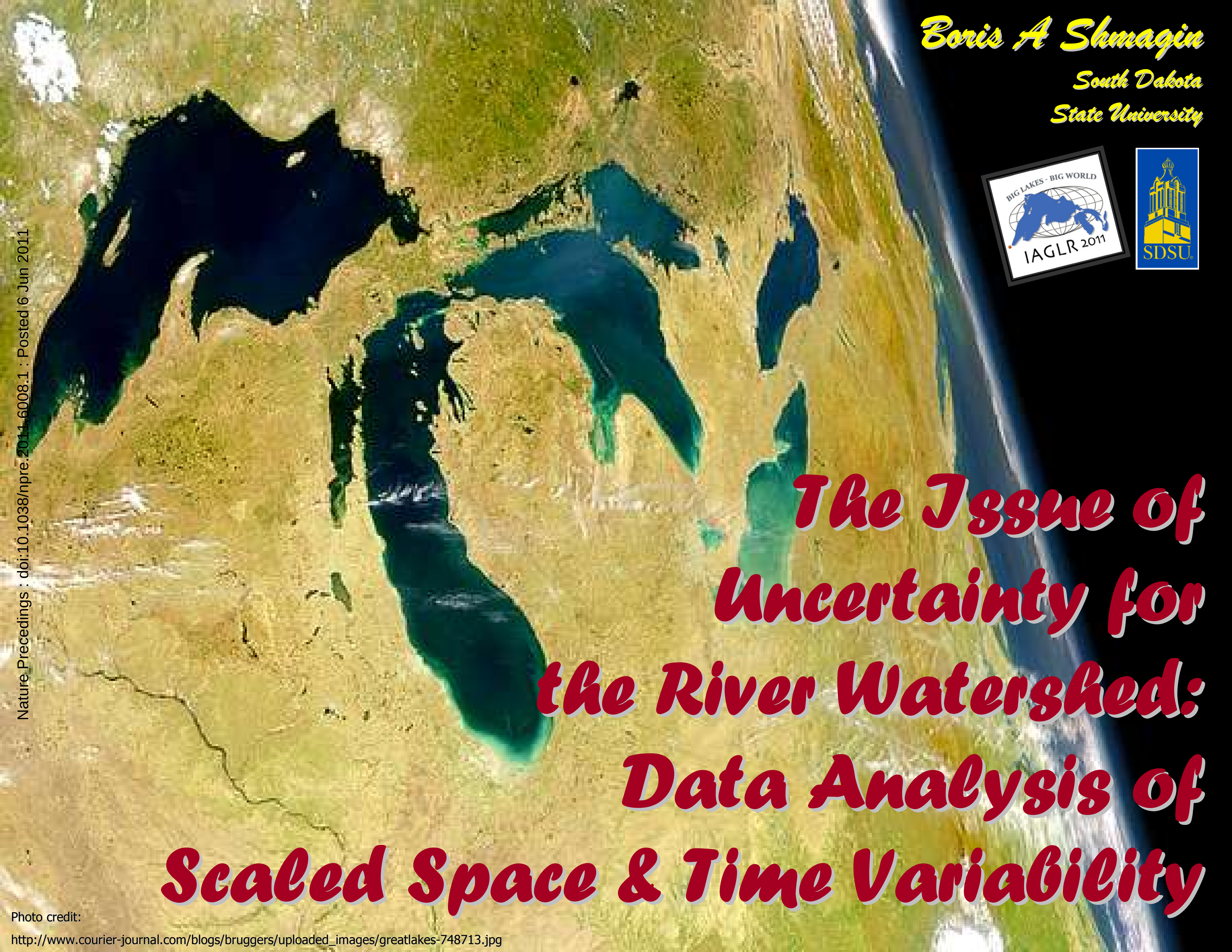


Boris A Shmagin

South Dakota
State University

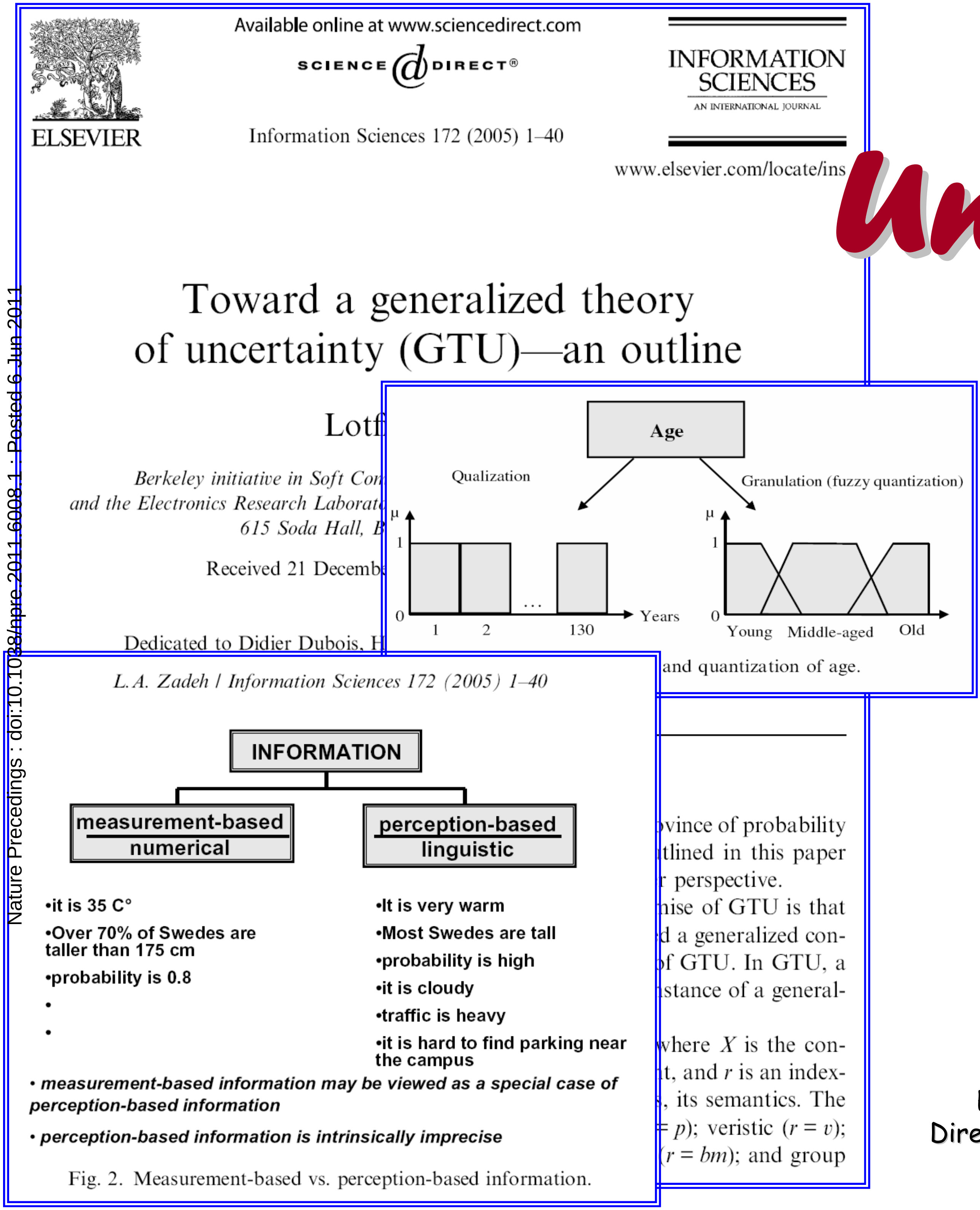
BIG LAKES - BIG WORLD
IAGLR 2011

SDSU

The Issue of Uncertainty for the River Watershed: Data Analysis of Scaled Space & Time Variability

Photo credit:
http://www.courier-journal.com/blogs/bruggers/uploaded_images/greatlakes-748713.jpg

The Uncertainty



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Information Sciences 172 (2005) 1–40
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Toward a generalized theory of uncertainty (GTU)—an outline

Lotf

Berkeley initiative in Soft Con
and the Electronics Research Laborat
615 Soda Hall, B

Received 21 Decemb

Dedicated to Didier Dubois, H

and quantization of age.

