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Neural Networks Emulations for Complex Multidimensional Mappings

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Vladimir M. Krasnopolsky
NOAA Center for Weather and Climate Prediction
Camp Spring, MD, USA

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To my daughter Katya and grandson Mark.

Preface

Scientific discovery consists in the interpretation for our own convenience of a system of existence which has been made with no eye to our convenience at all.

– Norbert Wiener, *The Human Use of Human Beings*

Science is triumphant with far-ranging success, but its triumph is somehow clouded by growing difficulties in providing for the simple necessities of human life on earth.

– Barry Commoner, *Science and Survival*

This book introduces some applications of Computational Intelligence (CI) to problems of Earth System Science (ESS). In my opinion, the meeting of CI and ESSs is not a coincidence. There is an affinity between these two fields of science at a very deep level. Both of them use a systems approach; they see their object as a complex system of partly autonomous, evolving, and adaptive subsystems intensively interacting with each other and with their environment, which also changes due to the interaction between subsystems and due to changes of the subsystems. This deep affinity between the two fields makes the approaches and tools developed in CI well suited for solving many problems in ESSs; therefore, CI can provide adequate models for modeling subsystems of the Earth System.

Such a system vision of objects of the study stimulates an understanding of similarity of many ESS problems from the mathematical point of view. In this book, I show that many subsystems of Earth System (ES) can be considered as complex multidimensional nonlinear mappings. CI provides a number of tools to approximate, emulate, or model such mappings; the particular tool considered in this book is the neural network (NN) technique. This book demonstrates many successful applications of NNs in ESSs. However, in addition to the use of the NN technique, I also attempt to demonstrate the advantages of using in ESS the CI vision of a subsystem (mapping) not as a static mapping but as an adaptive, evolving mapping interacting with the environment and adapting to it. The tremendous flexibility of the NN technique provides means for modeling such evolving adaptive mappings that function in a changing environment.

My goal in this book is to be tutorial in nature rather than to give a complete description of ESS NN applications. Thus, I selected some particular interesting applications and concentrated on a clear presentation of the methodological basis of these applications. Because both the ESS and CI fields are relatively new, in addition to presenting the NN background in Chap. 2, the book presents basic ESS background for each application that is introduced. For example, in Chap. 3, I include a detailed introduction into forward and inverse problems in remote sensing before discussing NN applications to satellite remote sensing; Chap. 4, which is devoted to NN applications in numerical climate and weather prediction, includes a brief introduction into numerical climate and weather modeling. This feature makes the book self-descriptive. The book presents a review of the field with the purpose of bringing the reader up-to-date on the state of the art. It can also serve as a convenient source book for researchers, teachers, and students who work in related fields.

College Park, MD, USA Vladimir M. Krasnopolsky

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Contents

Abbreviations

AC	Anomaly correlation
BT	Brightness temperatures
CAM	Community atmosphere model (NCAR)
CAMRT	CAM radiation package
CFS	Climate Forecast System (NCEP NOAA)
CGCM	Coupled general circulation (or climate) model
CI	Computational Intelligence
CLD	Cloudiness
CMC	Canadian Meteorological Center
CMCGLB	Global Model from CMC
ConUS	Continental US
CP	Compound parameterization
CPC	Climate Prediction Center (NOAA)
CRM	Cloud-resolving model
CSRM	Cloud-system-resolving model
CTL	Control
DA	Dynamical adjustment
DAS	Data assimilation systems
DIA	Discrete interaction approximation
DJF	December-January-February
DWD	Deutscher Wetterdienst
ECMWF	European Centre for Medium-Range Weather Forecasts
ENM	Environmental numerical model
ENSO	El Niño-Southern Oscillation
EOF	Empirical orthogonal function
EPS	Ensemble prediction systems
ERS-2	European Remote Sensing scatterometer
ES	Earth System
ESS	Earth System Sciences
ETS	Equitable Threat Score
FM	Forward model

