Titre: Title:	Performances of a Seq2Seq-LSTM methodology to predict crop rotations in Québec
Auteurs: Authors:	Ambre Dupuis, Camélia Dadouchi, & Bruno Agard
Date:	2023
Type:	Article de revue / Article
Référence: Citation:	Dupuis, A., Dadouchi, C., & Agard, B. (2023). Performances of a Seq2Seq-LSTM methodology to predict crop rotations in Québec. Smart Agricultural Technology, 4, 100180 (12 pages). https://doi.org/10.1016/j.atech.2023.100180

Smart Agricultural Technology 4 (2023) 100180

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

Performances of a Seq2Seq-LSTM methodology to predict crop rotations in Québec

Ambre Dupuis [a,b,c,*], Camélia Dadouchi [a,b,c], Bruno Agard [a,b,c]

[a] *Laboratoire en Intelligence des Données (LID), Canada*
[b] *Centre Interuniversitaire de Recherche sur les Réseaux d'Entreprise, la Logistique et le Transport (CIRRELT), Canada*
[c] *Département de mathématiques et génie industriel, Polytechnique Montréal, CP 6079, succursale Centre-Ville, Montréal, Québec, Canada*

ARTICLE INFO

Keywords:
Agriculture 4.0
Crop rotation
Deep learning
Seq2Seq
LSTM

ABSTRACT

To meet global food requirements while responding to the environmental challenges of the 21st century, an agri-environmental transition towards sustainable agricultural practices is necessary. Crop rotation is an ancestral practice and is a pillar of sustainable agriculture. However, this practice requires more organization on the part of producers for the management of crop inputs. That is why the development of a methodology for forecasting crop rotations in the medium term and at the field level is necessary. However, to date, only a methodology based on the Seq2Seq-LSTM has been theorized without being tested on a concrete case of application. The objective of this article is therefore to evaluate the performance of a Seq2Seq-LSTM methodology to predict crop rotations on a real case. The methodology was applied to a problem of crop rotation prediction for field crop farms in Québec, Canada. Using the Recall(N) metric and a historical sequence of length 6, the next 3 crops grown in a field can be predicted with over 81% success when considering 10 selected options. In addition, the methodology was augmented with contextual information such as economic and meteorological data to refine the forecasts. This augmentation systematically improves the performance of the model. This observation provides a relevant line of research for identifying other factors that influence producers' decision-making on crop rotation.

1. Introduction

The world's agricultural system must reinvent itself to face the current challenges of the century. It has to simultaneously meet ever-increasing food requirements [1] while ensuring the preservation of the environment despite the increasing scarcity of natural resources [2–4]. One of the paradigms that answers these concerns is called sustainable agriculture [5,6]. It is based, among other things, on the long-standing technique known as crop rotation [7,8].

Although this technique regenerates soil, breaks up pest invasions, as well as weed and disease proliferation [9], it also complexifies the management practices of producers. Agronomic recommendations such as fertilization must take into account the varying needs of the crops that will be grown [10,11]. It is therefore important to be able to predict the intentions of producers in the medium term in order to plan the most appropriate management practices for more sustainable agriculture.

Different studies have used agronomic knowledge [12–17] and/or various data analysis techniques [18–26] to predict the crops grown in a field in the coming year, and a methodology for predicting the crops grown in a field over the medium term has been theorized [27].

The objective of this study is to evaluate the performance of a Seq2Seq-LSTM methodology to predict crop rotations in Quebec.

The article is structured as follows. First, the concept and advantages of crop rotation, as well as the current tools used to predict these rotations are presented in Sections 2.1 and 2.2, respectively. Section 3 exposes the methodology used to evaluate the performance of the prediction tool. Then, Section 3.1 gives a brief overview of the methodology chosen to predict future crops in a field and provides a detailed case study of the application of this methodology on real data. The results obtained are discussed in Section 5 and finally, Section 6 concludes and outlines limitations and lines of research following this study.

2. State of the art

2.1. Grounds of crop rotation agronomy

Since antiquity, the benefits of crop rotation have been exploited by agricultural producers [7,8]. Changes in the type of crops cultivated in a

* Corresponding author.
E-mail address: ambre-manon.dupuis@polymtl.ca (A. Dupuis).

https://doi.org/10.1016/j.atech.2023.100180
Received 12 December 2022; Accepted 7 January 2023
Available online 14 January 2023

field during several successive growing periods helps to break disease cycles [28] and limit pests [29] and weeds invasions [30]. Therefore, this practice can reduce the amount of fungicides, pesticides and herbicides required by the crops. It also can limit the quantity of fertilizer required to obtain higher crop yields [11]. Crop rotation is also known for reducing soil erosion [31] and managing organic matter in soil [32]. For these reasons, crop rotation is considered one of the pillars of sustainable agriculture [5].

The cultivation of various crops during crop rotation cycles allows a diversification of the fauna and flora present in the soil. This diversity increases the quantity of nutrients in the soil and their accessibility to the crops grown. Indeed, the accessibility of nutrients for plants is determined by the action of fungi and bacteria present in the soil and enhanced by crop rotation. With this practice, the capacity of nitrogen fixation in the soil is improved as well as its capacity to ensure a nitrogen/phosphorus/potassium balance [33]. These being the nutrients used in chemical and organic fertilizers [34].

The beneficial effects of crop rotation were also highlighted in reducing GHG emissions (nitrogen and carbon dioxide) and increasing crop yields, particularly when using the corn-soybean scheme [35]. As stated by Singh and Kumar [36] "residues from increased rotation complexity and cover crops can improve nutrient use efficiency, increase SOC and mitigate GHG emissions". The crop rotation system therefore has an effect on GHG emissions. Not all crop rotation schemes will have the same impact on GHG emissions or soil nutrient requirements. A crop rotation should therefore aim to limit the amount of inputs (herbicides, pesticides, fungicides, fertilizers, etc.) needed in the fields, while lowering the emission of GHGs into the atmosphere [19].

Finally, crop rotation fits into the paradigm of sustainable development since it positively impacts all three spheres [37]. The reduction of crop inputs and the increase in production yields are definite economic advantages. This reduction also has an important social impact as it limits the exposure of producers to toxic agents. From an environmental point of view, the advantages of crop rotation are numerous. The reduction of soil erosion, the increase of soil fertility and the preservation in soil and water quality are just a few examples.

2.2. *Forecasting crop rotation*

As discussed in Section 2.1, crop rotations have a significant impact on soil fertility and the amount of fertilizer required. Since crop rotation patterns are determined over several years and crops do not have the same nutrient requirements [11], knowing the medium-term intentions of producers for crop rotations will help to predict and organize fertilizer inputs into crops [10]. This knowledge could be the basis for the optimization of crop inputs necessary to reduce soil and water pollution from agricultural activities [38].

Crop rotation is also critical to the development of farm models. More than 56% of the articles studied by Janssen and van Ittersum [39] mention constraints related to crop rotations in the definition of bio-economical farm mechanist models. These models would be extremely useful for the evaluation of agricultural and environmental policies that will shape the farms of tomorrow. Indeed, "In the context of the establishment of new economic, agronomic and governmental policies, farmers will be paid for re-establishing and increasing ecosystem services on agricultural land" [40].

Thus, there is a real need for medium-term crop forecasting. However, the intentions of producers in terms of crop rotation are linked to diverse factors that have varying degrees of impact on the decision made. For Klöcking et al. [41] for instance, the economic factor is often more important than the agronomic factor in the final decision of the producer. Yet agronomic principles are at the heart of many models [40].

The models based on theoretical knowledge use agronomic knowledge and mathematical tools to infer possible decisions by producers. Thus, Dogliotti et al. [15] and Bachinger and Zander [12] define models based solely on agronomic theory. Castellazzi et al. [13] use Markov chains on crop rotation patterns established by agronomists. Detlefsen and Jensen [14], Haneveld and Stegeman [16] define the problem of crop rotations as an optimization problem solved using linear programming and flow network modeling, while Salmon-Monviola et al. [17] uses agricultural scenario simulation.

The second direction of research is the use of agricultural historical data to create crop rotation forecasting models. For example, clustering methods have been used to highlight links between crops, agricultural conditions and practices [23,24], but these studies had no predictive power. Statistical methods such as Markov chains have also been used [18,21,22] but in this paradigm, they are generated from the analysis of historical data and not from agronomic knowledge. Approaches using deep learning techniques such as satellite image processing by convolutional neural networks [20,25] or artificial neural networks [26] are also proposed to analyse crop maps. A method for predicting medium-term crop rotations combining both statistical and deep learning approaches with recurrent neural networks has been theorized [27].It allows to determine, at the field level, the most probable sequences of crops to be exploited in the medium term, taking into account the cultivation habits of the producer. However, this methodology needs to be evaluated in a real situation.

A critical look at the literature shows that many studies enable predictions of crop rotations for year n or n+1 on a field scale [18,19,22,26] or regional trends for years n+1 to n+x [21]. Additionally, the methodology proposed by [27] to forecast crop rotations for years n+1 to n+x at the field level has not yet been evaluated in a real situation. The contribution of this article is to perform this evaluation on a real case study of crop rotations in Quebec.

