

Machine Learning Application for Evaluating River Plume Spreading: Identification and Modeling

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Abstract—Based on machine learning (ML) methods, a new problem-solving procedure is proposed here to enhance river-plume research, including data collection, data-mining processes, and characteristic analyses. A plume shape recognition model is developed, structured on convolutional neural networks (CNNs), and is named “PlumeCatcher.” This model is shown to extract various river-plume features from satellite images. The random forests (RFs) data-mining method was applied to investigate the significance of the controller on plume development, including dynamic factors such as wind, current, water discharge, and tides, all of which are potential factors that can influence plume properties on daily, seasonal, and annual timescales. Focusing on the Magdalena River in Columbia (South America), the results of the methodology indicate that wind is the factor with maximum sensitivity dominating plume movement starting from the river mouth. Moreover, the plume features including area, direction, and spreading range are varied from short timescales (tidal cycle) to long timescales (yearly) and demonstrate the dynamic nature of plume spreading. ML methods provide an effective and convenient way to map plume features and extract and analyze their properties, which is beneficial for future scientific analyses.

Index Terms—Machine learning (ML), Magdalena River, remote sensing, river plume.

I. INTRODUCTION

RIVER plumes, generated by sediment-laden water discharge into coastal seas, serve a key role in transporting fine suspended sediment and nutrients from terrestrial landscapes to the adjacent coastal marine regions [1], [2]. The hydrodynamics of plumes are affected by both fluvial and marine processes, thereby coupling onshore and offshore regimes. Recently, much attention has been focused on several factors affecting plume mixing and spreading using a variety

of study designs, including numerical modeling, remote sensing, and in situ data analysis. In particular, studies have sought to establish the influence of processes operating at the river mouth, including water and sediment discharge, and to evaluate the effects of marine conditions, such as tidal amplitude, ocean currents, wind stress, and Earth’s rotation. Additionally, physical qualities like coastal geometry and seabed bathymetry have been examined [3].

River discharge, as the main momentum contributor, is a primary control of plume spreading, affecting its size and direction of movement [4], [5]. Plume dynamics also have important morphodynamic feedbacks: as a combination of river discharge and plume-angle spread, the region of nonuniform flow associated with a river entering its terminal basin influences patterns of erosion and deposition for the coastal-river system [6]. Water surface slope and discharge also impact the hydrodynamic properties of plumes [7], including mixing with coastal water and plume spreading and thinning [8], [9], [10], [11]. Variables such as wind and waves are significant sources of near-surface oceanic turbulence that increases waterbody mixing [12], while tidal amplitude and coastal currents affect plume structure [13] and spreading [14], [15].

The dynamic nature of the structure and distribution of a river plume has recently been examined by evaluating lateral spreading on buoyancy flux [16]. For example, circulation and mixing of the Hudson River plume were examined based on high-frequency velocity and backscatter data from a moored ADCP [17]. Palma and Matano [18] used the Regional Ocean Model System (ROMS), a highly idealized model, to investigate the dynamics of near-equatorial river plumes. In recent years, it has become increasingly common to use satellite data to investigate plumes because these platforms cover large areas, can record over long time periods, and possess multiple sensors from which to extract various data. For example, satellite-derived salinity algorithms can distinguish plume boundaries [19], as has been shown for the Changjiang River plume, and several studies have sought to map the extent and dispersion pattern of river plumes using ocean color products as a proxy [20], [21]. Also, Shanmugam [22] used satellite data to illustrate the natural variability of configurations of density plumes in modern environments.

Although analysis of the mechanisms driving plume dynamics have been carried out by previous researchers, existing studies have focused more on a single factor considered over short-term time scales and limited spatial regions. For example, the analyses and scientific application of evaluating

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satellite data to assess plume dynamics have primarily examined specific images used for qualitative assessments, rather than quantitative time-series monitoring of plume evolution over daily, seasonal, and/or yearly time scales. In other words, the dense time-continuity characterizing a 40-year-long satellite record has not been exploited to evaluate plume dynamics. Thus, there remain few detailed, long-term studies of plume dynamics, with most existing models focused on discussing the effects of individual, idealized environmental parameters, rather than conducting a comprehensive analysis of the combined effects of multiple factors. Estuaries are complex hydrodynamic regions where the convergence and mixing of fresh and saline water are impacted by numerous physical and chemical conditions. Existing methods and data are limited in terms of describing how unique factors combine to influence plume structure and spreading. Herein, we propose a new method to provide time-continuous monitoring and analysis that identifies multiple factors affecting plume movement, evaluated for a range of spatial and temporal scales.

Machine learning (ML) methodologies, when applied to remotely sensed data, can be used to assess multiple co-evolving influences operating over a variety of spatial-temporal scales to analyze controlling mechanisms on plume evolution, thus informing analyses of sediment transport and depositional activity in estuarine-deltaic environments. As the amount of remotely sensed data continues to increase exponentially, building and training automated systems will optimize quantitative relations between dependent and independent variables [23]. For example, deep learning, as a recently developed ML tool to discover the intricate structures in high-dimensional data, is applicable to solve a variety of problems in science, business, and government [24]. Additionally, several successful applications of the combination between the ML method and satellite data have proved its efficiency and practicality [25], [26], [27], [28], [29], including in geoscience analysis [30], [31], [32], [33], [34], [35], [36].

Applying a new research approach may provide insights into plume structure while assessing the significance of related boundary condition changes across timescales. However, ML applications are based on large amounts of data, and satellites provide finite images per year. How to obtain as much useful information as possible from the limited data available is an important problem to solve. Herein, a procedure is utilized for big data mining that includes “data collection–data mining processes–characteristic analysis.” We organize our efforts in the following way. Section II discusses how to set up and configure the ML approach to river plumes, which includes the PlumeCatcher data extraction model and the data mining method. The datasets and preprocessing procedures are then explained in Section III. Section IV presents the performances of the proposed PlumeCatcher model on the case study of the Magdalena River, as well as sensitivity studies of plume retrieval to various boundary parameters. An abstract concept of representing specific plume stats is also established. Section V discusses the physical meaning of plume features, the detailed relation between plume and boundary conditions under different timescales, and describes future work that aims to investigate the feasibility and performance of plume data

collection, to define controlling factors operating over multiple timescales. The aim is to demonstrate how ML methods are advantageous in exploring the short-to-long-term plume characteristics and simulating the plume status of an actual river estuary based on its unique hydrodynamic and environmental conditions, thereby providing insights into estuarine sediment transport processes and deltaic accumulation patterns.

II. METHODOLOGY

A. Plume Data Extraction Model: PlumeCatcher

A river plume is a turbid freshwater flow, consisting of terrigenous sediment and organic matter, emanating from land into a receiving basin that is visually distinguishable from surrounding seawater by a contrast in color properties. The Landsat TM/OLI sensor, an optical multispectral/hyperspectral sensor spanning visible and near-infrared radiometric intervals, provides a global perspective of Earth surface conditions with good continuity and broad coverage and therefore is an appropriate platform from which to identify river plumes in nearshore marine environments. In this study, convolutional neural networks (CNNs), which are a deep learning architecture for visual pattern recognition that have recently demonstrated promising results on pattern recognition tasks [37], [38], [39], are used to build a plume data extraction model named “PlumeCatcher.” Featured by local receptive fields, shared weights, and subsampling, CNNs provide better effects with less training cost, which makes them suitable for image processing and analyses [40].

