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Research Paper

A flexible and practical approach for real-time weed emergence prediction based on Artificial Neural Networks

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Most popular emergence prediction models require species-specific population-based parameters to modulate thermal/hydrothermal accumulation. Such parameters are frequently unknown and difficult to estimate. Moreover, such models also rely on hardly available and difficult to estimate soil site-specific microclimate conditions, which in turn depend on soil heterogeneity at a field spatial level. On the other hand, modern agriculture benefits from easily available real-time information, in particular on-line meteorological data generated by forecasts and automatic local weather stations. In this context, Artificial Neural Networks (ANN) provide a flexible option for the development of prediction models, especially to study species which show a highly distributed emergence pattern along the year. In this work, an ANN approach based on easily obtainable meteorological data (daily minimum and maximum temperatures; daily precipitation) is proposed for weed emergence prediction. Relative Daily Emergence (RDE), expressed as a proportion of the total emergence, was the adopted output variable. Field emergence data recorded on a weekly basis were used to generate RDE patterns through linear interpolation. Results for three study cases from the Semiarid Pampean Region of Argentina (*Lolium multiflorum*, *Avena fatua* and *Vicia villosa*), which show irregular and time-distributed field emergence patterns, are reported. In all cases, ANN model selection was based on the Root Mean Square Error of the test set which showed better consistency than other typical Information Theory performance metrics. The combination of large ANN with a Bayesian Regularization Algorithm generated satisfactory estimations based on the RMSE values for independent Cumulative Emergence data.

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1. Introduction

Sigmoidal Regression Models (SRM) based on thermal or hydrothermal-time, adequately represent weed emergence patterns under certain ecological environments, such as in temperate regions with non-severe soil moisture restrictions (Gonzalez-Andujar, Chantre, Morvillo, Blanco, & Forcella, 2016). Conversely, weed emergence prediction under arid or semiarid environments with highly variable soil thermal and moisture conditions represents a challenging task due to the occurrence of irregular, time-distributed field patterns. Despite this fact, some SRM models have been successfully developed and validated (Royo-Esnal, García, Torra, Forcella, & Recasens, 2015).

In general, weed emergence modelling approaches require the implementation of thermal or hydrothermal indexes. Such indexes are based on soil microclimatic variables (soil temperature and water potential) which are in turn dependent on many site-specific variables (e.g. soil texture, surface cover, seed burial depth). Indexes construction depends on: (i) the assumption that emergence rates are proportional to the amount by which soil temperature and soil water potential exceed a given threshold value (Bradford, 2002); (ii) the estimation of site-specific soil microclimate variables using specific software (e.g. Soil Temperature and Moisture Model) (Spokas & Forcella, 2009). In addition, species-specific thresholds or cardinal parameters (i.e. base temperature and base water potential for seed germination/emergence) are generally obtained under laboratory-controlled conditions based on certain statistical principles (Bradford, 2002): (i) independence between threshold parameters and soil microclimatic variables (soil temperature and water potential); and (ii) a normal distribution of thermal/hydrothermal-time among individuals of a given seed population. Alternatively, these cardinal parameters can also be obtained through field trials and modelling (Royo-Esnal, Torra, Conesa, Forcella, & Recasens, 2010; Royo-Esnal et al., 2015).

In the Semiarid Pampean Region of Argentina (SPRA), *Avena fatua* L. and *Lolium multiflorum* Lam. are among the most conspicuous and invasive weed species in winter cereal crops. Both species present time-distributed multiple emergence cohorts *per* year, thus hindering the implementation of traditional SRM. In the southern area of the region under study, *Vicia villosa* Roth. is considered a problematic volunteer weed in winter cereals crop rotations, showing a “double-safety” seed dormancy mechanism (physical + physiological dormancy) (Renzi, Chantre, & Cantamutto, 2014) which regulates field emergence flushes. Recently, Renzi, Chantre, and Cantamutto (2018) made a considerable effort to develop and validate a field emergence model for *V. villosa* by integrating: (i) physical dormancy release dynamics, (ii) physiological dormancy release and germination thermal requirements, (iii) hydro-time requirements for germination, and (iv) pre-emergence growth.

In this regard, mechanistic or population-based models should be considered a valuable tool for the description of basic ecophysiological processes underlying seedling emergence (Boddy, Bradford, & Fischer, 2012; Chantre, Batlla, Sabbatini, & Orioli, 2009; Colbach & Mézière, 2013). Although such models are desirable from an explanatory biological process-based framework, their development and validation are usually very time consuming. As suggested by Grundy (2003), such models lack of the simplicity and flexibility that would be required for practical Integrated Weed Management Support Systems (IWMSS), which weather-based models do offer.

Based on previously exposed statements, it is clear that current weed emergence modelling is in some extent driven by a *precise-and-deterministic* view of a highly uncertain and complex ecological problem resulting from the interaction of weed biology and soil variables. In addition, bioecological limitations arise as seed dormancy processes and germination requirements of various weed species remain to be elucidated (Batlla & Benech-Arnold, 2010) in order to bridge the ecological knowledge gap for accurate weed emergence prediction.

