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Fully Convolutional Neural Network: A solution to infer animal behaviours from multi-sensor data

Lorène Jeantet[a,*], Vincent Vigon[b], Sébastien Geiger[a], Damien Chevallier[a,c]

[a] Université de Strasbourg, CNRS, IPHC UMR 7178, 67000 Strasbourg, France
[b] Université de Strasbourg, UFR math-info, 7 rue Descartes, 67081 Strasbourg cedex, France
[c] UMR BOREA, CNRS-7208/MNHN/UPMC/IRD-207/UCN/UA

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ABSTRACT

Animal-attached accelerometers have been widely used to monitor species that are difficult to observe, alongside the use of machine learning to identify behaviours from the obtained sequences. Artificial neural networks are powerful supervised learning algorithms that are based on deep learning and have been poorly exploited in movement ecology. Recently, the availability of sophisticated algorithmic architectures via open source libraries facilitates their use. In this study, we adapt a fully convolutional neural network that was originally developed for biomedical 3D image segmentation: the V-net. We test it on a labelled dataset collected from animal-borne video recorders combined with multi-sensors (accelerometers, gyroscopes and depth recorders) deployed on free-ranging immature green turtles (*Chelonia mydas*). The proposed model, fitted for 1D data, is able to predict six behavioural categories for green turtles with an AUC score of 88%. It shows a high ability to detect rare behaviours with low discriminative signals such as *Feeding* and *Scratching*. With a precision down to one centi-second, the V-net circumvents the segmentation process. We also show that the gyroscope is more informative than the accelerometer in identifying sea turtle behaviours and that the V-net is not able to discriminate *Feeding* from the raw data of accelerometer alone. However, human expertise can help to correct it with precise and adapted pre-processing. Thus, diverted from its initial purpose and tested on sea turtle, the V-net is a very efficient method of behavioural identification that should be easily generalized to a wide range of species. It could lead to considerable progress in remote accelerometric monitoring and help to understand the ecology of the species that are difficult to observe. Furthermore, as the model is light, there is also a huge potential to implement a trained V-net in satellite-relay data tag to remotely predict the expressed behaviours almost instantly.

1. Introduction

Machine learning has been widely used in behavioural studies to face the new challenges related to the development of animal-attached sensors (Valletta et al., 2017; Wilson et al., 2018). This technology allows scientists to remotely record a large amount of data on free-ranging animals for which direct observations are impracticable (Boyd et al., 2004; Brown et al., 2013). Their use grew rapidly in the 1990s with the development of microprocessors and the increase in memory capacity, but is now limited by the difficulties in processing the complexity and volume of the recorded data (Ropert-Coudert et al., 2010; Wilson et al., 2018). In this context, machine learning has showed up as a powerful tool to handle large datasets and automatically analyse multi-sensor data.

An emerging field requiring machine learning is the automatic behavioural identification from accelerometer. The accelerometer records the fine scale movements and body posture of the equipped animals from which behaviours can be identified (Brown et al., 2013). It is possible to label the acceleration signals with the animal behaviours through a first validation step using visual observations. Then the labelled dataset is used to teach a supervised learning algorithm to automatically identify the behaviours from the acceleration sequences (Jeantet et al., 2020a, 2018; Nathan et al., 2012; Shepard et al., 2008).

The best-known supervised learning algorithms used for behavioural identification have mainly been based on decision trees (CART, Random Forest or Extreme Gradient Boosting; Brewster et al., 2018; Graf et al.,

* Corresponding author.
E-mail address: lorene.jeantet@iphc.cnrs.fr (L. Jeantet).

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2015), linear hyperplane separation theorem (Support Vector Machine; Campbell et al., 2013; Martiskainen et al., 2009) or even the minimum distance between the unknown instance and the training data (K-Nearest Neighbors; Bidder et al., 2014). The advantages of these algorithms are that they are easy to implement thanks to the development of free computing libraries based on R and Python programming languages, and they produce a good outcome without requiring advanced skills. However, their effectiveness is still limited in identifying fine behaviours and they do not consider the temporal dimension of the data as they process data in independent segments.

Artificial neural networks are other powerful learning algorithms These networks are computational models that translate an input signal through successive layers where linear and non-linear transformation are performed, into an output layer expressing the contained information. Neural networks are thus able to automatically detect by themselves very complex and highly discriminating features and patterns in the data (Chollet, 2018). Such models have won numerous contests in machine learning and constitute a large part of 'Artificial Intelligence'. They are quite flexible and can be used to analyse images, sound, texts and temporal series (as multi-sensor recording).

So far, deep learning has been poorly exploited in automatic behavioural identification due to its complexity. We can find fully-connected neural networks, which correspond to the most basic form of neural network, but mainly in studies comparing the performance of machine learning in automatic animal behaviour classification (Ladds et al., 2016; Nathan et al., 2012; Resheff et al., 2014). However, machine-learning experts have recently provided the architecture for increasingly sophisticated and efficient neural networks via open-source libraries, such as TensorFlow by Google or PyTorch by Facebook for example. Taking this opportunity, and in order to automatically identify behaviour from multi-sensor records, we propose in this study to test a neural network that was originally developed for biomedical 3D image segmentation: the V-net (Milletari et al., 2016). Its good performances on pattern recognition are all the more interesting given that it required few training images despite a highly imbalanced dataset and it performed faster than other methods. Contrary to classical learning algorithms and fully-connected neural networks, the V-net takes the temporal structure of the data into account as it integrates the notion of neighbourhood. We present here an adaptive version of the V-net for the multi-sensor time series (i.e. 1D signals) to automatically identify the behaviours of green turtle *(Chelonia mydas)*.

Green turtles are long-distance migrants with high diving abilities (Chambault et al., 2015; Lutz and Bentley, 1985; Spotila, 2004) which make impossible long-term observation of their at sea behaviours. In order to improve conservation measures for this threatened species, classified as endangered species by the International Union for Conservation of Nature (Seminoff, 2004), it is essential to better know their behaviours and ecology. In this study, we focus particularly on immature green turtles residing on the coastal foraging grounds of Martinique. The population shows high fidelity to this developmental habitat where they spend many years foraging to grow before undertaking migration at the sexual maturity (Chambault et al., 2018; Siegwalt et al., 2020). During immature stage, green turtles are mostly grazing herbivores and mainly feed on seagrass and algae (Bjorndal et al., 2000; Howell, 2012). While studying feeding behaviours of green turtles is particularly important to understand their ecology, it is still difficult to identify it automatically from a sensor placed on the carapace.

