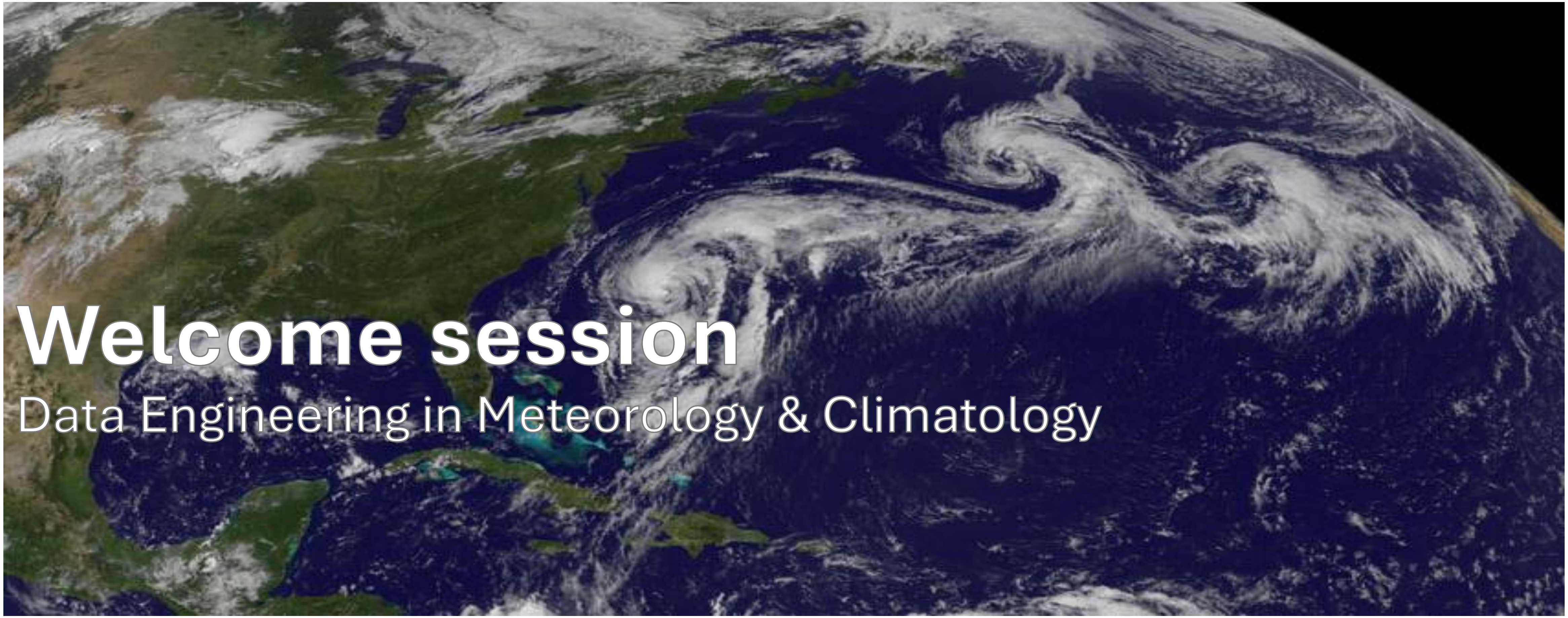


Welcome session

Data Engineering in Meteorology & Climatology

Proyectos en ingeniería de datos e inteligencia artificial

[redacted]

26 titulaciones encontradas

Filtrar

Madrid (Comunidad de) — Pública

UNIVERSIDAD COMPLUTENSE DE MADRID

Grado en Ingeniería de Datos e Inteligencia Artificial

Facultad de Informática (Centro propio)

Nota de corte del curso 2024-25 **12,68**

Cataluña — Pública

UNIVERSIDAD POLITÉCNICA DE CATALUNYA

Grado en Ciencia e Ingeniería de Datos

Facultad de Informática (Centro propio)

Nota de corte del curso 2024-25 **12,31**

Madrid (Comunidad de) — Pública

UNIVERSIDAD POLITÉCNICA DE MADRID

Grado en Ciencia de Datos e Inteligencia Artificial

Escuela Técnica Superior de Ingeniería de Sistemas Informáticos (Centro propio)

Nota de corte del curso 2024-25 **12,03**

26 titulaciones encontradas

Filtrar

Madrid (Comunidad de) — Pública

UNIVERSIDAD COMPLUTENSE DE MADRID

Grado en Matemáticas y Ciencia de Datos

Facultad de Ciencias Matemáticas (Centro propio)

Nota de corte del curso 2024-25 **11,96**

Madrid (Comunidad de) — Pública

UNIVERSIDAD AUTÓNOMA DE MADRID

Grado en Análisis de Datos en la Empresa / Bachelor in Business Analytics

Facultad de Ciencias Económicas y Empresariales (Centro propio)

Nota de corte del curso 2024-25 **11,91**

Murcia (Región de) — Pública

UNIVERSIDAD DE MURCIA

Grado en Ciencia e Ingeniería de Datos

Facultad de Informática (Centro propio)

Nota de corte del curso 2024-25 **11,88**

26 titulaciones encontradas

Filtrar

Comunitat Valenciana — Pública

UNIVERSIDAD POLITÉCNICA DE VALENCIA

Grado en Ciencia de Datos

Escuela Técnica Superior de Ingeniería Informática (Centro propio)

