Use of **Unmanned Aerial Vehicles** and machine learning tools for efficient beach litter monitoring

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Pills of…

**WASTE MANAGEMENT** in **SAUDI ARABIA**

15.3 Mt/y, 1.9 Mt/y only in Jeddah.

Waste disposal: **landfills, open dumps, combustion**, some compost facilities.

Plastic is the second most abundant waste (5 – 17%) after organic waste (40%), and only **15 - 20% is recycled**

Anjum et al., 2016
BEACH LITTER MONITORING: VISUAL CENSUS
BEACH LITTER MONITORING: **UAVs**

**DJJI Phantom 3 Adv**

**12 MP camera**

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**MATERIALS & METHODS**

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**RESULTS**

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**DISCUSSION**

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**FUTURE STEPS**

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**INTRO**
BEACH LITTER MONITORING: **UAVs**

**Automatic flights** in UgCS
Speed: 2 m/s, stills every ~2 sec
10 m side overlap for alignment w/ PhotoScan Pro
IMAGE PROCESSING: **VISUAL SCREENING**

**A** Drink bottles (a), Drink drums (b), Bottle caps (c), Plastic bags (d), Ropes (e), Footwear (f), Oil containers (g) Detergent and other liquids containers (h), Boxes-crates-baskets (i) and Others (j)

Left pictures: item from land
Right pictures: item from 10 m height
**IMAGE PROCESSING: MACHINE LEARNING TOOL**

1. Left pictures: item from land
   Right pictures: item from 10 m height

2. Drink containers (1),
   Bottle caps (2),
   Plastic bags (3).

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**INNOVATION. COLLABORATION. ACTION.**

**6th INTERNATIONAL MARINE DEBRIS CONFERENCE**
**IMAGE PROCESSING: MACHINE LEARNING TOOL**

1. **Training samples**
   - 1224 positive samples:
     - 1014 Drink bottles
     - 88 Bottle caps
     - 122 Plastic bags
   - >400 samples for each category after random selection and generation

2. **Histogram of oriented gradients (HoG)**

3. **Testing images**

4. **Random forest classifier**

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**Materials & Methods**

**Results**

**Discussion**

**Future Steps**
**IMAGE PROCESSING: MACHINE LEARNING TOOL**

1. Training samples
   - **1224** positive samples:
     - 1014 Drink bottles
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2. Histogram of oriented gradients (HoG)

3. Testing images

4. Random forest classifier
REMOTE SURVEY TIME EFFICIENCY

Remote survey:
- 10 sites, 19 flights
- 129,995 m² surveyed
- $758 \pm 20.2$ m² min⁻¹ (mean ±SE)

Visual census:
- 9 sites, 103 transects
- 3,956 m² surveyed
- $16.31 \pm 1.3$ m² min⁻¹ (from 1.25 to 30 m² min⁻¹ depending on density)
REMOTE SURVEY LITTER DENSITY ESTIMATES

Debris Categories | Abundance (n items) | Density (items.m⁻²) | Proportion (%) |
--- | --- | --- | --- |
Drink bottles | 738 | 0.12 | 42 |
Drink drums | 45 | 0.007 | 2.6 |
Bottle caps | 46 | 0.007 | 2.6 |
Plastic bags | 80 | 0.013 | 4.6 |
Oil containers | 38 | 0.006 | 2.2 |
Detergent and other liquids containers | 36 | 0.006 | 2.1 |
Ropes | 24 | 0.004 | 1.4 |
Footwear | 24 | 0.004 | 1.4 |
Boxes-crates-baskets | 20 | 0.003 | 1.1 |
Others | 705 | 0.11 | 40 |

~250 pictures
6400 m²
10-min flight
1756 items
0.27 items m⁻²
**REMOTE SURVEY VALIDATION**

**Visual census:**
- 123 items

**Remote survey:**
- 76 items
  - Detection probability: **61.8%**
  - Correction: 0.27 items m\(^{-2}\)
  - \(\rightarrow 0.44\) items m\(^{-2}\)

<table>
<thead>
<tr>
<th>Debris Categories</th>
<th>Abundance</th>
<th>Proportion</th>
<th>Visual Census</th>
<th>Remote Survey + Manual Screening</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drink bottles</td>
<td>45</td>
<td>36.6%</td>
<td>45</td>
<td>28</td>
</tr>
<tr>
<td>of which glass bottles</td>
<td>4</td>
<td>3.2%</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Bottle caps</td>
<td>14</td>
<td>11.4%</td>
<td>14</td>
<td>1</td>
</tr>
<tr>
<td>Plastic bags</td>
<td>8</td>
<td>6.5%</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Oil and detergent containers</td>
<td>10</td>
<td>8.1%</td>
<td>10</td>
<td>12</td>
</tr>
<tr>
<td>Ropes</td>
<td>4</td>
<td>3.2%</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Footwear</td>
<td>2</td>
<td>1.6%</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Others</td>
<td>40</td>
<td>32.5%</td>
<td>40</td>
<td>30</td>
</tr>
</tbody>
</table>

**Correction:**
- 0.27 items m\(^{-2}\)
- \(\rightarrow 0.44\) items m\(^{-2}\)
**MACHINE LEARNING ACCURACY**

### Visual screening: 413 items

**Machine learning:** 2103

Huge overestimation, but methodologies correlate

<table>
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<tr>
<th>Debris Categories</th>
<th>Manual Processing</th>
<th>Machine Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total abundance (n items)</td>
<td>Mean abundance ±SE (n items per picture)</td>
</tr>
<tr>
<td>Drink containers</td>
<td>367</td>
<td>28.23 ±5.14</td>
</tr>
<tr>
<td>Bottle caps</td>
<td>20</td>
<td>1.54 ±0.39</td>
</tr>
<tr>
<td>Plastic bags</td>
<td>26</td>
<td>2 ±0.51</td>
</tr>
</tbody>
</table>
**PROS & CONS**

**Time efficiency**
- No need to directly access the area
- Mostly, 100% coverage of the beach and back of the beach too
- More exposures of the same island
- Only one trained person needed

**Loss in accuracy**
- Underestimation from visual screening of aerial images due to low resolution (missed detection of small items mainly) \(\rightarrow\) **ground assessments**
- Overestimation of the machine learning due to
  - Low resolution of UAV images
  - Few training samples
  - High variability in within categories and of negative samples
  - Few contrast with background
METHODOLOGICAL IMPROVEMENTS

1 Phantom 4 Pro: 20 MP camera

Bottle caps, 10 m height:

Visual screening:
25.2 ± 6.8 drink containers
1.2 ± 1.3 bottle caps
0.8 ± 0.4 plastic bags

Machine learning:
21.2 ± 5.2, 2.4 ± 1.3, 0.4 ± 0.2

No significant difference in abundance!

2 Lower flight height
3 More training samples
4 Deep neuron network instead than fixed descriptors
TOWARDS THE FIRST **HIGH-SCALE** MONITORING IN THE **RED SEA**

1. Apply the improved random forest classifier to the **orthomosaic** for correct litter density estimates

2. Classification in **10 categories**

3. Cover more exposures to assess influence of **winds/currents** on marine debris distribution

4. Repeat measures over time to assess **seasonality**
THANK YOU!

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