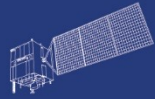


HY



HJ-1AB



CBERS



Gaofen



Beijing-2



Sentinel-1



Sentinel-2



Sentinel-3



Sentinel-5p



Aeolus

2023 DRAGON 5 SYMPOSIUM
3rd YEAR RESULTS REPORTING
11-15 SEPTEMBER 2023

[PROJECT ID.57971]

**[AUTOMATED IDENTIFYING OF
ENVIRONMENTAL CHANGES USING
SATELLITE TIME-SERIES]**

<13/SEPT/2023: 2:00PM - 3:30PM>

ID. 57971

PROJECT TITLE: MULTI-SOURCE AND MULTI-TEMPORAL REMOTE SENSING IMAGES FOR SHIPBUILDING PRODUCTION STATE MONITORING

PRINCIPAL INVESTIGATORS: [YAN SONG, YUNSHENG WANG]

CO-AUTHORS: [YAN SONG, YUHONG TU, ZEKAI LIU, WANROU QIN]

PRESENTED BY: [ZEKAI LIU]

Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since July 2020) for no. of scenes of high bit rate data (e.g. S1 100 scenes). If data delivery is low bit rate by ftp, insert “ftp”

ESA /Copernicus Missions	No. Scenes	ESA Third Party Missions	No. Scenes	Chinese EO data	No. Scenes
1. Sentinel-1	700	1. Google Earth		1. ZY-3	
2.		2. Map world		2.	
3.		3.		3.	
4.		4.		4.	
5.		5.		5.	
6.		6.		6.	
Total:	700	Total:		Total:	
Issues:		Issues:		Issues:	

- Use deep learning methods to observe shipyards based on multi-source and multi-temporal remote sensing image
- Explore the deep learning methods to analyse time-series Sentinel-1 datasets
- Develop deep learning architecture to fuse multi-source and multi-temporal RS images' features

The **shipbuilding industry** is important in national defense security, transportation, and marine development. Monitoring shipyard helps to master the profitability in time.

Satellite remote sensing data can monitor shipyard production state accurately from the perspective of space and time series efficiently, which makes up for the shortcomings of traditional methods of collecting order data.



Shipyards are located near the seashore or water shore, utilized to construct new ships and repair old ones, exerting a crucial effect in the shipbuilding industry.

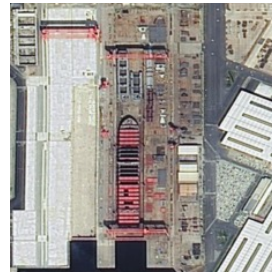
Photos of shipyards taken in Zhoushan, Hangzhou

RS images

Dock



Slipway



Ship under construction



Workshop



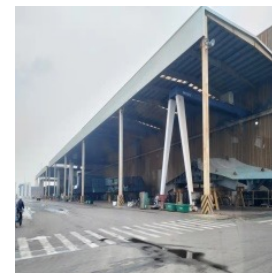
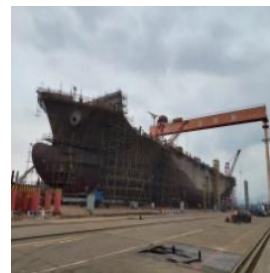
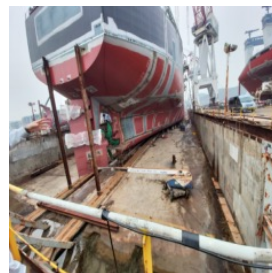
Material storage areas