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tlined in this paper
r perspective.
nise of GTU is that
d a generalized con-
f GTU. In GTU, a
stance of a general-
where X is the con-
t, and r is an index-
, its semantics. The
$= p$); veristic ($r = v$);
($r = bm$); and group

L.A. Zadeh / Information Sciences 172 (2005) 1–40

INFORMATION

measurement-based numerical	perception-based linguistic
•it is 35 C°	•It is very warm
•Over 70% of Swedes are taller than 175 cm	•Most Swedes are tall
•probability is 0.8	•probability is high
•	•it is cloudy
•	•traffic is heavy
	•it is hard to find parking near the campus

- ***measurement-based information may be viewed as a special case of perception-based information***
- ***perception-based information is intrinsically imprecise***

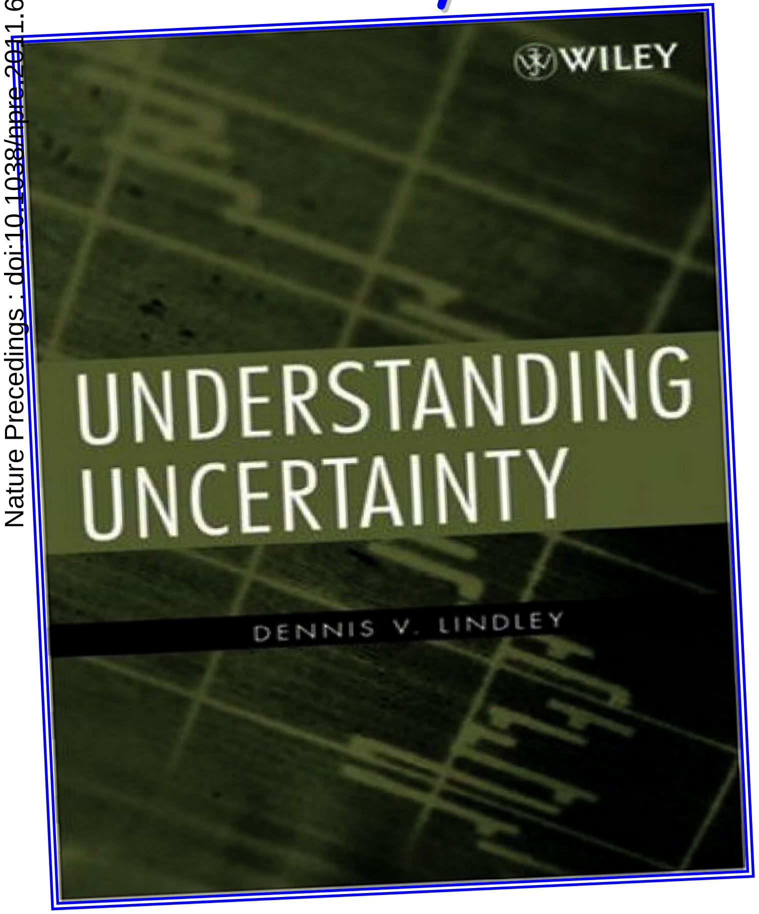
Fig. 2. Measurement-based vs. perception-based information.