The main purpose of the PlumeCatcher model is to obtain plume characteristics using satellite images, including plume parameter data such as direction/orientation (DIR), surface area (S), and spreading range plume spreading range (PSR).

Limited to the long revisit interval of Landsat and a small proportion of plume texture in a single image, the model cannot be trained well directly with original data directly. To improve the model efficiency and achieve detailed extractions, three steps are contained in the main process of PlumeCatcher, including: 1) classification; 2) object detection; and 3) semantic segmentation for plume contours after preprocessing the original satellite images. Relying on the three-step model structure, we can maximize the recognition rate with limited data. The framework employed to develop PlumeCatcher using CNNs is shown in Fig. 1. To achieve a better training result and reduce training cost, the hyperparameter tuning such as the learning rate (LR), batch size, and hidden units, has been applied before the training of each model step.

1) *Classification*: Classification, as the first step, is used to determine the existence of plumes in satellite images. The principle of constructing the classification model is to obtain a high recognition rate, with a simple structure and low training cost. Here, we used a customized CNN module to achieve image recognition, as shown in Fig. 2(a). Due to the concern that input has a relatively large image size with only two classes, the network needs to be capable of learning useful features, and not too deep to introduce overfitting issues simultaneously. Thus, the CNN module for classification only contains three convolutional units and two fully connected layers, while the model uses 300×300 pixels as the input

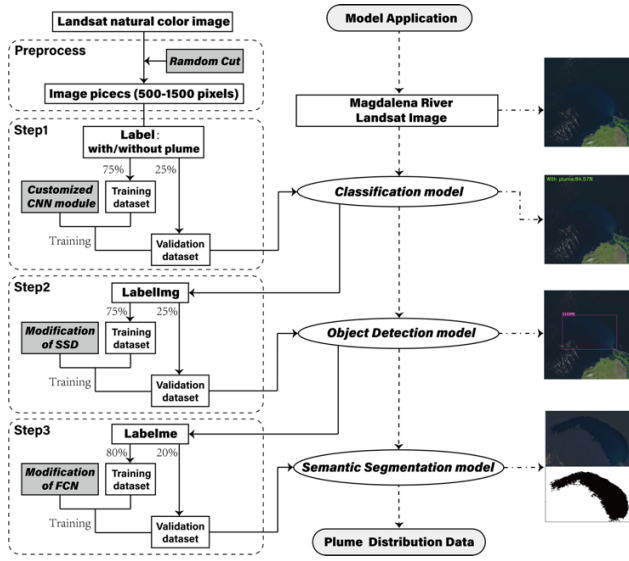


Fig. 1. Flowchart of the proposed PlumeCatcher method. Landsat 8 OLI data of Magdalena River are used as an example.

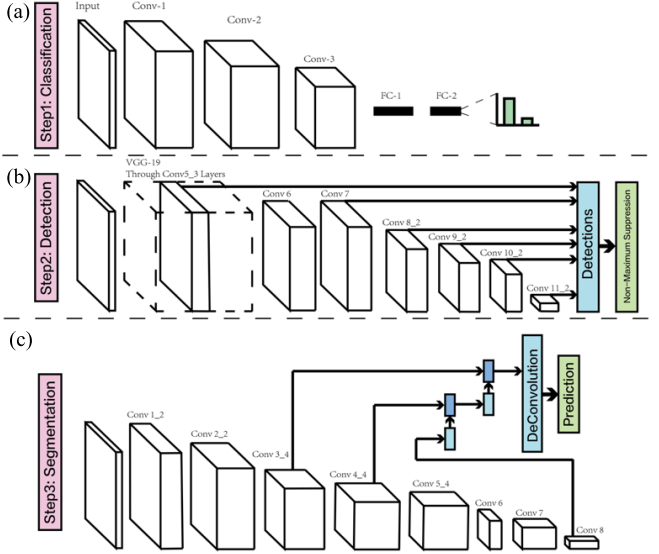


Fig. 2. Architecture of the proposed CNNs for the PlumeCatcher model. (a) Classification (customized CNN). (b) Object detection (modified by SSD structure [41]). (c) Semantic segmentation (modified by FCN structure [43]). Conv = a convolutional mode. FC = Fully connected layer.

dimension to guarantee the plume can be distinguished from most extracted objects. All images need to be resized before being fed into the classification model.

In convolutional units, featured maps generated by a fixed matrix (called filters) could represent multiple features of the image in the convolutional layer, and a subsequent subsampling layer (called pooling layer) is used for reducing the resolution of the feature map and reducing the sensitivity of the output to shifts and distortions. Here, the filter size is 5×5 , and the maximum pooling operation with a window of 2×2 is performed. The numbers of filters in the three convolutional layers are 20, 40, and 70, respectively. A ReLU function [38], as the nonsaturating nonlinearity neurons, could support a faster training process, while data augmentation

and a dropout method [38] have been used to enhance the generalization ability.

2) *Object Detection*: The second step of PlumeCatcher aims to extract the plume location from images if they are classified as having a plume, which is called Object Detection. This technology is used to identify the target position in an image. It needs to give the category information and position information of the target in the image and uses a bounding box to delineate the target. The CNN used in this study is based on a modified SSD [41], as Fig. 2(b) shows. The core of SSD is predicting category scores and box offsets for a fixed set of default bounding boxes using small convolutional filters applied to feature maps. To achieve high detection accuracy, predictions of different scales are produced from feature maps of different scales and explicitly separate predictions by the aspect ratio. The overall objective loss function is a weighted sum of the localization loss (loc) and the confidence loss (conf), which could be described as

$$L(x, c, l, g) = \frac{1}{N} (L_{\text{conf}}(x, c) + \alpha L_{\text{loc}}(x, l, g)) \quad (1)$$

where N is the number of matched default boxes, and the localization loss is the Smooth $L1$ loss [42] between the predicted box (l) and the ground-truth box (g) parameters. In the SSD network process, the model will generate 8732 boxes in total with different scales and aspect ratios from all locations of many feature maps.

3) *Semantic Segmentation*: The final step of PlumeCatcher is the extraction of the plume shape, which can be considered as a semantic segmentation question. To achieve pixel-wise prediction, a fully convolutional network structure modified by VGG-19 is used in our study [43], and the schematic of the structure is shown in Fig. 2(c). Here, a name data vector in a particular layer at location (i, j) is $\mathbf{x}_{ij}$, and $\mathbf{y}_{ij}$ for the following layer. The function between $\mathbf{x}_{ij}$ and $\mathbf{y}_{ij}$ is

$$\mathbf{y}_{ij} = f_{ks}(\{\mathbf{x}_{si+\delta i, sj+\delta j}\}, 0 \leq \delta i, \delta j \leq k) \quad (2)$$

where k is the kernel size, s is the stride or subsampling factor, and f_{ks} determines the layer type. Kernel size and stride obey the transformation rule as

$$f_{ks} \circ g_{k's'} = (f \circ g)_{k'+(k-1)s', s's'} \quad (3)$$

While a net with only layers of this form computes a nonlinear filter, it can be called a fully convolutional network. To realize image contour recognition, the fully convolutional versions of existing networks could analyze whole images at a time by dense feedforward computation and backpropagation, and in-network upsampling layers that enable pixel-wise prediction and learning in nets with subsampled pooling. Also, skips between layers have been used to fuse coarse, semantic, and local appearance information, thus improving the semantics and spatial precision of the output. As a necessary tool, transfer learning is also used in step three, with pretrained model training on the Pascal 2007 dataset.