Recently, Gonzalez-Andujar et al. (2016) highlighted the importance of a new generation of modelling approaches based on Soft Computing Techniques (SCT) to tackle the limitations of conventional nonlinear regression models. It was concluded in that work that SCT provide higher flexibility as well as better predictive accuracy in many cases.

SCT (unlike conventional or hard computing) are capable of dealing with complex biological systems because do not require strict mathematical definitions, thus providing a better rapport with reality (Das, Kumar, Das, & Burnwal, 2013). Among them, for example, Artificial Neural Networks (ANN) as modelling framework and Genetic Algorithms (GA) as optimization engines, have been applied in most fields of science and technology (Gen & Cheng, 2000; Paliwal & Kumar, 2009), and also in many fields of agriculture (Matsumura, Gaitan, Sugimoto, Cannon, & Hsieh, 2015; Pi et al., 2015). For example, Pi et al. (2015) proposed an ANN-GA combined model for the prediction of optimal sowing time and cultivars selection across different regions of China working with the grass *Poa pratensis* L.

ANN and GA have also been applied in weed research (Burgos-Artizzu, Ribeiro, Tellaeche, Pajares, & Fernández-Quintanilla, 2010; Burks, Shearer, Heath, & Donohue, 2005; Dyrmann, Karstoft, & Midtiby, 2016). However, soft computing modelling for weed emergence prediction remains largely unexplored (Gonzalez-Andujar et al., 2016). Haj Seyed Hadi and Gonzalez-Andujar (2009) compared GA with nonlinear regression for fitting emergence data of six weed species of Spanish cereal crops showing that the former often provided a better fit due to a higher capability to deal with ill-defined optimisation issues. Blanco et al. (2014) proposed a GA approach for *A. fatua* emergence prediction based on the disaggregation of dormancy release and germination/pre-emergence growth processes. Previously, Chantre et al. (2012) developed an ANN model using both thermal-time and hydro-time variables as independent explanatory variables for the biosystem under study in the SPRA. The same approach proved adequate for *A. fatua* emergence prediction in different temperate regions of the United States, Canada and south Australia (Chantre et al., 2012, 2014).

In previously mentioned studies, soft computing based models have proven to yield better prediction capacity than classical univariate hydrothermal-time based nonlinear regression models. However, some caveats were detected by the authors and further revised by Gonzalez-Andujar et al. (2016): (i) increasingly complex ANN architectures show a tendency to overfit cumulative emergence data, thus generating instability problems for accurate output variable estimation; (ii) significant level of expertise and programming skills are required to develop such models. These issues require further research to facilitate the applicability of soft computing models for weed emergence prediction within IWMSS by farmers and technicians.

Nowadays, agricultural practices offer real-time information, in particular on-line meteorological data provided by automatic local weather stations and forecasts. Management decision making from both, economic and environmental perspectives can benefit from the available real-time information used for predictive purposes (van Evert et al., 2017). In this context, soft computing in general, and ANN in particular, provide a flexible approach for real-time weed emergence prediction model development.

The aim of this work was to develop and validate a flexible and general ANN modelling framework for weed emergence prediction using easily available meteorological data (i.e. daily field temperature and precipitation), without the necessity of soil microclimatic derived indexes or previous knowledge on species-specific biology. The proposed ANN modelling framework utilise daily minimum and maximum air temperature and precipitation as meteorological input variables.

2. Materials and methods

2.1. Field experimental data

Lolium multiflorum and *A. fatua* emergence data were collected at weekly intervals at the Experimental Field of the Agricultural Experimental Station INTA-Bordenave (37°50′S; 63°01′W), located in Buenos Aires province, Argentina. *L. multiflorum* and *A. fatua* data periods were 2008–2016 and 2007–2015, respectively. *Vicia villosa* emergence data were also collected on a weekly basis at the Experimental Field of Agricultural Experimental Station INTA-Hilario Ascasubi (39°22′S, 62°39′W), Buenos Aires province, Argentina, in 2008, 2010 and 2013–2015. In all cases the counting initiated on January the first and lasted the whole year.

Experiments were conducted on an undisturbed field in order to emulate a non-tillage field scenario (without crop presence). Destructive seedling counting was performed on three quadrats (1 m^2 each) randomly distributed on the field. Meteorological data were registered by automatic on-line stations (EMA Davis, Mercobras S.A.) located in the experimental fields.

2.2. Artificial Neural Networks input variables

In the current modelling approach, the direct use of easily available real-time weather data is proposed. Specifically, ANN input variables were: (i) calendar day (d), (ii) daily minimum air temperature (T_{min}), (iii) daily maximum air temperature (T_{max}), and (iv) daily precipitation amount (Pp).