Lotfi A. Zadeh

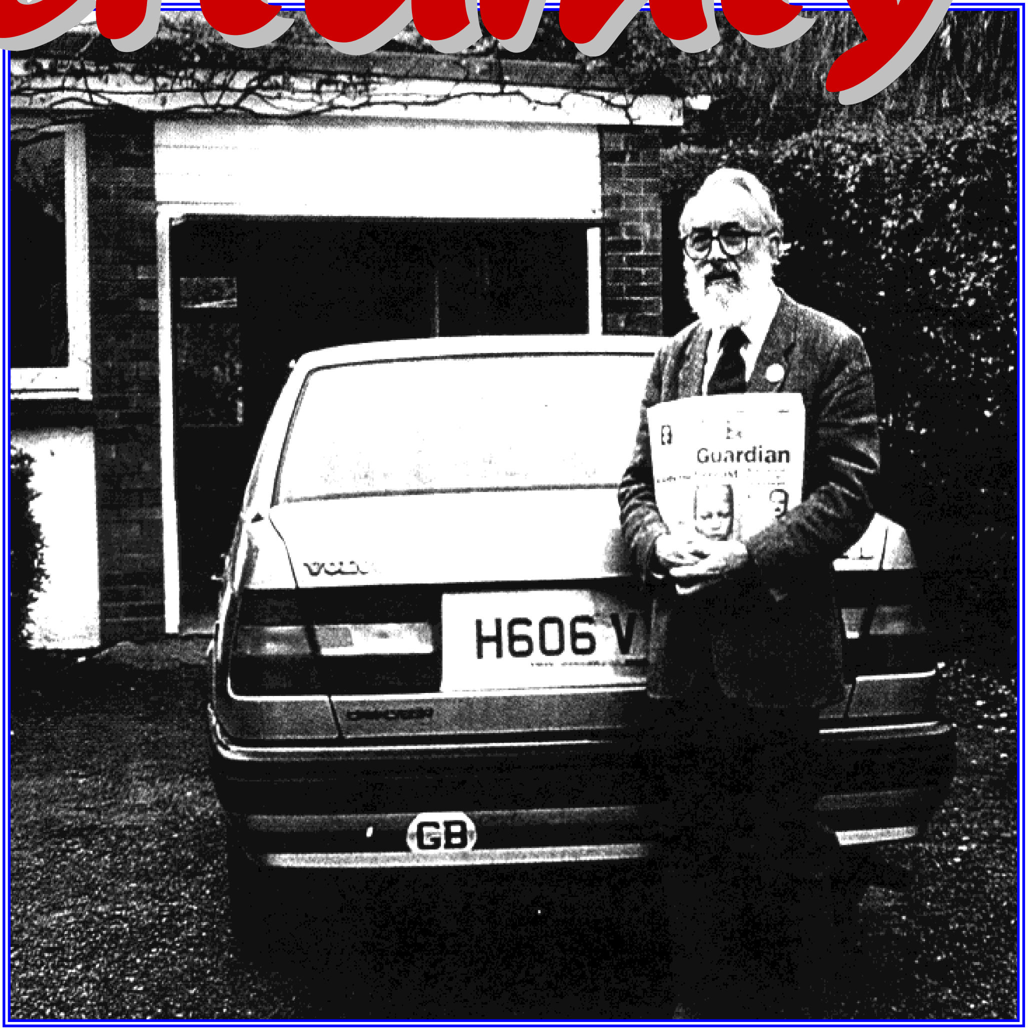
(born Feb 4, 1921)
Professor in the Graduate School,
Computer Science Division Department of
Electrical Engineering & Computer Sciences
Director, Berkeley Initiative in Soft Computing
University of California
Berkeley, CA 94720 -1776

(The) Uncertainty

"Uncertainty is a personal matter; it is not *the* uncertainty but *your* uncertainty."



