Remote sensing of sealed surfaces and its potential for monitoring and modeling of urban dynamics

Frank Canters
CGIS Research Group, Department of Geography
Vrije Universiteit Brussel
Remote sensing of sealed surfaces

Sealed surfaces = impervious surfaces = man-made surfaces

In the last decade the interest in remote sensing of sealed surfaces has substantially increased

Partly due to technological advances:

• Advent of high-resolution imagery (< 5m)
• Advances in hyperspectral remote sensing
• Development of multi-sensor/multi-resolution approaches
• Advances in multi-angle remote sensing
• More capable image interpretation (pixel, subpixel and object level)
• ...

Successful mapping and monitoring of geometrically and spectrally heterogeneous urbanised areas
Sealed surfaces as an indicator of environmental change

Key role in study of environmental change, human-environment interaction and sustainable development

Impact of urbanization on local and regional water balance

- Increase in volume and intensity of surface runoff
- Decrease of groundwater recharge → drought risk
- Higher risk of non-point source pollution → decrease of water quality
- Change in status of aquatic and riparian habitats

Monitoring of urban heath islands

- Shift from regional models to intra-urban modeling of heat fluxes
- Impact on health of population
Sealed surfaces for monitoring and modeling of urban dynamics

Study and modelling of urban processes (densification, sprawl) and its impact on the environment, both at local and regional level

Detailed analysis of urban morphology (intra-urban level) and link urban form/function

- Modelling of population distribution
- Calibration of land-use change models
Different perspectives on sealed surfaces

Urban materials

High spatial resolution
Hyperspectral data

Land cover

Medium spatial resolution
Multispectral data

Land use

Medium to high spatial resolution
Multispectral data
Ancillary data sources
Spectral characteristics of man-made materials

<table>
<thead>
<tr>
<th>Level 1</th>
<th>Level 2: Land cover types</th>
<th>Level 3: Material types</th>
<th>Level 4: Surface materials</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings/roofs</td>
<td>Mineral materials</td>
<td>Asbestos</td>
<td>Coated corrugated metal sheet (PVC, Polyethylene, coating color)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bitumen roof sheeting</td>
<td>Polyvinylchloride (PVC)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Clay tiles</td>
<td>Polyethylene (PE)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Concrete slabs</td>
<td>Polyisobutylene (PIB)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Concrete tiles</td>
<td>Plexiglas</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Fiber cement</td>
<td>Tar Paper</td>
</tr>
<tr>
<td>Metallic materials</td>
<td>Aluminum</td>
<td>Green roof</td>
<td>Spectral libraries based on field / image spectroscopy</td>
</tr>
<tr>
<td></td>
<td>Copper</td>
<td>Thatched roof</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Zinc</td>
<td>Wood shingles</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Steel with protective coating</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Corrugated metal sheet</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lead</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Gold leaf</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tin</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hydrocarbon materials</td>
<td>Coated corrugated metal sheet (PVC, Polyethylene, coating color)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Polyvinylchloride (PVC)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Polyethylene (PE)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Polyisobutylene (PIB)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Plexiglas</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tar Paper</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Biomass materials</td>
<td>Green roof</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Thatched roof</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Wood shingles</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Artificial open spaces</td>
<td>Partially impervious surfaces</td>
<td>Cinder</td>
<td>Asphal t</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Clay-baked paving stones</td>
<td>Concrete</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cobblestone pavement</td>
<td>Flagstone (Granite)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Concrete pavement</td>
<td>Synthetic turf</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gravel</td>
<td>Tarzan</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Grass pavers</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Loose chippings</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Railway tracks</td>
<td></td>
</tr>
<tr>
<td>Fully impervious surfaces</td>
<td>Asphalt</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Concrete</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Flagstone (Granite)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Synthetic turf</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tarzan</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water bodies with artificial bottom</td>
<td>Pool</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Garden pond</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Relatively few detailed studies done on spectral characteristics of man-made materials:

Ben-Dor et al. (2001), Herold et al. (2004), Heiden et al. (2007),...

Source: Roessner, 2011
Spectral characteristics of man-made materials

Strong spectral heterogeneity because of variations in the physical or chemical properties of materials and because of BRDF effects

Strong overlap between spectra for different materials making traditional hyperspectral classification approaches inappropriate
Definition of robust spectral features

Need for identifying a set of diagnostic spectral features for each type of material taking strong within-class spectral heterogeneity into account.

