

The Application of Multi-Modal Sensor Networks to the Monitoring of Coastal and Inland Marine Environments

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Aims and Objectives



- Identify one or more coastal locations where visual sensing can be used to complement and enhance the usefulness of other sensors
- Use this visual sensor network in measuring and tracking some feature of a defined coastal location
 - e.g. beach volume and beach erosion, water quality, algal blooms etc



Image: John Cleary

Sensor Networks



Logical extension of the greater 'networked world'

Provides a gateway through which the 'digital world' can sense and respond to changes in the real-world

Facilitates data acquisition at a scale and resolution not previously possible







Wireless Sensor Networks (WSNs)



In recent years, the concept of **WSNs** has been the focus of intense research

A world of **ubiquitous sensing** is envisaged, **continuously monitoring** our environment and instantly **detecting and reporting changes** in the quality of our environment



Sensor Web



In its ultimate manifestation this happens at **internet** scale with sensor technologies serving as peripherals for the internet

Bring a range of data concerning our physical environment to the wider web where it is aggregated, correlations identified, information extracted, and feedback loops used to take appropriate action

However there lie many challenges in the realision of this vision

Issues



Range of analytical devices which can be layered into a hierarchy in terms of sophistication, capabilities, operational costs and degree of autonomy

Chemo/bio sensors which need to be used as efficiently as possible





Issues



Even without the added complexity of chemo/bio sensing - still considerable issues e.g.

Sensors subject to harsh conditions

Bio-fouling

Limited spatial resolution

Difficult to monitor a wide area over a long period of time

Unsuitable for certain environments and for the immediate detection of certain events



Multi-modal sensor networks















Test Sites and Data Sources



Data Streams	River Lee	Galway Bay	River Tolka
In-situ sensors	SmartCoast, Deploy	SmartBay, Tide Gauge Network, Irish Weather Buoy Network	
Visual/Satellite sensors	Camera at Lee Maltings site	HRDDS, MERIS, AATSR, MODIS	Deployed Camera
Context information	Rainfall Radar Data	Rainfall Radar Data	Rainfall Radar Data
Identified possible future data streams	Further camera installations, publicly available weather and webcam data	Galway Bay web- cam, publicly available weather & web cam data	In-situ sensors, publicly available weather data

River Lee – Deploy Project Sites



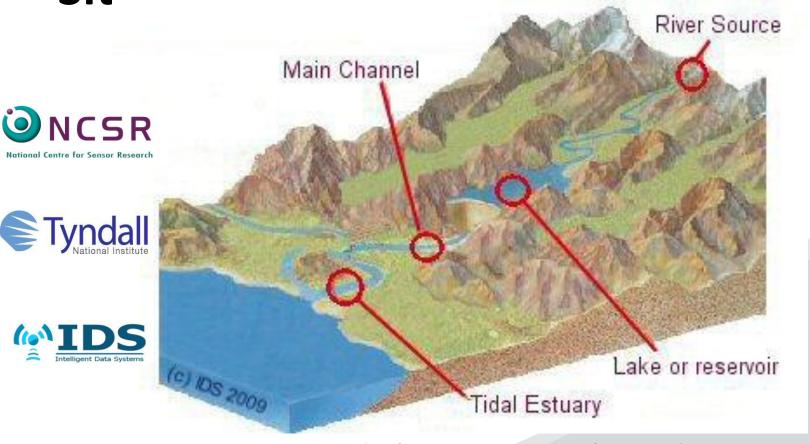


Image: www.deploy.ie (IDS: Intelligent Data Systems)







Lee Maltings Site



Dynamic

Tidal

Dam upstream

Located at Tyndall National Institute which provides network and power for the camera deployment

SmartCoast sensors deployed until January 2009

Deploy sensors deployed since April 2009



On-site camera



 An AXIS 212 PTZ Network camera was installed at the Lee Maltings site

The camera is controlled remotely from a desktop PC at DCU

 Images are automatically saved from the camera at four different angles at full zoom every minute.

