Deriving VIIRS High-spatial Resolution Ocean Color Data Over Coastal and Inland Waters Using Deep Convolutional Neural Network

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Website for VIIRS ocean color images, data and Cal/Val: http://www.star.nesdis.noaa.gov/sod/mecb/color/
Outline

• Motivation
• Convolution Neural Networks
• Training CNN for super-resolving normalized water-leaving radiance spectra $nL_w(\lambda)$
• Evaluation of super-resolved $nL_w(\lambda)$
• Applications of $nL_w(\lambda)$ in Chesapeake Bay, Lake Erie and Gulf of Mexico
• Re-training networks for super-resolving $K_d(490)$ and Chl-a
• Evaluation of super-resolved $K_d(490)$ and Chl-a
• Applications of $K_d(490)$ and Chl-a in Chesapeake Bay, Lake Erie, Bohai Sea and Gulf of Mexico
• Summary and Path Forward
Ocean color products derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership (SNPP) include normalized water-leaving radiance spectra $nL_w(\lambda)$ of five M-bands at the wavelengths of 410, 443, 486, 551 and 671 nm, and one I-band at 638 nm, $nL_w(638)$.

- Biological and biogeochemical products, such as chlorophyll-a (Chl-a) concentration and water diffuse attenuation coefficient at the wavelength of 490 nm ($K_d(490)$), are derived from $nL_w(\lambda)$ spectra.

- Spatial resolutions of VIIRS I-bands and M-bands are differed by a factor of two
  - M-band $nL_w(\lambda)$, $K_d(490)$ and Chl-a: 750 m
  - I-band $nL_w(638)$: 375 m

- It is useful to have high-spatial resolution data for M-band $nL_w(\lambda)$, $K_d(490)$ and Chl-a data with also 375 m, particularly over coastal/inland waters.

- Deep Convolutional Neural Network (CNN) is used to super-resolve M-Band $nL_w(\lambda)$, $K_d(490)$, and Chl-a from 750-m to 375-m spatial resolution.
$nL_w(\lambda)$ at VIIRS I-band and M-bands Images

Baltic Sea (14 August 2015)

(a) $nL_w(443)$
(b) $nL_w(551)$
(c) $nL_w(671)$
(d) $nL_w(638)$

Land

0 0 1.0 2.0 3.0
$nL_w(\lambda)$ (mW cm$^{-2}$ $\mu$m$^{-1}$ sr$^{-1}$)

Bohai Sea (15 April 2019)

(a) $nL_w(443)$
(b) $nL_w(551)$
(c) $nL_w(671)$
(d) $nL_w(638)$

Land

0 0 1.0 2.0 3.0 4.0
$nL_w(\lambda)$ (mW cm$^{-2}$ $\mu$m$^{-1}$ sr$^{-1}$)
Correlation between I-band and M-bands

Correlation coefficients of $nL_w(\lambda)$ between at the M-bands and the I1 band, $nL_w(638)$, in the Baltic Sea and Bohai Sea.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Baltic Sea</th>
<th>Bohai Sea</th>
</tr>
</thead>
<tbody>
<tr>
<td>$nL_w(410)$</td>
<td>0.8572</td>
<td>0.8181</td>
</tr>
<tr>
<td>$nL_w(443)$</td>
<td>0.8691</td>
<td>0.8550</td>
</tr>
<tr>
<td>$nL_w(486)$</td>
<td>0.8977</td>
<td>0.8601</td>
</tr>
<tr>
<td>$nL_w(551)$</td>
<td>0.9397</td>
<td>0.9077</td>
</tr>
<tr>
<td>$nL_w(671)$</td>
<td>0.9946</td>
<td>0.9942</td>
</tr>
<tr>
<td>$nL_w(745)$</td>
<td>0.6658</td>
<td>0.8229</td>
</tr>
</tbody>
</table>
Convolutinal Neural Networks

- CNN is a type of **deep learning neural network** for image processing. It is designed to automatically learn hierarchies of spatial patterns.

- CNN is typically composed of a stack of **layers**, and one of the key building blocks of CNN is the **convolution layer**.

