soy beans           1316.3999999999999
   Winter barley       174.9
   Summer oat          -44.0
   Lucerne (2 years)   645.6
   Winter barley       174.9
   Soy beans           1316.3999999999999
```

Fig. 8. DQN output — high rewarding sequences with Kolbe-based crop successor suitability matrix.

```
Epsiode: 83 Reward: 6743.1
   WINTER SPELT         514.8000000000001
   SUNFLOWER            568.8
   LUCERNES              591.8000000000001
   WINTER SOFT WHEAT    471.90000000000003
   WINTER RYE           34.1
   CLOVER                1163.8000000000002
   WINTER SOFT WHEAT    471.90000000000003
   OIL PUMPKIN          1247.4
   WINTER SPELT         514.8000000000001
   CLOVER GRASS          1163.8000000000002
Epsiode: 51 Reward: 7307.400000000001
   WINTER SOFT WHEAT    471.90000000000003
   OIL PUMPKIN          1247.4
   WINTER SPELT         514.8000000000001
   SUNFLOWER            568.8
   LUCERNES              591.8000000000001
   WINTER SOFT WHEAT    471.90000000000003
   SOYBEANS             1206.7
   WINTER SOFT WHEAT    471.90000000000003
   OIL PUMPKIN          1247.4
   WINTER SPELT         514.8000000000001
Epsiode: 44 Reward: 7361.4000000000015
   CLOVER                1163.8000000000002
   WINTER SOFT WHEAT    471.90000000000003
   OIL PUMPKIN          1247.4
   WINTER SPELT         514.8000000000001
   SUNFLOWER            568.8
   LUCERNES              591.8000000000001
   WINTER SOFT WHEAT    471.90000000000003
   OIL PUMPKIN          1247.4
   WINTER SPELT         514.8000000000001
   SUNFLOWER            568.8
```

Fig. 9. DQN output — high rewarding sequences with NDVI-measurement-based crop successor suitability matrix.

WHEAT 859 OIL PUMPKIN 1361

Episode: 41 Reward: 3244
SUNFLOWER 474 SPRING BARLEY 115 CLOVER 434 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361

Episode: 98 Reward: 2475
SUMMER OAT -40 BUCKWHEAT 1106 SPRING BARLEY 115 CLOVER 434 WINTER DURUM WHEAT 859

Episode: 12 Reward: 3199
SPRING SOFT WHEAT 429 OIL PUMPKIN 1361 SPRING BARLEY 115 CLOVER 434 WINTER DURUM WHEAT 859

Episode: 48 Reward: 2730
SUMMER OAT -40 CLOVER 434 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361 SPRING BARLEY 115

Episode: 38 Reward: 5115
SPRING SOFT WHEAT 429 BUCKWHEAT 1106 CLOVER 434 WINTER SOFT WHEAT 776 POTATOES 2369

Episode: 33 Reward: 4967
POTATOES 1974 WINTER TRITICALE 127 LUCERNES 646 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361

Episode: 79 Reward: 4391
SILO MAIZE 1061 CLOVER GRASS 398 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361 WINTER SOFT WHEAT 712

Episode: 3 Reward: 3736
GRAIN MAIZE 406 CLOVER GRASS 398 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361 WINTER SOFT WHEAT 712

7-step AI- and Kolbe-based crop rotation sequences

Episode: 43 Reward: 6662
POTATOES 1974 SPRING SOFT WHEAT 515 OIL PUMPKIN 1361 CLOVER 398 WINTER RYE 34 BUCKWHEAT 1106 SILO MAIZE 1273

Episode: 74 Reward: 4228
WINTER RAPE 83 CLOVER 434 WINTER RYE 34 BUCKWHEAT 1106 WINTER BARLEY 191 BUCKWHEAT 1106 SILO MAIZE 1273

Episode: 7 Reward: 6953
SILO MAIZE 1061 CLOVER GRASS 398 WINTER RYE 34 BUCKWHEAT 1106 SILO MAIZE 1273 WINTER SOFT WHEAT 712 POTATOES 2369

Episode: 26 Reward: 3004
WINTER RAPE 83 CLOVER 434 WINTER RYE 34 BUCKWHEAT 1106 SILO MAIZE 1273 WINTER TRITICALE 117 SUMMER OAT -44

Episode: 94 Reward: 7006
POTATOES 1974 CLOVER 398 WINTER RYE 34 BUCKWHEAT 1106 SILO MAIZE 1273 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361

5-step AI- and measured NDVI-based crop rotation sequences

Episode: 90 Reward: 4846