In the attempt to automatically identify the at-sea behaviours of green turtle, with a particular focus on the feeding events, we test the performance of the V-net to classify their behaviours from multi-sensor recordings. We use a labelled dataset collected from animal-borne video recorders combined with multi-sensor recorders (accelerometer, gyroscope and time-depth recorder) deployed on free-ranging immature green turtles in Martinique (Jeantet et al., 2020b). The outcome of the V-net could be compared to a method based on classical learning algorithms (such as RF, EGB, CART and SVM) developed from the same dataset in a previous study (Jeantet et al., 2020a). Furthermore, the use of the gyroscope is not so common in behavioural identification in ecology. Therefore we compare the performance of the V-net according to the measuring device; i.e. the gyroscope associated with the accelerometer, the gyroscope alone or the accelerometer alone.

2. Materials and methods

2.1. Dataset description and behavioural labelling

The used dataset contains the tri-axial acceleration and angular velocity of 13 free-ranging green turtles recorded at a frequency of either 20 Hz or 50 Hz (Jeantet et al., 2020b, 2020a). The depth profiles are also provided at 1 Hz. The devices were combined with a video recorder allowing us to validate the signals. The video footage, analysed using a handmade software written in python language (Hadetskyi, 2019), enables the identification of 46 different behaviours regrouped into six categories: *Breathing, Feeding, Gliding, Resting, Scratching and Swimming* (see Jeantet et al., 2020a, for the behavioural definitions). All other behaviours that cannot be considered into these six categories are grouped into the *Other* category. The precise description of the dataset is provided in Jeantet et al. (2020a) as well as the corresponding R-script to visualize the labelled data through the rblt package (Fig. 1, Geiger, 2019). To test the V-net, we synchronize the observed behavioural categories with the acceleration, angular velocity and depth data, subsample the 50 Hz data at 20 Hz and remove the unlabelled section.

We focus in particular on the *Feeding* category, which is particular difficult to discriminate. In this study, the green turtles mainly fed seagrass on the ground from which we identified two distinct behaviours: the action of pulling on the seagrass that we referred as *Grabbing*, and the action of mastication referred as *Chewing*. The device being on their carapace, those behaviours resulted in subtle variations hardly detectable (Fig. 1 and Supplementary materials.). Thus, in order to identify the *Feeding* category, we add specific adaptations to the V-net.

2.2. V-net architecture

The V-net was first described and developed by Milletari et al. (2016) to treat medical images (3D signals). It is an evolution of the U-net, developed for biomedical 2D images (Ronneberger et al., 2015). The implementation of the both algorithms can be found in the respective articles (Milletari et al., 2016; Ronneberger et al., 2015). In this work, we present an adapted architecture for the V-net which fits with our multi-sensor data, i.e. 1D temporal series (Fig. 2). It has been implemented with the Keras and Tensorflow libraries through their python interface.

The V-net is a fully convolutional neural network meaning that it is based only on a successive sequence of convolutions. It consists of two parts: an "encoder" path that compresses the signal and creates multiple features, thus performing a multiscale analysis, and a "decoder" path that synthesizes the created features to predict the output, which in our case is the behaviours. The breakdown of each step of the V-net is as follows:

- Input (**1**): This corresponds to a sequence of multi-sensor data containing all the descriptors (the three acceleration axes, the three gyroscope axes and the depth for example, $nb\_desc = 7$), over a window size fixed at 40 s ($WS = 800$ for sampling data at 20 Hz).
- Initialization (**2**): We first perform two 1D convolutions with a kernel size of 5, each followed by a Relu activation. In this step, we conserve the size of the window by adding a border of zero, and increase the number of channels from *nb_desc* to *depth*. The latter is a parameter tuned to 32 during the tuning process (see Section 2.4). Section 2.6
- Descending part (Encoder) (**3**): The output feature maps are first down-sampled by averaging a convolution of size 2 and stride 2. By doing this, the importance of the location of the highlighted features

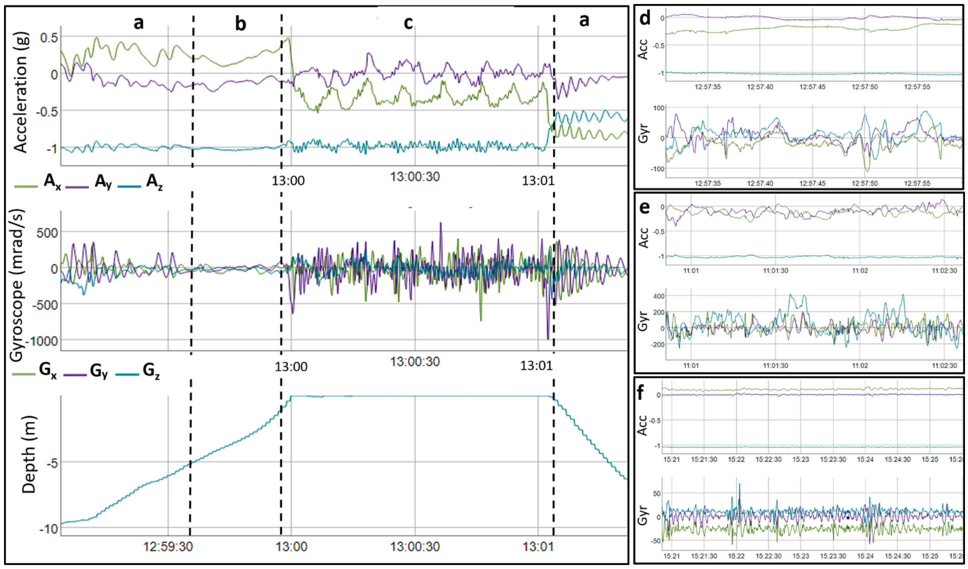

Fig. 1. Acceleration (Acc) and gyroscope (Gyr) signals with eventually the depth profile corresponding to the six main behavioural categories of green turtle: *Swimming* (a), *Gliding* (b), *Breathing* (c), *Feeding* (d), *Scratching* (e) and *Resting* (f). X corresponds to the rear-to-front body axis, Y to the right-to-left axis and Z to the bottom-to-top axis. For more details for the *Feeding* behaviours, see the Fig. 1 in the Supplementary Materials.