Camera Angles









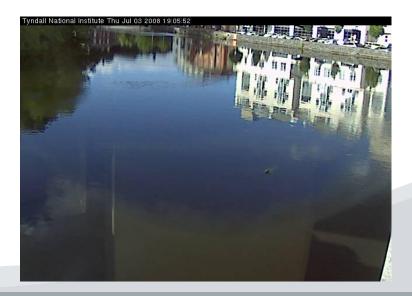


Varying Conditions











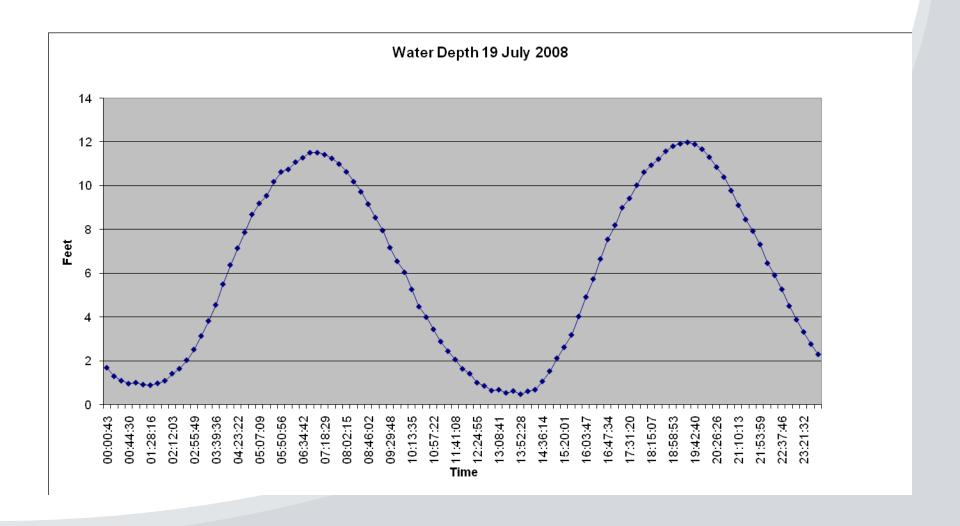
Water Depth Pilot Study



- To investigate the potential benefits from the use of multiple sensing signals to monitor the site, a pilot study was undertaken in relation to the detection of water level.
- Investigates the **complementary** use of the in-situ **SmartCoast** water depth sensor and the on-site camera in monitoring the level of water at the river location.
- The singular use of either sensing mechanism has potential drawbacks in environmental monitoring, however when used in unison, some of these potential issues may be compensated for.