POTATOES 1974 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247

Episode: 32 Reward: 3519
WINTER SOFT WHEAT 647 OIL PUMPKIN 1247 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712

Episode: 95 Reward: 2968
SPRING BARLEY 96 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247 WINTER SPELT 515

Episode: 63 Reward: 2880
GRAIN MAIZE 406 WINTER TRITICALE 117 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247

Episode: 0 Reward: 2581
BUCKWHEAT 922 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34

Episode: 85 Reward: 3988
BUCKWHEAT 922 WINTER SPELT 515 LUCERNES 592 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247

Episode: 79 Reward: 3472
GRAIN MAIZE 406 LUCERNES 592 WINTER SOFT WHEAT 712 OIL PUMPKIN

1247 WINTER SPELT 515

Episode: 89 Reward: 3713
WINTER SOFT WHEAT 647 OIL PUMPKIN 1247 WINTER SPELT 515 LUCERNES 592 WINTER SOFT WHEAT 712

Episode: 37 Reward: 2832
SUMMER OAT -40 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247 WINTER SPELT 515

Episode: 40 Reward: 3301
SPRING SOFT WHEAT 429 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247

7-step AI- and measured NDVI-based crop rotation sequences

Episode: 69 Reward: 5162
POTATOES 1974 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 BUCKWHEAT 1014 WINTER SPELT 515

Episode: 41 Reward: 4110
BUCKWHEAT 922 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 BUCKWHEAT 1014 WINTER SPELT 515

Episode: 66 Reward: 3827
GRAIN MAIZE 406 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 OIL PUMPKIN 1247 WINTER SPELT 515

Episode: 72 Reward: 3754
OIL PUMPKIN 1134 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 GRAIN MAIZE 447 WINTER SPELT 515

Episode: 49 Reward: 3169
BUCKWHEAT 922 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 SPRING SOFT WHEAT 472 WINTER TRITICALE 117

3.1.1. Validation results (Crop rotation expert)

Validation has been conducted with a crop rotation expert on 27.01.2023. The crop rotation sequences were presented to the expert to gather feedback based on the developed questionnaire:

1. Output data questions regarding AI- and Kolbe-based crop rotation sequence generation
   (a) How realistic and applicable are the generated crop rotation sequences?
   Much is possible, but only partly realistic or sensible in terms of position in the crop rotation.
   (b) Which rotations do you think are not realistic? And why not?
   See detailed description regarding each sequence below.
   (c) Can you find familiar crop rotation in the selection?
   See detailed description regarding each sequence below.
   (d) Does the output have the potential to encourage you to rethink your current crop rotations?
   In principle, yes. There are several ways in which crop rotations can be designed.
   (e) Are there any other comments, hints or suggestions for improvement that you would like to share with us?
   In organic farming, the positions of crops are to be assessed differently in part on the basis of experiential knowledge. E.g. sunflower would be favorable to place at the end of the crop rotation, since the weed pressure would then be lower. In the 7 step sequence some sequences are not as realistic as in the 5 step sequences. There are a few points to reconsider, e.g. winter rye should be further back in the crop rotation after forage legumes.
2. Output data questions regarding AI- and measured NDVI-effect-based crop rotation sequence generation
   (a) How realistic and applicable are the generated crop rotation sequences?
