Prediction of Profiling Float Trajectories Using Neural Network Forecasts of Subsurface Flow

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***Abstract*—Recently implemented engineering tools have improved the navigational capabilities of autonomous ocean-profiling floats. By altering dive profiles to take advantage of favorable ocean currents, tools like FloatCast and FlowPilot help maximize the value of regional ocean samples from deployed floats. This work presents a complimentary predictive tool that can inform decisions regarding fleet-level profiling strategy based on subsurface flow data from EM-APEX floats. This predictive method uses recurrent neural networks to forecast subsurface velocity profiles of EM-APEX floats, which are then integrated to estimate trajectories. The near-continuous stream of subsurface velocity training data from each EM-APEX float is discretized in a physically meaningful way and used to train the neural networks. We outline our full prediction methodology and present promising results from these subsurface velocity forecasting and integration techniques. We then isolate the contributions to the total prediction error from both the subsurface velocity forecast and the trajectory integration tools. These predictive tools provide valuable insights to operators making sampling strategy decisions.**

***Index Terms*—EM-APEX floats, machine learning, recurrent neural network, subsurface flow integration**

I. Introduction

Profiling floats have been used to monitor the global ocean for decades, most notably in the Argo program [1]. These autonomous devices drift freely in the ocean, routinely changing their depth to gather samples relevant to research objectives. Along with the base Argo suite of conductivity, temperature, and depth sensors [1], researchers have implemented a variety of additional payloads for measuring subsurface velocities [2], [3], ocean acoustics [4], [5], and biogeochemical variables [5], [6]. Floats capable of monitoring the deep ocean have also been deployed [7]. As float capabilities and mission requirements evolve, so to does the need for navigational schemes that maximize the effectiveness of these float technologies. Here, we focus on Electromagnetic Autonomous Profiling Explorer (EM-APEX) floats [2] and their ability to measure subsurface velocity. From an oceanographic perspective, subsurface velocities are valuable for understanding ocean-atmosphere interaction [2], [3], internal waves [8], and surface waves [9]. This work uses subsurface velocity measurements from EM-APEX floats to make trajectory predictions that compliment existing predictive control methods.

Recent efforts have investigated methods of profiling float navigation for targeted ocean sampling. In particular, [10]–[12] seek to satisfy the navigational goals of regional deployments by dynamically altering float dives to maximize drift from favorable currents. FloatCast selects new dive commands for a fleet by making data-driven forecasts of surface flow that are used in the prediction of float trajectories for different sets of dive commands [10]. The best set of dive commands are then chosen based on a scoring metric that evaluates how well the predicated trajectories achieve the particular sampling objective [10]. FlowPilot is designed to select a float's next command using input from multiple trajectory prediction methods, based either on recent prediction skill or alternate ways to synthesize the predictions [11]. In [12], floats were commanded to move between two discrete depth levels to improve station keeping.

We seek to enhance our prior work on FloatCast with prediction tools that use subsurface velocity measurements from EM-APEX floats to better estimate trajectories of the fleet. Fleet-wide trajectory prediction is accomplished by first training recurrent neural networks to forecast subsurface velocity profiles of EM-APEX floats. These velocity forecasts are then integrated to predict float trajectories and fleet dispersion. This prediction method is viable because the flow information contained in local, in situ float measurements is higher resolution than the altimeter measurements of surface velocity that are currently used in FloatCast. In the past, similar machine-learning prediction tools have been used to predict the trajectories of Lagrangian drifters [13], [14].

The specific research objective is to improve regional sampling capabilities of profiling floats through intelligent float control. The technical approach to reach this objective is to apply techniques from data assimilation and machine learning to increase the accuracy of float trajectory predictions that inform navigational decisions. The contributions of this work are (1) the application of a data-driven method for predicting subsurface velocity profiles for a given float; (2) a float trajectory prediction method based on subsurface velocity measurements and predictions; and (3) analysis of a hindcast case study to evaluate the application of this method on real experimental data. By using these prediction methods to anticipate likely float behavior, operators can change profiling patterns to direct floats to the sampling region of interest.

