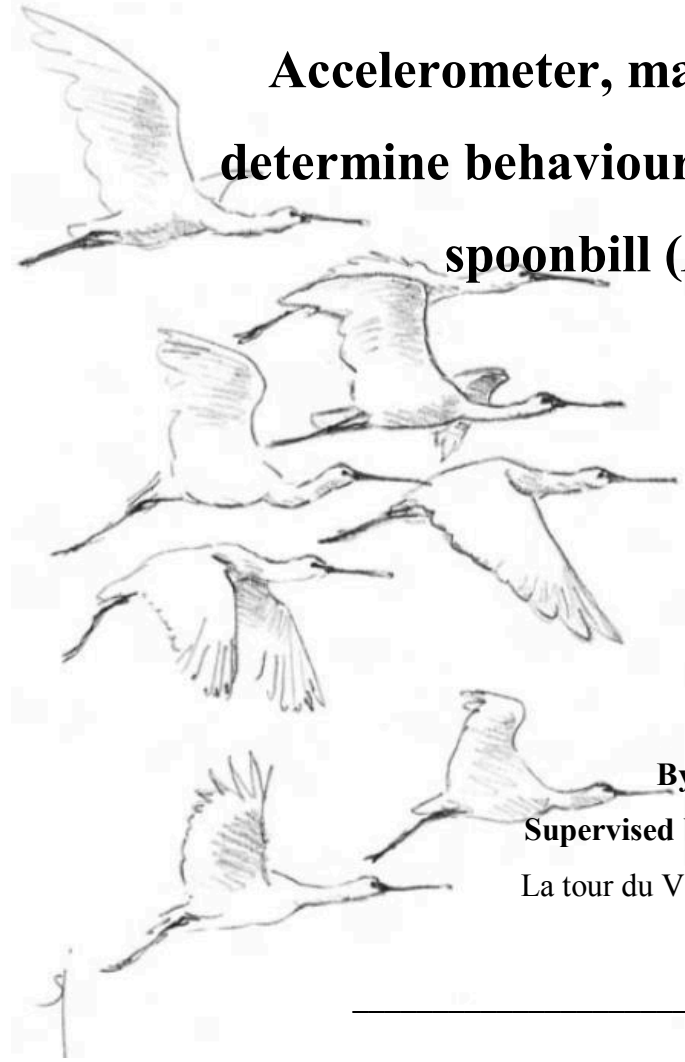
University of Burgundy Franche-Comté – Master STS – ETEC - Behavioural Ecology and Wildlife Management

Internship's thesis, 1rst year Master program BEWM 2017-2018



Accelerometer, machine learning, a method to determine behavioural time budget from Eurasian spoonbill (*Platalea leucorodia*).

By: Audrey MAZZA

Supervised by: Dr. Jocelyn Champagnon

La tour du Valat, Le Sambuc, 13200 Arles

INSTITUTION AND LAB PRESENTATION

The data from this internship was collected at 'Parc des oiseaux' in Villars-les-dombes, and complemented with other observations at the research center of 'Tour du Valat' (TDV) located in the Camargue, France. Collected data was analyzed at BIOGEOSCIENCES laboratory in Dijon.

The domain of TDV was purchased by Luc Hoffmann in 1947, a visionary naturalist and keen ornithologist, in 1954, he turned the domain into a biological station. This station is a nonprofit private research institution focusing its research activity in the conservation of Mediterranean wetlands**.** The station possesses a unique documentation resource specializing in wetland ecology in the Mediterranean. This domain contains all the representative natural habitats of the Fluvio-lacustrine in Camargue, covering 2921 hectares of land in which 1845 hectares are classified, since 2008, as a Regional Nature Reserve. Beyond its role of biodiversity conservation, it is also a privileged site to conduct research, test and develop agricultural or hunting activities compatible with the sustainability of this exceptional biodiversity. Around 80 employees are continuously working at the institution, including currently 45 researchers as members of the scientific team. Research is conducted by three different departments, of which Species conservation department is aiding this project. The general objective of this department is to contribute to animal species conservation in the Mediterranean wetlands and help in the managing of conflicts that may arise between the life of wild species land human activities.

The zoological park of 'Parc des oiseaux' has been opened in 1970 and is listed in the General Inventory of Cultural Heritage. Its one of the oldest ornithological parks of France, currently harboring in freely or semi-freely conditions, around three thousand birds from all over the world, in a 380-hectare reserve located in the heart of the Dombes. The park is a member of the European Association of Zoos and Aquariums and the National Association of Zoological Parks. It participates in about fifteen European breeding programs for the safeguarding and reintroduction of endangered species. Its also a member of the World Association of Zoos and Aquariums (WAZA).

BIOGEOSCIENCES laboratory is a Mixed Research Unit (UMR) composed of about one hundred people whose employers are the University of Burgundy, the National Center for Scientific Research (CNRS), the Ecole Pratique des Hautes Etudes (EPHE) and AgroSup Dijon. Research conducted in this institution are mainly focused in evolutionary ecology, environmental sciences, sedimentology, paleontology or climatology.

"Man goes to nature to learn what nature is, but, in so doing, he introduces possibilities of distortion through his own presence." – T.C. Schneirla

TABLE OF CONTENT

Institution and lab presentation.....

Introduction.....1

Materials and methods 4

Study species.....4

Experimental protocol.....4

Wild spoonbill.....*5*

Statistical analysis.....5

Data preparation. *5*

Summary statistics......*6*

Classification model. *7*

Data analyses.....*7*

Results 9

Random forest model 9

Behaviour time budget.....9

Discussion.....11

Conclusion 13

References.....

Appendix .....

Acknowledgement.....

Abstract.....

INTRODUCTION

The effectiveness of GPS-tracking allowed improvement of animal observation compared to direct observation. Indeed, direct observations are limited in time and space, especially in species living in inaccessible places (Graf et al. 2015) as well as human presence which can scare animals and affect their behavior (Brown et al. 2013). The GPS-tracking has improved knowledge about animal ecology, by following their move along their life, and the environment in which they evolve. However, several constraints are present by using classical observation methods as radio-tracking or GPS-tracking (Harris et al. 1990). In fact, radio or GPS-tracking can be interrupted by presence of vegetation or metal objects. Additionally, these methods cannot provide constant information about animal behaviour, without a constant observation, but only inference from their location (e.g. home range area; nest site). However, advances in biologging technologies and computing power have enabled scientists to deal with these difficulties (Hussey et al. 2015; Wilson et al. 2008).