2.3. Artificial Neural Networks output variable

The *Relative Daily Emergence* (RDE) was the adopted output variable of the proposed modelling approach. RDE is calculated as:

$$RDE_d = \frac{E_d}{\sum_{i=1}^{365} E_i} \quad d = 1, \ldots 365 \tag{1}$$

where E_d is the number of plants emerged each day. As field emergence data were collected at weekly intervals (40 points/year), the first step for the calculation of the output variable consisted on the *estimation* of the RDE values in the days between the counts (Fig. 1(a), dotted line). This way, a larger set of data points (365 points/year instead of 40 points/year) were utilised for modelling purposes.

In order to generate these missing data, a point-by-point (i.e. day-by-day) interpolation routine was implemented with GraphPad Prism software (2015). In this way, each input data set (d, T_{min}, T_{max}, Pp) matched a given value of RDE. Finally, the output variable of the model is the *predicted* RDE (Fig. 1(a)).

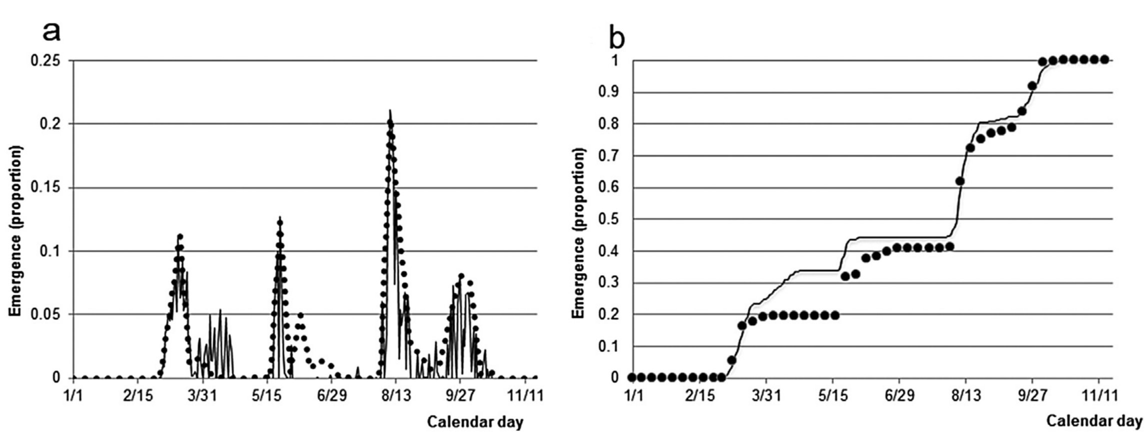

Fig. 1 – Theoretical *Relative Daily Emergence* (RDE) of a given weed species (a) and its corresponding *Cumulative Emergence* (CE) curve (b). In (a) the dotted line represents the *estimated* RDE obtained by a day-by-day interpolation routine, while the solid line represents the *predicted* RDE. In (b) the dotted line represents weekly observed CE data, while the solid line represents the *predicted* CE distribution.

However, it should be kept in mind that in practice less than 365 points/year were used for modelling purposes since once the weed field emergence period is finished many zero emergence data points do not provide any valuable information. For example, in Fig. 1(a) it could be observed that field emergence extends until mid-November and subsequent zero data points were chopped off from the data sets.

2.4. Cumulative emergence prediction

In order to generate a more intuitive and practical interpretation of the emergence dynamics, for visualization purposes, RDE patterns (Fig. 1(a)) were also represented as *predicted Cumulative Emergence* (CE) (Fig. 1(b)). Cumulative emergence curves were generated by summing RDE values from the onset till the end of the season:

$$CE_d = \sum_{i=1}^{d} RDE_i \quad d = 1, \ldots 365 \tag{2}$$

2.5. Artificial Neural Networks modelling

ANN are well known modelling tools for input–output data correlation. Many sources provide good coverage on the topic (e.g. Livingstone, 2008). For a brief introduction, a three-layer feed-forward ANN is shown (Fig. 2). The theoretical model has: (i) two input variables (x_1, x_2) connected each to a given receptor neuron of an entrance layer, (ii) an intermediate eight-neuron layer, and (iii) an output variable (y).

As observed in Fig. 2, each neuron of the entrance layer receives a given input variable (x_1, x_2) and broadcasts its value

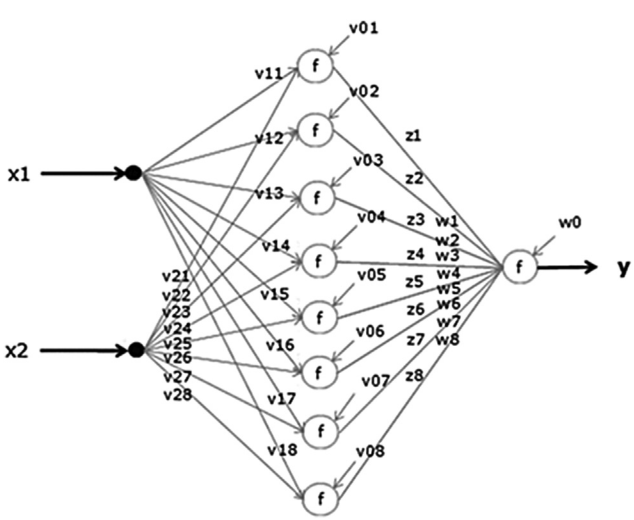

Fig. 2 – ANN architecture with three layers (entrance, intermediate and exit layer). x_1 and x_2 represent the input variables (each neuron of the first layer receives a given input variable); a hidden layer with eight nodes (e.i. processing units), and a unique exit neuron that produces the final response (output variable). f(.) represents the activation functions of the neurons; v_{ij} are the connection weights between input-hidden layer neurons; w_j are the connection weights between hidden and output layer neurons; v_{0j} is the bias of each hidden neuron j; while w_0 is the output neuron bias; z_j is the output signal of each hidden neuron. y stands for the output variable.