The rest of the paper is structured as follows. Section II discusses key characteristics of EM-APEX floats, the recurrent neural networks used, and how this work fits in with FloatCast. Section III describes the velocity profile prediction method and float model. Section IV demonstrates the prediction method on a hindcast case study. Section V summarizes this effort and discusses opportunities for ongoing and future work.

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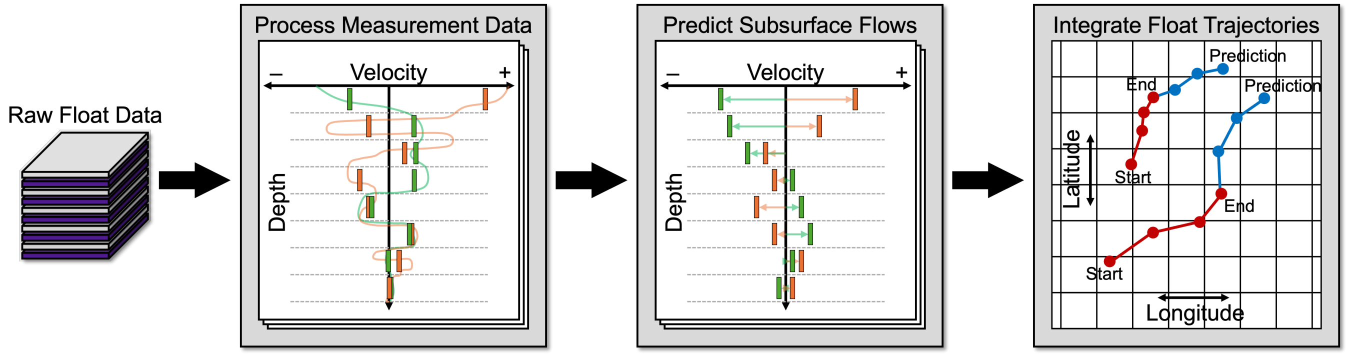

Fig. 1. Float trajectory prediction workflow. (Left) East/West subsurface float velocities (green) and North/South subsurface velocities (orange) are first discretized into depth bins via bin-wise averaging. (Middle) The discretized velocity data is used to train a recurrent neural network that predicts future subsurface flows. (Right) The subsurface flow predictions for each float are integrated to estimate expected float trajectories for each set of dive profiles considered. This prediction method assists human operators in making float navigation decisions.

II. Preliminaries

FloatCast maneuvers profiling floats by altering the park depth and duration of each dive to increase horizontal drift from favorable ocean currents and reduce unfavorable drift. In this work, we seek to augment existing predictive capabilities of FloatCast with new data-driven prediction methods based on local subsurface flow measurements from EM-APEX floats. The proposed method, sketched in Fig. 1, yields another decision aid for operators to use during active float deployments.

A. EM-APEX Float Operation

In addition to the standard Argo suite of salinity, temperature, and pressure sensors, EM-APEX floats provide measurements of horizontal velocity [2]. The velocity is only measurable when the float is actively descending or ascending. Thus, it is not uncommon for EM-APEX floats to perform rapid sawtooth dives, skipping the deep dive phase of the standard Argo mission, as demonstrated in [8]. One such EM-APEX profile is sketched in Fig. 2. This type of fast, repeated dive profile allows floats to take a near-continuous stream of subsurface velocity measurements. To prepare float velocity measurements for use in training the predictive model, we first group measurements by descent/ascent dive phase and further subdivide them into depth bins to obtain bin-averaged velocity profiles. Measurements with uncertainty greater than $3\ \mathrm{cm/s}$ are not taken into consideration in this analysis to prevent the averages from being distorted by unreliable values.

B. Velocity Prediction: Long Short-Term Memory Networks

In order to estimate float trajectories, we predict lateral float velocities and integrate them to obtain position, as shown in Fig. 1. We use a Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) to predict time-series profiles of subsurface velocity for each float considered. We also explored using an Echo State Network (ESN)—another type of RNN—for this purpose, but chose an LSTM because it provides more design flexibility in the early stages of testing. Moreover, the MATLAB Deep Learning Toolbox makes LSTM methods readily accessible such that the main training and prediction functionalities are handled with one line of code each. LSTMs have previously been used in analysis of ocean acoustics [4] and in prediction models of Lagrangian drifters [13].