4) *Transfer Learning and Data Augmentation*: Facing a limited dataset, several techniques have been applied here to reduce overfitting and improve the generalization ability, such as transfer learning and data augmentation.

Transfer learning works by training a network utilizing a large dataset sharing similar characteristics with the target dataset and then using those weights as the initial weights in a new task [44], [45]. The need for transfer learning occurs when there is a limited supply of target training data, which could be due to the data being rare, expensive to collect and label, or perhaps inaccessible [46]. Here, transfer learning has been used in the object detection and semantic segmentation step. The pretrained model used in this study has been trained on the Pascal (2007) dataset with 120 000 epochs, and the mean average precision (mAP) is 0.817. The pretrained model parameters are used to initialize the final model parameters, which made it possible to obtain relatively high model accuracy with a few (~ 400) river-plume satellite images.

In contrast to the transfer learning that focuses on the model architecture, data augmentation approaches worked mainly on the training dataset. Data augmentation is a data-space solution to the problem of limited data, encompassing a suite of techniques that enhance the size and quality of training datasets such that better deep learning models can be built using them [47]. Here, we used geometric transformations including flipping, rotation, cropping, and translation. Data augmentation is used before the training process of each step in PlumeCatcher and can artificially inflate the training dataset size.

B. Data Mining Algorithms: RFs

A data mining method is needed to investigate the relationship between plume structure and boundary conditions and develop inductive statements and optimized predictions directly from datasets, while an ML data mining algorithm is used to ensure a reliable regression result.

The random forests (RFs) method is a graphic method based on probability analysis and a combination of decision tree predictors where each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest [48], [49]. Considering the possible nonlinear relationship, the RF method, as a supervised algorithm, is powerful in both classification and regression tasks without overfitting, and it is an effective application in predicting landscape and establishing models [50], [51], [52].

The main target of the RF method here is to analyze how combined numerous dynamic elements can influence the plume form. Thus, the plume characteristics obtained from PlumeCatcher will be used as input along with the corresponding environmental boundary data, and the model can achieve the degree of influence in each factor as output. Trained RF models can also be run in inverse to predict the performance of identifying a plume under the combined control of different factors.

Here, the classification and regression trees (CARTs) method utilized is characterized by Gini coefficient and a bagging bootstrap aggregating algorithm. Taking the probability that a sample belongs to i as p_i ($i = 1, 2, \dots, k$), the Gini coefficient can be defined as

$$\text{Gini}(t) = \sum_{i=1}^K p_i(1 - p_i) = 1 - \sum_{i=1}^K p_i^2 \quad (4)$$

where Gini is equal to zero if only one type of sample is in the dataset. Therefore, maximizing the decrease of Gini is used as a criterion in tree building. Bootstrap sampling could be described as n samples being randomly selected from the data forming a classifier tree, and unselected data (called OOB, “out of the bag”) is used for testing the generalization performance of the tree. After repeating the process for m times, the prediction result is determined by the majority voting among all independent trees as

$$f^M(x) = \frac{1}{M} \sum_{m=1}^M T(x) \quad (5)$$

where $m = 300$ in this study.

III. DATA

A. Plume Data Extraction Model: PlumeCatcher

A river plume emanates from a river mouth, extending outside the bounds of the river channel. It is characterized by fresh water and possesses suspended terrestrial sediment. As mentioned, remote sensing data (Landsat TM/OLI sensor) with good time continuity and relatively high accuracy are used to analyze plume spreading.

Landsat series provides fine coverage of global surface remote sensing images, which is sufficient for worldwide monitoring of rivers with high sediment discharge [53], [54], including the Brazos River (North America), Godavari River (Asia), Hongho River (Asia), Indus River (Asia), Kaoping River (Asia), Kura River (Asia), Magdalena River (South America), and Yellow River (Asia), recorded since 1984. These rivers are selected due to their intact river mouth and distinct color differences that illustrate suspended sediment from surrounding (ambient) seawater. Typically, this contrast is due to the sediment suspended in the plume as water discharges from the river mouth.

Here, a set of natural-color data has been used including Landsat 4–5 (MSS, the Multispectral Scanner Sensor), Landsat 7 (ETM+, the Enhanced Thematic Mapper Plus), and Landsat 8 (OLI, Operational Land Imager). The data can be downloaded from USGS Global Visualization Viewer (<https://glovis.usgs.gov/>). The information on data sources, image amount, and spatial coverage for the CNN model training are shown in Table I.

The satellite data typically comprises 5700×6100 pixels, covering a wide area of 180×185 km, as illustrated in Fig. 3(a). The image encompasses diverse environmental features such as the coastline, rivers, and clouds. It can be challenging to identify the target for the model when implementing it directly on the original image. As the larger river plumes in the dataset have length scales that are typically 20–80 km, the original images were randomly cut into several patches with 300–1500 pixels in preprocessing steps to ensure that the detailed plume structures are included in the figure. This step aims to reduce the training time and cost, as indicated in Fig. 3(b). The smallest river estuary in the dataset is the Brazos River, which is located along the northern coastline of the Gulf of Mexico. The width of its plume is ~ 3 –5 km and is considered to be the minimum limit of recognition of PlumeCatcher.

TABLE I
DATA INFORMATION

Model	Dataset	Data resource	Time scale	Number	
Classification	Train	Landsat 8	2013-2018	791 (404+387)	Including Brazos River (North America),
	Test	Landsat 4/5	1984-1989	230 (130+100)	Yellow River (Asia), Magdalena River
Object detection	Train	Landsat 8	2013-2018	393	(South America), Hongho River (Asia),
	Test	Landsat 4/5	1984-1989	130	Kaoping River (Asia), Godavari River
Semantic	Train	Landsat 8	2013-2018	578	(Asia), Kura River (Asia), Indus River
Segmentation	Test	Landsat 4/5 & 7	1984-2013	128	(Asia)
					Magdalena River (South America)

