Automated Urban Footprint Mapping Over Large Areas: a Method Implemented for Massive Streams of Sentinel-2

Romain Wenger¹, David Michéa², Anne Puissant¹

avec les contributions de C. Carette et E. Ronsoille (Master OTG) and L. El Mendili, M. Chougrab, I. Sebari (IAVH2, Maroc)

¹. LIVE  UMR 7362 CNRS, 2. ICUBE UMR 7315 CNRS, 3. A2S Platform Unistra-CNRS
University of Strasbourg / anne.puissant@unistra.fr
✓ Since several years, methods for **mapping human settlement** with high spatial resolution imagery have reached a high degree of maturity

✓ **User’s needs** are increasing in the urban context due to future challenges for the next generation

✓ Users are confronted to **massive streams** of Sentinel data at high spatial and temporal resolution
Towards a High Performance processing chain for automatically mapping and monitoring urban footprint

From prototype developed by research laboratories to demonstrator for applications at large scale
Position in the national context

Part of THEIA Land Data and Service Center

Urban SEC  URB-OPT

The Urban SEC (Scientific Expertise Center)

Objective: carry out research based on urban user needs and develop innovative data and processing method:

- 10-20m to 50 cm
- Sentinel-1&2, Landsat-5/8, SPOT 6/7, Pléiades
- Annual or bio-annual product
- National coverage or/and maps on most important cities

-> adaptation to South Countries

Contact: A. Puissant (LIVE) Laboratories : IGN-LaStig, Cesbio, LETG-Rennes, IRD, ESP-DEV, Irstea-Tetis, ESPACE, INP-Bordeaux, CEREMA, ...
The URB-OPT processing chain (product 1)

✓ **Production mode:** On-demand or Stream

✓ **Input:** Mono or **Multi-temporal S2** data (10m) + thematic masks

✓ **Method:** Machine learning (Random Forest) with Object-oriented approach (segmentation)

✓ **Training:** existing database

✓ **Cross-validation** and comparison with existing products

✓ **Outputs:**
  - Confidence map and/or binary result (urban/not urban)
  - Confusion matrix
  - Statistics for comparison

http://a2s-earthobservation.eu/

Developed in 2019
The **URB-OPT** processing chain

... adapted for massive streams with

- a **development** platform for test
- a **production** platform (on-demand or stream)

... with fixed or chosen parameters:

- ID image or period of acquisition -> automatic pick-up of S2 images on several distributors (PEPS, CreoDias, etc) – B2,B3,B4,B8
- Segmentation algorithm
- Calculation of index (NDVI, texture) and zonal statistics
- Tiling of sampling data based on S2 grid
- ....
From prototype (2016-2017) ..... to deployment in production (France 2018)

Processed scenes

Strasbourg / Metz / Bordeaux
Rennes / Grenoble / Toulouse

92 tiles – mono-date 2016-2017
(without clouds)

n tiles – 1 year 2018
(multi-temporal + mask)
Processing chain – towards production

Production tests (out of Europe) – Cities in the South (computing 2017-2018-2019)

=⇒ On-going quantitative assessment / comparison with Global Urban Footprint

- Amérique du Sud (3)
- Afrique (8)
- Chine (4)
- Moyen-Orient (3)
Results (1)
Results (1)

Probability of urban

High (+1)

Low (-1)

Strasbourg

T32UMU - 2018
Strasbourg
T32UMU - 2018

Binary result (0.4) with confusion matrix
Results (1)

France
Région Grand-Est

Cadre:
France
Région Occitanie
Cadre:
Belgique

(cadre: Service Public de Wallonie)
On-going results (1)

Stream production
Mode selection: clouds < 30%
2017: 8 (full tile) + 4 (subset tile)
2018: 9 (full tile) + 7 (subset tile)
2019: 1 (full size) + 6 (subset tile)

South cities
Onithsa (Nigeria)
South cities

Onithsa (Nigeria)
On-going results (1)

South cities – Onithsa (Nigeria)

GUF (2015)  
GSHL (2018)  