3. Predictions of crop rotations in Québec

The present section presents a step-by-step application of the

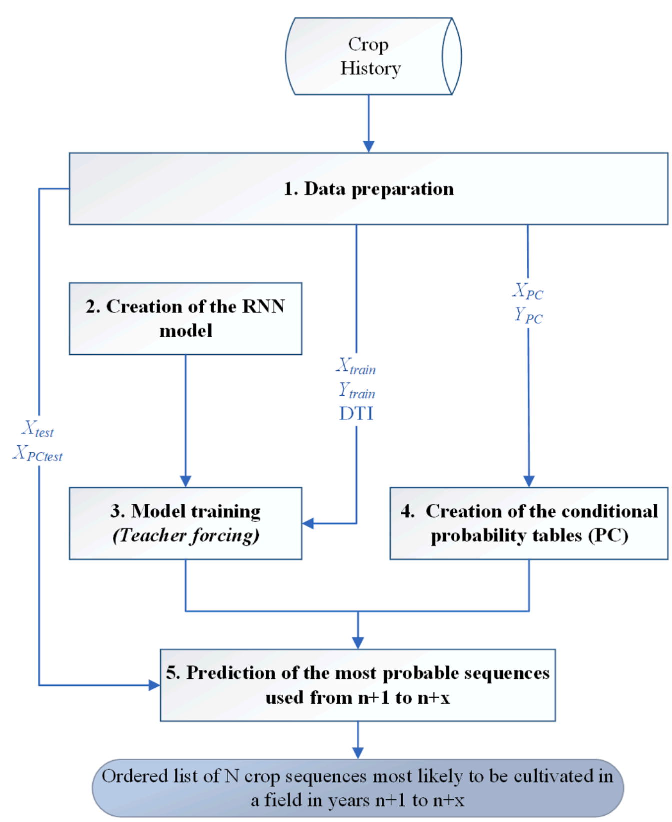

Fig. 1. Methodology for multi-temporal prediction of crop rotations using recurrent neural networks from Dupuis et al. [27].

methodology proposed in [27] (Section 3.1), visible on Fig. 1, as well as the results obtained in a case study (Section 3.2).

Crop history is used as input to the model. These data are then **(1)** prepared to obtain 8 distinct datasets (Section 3.1.1). The RNN model is **(2)** generated (Section 3.1.2) and then **(3)** trained on the training sets (Section 3.1.3). In parallel, **(4)** the statistical model based on the conditional probabilities of cropping patterns is created (Section 3.1.4). The results of the two models are combined in **(5)**, the prediction step allowing the generation of an ordered list of the N sequences of crops most likely to be cultivated in a field from year n+1 to n+x (Section 3.1.5).

The data used in the case study include agricultural data acquired from 4245 field crop farm fields in Quebec (Canada) between 2002 and 2016. The raw crop history dataset contains 42,271 records, each composed of 5 attributes presented in Table 1. In the raw crop history dataset, a record represents the crop grown in a field of an exploitation in a specific year.

The proposed methodology is applied, using Python 3.8.10, to the dataset by first preparing the data.

3.1. *Materials and methods*

In the following section we will present the methodology used to evaluate the performance of LSTMs, in a Seq2Seq architecture proposed by Dupuis et al. [27]. Fig. 2 gives a graphical overview of the steps used to predict the most probable scenarios of crop rotation to be exploited in a field in the next growing seasons according to cropping habits.

Crop history collected on Quebec farms are separated into two data sets. The first set (**Train set**) is used to train the model. The second set (**Test set**), which the model has never observed, is used in the trained model to predict different scenarios of crop rotations; those predictions are compared to real crop rotations (present in the test set), and their performances are evaluated.

3.1.1. *Step 1: Data preparation*

In the raw crop history dataframe, no attribute has the ability by itself to be used as an identification key of the fields. Therefore, there is a need to create an identification key to ensure the traceability of the crop sequences. The **Key** is created by concatenation of the **No** and **field** attributes (see Table 1). This ensures that the **Key** represents the unique identifier of a field in the dataframe. The **Key** attribute is used as the process identification key, while the **Year** attribute is used as the time marker and the **Culture** attribute is used as the activity. In this case study, a growing season is equated with a year. For clarity, the term "year" will be used to describe a growing season.

Next, duplicate records are identified and processed. To do this, the attributes **Culture, Key** and **Year** are selected and analyzed. For identical records (complete duplicates), the excess records are removed. For records with similar **Key** and **Year** values but different **Culture** values (partial duplicates), excess records are removed and the **Culture** value of the remaining record is changed to '<DUP>'. 116 partial duplicates are identified as '<DUP>' which is about 0.27% of the total data set. The dataset is then formatted using a pivot plot in order to represent crops sequences and identify missing data. The resulting table contains 4245 rows, representing the 4245 fields studied and 15 columns representing the years 2002 to 2016.

Table 1
Attributes of the raw crop history dataset used in the case study.

Attributes	Definition	Type
No	Unique identifier of an exploitation	String
Field	Unique identifier for an exploitation of a field	String
Centroïd	Geographical coordinates of the centroïd of the field	String
Year	Year of exploitation	Integer
Culture	Crop grown in the field at the specific year	String

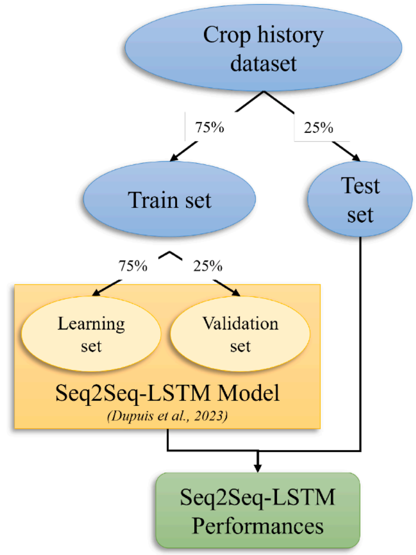

Fig. 2. Methodology used to evaluate the performances of the model proposed by Dupuis et al. [27].

To predict the next three years of crops in a field ($|n_{in}| = 3$, columns "Crop n+1" to "Crop n+3" in Table 2) using the crop history of the last 6 years ($|n_{in}| = 6$, columns "Crop n-5" to "Crop n" in Table 2), a moving window is created with L=15 and W=9. The hyperparameter L=15 allows the moving window to traverse all years between 2002 and 2016, to include as much available records as possible. The hyperparameter W is set to 9 since the input of W is defined by $|n_{in}| + |n_{out}|$.

This moving window is used to create sequences of length 9 respecting the two decision rules set for the management of missing data. As a reminder, the first rule consists of keeping only the sequences containing all the n_{out} data to be predicted. The second rule aims to keep the sequences containing a minimal threshold of information in the n_{in} information used for the forecast. In the case study, the filtering threshold SF is set to SF=75%, which means that for an input sequence of length n_{in}=6, a maximum of 2 missing elements are allowed in the input sequences for the prediction. The missing data presented in the generated sequences are encoded with the "<PAD>" mention.

These data manipulations allow the standardized sequences to go from 4245 records to 6760 records. Each sequence contains 9 elements that respect the decision rules on missing data and duplicate data. A fragment of the obtained dataset is presented in Table 2.

In Table 2, 7 crop sequences are shown. Duplicate and missing data processing generated '<DUP>' and '<PAD>' values. The data contained in columns **Crop n-5** through **Crop n** will be input used to predict the values in columns **Crop n+1** through **Crop n+3**. This separation is the basis for generating the 8 datasets used in the rest of the methodology.

The data is divided into a training dataset containing 75% of the records and a test dataset containing the remaining 25% records. This division is performed using the dedicated function of the scikit learn library. As a result, the 4 datasets X_{PC}, Y_{PC}, $X_{PC_{test}}$ and Y_{test} are created.

The sets X_{train}, Y_{train} and X_{test} are derived from X_{PC}, Y_{PC} and $X_{PC_{test}}$ respectively. The original datasets are encoded using the encoding dictionary shown in Fig. 3 to create X_{train}, Y_{train} and X_{test} datasets. Next, the *DTI* ("Data for Teaching Instructions") dataset is created using a copy of the Y_{PC} dataset, in which a column containing only <BOS> ("Beginning Of Sequence") values is added as the first column and the last column is deleted. Finally, the Y_{test} and *DTI* datasets are encoded using the same encoding dictionary shown in Fig. 3.

The summary of the characteristics and transformation of those 8 datasets are presented in Table 3.

Table 2
Extract of the dataframe after treating duplicates and missing data.