to each neuron of the hidden layer. Each neuron computes an activation function and generates an outcome (z_1, …, z_8) which is further transmitted to the output layer neuron which finally yields the network output (y). The output signal of each neuron in the hidden layer (z_j) is calculated as:

$$z_j = f\left(\sum_{i=1,2} v_{ij} x_i + v_{0j}\right) \quad j = 1, \ldots, 8 \tag{3}$$

while the output of the network is given by:

$$y = f\left(\sum_{j=1,8} w_j z_j + w_0\right) \tag{4}$$

where f(.) represents the transfer (activation) function; v_{ij} are the weights of the connections between the input and the intermediate neurons; v_{0j} is the bias on neuron w_j represent the weights of the connections between the intermediate and output neurons and w_0 is the bias on the output neuron.

In this contribution, hyperbolic tangent sigmoid transfer functions (Eq. (5)) were implemented, both in the intermediate and in output layers' nodes. Such function generates an outcome in the range [−1, 1] (Beale, Hagan, & Demuth, 2011):

$$Y = \frac{2}{1 + \exp(-2X)} - 1 \tag{5}$$

In this work, a feed-forward ANN with three layers was implemented (Fig. 2). For each case study, several ANN architectures (with different number of neurons in the intermediate layer) were investigated. Input/output data was normalised to fall in the range [-1, 1] to improve network's performance (Maier & Dandy, 2001). The Neural Network Toolbox of MatLab software (Beale et al., 2011) was used for programming the ANN.

A Bayesian Regularization Algorithm was used for training the models due to its excellent generalization capability (Burden & Winkler, 1999). This algorithm has shown some advantages compared to standard back-propagation techniques. As reviewed by Burden and Winkler (2009), the algorithm: (i) generate robust models with less chances of overtraining and overfitting (by incorporating a pruning method within the optimisation algorithm); (ii) do not require a validation set, thus all available data might be used to generate the model. The latter is a very important issue mainly when data is scarce or expensive to obtain.

2.6. Model analysis

Typical measures for model selection were investigated to assess the goodness-of-fit of the developed models. Specifically, the following Information Theory criteria were calculated in each case: Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC) and Network Information Criterion (NIC). Root Mean Square Error (RMSE) measures were considered to evaluate the approximation of the training set.

The following typical definitions are adopted. SSE is the training error that is minimised by the objective function:

$$SSE = \sum_{i=1}^{T} (y_i - \hat{y}_i)^2 \tag{6}$$

where T is the number of data points and y_i and $\hat{y}_i$represent observed and predicted data of the training set, respectively. Therefore:

$$MSE = \frac{SSE}{T} \tag{7}$$

$$RMSE = \sqrt{MSE} \tag{8}$$

Specifically, the AIC and BIC were calculated according to Qi and Zhang (2001):

$$AIC = \log(MSE) + \frac{2\log(m)}{T} \tag{9}$$

$$BIC = \log(MSE) + \frac{\log(m)\log(T)}{T} \tag{10}$$

The Network Information Criterion (NIC) was calculated as follows (Amari, 1993):

$$NIC = \log(MSE) + \frac{m}{T} \tag{11}$$

where m is the total number of parameters of the model. Additionally, the number of effective parameters (η) meaning the total amount of parameters (i.e. weights + biases) actually used for training the ANN is also reported.

Finally, the predictive capability of the developed models was based on the RMSE of the test set. In the cases where more than one test set is available, the RMSE $Test_{global}$ value was informed, which represents the average among the available test sets.

2.7. *Training and test sets*

For the three study cases, available data were randomly divided into training and test sets resembling a 3:1 proportion as close as possible. Therefore, for *L. multiflorum* and *A. fatua,* a total of seven years of experimental data were used for training while the remaining two years were used for testing. For the case of *V. villosa* a 4:1 split was utilised.

3. Results

Several ANN architectures were evaluated using NIC, AIC, BIC and RMSE measures for each weed species. In the following subsections a detail of the developed models is provided with a brief analysis of the performance criteria in each case.

