



# Fast Artificial Intelligence Detecting Climate Change Effects in Imaging Data

Birgitta Dresp<sup>1</sup>  
John M. Wandeto<sup>2</sup>

<sup>1</sup> CNRS UMR 7357 Strasbourg University, 67200  
Strasbourg, FRANCE

<sup>2</sup> Dedan Kimathi University of Technology, Nyeri,  
KENYA

[birgitta.dresp@cnrs.fr](mailto:birgitta.dresp@cnrs.fr)

[john.wandeto@dkut.ac.ke](mailto:john.wandeto@dkut.ac.ke)



## 1. Introduction

Satellites observe Earth and other planetary bodies via remote sensors

Remote sensors detect and record reflected or emitted energy represented in the form of pixelized image data for visual analysis

Satellite images provide important data relating to natural or urban landscapes

Alterations therein, observed in the course of time, may be the consequence of human impact or climate change



Affordable technology for detecting such changes early serves citizens, professionals, and policymakers

Assists adequate decision making for timely action

We used Self-Organized-Map (SOM)-based Artificial Intelligence (AI) for pixel-by-pixel analysis of remotely sensed imaging data showing landscapes across different moments in time

We show that the algorithm permits reliable quantification of critical landscape changes and their evolution with time, placed in a meaningful context of human impact and climate change



## 2. Study

### 2.1. Geographic region of interest

Lake Mead, Arizona-Nevada, 39 miles to the East of Las Vegas, USA

One of the USA's largest water reservoirs, surrounded by the Hoover Dam, which controls floods, provides water irrigation, produces hydroelectric power

Major supply source for Nevada, Arizona, and California

More than 20 million people in Greater Las Vegas depend on the Lake's supply, which also provides for the many farms in the extensive land areas beyond



## 2.1. Time period of interest

The years between 1984 and 2008

Over these years, climate change has led to hotter and drier conditions due to higher temperatures and reduced rainfall and snowpack, accelerating the depletion of Lake Mead

Water comes from the Colorado River, supplied by snowmelt from the Rockies

Climate change effects combine with human impacts due to the major restructuring of Las Vegas City Centre and the rapid spread of residential areas into the desert

Population counts grew from thousands in 1984 to millions in 2008, the number of visitors from ~10 to ~50 million *per annum*

## 2.3. Images

25 images extracted from time-lapse animations of Lake Mead captured by NASA Landsat sensors