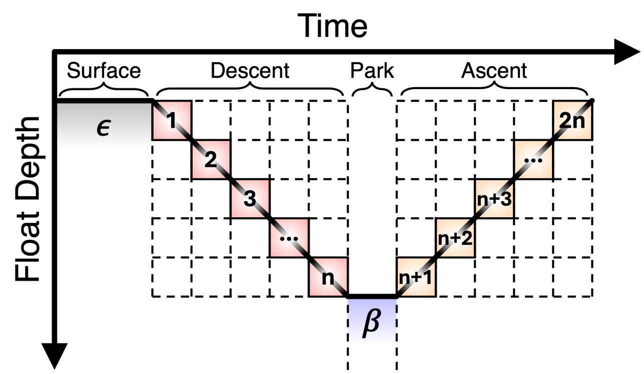

Fig. 2. Schematic of a sawtooth dive. Each dive consists of four phases: surface, descent, park, ascent. Profiles are discretized into depth bins and averaged to produce a regularized training data set for the LSTM. As no flow measurements are available for the ϵ and β bins, their velocities are assigned as the duration-weighted averages of velocities in adjacent depth bins. For this data set, the surface durations are typically around 30 minutes. The park durations are minimal, on the scale of a few minutes.

The broader system built on these LSTMs is expected to be most effective at predicting surfacing locations of floats doing continuous bursts of dives, each no longer than a few hours. In such cases, the operator can use these evaluations to determine if floats should maintain rapid profiling, or switch to dive profiles more closely resembling those of Argo or FloatCast-controlled dives to mitigate unwanted drift.

C. Overview of Relevant FloatCast Components

The broader objective of this research is to extend FloatCast [10] with prediction tools tailored to EM-APEX floats to improve the regional sampling performance of the fleet. FloatCast is composed of three modules that work together to direct floats to occupy the sampling region of interest. The first module forecasts surface flow by converting an ESN prediction of Sea Level Anomaly (SLA) into geostrophic velocity. The second module uses the geostrophic velocity forecast to predict float trajectories with a simple Lagrangian particle model. This model extrapolates surface flow forecasts downward in the integration step by assuming that floats move in the same direction as the surface current, but with reduced magnitude at depth. The third FloatCast module evaluates permutations of command sets for all floats using a mapping error scoring metric to select the best command set for navigation.

Although FloatCast and its assumptions about subsurface velocity have been used effectively in the past, there are locations and times at which the large-scale balanced flow resolved by SLA incompletely represents the actual subsurface velocity field. For example, a known limitation of FloatCast is that trajectory predictions tend to be quite poor for series of short, rapid dives. The prediction method introduced here uses in situ velocity profiles from EM-APEX floats to predict near-term trajectories with greater precision. Skillful predictions are then another decision aid for float operators. For simplicity, the data considered in this work are of short, rapid dives to seek to address the known weakness of FloatCast stated above.

III. Prediction Methodology

Subsurface velocities are incorporated into trajectory predictions in a two-step process. Subsurface velocity data from each float are first organized to train LSTMs that make time-series predictions of subsurface velocity profiles. These velocity profile predictions are then integrated to estimate float trajectories for the given dive profile considered.

A. Subsurface Velocity Prediction

In this framework, a float's LSTM can be retrained every time it calls in with new profile data. This is operationally feasible because float dive durations are on the order of hours, but it only takes around 30 seconds to train all LSTMs used in this work on a standard MacBook Pro with an Apple M2 chip and 16 GB of RAM. To make the LSTM training data sets, raw subsurface velocity data from EM-APEX floats are uniformly discretized into regular depth intervals. First, dive profiles are split by whether the float was descending or ascending. Within each descent and ascent profile, velocity data are subdivided into depth bins, resulting in bin-averaged velocity profiles, as sketched in Fig. 2. This discretization is performed for both easting and northing velocity data separately, and it allows average flow values for each dive to be combined into one training data matrix.

