

ADVANCING OCEAN PREDICTION SCIENCE FOR SOCIETAL BENEFITS

7.3. Fisheries and maritime operations

Tran-Vu LA Luxembourg Institute of Science and Technology

# **Insight into Maritime Surveillance Through Integrated Multi-Source Satellite Imagery**

Monitoring Oil Spills, Detecting Vessels, and Observing Extreme Weather

## **Oil Spill Detection and Monitoring**

40°E	45°E	50°E	55°E	60°E	_
30°N		S-1 (28-03-2	021, 14:33:06)	X	30°N
S5°N	Area of in	nterest S-2	(27-03-2021, 0	6;56:21) use Hard	25°N
20°N		-03-2021, 06:3	4:43)		20°N
40°E	45°E	50°E	55°E	60°E	
54°E	56°E	58°E	60°E	62°E	
20°S	- E	S-1 IW	(10-08-2020, 01	1:37:55) f interest	20°S

E 80°E	Floating Oil Slick		Offshore Qatar				
30°N	Case study	Date	Sensor	Time lag (hour)			
33:06)			Sentinel-2	Sentinel-3		S-2/S-3: 24 h	
2021, 06:56:21)	#Q1	27–28 March 2021	06:56:21	06:34:43	Sentinel 114:33:0628/03	S-3/S-1: 8 h	
THR /			27/03	28/03	114.35.00207.05	S-2/S-1: 32 h	
20°N			Sentinel-1	Sentinel-2	Landsat-8	S-1/S-2: 4 h	
E 60°E	#Q2	5–6 July 2021	02:23:25 05/07	06:56:21 05/07	06:58:26 06/07	S-2/L-8: 24 h	
60°E 62°E						S-1/L-8: 28 h	
Area of interest	#Q3	3 September 2021	Sentinel-1 02:23:54	Sentinel-2 06:56:21		S-1/S-2: 4 h	
0, 11:12:41)	Fixed-sou	arce oil slick		Offshore	Mauritius		
()							

Satellite imagery being one of the most effective tools for observing offshore oil spills over large areas, due to its high spatial resolution and wide swath coverage.

 $-\Box$  Radar sensors acquiring data in most weather conditions, while optical sensors providing more detailed information on oil characteristics (thickness and viscosity)  $\rightarrow$  <u>combine</u> images from multiple sensors not only detecting oil spills early and rapidly, but also monitoring oil drift over both short-term (within several hours) and long-term (over one or several days) periods. **Oil Spill Monitoring** 



**ICEYE-X (11-08-2** 

	Sentinel-1 IW	Sentinel-1 EW
-11 August 2020	01:37:55	14:36:16
	10/08	10/08

	IW/EW: 13 h
ICEYE-X 11:12:41 11/08	EW/ICE: 21 h
11.12.11 11, 00	IW/ICE: /34 h



### **Multi-Scale Vessel Detection**

- Deep Learning (DL)-based ship detection from optical imagery widely used in maritime surveillance, as it can efficiently process large volumes of data under cloud cover and challenging weather and ocean conditions.
- □ Numerous previous studies focusing on ship detection using high-resolution (HR) optical images, largely due to the availability of extensive HR datasets, relatively few studies have explored ship detection using medium- and low-resolution optical images.
- □ In maritime surveillance, especially in emergency situations, integrating images from different satellite sensors having proven to be an effective and practical

### **Performance of Various DL Models**



method for detecting and tracking ships, given the extended revisit times between image acquisitions  $\rightarrow$  need to propose appropriate learning approaches?

### □ Objectives:

- ◆ Building up various optical datasets (Planet, Sentinel-2, Gaofen-1/6, and Landsat-8)
- Training DL models on one dataset and testing them on others,
- Training DL models on the combination of various datasets consisting of diverse contexts and under different sea state conditions, and testing on others,
- Assessing the performance of the proposed strategies to assess the impact of small-scale cloud patterns and turbulent met-ocean on ship detection.

Dataset	Spatial resolution	Swath width	Repeat cycle	Data availability				
PlanetScope	3 m	25 km	daily	Commercial	Data division	One dataset	3 combined datasets	4 combine datasets
Sentinel- 2A/B	10 m	100 km	5 days	Public	Training	(sub-image)	(sub-image)	(sub-image
Gaofen-1/6	16 m	800 km	4 days	Limited	Validation	67	201	268
Landsat-8	30 m	185 km	16 days	Public	lest	67	201	268

Combining four datasets with varying spatial resolutions (high, medium, and low) significantly enhancing ship detection, especially for Gaofen-1/6 and Landsat-8/9 imagery, as the appearance of ships on the sea surface remains relatively consistent across most optical images.

□ Integrating multi-sensor images for training models being essential for effective ship detection  $\rightarrow$  help to overcome the limitations of scarce high-resolution images and insufficient annotations for training.

imagery to increase the diversity of training data, providing an effective and practical solution to enhance ship detection accuracy for limited optical datasets.

□ For future work, it would be valuable to explore whether combining small training datasets from multiple sensors can effectively compensate for the lack of extensive data from a single sensor.

## Mesoscale Convective System Observation and Monitoring



Extreme weather events, such as mesoscale convective



- systems (MCSs), thunderstorms, and squall lines, commonly observed in subtropical and tropical regions but increasingly affecting other areas, including Europe and the Middle East, due to climate change
- Severe CSs regularly produce hazards over the land and ocean, including strong surface winds (exceeding 25 m/s), heavy rainfall (above 10 mm/hr), and lightning.
- □ This study aiming to evaluate surface convective winds estimated from SAR data across numerous cases and to validate the relationship between strong surface winds and deep convective clouds, as proposed in previous works  $\rightarrow$  a significant step forward in enhancing our understanding of deep convection and its dynamics. Importantly, the results obtained are expected to enhance the prediction of convective winds.

#### SAR-estimated convective winds vs. in-situ measurements different periods of a convective wind gust

Case studies	Sentinel-1 sampling time (UTC)	Buoy (height, location, sampling time – UTC)	GOES-16 samplin time (UTC)
Case #1: early stage of a squall wind event	30 August 2020, 114940-115008	42012 (3.8 m, offshore New Orleans, 1100–1600)	114616-144116
Case #2: peak stage of a squall wind event	12 July 2019, 110954–111113	SPGF1 (6.6 m, offshore the Bahamas, 0900–1300)	104132-120132
Case #3: late stage of a squall wind event	5 May 2019, 231209–231349	41010 (4.1 m, off the east coast of Florida, 2100–0030)	214125-233125

Significant agreement between satellite-based wind speeds and in-situ data (not shown here) with even better matching for winds over 10 m/s.

□ Three specific cases illustrating various stages of convective squall events: before, during, and after the occurrence of a squall peak -> SAR-estimated wind speeds matching in-situ measurements, including the peak convective wind (18.90 m/s vs. 20.69 m/s), also matching deep convective clouds observed by GOES-16 sequential GEO images.

This study addressing multiple avenues for refining the Geophysical Model Functions to enhance surface wind speed estimation from SAR images. It also supports the development of both quantitative and qualitative climatology for convective versus synoptic events across different regions, as well as improvements in weather monitoring and forecasting.







Intergovernmental Oceanographic Commission



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