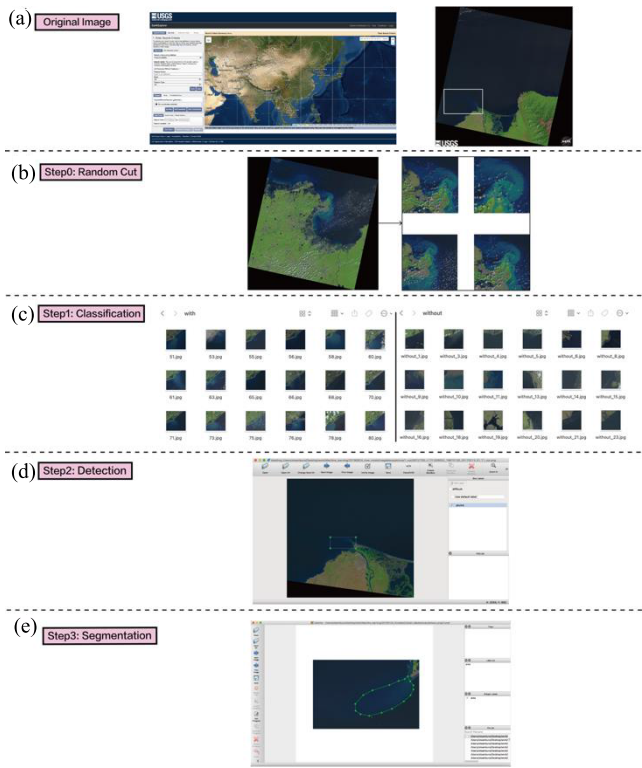


Fig. 3. Preprocessing method with examples of Landsat images in each step. (a) Download the original image. (b) Random cut, the preprocess step before model training. (c) Preprocessing method of Classification (Step 1). Classify the image into “with plume” and “without plume”. (d) Preprocessing method of Object Detection (Step 2). Using LabelImg as a tool to include a clearly visible area as plume boundary with the surrounding (ambient) marine water. (e) Preprocessing method of Semantic Segmentation (Step 3). Using Labelme as a tool to label the mid-field plume with a drop-shaped area of significantly high color contrast.

After the preprocessing steps, river plume images of suitable size were labeled to feed the classification model. Aiming to judge the plume existence in the image, the training dataset distinguished images into a “with plume” subset and a “without plume” subset, as labeled shown in Fig. 3(c). The “without plume” images include not only the normal shoreline areas but also the near-shore areas with high turbidity caused by bed sediment suspension and adjacent estuaries that possess high turbidity and, therefore, can be confused with the river plume area. The addition of the “without plume” subset can effectively improve the ability to recognize with-plume images and enhance the robustness of the model. The first model step (classification) was trained for 40 h using

the dataset, with 75% training samples and 25% validation samples, including 404 samples (images) with plumes and 387 samples without plumes. Some significant parameters used in the training process are as follows: the batch size of the classification model is 50, the epoch is 200, and the LR is $1e^{-4}$. After training, the model provides the probability of whether the test images have a plume structure.

Images with river plumes picked by the classification step were used for the second step (Object Detection) training and the essential labeling process. To obtain a complete plume structure with accurate identification, the criterion of labeling is using a rectangular box to include a clearly visible area based on distinct colors of adjacent water, representing the plume boundary with the surrounding (ambient) marine water. The plume tangent and dimension boundaries are established to minimize extraneous components. For example, when labeling, it is necessary to ensure that the edges of rectangular boxes are tangent to the plume to minimize extraneous components as possible. Using LabelImg as a tool, the example of labeling images is shown in Fig. 3(d). This step benefitted from the transfer learning and pretrain model, as the object detection model used 43.5 h and 7000 epochs to reach training completion on servers (32 Intel Xeon E5-2640 CPUs), with 75% training samples and 25% validation samples, including 393 labeled images. Some significant parameters used in the training process are as follows: the batch size is 16, and the LR is $1e^{-4}$ for the first 4000 steps until the decrease rate of loss slows down. Then, the LR is switched to $5e^{-5}$ for 2000-step training. After that, LR is reduced to $1e^{-5}$ until the loss curve stops falling further and oscillates around zero. After training, the model provided a concentrated area of the plume.

Plume shape extraction is based on the plume image cut from the boundary generated after objection detection. Using Labelme as a tool [Fig. 3(e)], the labeling process is focused on the mid-field plume with a drop-shaped area of significantly high color contrast. This means the label area has a clear contrast with the surrounding environment without a mixing area around its edge. A dataset with 578 samples is divided into an 80% train subset and a 20% validation subset. The model training is also run on the aforementioned computer server for 107 h. The batch size is 4 with the image size as 250×250 , when LR is set to be $5e^{-5}$ for the first 25 000 steps and $1e^{-5}$ for the last 75 000 steps to ensure the loss curve oscillates around zero and does not decrease further. Finally,

TABLE II
PLUME AND RELATED VARIABLES INFORMATION

Variables		Unit	Data resource	Time scale	Data Parameters				Number	Pearson correlation		
					Max	Min	Mean	Median		<i>S</i>	<i>DIR</i>	<i>θ</i>
Area	<i>S</i>	km ²	Landsat ^a	1984-2018	334.69	21.58	131.02	121.49	254	/	/	/
Direction	<i>DIR</i>	degree	Landsat ^a	1984-2018	359.71	267.21	309.67	307.67	254	/	/	/
Spreading angle	<i>θ</i>	degree	Landsat ^a	1984-2018	123.03	22.65	65.09	62.05	254	/	/	/
Wave height	<i>H_w</i>	m	WAVEWATCH ^b	1997-2018	2.665	0.210	1.080	1.089	204	-0.39	-0.52	-0.59
Wind speed	<i>U_w</i>	m/s	NCEP ^c	1982-2018	12.79	0.62	6.43	6.67	254	-0.35	-0.57	-0.61
Current speed	<i>U_c</i>	m/s	HYCOM ^d	1994-2015	0.651	0.018	0.241	0.223	158	-0.15	-0.42	-0.36
Tide height	<i>H_t</i>	m	CSFR ^e	1984-2018	0.281	-0.174	0.023	0.007	254	-0.10	-0.21	-0.20
Discharge	<i>Q</i>	m ³ /s	River and Reservoir Watch ^f	1998-2018	12761	2247	4348	4350	202	-0.16	-0.21	-0.20

PlumeCatcher implements pixel-level recognition and gives contours of plumes with grayscale and overlapping images, respectively.

B. Boundary Condition Data

For each extracted plume image, it is possible to find information about the dynamic ocean factors corresponding to the moment in time when the satellite image was collected. To discuss the interaction between a plume status and mixed multiple dynamical factors found for the given environment, we use the Magdalena River as a case study because its boundary conditions are well-constrained: a microtidal tropical estuary with high river and water discharges [55], where river water discharge (*Q*), wind speed (*U_w*), current speed (*U_c*), wave height (*H_w*), and tide height (*H_t*) data are provided by an ocean model (Table II).