Source: Heiden et al., 2007
Definition of robust spectral features

Heiden et al., 2007
Highest number of diagnostic features can be identified for bright materials that show clear absorption patterns

Few features can be defined for dark materials with relatively flat curve progression

Traditional classification approaches (unsupervised band reduction through PCA, MNF,..., followed by classification based on reduced number of bands) are not optimal

More appropriate to develop supervised data reduction techniques based on extraction of spectral features that allow optimal discrimination between the classes
Sealed surfaces from a land-cover perspective

Hydrological modeling:

- All sealed surfaces together define one impervious surface class
- Model resolution comparable or lower than pixel size of medium-resolution imagery (20-30m)
- Sometimes large area coverage (entire catchments)

Urban growth modeling:

- Sealed surfaces often considered as one land-cover class describing built-up area
- Models have relatively low resolutions (>= 100m)
- Applied at metropolitan or regional scale
- Need for data for different time steps
Mapping sealed surface cover from medium resolution data

Intrinsic scale of spatial variation of land cover in urban areas is smaller than the size of a medium resolution pixel

Sub-pixel classification:

Sealed surface fraction = \( f(XS_1, XS_2, \ldots, XS_N, TR_1, TR_2, \ldots, TR_N) \)
Sub-pixel approaches for sealed surface mapping

Three major groups of approaches:

- Linear spectral mixture analysis: SMA, normalised SMA, multiple endmember SMA, normalised multiple endmember SMA,...

- Multiple linear regression: independent variables may be spectral bands and transformations of these bands like band ratio’s or band-related indices (e.g. NDVI, SAVI,...)

- Machine learning approaches: artificial neural networks (MLP,...), regression trees, support vector machines,...
Standard spectral mixture analysis

Concept: V-I-S model (Ridd, 1995)

Conceptual model: pure pixels not necessarily correspond to physical endmembers
Standard spectral mixture analysis

Visualisation of image pixels in a PCA transformed feature space for an ETM+ image of Columbus, Ohio (Wu, 2004)
Normalised spectral mixture analysis

\[ r_{k,n} = \frac{r_k}{\mu} \times 100 \]

\[ \mu = \frac{1}{K} \sum_{i=1}^{K} r_i \]

Spectral heterogeneity of V-I-S components before (left) and after brightness normalisation (right) (Wu, 2004)
Normalised spectral mixture analysis

Visualisation of image pixels in a PCA transformed feature space for an ETM+ image of Columbus, Ohio, after spectral normalisation (Wu, 2004)
Machine learning techniques

Mostly used techniques: Multiple Layer Perceptrons and Regression Trees:

- Allow dealing with non-linear relationships between land-cover fraction and spectral variables
- Are able to better deal with within-class spectral heterogeneity

Usually produce better estimates of sealed surface cover than standard or normalised linear mixture models
Linear unmixing versus neural networks

Linear unmixing versus neural networks

Sealed surface proportion Landsat ETM+ based on MLP unmixing

Sealed surface proportion Ikonos image

Normalized linear spectral unmixing:
Multiple layer perceptron unmixing:

MAE = 0.129, ME = -0.026
MAE = 0.099, ME = -0.023
Linear unmixing versus neural networks

---

**Mean error per reference proportion interval for linear unmixing (not normalised)**

- **Mean absolute error per reference proportion interval for linear unmixing (not normalised)**

- **Mean error per reference proportion interval for MLP (not normalised)**

- **Mean absolute error per reference proportion interval for MLP (not normalised)**
Dealing with spectral confusion: two-step approach

To avoid spectral confusion between sealed surface cover and bare soil:

- Estimation of vegetation fraction within urban mask (multiple regression)
- Sealed surface fraction = 1 – vegetation fraction

Application on Landsat TM/SPOT imagery for Greater Dublin Area

1988
Time-series of MR sealed surface maps

2006
Fraction-based change analysis

Error bias and $\sigma$ is known for each image $t_1, t_2, \ldots$ from validation sample.

Errors can be propagated: $\sigma^2(t_2 - t_1) = \sigma^2(t_1) + \sigma^2(t_2) - 2\text{COV}(t_1, t_2)$

From this, a PDF can be positioned around the observed change for each pixel.

Chance of increase in sealed surface cover with 10% or more, for a pixel with an observed increase of 5% is 0.35.
Hot spot change detection

Chance of increase of > 10% (1988-2001)

Chance of increase of > 20% (1988-2001)

95% chance of increase of > 20% (1988-2001)
High-resolution versus medium-resolution imagery

High resolution
More detail
Only available for last 10 years

Medium resolution
Less detail
Long time-series available

Sealed surface proportion map for Antwerp (2012, SPOT-5)

Sub-pixel approaches: bridging the gap between high-resolution and medium-resolution data
Calibration of urban growth models

Calibration through hindcasting

Map 1990

Simulated map 2000    Actual map 2000

Comparison

Ok

not Ok

Simulated map 2020

New parameters
Use of medium-resolution sealed surface data in the calibration process

Objective: Can MR remote sensing data be used to improve the calibration of urban growth models?

