Drifting fish aggregation devices (FADs) trajectories forecasting using Long Short-Term Memory (LSTM) in Western and Central Pacific Ocean tuna purse seine fishery

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BACKGROUND

The drifting speed and trajectory of fish aggregation devices (FADs) influence the associative behavior of tunas and fishing strategies. Understanding and predicting the drifting trajectories of FADs is essential for both sustainable fishery management and ecological mitigation. FAD movement is primarily driven by surface and subsurface ocean currents, which exhibit high spatial–temporal variability. In this study, the drifting trajectories of FADs were forecasted using a Long Short-Term Memory (LSTM) model. Multi-layer ocean current velocities were used as inputs to predict FAD drifting speed and direction, and different network configurations were tested to identify the optimal model performance.

MATERIALS AND METHODS

- FADs are typically composed of floats and nylon netting using in purse seine fishery with submerged structure depth ranging from 70 m to 90 m.
- The GPS-tracking buoy data used in this study are collected from the Satlink PC system installed on tuna purse seine vessels in the Western and Central Pacific Ocean (WCPO).

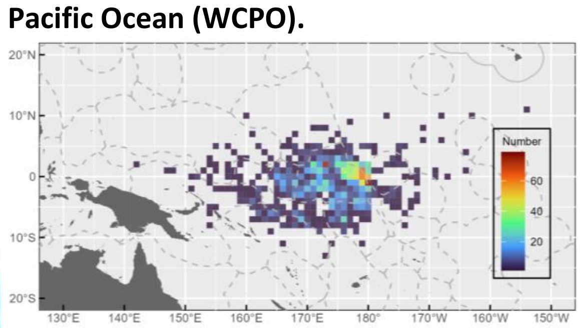


Fig. 1 The schematic diagram of the FAD (left) and Spatial distribution of FAD deployment numbers in the WCPO (right).

- The ocean current velocity data (uo and vo), location (Lat and Lon), FAD drifting speed and FAD drifting direction are used as input features.
- Location (Lat and Lon), FAD drifting speed and FAD drifting direction are the model output data.
- Four configurations of sliding windows were employed, with window sizes of 3, 5, 7, and 10 days.
- Each window develop 9 different layer structural LSTM model, total 36 LSTM models.
- The Average Displacement Error (ADE), Final Displacement Error, and Average Non-Linear Displacement Error (NL-ADE) are used for evaluating the model predictive accuracy.

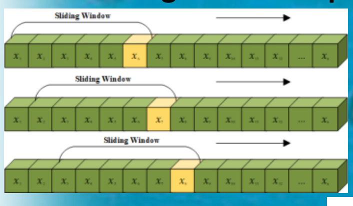
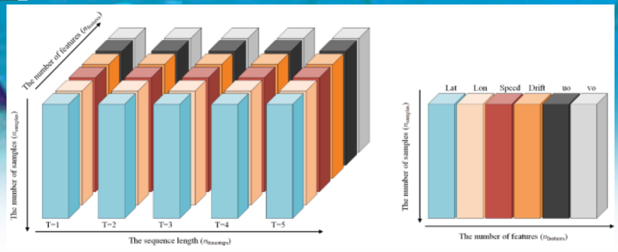


Fig. 2 Schematic diagram of the sliding window (example of a 5-day window).

Fig. 3 Illustration of the input data (left) and output data (right) structure (example of a 5-day window).