Nota de corte del curso 2024-25 **11,88**

Madrid (Comunidad de) — Pública

UNIVERSIDAD POLITÉCNICA DE MADRID

Grado en Ciencia de Datos e Inteligencia Artificial

Escuela Técnica Superior de Ingenieros Informáticos (Centro propio)

Nota de corte del curso 2024-25 **11,74**

Cataluña — Pública

UNIVERSIDAD AUTÓNOMA DE BARCELONA

Grado en Matemática Computacional y Analítica de Datos

Facultad de Ciencias (Centro propio)

Nota de corte del curso 2024-25 **11,67**

26 titulaciones encontradas

Filtrar

Navarra (Comunidad Foral de) — Pública

UNIVERSIDAD PÚBLICA DE NAVARRA

Grado en Ciencia de Datos

Escuela Técnica Superior de Ingeniería Agronómica y Biociencias (Centro propio)

Nota de corte del curso 2024-25 **11,59**

Cataluña — Pública

UNIVERSIDAD POMPEU FABRA

Grado en Ingeniería Matemática en Ciencia de Datos / Mathematical Engineering on Data Science

Escuela de Ingeniería (Centro propio)

Nota de corte del curso 2024-25 **11,52**

Madrid (Comunidad de) — Pública

UNIVERSIDAD CARLOS III DE MADRID

Grado en Data Science and Engineering/Ciencia e Ingeniería de Datos

Escuela Politécnica Superior (Centro propio)

Nota de corte del curso 2024-25 **11,46**

26 titulaciones encontradas — Filtrar

Madrid (Comunidad de) — Pública
UNIVERSIDAD POLITÉCNICA DE MADRID
Grado en Ingeniería y Sistemas de Datos
Escuela Técnica Superior de Ingenieros de Telecomunicación (Centro propio)
Nota de corte del curso 2024-25 **11,41**

Madrid (Comunidad de) — Pública
UNIVERSIDAD COMPLUTENSE DE MADRID
Grado en Ciencia de los Datos Aplicada
Facultad de Estudios Estadísticos (Centro propio)
Nota de corte del curso 2024-25 **11,30**

Madrid (Comunidad de) — Pública
UNIVERSIDAD AUTÓNOMA DE MADRID
Grado en Ciencia e Ingeniería de Datos
Escuela Politécnica Superior (Centro propio)
Nota de corte del curso 2024-25 **11,20**

26 titulaciones encontradas — Filtrar

Comunitat Valenciana — Pública
UNIVERSITAT DE VALÈNCIA (ESTUDI GENERAL)
Grado en Ciencia de Datos
Escuela Técnica Superior de Ingeniería (Centro propio)
Nota de corte del curso 2024-25 **11,11**

Castilla y León — Pública
UNIVERSIDAD DE LEÓN
Grado en Ingeniería de Datos e Inteligencia Artificial
Escuela de Ingenierías Industrial, Informática y Aeroespacial (Centro propio)
Nota de corte del curso 2024-25 **10,68**

Madrid (Comunidad de) — Pública
UNIVERSIDAD REY JUAN CARLOS
Grado en Ciencia e Ingeniería de Datos
Escuela de Ingeniería de Fuenlabrada (Centro propio)
Nota de corte del curso 2024-25 **10,54**

26 titulaciones encontradas — Filtrar

Asturias (Principado de) — Pública
UNIVERSIDAD DE OVIEDO
Grado en Ciencia e Ingeniería de Datos
Escuela Politécnica de Ingeniería de Gijón (Centro propio)
Nota de corte del curso 2024-25 **10,20**

Comunitat Valenciana — Pública
UNIVERSIDAD MIGUEL HERNÁNDEZ DE ELCHE
Grado en Ciencia de Datos e Inteligencia Artificial
Facultad de Ciencias Experimentales (Centro propio)
Nota de corte del curso 2024-25 **10,05**

Cataluña — Pública
UNIVERSIDAD AUTÓNOMA DE BARCELONA
Grado en Ingeniería de Datos
Escuela de Ingeniería (Centro propio)
Nota de corte del curso 2024-25 **9,88**

26 titulaciones encontradas — Filtrar

Cataluña — Pública
UNIVERSIDAD AUTÓNOMA DE BARCELONA
Grado en Ingeniería de Datos
Escuela de Ingeniería (Centro propio)
Nota de corte del curso 2024-25 **9,88**

Galicia — Pública
UNIVERSIDAD DE A CORUÑA
Grado en Ciencia e Ingeniería de Datos
Facultad de Informática (Centro propio)
Nota de corte del curso 2024-25 **9,75**

Murcia (Región de) — Pública
UNIVERSIDAD POLITÉCNICA DE CARTAGENA
Grado en Ciencia e Ingeniería de Datos
Escuela Técnica Superior de Ingeniería de Telecomunicación (Centro propio)
Nota de corte del curso 2024-25 **6,70**

26 degrees x 40 students =**1040 graduates per year**

Your skills

- **Strong mathematical background**
  - Trained in calculus, linear algebra, probability, and mathematical modeling—essential for building robust AI systems and analyzing complex datasets.
- **Computational mastery**
  - Skilled in programming, machine learning, data structures, and large-scale data processing—ready to tackle real-world challenges in AI and data-driven industries.