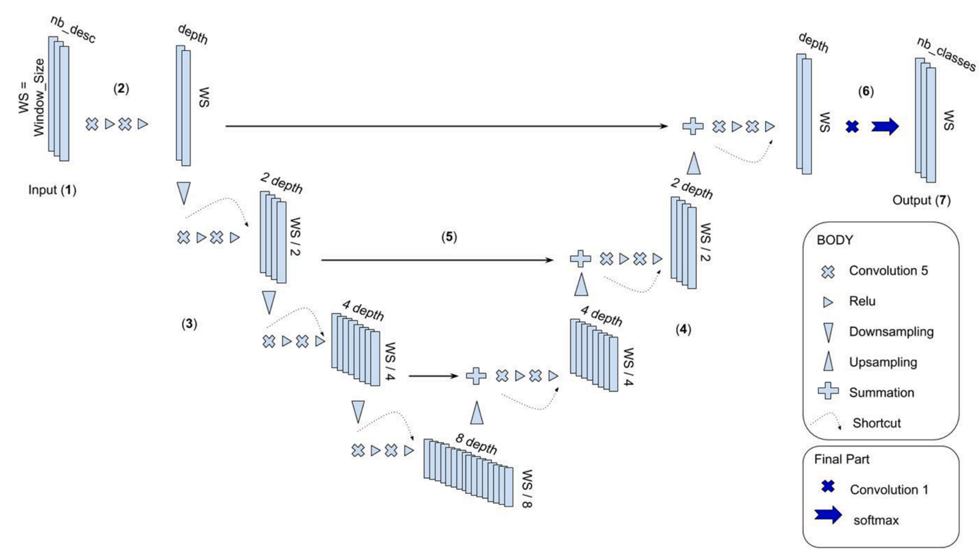

Fig. 2. Architecture of the V-net adapted for multi-sensor data (1D signals). Depth corresponds to the number of features to create (depth = 32), nb_desc to the number of input data and nb_classes to the number of behaviours (nb_classes=7).We choose a window size of 40 s (WS= Window_size=800).

is reduced. Then, we perform two convolutions of size 5 followed by Relu activations. The output of the convolutions is actually added to the input signal of the corresponded level and is thus seen as additive modifications of the main stream. This operation, also called 'Shortcut', is represented by the dotted arrows on Fig. 2. It has been shown that it accelerates the training process and limits gradient vanishing or explosion problems (see Section 2.3,Section 2.5, He et al., 2016). We obtain some feature maps with a window size divided by 2 and the number of channels multiplied by 2. This sequence is repeated three times.

- Ascending part (Decoder) (**4**): This works as a mirror of the descending part. Each transformation simultaneously increases the size of the window and decreases the number of channels by a factor of 2. Technically, we up-sample the data using a transposed-convolution (Dumoulin and Visin, 2016) of size 2 followed by two convolutions of size 5 with Relu activations.
- Horizontal arrows (**5**): At each level of the ascending part, the feature maps obtained in the ascents are combined with the features created by the descents, using a summation.
- Final convolutions and Softmax activation (**6**): We perform a convolution of size 1 to obtain a dimension corresponding to the number of possible predicted behaviours (*nb_classes* = 8). Then, a Softmax function normalizes the last layer to produce probabilities.
- Output (**7**): We obtain a window of the same length as the input signal (WS = 800), and therefore with the same temporal resolution. Its number of channels is *nb_classes*, where each channel indicates the probability of each behaviour.

2.3. *Training process*

The training process consists in adjusting the filter weights (*W*) of each convolution of the network in order to obtain the most accurate predictions. To do this, we train the network on several batches of windows randomly drawn with the corresponded labels. We use a Loss function (L) that calculates the distance between the predicted and actual labels for each input, and sum it all up to get the overall error of the batch. Through this function, we further penalize the mistakes made on *Feeding* to force the V-net to focus on it. The weights are then adjusted using the famous Adam optimizer (Kingma and Ba, 2015). It is an adaptive version of the classical gradient descent:

$$W \leftarrow W - lr\frac{dL}{dW}$$

where W represents the weights, $\frac{dL}{dW}$ is the gradient of L and lr is positive hyper-parameter called the learning rate. The latter, as well as the batch size (*batch_size*), are determined during the tuning process (see Section 2.4). Section 2.6. A high lr would reduce the computation time to minimize the loss, but too high a value could induce too large weight updates with the result that the optimal point will be missed. Moreover, to avoid overlearning, we add the well-known spatial dropout after each double convolutions with a rate of 0.5.

This training process requires that the labels are balanced in the data batches. However, this is rarely the case in ecology where some minority behaviours could be relevant (such as the feeding behaviours for sea turtles). To deal with this, we bias the random draw in order to increase the representativeness of the rare behaviours: 20% of the windows for each batch are randomly selected from randomly chosen turtles while the remaining 80% are chosen with biased dice. In further detail, a window is drawn as follows:

- A behaviour B is selected according to an assigned probability (0.25 for the minority behaviours, e.g. *Feeding, Gliding* and *Scratching*, 0.05 for the majority behaviours, e.g. *Swimming* and *Resting,* and 0.15 for *Breathing*)
- A turtle T is randomly selected with a probability proportional to its B expression.
- The window is drawn according to a probability distribution determined from the expression of B by T.

Fig. 3 illustrates this idea: each blue rectangle corresponds to the occurrence of B (here B = *Feeding* and T = individual **#6**). The orange signal represents the probability density obtained by smoothing the blue rectangles through a convolution. We show in red lines all the potential windows for which the centre can be drawn according to this probability density. They are vertically distributed for easier viewing.

As an example, Fig. 4 shows a possible behavioural distribution obtained over 2000 windows from the biased random draw (20% randomly and 80% biased) compared to the unbiased one.

2.4. Tuning and training processes performed simultaneously

We randomly split the 13 sea turtles into three distinct groups:

- Seven individuals are used to train the network
- Three are assigned to the validation dataset and used to adjust the hyper parameters (tuning process)
- Three turtles are kept to test the method at the very end of the process.