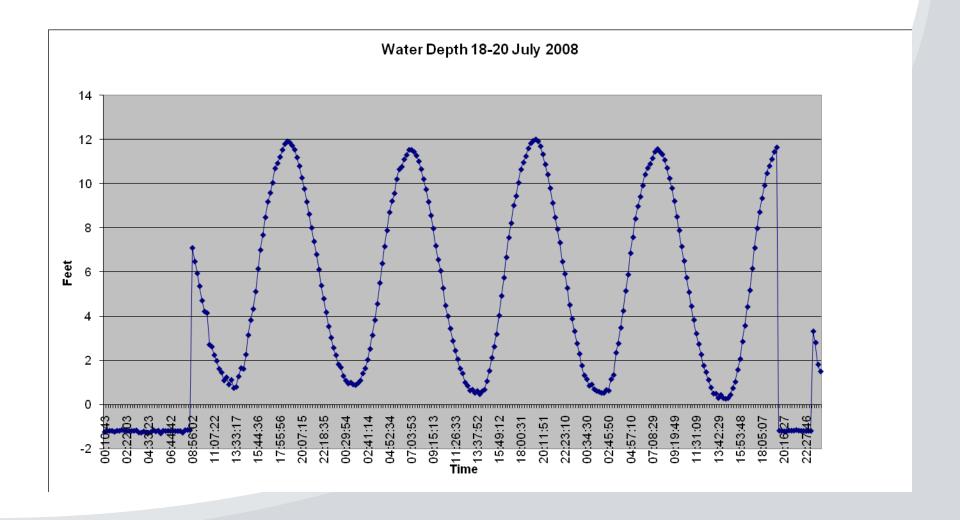
SmartCoast Water Depth 19 July 2008





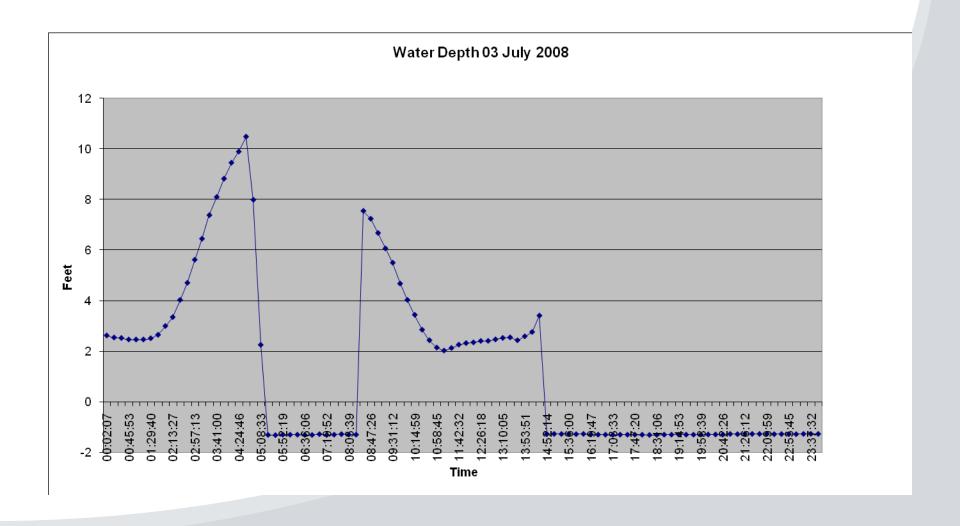
SmartCoast Water Depth 18-20 July 2008





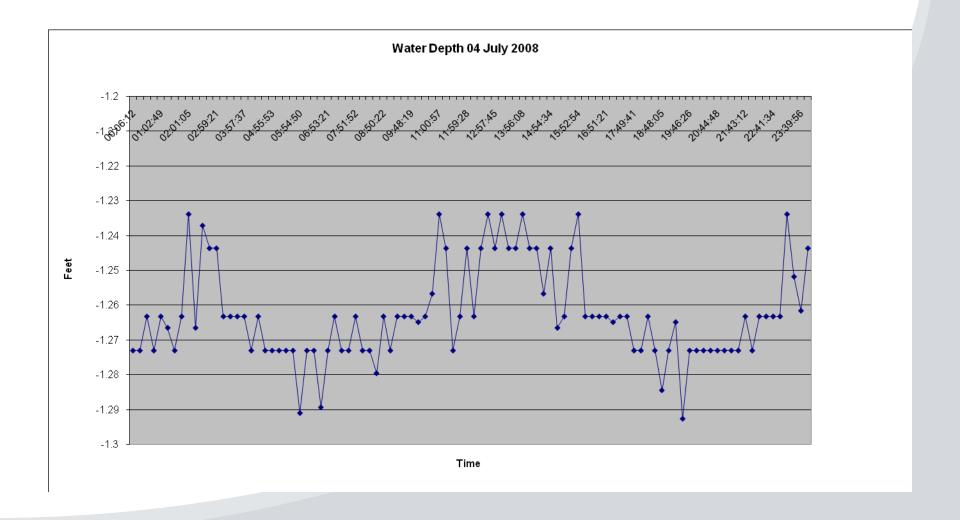
SmartCoast Water Depth 03 July 2008





SmartCoast Water Depth 04 July 2008





Visual Sensor

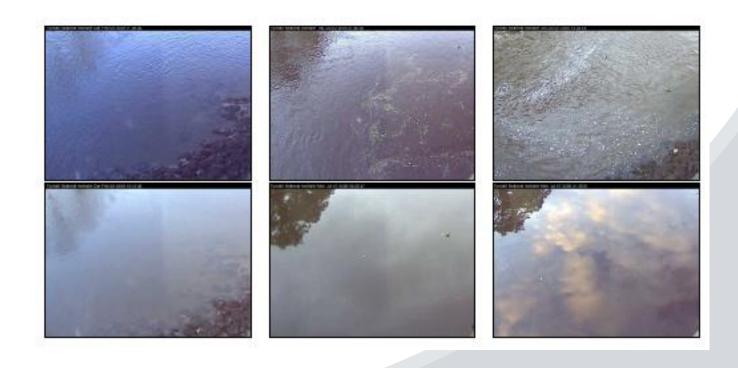


- Low cost and low maintainance
- Act as "eyes" on the water and either dispute or validate the readings from the in-situ sensor
 - May be also used as a tool to detect other types of events such as biofouling events – if it is disputing values produced by the in-situ sensor, it may be the case that the site needs to be managed – water manager needs to be alerted