Dennis Lindley (2006) Understanding Uncertainty



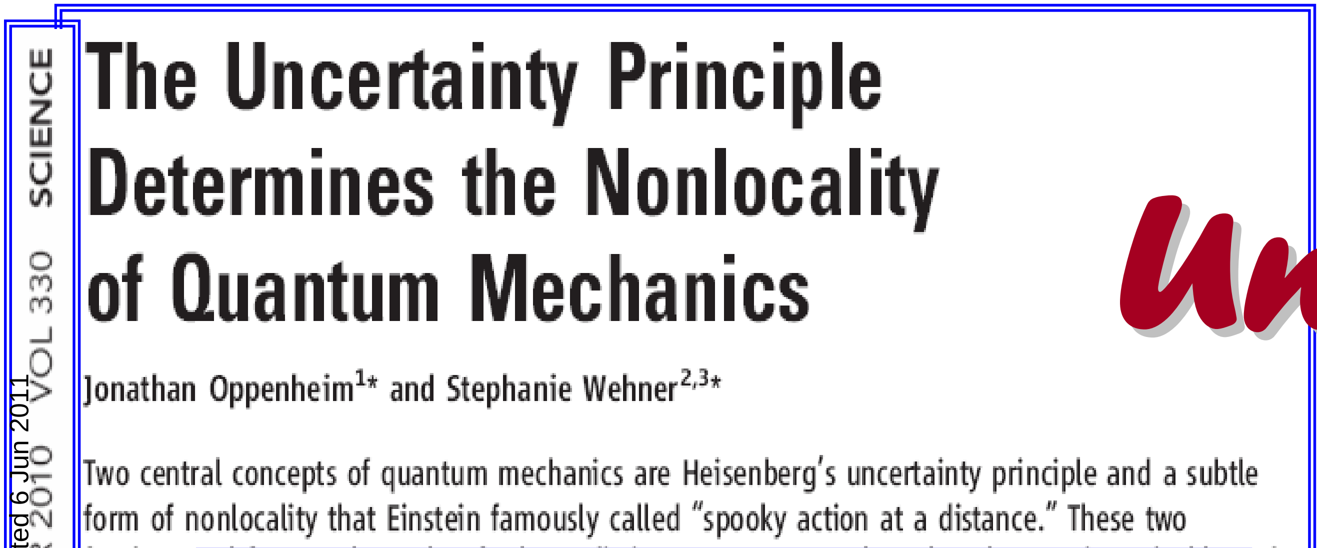
Dennis Victor Lindley

(born 25 July 1923)
Professor Emeritus of Statistics,
& past Head of Department,
at University College London (UK).
He is a British statistician, decision theorist &
leading advocate of Bayesian statistics

Topics

- Introduction: The Challenge of the Uncertainty in Science & Mathematic
  (presented earlier)
- The Uncertainty in Physic & Hydrology
- The Language, Information & Uncertainty for the Artificial Intelligence Creation
- The Complex Models
- The Cases of Cyber Model Application
- Hydrology with Structure
- The Coordinates for the River Watershed
- The Knowledge & Uncertainty about Great Lakes Watershed
- The Scientist & the Knowledge
- Results for Discussion
- Questions
- Appendix in Case of Specific Questions

The Uncertainty Principle in Physic



SCIENCE VOL 330 19 NOVEMBER 2010

The Uncertainty Principle Determines the Nonlocality of Quantum Mechanics

Jonathan Oppenheim[1]* and Stephanie Wehner[2,3]*

Two central concepts of quantum mechanics are Heisenberg's uncertainty principle and a subtle form of nonlocality that Einstein famously called "spooky action at a distance." These two fundamen nd
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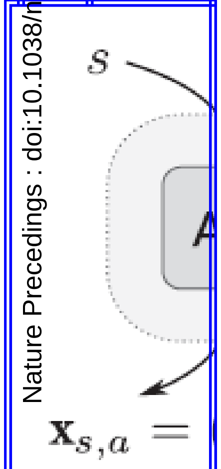

Fig. 1. Any
s and t and a
answer b for
such that b =
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putting $\mathbf{x}_{s,a}$ a

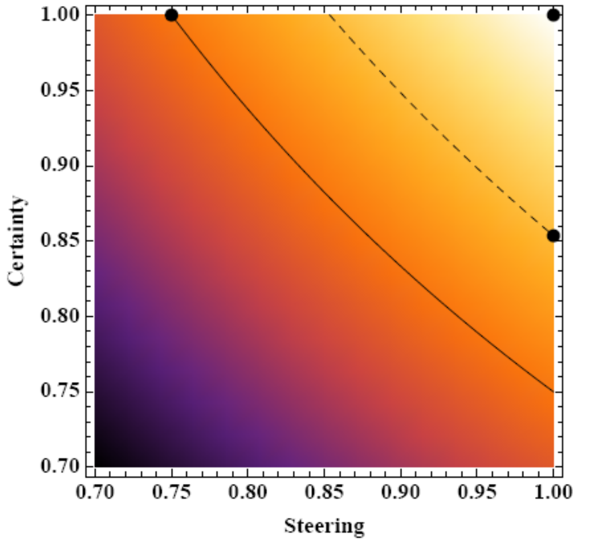

Figure S 1: A simplified example: Imagine a world in which the only steerable states are the maximally certain states of the uncertainty relations we consider, and we have an all or nothing form of steering. I.e., either Alice can steer to all ensembles with probability $p_{\rm steer}$, or fails entirely. The vertical axis denotes the certainty $p_{\rm cert}$ (that is, the lack of *uncertainty*), and the horizontal axis $p_{\rm steer}$. Lighter colours indicate a larger winning probability, which in this simplified case is just $P^{\rm game}(\mathcal{S},\mathcal{T},\sigma_{AB}) = p_{\rm steer}p_{\rm cert}$. The solid line denotes the case of $P^{\rm game}_{\rm max} = 3/4$, which can be achieved classically. The point on the line denotes the combination of values for a classical deterministic theory: there is no uncertainty ($\zeta_{\vec{x}_{s,a}} = 1$ for all $\vec{x}_{s,a}$), and no steering other than the trivial one to the state Alice and Bob already share as part of their strategy which yields 3/4 on average. The dashed line denotes the value $P^{\rm game}_{\rm max} = 1/2+1/(2\sqrt{2})$ achievable by a quantum strategy. The point on the line denotes the point reached quantumly: there is uncertainty, but we can steer perfectly to the maximally certain states. Finally, the point at (1, 1) denotes the point achievable by "PR-boxes": there is no uncertainty, but nevertheless perfect steering.