Key	Crop n-5	Crop n-4	Crop n-3	Crop n-2	Crop n-1	Crop n	Crop n+1	Crop n+2	Crop n+3
25949-15	Hay	Hay	Hay	Hay	Hay	Corn	Hay	Hay	<DUP>
25949-2	Hay	Oats	Hay	Hay	Hay	Hay	Corn	Corn	Barley
25949-21	Hay	Hay	Hay	Corn	Corn	Oats	Hay	Hay	Hay
25949–44136	Hay	Hay	Hay	Hay	Hay	Corn	Hay	Hay	<DUP>
25949–44137	Hay	Hay	Hay	Hay	Hay	Corn	Hay	Hay	<DUP>
25949-8A	Hay	Hay	Hay	Corn	Corn	Oats	Hay	Hay	Hay
25962-13	Barley	Barley	<PAD>	Hay	Hay	Hay	Hay	Corn	Barley
				...					

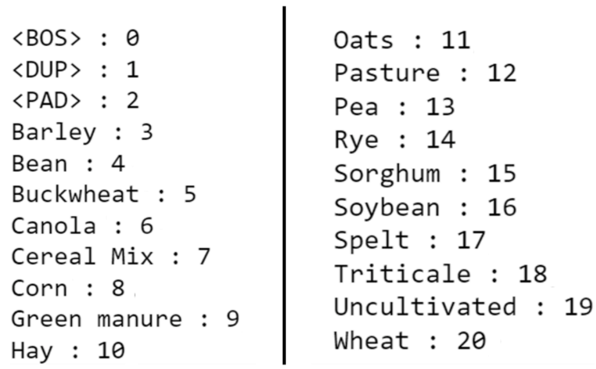

Fig. 3. Encoding dictionary used in the case study.

Table 3
Summary of the characteristics and transformations of the datasets.

Dataset	Size	Origin	Transformation
X_{train}	$5070 \times 6 \times 21$	Columns Crop n-5 to Crop n	One hot encoding
Y_{train}	$5070 \times 3 \times 21$	Columns Crop n+1 to Crop n+3	One hot encoding
X_{test}	$1690 \times 6 \times 21$	Columns Crop n-5 to Crop n	One hot encoding
Y_{test}	$1690 \times 3 \times 21$	Columns Crop n+1 to Crop n+3	One hot encoding
DTI	$5070 \times 3 \times 21$	<BOS> column and columns Crop n+1 to Crop n+2	One increment translation and One hot encoding
X_{PC}	5070×6	Columns Crop n-5 to Crop n	-
Y_{PC}	5070×3	Columns Crop n+1 to Crop n+3	-
$X_{PC_{test}}$	1690×6	Columns Crop n-5 to Crop n	-

3.1.2. Step 2: Creation of the RNN model

The architecture of the RNN depends on the data structure [27]. In this case study, 18 types of crops and 3 artificial codes (<BOS>, <DUP> and <PAD>) are considered (see Fig. 3). As such, the number of activities used to parameterize the model is set to $n_{activities} = 21$. Additionally, the length of the sequence to be predicted was set to $|n_{out}| = 3$, while the history considered for the prediction was set to $|n_{in}| = 6$. The number of neurons on the LSTM layer is determined by trial and error at $n_{neurons} = 282$ [42].

The resulting neural network is shown in Fig. 4.

It is important to note the match between the dimensions of the X_{train} and X_{test} datasets (Table 3) with the dimensions of the "seq_cult" input layer (Fig. 4). This adequacy is also observable between the dimensions of the *DTI* dataset (Table 3) and that of the input layer "decoder_in" (Fig. 4).

This consistency is necessary for the compilation of the model during the training phase.

3.1.3. Step 3: Model training

To train the model, the prevision Y_{pred} obtained as output of the Dense layer when using the history X_{train} is compared to the real data observed in the field Y_{train}. As Y_{train} is encoded in a One Hot Encoding format (see Table 3), the *categorical crossentropy function* proposed by Keras is used.

The Adam algorithm [43] is used as the optimizer to train the model. This stochastic gradient descent-based method is associated with a learning rate set to 0.001 and a batch size of 32. The use of a mini batch is intended to speed up the learning process and increase stability.

To avoid overfitting, a **validation set** containing 25% of the training data (**Train set**) is defined, as illustrated in Fig. 2. The calculation of the accuracy of the validation set is used as a stopping criterion for the callback function *Early Stopping*. A maximum of 2000 epochs is allowed, and at each epoch, the validation accuracy is evaluated in order to save the weights that achieve the best performance up to this point. The function *Early Stopping* is parameterized to maximize the accuracy over the validation set with a patience set to 50 epochs. Thus, if the accuracy of the validation does not improve in 50 epochs, training is stopped and the weights used in the previous accuracy improvement are used as the trained model.

3.1.4. Step 4: Creation of the conditional probability tables

In the proposed methodology, the PC model is created in parallel to the RNN model (Fig. 1 - Step 4). The larger the size of the considered history $|n_{in}|$, the more accurate the prediction will be. But, the larger $|n_{in}|$ is, the lower the probability of having already observed a specific sequence in the training set and therefore the less robust the model will be. To overcome this problem, n_{in} tables with different history lengths are generated. The use of different lengths of history allows to make a

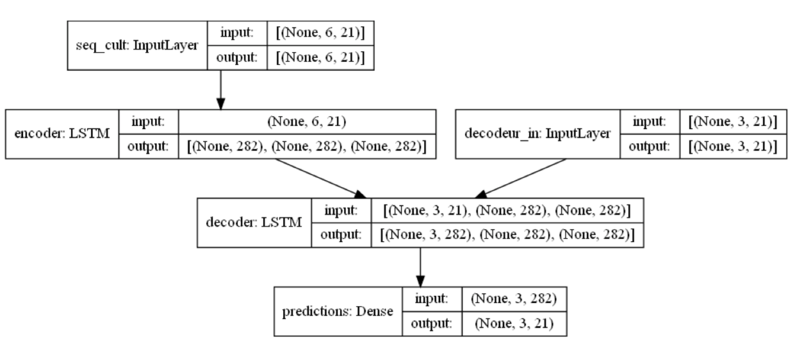

Fig. 4. Neural network architecture using crop history data.

trade-off between accuracy and robustness during the forecasting step (Fig. 1 - Step 5). Thus, the X_{PC} and Y_{PC} dataframes are used in order to create the $n_{in} = 6$ conditional probabilities tables.

The PC tables are created using the frequency table linking the input data X_{PC} to the output data Y_{PC}. The frequency of each combination is then divided by the frequency of occurrence of the input sequence from X_{PC}.

Table 4 indicates the dimensions of each of the PC table considered.

The Y_{PC} dataset contains 181 unique combinations while the number of combinations used as input increases exponentially with the length of the sequence considered. Table 5 represents a subset of the PC_6 table.

Once the PC tables created, the PC model and the RNN model are associated in the prediction step.

3.1.5. Step 5: Prediction of the most probable sequences used from n+1 to n+x

The RNN and PC models are then used to predict the most probable sequences used for period of n+1 to n+x.

To do this, the *BeamWidth* hyperparameter is set to $BeamWidth = 10$. Thus, for each record in X_{test}, the 10 sequences with the highest RNN (Seq) proposed by the RNN model are stored with their respective RNN (Seq). Fig. 5 represents the options obtained using the RNN model for given a historical sequence.

The historical sequence ['Soybean', 'Oats', '<PAD>', 'Soybean', 'Soybean', 'Corn'] is proposed to the trained RNN model. As a result, 10 options are proposed as scenarios that could be exploited by the producer in the subsequent 3 years. As presented in Fig. 5, the first option proposed by the model is the sequence ['Corn', 'Soybean', 'Corn']. This proposition is associated with RNN(['Corn', 'Soybean', 'Corn'])=-0.0084865. The ['Soybean', 'Soybean', 'Corn'] is considered by the RNN model as the second most probable sequence following the given history.

For each sequence **Seq** proposed by the RNN model for a given historical sequence from the $X_{PC_{test}}$ dataset, the conditional probabilities associated are found in each table of the PC model. Table 6 presents the conditional probabilities considering the historical sequence ['Soybean', 'Oats', '<PAD>', 'Soybean', 'Soybean', 'Corn'] and the sequences proposed by the RNN model.

In Table 6, the 10 options proposed by the RNN (see Fig. 5) are evaluated using the n_{in} PCs tables. Each column in Table 6 reports the conditioned probabilities obtained by the different PC tables for the sequences proposed by the RNN model.

Since the first sequence proposed by the RNN model is ['Corn', 'Soybean', 'Corn'], the first row of Table 6 represents the evaluation of this sequence using the PC tables. The first column of Table 6 represents the probability of having the sequence proposed by the RNN given the last value of the historical sequence (table PC1). Thus, the value 0.141805 in the PC1(Seq) column means that more than 14% of the historical data had the sequence ['Corn', 'Soybean', 'Corn'] following the ['Corn'] crop. Mathematically, the first row of Table 6 can be expressed as follows:

$$\begin{array}{l} For\ PC1(Seq) : P([{'}Corn{'},{'}Soybean{'},{'}Corn{'}]|[{'}Corn{'}]) = 14,1805\% \\ For\ PC2(Seq) : P([{'}Corn{'},{'}Soybean{'},{'}Corn{'}]|[{'}Soybean{'},{'}Corn{'}]) = 18,3544\% \\ For\ PC3(Seq) : P([{'}Corn{'},{'}Soybean{'},{'}Corn{'}]|[{'}Soybean{'},{'}Soybean{'},{'}Corn{'}]) = 21,1382\% \\ For\ PC4(Seq) : P([{'}Corn{'},{'}Soybean{'},{'}Corn{'}]|[{'}<PAD>{'},{'}Soybean{'},{'}Soybean{'},{'}Corn{'}]) = 100\% \\ \ldots \end{array}$$

>

It can be noted that the sequence ['Oats', 'Soybean', 'Corn'] has never been seen in the historical data used for training, hence the zero value observed in all of the PC tables for this specific sequence. The duality between the accuracy and robustness of the PC model can also be observed in Table 6.