The gap

Climatology and meteorology remain vast, underexplored frontiers—waiting for data and AI engineers to unlock their full potential.

Your contribution to climate intelligence

- Handling large-scale weather/climate datasets
- Data cleaning and quality control (QC)
- Integration of heterogeneous data sources (data fusion)
- Advanced analysis, visualization and dashboarding
- Time series analysis and anomaly detection

Real World applications

Predicting Tropical Cyclone Rapid Intensification From Satellite Microwave Data and Neural Networks

Francisco J. Tapiador, Andrés Navarro, Raúl Martín, Svetla Hristova-Veleva, and Ziad S. Haddad

***Abstract*— A new method to analyze the potential for rapid intensity change in tropical cyclones (TC) is presented. The method is based on satellite observations of precipitation derived from microwave (MW) radiometers. The approach is intended to condense the information in the environment and in the vortex using a low wavenumber representation of the rain index (RaIn, a multichannel nonlinear combination of passive MW observations), and train a deep-learning, multilayer neural network (NN) with the RaIn and the changes in the wind over the next 24 h. The resulting NN exhibits a near-perfect ability to identify rapid intensification (RI: changes in the hurricane wind speed in excess of 30 knots within a 24-h period). It is found that the spatial structure and amounts of the columnar water condensate within the extended environment is necessary to capture the most important information regarding the RI process. Analyses of the NN structure provide new insight into the physics of TC and can help improve model forecasting. Environmental conditions as far as 1050 km from the TC center might affect the process of RI by at least three physical processes: absolute angular momentum inflow, wind shear stabilization, and steering the outflow jets in the upper troposphere. The findings can be used to build a RI discriminant (RID) for real-time operations.**

***Index Terms*— Hurricanes, microwave (MW), radiometers, rapid intensification (RI), tropical cyclones (TC).**

model to forecast the evolution over the following 24 h, and calculate the resulting intensity of the storm. The problem with this proposition is threefold: 1) first, it is impossible to know the exact state of the atmosphere at the initial time. Even knowledge of the joint distribution of the portion of the state variables that would be most important to forecast the intensity would necessarily entail a large amount of uncertainty; 2) the evolution equations are highly nonlinear, implying that any initial uncertainty will inevitable grow and produce a forecast that can be wide of the mark; and 3) last, current knowledge of the evolution equations is still imperfect, especially when the dynamics of hydrometeors is involved [1].

The indirect approach to forecast TC intensification is to infer TC characteristics from synoptic data, but the approach can only provide a statistical-based answer, which is by definition tied to a particular set of conditions. Attempts to identify hurricanes in the outputs of Regional Climate Models (RCM) or—even better—high-resolution Earth System Models (ESM) or Global Climate/Circulation Models (GCMs) from present climate suffer from the same shortcomings, and preclude following such an approach for the future climates

Tapiador, F.J., Navarro, A., Martín, R., Hristova-Veleva, S., Haddad, Z. (2022). Predicting Tropical Cyclone Rapid Intensification From Satellite Microwave Data and Neural Networks 10.1109/TGRS.2021.3128076