   Many things possible, but only partially realistic or sensible in terms of position in the crop rotation.
   (b) Which rotations do you think are not realistic? And why not?
   See detailed description regarding each sequence below.
   (c) Can you find familiar crop rotation in the selection?
   Yes.
   (d) Does the output have the potential to encourage you to rethink your current crop rotations?
   In principle, yes. There are several ways in which crop rotations can be designed.
   (e) Are there any other comments, hints or suggestions for improvement that you would like to share with us?
   In the last crop rotation cereals are present 4 years in a row. The 7 years sequences are more realistic with NDVI than those created with Kolbe.

Feedback on 5-step AI- and Kolbe-based crop rotation sequences

Episode: 51 Reward: 4707
POTATOES 1974 CLOVER GRASS 398 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361 SPRING BARLEY 115
Potatoes and then clover grass is unusual, in practice rather unrealistic, as a good previous crop is not used, because after potatoes, for example, cereals can be grown.

Episode: 45 Reward: 3692
BUCKWHEAT 922 SPRING BARLEY 115 CLOVER 434 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361
Realistic.

Episode: 41 Reward: 3244
SUNFLOWER 474 SPRING BARLEY 115 CLOVER 434 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361
In principle possible, but with sunflowers there is a risk of shoot-through in the following crop, therefore it is better to plant sunflowers before clover.

Episode: 98 Reward: 2475
SUMMER OAT -40 BUCKWHEAT 1106 SPRING BARLEY 115 CLOVER 434 WINTER DURUM WHEAT 859
Realistic.

Episode: 12 Reward: 3199
SPRING SOFT WHEAT 429 OIL PUMPKIN 1361 SPRING BARLEY 115 CLOVER 434 WINTER DURUM WHEAT 859
Realistic.

Episode: 48 Reward: 2730
SUMMER OAT -40 CLOVER 434 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361 SPRING BARLEY 115
Realistic.

Episode: 38 Reward: 5115
SPRING SOFT WHEAT 429 BUCKWHEAT 1106 CLOVER 434 WINTER SOFT WHEAT 776 POTATOES 2369
Realistic.

Episode: 33 Reward: 4967
POTATOES 1974 WINTER TRITICALE 127 LUCERNES 646 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361
Realistic.

Episode: 79 Reward: 4391
SILO MAIZE 1061 CLOVER GRASS 398 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361 WINTER SOFT WHEAT 712

Basically realistic, but silage corn before clover grass rather unfavorable.

Episode: 3 Reward: 3736
GRAIN MAIZE 406 CLOVER GRASS 398 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361 WINTER SOFT WHEAT 712
Basically realistic, but grain corn before clover grass rather unfavorable.

Feedback on 7-step AI- and Kolbe-based crop rotation sequences

Episode: 43 Reward: 6662
POTATOES 1974 SPRING SOFT WHEAT 515 OIL PUMPKIN 1361 CLOVER 398 WINTER RYE 34 BUCKWHEAT 1106 SILO MAIZE 1273
Rather less realistic or favorable because of winter rye after clover, possibly put silage corn after clover.

Episode: 74 Reward: 4228
WINTER RAPE 83 CLOVER 434 WINTER RYE 34 BUCKWHEAT 1106 WINTER BARLEY 191 BUCKWHEAT 1106 SILO MAIZE 1273
Rather less realistic or favorable because of winter rye after clover, possibly put silage corn after clover. Winter rape before clover rather not so favorable either.

Episode: 7 Reward: 6953
SILO MAIZE 1061 CLOVER GRASS 398 WINTER RYE 34 BUCKWHEAT 1106 SILO MAIZE 1273 WINTER SOFT WHEAT 712 POTATOES 2369
Rather less realistic or favorable. Winter rye after clover grass, winter wheat would be better here, also for the Potatoes, earlier crop rotation would be better.