Equation (1) describes the depth bin groupings of average easting velocity data $\mathbf{u}$ based on the descent (dn) and ascent (up) phases of the dive:

$$\mathbf{u}^{\mathrm{dn}} = \begin{bmatrix} u_1^{\mathrm{dn}} \\ u_2^{\mathrm{dn}} \\ \vdots \\ u_n^{\mathrm{dn}} \end{bmatrix} \qquad \mathbf{u}^{\mathrm{up}} = \begin{bmatrix} u_{n+1}^{\mathrm{up}} \\ u_{n+2}^{\mathrm{up}} \\ \vdots \\ u_{2n}^{\mathrm{up}} \end{bmatrix}. \tag{1}$$

The elements of the vectors in (1) are average easting velocities of each depth bin. The index of each bin is denoted by

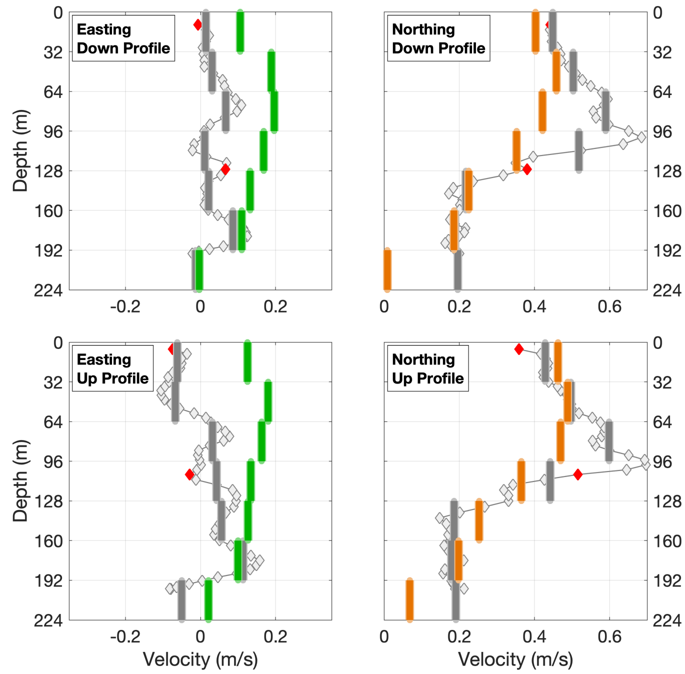

Fig. 3. Historical and predicted velocities for the 110th dive of float 9459, separated by dive phase and velocity direction. Raw historical velocities for this dive are plotted with diamonds (light gray). The averages from these velocities are plotted with vertical bars for each 32-m depth bin (dark gray). Velocity measurements with uncertainty greater than 3 cm/s (red) are not included in the average calculations. Predicted easting velocities (green) and northing velocities (orange) for each depth bin are also shown with vertical bars. These predicted values are for the third dive in the time-series prediction.

the subscript (e.g., u_i^{dn}). Analogous equations for the northing velocities $\mathbf{v}^{\mathrm{dn}}$ and $\mathbf{v}^{\mathrm{up}}$ are implied.

East and north velocity profiles are combined into the training data matrix U:

$$U = \begin{bmatrix} \mathbf{u}_1^{\mathrm{dn}} & \mathbf{u}_2^{\mathrm{dn}} & \cdots & \mathbf{u}_K^{\mathrm{dn}} \\ \mathbf{u}_1^{\mathrm{up}} & \mathbf{u}_2^{\mathrm{up}} & \cdots & \mathbf{u}_K^{\mathrm{up}} \\ \mathbf{v}_1^{\mathrm{dn}} & \mathbf{v}_2^{\mathrm{dn}} & \cdots & \mathbf{v}_K^{\mathrm{dn}} \\ \mathbf{v}_1^{\mathrm{up}} & \mathbf{v}_2^{\mathrm{up}} & \cdots & \mathbf{v}_K^{\mathrm{up}} \end{bmatrix}. \tag{2}$$