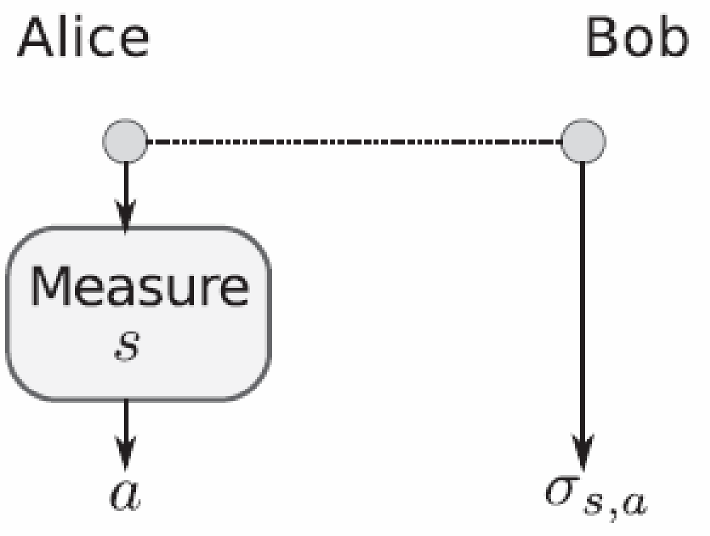

Fig. 2. When Alice performs a measurement labeled s and obtains outcome a with probability $p(a|s)$, she effectively prepares the state $\sigma_{s,a}$ on Bob's system. This is known as steering.

The Uncertainty Principle in Physic

Entanglement enhances classical communication

As a laboratory experiment shows, when Alice and Bob each have one of a pair of entangled photons, they can transmit data more accurately over a noisy channel.

Quantum entanglement, by itself, cannot be used to communicate. Meas-

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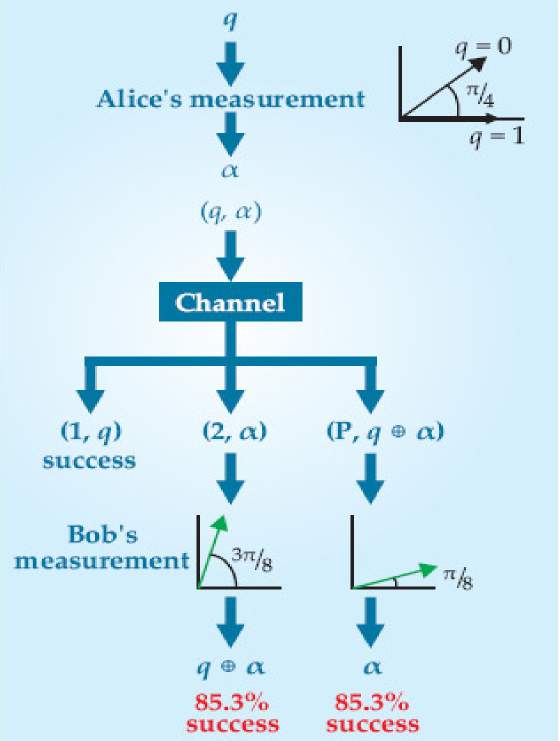


Figure 2. An entanglement-enhanced strategy for transmitting a bit q. Alice measures her photon's polarization in one of two directions, depending on q. She represents her result as a bit α and inputs (q, α) into the channel. Bob then measures his photon, the entangled partner of Alice's photon, in one of two directions, depending on the output he receives from the channel. Bob can then deduce q with an overall success probability of 90.2%.