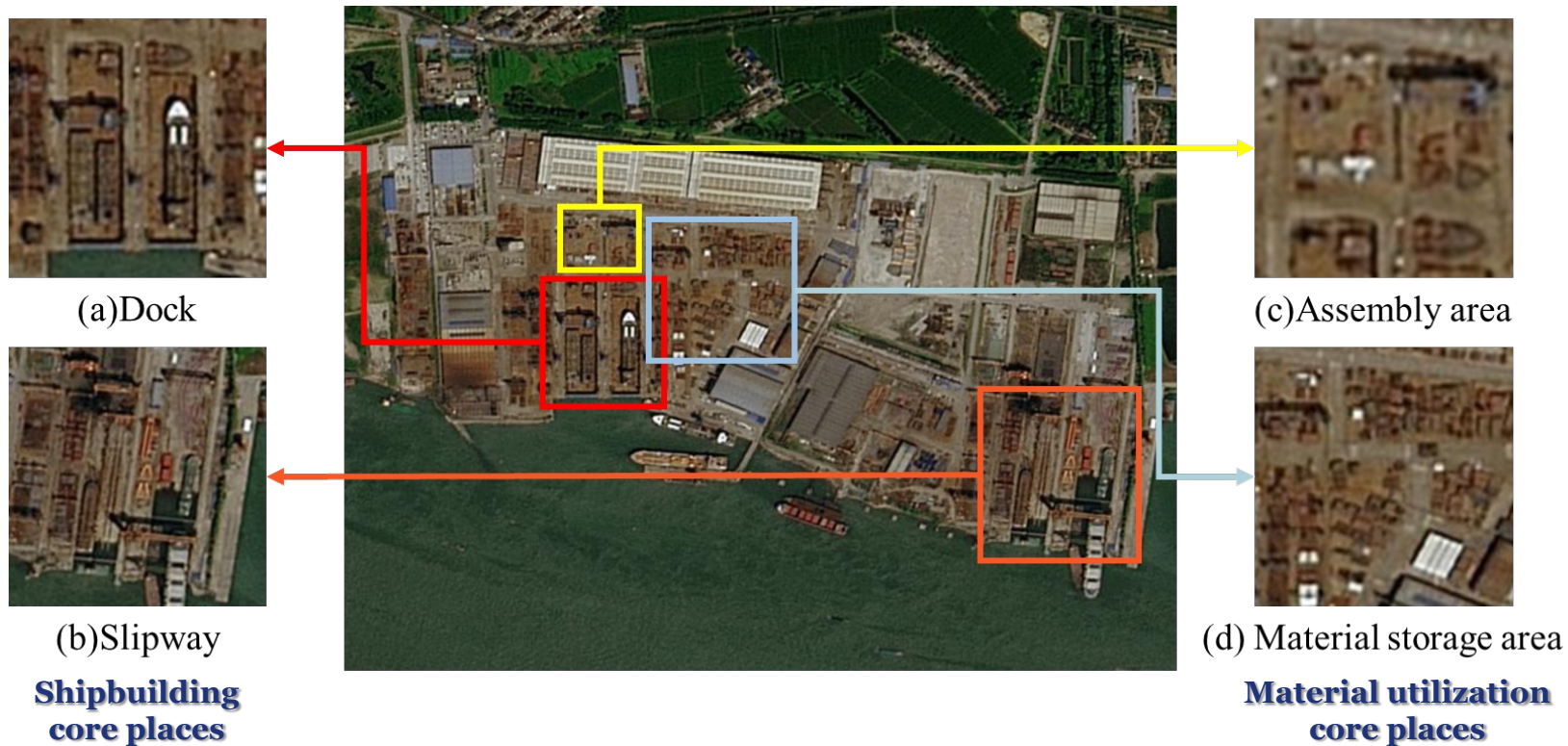
Assembly areas



Fieldwork photos



The shipyard scene includes the **docks**, **slipways**, **assembly areas** and **material storage areas** which are closely related to production.



This study performs **object detection network and status recognition network for docks** based on high-resolution remote sensing images and **deep learning methods**. Meanwhile, according to the imaging characteristics of optical remote sensing images and SAR images of shipbuilding places, we used satellite remote sensing data to dynamically monitor the **shipyard production state** from spatial and time series perspective.

In order to train the networks, a dock status dataset is proposed, which contains more than **1400 images** and **4600 docks**.