Episode: 26 Reward: 3004
WINTER RAPE 83 CLOVER 434 WINTER RYE 34 BUCKWHEAT 1106 SILO MAIZE 1273 WINTER TRITICALE 117 SUMMER OAT -44
Rather less realistic or favorable because of winter rye after clover. Buckwheat may also be placed further back. Put winter triticale and silage corn further to the front.

Episode: 94 Reward: 7006
POTATOES 1974 CLOVER 398 WINTER RYE 34 BUCKWHEAT 1106 SILO MAIZE 1273 WINTER DURUM WHEAT 859 OIL PUMPKIN 1361
Rather less realistic or favorable: because of position potatoes, before clover, winter rye, buckwheat after clover. Silage corn, winter durum wheat too far back in the crop rotation.

Feedback on 5-step AI- and measured NDVI-based crop rotation sequences

Episode: 90 Reward: 4846
POTATOES 1974 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247
Realistic.

Episode: 32 Reward: 3519
WINTER SOFT WHEAT 647 OIL PUMPKIN 1247 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712
Realistic.

Episode: 95 Reward: 2968
SPRING BARLEY 96 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247 WINTER SPELT 515
Realistic.

Episode: 63 Reward: 2880
GRAIN MAIZE 406 WINTER TRITICALE 117 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247
Realistic.

Episode: 0 Reward: 2581
BUCKWHEAT 922 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34
Realistic, but winter rye is very early in the rotation after two-year-old clover-grass. A later crop rotation of winter rye would be possible, also depends on the location and soil creditability.

Episode: 85 Reward: 3988
BUCKWHEAT 922 WINTER SPELT 515 LUCERNES 592 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247
Realistic.

Episode: 79 Reward: 3472
GRAIN MAIZE 406 LUCERNES 592 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247 WINTER SPELT 515
Realistic.

Episode: 89 Reward: 3713
WINTER SOFT WHEAT 647 OIL PUMPKIN 1247 WINTER SPELT 515 LUCERNES 592 WINTER SOFT WHEAT 712
Realistic.

Episode: 37 Reward: 2832
SUMMER OAT -40 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247 WINTER SPELT 515
Realistic.

Episode: 40 Reward: 3301
SPRING SOFT WHEAT 429 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 OIL PUMPKIN 1247
Realistic.

Feedback on 7-step AI- and measured NDVI-based crop rotation sequences

Episode: 69 Reward: 5162
POTATOES 1974 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 BUCKWHEAT 1014 WINTER SPELT 515
Realistic or possible, but winter rye is very early after clover-grass, could also be later in the Crop rotation, but wheat preceding crop favorable.

Episode: 41 Reward: 4110
BUCKWHEAT 922 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 BUCKWHEAT 1014 WINTER SPELT 515
Realistic or possible, but winter rye is very early after clover-grass, could also be later in the Crop rotation, but wheat preceding crop favorable.

Episode: 66 Reward: 3827
GRAIN MAIZE 406 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 OIL PUMPKIN 1247 WINTER SPELT 515
Realistic or possible, but winter rye is very early after clover-grass, could also be later in the Crop rotation, but wheat preceding crop favorable.

Episode: 72 Reward: 3754
OIL PUMPKIN 1134 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 GRAIN MAIZE 447 WINTER SPELT 515
Realistic or possible, but winter rye is very early after clover-grass, could also be later in the Crop rotation, but wheat preceding crop favorable.

Episode: 49 Reward: 3169
BUCKWHEAT 922 WINTER SPELT 515 CLOVER GRASS 398 WINTER SOFT WHEAT 712 WINTER RYE 34 SPRING SOFT WHEAT 472 WINTER TRITICALE 117
Not so favorable or realistic. 4 x cereals in sequence not recommended. Better to use buckwheat in between.