Table 4
Dimensions of the 6 PC tables considered.

Table	Size
PC_1	(13,182)
PC_2	(81,182)
PC_3	(266,182)
PC_4	(572,182)
PC_5	(935,182)
PC_6	(1215,182)

Since the RNN(Seq) from the RNN model is the logarithm likelihood of the proposed sequence Seq and since the PC probabilities have to be integrated to the RNN(Seq), those PC probabilities are transformed by the logarithmic function, as shown in Table 7.

Since the logarithmic function is an asymptotic one, the image of the null value is $-\infty$. However, unseen scenarios should not be excluded but only penalised. Thus, the value $-\infty$ is replaced by a constant k representing the value of the penalty. In this case study, k is set to $k = -10$.

Once the results of the RNN and PC models are obtained, the global score for each proposed sequence can be calculated. The integration of the RNN and PC results are done by a linear function. The PC results are weighted using a vector ω. For each PC table, the value of the associated coefficient ω_i is determined by trial and error. As the PC model contains 6 tables, the coefficients ω_6 and ω_5 are set to 0.45 and 0.15, while the other coefficients are assigned a null value.

Eq. 1 is an example of the calculation used to determine the score of the possible sequence ['Corn', 'Soybean', 'Corn'].

$$\begin{aligned} Score(SEQ) &= RNN(SEQ) + \omega_6 \times PC_6(SEQ) + \omega_5 \times PC_5(SEQ) \\ &= -0.0084865 + 0.45 \times 0 + 0.15 \times 0 \\ &= -0.0084865 \end{aligned} \tag{1}$$

The sequences are then put in order by increasing the order of the overall score obtained. The N best sequences are chosen to generate the ordered list of the N most likely sequences exploited from years n+1 to n+x.

Table 8 is the result of the prediction step for a field history of ['Soybean', 'Oats', '<PAD>', 'Soybean', 'Soybean', 'Corn'] for the following 3 crop years.

The confidence of the model in the prediction can be assessed by looking at the overall score of each sequence. The closer the score is to 0 and the larger the difference in score between two consecutive sequences, the higher the confidence of the model in the first proposed sequences. In Table 8, the first proposed option has a score of -0.008487, the next proposed sequence is -11.8257; in this case, we are extremely confident in the prediction of Top(1).

In fact, the sequence of crops actually grown after the historical sequence ['Soybeans', 'Oats', '<PAD>', 'Soybeans', 'Soybeans', 'Corn'] was in fact the sequence ['Corn', 'Soybeans', 'Corn'] correctly predicted by the model as the Top(1) option. This comparison between the predicted sequences and the actual sequences observed in the fields allows us to evaluate the model. This is the focus of the following section.

Table 5
Fragment of the PC_6 table.

	Output			
Input	**[Corn, Corn, Barley]**	**[Corn, Corn, Bean]**	**[Corn, Corn, Corn]**	…
[<PAD>, <PAD>, Corn, Corn, Corn, Bean]	0.0%	50.0%	0.0%	
[<PAD>, <PAD>, Corn, Corn, Corn, Corn]	0.0%	0.9%	64.8%	
[<PAD>, <PAD>, Corn, Corn, Corn, Hay]	0.0%	0.0%	0.0%	
[<PAD>, <PAD>, Corn, Corn, Corn, Pea]	0.0%	33.3%	66.7%	
[<PAD>, <PAD>, Corn, Corn, Corn, Soybean]	3.8%	0.0%	20.8%	
…	…			

```
Input Sequence :  ['Soybean', 'Oats', '<PAD>', 'Soybean', 'Soybean', 'Corn']
Option : SEQ, BeamScore
Option 1 : ['Corn', 'Soybean', 'Corn'], -0.008486500455109515
Option 2 : ['Soybean', 'Soybean', 'Corn'], -5.825711020684496
Option 3 : ['Oats', 'Soybean', 'Corn'], -6.169144881592859
Option 4 : ['Corn', 'Soybean', 'Soybean'], -6.395806962568327
Option 5 : ['Corn', 'Corn', 'Corn'], -6.731094635989389
Option 6 : ['Corn', 'Soybean', 'Wheat'], -7.831978563987422
Option 7 : ['Wheat', 'Soybean', 'Corn'], -9.170893412889505
Option 8 : ['Corn', 'Soybean', 'Hay'], -11.008856526703555
Option 9 : ['Soybean', 'Soybean', 'Soybean'], -12.213031482797714
Option 10 : ['Soybean', 'Corn', 'Corn'], -12.548319156218776
```

Fig. 5. Output of the RNN model after BeamSearch with $BeamWidth = 10$.

3.1.6. *Evaluation of the prediction model*

The model is evaluated using the $Recall(N)$ metric. $Recall(N)$ quantifies the ability of the model to predict the correct sequence of activities in the $TOP(N)$ of proposed sequences. Another measure of interest is proposed in view of the sequential nature of the value to be predicted. This new measure, called $Recall_{WO}(N)$ standing for RecallWithout Order), quantifies the ability of the model to predict the correct activities in the proposed sequences, even in a different order. Thus, the difference between $Recall(N)$ and $Recall_{WO}(N)$ lies in taking into account the order of activities within sequences.

On a global point of view, we have to evaluate, for each element (k) in the Test set, if the proposed list of N crop sequences most likely to be cultivated ($Top(N)$) contents or not the real sequence that has been realized (Y_{test}). $Recall(N)$ is increased if Y_{test} is exactly present in $Top(N)$, and $Recall_{WO}(N)$ is increased if Y_{test} is present in $Top(N)$ even if it's in a different order.

For that purpose, two variables are introduced PIO (for: Present In Order) and PWO (for: Present Without Order) and incremented separately. It means that for each element in the Test set, we compare Y_{test} with $Top(N)$ and increment (or not) PIO or PWO (See Algorithm 1).

Then, the performance measures $Recall(N)$ and $Recall_{WO}(N)$ are, respectively, evaluated as follows.

$$Recall(N) = \frac{PIO}{|Y_{test}|} \tag{2}$$

$$Recall_{WO}(N) = \frac{PWO}{|Y_{test}|} \tag{3}$$

$With:$
$|Y_{test}| = Number\ of\ records\ in\ Y_{test}$

Table 9 shows an example for 4 fields and N=3. The first field ($k = 1$) crop rotation is predicted in order in the second set of the $Top(3)$ propositions (in bold), then PWO and PIO make one point each. The second field ($k = 2$) crop rotation is predicted not in order in the first set of the $Top(3)$ proposition (in bold), then PWO makes one point, but not PIO. The third field ($k = 3$) crop rotation is not predicted correctly, then PWO and PIO do not make any point. For $k = 4$, the crop rotation is predicted correctly in the first proposition, then PWO and PIO make one point each. Finally, $Recall(3) = 2/4$ and $Recall_{WO}(3) = 3/4$

Finally, the evaluation of the ability of the model to predict the correct activity at position x of the Top(1) sequence allows us to quantify the loss of information over time due to the accumulation of errors in the model. For this reason, another performance measure is defined by Eq. 4.

Table 6
Conditional probabilities considering the historical sequence ['Soybean', 'Oats', '<PAD>', 'Soybean', 'Soybean', 'Corn'].

SEQ	PC1(Seq)	PC2(Seq)	PC3(Seq)	PC4(Seq)	PC5(Seq)	PC6(Seq)
[Corn, Soybean, Corn]	0.141805	0.183544	0.211382	1.0	1.0	1.0
[Soybean, Soybean, Corn]	0.036096	0.059494	0.113821	0.0	0.0	0.0
[Oats, Soybean, Corn]	0.000000	0.000000	0.000000	0.0	0.0	0.0
[Corn, Soybean, Soybean]	0.023204	0.026582	0.065041	0.0	0.0	0.0
[Corn, Corn, Corn]	0.283241	0.092405	0.105691	0.0	0.0	0.0
[Corn, Soybean, Wheat]	0.006998	0.020253	0.000000	0.0	0.0	0.0
[Wheat, Soybean, Corn]	0.001842	0.003797	0.000000	0.0	0.0	0.0
[Corn, Soybean, Hay]	0.000368	0.000000	0.000000	0.0	0.0	0.0
[Soybean, Soybean, Soybean]	0.014365	0.013924	0.048780	0.0	0.0	0.0
[Soybean, Corn, Corn]	0.124494	0.075949	0.073171	0.0	0.0	0.0

Table 7
Logarithmic results of the RNN and the PC models considering the historical sequence ['Soybean', 'Oats', '<PAD>', 'Soybean', 'Soybean', 'Corn'].