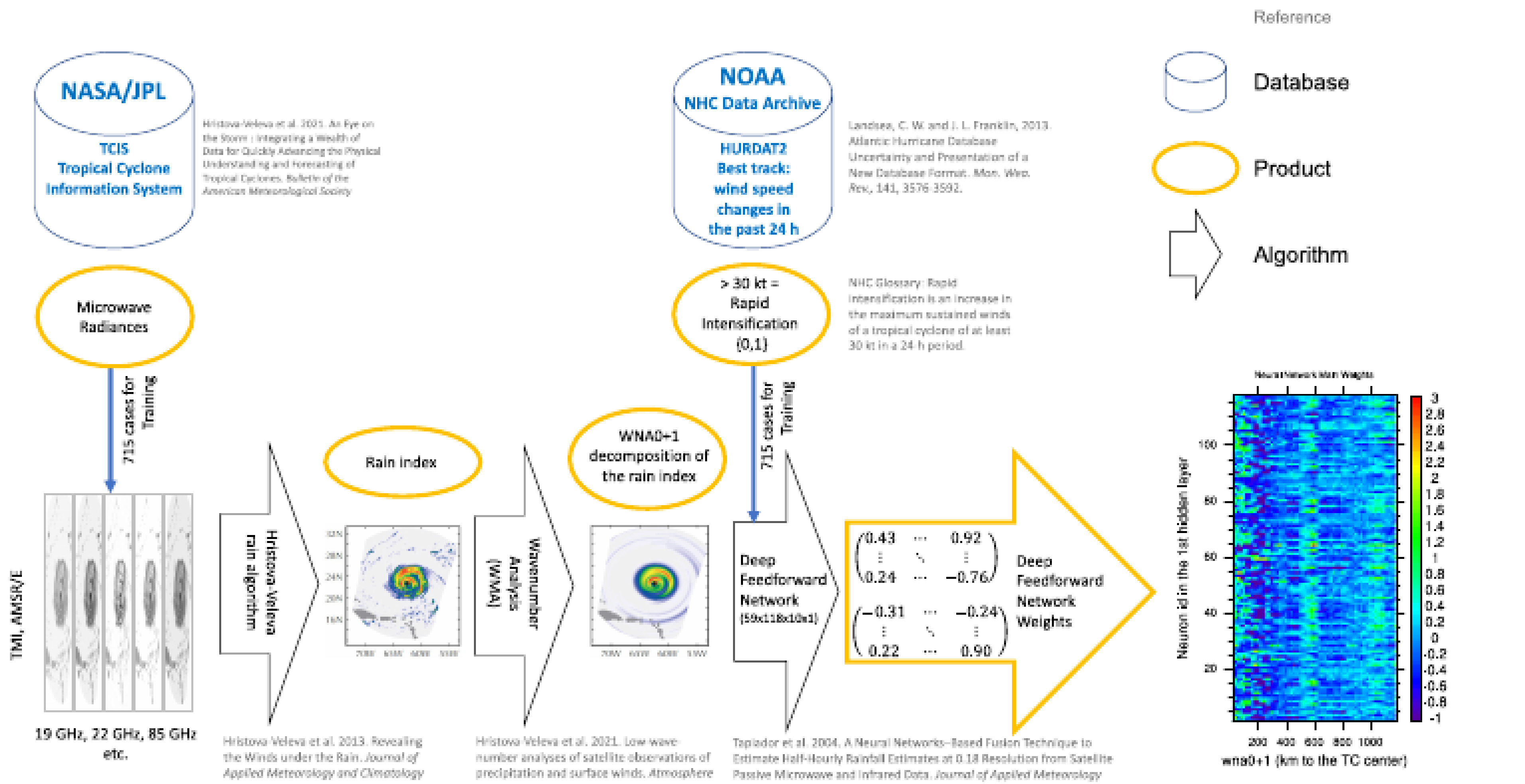


Fig. 6. Scheme of the data processing using NN no. 2 (NN2).

Tapiador, F.J., Navarro, A., Martín, R., Hristova-Veleva, S., Haddad, Z. (2022). Predicting Tropical Cyclone Rapid Intensification From Satellite Microwave Data and Neural Networks 10.1109/TGRS.2021.3128076

Article

A foundation model for the Earth system

https://doi.org/10.1038/s41586-025-09005-y

Received: 28 May 2024

Accepted: 9 April 2025

Published online: 21 May 2025

Open access

Check for updates

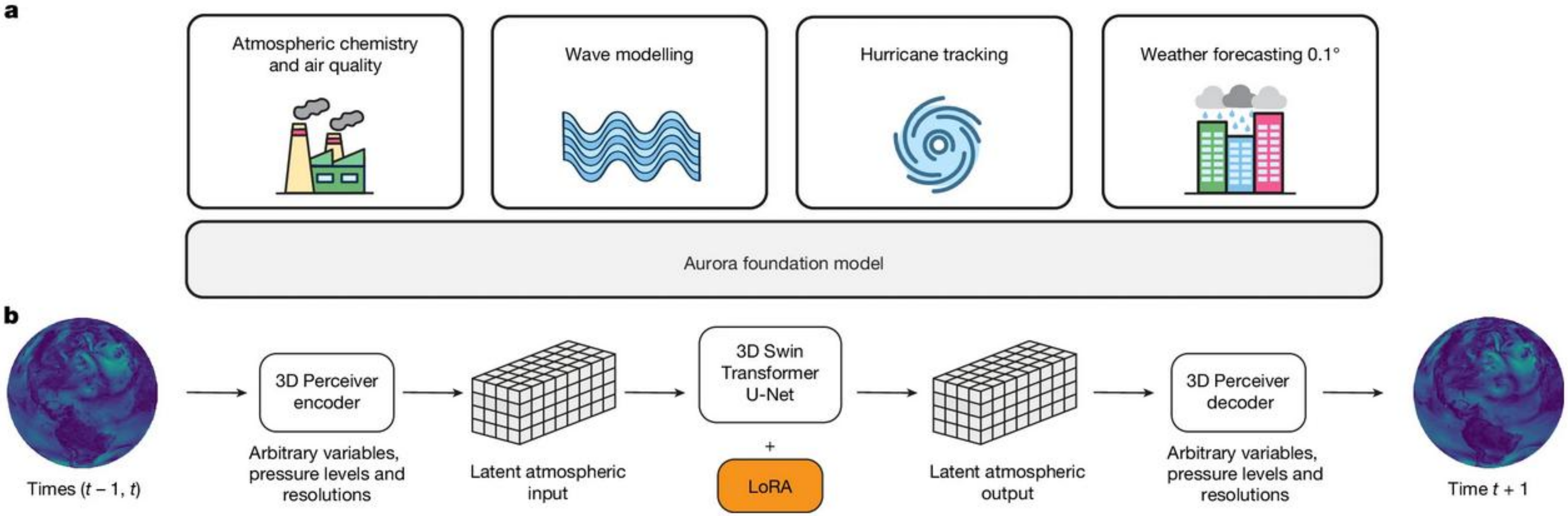
Cristian Bodnar[1,2,11], Wessel P. Bruinsma[1,11], Ana Lucic[1,3,11], Megan Stanley[1,11], Anna Allen[4,11], Johannes Brandstetter[1,5], Patrick Garvan[1], Maik Riechert[1], Jonathan A. Weyn[6], Haiyu Dong[6], Jayesh K. Gupta[2,7], Kit Thambiratnam[6], Alexander T. Archibald[4], Chun-Chieh Wu[8], Elizabeth Heider[1], Max Welling[1,3], Richard E. Turner[1,4,9] & Paris Perdikaris[1,10] ✉