1984

2008

Pre-processing for scale and alignment

Co-registration using *StackReg* in *ImageJ*

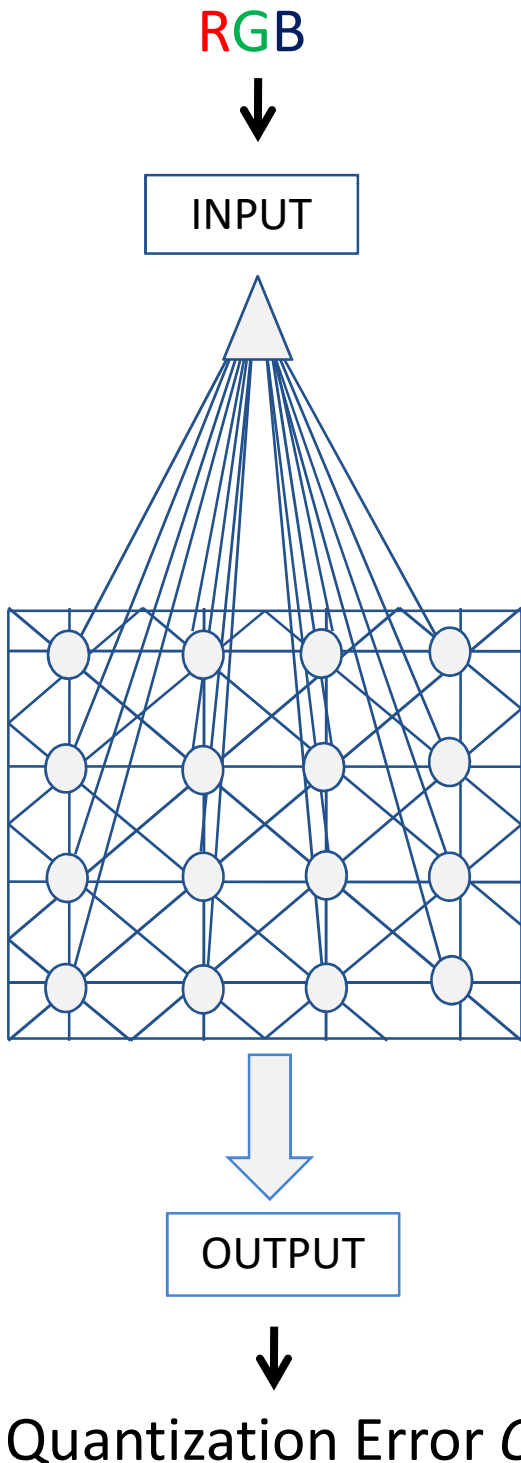
Luminance contrast normalization

$$L_{final} = (L - L_{min} / L_{max} - L_{min}) \times 255$$

Last image of time series for training the neural network



## 2.4. Self Organizing Map (SOM)



**« Has the color or contrast intensity of a single pixel in the image changed ? »**

Winner-Take-All Learning

$$\Delta w_{kj} = \alpha(x_j - w_j) \text{ for } j=1,2,\dots,n$$

Learning rate  $\alpha = 0.2$  for 10,000 iterations



RGB input is represented by a real vector  $x$  of  $n$ -dimensionality in the SOM

A model vector  $m_i$  of  $n$ -dimension associated with each  $x$

$d(x, m_i)$  gives the Euclidean distance between input  $x$  and model  $m_i$

The model  $m_c$  that yields the smallest  $d(x, m_i)$  best matches input  $x$

Model  $m_c$  is determined by Winner-Take-All Learning where all  $x$  are compared with all  $m_i$  in terms of  $\|x - m_i\|$

Models  $m_i$  topographically close in the map in terms of geometric distance ( $h_{ci}$ ) will activate each other to learn something from their common input  $x$

The difference between  $x$  and  $m_c$  yields the local error of quantization associated with a model  $m_c$  by comparison with an input  $x$



## 2.5. Winner-Take-All Learning in the SOM

$$m_i(t+1) = m_i(t) + \alpha(t) \frac{h_{ci}(t)}{\|x(t) - m_i(t)\|}$$

$t=1,2,3\dots n$  are discrete-time coordinates

$h_{ci}(t)$  is the neighborhood function at moment  $t$

$\alpha(t)$  is the learning rate

The final weights in the SOM are represented by a three dimensional output vector space  $X$  for  $R$ ,  $G$  and  $B$

Changes in the average SOM-QE selectively reflect the magnitude and direction of change in any such dimension from one image to another

The average QE of all  $x$  ( $X$ ) in an input image is given by

$$QE = \frac{1}{N} \sum^N \|X_i - m_c\|$$

$N$  is the total number of input vectors  $x$  in the image



### 3. Data Analysis

Software generated SOM-QE data were collected for each image from the time series after the learning phase

Stored in a file with labeled lines and columns, then submitted to linear regression analysis to assess statistical significance of trends in the data

Statistical correlation analysis (Pearson) was performed to establish covariance between SOM-QE and publically archived human impact statistics

Analyses were performed using the statistics toolbox in *Systat Sigmaplot 12*



Table 1. QE data from SOM analysis and Hoover Dam Control Room water level statistics (in feet above the sea level)