Stack temporel brut

On-going analyses  
of multi-temporal  
results by cross validation

URBAN SEC
Research developments (product 2) – mapping Urban Fabric

✓ **Input:** Mono or Multi-temporal S2 data (10m) -> 3 tiles

✓ **Method:** Semantic Segmentation

✓ **Training:** existing Landcover database

✓ **Outputs:**
  - Mono and Multi-classes maps
  - Quantitative assessment

**Hypothesis:** temporal resolution VS very high spatial resolution for up-to-date mapping of Urban Fabrics (UF)
Research developments (product 2) – mapping Urban Fabric

✓ Proposed methodology:

• **Step 1:** a mono-temporal model for the binary classification of urban footprint (urban / no-urban)

• **Step 2:** a mono-temporal model for the classification of UF (four classes)

• **Step 3:** a multi-temporal model for the classification of UF (four classes)

Identification of the best architecture (FCN-32s, FCN-16s, SegNet, Unet)

Proposition of an adapted architecture from Unet in order to use spatial and temporal features

✓ Algorithmic choices:

• S2 / imagettes 256x256
• Models with fine-tuning, initialisation ImageNet, diceLoss, Mini-batch Gradient descent)
• Keras
• Evaluation: Jacquard Index, Precision, Confusion matrix, Recall, F1, ROC Curves
Research developments (product 2) – mapping Urban Fabric

✓ **Step 1 - Five Models**: urban / no-urban

- Data for training (BDOCS-Alsace©GeograndEst, 2012) and pre-processing (rasterization, regularization, etc)
- Train ULU and tests on ULV/TLT -> mono-date (02/2017) + validation on 03/2017
- 90(train)/10(validation), 150 epochs, DiceLoss (0,01) Dropout (50%)

---

### Test 1: validation on ULV/TLT

<table>
<thead>
<tr>
<th>Model</th>
<th>IoU</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>Kappa coefficient</th>
<th>OA</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCN-32s</td>
<td>0.6303</td>
<td>0.7042</td>
<td>0.8572</td>
<td>0.7732</td>
<td>0.7078</td>
<td>0.8975</td>
</tr>
<tr>
<td>FCN-16s</td>
<td>0.6348</td>
<td>0.7279</td>
<td>0.8323</td>
<td>0.7766</td>
<td>0.7288</td>
<td>0.9210</td>
</tr>
<tr>
<td>SegNet</td>
<td>0.7773</td>
<td>0.9294</td>
<td>0.8283</td>
<td>0.8799</td>
<td>0.8338</td>
<td>0.9617</td>
</tr>
<tr>
<td>UNet</td>
<td>0.8437</td>
<td>0.9194</td>
<td>0.9111</td>
<td>0.9152</td>
<td>0.8941</td>
<td>0.9662</td>
</tr>
</tbody>
</table>

### Test 2: validation on ULU with other date

<table>
<thead>
<tr>
<th>Metrics</th>
<th>UNet</th>
<th>SegNet</th>
<th>FCN-16s</th>
<th>FCN-32s</th>
</tr>
</thead>
<tbody>
<tr>
<td>IoU</td>
<td>DffT</td>
<td>DiffZ</td>
<td>DffT</td>
<td>DiffZ</td>
</tr>
<tr>
<td>Precision</td>
<td>0.5106</td>
<td>0.5681</td>
<td>0.4721</td>
<td>0.5513</td>
</tr>
<tr>
<td>Recall</td>
<td>0.7039</td>
<td>0.7226</td>
<td>0.5915</td>
<td>0.8000</td>
</tr>
<tr>
<td>F1 score</td>
<td>0.6504</td>
<td>0.7265</td>
<td>0.7005</td>
<td>0.6395</td>
</tr>
<tr>
<td>Kappa coefficient</td>
<td>0.6760</td>
<td>0.7245</td>
<td>0.6414</td>
<td>0.7108</td>
</tr>
<tr>
<td>OA</td>
<td>0.9485</td>
<td>0.9304</td>
<td>0.9251</td>
<td>0.9342</td>
</tr>
</tbody>
</table>