A new method has been developed by including accelerometers into GPS tag allowing recording of individual movement, over long periods of time and without need of constant observations (Löttker et al. 2009). The use of accelerometry on wild animals started in 1998, mainly focused on marine species such as birds, seal, fish, turtle or penguins (Yoda et al. 1999), and increased since 2003, it has now been tested on more than 120 species (Brown et al. 2013). While positioned on the animal, the accelerometer records the inertial acceleration of a moving animal, in di or three-dimensional space, the latter dimension being the most used because it can represent movement realistically (Brown et al. 2013). The accelerometer, or sensor, can record acceleration at frequencies ranging from 0,5 to 10,000 Hz, but it is most common to sample from 8 to 100 Hz frequencies (e.g. 8 to 100 measures per second) (Brown et al. 2013). Accelerometers provide measures of two types of acceleration: static and dynamic acceleration. Under statics circumstances (e.g. rest, death), the accelerometer signal only represents the gravitational force acting on the sensors (measured in *g*; 1 $g = 9.8$ m/s^2) and so when the animal is in motion, the inertial acceleration generated by movement is combined with gravity acceleration (Gomez et al. 2009, Shepard et al. 2008). The output of the sensor logger is able to distinguish between several behavioural categories, the most commonly analyzed are resting, feeding, travelling (e.g. fly, walk, swim) and grooming behaviour (Shepard et al. 2008). However, depending on behaviours recorded it is important to choose carefully the attachment method used to positioned tags on the animal (e.g. neckband or backpack) (Kölzsch et al. 2016). By the end, billions of data are recorded each day, requiring an onerous analysis to rely each

movement to one behaviour. Thereby, a new approach has been explored, to allow a more efficient analysis, by creating ethograms from accelerometers using machine learning (Sakamoto et al. 2009).

The use of machine learning started in 1959 with Arthur Samuel, a pioneer of artificial intelligence and it nowadays allows the exploitation of big datasets, such as those obtained by accelerometry. Many methods exist and are used for the classification of accelerometry data, using supervised or unsupervised algorithm (Ladds et al. 2016). A supervised algorithm is programmed by the user, meaning that it requires dictated input to manually classify the wanted behaviour (input-output concept) and to 'teach' the program how to identify and distinguish each behaviour (Sathya et al. 2013). Conversely, unsupervised learning, works faster and with an unbiased view, tries to organized data into groups with no output specified (Sathya et al. 2013). Thus, several papers use supervised algorithms instead of unsupervised algorithms for creating ethograms from accelerometry data (Ladds et al. 2016; Nathan et al. 2012). This kind of analysis allows the identification of animal behaviour and, associated with GPS information, occurrence of it in time and space. This method might be helpful for use with birds because it can help identified the behaviour they adopt before and after an important ecological behaviour as migration.

Migration routes and stopover were first identified thanks to ringing recording and by GPS. The recent use of accelerometers allowed the elaboration of behavioural time budget according to the individual position, when coupled with a GPS. This method may help distinguish between unimportant places recorded by the GPS and important places during life-time of birds, like breeding or wintering areas. Wetlands, for example, are among the world's most productive environment and has a key role for water birds because they provide them food and shelter for reproduction (Ramsar 2007). Coastal habitats and wetlands in the Mediterranean region are particularly exposed to intense human activities, sensitivity to water regimes makes them especially susceptible to changes in precipitation or evapo-transpiration. Thanks to the loggers fitted on migratory birds, information collected will give insights on stopovers, as wetland, used by these species. Additionally, the use of accelerometer can help deepen understanding as to why an individual succeeded or failed to achieve their migration, where GPS data failed to explain this. We decided to focus on the migratory water birds, the Eurasian spoonbill (*Platalea leucorodia*), for which the population is actually increasing in France (Camargue) and seems to be constant or decreasing in east Europe (Aguilera et al. 1996; Morrison et al. 2001; Navedo et al. 2012). The population in Camargue is unique since it is overlapping on two flyways with some individuals wintering in Italy and Tunisia, while others

wintering in Spain, Mauritania and Senegal and a third group of approximately 200 individuals being residents. However, reduction of wetland connectivity, disturbance of migration routes because of climatic change and illegal hunting (Madsen & Fox 1995) are still present and identified as the main threats to the Eurasian spoonbill population decrease (Navedo et al. 2012*)*. This show the importance of stopover during migration and has led to an international plan management (Triplet et al. 2008) for Eurasian spoonbills. Indeed, like others migratory waterbird species, they are particularly vulnerable because they depend on interconnected sites. Spoonbills are faithful to their migration route chosen during their early life (Lok et al. 2011) and observation of a sudden stop or change of the migration might be explain by the weather or change in their behaviour. Identification of their behaviour would complete and provide an important source of knowledge to understand their migratory choice. Spoonbills are long-distance migratory birds and the use of frequent stopover, as in Eurasian green winged teal, helped increase their body mass during migration. Conversely, during last days of the prebreeding migration period, increase of feeding rate is observed for long-distance migratory birds, associated with the theory of "income breeder" (Guillemain et al. 2007; Jönsson 1997). Income breeder's birds usually acquire food resources directly at the breeding site. The other strategy is to acquires food resources in advance and store them until they are needed for offspring's production (Houston et al. 2007).

A good and interesting model to investigate this study is in the Camargue spoonbill population (43°28'32.2"N, 4°29'01.1"E), who have seen their population increasing exponentially for the last 15 years. One of the colony's individuals was equipped with an accelerometer tag in 2017 and ever since, data have been collected. The aim of this study was to create an ethogram from observation of a captive individual and apply the ethogram to the wild individual to assess time budget since 2017. Additionally, it was interesting to focus on the bird's behaviour before migration, identify any changes in behaviour, especially in key behaviour during migration such as rest and eat. Because random forest model is generally used to analyze data from accelerometry we expect to obtain a high level of accuracy. We expected that a week before early migration we would observe less feeding behavior and more resting behaviour, than the week before again. But, we should observe a difference in eating behaviour in the last week before migration, especially for pre-breeding migration. Additionally, time budget over a week should differ before migration compared to the wintering period.

Thus, we first elaborated, during this study, an ethogram from a captive spoonbill. Then we program a supervised algorithm, called random forest, with the data collected and all the parameters calculated from the captive spoonbill. We analyzed the data collected on the free-

living bird, with the model, before migration and during wintering. Finally, we compared the time-budget behavior calculate for each moment.

MATERIALS AND METHODS

Study species

We conducted this experiment on the Eurasian spoonbill, this water bird is included in the Threskiornithidae family and is usually seen in wetlands such as flooded lands, rivers, marshes and large water bodies. Mutual preening is one of their main activities consisting of cleaning their feather by small strumming movements with their beak, head or paws or long feather smoothing movement. When they do not preen, the Eurasian spoonbill walks slowly in shallow water with semi-open bill partially submerged to capture their prey, detected by a simply touch. More precisely, the spoonbill moves his head and bill from side to side into the water, alternatively opening and closing its bill allowing him to catch several small prey such as water bugs, caddisflies, locusts, flies (Aguilera et al. 1996) and three spines sticklebacks (Kemper et al. 1995). During flight, the spoonbills extends their neck and legs performing short glides interspersed with fast, shallow wing-beats. They spend most of their time resting, supporting the bill with their body feathers while standing either in one foot, two feet or "squatting on their knees".

Experimental protocol

The experiment was conducted at 'Parc des oiseaux' in Villars-les-dombes (45°59'35.5"N 5°01'36.4", France) from April 9th to 20th, 2017. A captive male spoonbill (Birth date: May 10th, 2010; Marking ring: RG; Weight at the time of the capture: 1555g; Tarsus length: 155mm; Wing length: 395mm; Bill length: 210mm) was captured with a net and equipped with a triaxial accelerometers (OrniTrack-E25 3G solar powered GPS-GSM/3G transmitter: 58 mm × 24 mm × 24 mm, 25 grams) to measure its movements. Because it has been considered the most appropriate for long-term studies, we used a backpack as the attachment method (Kölzsch et al. 2016), consisting of taping the accelerometer around the wings with a harness (less skin contact, non-constricting fit) (Thaxter et al. 2014). The spoonbill had three days for acclimatization, with the equipment, before being released into the aviary.