Training and tuning processes are performed simultaneously through 150 epochs. An epoch corresponds to one pass through the training dataset where 15,000 windows are drawn to feed the optimizer by batch of 200 (*batch_size* = 200). At the end of each epoch, we observe the loss relative to 3000 windows of the validation dataset (separate from the training dataset). Over the 150 epochs, we finally keep the weights corresponding to the lowest validation loss. The hyper parameters are tuned in order to best reduce this validation loss. The main ones are the *depth* which corresponds to the number of created features (*depth* = 32), the learning rate lr regulating the speed of the gradient descent (lr = 0.01), the *batch_size* and the sampling probabilities of behaviours.

2.5. Validation of the model

Once our model is tuned and trained, we predict the behaviours of the three remaining individuals which have never been exploited previously. Their entire sequence is cut into successive windows with a 10% overlap on the right and left, because the predictions are degraded on the edges due to the zero-padding of the convolutions. We run the trained model on all windows, and re-paste the predictions together.

The accuracy of the model is evaluated using the ROC-AUC score (Fawcett, 2006). In order to take into account the unbalanced distribution of classes, we apply the multi-class generalization of the AUC developed by Hand and Till (2001):

$$AUC_{total} = \frac{2}{|C|(|C|-1)}\sum_{\{c_i,c_j\}\in C} AUC(c_i,c_j)$$

where C is the set of classes, |C| its cardinal, AUC(c_i,c_j) the area under the two-class ROC curve for classes i and j calculated over all pairs of classes, and |C|(|C|−1)/2 the number of pairs.

We also compare the predictions of the model to the true behaviours through an overall confusion matrix. Thus, the well-identified behaviours (TP: true positive, TN: true negative) and the misclassified windows (FN: false negative, FP: false positive) are identified and used to calculate the classical indicators for each behaviour (Powers, 2011):

$$Recall = \frac{TP}{TP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

In order to compare the ability of the network to identify the behaviours of sea turtles to the previous study on the same dataset, we calculate the global accuracy (Powers, 2011):

$$Global\ Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

2.6. Comparison of the V-net performance according to the measuring device

We test the V-net on three combinations of the measuring devices:

- Case I: Accelerometer, gyroscope and depth recorder (*nb_desc* = 7)
- Case II: Accelerometer and depth recorder (*nb_desc* = 4)
- Case III: Gyroscope and depth recorder (*nb_desc* = 4)

Fig. 3. Representation of the occurrence of *Feeding (in blue)* and the associated probability density (in orange) for individual #6. The red lines show the potential drawn windows according to this probability density.

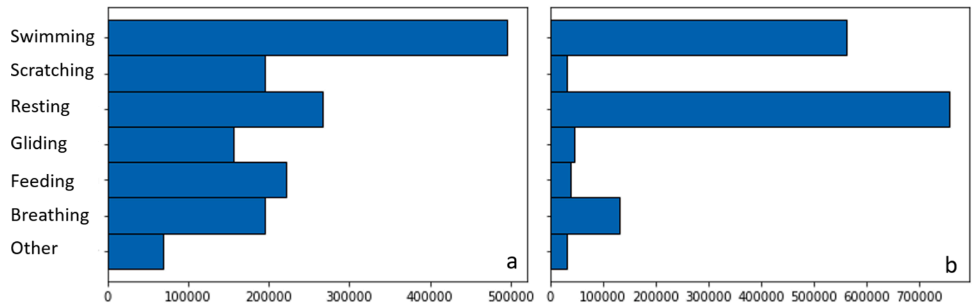

Fig. 4. Distribution of behavioural dots obtained over 2000 windows from the biased random draw (20% randomly and 80% biased, a) compared to the unbiased draw (b).

In each case, we run the algorithm on the raw data for which the descriptors are standardized one by one and for one turtle at a time. As the Case II gives lower global accuracy, in particular in the *Feeding* identification, and that the scientist community has mainly deployed accelerometers with depth recorders on marine animals without gyroscopes, we go further in the pre-processing of the acceleration data to improve the predictions. We calculate the static and dynamic acceleration for the three axes and the Dynamic Body Acceleration (DBA) as described in Jeantet et al. (2020a). In a similar way, we attempt to highlight some *Feeding* signal characteristics by filtering the raw acceleration through a pass-band Butterworth filter at 2 and 3 Hz frequency. Thus we obtain a supplementary case:

- Case IV: Static, dynamic and filtered acceleration, DBA and depth values ($nb\_desc = 11$)

2.7. Variable importance

We attempt for each case (case I, II, III and IV) to identify the most important input variables in the classification process, i.e. those containing the most information and mostly used by the V-net. We adapt the class activation map (CAM) visualization (Chollet, 2018; Selvaraju et al., 2019) developed in image classification from deep learning. From the tested dataset, we compute the gradients of the model's predictions for one given behaviour to the input features and average their absolute value. We obtain thus the contribution of each single input variable on the classification of one specific behaviour.

Moreover, we also perform a variable selection by backward elimination to identify the impact of each variable on the classification accuracy (Derksen and Keselman, 1992; Heinze et al., 2018). Thus we apply the V-net on the tested dataset from which variables are subsequently eliminated one at a time. At each time, we eliminate the variable that have the lower impact on the AUC by replacing it with the constant value of its mean.

3. Results

3.1. Behavioural classification by the V-net

The adapted V-net model discriminates the six behavioural categories (*Breathing, Feeding, Gliding, Resting, Scratching* and *Swimming*) of the free-ranging green turtles from a combined accelerometer, gyroscope and depth recorder with an AUC score of 88.1% (Case I, Table 1). Although deep learning models usually have a large number of parameters, our model is relatively light: 1259,335 parameters due to its fully convolutional structure and to the data in one dimension.