The dataset is collected from **Google Earth**, **map world (MW)**, and **ZY-3**. And the resolutions of the images are 2m, 0.5m, 0.5m, respectively

Dock dataset



GE

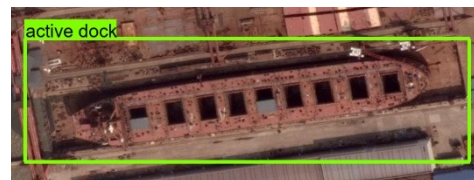


MW

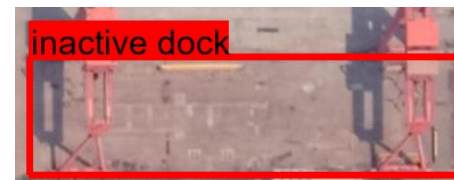


ZY-3

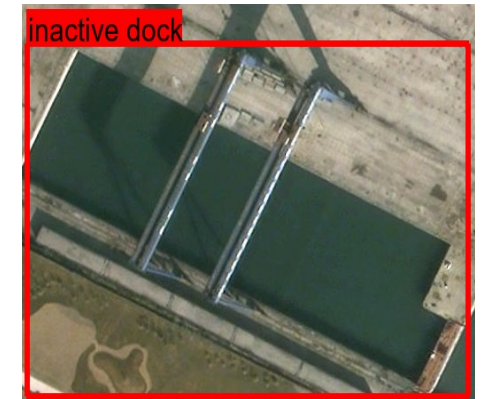
Status dataset



active

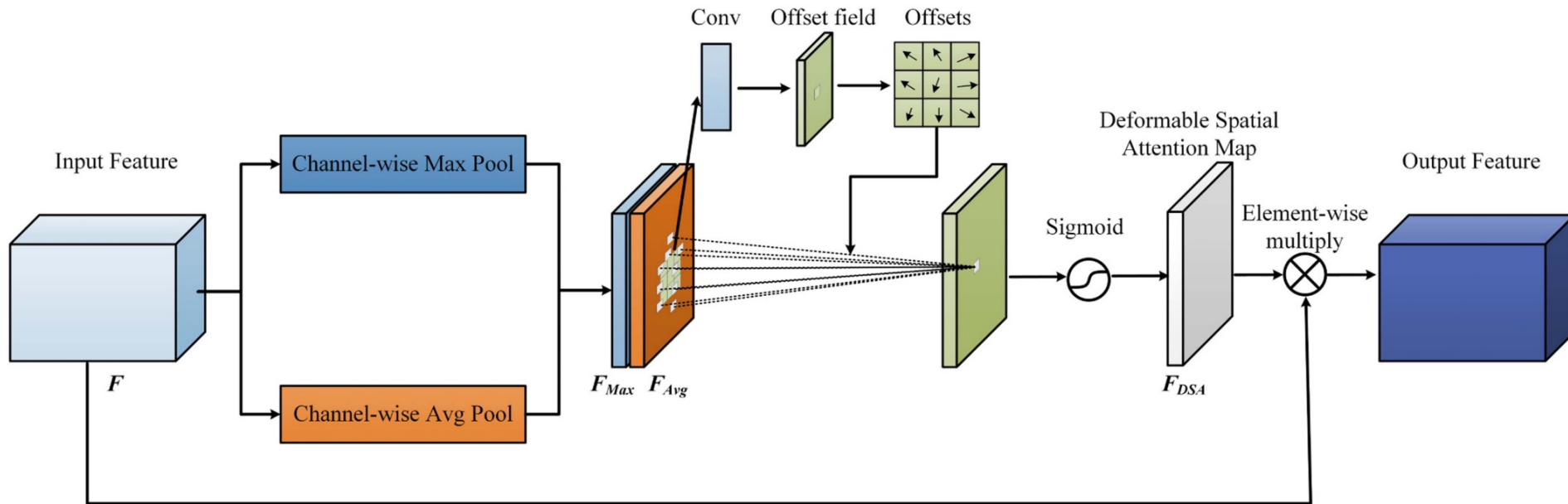


inactive



DSAM

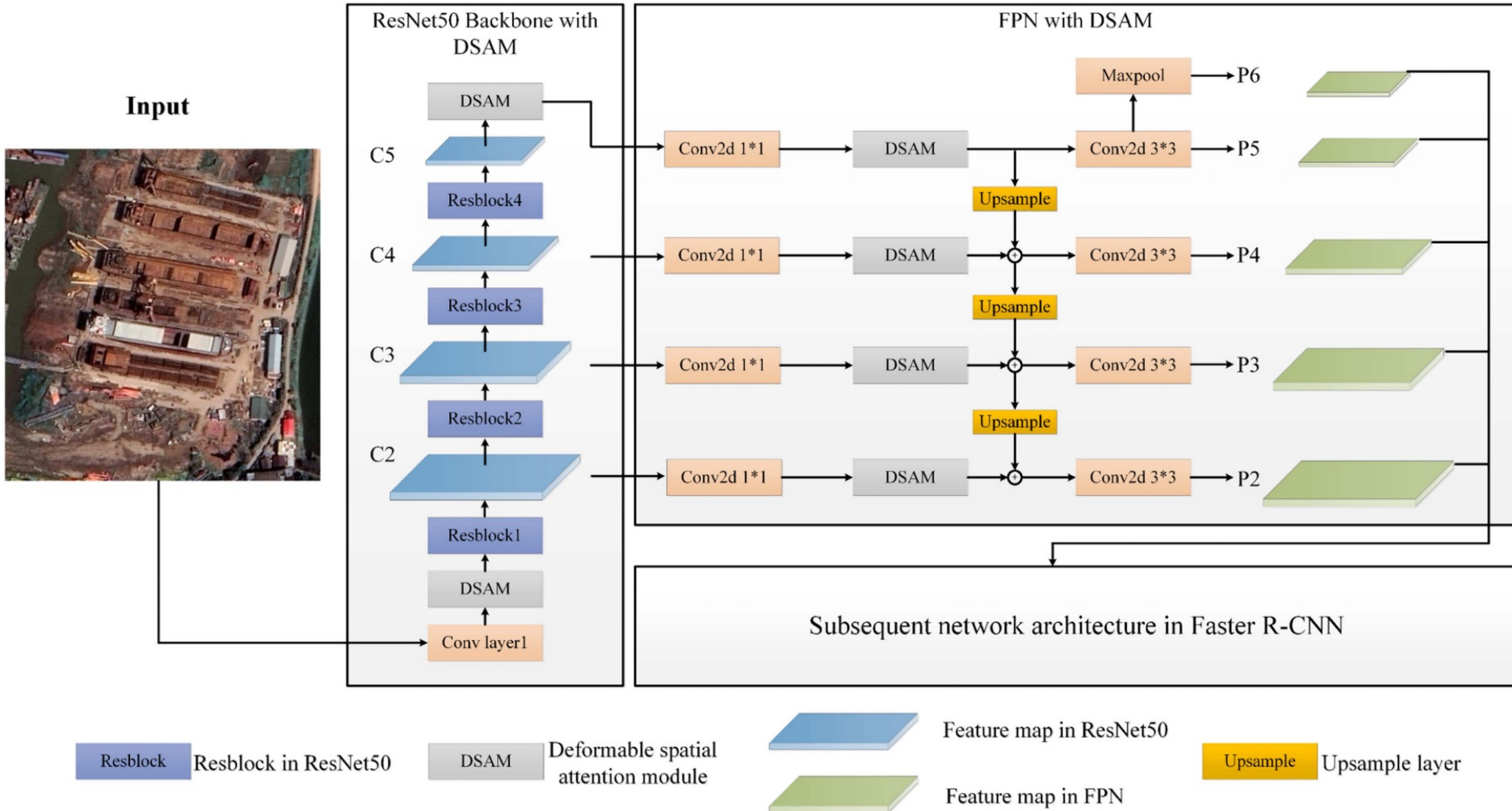
We use an object detection network based on the **deformable spatial attention module (DSAM)**, which can be used to detect the docks on high spatial resolution remote sensing image.



$$\begin{cases} F_{Avg} = AvgPool(F) \\ F_{Max} = MaxPool(F) \end{cases}$$

$$F_{DSA} = \sigma \left(f_{DC}^{N \times N}([F_{Avg}; F_{Max}]) \right)$$

$$F_{Out} = F \otimes F_{DSA}$$



Results of different kernel size in DSAM

Kernel size	Param.	mAP
9*9	41.50M	67.43%
7*7	41.41M	71.02%
5*5	41.37M	68.61%
3*3	41.36M	66.88%