Image Year	SOM-QE	Water Level
1984	0,5534	1214,9100
1985	0,5544	1209,4600
1986	0,5478	1209,7400
1987	0,5459	1208,8400
1988	0,5407	1204,5600
1989	0,5356	1192,0000
1990	0,5352	1183,6900
1991	0,5208	1175,4300
1992	0,5204	1188,5900
1993	0,5238	1176,3900
1994	0,5211	1182,1800
1995	0,5276	1182,4000
1996	0,5280	1191,9800
1997	0,5383	1202,9300
1998	0,5448	1213,7100
1999	0,5442	1210,4100
2000	0,5338	1204,2200
2001	0,5077	1185,8000
2002	0,4900	1163,1700
2003	0,4953	1145,9300
2004	0,4603	1131,7600
2005	0,4657	1139,8700
2006	0,4607	1131,6600
2007	0,4725	1118,0000
2008	0,4588	1099,7200



Figure 1. Linear regression analysis

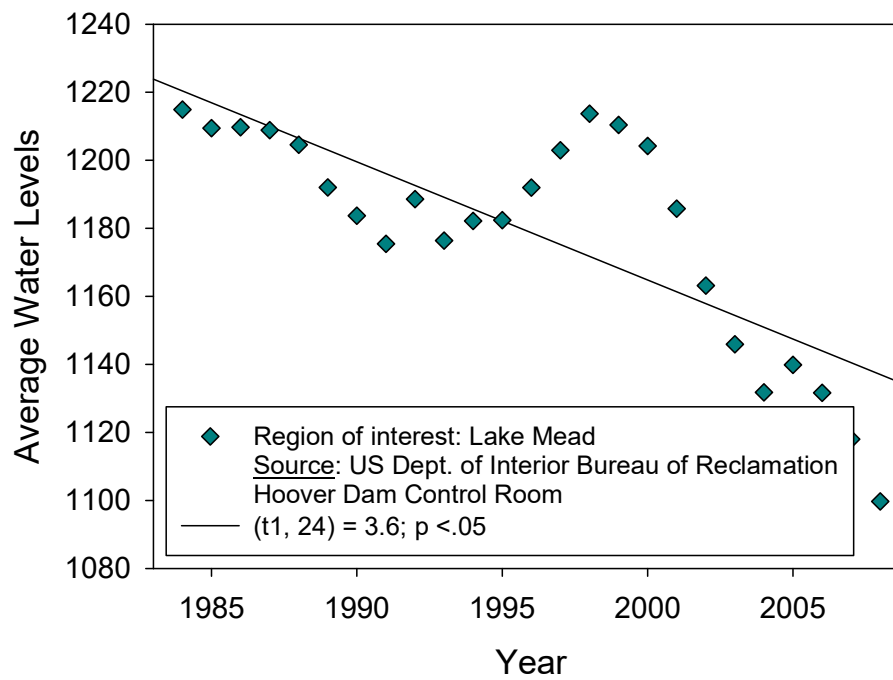
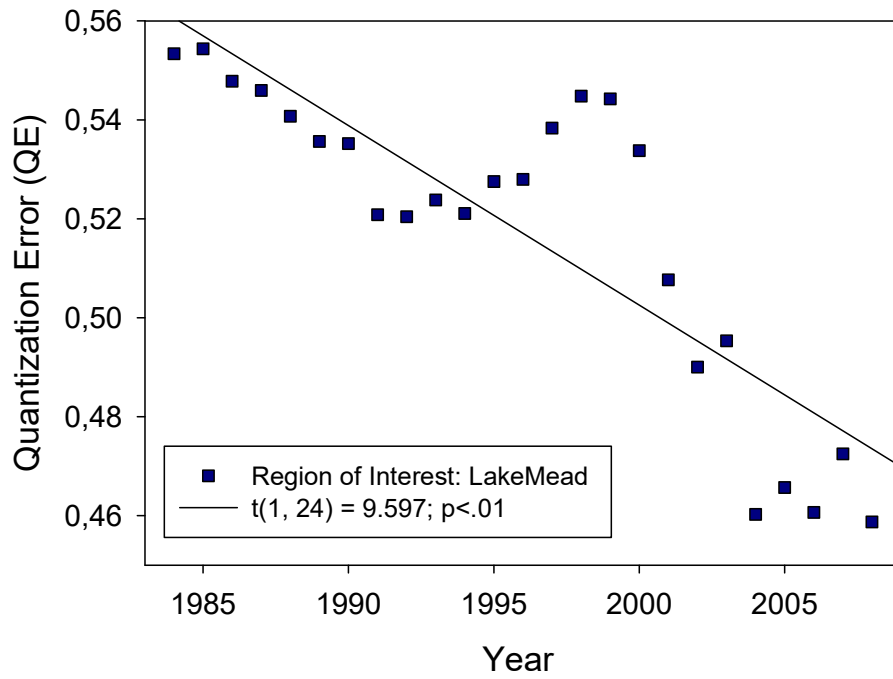