3.1. *Lolium multiflorum*

Information theory criterions (NIC, AIC, BIC) showed a monotonic increment in goodness of fit as the number of model parameters increased, thus selecting for the largest investigated model (ANN_{55}) (Table 1, bold highlighted). A correspondence between these indexes and RMSE train values was also observed (Table 1, underlined) as both, the total and effective number of parameters increased. However, RMSE test values (both global and individual of predicted vs observed cumulative emergence data) indicated ANN_{25} as the best model for the analysed data set (Table 1, gray cell). The capability of ANN_{25} to closely represent *L. multiflorum* relative field emergence patterns during both tested years (Fig. 3(a) and (b)) could be easily tracked by their corresponding cumulative emergence patterns (Fig. 3(c) and (d)).

3.2. *Avena fatua*

NIC, AIC and BIC metrics monotonically increased goodness of fit with the number of parameters (Table 2, bold highlighted). The largest investigated model (ANN_{70}) showed the lowest RMSE train values (Table 2, underlined). As observed for *L. multiflorum*, the lowest global RMSE test was obtained at ANN_{65} (Table 2, gray cell). RDE and CE dynamics for both tested years are shown in Fig. 4.

3.3. *Vicia villosa*

ANN_{35} showed the lowest RMSE test (Table 3, gray cell; Fig. 5). The feasibility of the selected model could be envisioned

Table 1 – ANN models with increasing number of neurons for *Lolium multiflorum*. *m* = *total number of model parameters,* η = *number of effective parameters, NIC* = *Network Information Criterion; AIC* = *Akaike's Information Criterion; BIC* = *Bayesian Information Criterion; RMSE* = *Root Mean Square Error; RDE is the predicted Relative Daily Emergence; CE is the predicted Cumulative Emergence.*

Model	m	η	NIC	AIC	BIC	RMSE			
						RDE	CE		
						Train	$Test_{2013}$	$Test_{2015}$	$Test_{global}$
ANN_5	31	29	−2.63	−2.64	−2.64	0.048	0.091	0.189	0.145
ANN_{10}	61	56	−2.64	−2.67	−2.67	0.046	0.110	0.154	0.133
ANN_{15}	91	83	−2.73	−2.77	−2.77	0.041	0.062	0.116	0.092
ANN_{20}	121	118	−2.75	−2.81	−2.81	0.039	0.049	0.064	0.057
ANN_{25}	151	145	−2.77	−2.84	−2.83	0.038	0.036	0.048	0.042
ANN_{30}	181	177	−2.85	−2.93	−2.93	0.034	0.065	0.062	0.063
ANN_{35}	211	194	−2.77	−2.87	−2.87	0.037	0.071	0.050	0.062
ANN_{40}	241	231	−2.88	−2.99	−2.99	0.032	0.067	0.057	0.063
ANN_{45}	271	251	−2.89	−3.02	−3.01	0.031	0.091	0.054	0.076
ANN_{50}	301	287	−2.93	−3.07	−3.07	0.029	0.083	0.052	0.070
ANN_{55}	331	310	**−3.02**	**−3.17**	**−3.17**	<u>0.026</u>	0.079	0.048	0.066