  ![Example of Layer 3](https://bdtechtalks.com/2020/01/06/convolutional-neural-networks-cnn-convnets/)

- Some popular CNN architectures include AlexNet, VGGNet, GoogLeNet, U-Net, and **ResNet**, etc.
Convolutional Neural Networks

• CNN developed by Lanaras et al. (2018)

• One network for each M-band in two regions
  • Baltic Sea: CNN-Baltic-\(nL_w(\lambda)\)
  • Bohai Sea: CNN-Bohai-\(nL_w(\lambda)\)

• Assumption: networks trained for super-resolving images on a lower scale from 1.5-km to 750-m spatial resolution are also valid for super-resolving \(nL_w(\lambda)\) images on the original scale from 750-m to 375-m spatial resolution (Shechtman et al. 2007; Glasner et al. 2009)

• The networks are implemented with TensorFlow (version 1.2.1) in Python (version 3.6.7) environment, and trained on CentOS 6.10 with four core Intel(R) Xeon(R) CPU E7-4820 of 2.00 GHz and 128 GB memory.
List of VIIRS granules and data acquired dates for training networks in the **Baltic Sea** and **Bohai Sea**.

<table>
<thead>
<tr>
<th>Granule</th>
<th>Date</th>
<th>Granule</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>V2019070042852</td>
<td>03/11/2019</td>
<td>V2015213113614</td>
<td>08/01/2015</td>
</tr>
<tr>
<td>V2019073051140</td>
<td>03/14/2019</td>
<td>V2015215105822</td>
<td>08/03/2015</td>
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<tr>
<td>V2019073051305</td>
<td>03/14/2019</td>
<td>V2015216103927</td>
<td>08/04/2015</td>
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<td>V2019074045411</td>
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<td>V2015221104550</td>
<td>08/09/2015</td>
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<tr>
<td>V2019075043516</td>
<td>03/16/2019</td>
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<td>08/11/2015</td>
</tr>
<tr>
<td>V2019084050531</td>
<td>03/25/2019</td>
<td>V2015225111108</td>
<td>08/13/2015</td>
</tr>
<tr>
<td>V2019090045259</td>
<td>03/31/2019</td>
<td>V2015227103444</td>
<td>08/15/2015</td>
</tr>
<tr>
<td>V2019091043404</td>
<td>04/01/2019</td>
<td>V2015228115523</td>
<td>08/16/2015</td>
</tr>
<tr>
<td>V2019100050545</td>
<td>04/10/2019</td>
<td>V2015229113502</td>
<td>08/17/2015</td>
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<tr>
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</tr>
<tr>
<td>V201916050558</td>
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<td>08/18/2015</td>
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<td>08/19/2015</td>
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<td>V2015232103942</td>
<td>08/20/2015</td>
</tr>
<tr>
<td>V2019143050004</td>
<td>05/23/2019</td>
<td>V2015235112355</td>
<td>08/23/2015</td>
</tr>
</tbody>
</table>

[https://www.star.nesdis.noaa.gov/sod/mecb/color/](https://www.star.nesdis.noaa.gov/sod/mecb/color/)
Evaluations

- Super-resolving downsampled images from 1.5-km to 750-m spatial resolution, and the original 750-m spatial resolution data are treated as ground truth.

Density-scatter plot of super-resolved vs. original $nL_w(\lambda)$ images in Baltic Sea: Aug. 14, 2015 (top row); Bohai Sea: April 15, 2019 (bottom row)
Evaluations

Mean, median, and standard deviation (STD) of the ratio (super-resolved/original) and difference (diff) (super-resolved – original) between the super-resolved and original $nL_w(\lambda)$ images