- Act as a back-up sensing mechanism if the in-situ sensor goes offline
- Alert if something of interest seems to be happening for adaptive sampling
 - Can subsequently decide to move more in-situ sensors to this location or sample more often

Water level estimation from image data





None





Low





Medium-Low





Medium-High





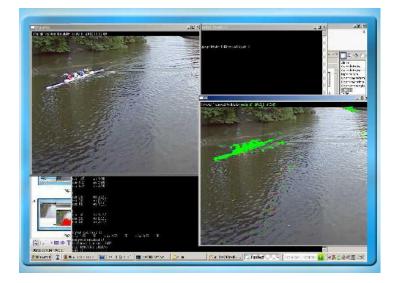
High

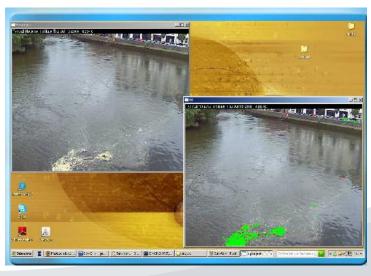


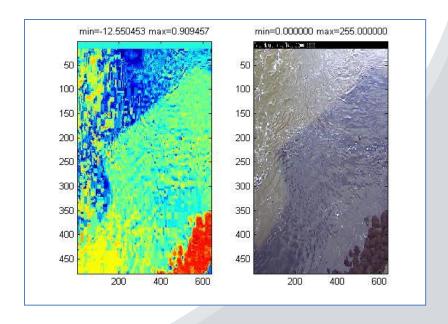


Image Classification System



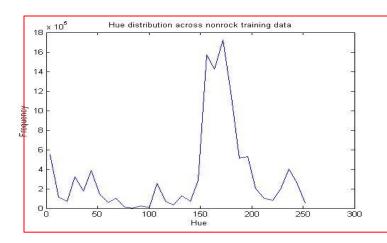


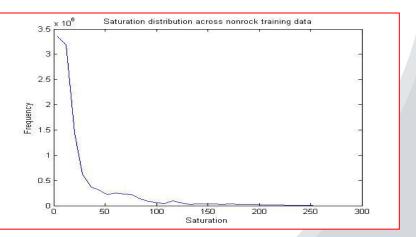


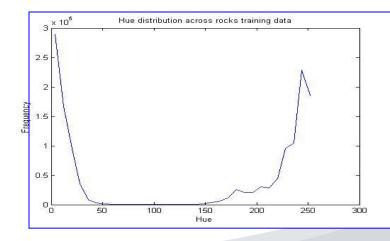


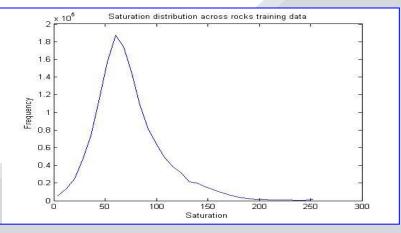
Modelling Rock







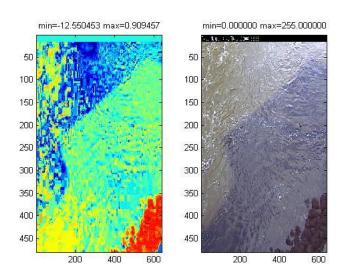


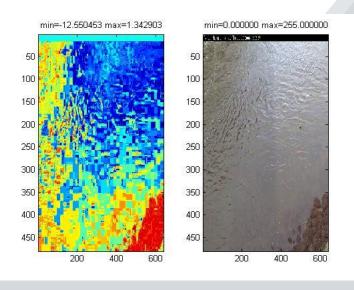




Log-likelihood Images

Given an image, an LL coefficient is calculated for each pixel based on their hue and saturation values from the training data