3.1.2. Validation results (Practitioner 1)

Validation has been conducted with a practitioner (farmer) on 31.01.2023. The crop rotation sequences were presented to the expert to gather feedback based on the developed questionnaire:

1. Output data questions regarding AI- and Kolbe-based crop rotation sequence generation

(a) How realistic and applicable are the generated crop rotation sequences?
Doable, but in some parts not realistic.
(b) Which rotations do you think are not realistic? And why not?
5-step AI- and Kolbe-based crop rotation sequences were fine. Feedback for the 7-step AI- and Kolbe-based crop rotation sequences: Episode 74 - Winter rape before clover rather not so favorable. Episode 7 - Unrealistic, change wheat and rye. Episode 26 - Winter rape before clover rather not so favorable. Episode 94 - doable but unusual sequence.
(c) Can you find familiar crop rotation in the selection?
Yes, most of them.
(d) Does the output have the potential to encourage you to rethink your current crop rotations?
Yes. Provides another point of view, and shows opportunities.
(e) Are there any other comments, hints or suggestions for improvement that you would like to share with us?
Some of the generated sequences are not implemented in the suggested way in practice (see comments above).

2. Output data questions regarding AI- and measured NDVI-effect-based crop rotation sequence generation

(a) How realistic and applicable are the generated crop rotation sequences?
The sequences are realistic.
(b) Which rotations do you think are not realistic? And why not?
All sequences are realistic and doable.
(c) Can you find familiar crop rotation in the selection?
Yes.
(d) Does the output have the potential to encourage you to rethink your current crop rotations?
Yes, the sequences reflect my own experience.
(e) Are there any other comments, hints or suggestions for improvement that you would like to share with us?
No further comments.

3.1.3. Validation results (Practitioner 2)

Validation has been conducted with a practitioner (farmer) on 06.02.2023. The crop rotation sequences were presented to the expert to gather feedback based on the developed questionnaire:

1. Output data questions regarding AI- and Kolbe-based crop rotation sequence generation

(a) How realistic and applicable are the generated crop rotation sequences?
In some parts not realistic, but some problems are not taken into account (see below).
(b) Which rotations do you think are not realistic? And why not?
Too much summer crops in Episode 12, 43, and 98, problem of the proliferation in the following crop (Episode 45 after buckwheat, Episode 41 after sunflower), no leaf spar sequences, with the 7-step sequences energy of the clover is wasted for undemanding crops (Episode 74).
(c) Can you find familiar crop rotation in the selection?
Yes.
(d) Does the output have the potential to encourage you to rethink your current crop rotations?
No, because too few crops are listed within the sequences.
(e) Are there any other comments, hints or suggestions for improvement that you would like to share with us?
Improve the sequences in terms of leaf, spar, summer-, and winter-crops combinations.

2. Output data questions regarding AI- and measured NDVI-effect-based crop rotation sequence generation

(a) How realistic and applicable are the generated crop rotation sequences?
The sequences are realistic.
(b) Which rotations do you think are not realistic? And why not?
Most of them are realistic.
(c) Can you find familiar crop rotation in the selection?
Yes.
(d) Does the output have the potential to encourage you to rethink your current crop rotations?
No, because too few crops are listed within the sequences.
(e) Are there any other comments, hints or suggestions for improvement that you would like to share with us?
Minor: Improve the sequences in terms of leaf, spar, summer-, and winter-crops combinations. Observe cultivation dates.

3.1.4. Validation results overview

Table 2 provides an overview in terms of how many sequences were considered as realistic by the crop rotation expert and the practitioners. While the 7-step AI- and Kolbe-based crop rotation sequences were rated as mostly unrealistic, the 5-step sequences and the 7-step AI- and measured NDVI-based crop rotation sequences were rated as mainly realistic. Overall, it can be concluded that the approach has the potential to generate meaningful and reasonable crop rotation sequences, but needs to support more crops to increase acceptance.