Funding: MAMUD/ASIMUD projects, BELSPO-STEREO
Partners: universities of Brussels, Liège, Ghent, Utrecht, VITO, JRC
Use of medium-resolution sealed surface data in the calibration process

Main challenges:

- Is it possible to derive land-use information relevant for model calibration from sealed surface fraction maps at medium resolution?

- What methods/metrics are suitable to compare remote sensing based land-use maps with the maps produced by the land-use change model in the context of model calibration?

- How to define an operational framework for (semi-)automated model calibration?
MOLAND urban growth model

Zoning & Suitability & Accessibility & Transition Potentials

Time Loop

Land use & Stochastic perturbation

\[ v = 1 + (\ln(rand))^\alpha \]

\[
\begin{array}{c}
0 \\
0.5 \\
1 \\
\end{array}
\]

Interaction weights

Transition Rule

Change cells to land-use for which they have the highest transition potential until the demands are met.

Land use at time T+1

Transition Potentials

Accessibility & Zoning & =

MACRO-SCALE MODEL

Natural sub-system

Social sub-system

Economic sub-system

Natural Systems

Coastal Rivers
Beaches
Forests

Natural growth

Human impacts on growth

Pollution
Emission

Land use Demand

Natural land-use

Residential land-use

Economic land-use

Population

Mobility - Mortality

Land use Demand

Total Jobs

Primary Industry
Tertiary

Suppy

Demand

Total land area

Human Impacts on growth

Land use

Stochastic perturbation

Land use at time T+1

\[
\begin{array}{c}
\alpha \\
rand \\
v \\
t \ln \\
1 - \alpha \\
\end{array}
\]
Main hypothesis: relationship between urban form and function

- Much research in urban remote sensing has focused on inferring urban function from urban form.
- Recent work mainly focuses on inferring land use from high-resolution sealed surface data.
- A popular approach is to describe urban form based on spatial metrics.
  - Traditional metrics from landscape ecology (FragStats, ...)
  - Specific “urban” metrics more apted to describe urban structures.
Urban form and spatial metrics

Inferring urban land-use from Ikonos-derived sealed surface maps using spatial metrics (Herold et al., 2003)
Urban form and spatial metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description/Calculation Scheme</th>
<th>Units</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>PLAND - Percentage of landscape</td>
<td>PLAND equals the sum of the areas (m²) of a specific land cover class divided by total landscape area, multiplied by 100.</td>
<td>Percent</td>
<td>0 &lt; PLAND ≤ 100</td>
</tr>
<tr>
<td>PD - Patch density</td>
<td>PD equals the number of patches of a specific land cover class divided by total landscape area.</td>
<td>Numbers per 100 ha</td>
<td>PD ≥ 1, no limit.</td>
</tr>
<tr>
<td>AREA_MN - Mean patch size</td>
<td>AREA_MN equals the average size of the patches of a land cover class.</td>
<td>Hectares</td>
<td>AREA_MN ≥ 0, no limit.</td>
</tr>
<tr>
<td>AREA_SD - Area standard deviation</td>
<td>AREA_SD equals the standard deviation in size of the patches of a land cover class.</td>
<td>Hectares</td>
<td>AREA_SD ≥ 0, no limit.</td>
</tr>
<tr>
<td>ED - Edge density</td>
<td>ED equals the sum of the lengths (m) of all edge segments involving a specific class, divided by the total landscape area (m²) multiplied by 10000 (to convert to hectares).</td>
<td>Meters per hectare</td>
<td>ED ≥ 0, no limit.</td>
</tr>
<tr>
<td>LPI - Largest patch index</td>
<td>LPI equals the area (m²) of the largest patch of the corresponding class divided by total area covered by that class (m²), multiplied by 100 (to convert to a percentage).</td>
<td>Percent</td>
<td>0 &lt; LPI ≤ 100</td>
</tr>
<tr>
<td>ENN_MN - Euclidian mean nearest neighbor distance</td>
<td>ENN_MN equals the distance (m) mean value over all patches of a class to the nearest neighboring patch based on shortest edge-to-edge distance from cell center to cell center.</td>
<td>Meters</td>
<td>ENN_MN &gt; 0, no limit.</td>
</tr>
<tr>
<td>ENN_SD - Euclidian nearest neighbor distance standard deviation</td>
<td>ENN_SD equals the standard deviation in euclidian mean nearest neighbor distance of land cover class.</td>
<td>Meters</td>
<td>ENN_SD &gt; 0, no limit.</td>
</tr>
<tr>
<td>FRAC-AM - Area weighted mean patch fractal dimension</td>
<td>Area weighted mean value of the fractal dimension values of all patches of a land cover class, the fractal dimension of a patch equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m²); the perimeter is adjusted to correct for the meter bias in perimeter.</td>
<td>None</td>
<td>1 ≤ FRAC_AM ≤ 2</td>
</tr>
<tr>
<td>FRAC-SD - Fractal dimension standard deviation</td>
<td>FRAC_SD equals the standard deviation in fractal dimension of land cover class.</td>
<td>None</td>
<td>FRAC_SD &gt; 0, no limit.</td>
</tr>
<tr>
<td>COHESION</td>
<td>Cohesion is proportional to the area-weighted mean perimeter-area ratio divided by the area-weighted mean patch shape index (i.e., standardized perimeter-area ratio).</td>
<td>Percent</td>
<td>0 &lt; COHESION &lt; 100</td>
</tr>
<tr>
<td>CONTAG - Contagion</td>
<td>CONTAG measures the overall probability that a cell of a patch type is adjacent to cells of the same type.</td>
<td>Percent</td>
<td>0 &lt; CONTAG ≤ 100</td>
</tr>
</tbody>
</table>