Before additional processing, it is necessary to conduct a cross-correlation analysis to determine the related variables belonging to the same distribution; additionally, the absolute value of the Pearson correlation coefficient (PCC; a measure of linear correlation according to Cauchy–Schwarz inequality) must be larger than 0.1 for each parameter shown in Table II. It should be noted that wind speed and wave height have strong statistical correlations (Pearson correlation coefficient = 0.87) when calculating related environment variable pairs, indicating that wave height is controlled by wind speed. In this circumstance, it is better to use the main control: wind speed. Besides wind and waves, other variable pairs show weak correlations, suggesting they exert largely independent controls on plume formation. It needs to be noted that wind direction is dominated by the north- and east-oriented winds that persist throughout the year, with the average value being 65°, while the current direction is mainly from the west, with a few reversing conditions; thus, the mostly unchanging and steady wind and current directions are not considered in additional analysis. Also, tide amplitude is used to represent flood and ebb currents, which reciprocate with W-to-NW directions, based on the NCEP Climate Forecast System Reanalysis (CFSR) model. In addition, monthly and yearly data are included in cases of seasonal and interannual variations (these influences are discussed below, in Section V-B). As a statistical measurement describing a value's relationship to the mean of a group of values, the Z-score, measured in terms of standard deviations from the mean, is an effective way of standardizing

and normalizing. For a given *x* value, the calculation of *z* is as

$$z = \frac{(x - \mu_0)}{\sigma} \quad (6)$$

where μ_0 is the mean value and σ is the standard deviation. A Z-score with a positive value indicates that the score is above the mean, and a negative score indicates that it is below the mean. Before feeding the model, data were processed as a Z-score result for normalization and mean subtraction to effectively avoid influence from different scales, and data with an absolute value modified Z-score >3.5 are considered outliers and thus removed from analyses.

IV. RESULT

A. Application of the PlumeCatcher Model: Magdalena River

As Table I shows, testing data from TM (Landsat 4/5) was used to verify whether the PlumeCatcher model learned to distinguish plume contours. The classification step has an accuracy of 90.8% (209/230) on the test dataset and, as Fig. S1 shows, the ability to distinguish confusing areas such as the abandoned portions of the Yellow River delta, which possesses elevated suspended sediment concentration (18/19), and the fan-shaped area formed by sand bars and waves near the Brazos River (3/3). Other confusing areas include where winter sea ice is present, as well as the occurrence of thin clouds [Fig. S1(b)].

For plume location identification, the object detection step marked 93/130 images with a correct location without omissions or error identification on images with more than one plume per figure. Some results are shown in Fig. S2(a). Most of the erroneous results come from large rivers with multiple estuaries, such as the Kula River and Indus River, where small-scale plumes may be missed. Still, the main plume, with its large size and complete shape, can be accurately captured and used in the next step.

To quantify the model performance better using the example river, 128 images only from Magdalena River were used to test the plume area recognition for the Semantic Segmentation step. Some results from different satellite resources are shown in Fig. S2(b). Using the number of pixel points of the recognition result as area model data and compared with the labeled result, the quantile–quantile plot in Fig. 4(a) shows that the labeled dataset and model dataset obey the same distribution with good correlation (PCC = 0.6), similar to the accuracy result (0.668) of the FCN model trained with a large

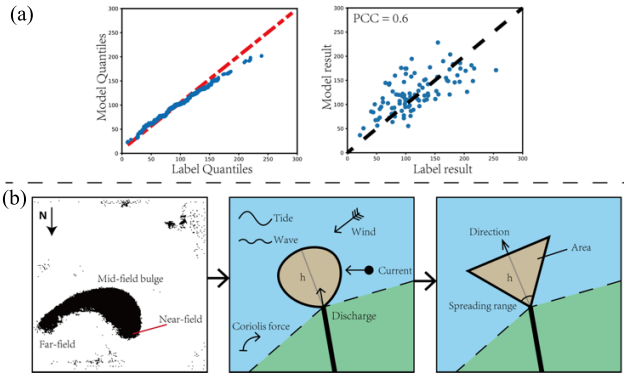


Fig. 4. (a) Quantiles–quantiles figure and comparison between label result and model result with the PCC-value. The comparison test is based on label data and model results in plume area calculation. (b) Plume feature data schematic. Plume area (S) is calculated from the PlumeCatcher model result. Related dynamic variables and corresponding directions near the Magdalena River estuary have been marked including wind, current, wave, tide, and discharge.

dataset of normal images [56]. This indicates that the PlumeCatcher model could be used to explore high-quality plume data.

A reason for using the Magdalena River is that, among the river datasets described in Table I, Magdalena River is only the natural river system maintaining high sediment concentration with a single channel and coherent, identifiable plume, that is, the river does not maintain a braided network with multiple active channels that could produce overlapping plumes. To analyze the physical meaning and the evolutionary trend over time, the example river should have not only abundant clear satellite image with few clouds, but also only one main channel straight into the sea and a complete plume profile without the impact of surrounding coast, and the Magdalena River is a perfect example for this analysis. Additionally, the geographic region of the Magdalena River renders it with abundant clear satellite images (i.e., few clouds). Hence, the Magdalena River, with its channel extending to the coastal area and common occurrence of cloudless weather throughout the year, means that it characterized by an abundance of data with good recognition results to train the PlumeCatcher model, and so this system is a natural laboratory for our data-driven plume analysis research.

Located in South America, the Magdalena River debouches into the Caribbean Sea at $11^{\circ}06'N$, $74^{\circ}50'W$ with abundantly available coastal hydrodynamic data to assess. Finally, 254 plume contours of Magdalena River were obtained by the PlumeCatcher model based on Landsat satellite images from 1984 to 2018. Previous research indicates that the plume width is proportional to the radial distance from the mouth [57], thus it is possible to consider an isosceles triangle to represent its geometry, whereby the orientation can be used as a symbol to describe plume planform. Furthermore, the related parameters include plume area (S), plume direction (DIR), and PSR. S is calculated from the PlumeCatcher model output based on the conversion of recognized plume pixels from an image to an area of coverage. DIR is defined by the vector direction from the river mouth to the point of maximum distance for the plume margin, and PSR is

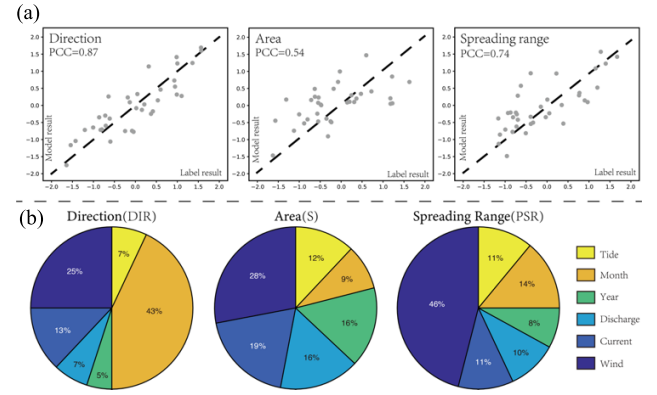


Fig. 5. (a) Comparison between data and regression model results using RF data mining algorithm with PCC result. Both label and model data use the Z-score method for normalization. (b) Importance of variables (normalized score) in the RF regression model.

calculated based on the area and distance measured for the plume shape and its geometric form [Fig. 4(b)].

According to the above calculation methods, data extraction was carried out based on the 254 identified plumes, with the results of the corresponding parameters shown in Table II. The area (S) shows significant variability: $21.58\text{--}334.69\text{ km}^2$ with a mean value of 131.02 km^2 . The spreading angle (PSR) has a minimum value of 22.65° and a maximum value of 123.03° . The plume direction (DIR) is northwest (mean value: 310°), with a range of $267^{\circ}\text{--}359^{\circ}$.