The captive spoonbill was maintained in an aviary (Area: 1000 m2, height: 12 m), open to visitors, where characteristics of tropical jungle were recreated (e.g. flora, small river). He shared the space with 2 others spoonbill females and 30 others species. To feed, birds have access to *ad libitum* food, made of dry fish (smelt) and granules (lundi regular).

Accelerometers were set to recorded at 10 samples per second (10 Hz) on each axis during 30 seconds. In the first week, the recording was done every minute and for the second week, it was done continuously. We recorded all traits (focal sampling) randomly between 8am and 6pm each day with one camera (Canon LEGRIA HF R106) and we obtained approximatively 25 hours of recording. Video were scored, using BORIS software (Friard 2016), to an ethogram consisting of 12 behaviours developed during observation (Annex 1). We time-matched the videos and the accelerometry output (using the universally time available with www.time.is website) to generate annotated acceleration data sets.

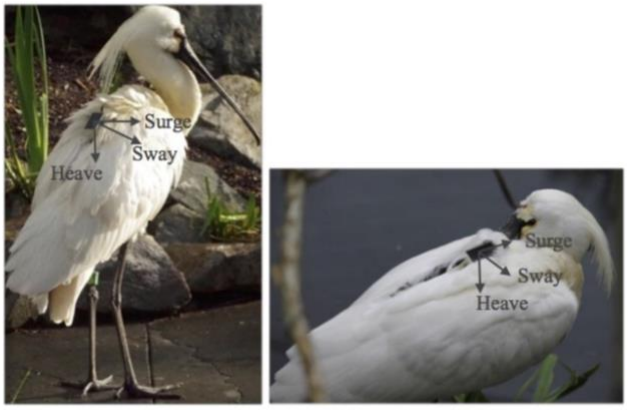


Figure 1. Accelerometer tag used in this study, mounted on Eurasian spoonbill, recording linear acceleration along the x (medial-lateral, sway), y (anterior-posterior, surge) and z (inferior-superior, heave) axes.

Wild spoonbill.

A wild female spoonbill was equipped with an accelerometer in May 2017 (Marking ring: ATZF; Weight: 1550g; Tarsus length: 138mm; Wing length: 395mm; Bill length: 210mm), by the team of Tour du Valat research centre. The data from the equipment were collected every 15 minutes for 10 seconds at 10 Hz, and GPS data were also collected.

Statistical analysis

Data preparation. The acceleration data were downloaded from Ornitrack website (Global Location & Sensor Data Acquisition Systems) and we coded the behaviours manually using Microsoft Excel (Microsoft Corporation). We coded 12 behaviours, but there were not enough samples of each of the individual behaviours, so we grouped 9 of the behaviours into five categories: flying, resting, walking, eating, preening. We removed 3 of the behaviours from the analysis as they seemed to be captive shaped or their occurrence was not ecologically interesting (e.g. drink, search, jump in Annex 1). We divided the dataset into approximatively

two subsamples in which 70% was used for training the model and 30% used to test the algorithm. This division is commonly used and it is call the 'repeated random subsampling cross-validation procedure' in Nathan et al. 2012.

Summary statistics. We created 63 summary statistics as the inputs of the machine learning model. We used R software (R Core Development Team.) to calculate, for each of the three axes (x, y, z), mean, median, minimum, maximum, standard deviation, skewness, kurtosis, inverse covariance, autocorrelation trend (the coefficient derived from a linear regression) and the 10th and 90th percentiles. Pairwise correlation of the three axes (y-z, x-y, x-z) (Ravi et al. 2015) and q as the square root of the sum of squares of the three axes (Nathan et al. 2012) were also used. The inclination ($\theta = cos^{-1}[z/q]$) and azimuth ($\varphi = tan^{-1}[y/x]$) for the q axis were determined (Nathan et al. 2012.). To estimate dynamic body acceleration (DBA) we used the running mean of each axis over two seconds to create a value for static acceleration (Shepard et al. 2008). Static acceleration values were subtracted at each point from the raw acceleration to create a value for partial dynamic body acceleration (PDBA) for each axis. We then used PDBA value to estimated overall dynamic body acceleration (ODBA) (1) (Shepard et al. 2008) using

$$ODBA = |PDBA_x| + |PDBA_y| + |PDBA_z| \quad (1)$$

We calculated vectorial dynamic body acceleration (VeDBA) (2) (Nathan et al. 2012) using

$$VeDBA = \sqrt{PDBA_x{}^2 + PDBA_y{}^2 + PDBA_z{}^2} \quad (2)$$

The maximum and minimum were calculated for PDBA, ODBA and VeDBA, as 10th and 90th percentiles. Finally, we used the area under the curve for both ODBA and VeDBA using the package "MESS" in R (Ekstrom, 2014), as summary statistics too.

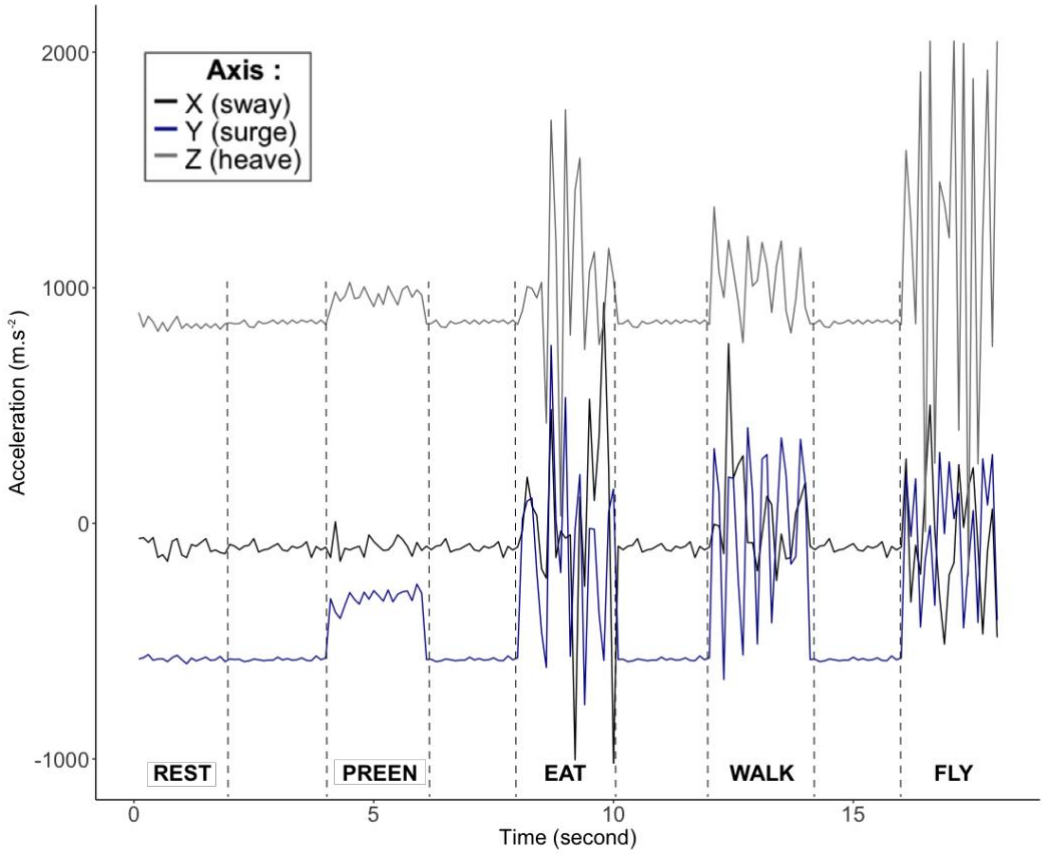


Figure 1. Example of dynamic acceleration data for a series of behaviours of captive Eurasian spoonbill (Platalea leucorodia).