Reliable forecasting of the Earth system is essential for mitigating natural disasters and supporting human progress. Traditional numerical models, although powerful, are extremely computationally expensive[1]. Recent advances in artificial intelligence (AI) have shown promise in improving both predictive performance and efficiency[2,3], yet their potential remains underexplored in many Earth system domains. Here we introduce Aurora, a large-scale foundation model trained on more than one million hours of diverse geophysical data. Aurora outperforms operational forecasts in predicting air quality, ocean waves, tropical cyclone tracks and high-resolution weather, all at orders of magnitude lower computational cost. With the ability to be fine-tuned for diverse applications at modest expense, Aurora represents a notable step towards democratizing accurate and efficient Earth system predictions. These results highlight the transformative potential of AI in environmental forecasting and pave the way for broader accessibility to high-quality climate and weather information.

Bodnar, C., Bruinsma, W.P., Lucic, A. *et al.* A foundation model for the Earth system. *Nature* **641**, 1180–1187 (2025). https://doi.org/10.1038/s41586-025-09005-y

Fig. 1: Aurora is a 1.3-billion-parameter foundation model for the Earth system.

From: A foundation model for the Earth system



Icons are for illustrative purposes only. **a**, Aurora is pretrained on several heterogeneous datasets with different resolutions, variables and pressure levels. The model is then fine-tuned for several operational forecasting scenarios at different resolutions: atmospheric chemistry and air quality at 0.4°, wave modelling at 0.25°, hurricane tracking at 0.25° and weather forecasting at 0.1°. **b**, Aurora is a flexible 3D Swin Transformer[19] with 3D Perceiver-based[21] atmospheric encoders and decoders. The model is able to ingest inputs with different spatial resolutions, numbers of pressure levels and variables.

Bodnar, C., Bruinsma, W.P., Lucic, A. *et al.* A foundation model for the Earth system. *Nature* **641**, 1180–1187 (2025). https://doi.org/10.1038/s41586-025-09005-y

“Join the Dark Side... of Atmospheric Science”
Where clouds aren't the only thing with layers.

Schedule

TOPIC	HOURS
WELCOME & TOOLS	2
DATA PRODUCTS	4
CLIMATOLOGIES	2
ENSEMBLE	2
ANOMALIES	2
CCS (THEORY)	2
CCS (PRACTICE)	4
CCS (PRESENTATIONS)	2
NLP (THEORY)	2
NLP (PRACTICE)	4
NLP (PRESENTATIONS)	2

Schedule

TOPIC	HOURS	
WELCOME & TOOLS	2	Climate fundamentals
DATA PRODUCTS	4	
CLIMATOLOGIES	2	
ENSEMBLE	2	
ANOMALIES	2	
CCS (THEORY)	2	Project #01
CCS (PRACTICE)	4	
CCS (PRESENTATIONS)	2	
NLP (THEORY)	2	Project #02
NLP (PRACTICE)	4	
NLP (PRESENTATIONS)	2	

Deliverables

TOPIC	DELIVERABLE
WELCOME & TOOLS	
DATA PRODUCTS	
CLIMATOLOGIES	YES (single)
ENSEMBLE	YES (single)
ANOMALIES	YES (single)
CCS (THEORY)	
CCS (PRACTICE)	
CCS (PRESENTATIONS)	YES (group)
NLP (THEORY)	
NLP (PRACTICE)	
NLP (PRESENTATIONS)	YES (group)

Assignment: Regional Climate Normals Analysis Using Data Science

Andrés Navarro
andres.navarro@unileon.es

1 Introduction

This assignment focuses on the analysis of regional climate normals using real-world precipitation data. Students will investigate the typical monthly precipitation patterns over Europe by computing climatological means for a defined reference period. The goal is to understand what constitutes "normal" climate conditions and how these can serve as a baseline for future anomaly detection and climate trend analysis.

The core objective is to compute monthly climate normals for the period **January 1979 to December 2008**, and to visualize these normals **over Europe**. Additionally, students will compare these normals with observed precipitation for a specific month—**June 2022**—to illustrate how deviations from the norm can be identified.

This project provides hands-on experience with climate data formats such as NetCDF and reinforces essential data science skills including data wrangling, spatial analysis, and scientific visualization.

2 Objectives

- Explore and understand the structure of climate data in NetCDF format.
- Understand the concept of climate normals and their scientific relevance.
- Calculate monthly climate normals for a defined baseline period.
- Visualize climate normals using spatial maps.
- Compare climate normals with observed data to identify deviations.
- Develop and communicate insights using data science tools and techniques.