B. Plume Impacting Factor Analysis

To discuss quantitatively how environmental factors impact plume structure and spreading under multiple timescales, visible or potential, the RFs method is applied here to obtain the coupling degree of multiple factors and help with the plume state inversion.

To meet the assumption of the RF model, the dataset of plume parameters and boundary conditions should have the same time scale without multicollinearity and outliers. Focusing on the example from the Magdalena River, the final dataset includes 146 samples from 1998 to 2015, which are randomly separated into training (75%, 110 samples) and validation (25%, 36 samples) subsets.

The RF regression model used here contains 300 estimators. As a black-box algorithm, the RF model does not provide an exact regression basis; still, it can be used to rank the importance of variables through a normalized score [48]. An abstractive definition method examines the plume as a triangle limited by the area (S), direction (DIR), and spread (PSR), values obtained from PlumeCatcher. To test the accuracy, a validation subset has been used in comparison to the RF model result with the PCC test [Fig. 5(a)]. The analysis shows a relatively accurate result as most points are located around a 1:1 line, while PCC marks a medium to strong correlation (0.54–0.87), indicating the RF model could be used to estimate the plume shape and features near the estuary.

In the analysis of the Magdalena River plume, score values result for plume features based on the training set [Fig. 5(b)]. For plume area (S), the related variable range is

$$U_w(0.28) > U_c(0.19) > Q(0.16) \\ \approx Y(0.16) > H_t(0.12) > M(0.09)$$

indicating that wind is the most significant factor and that time series is unimportant. For plume direction (DIR), the sorting result is

$$M(0.43) > U_w(0.25) > U_c(0.13) > H_t(0.07) \approx Q(0.07) \approx Y(0.05)$$

clearly showing the seasonal variation trend. For PSR, the importance ranking is as follows:

$$U_w(0.46) > M(0.14) > U_c(0.11) \approx H_t(0.11) > Q(0.10) > Y(0.08).$$

As indicated, the wind is the undisputed controlling factor of PSR.

V. DISCUSSION

A. Model Evaluation

The development of the PlumeCatcher model makes it possible to evaluate large quantities of data automatically and quickly using satellite images, thereby enhancing temporal analyses of rivers with visible plumes and related high turbidity areas.

As a widely applicable and efficient method, ML algorithms play a significant role in supporting data analyses and supplementing original results, to help provide breakthroughs in scientific understanding. Using the CNN structure, the trained PlumeCatcher is shown to be an efficient and accurate model for supplying data on the evolution of river plumes, which can be used for evaluating the development of these features with changing environmental boundary conditions. Based on the three-step structure developed here, the model provides significant data pertaining to the plume and requires only limited training and cost, minimizing difficulty in adapting the model for application to other systems. Furthermore, the time required is short: after training, each step of PlumeCatcher requires only 5–6 s to recognize the image and collate data, and therefore large quantities of satellite images can be analyzed quickly. Also, the model can distinguish the river plume area from high-turbid near-shore regions where coastal processes, including wave- and upwelling-induced bottom currents resuspend coastal sediment.

Compared with the existing methods that identify plumes and relate this information to sediment transport research, PlumeCatcher provides a large data source from which to supplement in situ data collection and enhance environmental factor analyses.

B. Plume Features and Physical Form

The transport of terrestrial material to coastal regions is, to a certain extent, dependent on how river mouth plumes spread and mix with marine water, which is primarily affected by dynamic coastal processes. As described, three features are used in the RFs method to determine plume metrics [Fig. 4(b)], so it is pertinent to discuss the physical meaning of each feature.

The plume distribution identified in this study marks the area of contrasting, visible color differences, which indicates the boundary between near-shore (marine) water and river

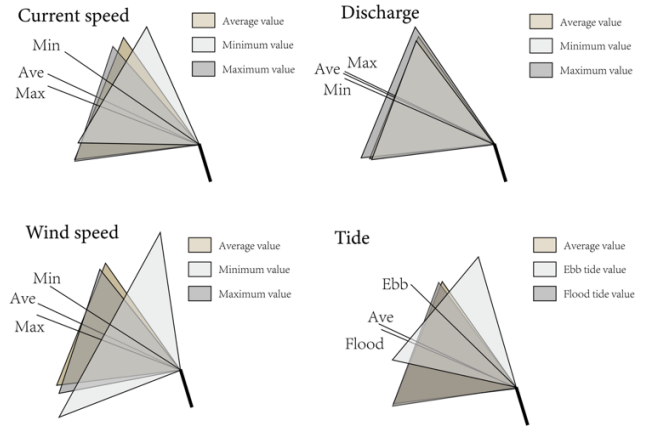


Fig. 6. Plume shape variation under short-timescale event, including current speed, discharge, wind speed, and tide. Except for the varied factor, all other control factors are based on the value of May 2007. The research time is from 1998 to 2015.

discharge that maintains a comparatively high suspended-sediment concentration. As an important intersection of the source-to-sink system, the plume disperses sediment and other terrestrial materials and plays a key role in sediment supply, thereby influencing the dispersal of terrigenous sediment, nutrients, and contaminants along the coast and subaqueous delta [1], [58]. Typically, the larger the plume area, the greater the coastal region that is affected by river sediment delivery.

As the vector direction from the estuary to the farthest point of the plume contour, the parameter of plume direction indicates the farthest location of the high-turbidity water body, reflecting the directional movement of the sediment suspended within the plume.

Here, we differentiate the PSR from previous studies, which typically treat the water emanating from the river mouth as a jet with a certain spreading angle and a width proportional to the percent change in radial distance from the mouth [2], [57]. The PSR is a description of the overall shape of the plume rather than a theoretically derived, partial status. Thus, the PSR is an intrinsic parameter that describes the overall shape of the plume and is determined by the form identified and extracted from PlumeCatcher. The larger PSR, the wider sediment distribution, possibly resulting in the greater delta lateral expansion; conversely, the smaller PSR, the more dispersal basinward, possibly causing river mouth progradation. Thus, the unique shape of each plume could be identified by understanding S , PSR, and DIR, which can determine the related dynamic sedimentation distribution.

C. Plume Performance Under Different Timescales

Not only does the RF method provide an opportunity to analyze the dominant environmental factors affecting the Magdalena River plume, but it also gives the ability to establish a data-driven plume model and simulate plume status. Figs. 6 and 7 show the result of testing the model sensitivity for various boundary conditions, and the model result based on average boundary conditions is used as the standard for comparing. The maximum and minimum values of variable environmental conditions shown in Table II are

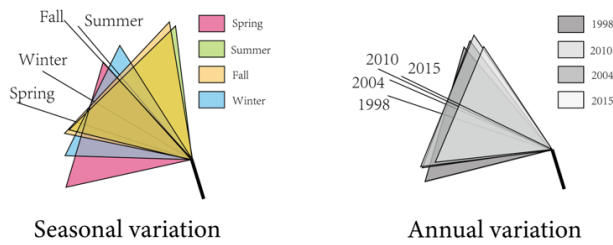


Fig. 7. Plume shape variation under long-timescale process, including seasonal variation and annual variation. For seasonal variation, the basic plume shape is generated with average environment conditions in 2007 under ideal status. Winter indicates January, Spring is April, Summer is July, and October is Fall. For annual variation, the basic plume shape is with average environment conditions in May under ideal status. The research time is from 1998 to 2015.

used to demonstrate plume variation trends under different timescales.