SEQ	RNN(Seq)	PC1(Seq)	PC2(Seq)	PC3(Seq)	PC4(Seq)	PC5(Seq)	PC6(Seq)
[Corn, Soybean, Corn]	-0.008487	-1.953304	-1.695299	-1.554088	0.0	0.0	0.0
[Soybean, Soybean, Corn]	-5.825711	-3.321580	-2.821885	-2.173127	-inf	-inf	-inf
[Oats, Soybean, Corn]	-6.169145	-inf	-inf	-inf	-inf	-inf	-inf
[Corn, Soybean, Soybean]	-6.395807	-3.763413	-3.627511	-2.732743	-inf	-inf	-inf
[Corn, Corn, Corn]	-6.731095	-1.261456	-2.381574	-2.247235	-inf	-inf	-inf
[Corn, Soybean, Wheat]	-7.831979	-4.962108	-3.899444	-inf	-inf	-inf	-inf
[Wheat, Soybean, Corn]	-9.170893	-6.297109	-5.573421	-inf	-inf	-inf	-inf
[Corn, Soybean, Hay]	-11.008857	-7.906547	-inf	-inf	-inf	-inf	-inf
[Soybean, Soybean, Soybean]	-12.213031	-4.242986	-4.274138	-3.020425	-inf	-inf	-inf
[Soybean, Corn, Corn]	-12.548319	-2.083501	-2.577688	-2.614960	-inf	-inf	-inf

Table 8
Summary of the results of the RNN and PC models as well as the general score of each of the sequences considered.

SEQ	RNN(Seq)	PC1(Seq)	PC2(Seq)	PC3(Seq)	PC4(Seq)	PC5(Seq)	PC6(Seq)	Score
[Corn, Soybean, Corn]	-0.008487	-1.953304	-1.695299	-1.554088	0.0	0.0	0.0	-0.008487
[Soybean, Soybean, Corn]	-5.825711	-3.321580	-2.821885	-2.173127	-10.0	-10.0	-10.0	-11.825711
[Oats, Soybean, Corn]	-6.169145	-10.000000	-10.000000	-10.000000	-10.0	-10.0	-10.0	-12.169145
[Corn, Soybean, Soybean]	-6.395807	-3.763413	-3.627511	-2.732743	-10.0	-10.0	-10.0	-12.395807
[Corn, Corn, Corn]	-6.731095	-1.261456	-2.381574	-2.247235	-10.0	-10.0	-10.0	-12.731095
[Corn, Soybean, Wheat]	-7.831979	-4.962108	-3.899444	-10.000000	-10.0	-10.0	-10.0	-13.831979
[Wheat, Soybean, Corn]	-9.170893	-6.297109	-5.573421	-10.000000	-10.0	-10.0	-10.0	-15.170893
[Corn, Soybean, Hay]	-11.008857	-7.906547	-10.000000	-10.000000	-10.0	-10.0	-10.0	-17.008857
[Soybean, Soybean, Soybean]	-12.213031	-4.242986	-4.274138	-3.020425	-10.0	-10.0	-10.0	-18.213031
[Soybean, Corn, Corn]	-12.548319	-2.083501	-2.577688	-2.614960	-10.0	-10.0	-10.0	-18.548319

$PIO = 0, PWO = 0$
for $k = 1, \ldots, |Y_{test}|$ **do** *(for each element in the Test set)*
    for $i = 1, \ldots, N$ ***do*** *(for each proposed rotation crop)*
        if $Y_{test}(k) == Top(i)_k$ ***then*** *(the lists are the same)*
            PIO=PIO+1
        end if
        if $set\big(Y_{test}(k)\big) == set\big(Top(N)_k\big)$ ***then*** *(the sets are the same)*
            PWO=PWO+1
        end if
    end for
end for

Algorithm 1. Calculation of PIO and PWO.

$$Pos_i = \frac{\sum_k^{|Y_{test}|} L_{i_k}}{|Y_{test}|} \tag{4}$$

With :

$$L_{i_k} = \begin{cases} 1 \ \textit{if the } i^{th} \textit{ term of } Y_{test_k} \textit{ correspond to } L_{i_k} \\ 0 \ \textit{Else} \end{cases}$$

In the context of crop rotation prediction, the crops grown in a field can be seen as the activities performed within a process.The methodology is based on the use of a Seq2Seq-LSTM model to propose likely crop sequences to be grown in a field and a PC model to refine these predictions by prioritizing those already observed in the dataset.

According to this definition, the PC model is not essential to achieve the main objective of this article, i.e. the prediction of crops grown in a

Table 9
Example of calculation of variables for the $Recall(3)$ and $Recall_{WO}(3)$ metrics .

k	Y_{test}	$Top(3)$	PIO	PWO
1	[a, b, a]	[a, b, b] **[a, b, a]** [b, a, b]	1	1
2	[o, d, a]	**[d, a, o]** [d, b, a] [o, a, a]	0	1
3	[a, e, i]	[a, a, a] [a, o, i]	0	0
4	[a, e, c]	**[a, e, d]** [a, e, 1] [b, a, e]	1	1

field from year n+1 to n+x. That being said, the addition of the PC model should make it possible to refine the forecasts and thereby improve the performance of the general model.

During the forecast, two cases are considered:

- In the case **RNN**, only the results from the RNN model are taken into account.
- In the case of **RNN+PC**, the relation that allows the predictions of the RNN to be linked to those of the PC is parameterized with $\omega_6 = 0.45$, $\omega_5 = 0.15$ and the other weights are null.

3.2. Results

The empirical results of the study are presented in Fig. 6 and Fig. 7. Fig. 6 validates this hypothesis since the hybrid model (RNN+PC) consistently outperforms the model (RNN) in all scenarios considered. However, it is important to note that the performance gap between the model (RNN+PC) and the model (RNN) tends to decrease with an increase of in number of options considered. Thus, the performance of the two models is similar when 10 crop sequence options are considered (see Fig. 6, Top 10).

In addition, the performance of both RNN and RNN+PC models are evaluated in predicting Top(1). The results are presented in Fig. 7. When only one option is considered (Top(1)), the ability of the hybrid model (RNN+PC) to predict the correct crop at the correct position is again superior to the model (RNN). This superiority increases with the length of the sequence to be predicted.

As shown in Fig. 7, the RNN model and the RNN+PC model perform equally when predicting the first element of the output sequence (pos1). However, the RNN+PC model has an advantage when predicting the second element of the output sequence (pos2). This advantage is confirmed when predicting the third element of the sequence (pos3). Therefore, we argue that the hybrid model (RNN+PC) should be

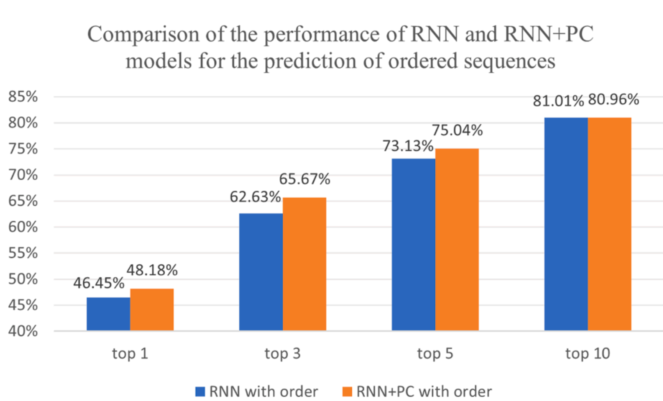

Fig. 6. Comparison of the empirical performances of RNN and RNN+PC models for the prediction of ordered sequences of the case study.

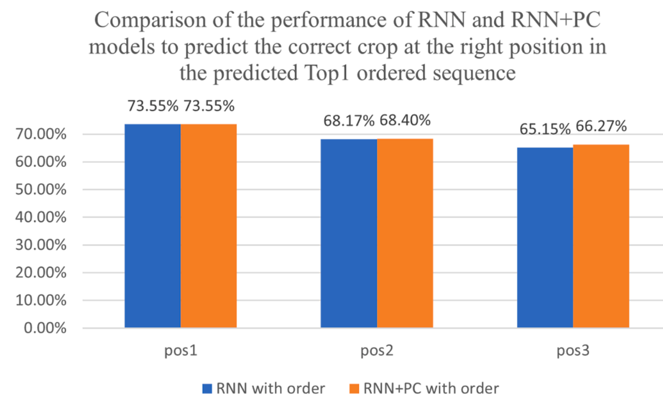

Fig. 7. Comparison of the empirical performances of RNN and RNN+PC models to predict the correct crop at the right position in the predicted Top(1) ordered sequence of the case study.

preferred in multistage temporal prediction, as is the case when predicting the sequence of future crops grown in the field.