Class Models



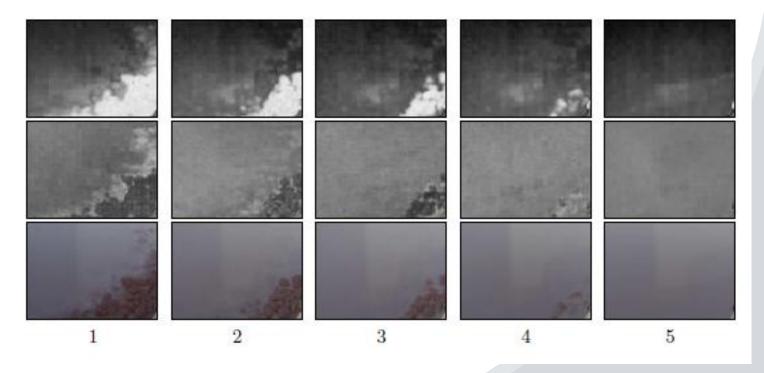
Likelihood mean image

Likelihood stDev image

Mean image

– raw pixel

values



Classifier 1 (C1): Gaussian model

Classifier 2 (C2): Log-likelihood NCC

Classifier 3 (C3): Class average NCC

Performance Metrics



Class Distance Error:

$$P_1 = \frac{1}{N} \sum_{i=1}^{N} |C_i - E_i|$$

- Where N is the number of testing samples, C_i is the true class image of image i and E_i is the estimated class for image I
- Classification Rate:

$$P_2 = \frac{1}{N} \sum_{i=1}^{N} \delta(C_i - E_i)$$

• Where $\delta(x)$ is the impulse function which equals one when x=0 and is equal to zero otherwise

Results: Overall Accuracy



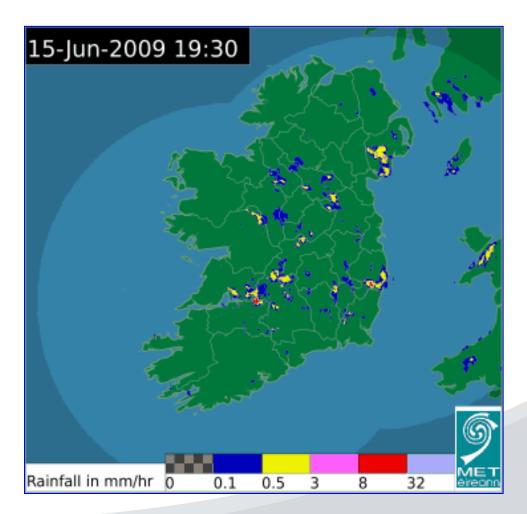
	C ₁	C ₂	C ₃
Class Distance Error	0.642	0.537	0.302
Classification Rate	0.467	0.732	0.750

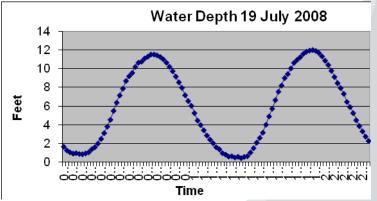
The best performing classifier was C₃ classifying 75% of the images correctly.

Future work: Examine more sophisticated algorithims for investigating classification of various visual features and examines correlations between in-situ sensor readings and image features.