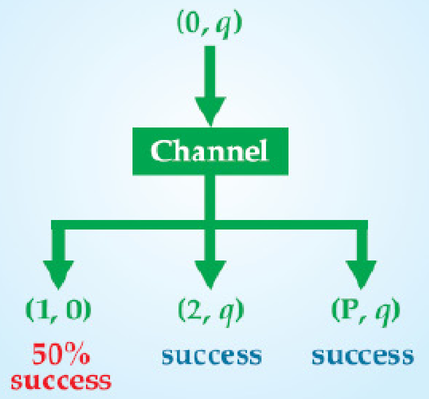


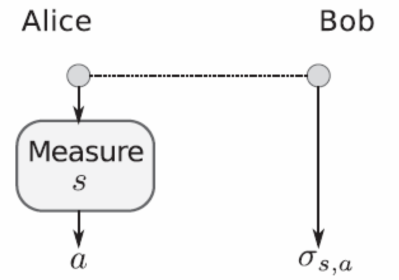
Figure 1. A classical strategy for transmitting a bit q over a noisy communication channel. The channel takes two bits as input; it outputs either the first bit, the second bit, or their parity P, each with equal probability. Inputting $(0, q)$ gives a success probability of 5/6, or 83.3%. Several other strategies do equally well.

April 2011 Physics Today

The Uncertainty Principle Determines the Nonlocality of Quantum Me

Jonathan Oppenheim[1]* and Stephan

Two central concepts of quantum mec
form of nonlocality that Einstein famo
fundamental features have thus far be
quantitatively linked: Quantum mechan
the uncertainty principle. In fact, the l
theories. More specifically, the degree
the strength of the uncertainty principl
determines which states can be prepar



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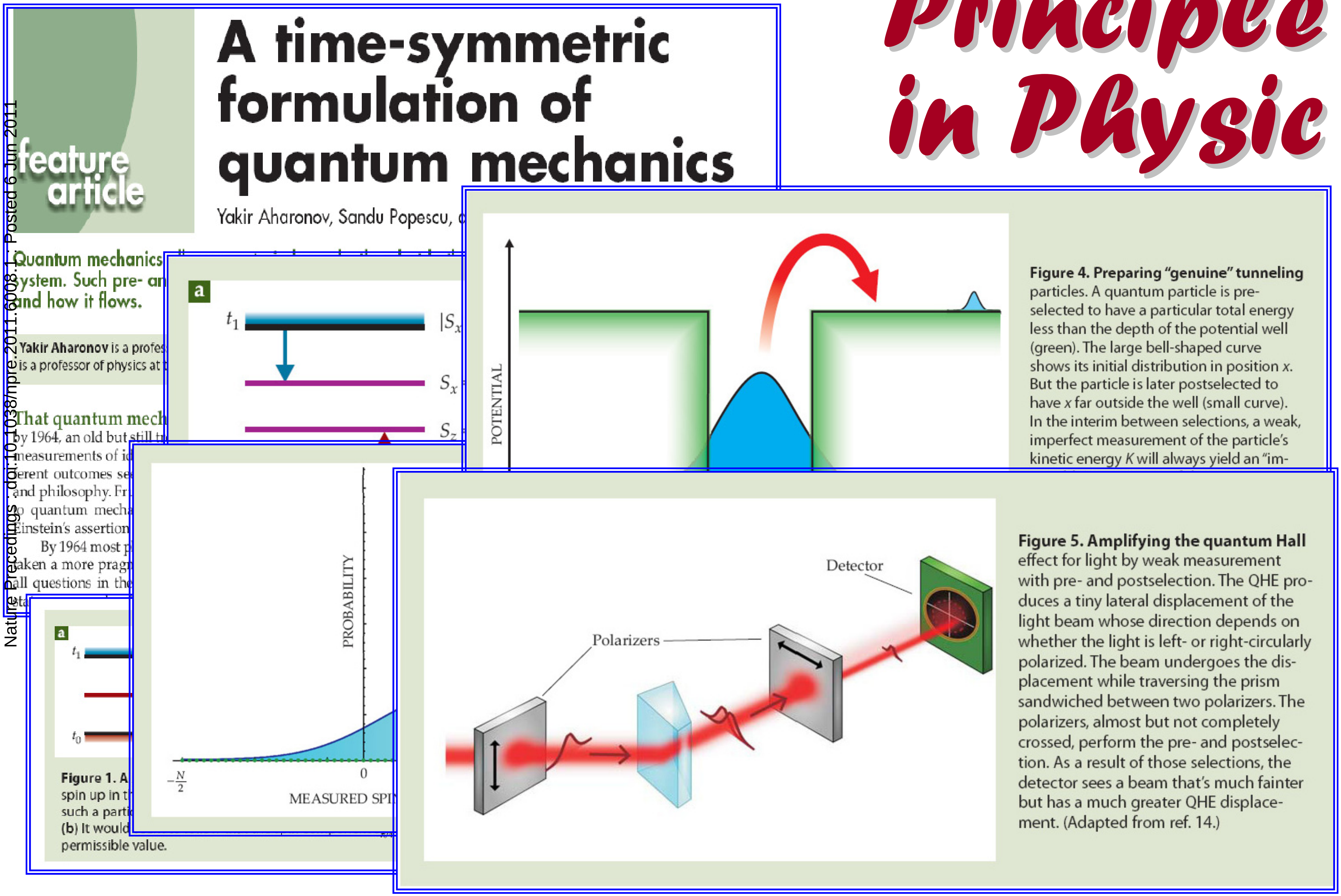
The Uncertainty Principle in Physic