Ground truth



Prediction



Results of different network architecture

Network	Backbone	mAP
Faster R-CNN	Proposed architecture	71.02%
	ResNet50+FPN(Without intermediate DSAM)	68.23%
	ResNet50+FPN(Baseline)	66.03%
	ResNet101+FPN	65.89%
	Xception	60.26%
	MobileNet	59.72%
R-FCN	ResNet50	63.47%
Sparse R-CNN	ResNet50	65.30%

Ground truth



Proposed

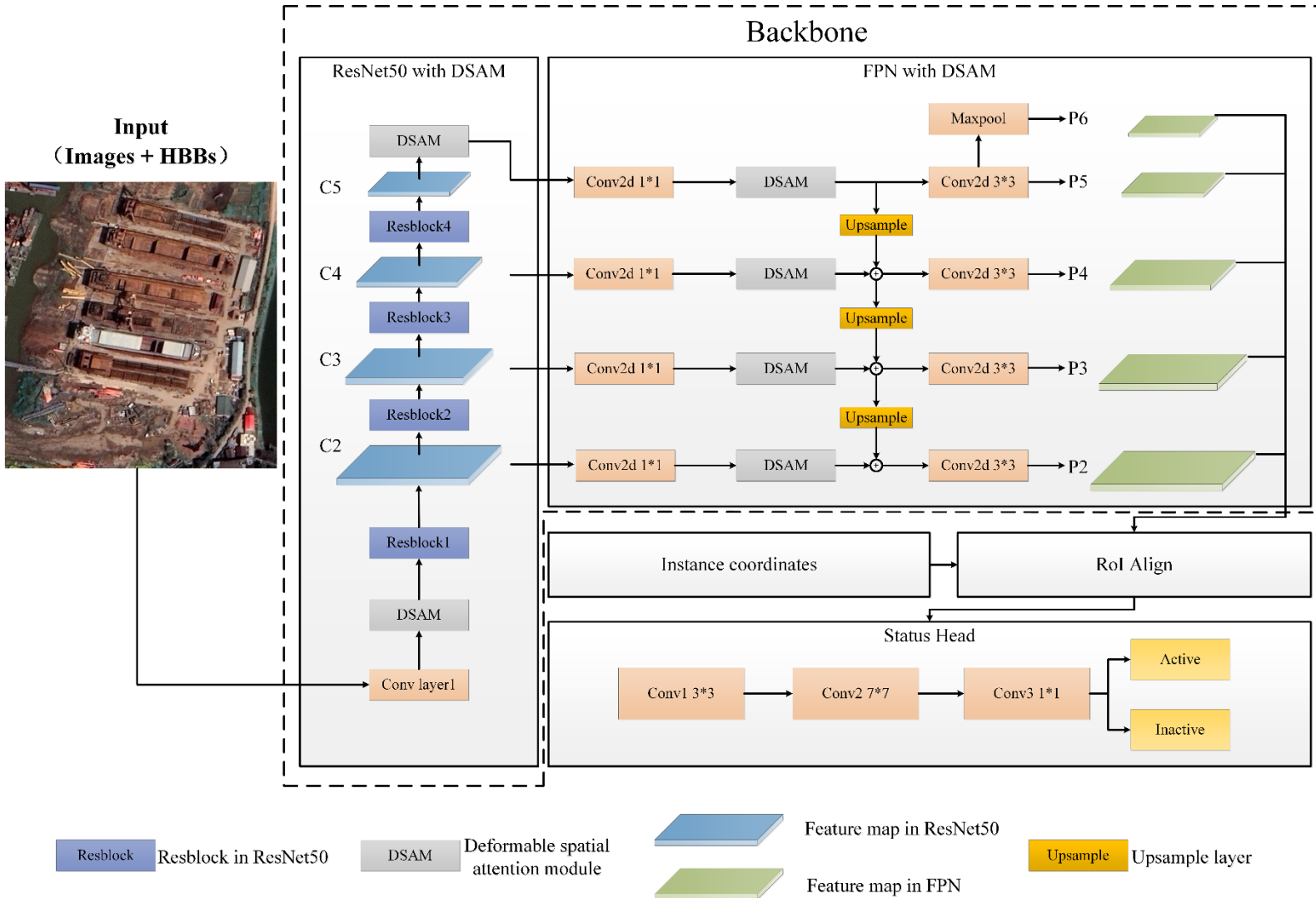


Baseline



Results of Ablation Experiments

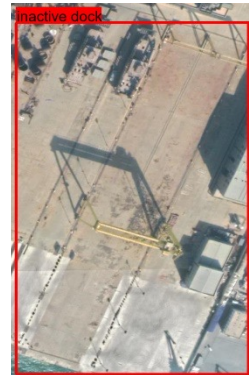
	Baseline	Baseline + Different settings				
DSAM	Faster R-CNN	√				√
CAM			√		√	√
SAM				√	√	
mAP	66.03	71.02	67.11	68.45	69.13	66.78
FPS	10	8	8	8	7	6
Param.	41.35M	41.41M	41.38M	41.36M	41.39M	41.45M



Since the backbone of the dock object detection network is with the excellent feature extraction capability for docks, this study connects the backbone with a lightweight status recognition network (Status Head) to determine the dock production status information based on the features extracted from the backbone.