Multi-modal sensor networks – Adaptive Sampling



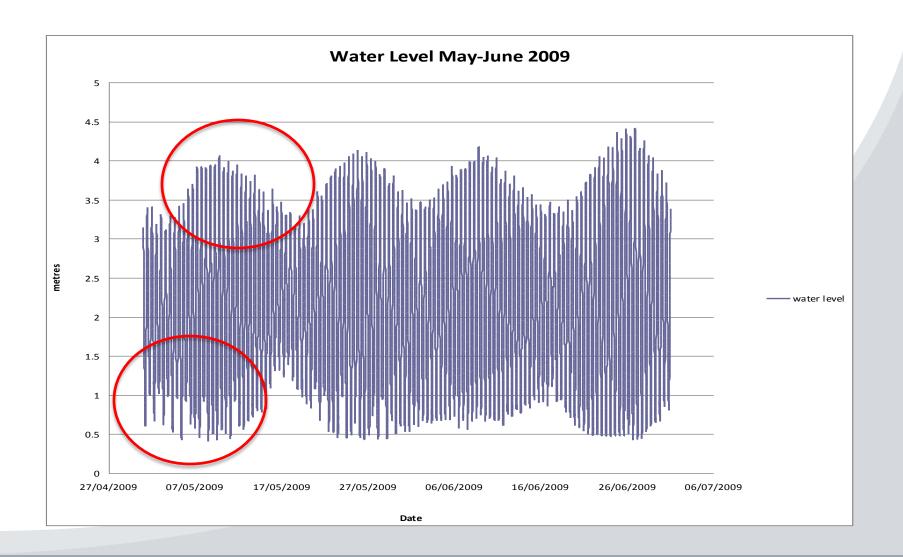






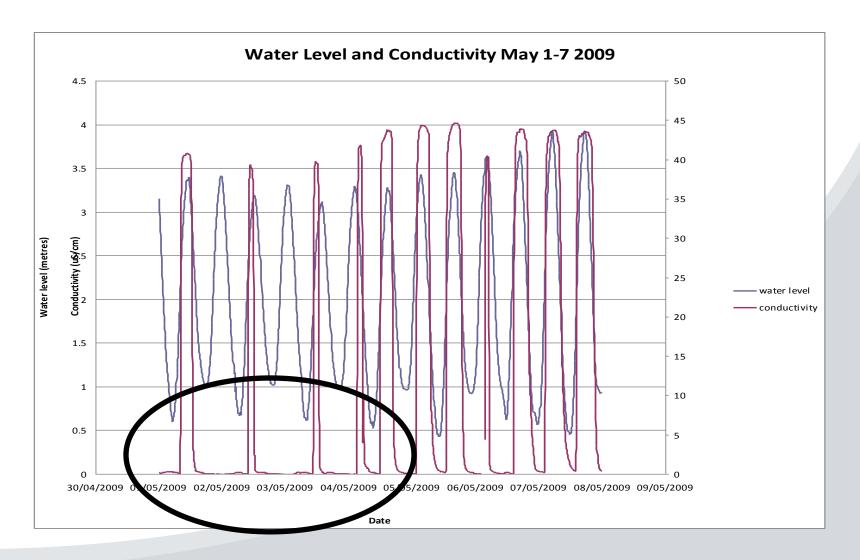
Deploy Water Depth Lee Maltings May-June 2009





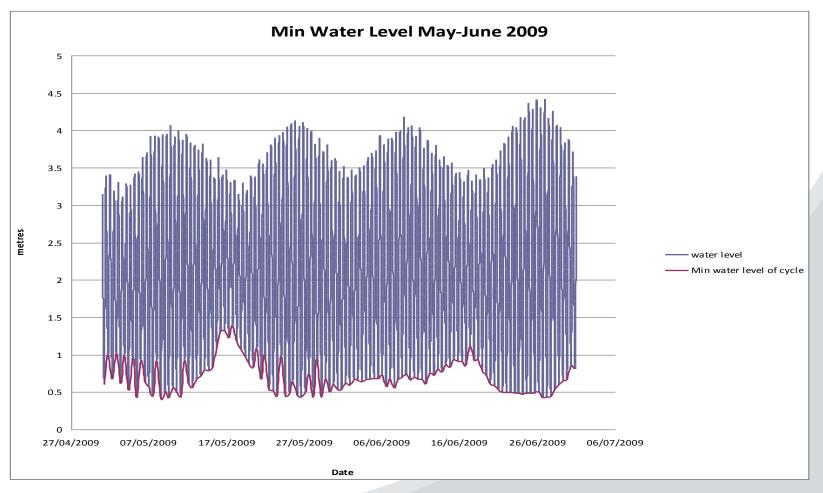
Deploy Water Depth & Conductivity Lee Maltings May-June 2009