The V-net demonstrates good capabilities to detect the rare behaviour of *Feeding* with a respectable Recall index and a high Precision

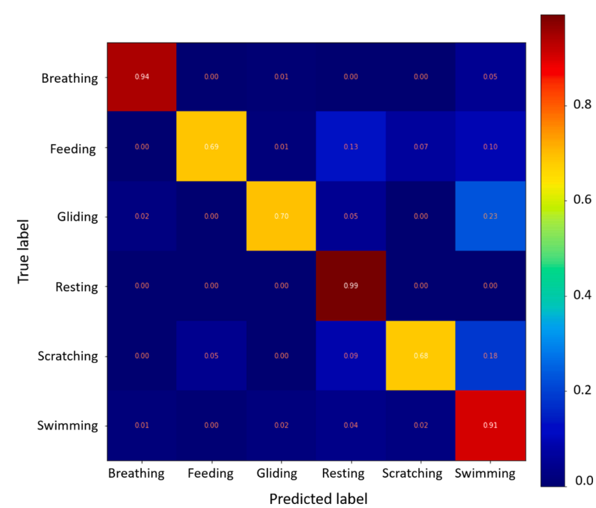

Fig. 5. Confusion matrix of the predictions of the V-net on the three tested green turtles using the seven descriptors obtained from acceleration and angular speed data. The numbers correspond to the proportion of the identified dots of each behaviour.

Table 1
Comparison of the Recall and Precision index obtained for the six behavioural categories with V-net trained with and without additional information from the gyroscope.

Behaviour	Case I		Case II		Case III		Case IV	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
Breathing	0.94	0.96	0.84	0.91	0.94	0.93	0.93	0.96
Feeding	0.69	0.82	0.02	0.03	0.75	0.65	0.62	0.62
Gliding	0.70	0.83	0.73	0.71	0.63	0.83	0.68	0.76
Resting	0.99	0.97	0.99	0.89	0.98	0.97	0.98	0.96
Scratching	0.68	0.69	0.66	0.56	0.82	0.54	0.78	0.58
Swimming	0.91	0.90	0.70	0.85	0.86	0.91	0.86	0.90
Global Accuracy:	97.8		95.0		97.1		97.1	
AUC (%)	88.1		79.4		87.3		85.0	

score, with only 13% of the *Feeding* dots misinterpreted as *Resting* (Case I, Table 1, Fig. 5). *Scratching*, which is the least expressed behaviour, shows the lowest indices (0.68 and 0.69 for the Recall and Precision index, respectively, Table 1) with a model that tends to overestimate this behaviour (Fig. 6).

Although the combined use of the gyroscope and accelerometer gives the best accuracy, the V-net successfully classifies the behaviours of the green turtles from the gyroscope alone (AUC = 87.3%, Case III, Table 1). In Case III, the rare behaviours *Feeding* and *Scratching* are better detected than in Case I but also associated with a slight increase in overestimation. However, from the accelerometer alone (Case II), the V-net only identifies 2% of the *Feeding* dots, suggesting that the subtle variations generated by the feeding movements are easier detectable from the gyroscope than the accelerometer. Nevertheless, a pre-processing of the acceleration data enables the V-net to predict with an accuracy comparable to Case I and III (Table 1), with 62% of the *Feeding* dots correctly identified and 20% misclassified as *Resting* (Fig. 2 in Supplementary materials). The *Chewing* behaviour represents 74% of those *Feeding* dots wrongly identified as *Resting*.

The backward elimination process allows us to identify the most important variables for the V-net in the classification of the green turtle behaviours. It clearly appears that the Y-axis of the gyroscope, corresponding to the angular velocity around the right-to-left axis and thus related to movements on the rear-to-front axis, is the most informative variable (Figs. 7and 8). The V-net is even capable of classifying behaviours with an AUC score of 72.2% with the Y-gyroscope alone. However, in absence of gyroscope (Case II), the three accelerometer axes as well as the depth are used equally by the V-net (Fig. 8), but are not sufficient to identify *Feeding* (Table 1). From the pre-processed acceleration data (Case IV), the variables associated with the dynamic acceleration, and therefore motion; Dynamic Body Acceleration (DBA) and the dynamic acceleration on the rear-to-front axis (DX), have the highest important gradient (Fig. 8). The filtered acceleration data between 2 and 3 Hz on the rear-to-front axis (AccX_high) is also particularly used by the V-net to classify *Feeding* and to dissociate it from *Resting* (Fig. 3 in Supplementary Materials). The backward elimination process applied to Case IV shows that removing AccX_high results in a drop in the *Feeding* Recall index; only 6% of the *Feeding* dots are identified.

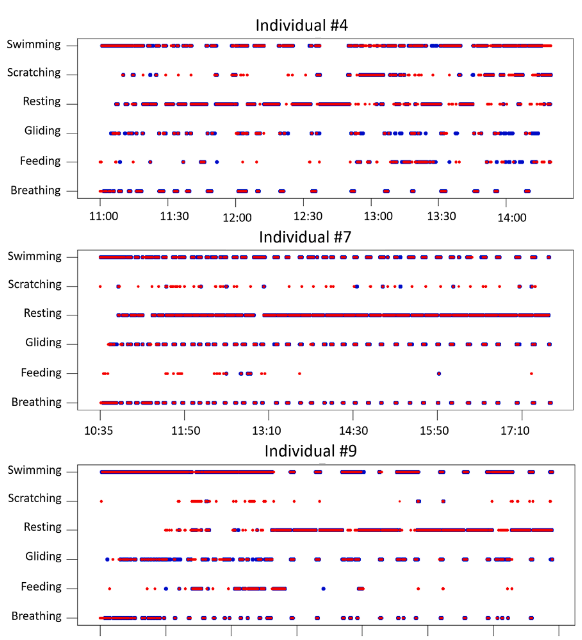

Fig. 6. Time budget of the three tested green turtles showing the behavioural categories inferred by the V-net (in red) compared to actually observed behaviours (in blue).

3.2. Sensitivity and uncertainty analyses

Deep learning are known to be very sensitive to small perturbation (Shu and Zhu, 2019). We test the sensitivity of the V-net by classifying sea turtle behaviours from degraded data. We randomly select 500 windows (window size = 40 s) from the tested dataset in Case I and gradually add some noise on each input variable for each time t_i.

$$\widetilde{X}_{t\_i} = X_{t\_i} + \sigma * N_{t\_i}$$

Where N_{t_i} are standard Gaussian random variables and σ is a constant that we increase from 0 to 0.5. We perform the AUC score on the obtained classification and visualisation its evolution according to the noise level (Fig. 9). In this way, by inducing a σ value of 0.05, corresponding to add 5% of noise to the inputs as they are also standardized, we impact the AUC by 5% (AUC score = 80.49% against 85.67 without noise). However above 10% of noise, the performance of the V-net drops.

