

Detecting Desert Locust: the UAV Way



The potential use of UAVs in a Desert Locust early warning system for preventive control

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Introduction

When areas get a bit of extra rain and subsequent boost in fresh vegetation, Desert Locust populations, *Schistocerca gregaria* can proliferate into outbreaks which can lead to vast plagues.

Technical staff of National Locust Control Centres (NLCC), carry out control operations in the field to detect locusts. The Food and Agricultural Organisation of the United Nations provides satellite-based estimates of large locust habitat areas supported by rainfall and green vegetation data for the staff to reduce and monitor these populations. Despite this technology there is still room for further improvement to address the inherent difficulties in Desert Locust monitoring, as the current systems lacks real time data and accuracy.

Our review of current technologies showed that the most efficient method available for the monitoring of Desert Locusts within such vast areas is to use a hyperspectral camera mounted on a UAV.

Research Question:

To what extent can remotely-sensed UAV mounted spectral information of Desert Locust habitats contribute to the Desert Locust Information Service?

Desert Locust Recession Area



Experimental stage

What are the spectral signatures of the components of a Desert Locust habitat?

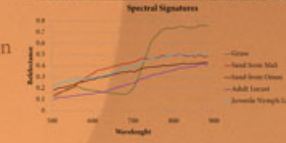
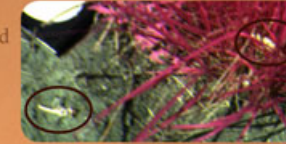


Methods:

Adults and juvenile nymphs were used in an outdoor, a lab and a zoo set-up and analysed for their spectrum and surroundings. The hyperspectral data was collected using a Rikola hyperspectral imager.

Results :

- 744-900 nm is significant for detection locust from vegetation
- Nymph locust reflects more than the adult locust
- Results from outdoor zoo and lab were consistent
- No significant difference of locust from sand



Automation stage

How to automate the process of Desert Locust identification with UAVs?

```

import numpy as np
import cv2
import sys
import os
import glob
import math
import random
import time
import datetime
import shutil
import subprocess
import argparse
import json
import pickle
import logging
import warnings
import warnings

def main():
    parser = argparse.ArgumentParser()
    parser.add_argument('--input_dir', type=str, required=True, help='Input directory')
    parser.add_argument('--output_dir', type=str, required=True, help='Output directory')
    parser.add_argument('--mask_dir', type=str, required=True, help='Mask directory')
    parser.add_argument('--log_dir', type=str, required=True, help='Log directory')
    parser.add_argument('--verbose', type=bool, default=False, help='Verbose output')
    args = parser.parse_args()

    input_dir = args.input_dir
    output_dir = args.output_dir
    mask_dir = args.mask_dir
    log_dir = args.log_dir

    # Create output and log directories
    os.makedirs(output_dir, exist_ok=True)
    os.makedirs(log_dir, exist_ok=True)

    # Get list of input files
    input_files = glob.glob(os.path.join(input_dir, '*.*'))

    # Process each file
    for input_file in input_files:
        # Extract filename
        filename = os.path.splitext(os.path.basename(input_file))[0]

        # Read input image
        img = cv2.imread(input_file)

        # Calculate vegetation index
        vi = calculate_vegetation_index(img)

        # Create mask
        mask = create_mask(vi)

        # Save mask
        mask_path = os.path.join(mask_dir, filename + '.mask.png')
        cv2.imwrite(mask_path, mask)

        # Save log
        log_path = os.path.join(log_dir, filename + '.log.txt')
        with open(log_path, 'w') as f:
            f.write('Input file: %s\n' % input_file)
            f.write('Output mask: %s\n' % mask_path)
            f.write('Vegetation index: %s\n' % str(vi))
            f.write('Mask creation time: %s\n' % str(time.time()))
    
```

Methods:

The automation uses preprocessed images, which are transformed using a specified vegetation index. A limit threshold of the VI is calculated and a mask is created. Pixels are transformed to points and the density is analysed, from which contour lines are formed. The contours are transformed to polygons of which the centroids are calculated.

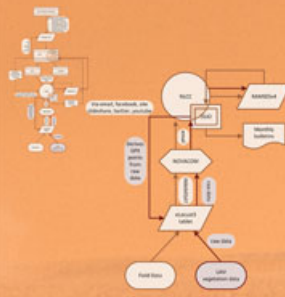
Results:

The output are KML and GPX coordinates. Script is computation heavy, so onboard computing is less likely.



Integration stage

How can the acquired data be integrated into the early warning system of the Desert Locust Information Service?



Methods:

FAO documentation and info provided by DLIS experts is combined with previous results. A survey was sent to the DLIO and NLCC field personnel to gain their opinions.

Results:

From the analysis we were able to construct the framework and the data flow for all the different organisations involved in the eLocust system. UAV technology is shown to be able for incorporation in DLIS. We expect to support these results with the survey.



Discussion

Detection with by analysing hyperspectral images appears promising. Desert Locust have a distinct reflectance difference in the Red bands compared to vegetation. Comparing Desert Locust to desert soil was more difficult, because the spectral signatures looked more alike.

Using UAV flights, mounted with hyperspectral cameras, to contribute to Desert Locust detection is an improvement for the monitoring system. More detailed images than satellite imagery can be produced of up to 1000 ha in 6 hours.

UAV integration into the current system is feasible. An automated system removes human errors made in the field and increases analysis speed. GPX coordinates can outputted back to the NLCCs for their employees to navigate to.

Conclusion:

Higher accuracy and coverage from UAVs will greatly improve the effectiveness of NLCC teams. Via spectral unmixing Desert Locust will be identified when aggregated in sparse vegetation. UAVs can be well integrated into the current eLocust3 system.