1) *Instantaneous Timescale (Tidal-Cycle Variation)*: Tidal forcing is highlighted to play a crucial role in terms of modulating river plumes, by way of directing ambient water [59]; hence, regular reversals of water movement caused by the ebb and flood tides should influence plume spreading.

The Magdalena River mouth region experiences diurnal mixed tides (Fig. 6), and the plume diagram indicates that the ebb and flood tides influence it by setting the direction (DIR), as the area stretches and expands. The tidal influence on the Magdalena River plume corresponds to field observations from the River Teign [60], MODIS observations from the Cantabrian River [61], and numerical experiment results from the Changjiang River [62], all of which show greater and more turbid plumes during ebb tide. Tidal forcing influences the plume by triggering vertical mixing of the water column through stratified-shear flow instability [63].

The most notable characteristic of the Magdalena River plume structure is the asymmetry in the displacement over a tidal cycle. With ebb tides, the plume is extended in the seaward direction, whereas the plume has no clear variation on the flood tide. Basdurak et al. [64] described a similar response in modeling river plumes and explained the phenomenon as the result of the combined effects of river discharge, near-shore currents, and Coriolis forcing.

2) *Short-Term Timescale (Daily Variation)*: As largely a competition between the cross-stream pressure gradient and Coriolis forces, plume spreading is primarily controlled by wind, currents, and river discharge [65]. While daily hydrodynamic data have been used in RF analysis, plume features model results reveal plume variation over a short (daily) time scale.

Wind, as the dominant variable, is the primary influencing factor of S and PSR, and the secondary factor of DIR. Opposite to Coriolis force, wind near the Magdalena River mouth induces upwelling, increasing the seaward excursion of the plume and reducing the original along-shelf momentum, which makes the plume advect offshore by cross-shore Ekman transport, and enhances freshwater into coastal flows instead of spreading near the mouth [8], [11]; hence, the plumes tend to shrink and turn left with increasing wind speed (Fig. 6).

Similar to wind, the ambient coastal current is an external forcing agent that significantly influences the plume, therefore the plume PSR shrinks, and DIR turns left, with increasing current speed. Unlike the wind force, which is confined to near the sea surface, the entire water body may be affected by currents, which leads to a more sensitive result: even a relatively small current speed is sufficient to influence the transport of water and suspended sediment [66].

Though external forcing parameters have similar trends, a bulge, an unsteady and anticyclonic eddy circulation controlled only by wind speed [3], will significantly influence PSR and shrink the plume area even for minimum wind speed. A bulge will form offshore of the river mouth in low-wind-speed situations, expanding continuously and accumulating 25%–75% river discharge [67], which will result in an expansion of the plume area as indicated by satellite images and far-field transportation diminution. Fig. 6(a) shows an obviously wider and flatter plume area under minimum wind speed, while minimum current has a similar area trend compared with the standard area.

Different from other external influences, river discharge mainly affects the plume by changing its momentum such that a high initial status tends to maintain the original state of the river water, and does easily change even due to other changing forces [68]. The north-east direction and larger PSR coincide with maximum discharge. The higher discharge could provide more fresh water to extend the plume, resulting in a larger plume area. Meanwhile, river water discharge plays a primary role in the near-field, with a diminishing influence farther from the mouth. Therefore, the plume has a similar seaward transportation trend across a range of discharge conditions.

3) *Mid-Term Timescale (Seasonal Variation)*: The most obvious effect of seasonal variations is to produce fluctuating boundary conditions including wind speed and river water discharge. However, it is worth noting that other environmental factors may also have some potential seasonal impacts that cannot be discerned quantitatively. These include the possible density and salinity variations in ambient near-shore water, which could be caused by thermohaline changes in the ocean, rainfall changes, possible variations in river sediment loads that could encourage hyperpycnal (plunging) plumes [1], and increasing terrigenous sediment runoff due to changing vegetation coverage [69]. Here, the analysis of the monthly time scale reveals seasonal variations of the plume (Fig. 7) under ideal status given average environmental conditions.

As shown, Winter (December–January–February, or DJF) and Spring (March–April–May, or MAM) have similar characteristics, while Summer (June–July–August, or JJA) and Autumn (September–October–November, or SON) share the resemblance of the example year (2014). Fig. 8 shows the environmental parameters' daily values, which could be combined with a seasonal timescale analysis. Continuously strong wind forcing during DJF minimizes the plume area, as indicated by a shrinking PSR. The enhanced coastal current speed makes the spring plume deflect to the west, while a variation in water density caused by temperature changes may also facilitate directional changes. In summer months, the plentiful freshwater supplied by the wet season results in the expanding

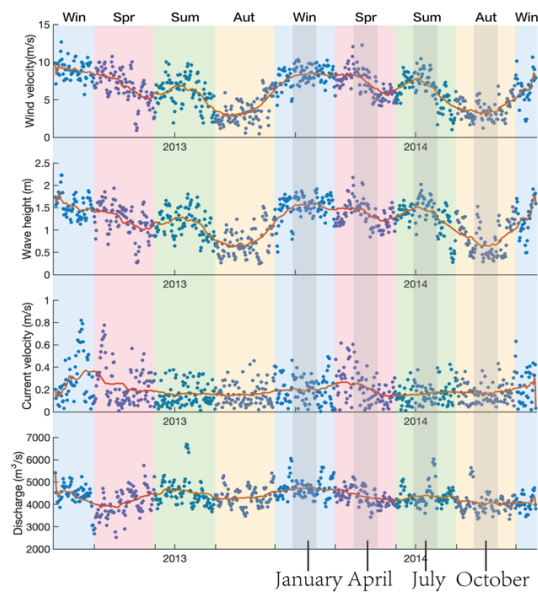


Fig. 8. Environment parameter daily value, 2013–2014, including wind velocity (m/s), wave height (m), current velocity (m/s), and river discharge (m^3/s). Marked with blue, Win means Winter, including December, January, and February. Marked with red, Spr means Spring, including March, April, and May. Marked with green, Sum means Summer, including June, July, and August. Marked with yellow, Aut means Autumn, including September, October, and November.

plume area as indicated by PSR values, while the plume trend is carried into the Autumn (SON) season with steadily decreasing wind and current speeds.

4) *Long-Term Timescale (Annual Variation)*: As an instantaneous process, the data used to observe plumes represent snapshots in time. This limitation leads to few studies that evaluate decadal variations in plume changes and regulation mechanisms. However, possible changes in environmental factors over longer-term time scales and impact on plumes, cannot be ignored, and such assessments could help analyze trends in coastal river processes. Here, the yearly parameter has been used in the RF analysis, and several time periods are chosen for comparative purposes, including 1998, 2004, 2010, and 2015 (Fig. 7).