In (2), the subscripts of each matrix entry denote profile dive number. Thus, $U \in \mathbb{R}^{4n\times K}$, where n is the number of bins in one descent/ascent, and K is the total number of dive profiles considered in training. Consequently, the dive number acts as the time step with time progressing from left to right across matrix U. This matrix is used to train the LSTM for a given float. Once trained, the LSTM generates time-series predictions of velocity profiles. These predictions of future dive profile velocities line up such that they could directly augment U from the right. Fig. 3 depicts an example LSTM prediction for one dive and the historical velocity ground truth data set, organized by dive phase and velocity direction, as described by vectors $\mathbf{u}_i^{\mathrm{dn}}$, $\mathbf{u}_i^{\mathrm{up}}$, $\mathbf{v}_i^{\mathrm{dn}}$, and $\mathbf{v}_i^{\mathrm{up}}$ in (2).

While training multiple LSTMs to separately predict easting and northing is possible, the components are strongly correlated and thus we believe that using one LSTM to predict both quantities should be superior, as it can capture relationships between each set of data. We opted to discretize velocities with respect to depth rather than dive duration because it more easily accounts for dissimilar profiles. If a float dive is shallower than bin n, then the missing velocities in U are filled in with zeros to maintain matrix dimension with as minimal bias to the data as possible. Conversely, if a float dives deeper than bin n, these values are truncated to maintain the dimension of U. On the other hand, exception-handling for bin groupings based on duration would be much more complex and harder to justify when dive durations vary. Effectively, our use of dive number in the construction of U implicitly provides a reasonably accurate time-spacing approximation for regularly repeated dives to the same depth.

B. Float Trajectory Prediction

To estimate float trajectories, we use an integration scheme based on a state-space system that describes the descend-park-ascend profiling pattern sketched in Fig. 2. Both historical and predicted subsurface velocity profiles can be used in this model, which is helpful for identifying sources of error. Equations (3), (4), and (5) define the model:

$$\dot{x}(t) = u_k(z(t)) \tag{3}$$

$$\dot{y}(t) = v_k(z(t)) \tag{4}$$

$$\dot{z}(t) = \begin{cases} 0 & \text{surfaced or parked} \\ w_k(z(t)) & \text{descending} \\ -w_k(z(t)) & \text{ascending} \end{cases} \tag{5}$$

The easting and northing velocity of a given float at time t is $\dot{x}(t)$ and $\dot{y}(t)$, respectively. The corresponding vertical velocity is $\dot{z}(t)$. Operationally, the $u_k(\cdot)$ and $v_k(\cdot)$ functions are lookup tables indexed by dive number k and depth z that return scalars describing easting and northing velocity of the float, respectively. These horizontal velocity values effectively come from the U matrix (see (2)). The $w_k(\cdot)$ function is also a lookup table, returning vertical velocity of the float for the given dive number and depth. The piecewise analytic solutions to these equations are used to predict float trajectories under the modeling assumption that horizontal and vertical velocity values are constant in each depth bin.

Trajectory predictions made from historical and LSTM-predicted data both assume a constant vertical velocity in each depth bin, but differ in how they obtain this value. When integrating historical data, vertical velocity is calculated separately for the descent and ascent phases of a dive. The vertical velocity for each phase is computed via:

$$w^{\mathrm{dn}} = \frac{bN^{\mathrm{dn}}}{T^{\mathrm{dn}}}, \qquad w^{\mathrm{up}} = -\frac{bN^{\mathrm{up}}}{T^{\mathrm{up}}}. \tag{6}$$

In (6), N^{dn} and N^{up} are the number of bins traversed, completely or partially, by a float in its descent and ascent, respectively. The bin length is b (e.g., 32 m). The descent duration is T^{dn} and the ascent duration is T^{up}. The resulting vertical velocities are w^{dn} and w^{up}, respectively, and are constant for the whole dive. Equation (6) thus maps raw depth-time data to estimates of vertical velocity.