Fig. 6 validates this hypothesis since the hybrid model (RNN+PC) consistently outperforms the model (RNN) in all scenarios considered. However, it is important to note that the performance gap between the model (RNN+PC) and the model (RNN) tends to decrease with an increase of in number of options considered. Thus, the performance of the two models is similar when 10 crop sequence options are considered (see Fig. 6, Top 10).

4. Augmented models with economical and meteorological information

The case study conducted in Section 3 enabled an evaluation of the methodology proposed by [27]. The results presented in Section 3.2 show a correct prediction rate of more than 73% when 5 options are considered (Recall(Top(5))=73.13%), and exceeds 81% when 10 options are considered (Recall(10)=81.01%). These results are very encouraging They since they allow medium-term forecasts of the intentions of the producers at the field level, which was previously impossible. However, it would be interesting to know if these results could be improved with contextual information.

The choice of crops grown depends on not only a crop history. It also relies on the economical and weather contexts in which a decision is made by a farmer. Thus, grain price data [44] and weather data [45] are integrated into the model as highlighted in Fig. 9.

4.1. Materials and methods

The general methodology to evaluate the performance of the model proposed by Dupuis et al. [27] when augmented with economic and/or meteorological context is presented in Fig. 8.

The data from the crop history, the economical context and the meteorological context are separated in two sets allowing the training and the evaluation of the four different models. They differ by the presence or absence of information related to the economical and meteorological context. The performances obtained on the test set by the four models are synthesized in a summary table (Table 10) allowing for a comparison of the results.

According to Québec agronomists, choosing which crops will be grown in a field is a decision that is usually made between November and January.This hypothesis was confirmed by comparing the results obtained when all the months available in the dataset are used and when only month from November to January are used. In the first case, the model takes longer to train and does not provide more convincing results than when only the months of November through January are considered. Thus, economic data has 18 attributes, corresponding to grain

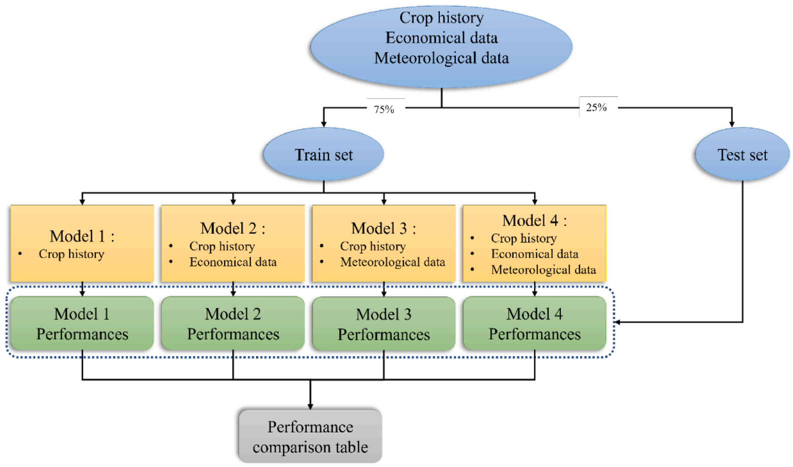

Fig. 8. General methodology for testing the performances of the augmented models.

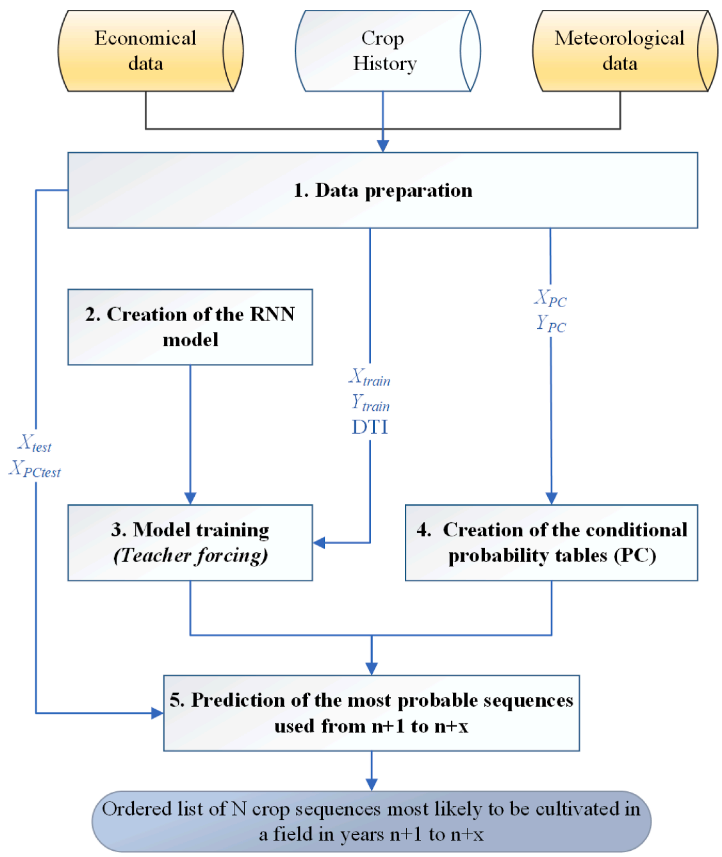

Fig. 9. Augmented methodology with economical and meteorological context.

prices for Corn, Soybeans, Barley, Oats, Wheat and Canola for the months of November to January, from 2002 to 2016.

The meteorological data has 84 attributes related to temperature and precipitation, observed monthly. Each field is coupled with the nearest weather station. This association is done by calculating the matrix of Euclidean distances separating the coordinates of the field centroïd from those of the available weather stations.

It is assumed that the choice of crop grown in year n depends on the economic and meteorological context of year n-1. Thus, for each sequence of X_{PC} and $X_{PC_{test}}$ considered, the sequence of grain prices in previous years is generated, creating the sets eco_{train} and eco_{test}. The same is true for the weather data. For each sequence of X_{PC} and $X_{PC_{test}}$ considered, the sequence of weather data from the station associated with the field under consideration from previous years is generated creating the sets $meteo_{train}$ and $meteo_{test}$.

The four new data sets are numerical sets. To facilitate the model's learning, these sets are normalized using the normalization MinMax.

As shown in Fig. 10, the architecture of the neural network is slightly modified to take into account the new data sets. Two new inputs allow the integration of the sets into the model and a concatenation layer allows the economic, weather and crop history data to be combined into a single matrix. The orange boxes in Fig. 10 highlight the elements added to the initial model.

The case study proposed in Section 3 will be expanded with the

Table 10
Synthesis of the empirical results for the four tested RNN models.

	Consideration of the order			
	Yes		*No*	
Model	RNN	RNN+PC	RNN	RNN+PC
Top(1)				
Model 1	46.45%	48.18%	51.94%	55.28%
Model 2	49.61%	50.99%	55.70%	57.13%
Model 3	56.30%	57.73%	61.37%	62.93%
Model 4	56.66%	57.61%	61.61%	62.27%
Top(3)				
Model 1	62.63%	65.67%	75.64%	75.94%
Model 2	65.61%	68.96%	77.61%	78.15%
Model 3	70.21%	71.70%	81.07%	81.13%
Model 4	69.25%	70.93%	80.60%	80.42%
Top(5)				
Model 1	73.13%	75.04%	82.39%	81.31%
Model 2	73.73%	75.16%	82.93%	81.97%
Model 3	76.42%	77.55%	86.87%	86.15%
Model 4	75.52%	76.18%	85.19%	84.66%
Top(10)				
Model 1	81.01%	80.96%	88.18%	86.87%
Model 2	81.01%	80.84%	88.72%	87.88%
Model 3	81.13%	81.37%	90.03%	89.61%
Model 4	80.42%	80.78%	89.73%	88.66%

addition of economical and meteorological information. The previously defined hyperparameters remain unchanged.

During the evaluation, two cases are considered for each model:

- In the first case, the order of events within the predicted sequence is taken into account. For example, if the predicted sequence is [A,B,A] while the actual sequence is [A,A,B], the prediction would be considered false.
- In the second case, the order of events within the predicted sequence is not taken into account. For example, if the predicted sequence is [A,B,A] while the actual sequence is [A,A,B], the prediction will be considered true.

4.2. Results

Table 10 summarizes the empirical results obtained in the study with the 4 models and the 4 scenarios described above.

Model 1 only considers crop history data (i.e. the model presented in Section 3). **Model 2** and **Model 3** are an augmented version of **Model 1** with the addition of economical and meteorological data respectively. Finally, **Model 4** takes into account all available data, namely crop history, economical data and meteorological data.

As presented in Table 10 (**Model 4**), adding information about the economic and weather context of decision making improves the forecast. The addition of information makes it possible to refine the forecast with an almost 10% increase in the Recall(Top(1)) performance of the scenarios, taking into account the order of the sequences.

The best performance is achieved by **Model 3** in the scenario *RNN-Without order* with 90% good predictions when 10 options are considered. When the output sequence order is considered, **Model 3** remains the best performer but the preferred scenario uses the PC model *RNN+PC-With Order* to obtain a performance of 81.37% correct forecasts.