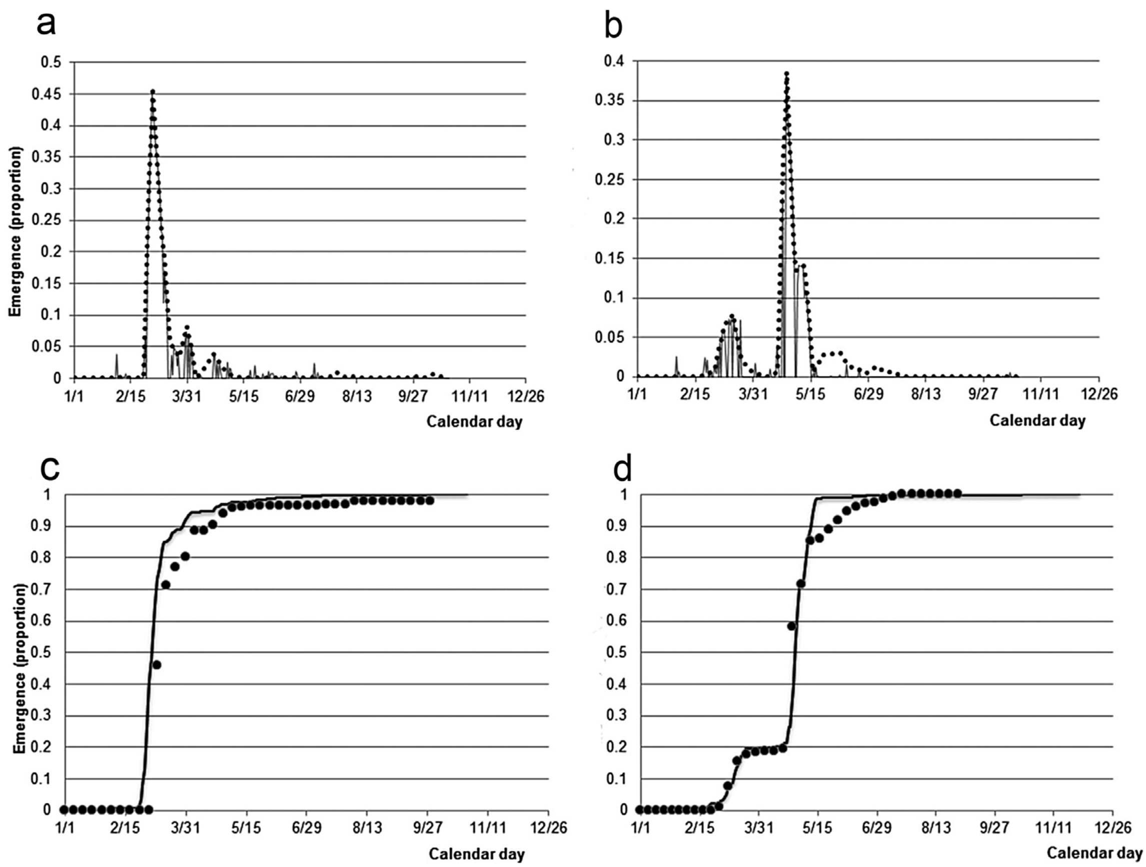

Fig. 3 – *Relative Daily Emergence* patterns (a, b) and cumulative emergence curves (c, d) for *Lolium multiflorum* for both test years, 2013 and 2015. Dotted lines represent observed data while solid line stands for ANN_{25} predictions.

Table 2 – ANN models with increasing number of neurons for *Avena fatua*.

Model	m	η	NIC	AIC	BIC	RMSE			
						RDE	CE		
						Train	$Test_{2008}$	$Test_{2011}$	$Test_{global}$
ANN_5	31	28	−2.93	−2.94	−2.94	0.034	0.092	0.185	0.147
ANN_{10}	61	55	−2.95	−2.98	−2.97	0.032	0.088	0.173	0.138
ANN_{15}	91	81	−2.93	−2.97	−2.97	0.033	0.083	0.164	0.130
ANN_{20}	121	111	−2.98	−3.03	−3.03	0.031	0.074	0.142	0.113
ANN_{25}	151	132	−2.96	−3.03	−3.03	0.031	0.074	0.139	0.112
ANN_{30}	181	146	−2.96	−3.03	−3.03	0.030	0.075	0.153	0.121
ANN_{35}	211	189	−2.98	−3.07	−3.07	0.029	0.069	0.118	0.097
ANN_{40}	241	196	−2.98	−3.08	−3.08	0.029	0.067	0.108	0.090
ANN_{45}	271	259	−3.08	−3.20	−3.19	0.025	0.051	0.049	0.050
ANN_{50}	301	282	−3.06	−3.19	−3.19	0.025	0.056	0.074	0.066
ANN_{55}	331	308	−3.09	−3.23	−3.23	0.024	0.049	0.029	0.040
ANN_{60}	361	336	−3.13	−3.28	−3.28	0.023	0.051	0.036	0.044
ANN_{65}	391	371	−3.15	−3.32	−3.31	0.022	0.036	0.029	0.033
ANN_{70}	421	409	**−3.24**	**−3.42**	**−3.42**	<u>0.019</u>	0.050	0.031	0.042

m = total number of model parameters, η = number of effective parameters, NIC = Network Information Criterion; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; RMSE = Root Mean Square Error; RDE is the predicted Relative Daily Emergence; CE is the predicted Cumulative Emergence.