3 Dataset Description

- **Source**:Global Precipitation Climatology Project (GPCP) Monthly Analysis Product.
- **URL**: https://psl.noaa.gov/data/gridded/data.gpcp.html
- **Variable**: Monthly mean precipitation (`precip`)
- **Units**: mm/day (to be converted to mm/month)
- **Temporal coverage**: 1979–present
- **Spatial resolution**: 2.5° x 2.5°
- **Format**: NetCDF

4 Study Region and Period

- **Geographic focus**: Europe
- **Baseline period for climate normals**: January 1979 – December 2008
- **Comparison month and year**: June 2022

5 Workflow

1. Load and explore the provided NetCDF dataset.
2. Convert precipitation units from mm/day to mm/month.
3. Extract data for the baseline period (1979–2008).
4. Compute monthly climate normals (mean for each calendar month).
5. Extract observed data for June 2022.
6. Visualize:
   - A map of the climate normal for June.
   - A map of observed precipitation for June 2022.
7. Optionally, compute and visualize the anomaly (difference between 2022 and the normal).

6 Suggested Tools

- Python libraries: `xarray`, `numpy`, `matplotlib`, `cartopy`
- Optional: Climate Data Operators (CDO) for command-line processing of NetCDF files

7 Deliverables

- Python script(s) used for data processing and visualization.
- Two maps:
  - Climate normal for June (1979–2008)
  - Observed precipitation for June 2022
- A brief report summarizing the methodology and key insights.

8 Optional Extensions

- Compute and visualize the anomaly (difference between 2022 and the normal).
- Compare climate normals across different baseline periods (e.g., 1991–2020).