With changing years, the most obvious variation in the plumes of the Magdalena River is reflected in the continuous eastward deviation of the direction (DIR). Considering those dynamic parameters, including discharge and wind speed, did not change significantly over the study period [Fig. 9(a)], the evident variation in plume direction could be caused by other environmental factors. Through the long-term observations of Magdalena River by Landsat satellite image [Fig. 9(b)], it can be seen that there are constantly accumulating sand bars near the north-eastern river mouth. Sand bar accumulation tends to be a long-term and relatively slow process, resulting in nonnegligible sediment flux and deposition that revises the plume direction [Fig. 9(c)], such that the variation of discharge incident angle causes changes in the plume direction [7].

D. Method Caveat

The analytical model and method performance presented herein relies upon considerable conditions; thus, limitations

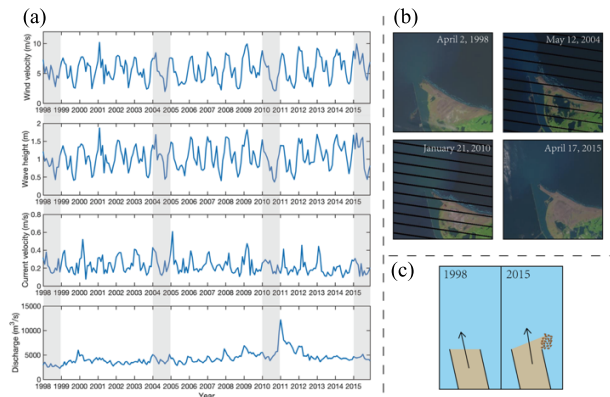


Fig. 9. (a) Environment parameter month average value in 1998–2015, including wind velocity (m/s), wave height (m), current velocity (m/s), and river discharge (m^3/s). The gray line marked the years 1998, 2004, 2010, and 2015. (b) Satellite images of Magdalena River on April 2, 1998 (Landsat 4–5), May 12, 2004 (Landsat 7), January 21, 2010 (Landsat 7), and April 17, 2015 (Landsat 8). (c) Diagram of sand bar accumulation near the river from 1998 to 2015.

must be discussed. First, plume features calculated from PlumeCatcher describe the dynamic characteristics of plumes when features including area, direction, and spreading angle can be combined to determine the approximate distribution state of the plume at the river mouth. Thus, the geometric form may not be completely consistent with the actual environmental situation.

Second, due to changes in suspended sediment concentration within the plume, the variations in the color between the plume and the surrounding seawater may also lead to inaccurate data extraction. Our model may not be applicable for plumes with low suspended sediment concentration.

Finally, though preprocessing and the steps outlined for PlumeCatcher have been applied for the goal of extracting data and reducing the difficulty of training, the approach likely represents the minimum amount of data required for a usable model, so that the model cannot be trained well if using less data. The recognition rate of the satellite data is still low compared to general image recognition, so limited satellite images could restrict accuracy. For example, in the first step of the classification, only about ~ 100 images are needed to finish the training for typical image recognition (e.g., as has been applied for studies considering objects such as cats, dogs, cars, etc.), but in our case, approximately 400 satellite images were used to achieve a similar recognition level. Also, the existing basic structure used in PlumeCatcher, such as SSD and FCN, is reliable and relatively easy to train, but it has a limited recognition rate. Additionally, the model remains less effective at identifying complex water environments, such as multiple channels, compared to a complete plume emanating from a single channel.

E. Future Work

The suitability and accuracy of plume recognition will improve with an expanded dataset and an improved ML structure. For example, alongside the Landsat series, images from MODIS and GOCI could be added to the data pool to supplement the analyses. To solve the problem that the model

can only identify under turbid water conditions, satellite salinity data can be introduced to improve the applicability of the model by using the saltwater–freshwater interface as a more accurate plume edge. Also, the new satellite-filling method can eliminate the gaps in the picture [70], without being affected by external environmental factors such as sand content and clouds.

The performance of the new semantic segmentation model can be expected on more detailed segmentation and more accurate recognition, such as DeepLabv3+ [71] and Mask-RCNN [72], while the first use spatial pyramid pooling module and encode–decoder structure to capture sharper object boundaries faster, and the last with region-CNN structure performs foreground/background segmentation by combining semantic and direction prediction.

With the help of more data and efficient network structures, the next focus of our research is to extend the applicability of the model and provide more plume data for worldwide analysis. The improved model result will enable the plume inversion to carry out data-driven synergistic analysis of spatial and temporal variations of the multiriver estuary and to improve the knowledge of estuarine plume morphology under complex environmental conditions.

VI. CONCLUSION

Existing studies on plumes have focused mainly on the instantaneous state variations, using in situ measurements, laboratory/experimental data, and numerical modeling. Limited by the data quantity and quality over time and space, it is difficult to discuss the significance and degree of coupling between different factors of the dynamical near-shore environment, and therefore rarely have studies focused on analyzing variations in plume trends across variable time scales. Alongside data collection, the data mining process and characteristic analyses provided herein demonstrate a new method for analyzing river plumes with relatively high suspended-sediment concentration, to understand how the plume is affected by diverse environmental factors.

To achieve the plume data extraction, a deep CNN model, PlumeCatcher, is trained to analyze plume spreading shape as depicted based on a collection of natural-color Landsat images for rivers of relatively high sediment discharge from around the world. To obtain better recognition on a relatively small satellite image dataset, the model uses multiple steps, including a preprocessing step, classification step, object detection step, and semantic segmentation step, to improve recognition efficiency and reduce training difficulty. The original satellite images provide plume information, including area (S), direction (DIR), and spreading range (PSR), based on the model outputs. The Magdalena River is used as a test example, providing more than 250 images for analysis.

An RF data mining algorithm was used for plume controller analysis, obtaining plume status description (with significance order for several factors). It is determined that wind has been the most sensitive factor among the Magdalena River plume environment controls, while other factors can have impacts on different timescales. Impacted by ebb tides, the plume is clearly modified over instantaneous timescales, including

an eastward direction and larger area. The wind affects not only the river mouth, where the plume emanates, but also the range of seaward sediment transport, thus stronger wind will initiate a shrinking spreading range and increasing seaward excursion. Furthermore, near-shore currents and river water discharge have opposite actions on the plume structure over daily timescales, illustrating the competition between self-momentum and external force. Seasonal fluctuations in the plume demonstrate the sum of the quantifiable and unquantifiable boundary conditions, including thermohaline variation, sediment loads, and precipitation, while statuses throughout winter and summer contrast. Over longer timescales (years), discharge changes resulted in sediment accumulation near the river mouth that affects the plume direction.

The proposed machine-learning-based methodology demonstrates its capability of using remote data to analyze multiple factors affecting the dynamics of river plumes. The PlumeCatcher model provides data with overall parameters that are otherwise difficult to obtain by traditional in situ measurement methods for river plumes. Future work combining the model and real-time field observations will improve its performance. Data obtained by PlumeCatcher show the ability to quantify the impact of features over multiple timescales, to evaluate the importance of factors that modulate plumes, using data mining algorithms. This technique can be extended to provide assessments of long-term shifts in the processes of rivers and near-shore coastal environments.

It is expected that the methodology presented in this study could be replicated for other large rivers worldwide that maintain high sediment concentrations, which could be helpful for studies assessing the movement of terrestrial materials across the source-to-sink continuum.

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