Classification model. As it has been qualified as the best model for classifying behavioral accelerometry data several times, we used the supervised algorithm, random forests model, for the analysis (Ladds et al. 2016; Ladds et al. 2017; Nathan et al. 2012). Random forests are a combination of different classifiers in which a set of classification trees are constructed, using a method similar to CART, classification and regression tree (Breiman et al. 2001). Stochasticity is also included in this model by bias of subsample analyzation, which differ for each tree. Those subsamples are randomly drawn in the initial dataset and randomly distributed, for analyses, to each tree. The algorithm continues running until no more splits can be performed or it is halted by a stopping criteria initially programmed. The random forest model (number of tree = 500, variables tried at each split = 7) was implemented using the R package "randomForest" (Liaw & Wiener 2002.). A classification tree was created using the parameters previously calculated (Nathan et al. 2012). Finally, we used the random forest model, initially programmed, to analyze data collected from the wild spoonbill (ATZF) since 2017.

Data analyses.

We extracted two weeks of data from ATZF spoonbill recording for each of the following periods: before wintering migration (from Camargue, France, to Gambia, Africa), in October,

and during the return, in February (from Gambia to Camargue). The return in Camargue was interspersed with a stopover in Mauritania, so we also analyzed two weeks before its departure from this stopover. One week of data was also analyzed during wintering, at the end of December (Table 1). Time budget, for each separate week and for each day, were calculated. We focused on the resting and eating behaviour and compared their frequency between each day during the week, using a general linear model, on R software (R Core Development Team 2015).

Due to a behavioural bias of the captive behaviour individual not eating fresh and live food, we regrouped the data concerning the walking and eating behaviour into one variable. Indeed, in captivity both behaviours are distinct but in the wild the spoonbill walked during feeding in order to capture prey (Annex1).

Due to lack of replicates, some of the results could not be statistically tested (e.g. overall activity time budget of the week).

Table 1. Stopover description of ATZF spoonbill for its post- and pre-breeding migration (NA: data were not send to the website platform because of no signal)

Migration	Departure (M/D/Y)	Departure country (GPS)	Arriving (M/D/Y)	Arriving country (GPS)
Post-breeding (1)	10/07/17	France 43°28'32.2"N 4°29'01.1"E	10/09/17	Spain 37°03'23.47"N 6°12'28.03"E
Post-breeding (2)	10/30/17	Spain	11/06/17	Mauritanie 16°10'01.26"N 13°39'51.63"E
Post-breeding (3)	12/14/17	Mauritania	12/18/17	Gambia 13°29'05.4"N 15°19'26.7"W
Wintering period	Gambia			
Pre-breeding (1)	03/01/18	Gambia	03/05/18	Mauritania 21°11'19.3"N 16°53'10.1"W
Pre-breeding (2)	04/18/18	Mauritania	Na	Gambia

RESULTS

Random forest model

We obtained a training model with an error rate between two and four percent and an accuracy of 0.95 (Accuracy for each behaviour: eat = 0.89; fly = 0.95; preen = 0.97; rest = 0.98; walk = 0.96).

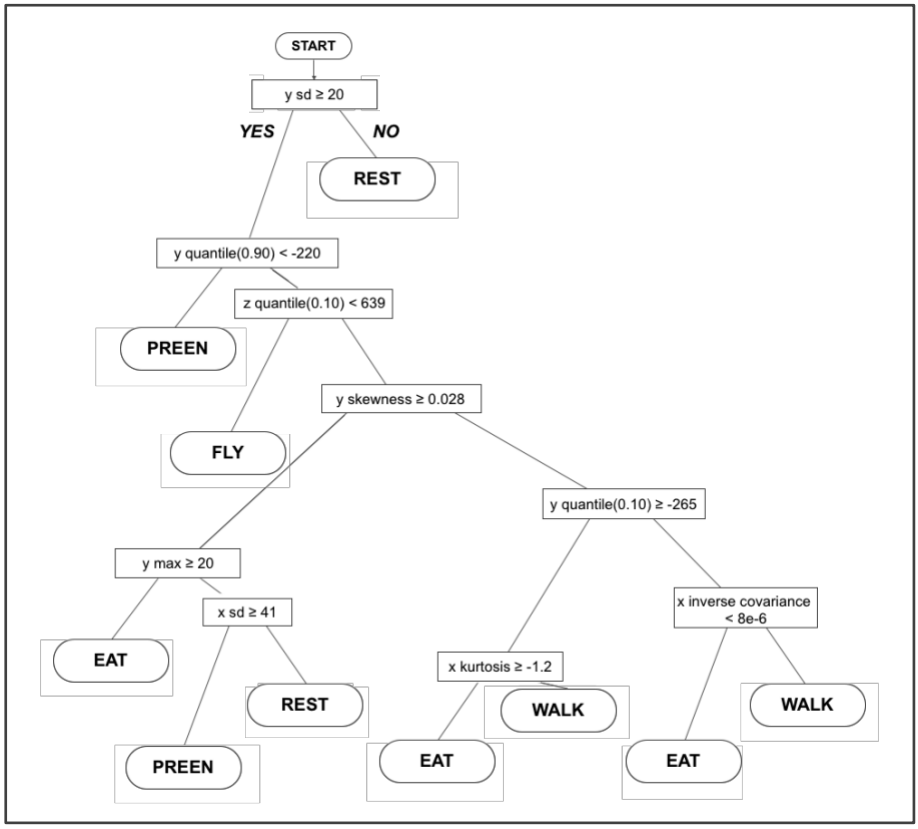


Figure 2. Decision tree. At each branch node, a lefttward move indicates a 'yes' or 'true' evaluation of the expression in the oval, whereas a rightward move indicates a 'no' or 'false' evaluation. Only the primary category for each leaf is shown. (sd: standard deviation; x, y and z indicating the concern axes)

The decision tree (Figure 2) showed that the model discriminates with difficulty eat and walk pattern behaviour, compared to the discrimination of rest, preen and fly behaviours.