F2F	Field-to-field
F2P	Field-to-point
GCM	General circulation (or climate) model
GCRM	Global cloud-resolving model
GFS	Global Forecast System (NCEP NOAA)
GS	Goodberlet and Swift
GSW	Goodberlet, Swift, and Wilkerson
GSWP	Goodberlet, Swift, Wilkerson, and Petty
HEM	Hybrid environmental model
HGCM	Hybrid general circulation (or climate) model
HP	Hybrid parameterization
HPC	Hydro-meteorological Prediction Center (NOAA)
HYCOM	Hybrid Coordinate Ocean Model
iNN	Inverse NN
JJA	June-July-August
JMA	Japan Meteorological Agency
LW	Long wave
LWR	Long-wave radiation
MLP	Multilayer perceptron
MME	Multi-model ensemble
MMF	Multiscale modeling framework
NAM	North American Mesoscale Forecast System (NCEP NOAA)
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NN	Neural network
NNEM	NN ensemble mean
NNIA	Neural network interaction approximation
NNIAE	Neural network interaction approximation that uses the EOF basis
NOAA	National Oceanic and Atmospheric Administration
NSIPP	Natural Seasonal-to-Interannual Predictability Program (NASA)
NWP	Numerical weather prediction
OLR	Outgoing Longwave Radiation
PB	Physically based
PDE	Partial differential equations
PICE	Perturbed initial condition ensemble
PK	Petty and Katsaros
PPE	Perturbed physics ensemble
PRMSE	Profile RMSE
PSL	Pressure at the surface level
P2P	Point-to-point
QC	Quality control
RMSE	Root mean square error

RRTM	Rapid radiative transfer model
RS	Remote sensing
SD	Standard deviation
SLT	Statistical learning technique
SSH	Sea surface height
SSM/I	Special Sensor Microwave Imager
SST	Sea surface temperature
STPPE	Short-term perturbed physics ensemble
SWR	Short-wave radiation
TF	Transfer function
TOGA-COARE	Tropical Ocean Global Atmosphere Coupled Ocean–atmosphere Response Experiment
UKMO	United Kingdom Meteorological Office
WAVEWATCH III	NCEP wind wave model (NCEP NOAA)
WEM	Weighted ensemble mean

Chapter 1
Introduction

Life was simple before World War II. After that, we had systems.
– Grace Murray Hopper

There are no separate systems. The world is continuum. Where to draw a boundary around a system depends on the purpose of the discussion.
– Donella H. Meadows, *Thinking in Systems: A Primer*

Abstract In this chapter, a notion of Earth System (ES) as a complex dynamical system of interacting components (subsystems) is presented and discussed. Weather and climate systems are introduced as subsystems of the ES. It is shown that any subsystem of ES can be considered as a multidimensional relationship or mapping, which is usually complex and nonlinear. Evolution of approaches to ES and its subsystems is discussed, and the neural network (NN) technique as a powerful nonlinear tool for emulating subsystems of ES is introduced. Multiple NN applications, which have been developed in ES sciences, are categorized and briefly reviewed. The chapter contains an extensive list of references giving extended background and further detail to the interested reader on each examined topic.

We consider our planet as a complex, dynamical system of interacting components (subsystems), which is often simply referred to as the ES. ES contains the main components of planet Earth – the atmosphere, oceans, freshwater, soils, lithosphere, biosphere, and cryosphere (Lawton 2001) as its subsystems. To understand the major ES patterns and processes in their dynamics, we need to study not only the processes that go on within each component or subsystem of ES (traditionally the realms of atmospheric physics, oceanography, hydrology, geology, and ecology, to name some) but also the *interactions, relationships,* and *feedbacks between* them. The Earth, in fact, is only habitable because of these complex linkages and feedbacks between the atmosphere, oceans, land, biosphere, and cryosphere.

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The interactions between subsystems condition, change, and manage many processes inside subsystems. It is the need to study the evolution of ES and understand these inter-component interactions, relationships, and the changes they cause in subsystem processes that defines ESS as a discipline in its own right. We still do not understand all of these feedbacks and cannot, as yet, build a model that reproduces all of the changes in ES, but these problems now hold center stage in ESS.

A large variety of highly nonlinear processes with tremendously wide spectrum of spatial and temporal scales contributes to ES, which adds to its extreme complexity. The temporal scales range from hundreds of millions of years (paleoclimatic phenomena) to several minutes (microscale weather events), and the spatial scales range from thousands of kilometers (global phenomena) to several millimeters (size of water droplets in the clouds).

Considering subsystems of ES formally, we can say that each subsystem in ES receives information (input) from other subsystems. This information comes as a set or a vector of input signals or parameters, which inform the subsystem about the status of the system as a whole and about the states of the related subsystems. Air and ocean water temperature and pressure, concentration of CO_2, radiation, and heat fluxes are just several examples of such parameters. The subsystem, in turn, communicates with the system and other subsystems, transmitting information to them concerning its state as a part of ES. This output information is transmitted as a set or vector of output parameters or signals. Thus, formally speaking, any subsystem of ES can be considered as a relationship, usually complex and nonlinear, between two vectors: a vector of input and a vector of output parameters. Such a relationship is called *mapping*.