<table>
<thead>
<tr>
<th></th>
<th>CNN-Baltic (ratio)</th>
<th>CNN-Bohai (ratio)</th>
<th>CNN-Baltic (diff)</th>
<th>CNN-Bohai (diff)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$nL_w(410)$</td>
<td>Mean: 0.997, Median: 0.994, STD: 0.117</td>
<td>Mean: 1.001, Median: 0.999, STD: 0.039</td>
<td>Mean: 0.000, Median: -0.001, STD: 0.078</td>
<td>Mean: -0.001, Median: -0.001, STD: 0.027</td>
</tr>
<tr>
<td>$nL_w(443)$</td>
<td>Mean: 0.997, Median: 0.996, STD: 0.099</td>
<td>Mean: 1.000, Median: 1.000, STD: 0.021</td>
<td>Mean: -0.001, Median: -0.001, STD: 0.075</td>
<td>Mean: -0.001, Median: -0.001, STD: 0.022</td>
</tr>
<tr>
<td>$nL_w(486)$</td>
<td>Mean: 1.000, Median: 0.999, STD: 0.070</td>
<td>Mean: 0.990, Median: 0.999, STD: 0.067</td>
<td>Mean: 0.000, Median: -0.001, STD: 0.071</td>
<td>Mean: -0.001, Median: -0.001, STD: 0.019</td>
</tr>
<tr>
<td>$nL_w(551)$</td>
<td>Mean: 1.000, Median: 1.000, STD: 0.041</td>
<td>Mean: 1.000, Median: 1.000, STD: 0.008</td>
<td>Mean: 0.000, Median: 0.000, STD: 0.055</td>
<td>Mean: -0.001, Median: -0.001, STD: 0.014</td>
</tr>
<tr>
<td>$nL_w(671)$</td>
<td>Mean: 0.996, Median: 0.997, STD: 0.066</td>
<td>Mean: 1.000, Median: 1.000, STD: 0.017</td>
<td>Mean: -0.001, Median: -0.001, STD: 0.032</td>
<td>Mean: -0.001, Median: 0.000, STD: 0.015</td>
</tr>
</tbody>
</table>
Application to Original Scale

Baltic Sea: V2015226105214, acquired on August 14, 2015

Resolution 750-m

(a) $nL_w(443)$

(b) $nL_w(551)$

(c) $nL_w(671)$

Resolution 375-m

(d) $nL_w(443)$

(e) $nL_w(551)$

(f) $nL_w(671)$

$nL_w(\lambda) \text{ (mW cm}^{-2} \text{ } \mu\text{m}^{-1} \text{ } \text{sr}^{-1})$

Legend:
- Land
Application to Original Scale

VIIRS-derived $nL_w(\lambda)$ along the pink dotted line in the last slide for (a) normalized original $nL_w(551)$ in blue solid line compared with those of $nL_w(638)$ in red, (b) normalized super-resolved $nL_w(551)$ in green solid line compared with those of $nL_w(638)$ in red, and (c) the difference between normalized original $nL_w(551)$ and $nL_w(638)$ (blue solid line), and between normalized super-resolved $nL_w(551)$ and $nL_w(638)$ (green dotted line).

Standard deviation (STD) of the difference between the original and super-resolved $nL_w(\lambda)$ image (normalized) with the $nL_w(638)$ along the pink line in last slide for the Baltic Sea and the pink line in the next slide for the Bohai Sea.

<table>
<thead>
<tr>
<th>Original $- nL_w(638)$</th>
<th>Super-resolved $- nL_w(638)$</th>
<th>Original $- nL_w(638)$</th>
<th>Super-resolved $- nL_w(638)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$nL_w(410)$</td>
<td>0.4561</td>
<td>0.4182</td>
<td>0.1334</td>
</tr>
<tr>
<td>$nL_w(443)$</td>
<td>0.4465</td>
<td>0.3551</td>
<td>0.1276</td>
</tr>
<tr>
<td>$nL_w(486)$</td>
<td>0.3892</td>
<td>0.2633</td>
<td>0.1391</td>
</tr>
<tr>
<td>$nL_w(551)$</td>
<td>0.3515</td>
<td>0.1773</td>
<td>0.1326</td>
</tr>
<tr>
<td>$nL_w(671)$</td>
<td>0.3662</td>
<td>0.2393</td>
<td>0.0438</td>
</tr>
<tr>
<td>$nL_w(745)$</td>
<td>0.2101</td>
<td>0.1125</td>
<td>0.1181</td>
</tr>
</tbody>
</table>
Application to Original Scale

Bohai Sea: V2018252050036, acquired on Sep. 9, 2018
Applications

Chesapeake Bay (3 March 2018)

(a) $nL_w(443)$
(b) $nL_w(551)$
(c) $nL_w(671)$
(d) $nL_w(638)$

Gulf of Mexico (19 November 2019)

(a) $nL_w(443)$
(b) $nL_w(551)$
(c) $nL_w(671)$
(d) $nL_w(638)$

$nL_w(\lambda)$ (mW cm$^{-2}$ $\mu$m$^{-1}$ sr$^{-1}$)

Color scale:

- $nL_w(551)$
- $nL_w(443)$
- $nL_w(671)$
- $nL_w(638)$

Legend:

- Land

Values:

- 0
- 2.0
- 3.0
- 4.0
Applications

Lake Erie (29 April 2018)