The recognition results of different methods

Methods	R	P	A	AP	F1 score
Proposed method	94.36%	88.11%	85.48%	87.68%	91.12%
ResNet50	86.53%	87.97%	80.01%	83.27%	87.25%
GoogleNet	83.26%	86.65%	76.64%	81.23%	84.92%
Xception	80.71%	84.72%	73.26%	77.14%	82.67%
VGG	80.07%	87.39%	75.13%	77.26%	83.57%



(1) As shipbuilding period takes long, single phase observation data cannot fully reflect the production state in different shipbuilding stages.

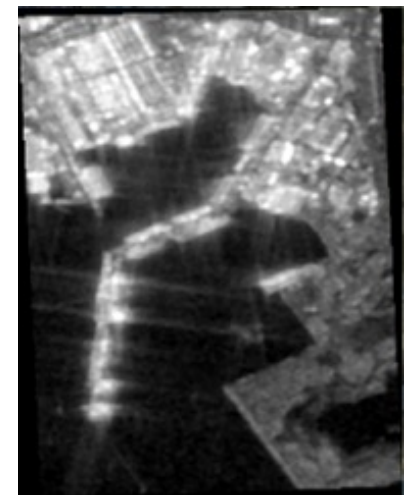
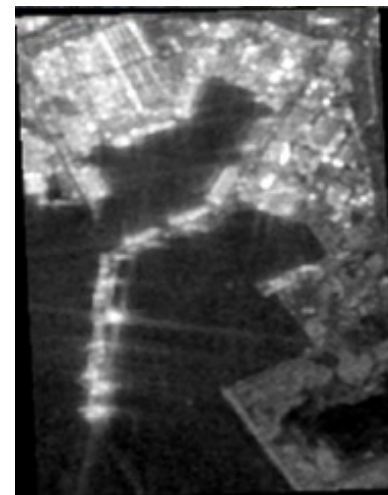
(2) Shipyards located in coastal areas or along rivers, so that cloudy or rainy day is common.

(3) Assembly areas and material storage areas are also closely related to production.

Multi-temporal SAR images for production status recognition

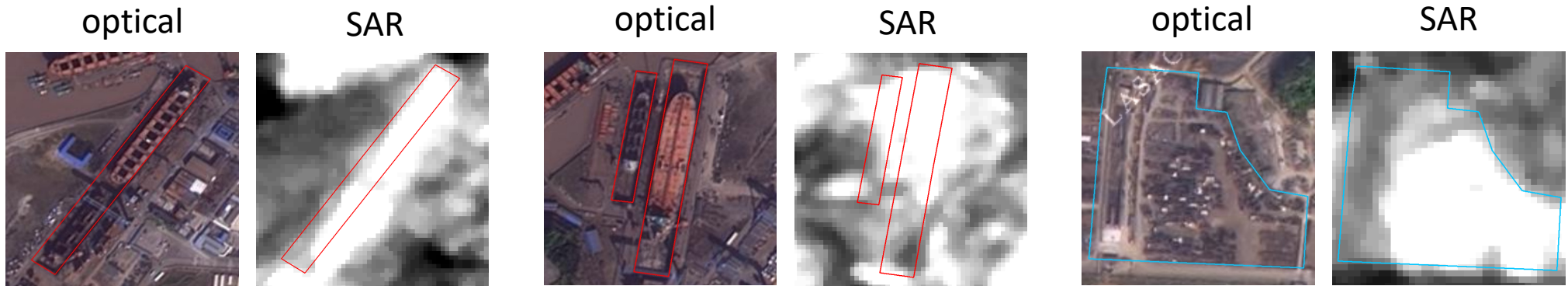
Synthetic Aperture Radar (SAR) with the merits of unaffected by weather can complement the optical satellite imagery for monitoring the shipyard production state fully.