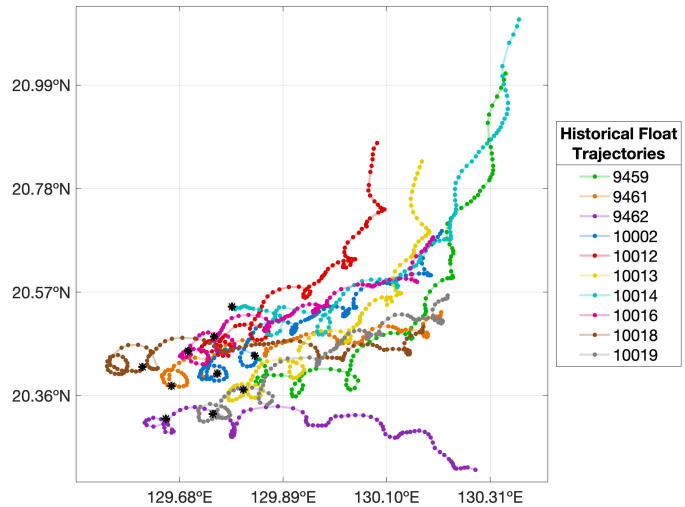

Fig. 4. Historical trajectories over about one week for ten floats deployed in the Philippine Sea in February 2025, beginning from the black stars. Each dot marks a GPS-measured dive endpoint where a float came to the surface. There are roughly 100 profiles for each float. The velocity profiles from all but the last ten dives of each float are used as training data to make the LSTMs in Section IV. These batches of dives are reserved for evaluating LSTM velocity predictions.

Conversely, when LSTM subsurface velocities are integrated, w^{dn} and w^{up} are assumed to be 0.12 and -0.12 m/s, respectively, to match FloatCast assumptions [10]. Moreover, the surface and park durations used are the average values from these phases of the dives in the training data set. For both historical and LSTM trajectory integrations, the vertical velocity of the float is assumed to be zero when the float is on the surface or in the parking phase. Exceptions can arise when integrating historical data if the endpoints of descent or ascent depth columns do not match[1]. In such cases, the gap is assumed to be filled with the vertical velocity needed for the float to connect the descent and ascent columns.

In prior work, a model has been used that extrapolates surface velocity downward using an exponential decay function to obtain subsurface velocities [10], [11]. The FloatCast model in particular assumes that subsurface velocities point in the same direction as the surface velocities with speed that decreases with depth [10]. This model has been used in the past with some degree of success, but we expect the model introduced here to be better at short-term trajectory predictions. The historical flows in Fig. 3 show how FloatCast assumptions of subsurface velocity are an oversimplification.

IV. Hindcast Case Study

This section presents a case study demonstrating the prediction method and evaluates the performance of each component. Two sets of trajectory predictions are presented: one based on historical subsurface velocity profiles, and one based on LSTM predictions of velocity profiles. LSTM velocity predictions are evaluated separately to isolate sources of error.

[1]This can occur if many velocities at the beginning or end of the descent or ascent are excluded from the analysis due to high uncertainty of measurement.