5. Discussions

The experiment conducted in Section 3 allowed an evaluation of the performances of the methodology proposed by Dupuis et al. [27]. The methodology was applied to a real case study of farm lands from the region of Québec, Canada. The results presented in Section 3.2 show a correct prediction rate of more than 73% when 5 options are considered (Recall(Top(5))=73.13%) and exceeds 81% when 10 options are considered (Recall(10)=81.01%). It is interesting to note that the inclusion of a statistical component (PC table) in the model improves the predictive capacity of the most distant elements of the sequence as shown in Fig. 7.

Crop rotation decisions do not depend solely on the crop history of the field. As mentioned in Section 4, economic and meteorological contexts have an impact on crop rotation decisions. This assumption is verified by the addition of meteorological and economic data that improve the accuracy of the model. Indeed, when only one option is considered, the addition of meteorological data (**Model 3**) increases the rate of good prediction of the model by nearly 10% compared to **Model 1** using only crop history (see Table 10, $Recall_{Model3}(Top(1)) = 57.73\%$ and $Recall_{Model1}(Top(1)) = 48.18\%$). However, those results have to be nuanced.

As expected, an increase in the number of options considered leads to an increase in the Recall(N) performance in all considered models (Table 10). This phenomenon has been observed and is discussed in Dupuis et al. [19]. The integration of meteorological and economical data into the model has undoubtedly improved its predictive power. These results show the importance of these factors on the decision making of farmers, despite the impossibility of predicting the data accurately. We also note that the economic data allows an improvement in the model, but this improvement is limited (see **Model 2** results in Table 10). This phenomenon can be explained by the little information held in the dataset. Indeed, only the prices of six of the eighteen crops in the dataset are considered. The acquisition of more economic information would improve the performance of the model. Finally, the results in Table 10 show that the PC model has a beneficial effect on the Top(1) and Top(3) results with an increase in the Recall value of about 3% in **Model 1**. However, the impact of the PC model may become negative when the "With order" and "Without order" scenarios are respectively

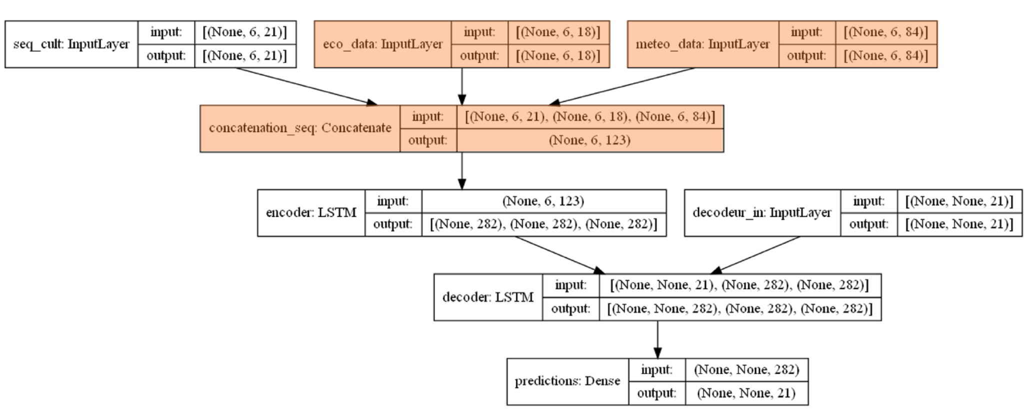

Fig. 10. Neural network architecture using crop history data, economic data and weather data.

considered with ten (Top(10)) and five (Top(5)) possible options. This observation supports the need for better calibration of Eq. 1.Thus, an optimal determination of ω weights in the prediction phase presented as the 5th phase of the methodology illustrated in Fig. 1, remains a current limitation that needs to be studied in more detail.

6. Conclusion

The challenges of the 21st century require a rethinking of agricultural practices in order to ensure their sustainability. Crop rotation is a pillar of sustainable agriculture whose medium-term forecast would allow a better organization of cropping strategies such as fertilization. A methodology has been theorized to predict the intentions of producers regarding the crops grown in a field in the medium term [27]. The present study aims to evaluate the performances of this new methodology in a real case study. Therefore, it has been applied to real data in a case study of 4245 fields of field crops in Quebec between 2002 and 2016, with 18 crops represented.

Various factors were taken into account, such as farming habits, the economic context and the meteorological context, in order to predict the operating intentions of agricultural producers. These factors led to the creation of 4 different models (models 1 to 4) evaluated in two configurations (RNN and RNN+PC) and two different metrics (with and without order).

Considering the last 6 crops grown in a field, more than 46% of the sequences of the next 3 crops were successfully predicted.The success rate reaches more than 81% when 10 options are considered. It is of interest to note that the addition of information such as the economic and meteorological context systematically improves the performance of the model. These remarks allow us to identify a relevant research axis in the identification of other influencing factors in the decision making of producers with regards to their crop rotation choices.

The proposed Québec case study provides promising results with regards to the applicability of this new methodology. However, other case studies in other production contexts will have to be undertaken in order to validate its relevance and performance. As mentioned in [27] the choice of hyperparameters remains an important limitation of this methodology. A more thorough study of the selection methods of the hyperparameters remains to be conducted.

Thus, this study has shown the potential of the methodology of [27] in the treatment of real data. This is a positive indication for the integration of this methodology in growth models to move towards more sustainable agriculture.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgements

We would like to thank our industrial partner for their collaboration in the project as well as CRSNG and FRQNT for their financial support.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2023.100180.

References

[1] M. Eldakak, S. Milad, A. Nawar, J. Rohila, Proteomics: a biotechnology tool for crop improvement, Front. Plant Sci. 4 (2013) 35, https://doi.org/10.3389/fpls.2013.00035.https://www.frontiersin.org/article/10.3389/fpls.2013.00035
[2] FAO, Competition for Natural Resources, FAO, Rome, Italy, 2017, p. 32. http://www.fao.org/3/i6583e/i6583e.pdf
[3] H. Godfray, J. Beddington al, Food security: the challenge of feeding 9 billion people, Science 327 (5967) (2010) 812–818, https://doi.org/10.1126/science.1185383.https://www.science.sciencemag.org/content/327/5967/812
[4] D. Tilman, C. Balzer, J. Hill, B. Befort, Global food demand and the sustainable intensification of agriculture, Proceedings of the National Academy of Sciences 108 (50) (2011) 20260–20264, https://doi.org/10.1073/pnas.1116437108.https://www.pnas.org/content/108/50/20260
[5] Z. Cui, Y. Liu, Z. Huang, H. He, G. Wu, Potential of artificial grasslands in crop rotation for improving farmland soil quality, Land Degrad. Dev. 30 (18) (2019) 2187–2196, https://doi.org/10.1002/ldr.3415.https://www.onlinelibrary.wiley.com/doi/abs/10.1002/ldr.3415
[6] Y. Ma, Seed coating with beneficial microorganisms for precision agriculture, Biotechnol. Adv. 37 (7) (2019) 107423.https://www.sciencedirect.com/science/article/pii/S0734975019301235
[7] V. Papanastasis, M. Arianoutsou, K. Papanatasis, Environnemental concervation in classical greece, J. Biol. Res. Thessaloniki 14 (2010) 123–135.
[8] M. Tariq, H. Ali, N. Hussain, W. Nasim, M. Mubeen, S. Ahmad, M. Hasanuzzaman, Fundamentals of crop rotation in agronomic management, in: M. Hasanuzzaman (Ed.), Agronomic Crops volume 1: Production Technologies, Springer Singapore, Singapore, 2019, pp. 545–559, https://doi.org/10.1007/978-981-32-9151-5_24.
[9] C. Sheaffer, K. Moncada, Introduction to agronomy : food, crops and environment, 2, Cengage learning, 2011, pp. 340–367.
[10] CRAAQ, Guide de reference en fertilisation, 2 actualisée, Centre de référence en agriculture et agroalimentaire du Québec, 2015.
[11] D. Reeves, Principales of Crop Rotation. Crops Residue Management, 1st, CRC press, 1994, p. 136, https://doi.org/10.1201/9781351071246.
[12] J. Bachinger, P. Zander, Rotor, a tool for generating and evaluating crop rotations for organic farming systems, Eur. J. Agron. 26 (2) (2007) 130–143, https://doi.org/10.1016/j.eja.2006.09.002.https://www.sciencedirect.com/science/article/pii/S1161030106001249
[13] M. Castellazzi, G. Wood, P. Burgess, J. Morris, K. Conrad, J. Perry, A systematic representation of crop rotations, Agric. Syst. 97 (1) (2008) 26–33, https://doi.org/10.1016/j.agsy.2007.10.006.https://www.sciencedirect.com/science/article/pii/S0308521X07001096
[14] N. Detlefsen, A. Jensen, Modelling optimal crop sequences using network flows, Agric. Syst. 94 (2) (2007) 566–572, https://doi.org/10.1016/j.agsy.2007.02.002.https://www.sciencedirect.com/science/article/pii/S0308521X07000108
[15] S. Dogliotti, W. Rossing, M. van Ittersum, Rotat, a tool for systematically generating crop rotations, Eur. J. Agron. 19 (2) (2003) 239–250, https://doi.org/10.1016/S1161-0301(02)00047-3.https://www.sciencedirect.com/science/article/pii/S1161030102000473
[16] W. Haneveld, A. Stegeman, Crop succession requirements in agricultural production planning, Eur J Oper Res 166 (2) (2005) 406–429, https://doi.org/10.1016/j.ejor.2004.03.009.https://www.sciencedirect.com/science/article/pii/S0377221704002358
[17] J. Salmon-Monviola, P. Durand, F. Ferchaud, F. Oehler, S. Sorel, Modelling spatial dynamics of cropping systems to assess agricultural practices at the catchment scale, Comput. Electron. Agric. 81 (2012) 1–13, https://doi.org/10.1016/j.compag.2011.10.020.https://www.sciencedirect.com/science/article/pii/S0168169911002596
[18] J. Aurbacher, S. Dabbert, Generating crop sequences in land-use models using maximum entropy and Markov chains, Agric. Syst. 104 (6) (2011) 470–479, https://doi.org/10.1016/j.agsy.2011.03.004.https://www.sciencedirect.com/science/article/pii/S0308521X11000424
[19] A. Dupuis, C. Dadouchi, B. Agard, Predict crop rotations using process mining techniques and markov principals, Comput. Electron. Agric. 194 (2022) 106686, https://doi.org/10.1016/j.compag.2022.106686.
[20] N. Kussul, M. Lavreniuk, S. Skakun, A. Shelestov, Deep learning classification of land cover and crop types using remote sensing data, IEEE Geosci. Remote Sens. Lett. 14 (5) (2017).
[21] F. Le Ber, M. Benoît, C. Schott, J.-F. Mari, C. Mignolet, Studying crop sequences with carrotage, a hmm-based data mining software, Ecol. Modell. 191 (1) (2006) 170–185, https://doi.org/10.1016/j.ecolmodel.2005.08.031.https://www.sciencedirect.com/science/article/pii/S0304380005003844
[22] J. Osman, J. Inglada, J. Dejoux, Assessment of a markov logic model of crop rotations for early crop mapping, Comput. Electron. Agric. 113 (2015) 234–243, https://doi.org/10.1016/j.compag.2015.02.015.https://www.sciencedirect.com/science/article/pii/S0168169915000575
[23] S. Stein, H.-H. Steinmann, Identifying crop rotation practice by the typification of crop sequence patterns for arable farming systems - a case study from central europe, Eur. J. Agron. 92 (2018) 30–40, https://doi.org/10.1016/j.eja.2017.09.010.https://www.sciencedirect.com/science/article/pii/S1161030117301405
[24] S. Stein, H.-H. Steinmann, J. Isselstein, Linking arable crop occurrence with site conditions by the use of highly resolved spatial data, Land (Basel) 8 (4) (2019), https://doi.org/10.3390/land8040065.https://www.mdpi.com/2073-445X/8/4/65
[25] R. Yaramasu, V. Bandaru, K. Pnvr, Pre-season crop type mapping using deep neural networks, Comput. Electron. Agric. 176 (2020) 105664, https://doi.org/10.1016/