RESULTS

Table 1 The random search results of the 36 LSTM models

No.	Sliding window	Model name	Ls_1	Ls_2	Ls_3	Dr_1	Dr_2	Lr	Validation loss	Validation MAE
1		1ls_1dr_1de	128	\	\	0.2	\	0.001	0.008420	0.040270
2		1ls_1dr_2de	128	\	\	0.2	\	0.001	0.007989	0.038994
3		1ls_1dr_3de	128	\	\	0.2	\	0.001	0.007936	0.039357
4		2ls_2dr_1de	128	128	\	0.2	0.3	0.001	0.008007	0.039054
5	3-day	2ls_2dr_2de	64	128	\	0.2	0.2	0.001	0.007964	0.039010
6		2ls_2dr_3de	128	128	\	0.2	0.3	0.001	0.007979	0.039448
7		3ls_2dr_1de	64	128	32	0.2	0.4	0.001	0.007979	0.038852
8		3ls_2dr_2de	128	128	32	0.2	0.3	0.001	0.007965	0.038892
9		3ls_2dr_3de	128	128	32	0.2	0.3	0.001	0.007947	0.039019
10		1ls_1dr_1de	128	\	\	0.3	\	0.001	0.009241	0.042384
11		1ls_1dr_2de	128	\	\	0.2	\	0.001	0.008707	0.040594
12		1ls_1dr_3de	128	\	\	0.3	\	0.001	0.008662	0.040740
13		2ls_2dr_1de	128	128	\	0.2	0.3	0.001	0.008775	0.040576
14	5-day	2ls_2dr_2de	32	128	\	0.2	0.2	0.001	0.008693	0.040796
15		2ls_2dr_3de	128	128	\	0.4	0.2	0.001	0.008644	0.040583
16		3ls_2dr_1de	32	128	32	0.2	0.2	0.001	0.008673	0.040375
17		3ls_2dr_2de	64	128	32	0.2	0.3	0.001	0.008666	0.040234
18		3ls_2dr_3de	128	32	32	0.3	0.3	0.001	0.008682	0.040860
19		1ls_1dr_1de	128	\	\	0.3	\	0.001	0.008860	0.042208
20		1ls_1dr_2de	128	\	\	0.2	\	0.001	0.008409	0.040761
21		1ls_1dr_3de	128	\	\	0.2	\	0.001	0.008302	0.040509
22		2ls_2dr_1de	128	64	\	0.4	0.3	0.001	0.008576	0.041688
23	7-day	2ls_2dr_2de	128	128	\	0.4	0.2	0.0001	0.008809	0.041766
24		2ls_2dr_3de	128	128	\	0.4	0.2	0.0001	0.008672	0.041701
25		3ls_2dr_1de	64	128	128	0.4	0.3	0.001	0.008382	0.040497
26		3ls_2dr_2de	64	128	32	0.2	0.3	0.001	0.008391	0.040544
27		3ls_2dr_3de	64	128	32	0.2	0.3	0.001	0.008353	0.040642
28		1ls_1dr_1de	128	\	\	0.4	\	0.001	0.009721	0.044312
29		1ls_1dr_2de	128	\	\	0.2	\	0.001	0.008822	0.041324
30		1ls_1dr_3de	128	\	\	0.2	\	0.001	0.008816	0.041436
31		2ls_2dr_1de	128	128	\	0.3	0.2	0.001	0.009008	0.041975
32	10-day	2ls_2dr_2de	128	128	\	0.2	0.3	0.001	0.008804	0.041364
33		2ls_2dr_3de	128	128	\	0.2	0.3	0.001	0.008775	0.041350
34		3ls_2dr_1de	64	64	32	0.3	0.3	0.001	0.008832	0.041368
35		3ls_2dr_2de	128	128	128	0.2	0.3	0.001	0.008802	0.040952
36		3ls_2dr_3de	64	128	64	0.2	0.3	0.001	0.008792	0.041301

Table 2 The summary of the optimal sliding window of the LSTM models

No.	Sliding window	Model name	Validation loss	Validation MAE	ADE (km)	FDE (km)	NL-ADE (km)
1	3-day	3ls_2dr_3de	0.007964	0.038892	1023.4±782.9	81.0±57.5	44.4±23.4
2	5-day	2ls_2dr_1de	0.008774	0.040575	1255.7±999.0	97.6±66.6	53.4±29.9
3	7-day	3ls_2dr_2de	0.008390	0.040544	1345.6±1177.8	108.5±74.5	55.0±35.8
4	10-day	3ls_2dr_2de	0.008802	0.040951	1368.1±1387.6	124.2±82.7	49.3±43.2

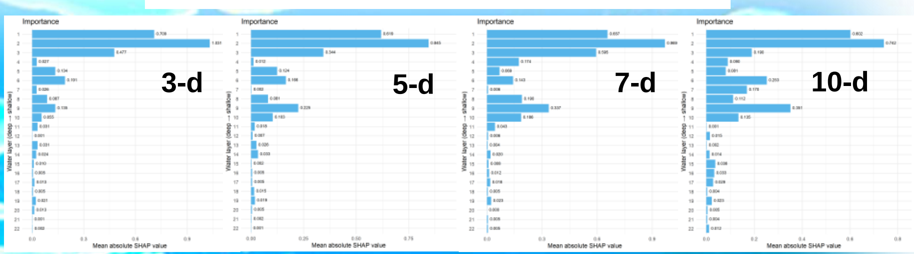


Fig. 4 SHAP results of the influence of current velocity by depth (first day).

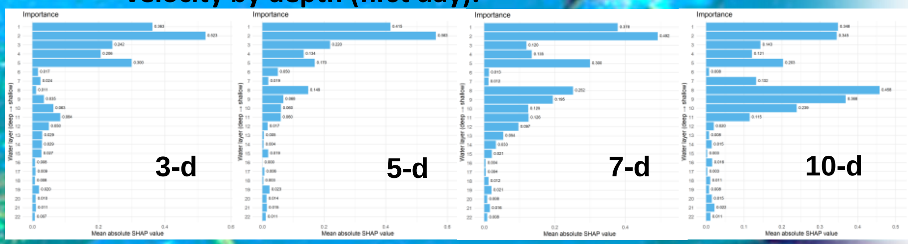


Fig. 5 SHAP results of the influence of current velocity by depth (last day).

CONCLUSIONS

- A multi-layer model structure will result in a relatively low loss rate of model training results.
- The sliding window of the 3-day model showed the lowest three evaluation indicators and higher prediction accuracy.
- The SHAP results indicate that the FAD drifting speed is predominantly influenced by mid-to-upper layer current velocity, with the strongest contribution from near-surface currents.