We measure the uncertainty of the model using Monte Carlo Dropout method (Abdar et al., 2020; Gal and Ghahramani, 2016). This method consists in predicting a single window multiple times (n = 1000) but with dropout layers activated in the prediction process, forcing the V-net to masque some connections. The variance of the predicted probabilities indicates the uncertainty of the model. Fig. 10 shows the obtained variance for two windows from the tested dataset in Case I, where the V-net misclassifies *Feeding* as *Scratching* and, at the opposite, successfully identifies it. It appears that, most of the time, the correct predictions are associated with low uncertainty while the variance increases for the misclassified parts. Thus the variance can help to estimate the robustness of the predictions because the V-net is not too confident when it misclassifies.

4. Discussion

The V-net is a powerful fully convolutional neural network developed for the segmentation of 3D images (Milletari et al., 2016). The proposed architecture, adapted to multi-sensor signals, also proves to be very efficient in classifying sea turtle behaviours. Identifying the six behavioural categories (*Breathing, Feeding, Gliding, Resting, Scratching* and *Swimming*), we obtain an AUC score of 88.1%. With a global accuracy of 0.98, it represents significant improvement compared to methods based on classification trees for the same species (global accuracy of 0.87 from captive individuals in Jeantet et al. (2018) and 0.95 from the same dataset in Jeantet et al., 2020a).

4.1. Advances in automatic behavioural classification using deep learning

The V-net improves the automatic animal behavioural classification from multi-sensor datasets by avoiding the segmentation problem. Classical machine learning requires cutting the dataset into segments from which statistics (maximum, mean, minimum, standard deviation, etc.) are calculated and used to feed the model. It is a particularly difficult processing step as it has to be automatic, in the real application conditions (i.e. without knowing the beginning and ending of the behavioural labels) and impacts the performance of the algorithms. To date, the most common segmentation method has been the windowing approach based on fixed time segments (Lagarde et al., 2008; Martiskainen et al., 2009; Watanabe et al., 2005) or a sliding window with a fixed length (Ladds et al., 2017; Lush et al., 2018a). Quite quickly, the size of the window impacts the accuracy of the models in that some behaviours are better characterized than others (Allik et al., 2019; Banos et al., 2014; Lush et al., 2018b). Other methods such as change point algorithms (Killick et al., 2012) or hierarchical segmentation (Jeantet et al., 2020a) can also be used to overcome the limits generated by the fixed-size windowing approach. However, these methods require ruling parameters based on the most characteristic variations between

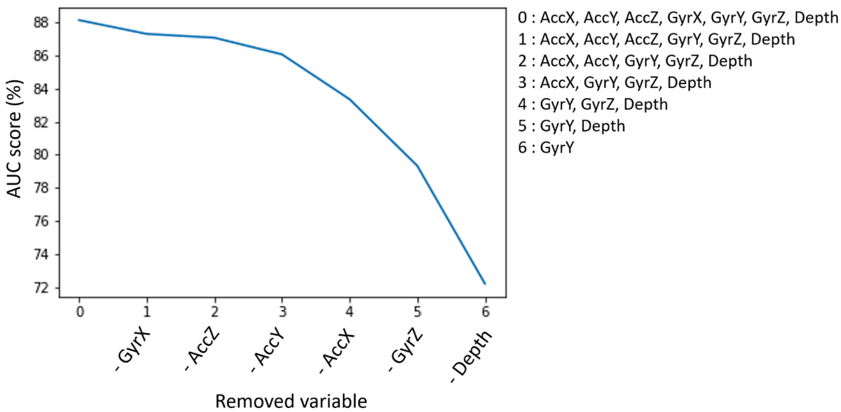

Fig. 7. Evolution of the AUC score of the behavioural classification of the V-net on the green turtle tested dataset from which variables are subsequently eliminated one at a time. The x-axis indicates the removed variable at each step and the number is associated with the variables used by the V-net. AccX, AccY, AccZ correspond to the three axis of the acceleration and GyrX, GyrY, GyrZ to the three axis of the gyroscope with X the rear-to-front body axes, Y the right-to-left axis and Z the bottom-to-top axis.

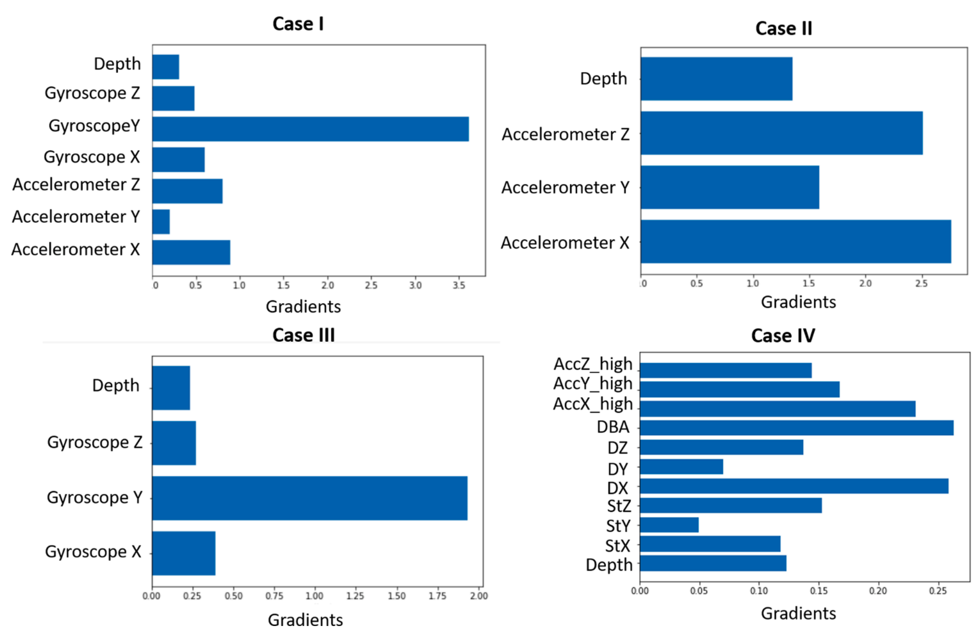

Fig. 8. Gradient importance of the V-net associated with the classification of the *Swimming* behaviour of the green turtles. In Case IV, DBA corresponds to the Dynamic Body Acceleration, StX, StY, StZ to the three axes of the static acceleration, DX, DY, DZ to the dynamic acceleration, and AccX_high, AccY_high, AccZ_high to the acceleration filtered between 2 and 3 Hz with X the rear-to-front body axes, Y the right-to-left axis and Z the bottom-to-top axis.

behaviours that are generally not suitable for all the behaviours. Also, in general, the segmentation process generates segments that contain the expression of several behaviours and induces confusion in the learning process of the algorithms. Thus, all these methodological limitations induced by the segmentation process, which reduce the accuracy of the prediction, no longer apply to the V-net given that it makes predictions with a precision down to the centisecond, assigning a behaviour to each time-point of the recorded values.