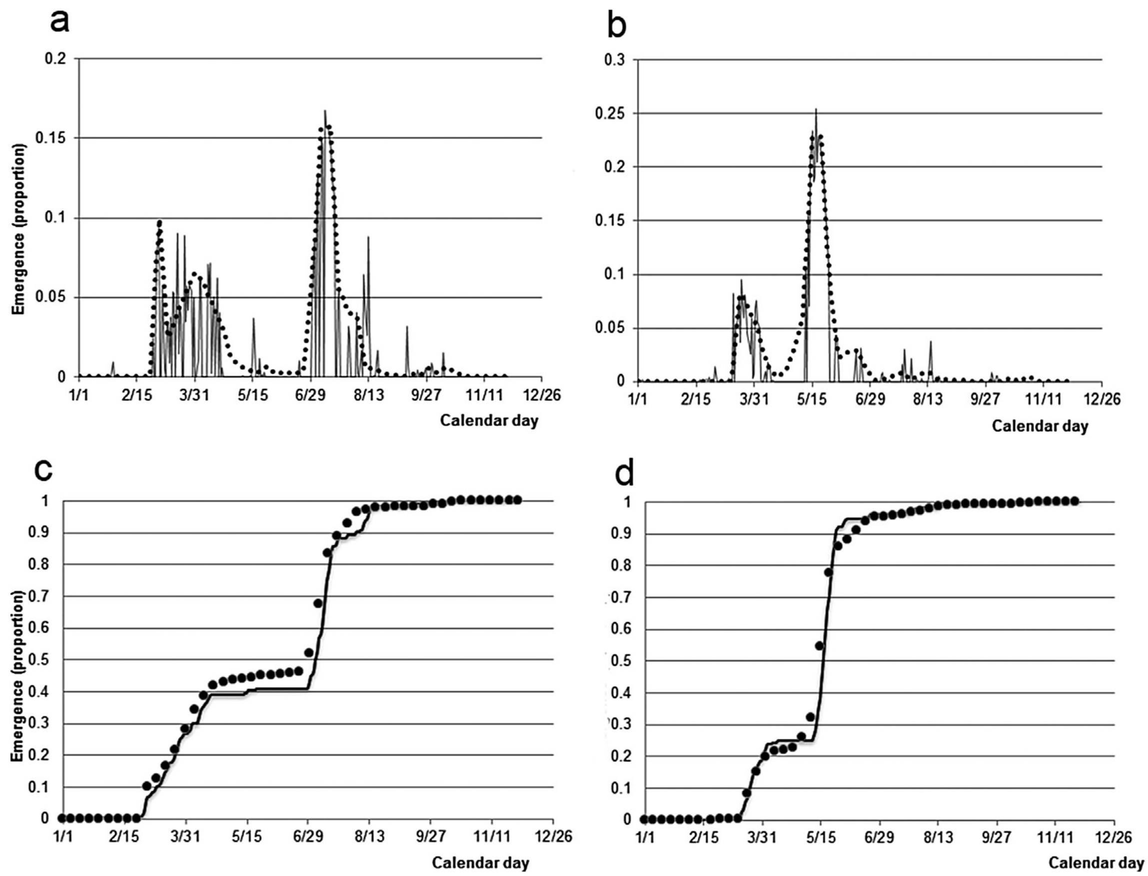

Fig. 4 – *Relative Daily Emergence* patterns (a, b) and cumulative emergence curves (c, d) for *Avena fatua* for both test years, 2008 and 2011. Dotted lines represent observed data while solid line stands for ANN_{65} predictions.

Table 3 – ANN models with increasing number of neurons for *Vicia villosa*.

Model	m	η	NIC	AIC	BIC	RMSE	
						RDE	CE
						Train	$Test_{2015}$
ANN_5	31	27	−2.06	−2.10	−2.10	0.089	0.237
ANN_{10}	61	53	−2.06	−2.14	−2.14	0.085	0.226
ANN_{15}	91	76	−2.04	−2.16	−2.16	0.083	0.211
ANN_{20}	121	107	−2.11	−2.26	−2.26	0.073	0.219
ANN_{25}	151	133	−2.21	−2.41	−2.40	0.062	0.149
ANN_{30}	181	164	−2.26	−2.50	−2.50	0.056	0.135
ANN_{35}	211	192	−2.33	−2.61	−2.61	0.049	0.067
ANN_{40}	241	197	−2.33	−2.65	−2.64	0.047	0.088
ANN_{45}	271	231	−2.38	−2.74	−2.74	0.042	0.067
ANN_{50}	301	257	**−2.39**	−2.79	−2.79	0.040	0.081
ANN_{55}	331	255	−2.37	**−2.81**	**−2.81**	<u>0.039</u>	0.095
ANN_{60}	361	242	−1.60	−2.08	−2.07	0.091	0.214

m = total number of model parameters, η = number of effective parameters, NIC = Network Information Criterion; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; RMSE = Root Mean Square Error; RDE is the predicted Relative Daily Emergence; CE is the predicted Cumulative Emergence.

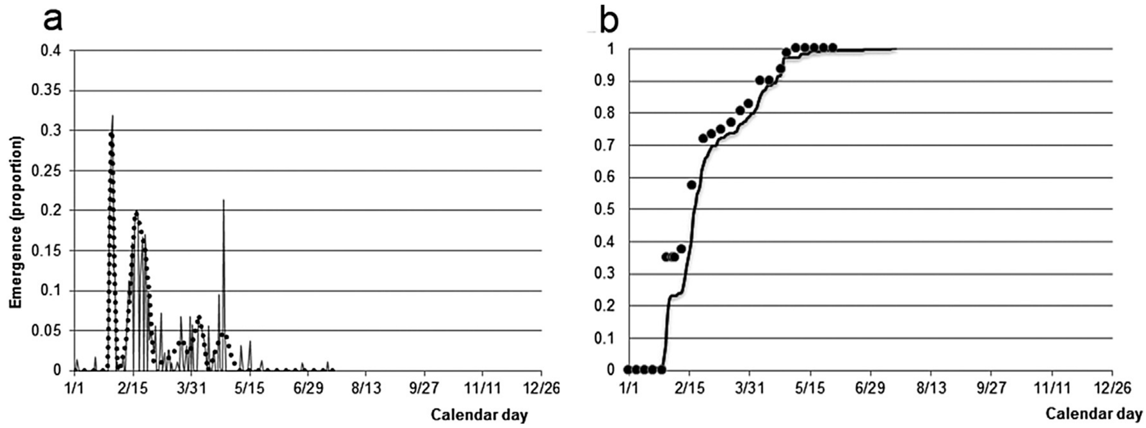

Fig. 5 – *Relative Daily Emergence* pattern (a) and cumulative emergence curve (b) for *Vicia villosa* for test year 2015. Dotted lines represent observed data while solid line stands for ANN_{35} predictions.

straightforwardly by comparison with the outcomes obtained by the mechanistic modelling approach developed by Renzi et al. (2018) for the same data set (RMSE test = 0.05). Similarly, to the previous cases, all information indexes and the RMSE train value, points out more complex architectures (Table 3, bold/underlined highlighted).