Behaviour time budget

Rest and eating occurrence during a week's behaviour seems different between the first and second week before migration in October. Additionally, the time activity budget of the post-breeding migration (1) and the pre-breeding migration in February seems not to be different from the wintering one (Figure 3). Finally, it seems that the spoonbill spent more time eating before its pre-breeding migration in April than before post-breeding migration (Figure 3).

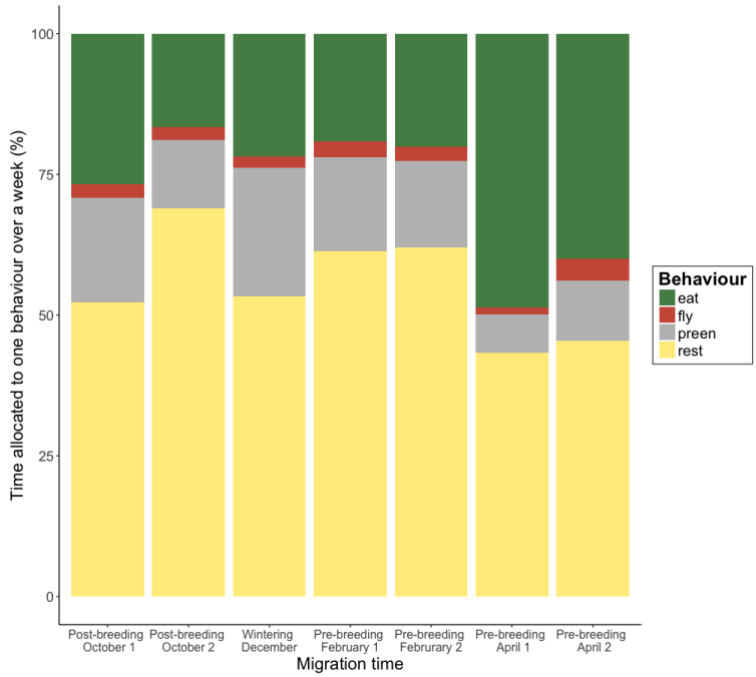


Figure 3. Frequency of each behaviour (time budget) from the ATZF spoonbill over a week, before migration and during wintering (1: two weeks before; 2: one week before)

There is a significant increase of eating behaviour during the fourteen days in April while a significant decrease is observed during in October (GLM model delta.AIC < 2; October: $p < 0.001$; April: $p < 0.1$) (Figure 4.A, Annex 2).

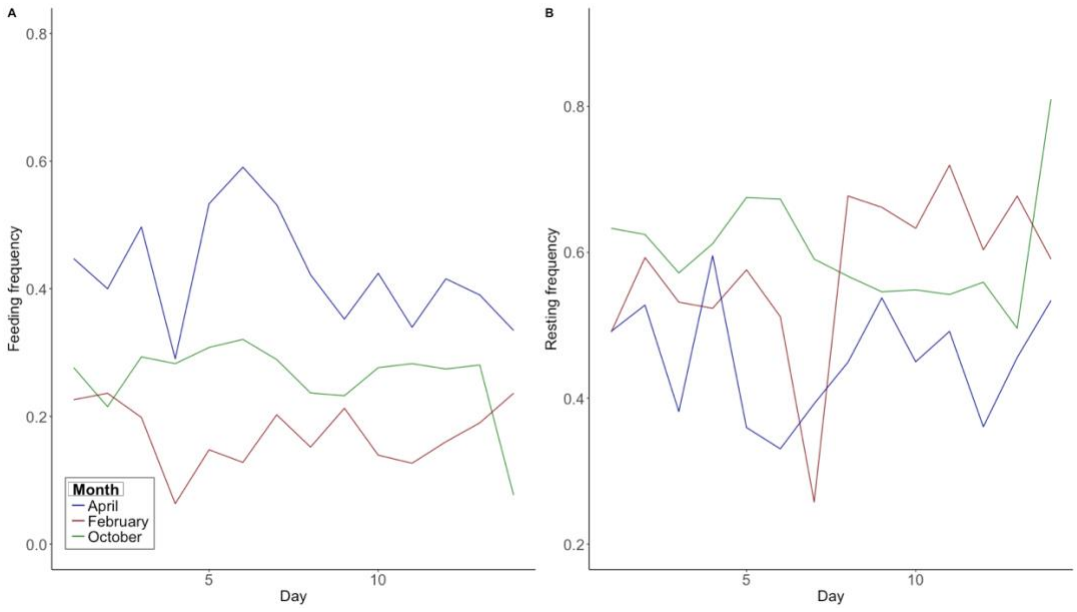


Figure 4. Feeding (A) and resting (B) behaviour frequency (number of behaviour/ total number of behaviour during the day) of ATZF spoonbill during the week preceding each migration.

A significant increase of the resting behaviour was observed during the week before migration in October, while a decrease of rest time was observed in February. No significant differences were observed in April (GLM model: deltaAic < 2; October: $p < 0.001$; February $p < 0.001$) (Figure 4.B, Annex 2).

DISCUSSION

The elaboration of an ethogram using machine learning is an efficient method to analyze data from accelerometry and workout behavioural time budget of the ATZF wildlife spoonbill. Through this approach, we were available to identify an increase of the eating behaviour before the second pre-breeding migration (April). An increase of the resting behaviour during the last week before post-breeding migration was also observed. Conversely, time allocated to each behaviour category do not seems to be different from the spoonbill wintering time budget.

The random forest model was elaborated from the captive spoonbill behaviour and allowed the construction of 5 different behavioural categories (eat, preen, rest, walk, fly). The accuracy rate obtained for the model was high and confirm the random forest efficiency for classifying accelerometry data. Otherwise, as observed by direct behavioural observation, when in the wild, the spoonbill's walk and eat behaviours are not distinguishable. Indeed, the spoonbills usually eat by walking while putting their bill into water, with a constant movement from left to right (Swennen et al. 2009). In black-faced spoonbills, for example, this behaviour usually last for ten minutes and at the end the spoonbill has 65% of chance of swallowing prey (Swennen et al. 2009). Recent research showed that it is now possible to estimate energy expenditure of an individual wearing an accelerometer (Halsey et al. 2009). Indeed, dynamic body acceleration (DBA) is correlated with mass-specific energy expenditure, and allows the estimation of energy expenditure in free-ranging water birds (Stothart et al. 2016). Thus, by obtaining a more precise ethogram of wild spoonbills it would allow more precision about their feeding behaviour and its possible relation with other parameters such as survival or reproduction rate. Because observation of wild spoonbills, as well as the elaboration of a wild ethogram, is difficult due to their shyness, another option would be to estimate the body angle of the spoonbills when they are eating, following the method used by Wilson et al. 2008. Thereby, it would be possible, while keeping the ethogram from the captive spoonbill, to identify whether the wild spoonbill is eating or not.