It is still difficult to identify signals that are not clearly distinct in classical machine learning (Bom et al., 2014; Fehlmann et al., 2017; Wang et al., 2015). One possible cause could be the selected hand-made features on which they rely. There are multiple ways to digitally describe multi-sensor signals without consensus on the best practise. Thus, we can find studies where several thousand features were calculated compared to roughly fifty in other studies (Figo et al., 2010; Graf et al., 2015; Zdravevski et al., 2017). Given that having too many features can impair the performance of the algorithms, the current solution to deal with difficult classification tasks is to calculate a large number of features and to select the most highly informative combination using a complex optimizer (Allik et al., 2019; Mirjalili, 2015). All in all, this adds a selection process that makes the model more complex and computationally expensive with a questionable gain in performance. Conversely, the performance of the V-net lies on a form of its own intelligence as it detects highly discriminative features by itself through the deep layers. The analysis through these different layers increases the level of abstraction of the produced features and makes the V-net able to detect information that goes beyond the human knowledge domain (Milletari et al., 2016). It enables the model to extract information that could not be identified through the handcrafted features and thus makes it very powerful for detecting fine-scale behaviours such as *Feeding* and *Scratching*. The V-net is thus a very powerful tool that currently outperforms classical machine learning.

However, we show in this study that handcrafted features can also help the V-net to identify the behaviours of sea turtles from acceleration data. The V-net is not able to identify *Feeding* from the raw acceleration data because the oscillations recorded by a logger on the carapace are very small and subtle (Figs. 1 and 2 in Supplementary Materials). The visualisation of the data and the identification of discriminating characteristics of *Feeding* have allowed us to orientate the V-net in its automatic feature detection. By feeding it with pre-processed data carefully chosen to discriminate *Feeding* (the filtered acceleration between 2 and 3 Hz), we make the V-net capable of identifying this behaviour from the

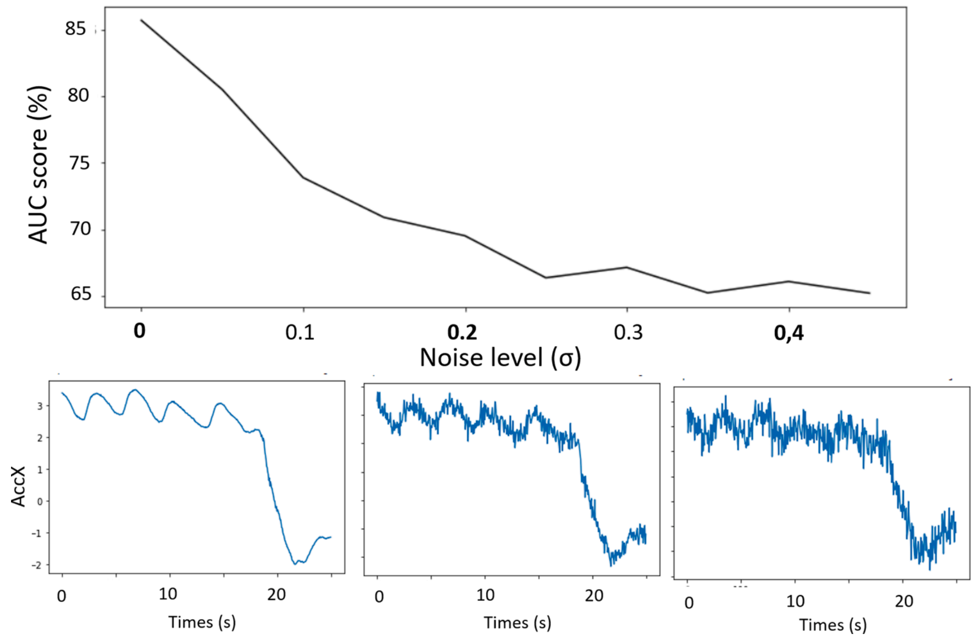

Fig. 9. Sensitivity curve: AUC score obtained by the V-net classifying sea turtle behaviours of the tested dataset from gyroscope, accelerometer and depth recorder according to the noise added to the data. The lower boxes illustrate the added noise on the X-axis acceleration (AccX); with the raw data (left), with a noise level of 0.2 (centre) and 0.4 (right).

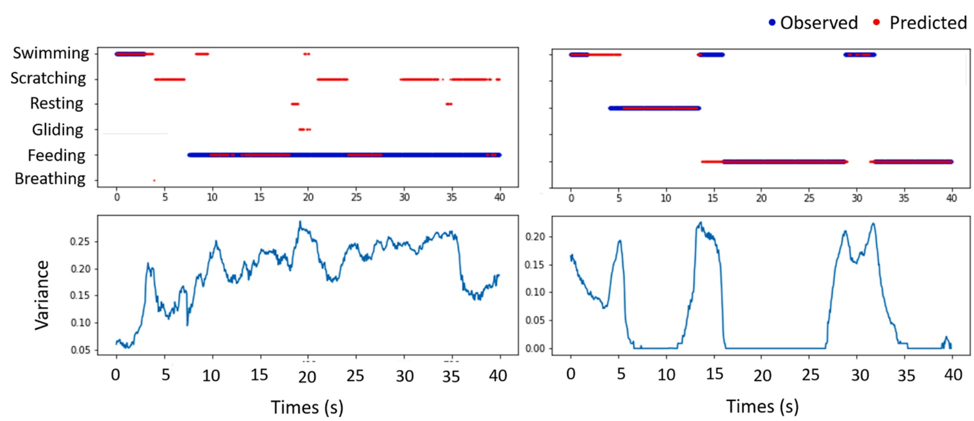

Fig. 10. Uncertainty of the V-net in the classification of sea turtle behaviours. The uncertainty is represented by the variance of the probabilities predicted multiple time by the model with the dropout layers activated.

acceleration data alone. This compromise between deep learning and hand-made features allows us to take advantage of the automatic discrimination ability of the neural network and to not compute a large number of handcrafted features, while maintaining a simple deep learning architecture. Although the deep learning is increasingly powerful and used in many field, human expertise is still relevant to perform automatic behavioural identification from accelerometer.