\( nL_w(443) \)
\( nL_w(551) \)
\( nL_w(671) \)
\( nL_w(638) \)

\( nL_w(\lambda) \) (mW cm\(^{-2}\) \( \mu \)m\(^{-1}\) sr\(^{-1}\))

0 4.0
0 4.0
0 6.0

Land
Applications

Density-scatter plot of super-resolved $nL_w(\lambda)$ image derived from the Bohai model vs. Baltic model in Chesapeake Bay (top row), Gulf of Mexico (middle row), and Lake Erie (bottom row).
The **mean**, **median**, and **STD** of the $nL_w(\lambda)$ ratio between using the CNN-Bohai-$nL_w(\lambda)$ and CNN-Baltic-$nL_w(\lambda)$ in the Chesapeake Bay, Gulf of Mexico, and Lake Erie.

<table>
<thead>
<tr>
<th></th>
<th>Chesapeake Bay</th>
<th>Gulf of Mexico</th>
<th>Lake Erie</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>STD</td>
</tr>
<tr>
<td>$nL_w(410)$</td>
<td>1.005</td>
<td>1.006</td>
<td>0.078</td>
</tr>
<tr>
<td>$nL_w(443)$</td>
<td>1.000</td>
<td>1.000</td>
<td>0.038</td>
</tr>
<tr>
<td>$nL_w(486)$</td>
<td>0.995</td>
<td>0.995</td>
<td>0.022</td>
</tr>
<tr>
<td>$nL_w(551)$</td>
<td>1.001</td>
<td>1.000</td>
<td>0.020</td>
</tr>
<tr>
<td>$nL_w(671)$</td>
<td>1.001</td>
<td>1.001</td>
<td>0.016</td>
</tr>
</tbody>
</table>
Super-resolving $K_d(490)$ and Chl-a

- We do not directly super-resolve $K_d(490)$ and Chl-a images from coarse resolution to fine resolution. Rather, high-resolution $K_d(490)$ and Chl-a images are derived from super-resolved $nL_w(\lambda)$ images.
- The $K_d(490)$ algorithm is a combination of standard (for clear oceans) and turbid $K_d(490)$ models for accurate retrieval of $K_d(490)$ products for both clear and turbid ocean waters.
- The Chl-a algorithm uses the ocean color index (OCI) method, which has been proved to be more stable than the classic OCx-based algorithm.
# Training Dataset

<table>
<thead>
<tr>
<th>Case</th>
<th>Baltic Sea</th>
<th>Bohai Sea</th>
<th>La Plata Estuary</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>V2019070042852 03/11/2019</td>
<td>V2015213113614 08/01/2015</td>
<td>V2020019175116 01/19/2020</td>
</tr>
<tr>
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<td>V2020062174536 03/02/2020</td>
</tr>
<tr>
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<td>V2015223114859 08/11/2015</td>
<td>V2020063172640 03/03/2020</td>
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<td>6</td>
<td>V2019084050531 03/25/2019</td>
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<td>V2020083175048 03/23/2020</td>
</tr>
<tr>
<td>8</td>
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<td>V2015228115523 08/16/2015</td>
<td>V2020084173317 03/24/2020</td>
</tr>
<tr>
<td>9</td>
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<td>V2015229113502 08/17/2015</td>
<td>V2020095172707 04/04/2020</td>
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<td>V2015231105836 08/19/2015</td>
<td>V2020131175128 05/10/2020</td>
</tr>
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<td>14</td>
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<td>V2015232103942 08/20/2015</td>
<td>V2020133171337 05/12/2020</td>
</tr>
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<td>V2019143050004 05/23/2019</td>
<td>V2015235112355 08/23/2015</td>
<td>V2020137173857 05/16/2020</td>
</tr>
</tbody>
</table>

[https://www.star.nesdis.noaa.gov/sod/mecb/color/](https://www.star.nesdis.noaa.gov/sod/mecb/color/)
Re-Training Networks

La Plata River Estuary, February 27, 2020

\[ nL_w(443) \quad nL_w(551) \quad nL_w(671) \quad K_d(490) \quad Chl-a \]

- Original
  - (a)
  - (b)
  - (c)
  - (d)
  - (e)

- Old Training
  - (f)
  - (g)
  - (h)
  - (i)
  - (j)

- New Training
  - (k)
  - (l)
  - (m)
  - (n)
  - (o)