We noticed that before the pre-breeding migration, in April, the ATZF spoonbill spent significantly more time eating than before the other weeks. This result supposed that the female

spoonbill might using a capital breeder strategy in approach to reproduction period (Jönsson 1997). The strategy that individual adopt might depend on metabolic system and alternative thermoregulatory (Bonnet et al. 1998). same strategy should be observed in male Eurasian spoonbill, as they needed energy to reproduce. Concerning the other weeks, no difference was observed at the feeding level, compared to wintering period, except for the week before post-breeding migration, were the spoonbill seems to spend more time resting than eating. We supposed that spoonbill adjust its body mass, for a trade-off between energy and body mass load, that might improve flight performance (Zimmer et al. 2011). In Zimmer et al. 2011 paper, its shows that duck starve themselves in a way to being more efficient during predation, and increases power for flight. However, it has also been showed in Bairlein 1990, that long-distance migratory birds exhibit biggest changes in body mass and it seems to increase with the distance. In a way to determine whether the starvation or the fatten strategy is used by the Eurasian spoonbill further information is needed, such as the intake rate and the energy expenditure (cited below). Finally, the last GPS data collected by the accelerometer showed that ATZF spoonbill failed to reach its breeding site in Camargue. The first reason for it can be the fact that the accelerometer tag attached, caused a dragging effect, giving difficulties to the spoonbill during flight (Bowlin et al. 2010). This, associated with bad weather like strong contrary wind or rainy day, can affect the migration success of the individual. The second explanation is that low habitat quality along the west coast of Africa is likely to cause fail or mortality during pre-breeding migration. And, as Lok et al. 2015 noticed in his paper, birds that wintered in Mauritania and using the Atlantic flyway during spring migration has higher mortality that spoonbills wintering in France or Iberia. Finally, climate change might have an impact on migration success because of lack of food availability and earlier migration start (Maclean et al. 2008; Navedo et al. 2010) of water birds. Indeed, the ATZF spoonbill left its wintering place later than the past year, and it might have encountered problem finding food. With accelerometer technology, it is now possible to estimate energy expenditure (Wilson et al. 2006) and associated with behavioural identification and GPS information, cost of each behaviour can be estimated according to his place. For further studies, it would help estimate cost of spoonbill effort during migration and see if there is a link with its migration success.

Highlighting frequency of each spoonbill behaviour according to its location allow the identification of key site as in Mauritania, were the spoonbill made food stock in prevention of the breeding period. Knowing those sites, and their importance can help adjustment of conservation plans, and enhance protection of key stopover during spoonbill migration. Particularly water birds are the most used tool to identify and justify the protection of wetlands

(Stroud et al. 2001). Their sensitivity to environmental change, their tendency to aggregate at key locations and the ease of counting them, make them effective proxies (Stroud et al. 2001). Thereby, by identifying time budget for each GPS location during the bird's life, would have brought more precise information about key location along spoonbill life.

Conclusion

All parameters used, for elaborating the random forest in this study, can be apply and improve by further study. Otherwise, it would be interesting to use a super machine learner in a way to identify the best model to analyze data from accelerometry in Eurasian spoonbill (Ladds et al. 2017). Indeed, the accuracy of the model can differ for each data set and the behaviour type that is to be predicted (Ladds et al. 2016). In further project, it would be interesting to extend data analysis to one month before migration departure in a way to see any variation in behaviour along this month that might help differentiating wintering period from post migration period. In addition, identifying begging behavior in juvenile, during its early life, might be interesting to see if there is any relation between begging frequency and survival rate of juvenile. As well as identifying the incubation behaviour, in female spoonbill to see if there is any relation between time spent incubating and survival rate of juvenile. Finally, the data should be collected on more than one individual, by equipping more individual or using data from other paper, to see any variance in the behaviour and result obtained.

REFERENCES

Aguilera, E., Ramo, C., & Court, C. 1996. Food and feeding sites of the Eurasian spoonbill (*platalea leucorodia*) in southwestern spain. *Colonial Waterbirds*, 19, 159.

Bairlein, F. 1990. Nutrition and food selection in migratory birds. In *Bird Migration*, 198–213.

Bonnet, X., Bradshaw, D., & Shine, R. 1998. Capital versus income breeding: an ectothermic perspective. *Oikos*, *83*(2), 333.

Bowlin, M. S., Henningsson, P., Muijres, F. T., Vleugels, R. H. E., Liechti, F., & Hedenström, A. 2010. The effects of geolocator drag and weight on the flight ranges of small migrants. *Methods in Ecology and Evolution*, 1(4), 398–402.

Breiman, L. 2001. Random Forests. *Machine Learning*, 45(1), 5–32.

Brown, D. D., Kays, R., Wikelski, M., Wilson, R., & Klimley, A. 2013. Observing the unwatchable through acceleration logging of animal behavior. *Animal Biotelemetry*, 1(1), 20.

Ekstrom, C. 2014. MESS: miscellaneous esoteric statistical scripts. In: R package version 03-2 R package version 0.3-2.

Friard, O., & Gamba, M. 2016. BORIS: a free, versatile open-source event-logging software for video/audio coding and live observations. *Methods Ecology Evolution*, 7: 1325–1330.

Global Location & Sensor Data Acquisition Systems (n.d). https://www.glosendas.net/users/ (accessed May 2018)

Gómez Laich, A., Wilson, R., Quintana, F., & Shepard, E. 2009. Identification of imperial cormorant *Phalacrocorax atriceps* behaviour using accelerometers. *Endangered Species Research*, 10, 29–37.

Graf, P. M., Wilson, R. P., Qasem, L., Hackländer, K., & Rosell, F. 2015. The use of acceleration to code for animal behaviours; a case study in free-ranging Eurasian beavers castor fiber. *PLOS ONE*, 10(8).

Guillemain, M., Elmberf, J., Arzel, C., Johnson, A. R., & Simon, G. 2007. The income-capital breeding dichotomy revisited: late winter body condition is related to breeding success in an income breeder. *Ibis*, 150(1), 172–176.

Halsey, L. G., Green, J. A., Wilson, R. P., & Frappell, P. B. 2009. Accelerometry to estimate energy expenditure during activity: best practice with data loggers. *Physiological and Biochemical Zoology: PBZ*, 82(4), 396–404.

Harris, S., Cresswell, W. J., Forde, P. G., Trewhella, W. J., Woollard, T., & Wray, S. 1990. Home-range analysis using radio-tracking data–a review of problems and techniques particularly as applied to the study of mammals. *Mammal Review*, 20(2–3), 97–123.

Houston, A. I., Stephens, P. A., Boyd, I. L., Harding, K. C., & McNamara, J. M. 2007. Capital or income breeding? A theoretical model of female reproductive strategies. *Behavioral Ecology*, 18(1), 241–250.

Hussey, N. E., Kessel, S. T., Aarestrup, K., Cooke, S. J., Cowley, P. D., Fisk, A. T., … & Whoriskey, F. G. 2015. Aquatic animal telemetry: a panoramic window into the underwater world. *Science (New York, N.Y.)*, 348(6240), 1255642.

Jönsson, K. I. 1997. Capital and income breeding as alternative tactics of resource use in reproduction. *Oikos*, 78(1), 57.

Kemper, J. H. 1995. Role of the Three-Spined Stickleback *Gasterosteus Aculeatus L.* in the food ecology of the spoonbill *Platalea Leucorodia*. *Behaviour*, 132(15), 1285–1299.

Kölzsch, A., Neefjes, M., Barkway, J., Müskens, G. J. D. M., van Langevelde, F., de Boer, W. F., & Nolet, B. A. 2016. Neckband or backpack? Differences in tag design and their effects on GPS/accelerometer tracking results in large waterbirds. *Animal Biotelemetry*, 4(1), 13.