4.2. Improve the ecological knowledge

In this study, we test the relevance of adding a gyroscope to an accelerometer in automatic identification of sea turtle behaviour. So far, the gyroscope has been mainly used in addition to an accelerometer and magnetometer to improve the estimation of the static and dynamic acceleration (Fourati et al., 2011; Noda et al., 2012). And, it has been poorly exploited in automatic behavioural identification while its high sensitivity enables to measure fine and/or fast angular rotation that cannot be detected from the linear acceleration (Clark, 2009; Noda et al., 2014; Wilson et al., 2013). In this study, we show that the V-net mainly uses the gyroscope variables to identity the sea turtle behaviours, in particular the angular velocity around the right-to-left axis (Fig. 8), and it is less performant without gyroscope. This is due to the fact that the sea turtle's posture is not very informative and the behaviours differ from one another mainly by the associated oscillations of the rear-to-front body axis. However, the gyroscope does not provide information about change in posture and its use alone may therefore not be sufficient for other animal species for which postures characterize their behaviours (Shepard et al., 2008; Watanabe et al., 2005). We highlight that identification of the sea turtle behaviours with an accelerometer alone is also possible but requires an upstream fine analyse and good understanding of the signals. In this way, it is relevant to ask for each situation if the combined used of gyroscope and accelerometer is necessary as it requires more memory and larger battery capacity, and thus a larger logger. While the scientist community tends to study increasingly smaller species (Portugal and White, 2018), increasing sensor possibilities should come with an ethical concern to match the most appropriate tag design to ensure the animal welfare while answering the biological question (Williams et al., 2019). Besides, as the relevance of the measuring device used mainly depends on the behavioural characteristics of the studied species, this should be considered and tested in each case.

We particularly focus on the identification of the scarce behaviours of sea turtle; *Feeding* and *Scratching,* as they have both a high ecological interest. Studying the feeding behaviours of free-ranging animals is crucial to better understand their energetic tactics and how they maximize their fitness according to their environment. Although *Scratching* has been rarely reported in sea turtle behavioural research using animal-borne video recorder (Arthur et al., 2007; Okuyama et al., 2013; Reina et al., 2005; Seminoff et al., 2006), it seems to have an important physiology role as it could be associated with a cleaning function (Heithaus et al., 2002; Thomson and Heithaus, 2014). However, in general, behaviours with a small number of observations available and associated with fine-scale signals, such as *Feeding* and *Scratching*, are hard to detect by an automatic method (Jeantet et al., 2018; Wang et al., 2015). The V-net has been thought to deal with strong imbalance dataset and/or limited in the number of labelled data (Milletari et al., 2016). Hence, enhanced by an adapted *Loss* function and a biased random drawn for the training process, the convolutional neural network precisely detects both behaviours and slightly overestimates *Scratching*. Whereas, classical learning algorithms have still been poorly efficient to identify complex signals in other animal species (Bom et al., 2014; Ladds et al., 2018; Wang et al., 2015), the V-net position itself as an alternative to discriminate the fine-scaled behaviours. Easily generalizable to other species, the V-net could lead to considerable progress in remote accelerometric monitoring by allowing the identification of very fine behaviours that could play an important role in understanding the ecology of the species.

Finally, the obtained model is light with only roughly one million parameters. It makes it very easy to transfer a trained V-net and to run it from one machine to another. Thus with the development of the satellite-relay data tags which are already able to remotely transmit a summary of the tri-axial acceleration (Cox et al., 2017; Harcourt et al., 2019; Heerah et al., 2019) and environmental data (Treasure et al., 2017), there is a huge potential to directly implement a trained V-net in an animal-attached multi-sensor tag in order to predict the expressed behaviour almost instantly. Researchers would be able to directly follow the activities of an animal in real-time with respect to its location and the environmental parameters. As it would not require recapturing the animal, this breakthrough would open up new horizons in the study of migratory animals that are difficult to track during several consecutive months or years.

5. Conclusion

Deep learning is an emerging field that is particularly powerful for automatically processing large datasets and the information they contain. It is therefore not surprising to see its application extended to ecology by the automatic behavioural identification from multi-sensor recorders. An adapted fully convolutional neural network, the V-net, reveals high ability to automatically identify the behaviours of sea turtles from multi-sensor signals and outperforms classical machine learning. Its use is particularly interesting to avoid the segmentation process and the manual calculation of a large number of discriminant features required, until now, to identify the behaviours from accelerometer. We also show in this study that the gyroscope is more informative that the accelerometer in identifying the behaviours of sea turtles and that the V-net is not able to discriminate fine-scale behaviours from the raw data of accelerometer alone. However, human expertise can help to correct it with precise and adapted pre-processing. There is great interest in developing deep learning for automatic identification of behaviours in ecology as it does not require significant pre-processing of data and could be directly implemented in the logger to identify and transmit the expressed behaviour by the equipped animal almost instantly.

Data accessibility statement

Data available from the Dryad Digital Repository: https://doi.org/10.5061/dryad.hhmgqnkd9 (Jeantet et al. 2020b). The R-script to visualize the data are provided in Jeantet et al. (2020a).

CRediT authorship contribution statement

DC contributed conception and design of the study. LJ and SG performed the data acceleration analysis and visualisation. VV built the V-net architecture and adapted it to the 1D data. LJ applied the V-net on the sea turtle dataset. LJ and VV wrote the first draft of the manuscript and SG, and DC contributed critically to subsequent versions.

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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.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2021.109555.

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