Color scales:
- **\[ nL_w(443) \] (mW cm^{-2} \mu m^{-1} sr^{-1})**
  - 0.00 to 0.03
  - 1.5 to 3.0

- **\[ nL_w(551) \] (mW cm^{-2} \mu m^{-1} sr^{-1})**
  - 0.00 to 0.06
  - 3.0 to 6.0

- **\[ nL_w(671) \] (mW cm^{-2} \mu m^{-1} sr^{-1})**
  - 0.00 to 0.08
  - 4.0 to 8.0

- **\[ K_d(490) \] (m^{-1})**
  - 0.00 to 0.64
  - 0.60 to 7.0

- **Chl-a (mg m^{-3})**
  - 0.00 to 0.64
  - 0.60 to 7.0

*Legend: Land*
Re-Training Networks

(a) Line A in Fig. 1(a)

(b) Line A in Fig. 1(a)

(c) Line A in Fig. 1(a)

(d) Line A in Fig. 1(a)
Evaluations (1)

(a) (b)

(c) (d)

$K_d(490)$ - original

$K_d(490)$ – super-resolved

$Chl-a$ - original

$Chl-a$ – super-resolved

Baltic Sea: V2015226105214, acquired on August 14, 2015
Evaluations (2)

(a) Line B in Fig. 3(a)

(b) Line B in Fig. 3(a)
Evaluations (3)

- **$K_d(490)$**
  - Mean: 0.997
  - STD: 0.045

- **Chl-a**
  - Mean: 1.008
  - STD: 0.062
Application to Lake Erie

Lake Erie on April 29, 2018 (V2018119182603)
Application to the Bohai Sea

Bohai Sea, September 9, 2018 (Granule V2018252050036)
Application to the Gulf of Mexico

Gulf of Mexico, November 19, 2019 (V2019323185429)

Original

Super-resolved

\( K_d(490) \)

\( Chl-a \)

\[ \begin{array}{c|c|c|c}
0.0 & 0.01 & 0.1 & 1.0 \\
2.5 & 10.0 & 64.0 & 5.0 \\
1.3 & \end{array} \]

\( Ratio \)

\( \text{Land} \)

\( \text{No Data} \)
Application to the Chesapeake Bay

Chesapeake Bay, March 3, 2018 (V2018062175339)
The **mean**, **median**, and **STD** of the super-resolved/original ratio of $K_d(490)$ and **Chl-a** in the Bohai Sea, Chesapeake Bay, Lake Erie and Gulf of Mexico.

<table>
<thead>
<tr>
<th></th>
<th>Bohai Sea</th>
<th>Chesapeake Bay</th>
<th>Lake Erie</th>
<th>Gulf of Mexico</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>$K_d(490)$</strong></td>
<td>Mean</td>
<td>Median</td>
<td>STD</td>
<td>Mean</td>
</tr>
<tr>
<td></td>
<td>1.003</td>
<td>1.000</td>
<td>0.056</td>
<td>1.010</td>
</tr>
<tr>
<td><strong>Chl-a</strong></td>
<td>Mean</td>
<td>Median</td>
<td>STD</td>
<td>Mean</td>
</tr>
<tr>
<td></td>
<td>0.999</td>
<td>1.000</td>
<td>0.060</td>
<td>1.004</td>
</tr>
</tbody>
</table>
Summary and Path Forward

• Deep convolutional neural network (CNN) is used to super-resolve VIIRS M-band $nL_w(\lambda)$ from 750-m to 375-m spatial resolution.

• High-resolution (375-m) super-resolved $nL_w(\lambda)$ images are much sharper, and show more fine structures than the original $nL_w(\lambda)$ images. Therefore, practically the performance of the networks is acceptable for super-resolving $nL_w(\lambda)$ images of the all VIIRS six M-bands to 375-m spatial resolution.

• High spatial resolution Chl-a and $K_d(490)$ are further derived from $nL_w(\lambda)$.

• We are working on the implementation of the networks for routine VIIRS ocean color data processing to super-resolve VIIRS M-band $nL_w(\lambda)$ images in coastal and inland waters.

• Applications to other satellite sensors, such as VIIRS on the NOAA-20, the Operational Land Imager (OLI) on the Landsat-8 and the Ocean and Land Colour Instrument (OLCI) on the Sentinel-3A/3B, will be tested.
References:


Thank You!