Definition of spatial metrics used in Santa Barbara case study (Herold et al., 2003)
Urban form and spatial metrics

Comparison of class-specific classification accuracies for the Santa Barbara case study using texture measures, spatial metrics and both (Herold et al., 2003)
Urban form and spatial metrics

Land-use map obtained in Santa Barbara case study (Herold et al., 2003)
And what about surface fraction maps?

Can urban form at block level be described based on sealed surface fraction maps? Will this allow us to infer LU information from form description?

Industrial

Residential
Metrics describing sealed surface fractions

- Average proportion sealed
  - Characterizes density

- Cumulative frequency distribution
  - 4 parameters of fitted logistic function
  - Characterises distribution

\[ P_i(f) = \gamma \frac{1}{1 + e^{-(\alpha f + \beta)}} + \delta \]

- Spatial variance
  - Characterises spatial distribution
  - Calculated for adjacent pixels

\[ SV = \frac{\sum_{i}^{n} \sum_{j}^{k_i} (f_i - f_j)^2}{\sum_{i}^{n} k_i} \]
Inferring function from form using sealed surface fraction maps

Land-use mapping of the Greater Dublin Area from sealed surface fraction maps derived from Landsat TM/SPOT data (Van de Voorde and Canters, 2011)
Defining a suitable goodness-of-fit metric for model calibration

Comparison between model output and observed land use cannot be compared on cell-by-cell basis!

- Maps may not be comparable due to uncertainty in observed data

- *For land-use maps*: vagueness in class definitions / differences in level of generalisation

- *For remote sensing maps*: uncertainty in the land-use mapping process, different level of thematic and spatial detail

- Land-use models are used to forecast spatial trends, not to predict the exact location where change will occur

Model output should be compared with observed data at higher level of abstraction
Spatial metrics for model calibration

Need for metrics that capture specific spatial properties of urban growth patterns → focus on metrics proposed for characterizing urban sprawl

Should be sensitive to changes in the urban land-use pattern, while not being oversensitive to differences caused by the nature of the data

Definition of set of metrics fulfilling the required properties
MAMUD Calibration Framework

Remote sensing image

Image interpretation

Inferred land use

Model initiation

Simulation

Simulated land use

Correct model parameters

Compare using spatial metrics
Selection of spatial metrics for model calibration

Urban mask 1997

Reference scenario

Remote sensing

Landscape Shape Index


Year

LSI ( )

Reference scenario

Extreme scenario

Remote sensing

LSI = 1.4

LSI = 2.5

SAGEO 2012, November 7-9, 2012
Université de Liège
Selection of spatial metrics for model calibration

Population/employment 1997

Remote sensing

Extreme

Reference

Landscape Shape Index Employment

LSI = 1.4

LSI = 2.5

Year


LSI (-)

Reference scenario
Extreme scenario
Remote sensing

Low density residential
Medium density residential
Employment
Final thoughts

High-resolution hyperspectral remote sensing opens new opportunities for mapping of urban surfaces at material level and for high-resolution modelling, yet need for:

- Development of effective approaches for diagnostic feature extraction from spectroscopic data

Many studies have focused on mapping of sealed surface cover from medium-resolution multispectral data, yet more efforts are needed on:

- Effective use of sealed surface maps in a broad range of applications and modeling approaches

- Calibration of urban growth models: How to calibrate model parameters while acknowledging uncertainty in the “observed” data, obtained through remote sensing?