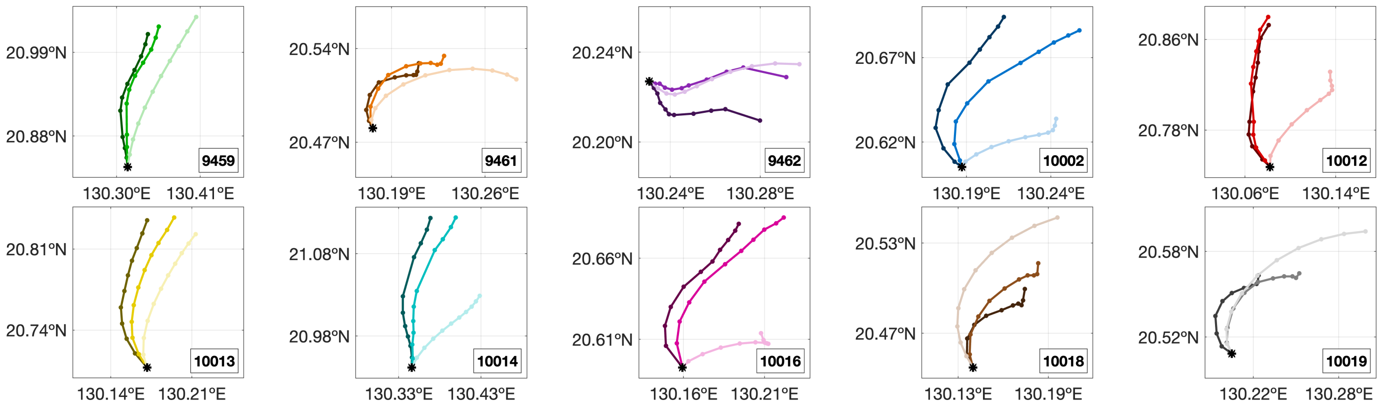

Fig. 5. Historical and predicted float trajectories for ten floats in the Philippine Sea in February 2025. Trajectories over ten dives are shown for each float (ID number in bottom right), beginning from the black star. Historical trajectories (dark shades) provide a reference. Trajectory predictions based on historical subsurface velocities (medium shades) and LSTM-predicted subsurface velocities (light shades) illustrate the capabilities of this prediction method. Differences between the dark and medium shades highlight inherent limitations of the state-space prediction model, while differences between the medium and light-shade trajectories arise from differences in the historical and LSTM-predicted velocities.

A. Float Trajectory Hindcasts

For this experiment, we predicted trajectories based on the historical float data shown in Fig. 4. This data set consisted of hundreds of sawtooth dive profiles from ten floats. With only a few exceptions, all float dives were under one hour in length with maximum depths shallower than $224\ \mathrm{m}$. The raw velocity data was discretized using velocity averages from seven depth bins, each $32\ \mathrm{m}$ in length and spanning 0 to $224\ \mathrm{m}$. Each float had velocity data for roughly 100 dives that were used in training the LSTM. The last ten dives of each float were excluded from training to evaluate prediction performance.

Ten LSTMs were trained following the steps in Section III-A, one for each float. Once trained, the LSTMs made time-series predictions of the expected subsurface velocity profiles. Each set of ten profile predictions line up so that they can augment the float's training data matrix U on the right. Predicted and historically measured flow profiles were used to help make trajectory predictions with the model in Section III-B.

Fig. 5 compares float trajectory predictions based on historic and LSTM-predicted flows for all ten floats in this case study. The trajectory predictions made using historic flows serve as an upper bound on the expected performance of trajectory predictions based on LSTM-predicted flows. Thus, the additional error in the trajectory predictions based on LSTM-predicted flows suggests that the contribution of velocity prediction errors is of the same magnitude or larger than the intrinsic uncertainty of the state-space model.

B. Hindcast Prediction Performance

To evaluate the performance of both sets of trajectory predictions shown in Fig. 5, prediction error was computed as the distance between dive endpoints from reference and predicted trajectories over the full testing set. The mean and standard deviation of the prediction error was then evaluated for these series of dive predictions across all floats, with results shown in Fig. 6. The performance of trajectory predictions based on historic flows is the upper bound on expected performance of trajectory predictions that used LSTM-predicted flows. The additional error in trajectory predictions from LSTM-predicted flows is characterized by the steeper slope and wider uncertainty margins in Fig. 6. The performance of trajectory predictions based on LSTM-predicted flows varied.