Ladds, M. A., Thompson, A. P., Kadar, J.-P., J Slip, D., P Hocking, D., & G Harcourt, R. 2017. Super machine learning: improving accuracy and reducing variance of behaviour classification from accelerometry. *Animal Biotelemetry*, 5(1), 8.

Ladds, M. A., Thompson, A. P., Slip, D. J., Hocking, D. P., & Harcourt, R. G. 2016. Seeing it all: evaluating supervised machine learning methods for the classification of diverse otariid behaviours. *PLOS ONE*, 11(12).

Liaw, A., Wiener, M. 2002. Classification and regression by randomforest. *RNews*. 2(3):18–22. 40.

Lok, T., Overdijk, O., & Piersma, T. 2015. The cost of migration: spoonbills suffer higher mortality during trans-Saharan spring migrations only. *Biology Letters*, 11(1), 20140944.

Lok, T., Overdijk, O., Tinbergen, J. M., & Piersma, T. 2011. The paradox of spoonbill migration: most birds travel to where survival rates are lowest. *Animal Behaviour*, 82(4), 837–844.

Löttker, P., Rummel, A., Traube, M., Stache, A., Šustr, P., Müller, J., & Heurich, M. 2009. New possibilities of observing animal behaviour from a distance using activity sensors in gps-collars: an attempt to calibrate remotely collected activity data with direct behavioural observations in red deer *Cervus elaphus*. *Wildlife Biology*, 15(4), 425–434.

Maclean, I. M. D., Rehfisch, M. M., Delany, S., & Robinson, R. A. 2008. The effects of climate change on migratory waterbirds within the african-eurasian flyway. In: 8th meeting of the technical committee (British trust for ornithology). Bonn, Germany

Madsen, J., & Fox, A.D. 1995.Impacts of hunting disturbance on water birds. *Wildlife biology*, 1: 193-207

Morrison, R.I.G., Y. Aubry, R.W. Butler, G.W. Beyersbergen, C. Downes, G.M. Donaldson, C.L. Gratto-Trevor, P.W. Hicklin, V.H. Johnston & R.K. Ross. 2001. Declines in North American shorebird populations. *Wader Study Group Bull.* 94: 34–38.

Nathan, R., Spiegel, O., Fortmann-Roe, S., Harel, R., Wikelski, M., Getz, WM. 2012. Using tri-axial acceleration data to identify behavioral modes of free-ranging animals: general concepts and tools illustrated for griffon vultures. *Journal of Experimental Biology*.215:986–96.

Navedo, J. G., & Garaita, R. 2012. Do systematic daily counts reflect the total number of birds using stopover sites during migration? A test with Eurasian Spoonbill. *Journal for Nature Conservation*, 20(4), 242–246.

Navedo, J. G., Masero, J. A., Overdijk, O., Orizaola, G., & Sánchez-Guzmán, J. M. 2010. Assessing the role of multiple environmental factors on Eurasian spoonbill departure decisions from stopover sites. *Ardea*, 98(1), 3–12.

R Core Development Team. 2015. R: a language and environment for statistical computing. In: R version 331, R package version 3.2.3 edition. Vienna: R Foundation for Statistical Computing.

Ramsar. 2007. What are wetlands? In *Ramsar Information Paper*, vol. 1. Gland: The Ramsar Convention Secretariat.

Ravi, N., Dandekar, N., Mysore, P., & Littman, M. L. 2005. Activity recognition from accelerometer data. *American Association for Artificial Intelligence*.

Sakamoto, K. Q., Sato, K., Ishizuka, M., Watanuki, Y., Takahashi, A., Daunt, F., & Wanless, S. 2009. Can ethograms be automatically generated using body acceleration data from free-ranging birds? *PLOS ONE*, 4(4).

Sathya, R., & Abraham, A. 2013. Comparison of supervised and unsupervised learning algorithms for pattern classification. *International Journal of Advanced Research in Artificial Intelligence*. 2(2):34–8.

Shepard, E., Wilson, R., Halsey, L., Quintana, F., Gómez Laich, A., Gleiss, A., … & Norman, B., 2008. Derivation of body motion via appropriate smoothing of acceleration data. *Aquatic Biology*, 4(3), 235–241.

Shepard, E., Wilson, R., Quintana, F., Gómez Laich, A., Liebsch, N., Albareda, D., … & McDonald, D. 2008. Identification of animal movement patterns using tri-axial accelerometry. *Endangered Species Research*, 10, 47–60.

Stothart, M. R., Elliott, K. H., Wood, T., Hatch, S. A., & Speakman, J. R. 2016. Counting calories in cormorants: dynamic body acceleration predicts daily energy expenditure measured in pelagic cormorants. *Journal of Experimental Biology*, 219: 2192-2200.

Stroud, D.A., Chambers, D., Cook, S., Buxton, N., Fraser, B., Clement, P., Lewis, P., McLean, I., Baker, H. & Whitehead, S. 2001. In: The UK SPA network: its scope and content (Joint nature conservation committee). Peterborough, JNCC.

Swennen, C., & Yu, Y.-T. 2009. Food and Feeding Behavior of the black-faced spoonbill. *Waterbirds*, 28(1):19-27.

Thaxter, C. B., Ross-Smith, V. H., Clark, J. A., Clark, N. A., Conway, G. J., Marsh, M., … & Burton, N. H. K. 2014. A trial of three harness attachment methods and their suitability for long-term use on Lesser Black-backed Gulls and Great Skuas. *Ringing & Migration*, 29(2), 65–76.

Triplet, P., Overdijk, O., Smart, M., Nagy, S., Schneider-Jacoby, M., Karauz, ES., Pigniczki, CS., Baha El Din, S., Kralj, J., Sandor, A., Navedo, JG. 2008. International single species action plan for the conservation of the eurasian spoonbill *Platalea leucorodia*. AEWA Technical Series no 35. Bonn, Germany, p. 40

Wilson, R. P., White, C. R., Quintana, F., Halsey, L. G., Liebsch, N., Martin, G. R., & Butler, P. J. (2006). Moving towards acceleration for estimates of activity-specific metabolic rate in free-living animals: the case of the cormorant. *Journal of Animal Ecology*, 75(5), 1081–1090.

Wilson, R., Shepard, E., & Liebsch, N. 2008. Prying into the intimate details of animal lives: use of a daily diary on animals. *Endangered Species Research*, 4(1–2), 123–137.

Yoda, K., Sato, K., Niizuma, Y., Kurita, M., Bost, C., Le Maho, Y., Naito, Y. 1999. Precise monitoring of porpoising behaviour of Adélie penguins determined using acceleration data loggers. *Journal of Experimental* Biology, 202: 3121-3126.

Zimmer, C., Boos, M., Poulin, N., Gosler, A., Petit, O., & Robin, J.-P. 2011. Evidence of the trade-off between starvation and predation risks in ducks. *PLOS ONE*, *6*(7).