4. Discussion

In this paper, we presented a novel approach to crop rotation planning using reinforcement learning. We used literature- and NDVI-measurement-based successor crop suitability matrices and crop-specific attributes such as contribution margin and nitrogen demand as input for training a DQN-based reinforcement learning agent to generate crop rotation sequences. We evaluated the generated sequences with practitioners and crop rotation experts and found that most of them were realistic, complied with existing rule sets, and could be applied in practice.

Our approach has several advantages over existing methods for crop rotation planning. First, it is data-driven and does not rely on predefined rules or heuristics, which may not capture the complexity and variability of crop rotation systems. Second, it is flexible and can adapt to different scenarios, such as changing market conditions, environmental factors, or farmer preferences. Third, it is scalable and can handle large-scale problems with multiple crops and fields.

Our approach also has some limitations and challenges that need to be addressed in future work. One limitation is that we assumed that the successor crop suitability matrices and the crop-specific attributes were fixed and known in advance, which may not be realistic in some cases. For example, the suitability of a crop may depend on the weather conditions, soil quality, or pest infestation of a specific year, which are uncertain and dynamic. Similarly, the contribution margin or nitrogen demand of a crop may vary depending on the input costs, output prices, or fertilizer application of a specific year, which are also uncertain and dynamic. Therefore, a possible improvement is to incorporate uncertainty and dynamics into the input data and the reinforcement learning model, such as using stochastic or adaptive successor crop suitability matrices and crop-specific attributes.

Another challenge is that we did not consider the possibility of planting more than one crop in the same field in the same year, which may increase the diversity and productivity of the system. Therefore, a possible improvement is to use a more realistic representation of the crop rotation problem, such as using raster or vector data for spatial information, using time windows or calendars for temporal information, or using mixed-integer programming for intercropping.

Table 2
Final validation round — results.

	Total sequences	Realistic sequences - Crop rotation expert	Realistic sequences - Practitioner 1	Realistic sequences - Practitioner 2
5-step AI- and Kolbe-based crop rotation sequences	10	9 (90%)	10 (100%)	3 (33.33%)
7-step AI- and Kolbe-based crop rotation sequences	5	0 (0%)	2 (40%)	0 (0%)
5-step AI- and measured NDVI-based crop rotation sequences	10	10 (100%)	10 (100%)	10 (100%)
7-step AI- and measured NDVI-based crop rotation sequences	5	4 (80%)	5 (100%)	5 (100%)

We believe that our approach has great potential for supporting agricultural decision making and improving crop rotation systems. We hope that our paper will inspire further research on applying reinforcement learning to crop rotation planning and other agricultural problems.

5. Conclusion

In this paper, we developed a new method for crop rotation planning using reinforcement learning. We trained a DQN-based reinforcement learning agent to generate crop rotation sequences using successor crop suitability matrices and crop-specific attributes from literature and NDVI measurements as input. We validated the generated sequences with experts and practitioners and showed that they were mostly realistic, followed existing rule sets, and were applicable in practice.

Our method has several benefits over existing methods for crop rotation planning. It is data-driven, flexible, and scalable. It can account for the complexity and variability of crop rotation systems, adjust to different scenarios, and deal with large-scale problems. Our method also has some drawbacks and challenges that require further work. One drawback is that we assumed that the input data were constant and known beforehand, which may not be true in some cases. Another challenge is that we used a simplified representation of the crop rotation problem, which neglected some important aspects such as spatial heterogeneity, temporal constraints, or intercropping.

We think that our method has great potential for supporting agricultural decision making and improving crop rotation systems. We hope that our paper will encourage more research on applying reinforcement learning to crop rotation planning and other agricultural problems. In future work we plan to extend the crops used for generating the sequences to provide farmers with more diverse crop rotation sequences.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Stefan Fenz reports financial support was provided by Austrian national funding agency (FFG).

Data availability

All data generated or analyzed during this study are included in this published article. Code for training the described reinforcement learning agent is available at https://colab.research.google.com/drive/13v0_gHZwpPLOjI9vb16f-Ww4m8Sa5WGK.

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