---

(a) [Image] (b) [Image] (c) [Image] (d) [Image]
Research developments (product 2) – mapping Urban Fabric

✓ **Step 2/3 – UNet** mono-temporal / multi-temporal: 4 classes

  • Un-balanced classes -> One model per class
  • Training augmentation, dropout (60%)

<table>
<thead>
<tr>
<th>Model</th>
<th>IoU</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>Kappa coefficient</th>
<th>OA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuous UF</td>
<td>0.623</td>
<td>0.723</td>
<td>0.819</td>
<td>0.768</td>
<td>0.764</td>
<td>0.992</td>
</tr>
<tr>
<td>Discontinuous UF</td>
<td>0.668</td>
<td>0.789</td>
<td>0.813</td>
<td>0.801</td>
<td>0.786</td>
<td>0.972</td>
</tr>
<tr>
<td>Industrial and tertiary</td>
<td>0.654</td>
<td>0.843</td>
<td>0.745</td>
<td>0.791</td>
<td>0.785</td>
<td>0.988</td>
</tr>
<tr>
<td>facilities</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Road and road network</td>
<td>0.505</td>
<td>0.661</td>
<td>0.677</td>
<td>0.669</td>
<td>0.665</td>
<td>0.988</td>
</tr>
</tbody>
</table>

Mono-temporal model – 4 classes (02/2017)

<table>
<thead>
<tr>
<th>Model</th>
<th>Test set</th>
<th>IoU</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>Kappa coefficient</th>
<th>OA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuous UF</td>
<td>Feb2018</td>
<td>0.380</td>
<td>0.457</td>
<td>0.693</td>
<td>0.551</td>
<td>0.548</td>
<td>0.995</td>
</tr>
<tr>
<td></td>
<td>Mai2018</td>
<td>0.347</td>
<td>0.491</td>
<td>0.5424</td>
<td>0.516</td>
<td>0.513</td>
<td>0.996</td>
</tr>
<tr>
<td></td>
<td>Aug2018</td>
<td>0.313</td>
<td>0.442</td>
<td>0.519</td>
<td>0.477</td>
<td>0.475</td>
<td>0.995</td>
</tr>
<tr>
<td>Multi-temporal test set</td>
<td>Feb2018</td>
<td>0.466</td>
<td>0.572</td>
<td>0.583</td>
<td>0.577</td>
<td>0.576</td>
<td>0.996</td>
</tr>
<tr>
<td>Industrial and tertiary</td>
<td>Feb2018</td>
<td>0.322</td>
<td>0.710</td>
<td>0.370</td>
<td>0.486</td>
<td>0.481</td>
<td>0.987</td>
</tr>
<tr>
<td>facilities</td>
<td>Apr2018</td>
<td>0.228</td>
<td>0.694</td>
<td>0.254</td>
<td>0.371</td>
<td>0.366</td>
<td>0.986</td>
</tr>
<tr>
<td></td>
<td>Aug2018</td>
<td>0.298</td>
<td>0.524</td>
<td>0.409</td>
<td>0.459</td>
<td>0.451</td>
<td>0.984</td>
</tr>
<tr>
<td>Multi-temporal test set</td>
<td>Feb2018</td>
<td>0.380</td>
<td>0.672</td>
<td>0.467</td>
<td>0.551</td>
<td>0.545</td>
<td>0.987</td>
</tr>
</tbody>
</table>

Mono and multi-temporal models – 4 classes

The proposed architecture to perform multi-temporal learning

Wenger, Michéa, Puissant, 30-31 May 2019, Rennes, France  22
✓ Production step of **URB-OPT** (V1) over national territory (France / Belgium)

✓ On-going validation step of **URB-OPT** (V1) over South cities (on-demand)

⇒ Product (V1) disseminated on a Data repository accessible through A2S and on the THEIA Land websites (on-going)

✓ On-going research:
  
  • Semantic segmentation with Deep Learning algorithm (U-Net) to map landcover classes (urban fabric, etc) on mono-date, multi-dates and on times series (S2) + integration of multi-sources data (S1)
  
  • Transfer learning
Thanks for your attention