j.compag.2020.105664.https://www.sciencedirect.com/science/article/pii/S0168169920307742

[26] C. Zhang, L. Di, L. Lin, L. Guo, Machine-learned prediction of annual crop planting in the U.S. corn belt based on historical crop planting maps, Comput. Electron. Agric. 166 (2019) 104989, https://doi.org/10.1016/j.compag.2019.104989. https://www.sciencedirect.com/science/article/pii/S0168169919309482

[27] A. Dupuis, C. Dadouchi, B. Agard, Methodology for multi-temporal prediction of crop rotations using recurrent neural networks, Smart Agricultural Technology 4 (2023) 100152, https://doi.org/10.1016/j.atech.2022.100152.

[28] N. Lanoie, A. Vanasse, Effets des rotations et autres pratiques culturales sur les maladies dans les grandes cultures, in: CRAAQ (Ed.), Revue De Littérature, Centre De Référence en Agriculture Et Agroalimentaire du Québec, 2017.

[29] N. Lanoie, A. Vanasse, Effets des rotations et autres pratiques culturales sur les insectes dans les grandes cultures, in: CRAAQ (Ed.), Revue de Littérature, Centre de Référence En Agriculture Et Agroalimentaire Du Québec, 2017.

[30] N. Lanoie, A. Vanasse, Effets des rotations et autres pratiques culturales sur les mauvaises herbes dans les grandes cultures, in: CRAAQ (Ed.), Revue De Littérature, Centre De Référence En Agriculture Et Agroalimentaire Du Québec, 2017.

[31] USDA, Crop rotation practice standard, s.d, (https://www.ams.usda.gov/grades-standards/crop-rotation-practice-standard).

[32] N. Lanoie, A. Vanasse, Effets des rotations et autres pratiques culturales sur la matiére organiquedu sol en grandes cultures, in: CRAAQ (Ed.), Revue De Littérature, Centre De Référence En Agriculture Et Agroalimentaire Du Québec, 2017.

[33] FAO, Agriculture de conservation, diversification des esp-ces, 2021, (http://www.fao.org/conservation-agriculture/in-practice/species-diversification/fr/). http://www.fao.org/conservation-agriculture/in-practice/species-diversification/fr/.

[34] S. Shahena, M. Rajan, V. Chandran, L. Mathew, Conventional methods of fertilizer release, in: F. Lewu, T. Volova, S. Thomas, R. K.R. (Eds.), Controlled Release Fertilizers for Sustainable Agriculture, Academic Press, 2021, pp. 1–24. https://www.sciencedirect.com/science/article/pii/B9780128195550000017. 10.1016/B978-0-12-819555-0.00001-7.

[35] G. Behnke, S. Zuber, E. Pittelkow C.M. andX Nafziger, M. Villamil, Long-term crop rotation and tillage effects on soil greenhouse gas emissions and crop production in illinois, usa, Agric. Ecosyst. Environ. 261 (2018) 62–70, https://doi.org/10.1016/j.agee.2018.03.007.https://www.sciencedirect.com/science/article/pii/S0167880918301221

[36] J. Singh, S. Kumar, Responses of soil microbial community structure and greenhouse gas fluxes to crop rotations that include winter cover crops, Geoderma 385 (2021) 114843, https://doi.org/10.1016/j.geoderma.2020.114843.https://www.sciencedirect.com/science/article/pii/S0016706120325982

[37] A. Clark, Managing Cover Crops Profitably, 3 edition, 2007. https://www.sare.org/wp-content/uploads/Managing-Cover-Crops-Profitably.pdf.

[38] N. Beaudoin, J. Saad, C. Van Laethem, J. Machet, J. Maucorps, B. Mary, Nitrate leaching in intensive agriculture in northern france: effect of farming practices, soils and crop rotations, Agric. Ecosyst. Environ. 111 (1) (2005) 292–310, https://doi.org/10.1016/j.agee.2005.06.006.https://www.sciencedirect.com/science/article/pii/S0167880905002896

[39] S. Janssen, M. van Ittersum, Assessing farm innovations and responses to policies: a review of bio-economic farm models, Agric. Syst. 94 (3) (2007) 622–636, https://doi.org/10.1016/j.agsy.2007.03.001.https://www.sciencedirect.com/science/article/pii/S0308521X07000443

[40] Y. Xiao, C. Mignolet, J.-F. Mari, M. Benoît, Modeling the spatial distribution of crop sequences at a large regional scale using land-cover survey data: a case from france, Comput. Electron. Agric. 102 (2014) 51–63, https://doi.org/10.1016/j.compag.2014.01.010.https://www.sciencedirect.com/science/article/pii/S016816991400012X

[41] B. Klöcking, B. Ströbl, S. Knoblauch, U. Maier, B. Pfützner, A. Gericke, Development and allocation of land-use scenarios in agriculture for hydrological impact studies, Physics and Chemistry of the Earth, Parts A/B/C 28 (33) (2003) 1311–1321, https://doi.org/10.1016/j.pce.2003.09.007.https://www.sciencedirect.com/science/article/pii/S1474706503002262

[42] M. Schrimpf, S. Merity, J. Bradbury, R. Socher, A flexible approach to automated RNN architecture generation, CoRR abs/1712.07316 (2017).http://arxiv.org/abs/1712.07316

[43] D. Kingma, J. Ba, Adam: a method for stochastic optimization, in: Y. Bengio, Y. LeCun (Eds.), 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7–9, 2015, Conference Track Proceedings, 2015. http://arxiv.org/abs/1412.6980

[44] FADQ, Historique de prix de la financiére agricole du québec – documents pertinents, 2020, Consulted the 9 février 2022 on https://www.pgq.ca/programmes-et-services/economie/securite-du-revenu/historique-de-prix-de-la-financiere-agricole-du-quebec/.

[45] Gouvernement du Canada, Conditions météorologiques et climatiques passées – données historiques, 2021, Consulted the 9 février 2022 on https://wwww.climat.meteo.gc.ca/historical_data/search_historic_data_f.html/.