Various mathematical methods are applied to describe, model, and emulate mappings that represent the subsystems of ES. Deterministic and statistical approaches are both employed. The deterministic approach is based on a more or less complete understanding of *first principles* or basic processes in the subsystem. This understanding is usually codified into a set of partial differential equations (PDE). Statistical approaches are based on working with data and extracting information directly from the data. They are also called statistical learning (a.k.a. machine learning, learning from data, predictive learning, data-driven) techniques because, in a sense, they learn relationships or mappings directly from the data. Such approaches are used when the understanding of processes in the subsystems is poor or incomplete or when deterministic approaches become too resource intensive (e.g., numerical solutions of PDE).

This book introduces a particular nonlinear CI or statistical learning technique (SLT), namely, the NN approach, and demonstrates how to apply it for modeling or emulation of important subsystems of ES. In this chapter in Sect. 1.1, a notion of ES as a complex dynamical system of interacting components (subsystems) is presented; the role of organization and structure of a system is discussed. Weather and climate systems are introduced as subsystems of the ES. It is shown that any subsystem of ES can be considered as a multidimensional relationship or mapping, which is usually complex and nonlinear. In Sect. 1.2, evolution of approaches to ES and its subsystems is discussed, and in Sect. 1.3 the neural network (NN) technique as a powerful nonlinear tool for emulating subsystems of ES is introduced. Multiple NN applications, which have been developed in ES sciences, are categorized and briefly reviewed, and the structure of the book is outlined.

1.1 Systems, Subsystems, Organization, and Structure

Formally, a system can be defined as a set of *elements* or *parts* that is *coherently organized* and interconnected in a *pattern* or *structure* that produces a characteristic set of behaviors, often classified as its *function* or "purpose" (Meadows 2008). Thus, any system is composed of components or parts. In aggregations parts are added; in systems components or parts are arranged or organized; hence, each system has a well-defined structure. Systems are significant because of organization-positional values, because of their structure. If a system is properly structured or organized, then it is more than the total sum of its parts and the whole system may demonstrate behavior (quality) that cannot be predicted by the behavior of its parts. In such cases we are talking about a *synergy* of the parts in the system.

In ES and in many other systems, the constituent parts of the system are systems by themselves. For example, a complex climate and weather system (see Fig. 1.1) is a constituent of ES. The atmospheric constituent of the climate system is a complex

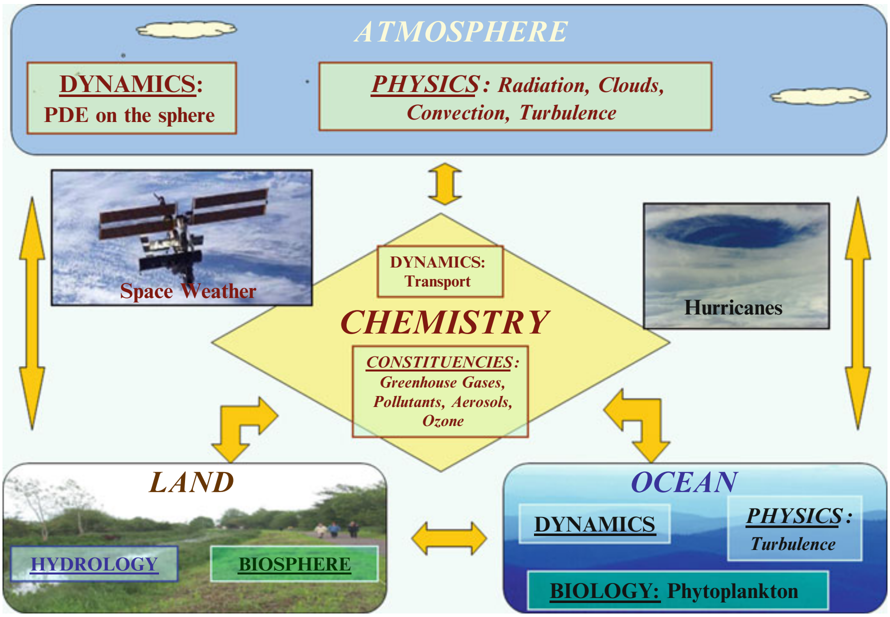

Fig. 1.1 Interdisciplinary complex climate and weather systems. Only several major interactions (feedbacks) between major subsystems are shown with *arrows*