Min Water Depth Lee Maltings May-June 2009





River Lee Catcment – Deploy Project Sites



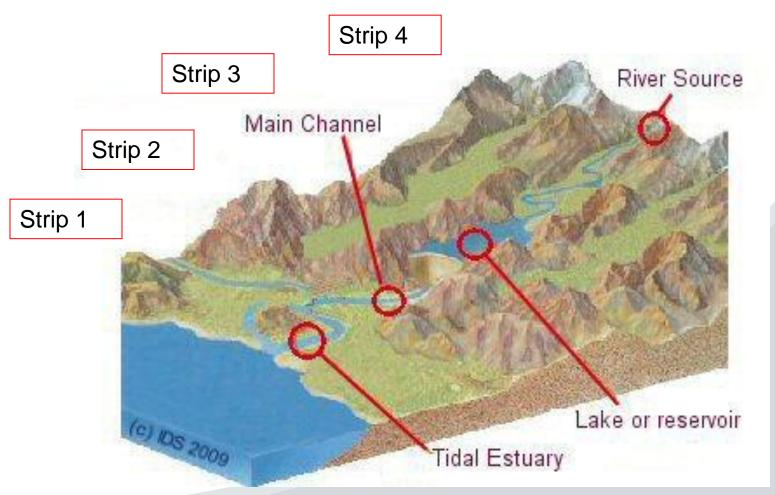
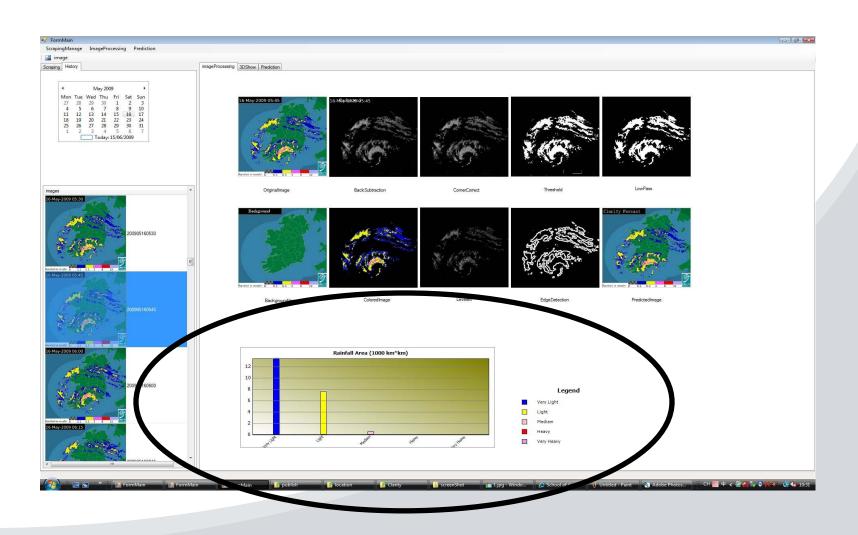


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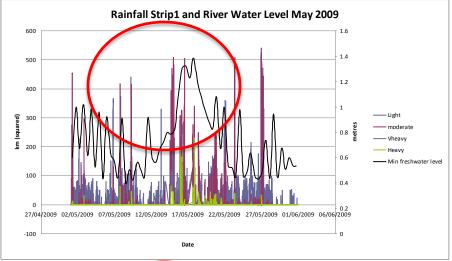
Rainfall Radar Processing

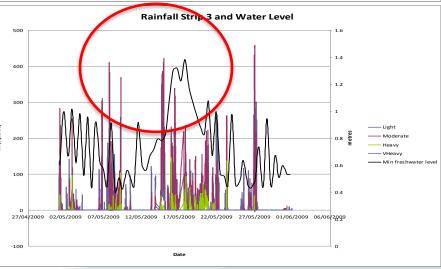


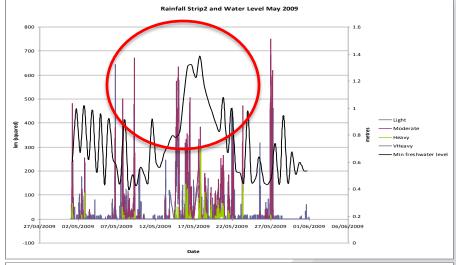


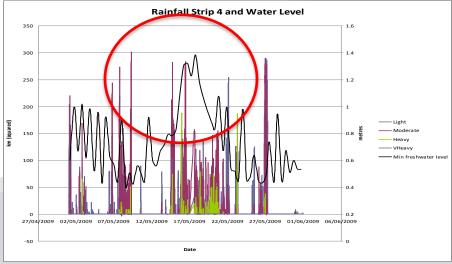
River Lee Catchment – Rainfall and Water Level (Lee Maltings)