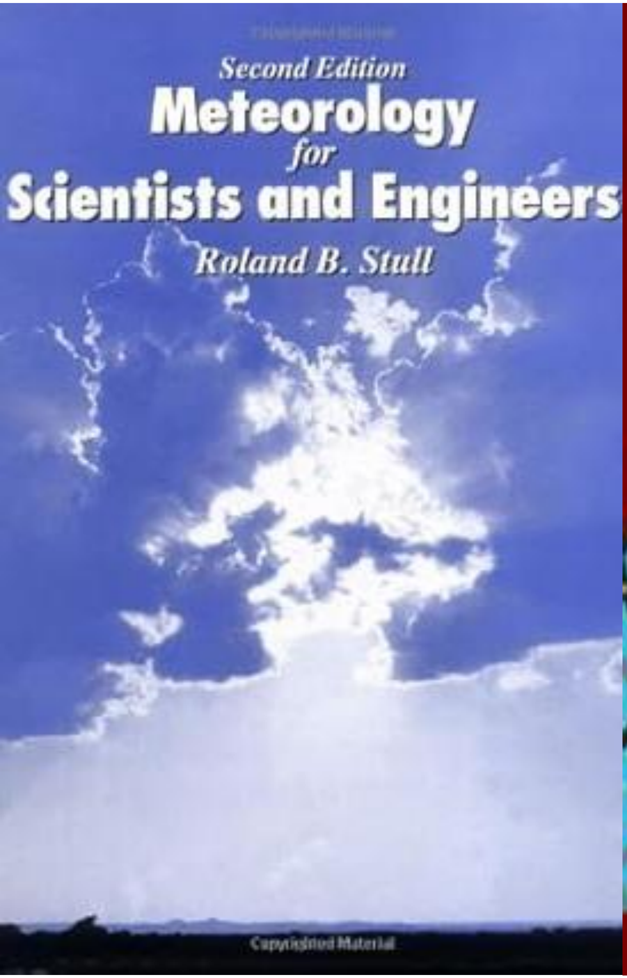
Evaluation

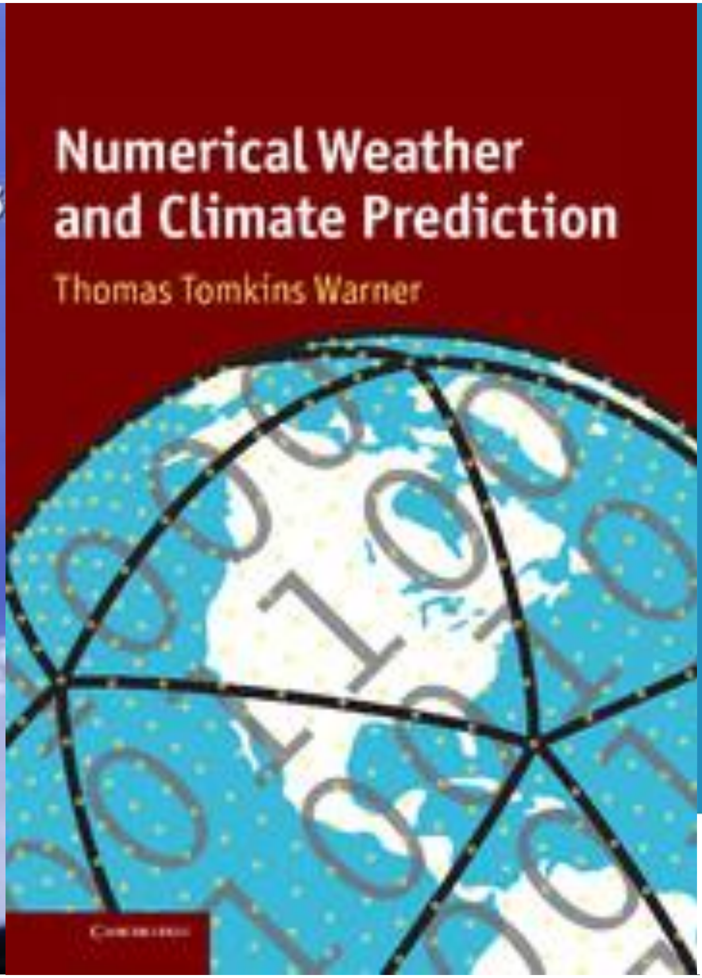
Evaluación

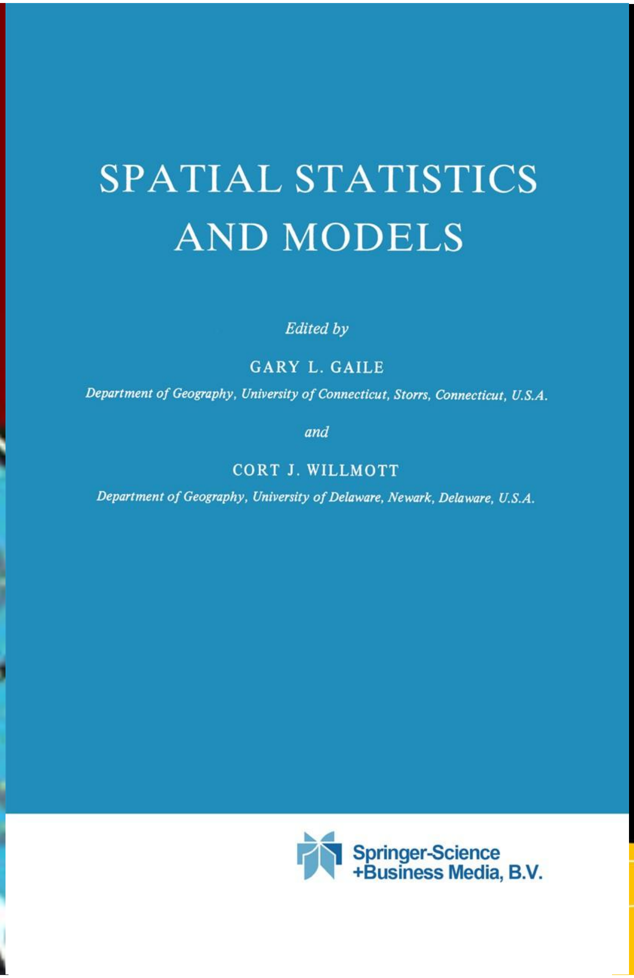
Estrategia de evaluación	Descripción	Porcentaje
Trabajos	Evaluación de las actividades correspondientes a las sesiones de prácticas	70%
Pruebas mixtas	Pruebas que combinan preguntas de desarrollo, preguntas objetivas de preguntas cortas y / o pruebas objetivas tipo test.	10%
Evaluación continua	Asistencia activa, participación en dinámicas, debates y tareas de evaluación continua.	20%
Total		**100%**

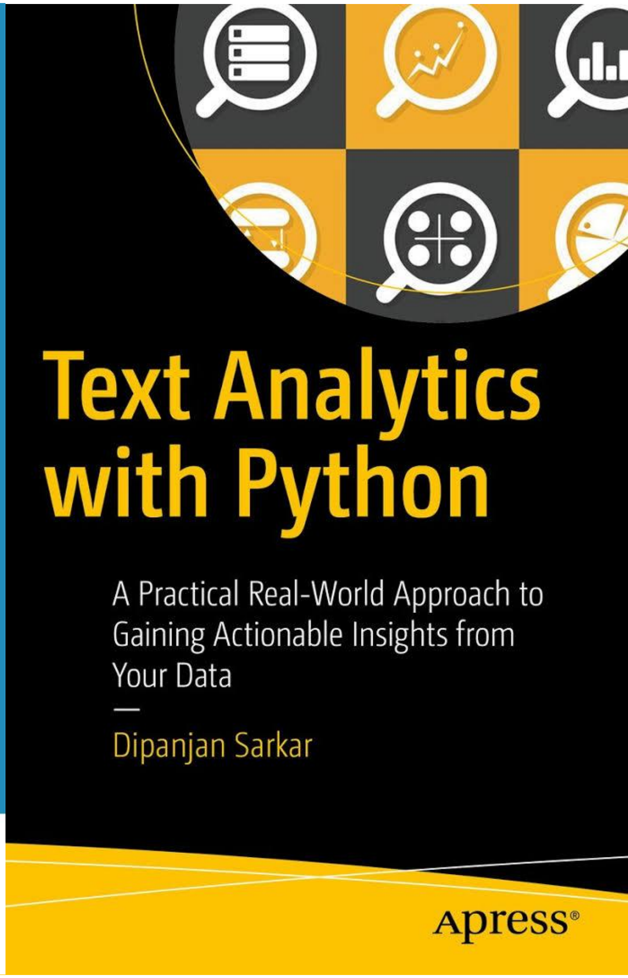
https://visor-guiadocente.unileon.es/snapshots/2025-2026/0717035