Figure 2. Correlation analysis

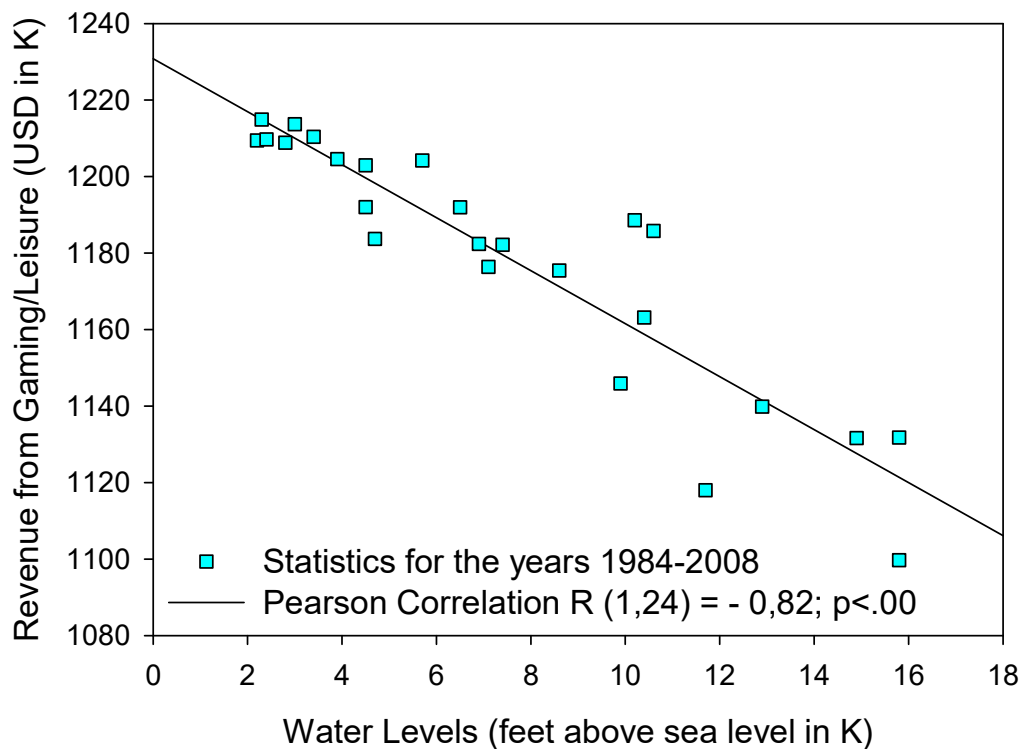
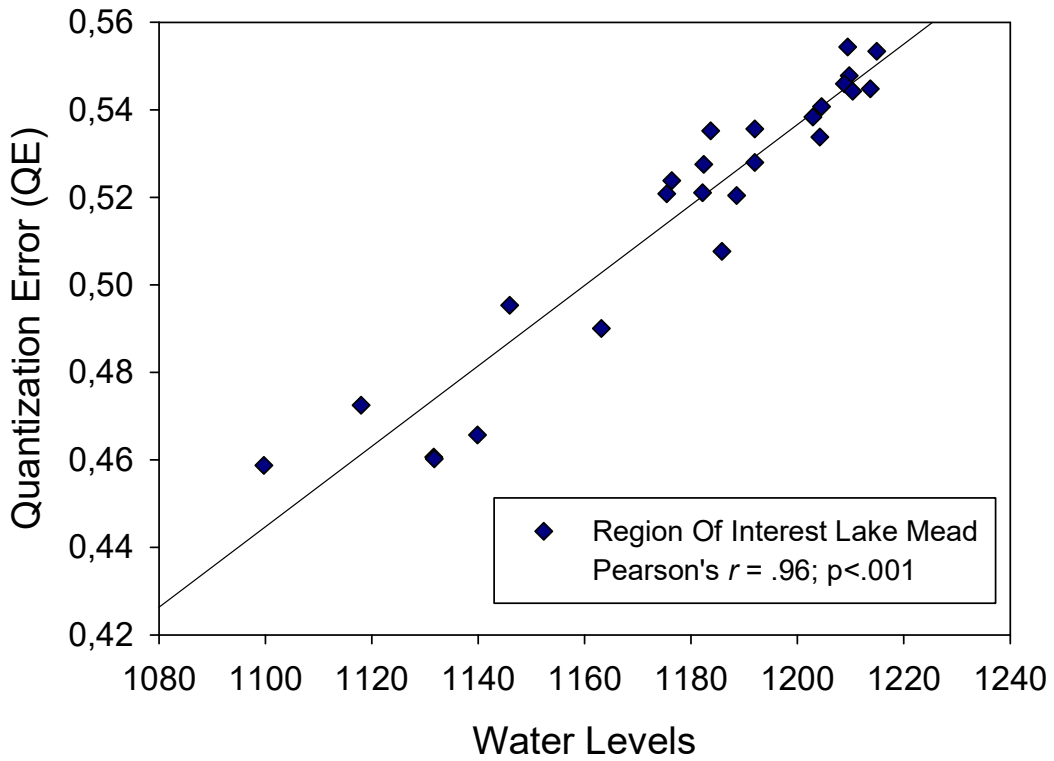
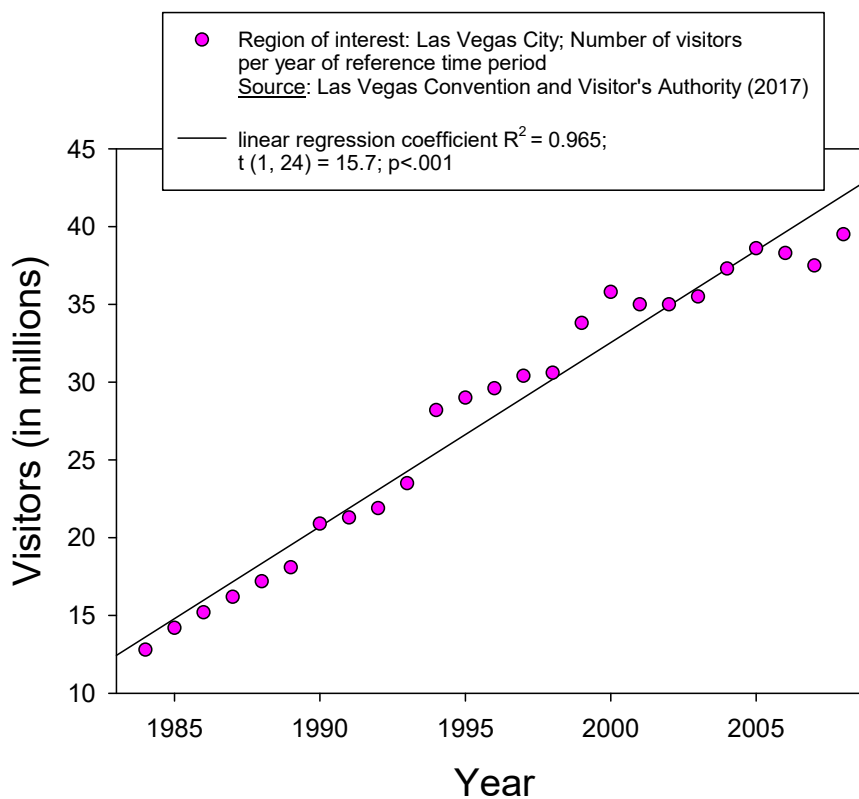
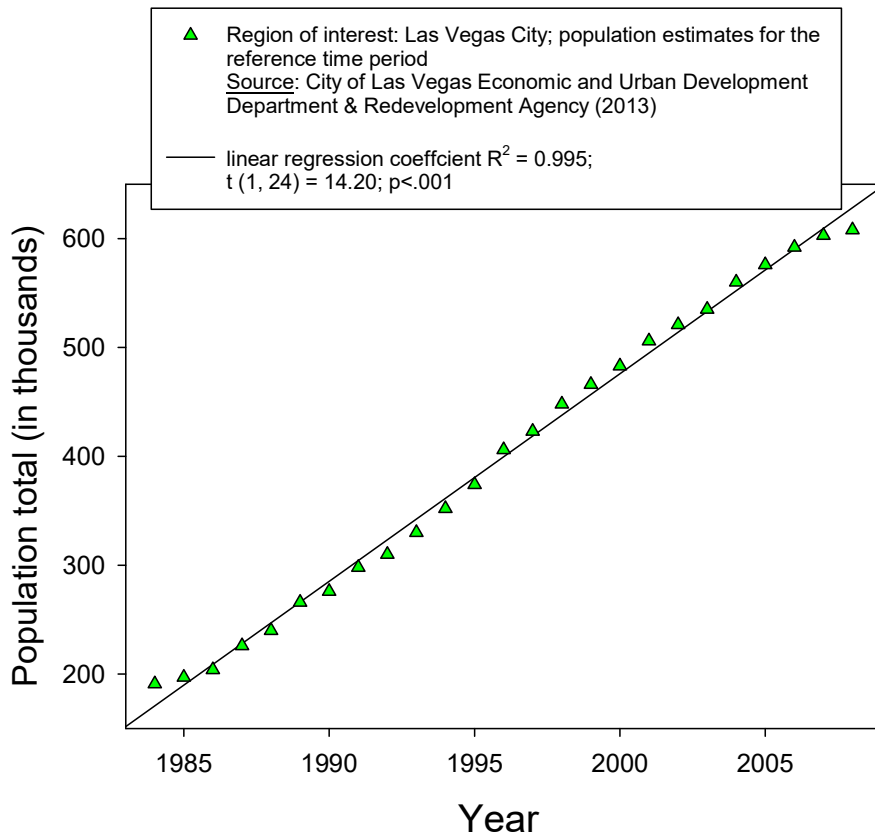




Figure 3. Human impact data 1984-2008



## 4. Conclusions

The SOM-QE reliably captures changes in image pixels relating to dramatic landscape change that has its consequences

Meaningful data interpretation must take into account data relating to human activities and economic development in the given context

Other pixel colour-based methods, such as selective principal component analysis, have been applied to Earth images from satellites to study temporal changes relating to effects of climate change in arctic regions

SOM-QE analysis classifies pixel color-coded image data in seconds without any need of prior annotation by a human

SOM is a classic, parsimonious and explainable AI tool that may be combined with other methods and algorithms of image analysis depending on objectives



## References

Kohonen T (1998) The Self-Organizing Map. *Neurocomputing*, 21, 1–6.

Kohonen T (2014) Matlab Implementations and Applications of the Self-Organizing Map. Unigrafia Oy, Helsinki, Finland.

Wandeto J, Dresp-Langley B (2019) The quantization error in a self-organizing map as a contrast and colour specific indicator of single-pixel change in large random patterns. *Neural Networks*, 119, 273-285.

Wandeto J, Dresp-Langley B (2023) SOM-QE ANALYSIS: a biologically inspired technique to Detect and track meaningful changes within image regions. *Software Impacts*, 17, 100568.