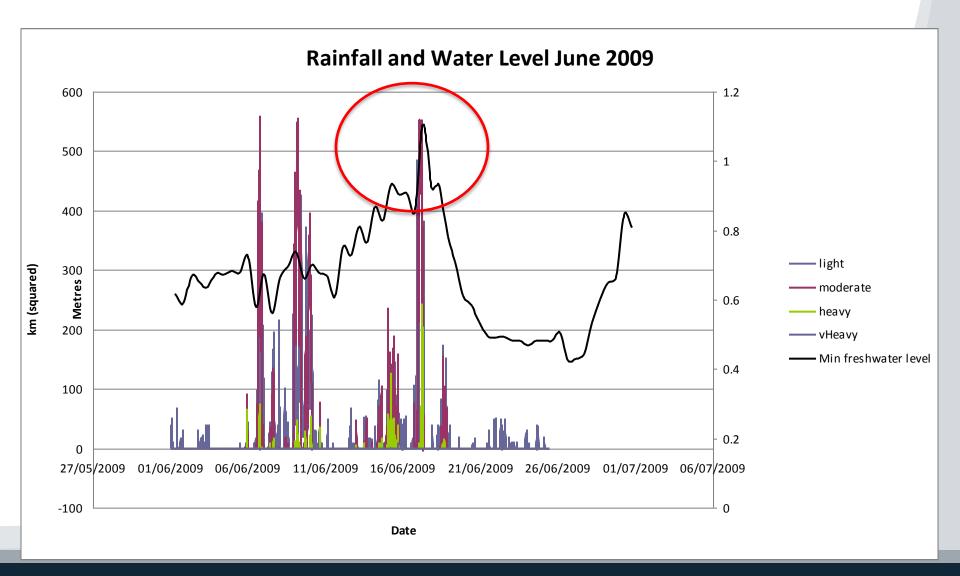






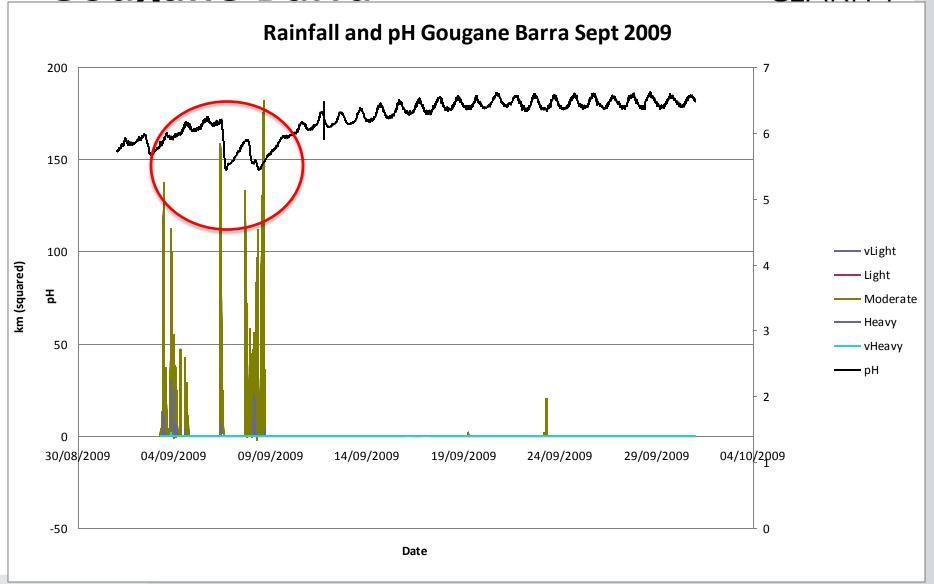
River Strip1 Rainfall and Water Level (Lee Maltings) June 2009





Gougane Barra





River Tolka











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