As the shipbuilding procedure is long, the application of multi-temporal RS data to monitor shipyard production state is proposed to increase the amount of observation data avoiding errors caused by single phase data.

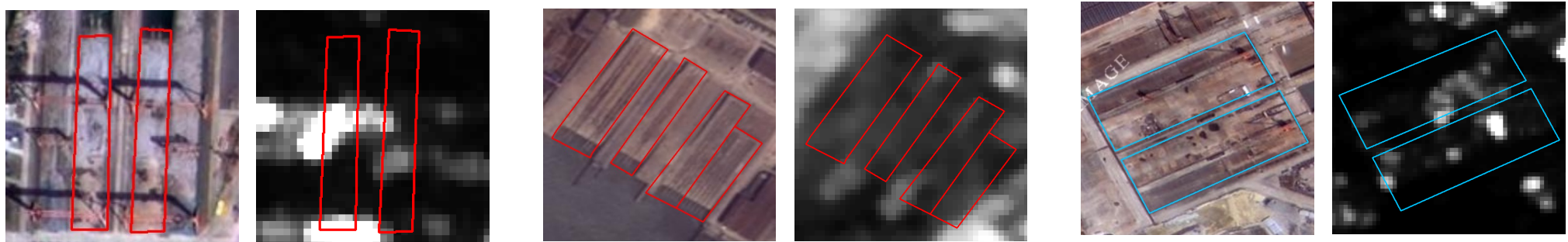


In order to find the connection between SAR images and shipbuilding production status, we statistics more than **150** shipyards and **1700** areas.

Active

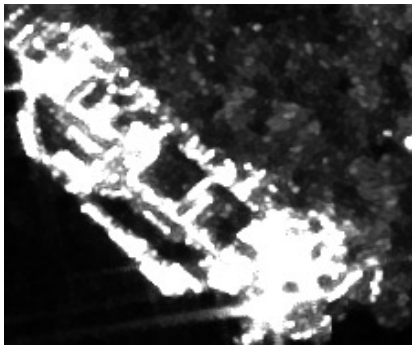


Inactive



dock/slipway

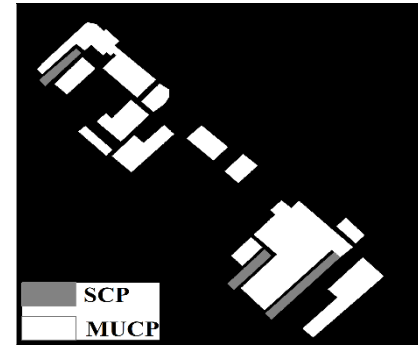
material storage area/assembly area



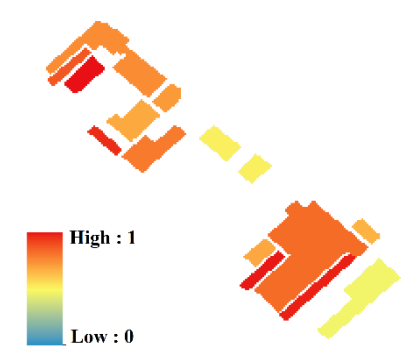
(a) SAR image



(b) Binary result



(c) Core places map



(d) Percentage of strong backscattered pixels

Pearson correlation coefficients between backscattered intensity features and production states for the SCP and the MUCP are **0.796** and **0.764**.

SAR images are very sensitive to metal materials , as a result, it is difficult to distinguish between the production core places and other places from SAR.

We are going to develop deep learning architecture to fuse optical remote sensing images and SAR images' features.