APPENDIX

Annex 1. Ethogram of captive *Platalea leucorodia*

TYPE OF BEHAVIOUR	DESCRIPTION
Preen	Feather care
With beak	Scratching feather with beak, small and fast movement
With head	Rubbing back feather with head, long movement
With foot	Scratching head with one foot
Smooth feathers	Long movement from the top to the bottom of the feather
Drink (Captive shape)	Drink water, long and circular movement. Beak immersed into water following by a rise of the head and a light head back.
Search (ground)	Rapid search movement by scrapping into the ground
Resting	Rest moment on one or two feet, head into feather or not, can be on the "knees" also
Head move	Shake head from left to right, more or less intensely
Beak	
Search	Head movement from left to right into water (research)
Catch	Take something into beak (e.g. wood stick)
Soak	Quick movement, soaking beak into water
Walk	
Run	Fast walk
Eat	Catching prey and sudden recoil of the head

Fly	Short glides interspersed with fast, shallow wing-beats
Flap wings	Flap wings while staying on the ground
Jump	Short movement of jump

Annex 2. Time budget of each behaviour, over a day, during the week preceding migration from ATZF spoonbill.

Migration time	Day before migration	Time allocated to one behaviour over a day (%)			
		Eat	Fly	Preen	Rest
October	1	27.6	1.9	21.5	48.9
	2	21.5	3.0	16.2	59.3
	3	29.3	1.3	16.2	53.2
	4	28.3	3.6	15.8	52.3
	5	30.8	1.5	10.1	57.6
	6	32.1	2.3	15.0	50.6
	7	28.9	3.8	10.1	57.2
	8	23.6	4.4	15.1	56.7
	9	23.2	3.8	18.3	54.5
	10	27.6	1.4	16.0	54.8
	11	28.2	5.4	12.0	54.2
	12	27.4	4.4	12.2	55.9
	13	28.0	5.9	16.4	49.5
	14	7.6	1.3	10.0	80.9
February	1	22.6	0.0	14.0	63.4
	2	23.6	5.3	8.6	62.4
	3	19.8	3.6	19.4	57.2
	4	6.3	2.3	30.2	61.2
	5	14.8	3.4	14.3	67.5
	6	12.8	0.9	18.3	68.0
	7	20.3	1.9	18.8	59.1
	8	15.1	0.4	16.6	67.7
	9	21.2	2.5	10.0	66.1
	10	13.9	3.3	19.4	63.2
	11	12.6	2.1	13.2	71.9
	12	16.0	5.2	18.3	60.3
	13	18.9	2.1	11.1	67.7
	14	23.6	6.3	10.9	59.0
April	1	44.7	1.5	4.6	49.2
	2	40.0	0.6	6.6	52.8
	3	49.7	3.0	9.2	38.2
	4	29.0	0.0	11.4	59.5
	5	53.3	0.4	10.3	36.0
	6	58.4	1.5	7.4	32.7
	7	53.2	1.1	6.5	39.2
	8	42.1	2.1	10.7	44.9
	9	35.2	2.8	8.1	53.7
	10	42.4	2.9	9.5	44.9
	11	33.9	4.0	12.8	49.1
	12	41.5	14.5	7.8	36.0
	13	30.0	2.5	12.8	45.5
	14	33.4	1.2	11.8	53.3

ACKNOWLEDGEMENT

I would like to thank mostly Jocelyn Champagnon for including Amelia and I in his captivating project, and trusted us for the implementation of the experiment. This was a really interesting project to get involve in, even if the lack of time did not allow me to go more deeply in the analysis and did more observation. I would really like to thank all the people (intern, employee, civil service) with whom I shared these three weeks at the Tour du Valat, for their good mood every day, their help during my internship, and to show me their work and let me accompany them on the field. A huge thank you to my desk partner Hugo for being very friendly since the first day. I would like to thank also Eric Bureau (vet), Christophe Bec (animal manager) to have welcome us to the 'Parc des oiseaux' and all staff members we had met, especially Jeremy and Yanik who shared with us their wide knowledge about birds. I also would like to thank Frank Cezilly for presenting this internship offer, in the context of the master, and made all things necessary for this to be feasible. Finally, I would like to thank Amelia, my internship partner.

ABSTRACT

To deal with problem of classical **behavioural observation** method (e.g. GPS or radio-tracking, direct observation), a new method has been developed consisting in including **accelerometer** into GPS tag, which allow the recording of individual movement acceleration along three axes: x (sway), y (surge) and z (heave). This method can result in the record of thousands of data per day, that can be classify into different behavioural category by the bias of machine learning algorithm. The study focused on behaviour of **Eurasian spoonbil**l (*Platalea leucorodia*) before its different period of migration: **pre- and post-breeding period**, in a way to identify any variation in its time activity budget, particularly for rest and eating behaviour. We first elaborate an ethogram (e.g. eat, walk, rest, fly, preen) from a captive spoonbill to generate 63 parameters as an input of the **random forest** model. Then, once the model train, accelerometry data, two weeks before post- and pre-breeding **migration**, from a wild spoonbill (tag in 2017), were analyzed. We obtained a model with an accuracy of 0.95. We then observed a significant increase of the eating behaviour before the pre-breeding migration, assuming the spoonbill evolving a capital breeder strategy before reproduction. The individual tag failed to attempt its destination, for which we supposed influence of a drag effect or climate change. Finally, we observed an increase of the resting time before post-breeding migration for which we supposed an adjustment of the body mass in a way to improve flight performance.

Keywords: accelerometer, random forest, Eurasian spoonbill, migration, behavioural observation, pre- and post-breeding period

Pour surpasser les problèmes liés aux méthodes **d'observations comportementales** (i.e. suivi GPS et radio), une nouvelle approche a été mise en place consistant à inclure un **accéléromètre** dans une balise GPS, ce dispositif permettant l'enregistrement de l'accélération de l'individus en trois axes : x (sway), y (surge) et z (heave).Cette méthode permet d'obtenir jusqu'à des milliers de données par jours, pouvant être classés dans différentes catégories comportementales à l'aide d'un algorithme de machine learning. L'étude se concentre sur le comportement des **spatules Eurasienne** (*Platalea leucorodia*) avant différentes périodes de migrations : **hivernale et de reproduction**, dans le but d'identifier des variations dans le comportement, particulièrement ceux de repos et de nourrissage. Tout d'abord un éthogramme (i.e. mange, marche, repos, vol, toilettage) d'une spatule en captivité, fût élaboré, générant 63 paramètres comme « input » au modèle de **random forest**. Les données d'accéléromètre, d'une spatule sauvage (balisé en 2017), sont ensuite analysés, deux semaines avant la **migration** de reproduction et hivernale, permettant d'obtenir un modèle avec une précision de 0.95. Une augmentation significative du comportement de nourrissage avant la migration de reproduction a été observé, supposant que la spatule développe une stratégie de « capital breeder ». L'individu n'ayant pas atteint sa destination nous supposons le « drag effect » ou le changement climatique comme ayant un impact sur sa migration. Enfin, nous avons observé une augmentation du temps de repos avant la migration hivernale, supposant un ajustement de la masse corporelle dans le but d'augmenter les capacités de vol.

Mots clés : accéléromètre, random forest, spatule Eurasienne, migration, observation comportementale, période de reproduction et hivernale