4. Discussion

Previous versions of ANN models (Chantre et al., 2012, 2014) suffered of over-fitting issues producing unrealistic reductions in the CE dynamics, mainly when large architectures were tested. Such modelling drawback was not observed in these experiments.

The inclusion of estimations of daily emergence in the training set (totalising a maximum of 365 input–output data points), rather than simply using the weekly available field data (40 input–output data points) probably had the larger effect on smoothing the CE profiles. The impact of using daily emergence (RDE) instead of cumulative emergence (CE) as output variable (punctual vs. integrated information) is also considered influential in this behaviour but its extent requires further investigation.

The preferred criteria for ANN model selection was in all cases the global RMSE test (predicted vs. observed cumulative emergence data). Such index showed a clear local minimum among increasingly complex models allowing for an adequate balance between complexity and parsimony. Conversely, goodness of fit measures (AIC, BIC, NIC and RMSE train) showed a monotonically increasingly behaviour as the size of the model increased. Therefore, they did not allow for a clear model selection criterion. Our results agree with Qi and Zhang (2001) as neither Information Theory (penalty-based in-sample criteria) nor no-penalty-related training measures (RMSE train) proved adequate for model selection. In addition, as stated by these authors and further corroborated by Chantre et al. (2012), goodness of fit measures are not always consistent with the best performances in out-sample data (RMSE test). This could be considered an '*expected outcome*' since no universal information metric could be defined for model selection (Aho, Derryberry, & Peterson, 2014; Burnham & Anderson, 2003). This behaviour, named by Breiman (2001) as the '*Rashomon Effect*', occurs when different models are crowded together and they have about the same training or test errors.

In any case, for prediction purposes, and especially for ANN based predictive tools, the main objective is to achieve an adequate predictive capacity irrespective of model's complexity. As highlighted by Breiman (2001), the goal of predictive modelling is to obtain accurate information. In this context, and from a practical point of view, obtained ANN models closely represented time-distributed and irregular emergence patterns of the three selected weed species.

However, it should be mentioned that although ANN are powerful tools for data interpolation they have little explanatory capabilities, basically limited to point out which input variables have the largest relative contribution to the output/s of the system (see Olden & Jackson, 2002). Therefore, phenomenological conclusions could hardly be drawn from the ANN structure and its parameters. Additionally, such modelling approach also lack of extrapolation power. Therefore, their use for current decision making should be carefully considered if limited amounts of data for training and validation/test are available.

Nevertheless, besides the "modest" sized models proposed in this work, current programming and computational technology allow the development of "really large" neural networks (hundreds of neurons) giving rise to the so-called "deep learning" paradigm aimed at dealing with "big data" (Chen & Lin, 2014; van Evert et al., 2017). Such technology, which is easily available and economically affordable, boosts the application of soft computing techniques to develop, in a systematic fashion, models of agronomical interest making use of the large volume of agrometeorological data produced on a daily basis. Therefore, future work should aim to maximise the data processing capability and extensive flexibility of ANN.

5. Conclusions

The presented modelling procedure using "large" ANN showed reliable predictions for three complex weed species. The main strength of the proposed approach is the absence of specific underlying modelling assumptions and the direct use of commonly available field meteorological data. Unlike most of the available weed emergence models, the proposed modelling approach is able to establish functional relationships between easily available meteorological information and field emergence data without the necessity of soil microclimatic derived indexes (i.e. thermal/hydrothermal-time) or species-specific population-based knowledge (i.e. threshold or cardinal parameters for germination/emergence). These features suggest the potential practical use of this modelling framework for decision-making support in weed management. However, further work should be carried out to draw categorical conclusions on the models' validity based on a larger pool of data.

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Nomenclature

Acronyms

AIC	Akaike's Information Criteria
BIC	Bayesian Information Criterion
ANN	Artificial Neural Network(s)
NIC	Network Information Criterion
SSE	Sum of Square Error
MSE	Mean Square Error
RMSE	Root Mean Square Error
SRM	Sigmoidal Regression Models
IWMSS	Integrated Weed Management Support Systems
SCT	Soft Computing Techniques

Parameters/Variables

d	calendar day
CE	Cumulative emergence
E	Emergence
m	number of model parameters
Pp	Precipitation
RDE	Relative Daily Emergence
T_{min}	Minimum air temperature
T_{max}	Maximum air temperature
T	number of data points
x_1, x_2	ANN inputs
z_i	ANN hidden layer outputs
Y	ANN output
v_i, w_i	ANN weights
y	observed data
$\hat{y}$	predicted data

Conflicts of interest

The authors declare no conflict of interest.

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