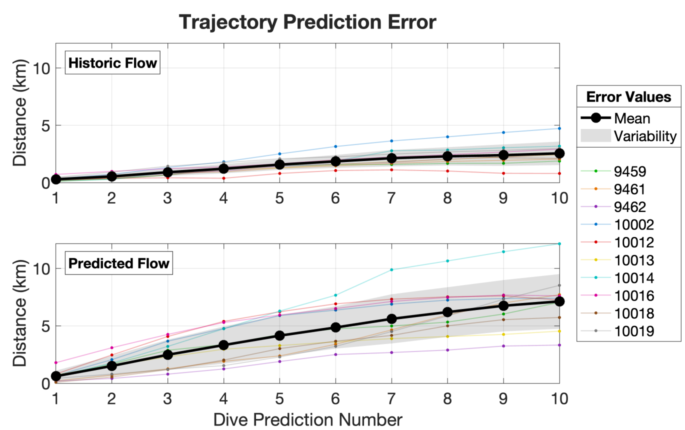

Fig. 6. Trajectory prediction error for predictions based on the historical flows (top) and the LSTM-predicted flows (bottom). Both plots show the mean prediction error (black) plus or minus one standard deviation (gray shading) for all predicted dives from each float. Raw prediction error for each float is shown in thin lines, colored by float.

To assess the quality of LSTMs and characterize the contribution of velocity prediction error, we computed the Root Mean Square Error (RMSE) for all bins in each dive prediction, as shown in Fig. 7. Interestingly, the change in average RMSE across the ten dives considered is quite gradual and not always increasing with dive number. It is encouraging that reasonable trajectory prediction performance is possible with this level of RMSE from the LSTM flow predictions because it shows that perfect velocity predictions are not required in the broader scope of the prediction pipeline. Based on this analysis, the increase in trajectory prediction error from

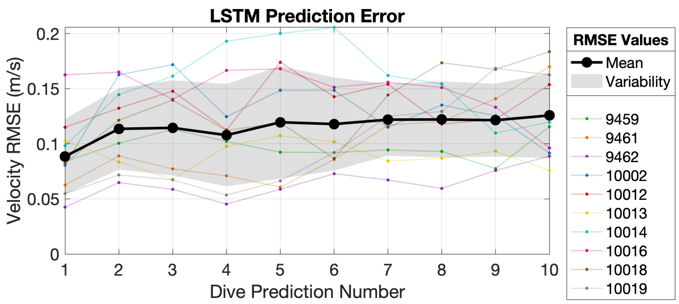

Fig. 7. Velocity prediction error for each float's LSTM based on the RMSE metric. The collective mean RMSE (black) plus or minus one standard deviation (gray shading) is shown for each dive prediction. The individual RMSE values from each float's LSTM are also shown with thin lines in a variety of colors. Each float's LSTM was trained only on dive data for that float and made hindcast predictions for ten dives.

integrating predicted flows shown in Fig. 6 can be attributed to the LSTM velocity prediction error shown in Fig. 7.

V. Conclusion

This paper outlines a new method to predict trajectories of EM-APEX profiling floats that is particularly helpful over short time scales. The method combines machine-learning and mathematical integration techniques in two steps. First, trained LSTMs forecast subsurface velocity profiles of EM-APEX floats. Then, these forecasts are integrated to make predictions of float trajectories. This can be especially helpful for anticipating fleet dispersion when float dive profiles are consistently repeated. As such, the predictive tool presented here can be a useful decision aid for float operators.

The prediction method introduced here performed reasonably well in the hindcast case study. However, there is a key limitation preventing this method from being used directly in FloatCast in a meaningful way. Because the LSTM training data is adapted and discretized to roughly fit a standardized dive profile, this means that only one type of dive profile (i.e., one park depth and park duration) can be predicted at a time. As a result, the method only gives one dive command from which the FloatCast evaluation tools can choose for navigation. Despite this limitation, the trajectory prediction method shown here can still be a valuable decision aid.

In ongoing and future work, the prediction method can be further refined for real-world applications. In particular, its systematic assumptions can be modified to explore how multiple types of dive profiles can be predicted at once. The main challenge is that real-world measurements only contain information on one type of dive profile at a time. To assimilate real-world data to predict different dive profile patterns, more sophisticated and/or irregular selections of depth bin intervals could be used for each dive profile. The exponential decay model from FloatCast could also be used to extrapolate altimetric surface velocity downward in order to fill in flow values for depths with no velocity measurements. In either case, this could allow existing FloatCast tools to evaluate multiple dive commands from these predictions and select those that best suit navigational goals.

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