References

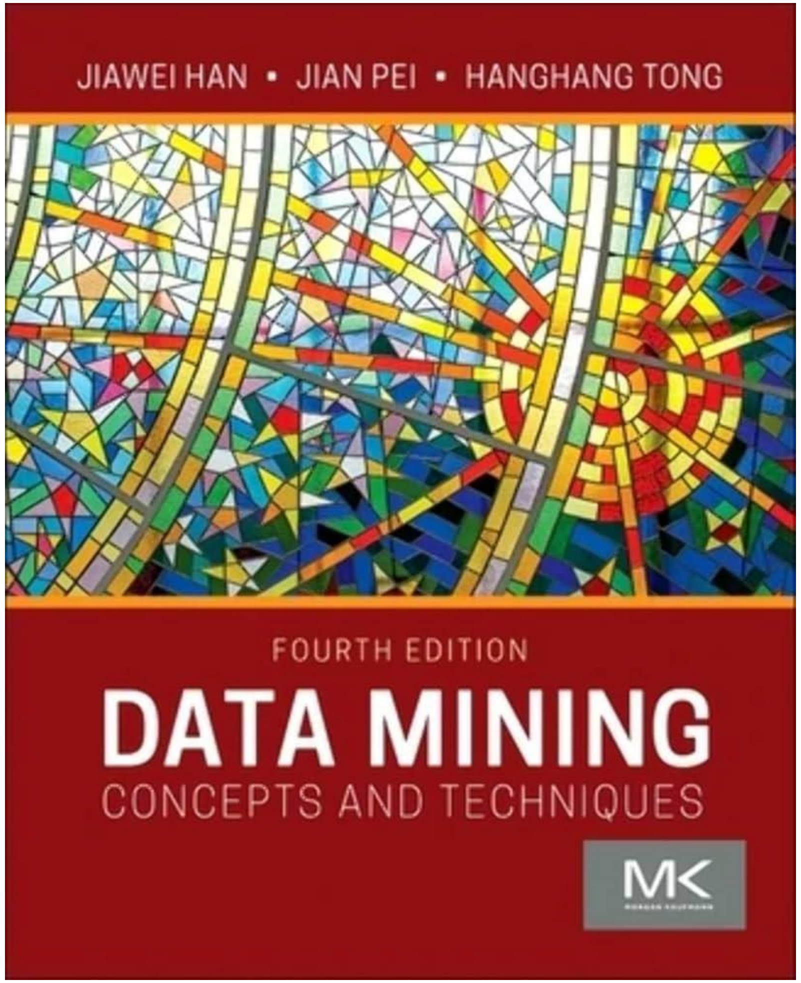

Second Edition
Meteorology for Scientists and Engineers
Roland B. Stull
Copyrighted Material

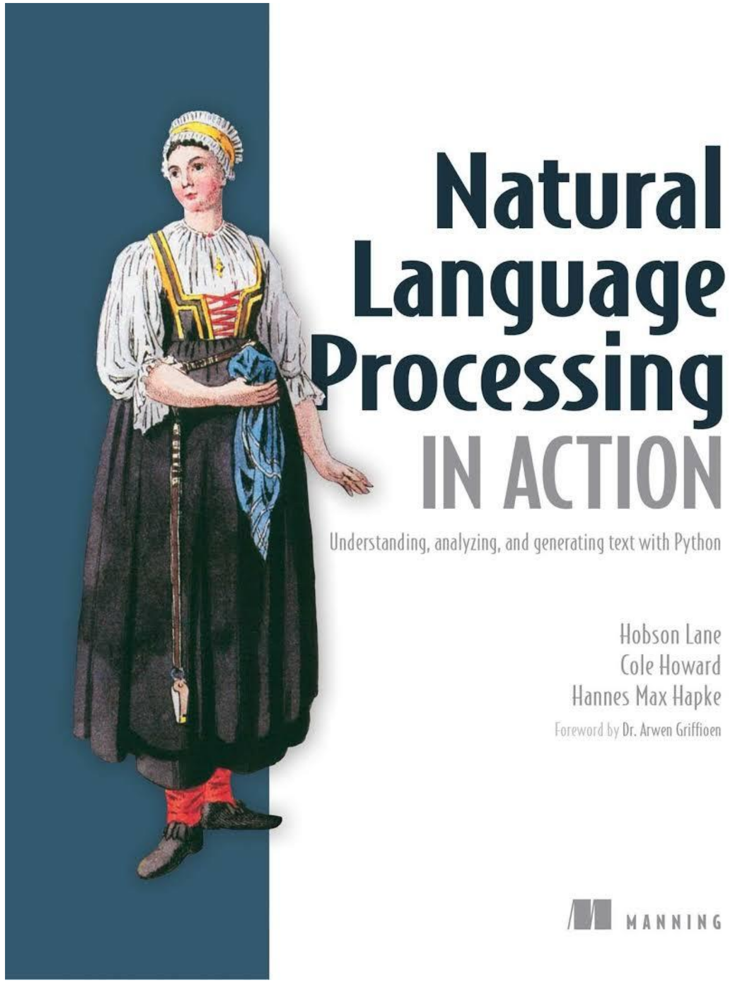

Numerical Weather and Climate Prediction
Thomas Tomkins Warner


SPATIAL STATISTICS AND MODELS
Edited by
GARY L. GAILE
Department of Geography, University of Connecticut, Storrs, Connecticut, U.S.A.
and
CORT J. WILLMOTT
Department of Geography, University of Delaware, Newark, Delaware, U.S.A.
Springer-Science +Business Media, B.V.


Text Analytics with Python
A Practical Real-World Approach to Gaining Actionable Insights from Your Data
Dipanjan Sarkar
Apress®

References [extra]





Questions?