feature article

A time-symmetric formulation of quantum mechanics

Yakir Aharonov, Sandu Popescu, a

Quantum mechanics
system. Such pre- an
and how it flows.

Yakir Aharonov is a profes
is a professor of physics at t

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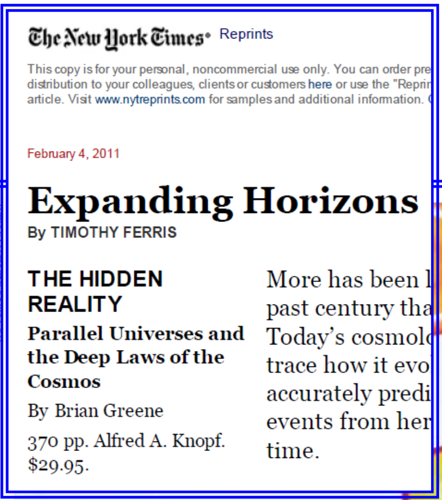
Figure 4. Preparing "genuine" tunneling particles. A quantum particle is preselected to have a particular total energy less than the depth of the potential well (green). The large bell-shaped curve shows its initial distribution in position *x*. But the particle is later postselected to have *x* far outside the well (small curve). In the interim between selections, a weak, imperfect measurement of the particle's kinetic energy *K* will always yield an "im-

Figure 5. Amplifying the quantum Hall effect for light by weak measurement with pre- and postselection. The QHE produces a tiny lateral displacement of the light beam whose direction depends on whether the light is left- or right-circularly polarized. The beam undergoes the displacement while traversing the prism sandwiched between two polarizers. The polarizers, almost but not completely crossed, perform the pre- and postselection. As a result of those selections, the detector sees a beam that's much fainter but has a much greater QHE displacement. (Adapted from ref. 14.)

The Uncertainty in Physic



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February 4, 2011

Expanding Horizons

By TIMOTHY FERRIS

THE HIDDEN REALITY

Parallel Universes and the Deep Laws of the Cosmos

By Brian Greene

370 pp. Alfred A. Knopf. $29.95.

More has been l
past century tha
Today's cosmolo
trace how it evo
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events from her
time.

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Izabella Godlewska de Aranda's painting *Cosmic Joy!* (2009) hints at the idea of many universes.

COSMOLOGY

The untestable multiverse

George Ellis reminds us that Brian Greene's beguiling book on parallel worlds is more theory than fact.

Cosmology must seem odd to scientists in other fields. More and more accurate data about the distant Universe are being generated by high-tech observational techniques, giving rise to an era of 'precision cosmology' — but to explain these impressive data, cosmologists are increasingly turning to untestable theories.

In *The Hidden Reality*, theoretical physicist Brian Greene explores one of the strangest proposals: that we live in a multiverse.

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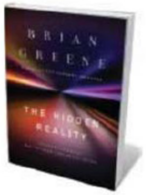
it might be true.

and convincing on their own terms. But they inexorably lead us farther from the gold standard of testability that is the scientific method. The beguiling text moves beyond established science into philosophical speculation.

Greene's nine types of multiverse are as



The Hidden Reality: Parallel Universes and the

Realistic simulations. A simulated ship upon a simulated ocean. Here, the film industry's Naiad software is used to evolve the incompressible Navier-Stokes equations for the water, strongly coupled with the rigid-body dynamics of the longboat, with additional phenomenological simulation of foam and spray.

COMPUTER SCIENCE

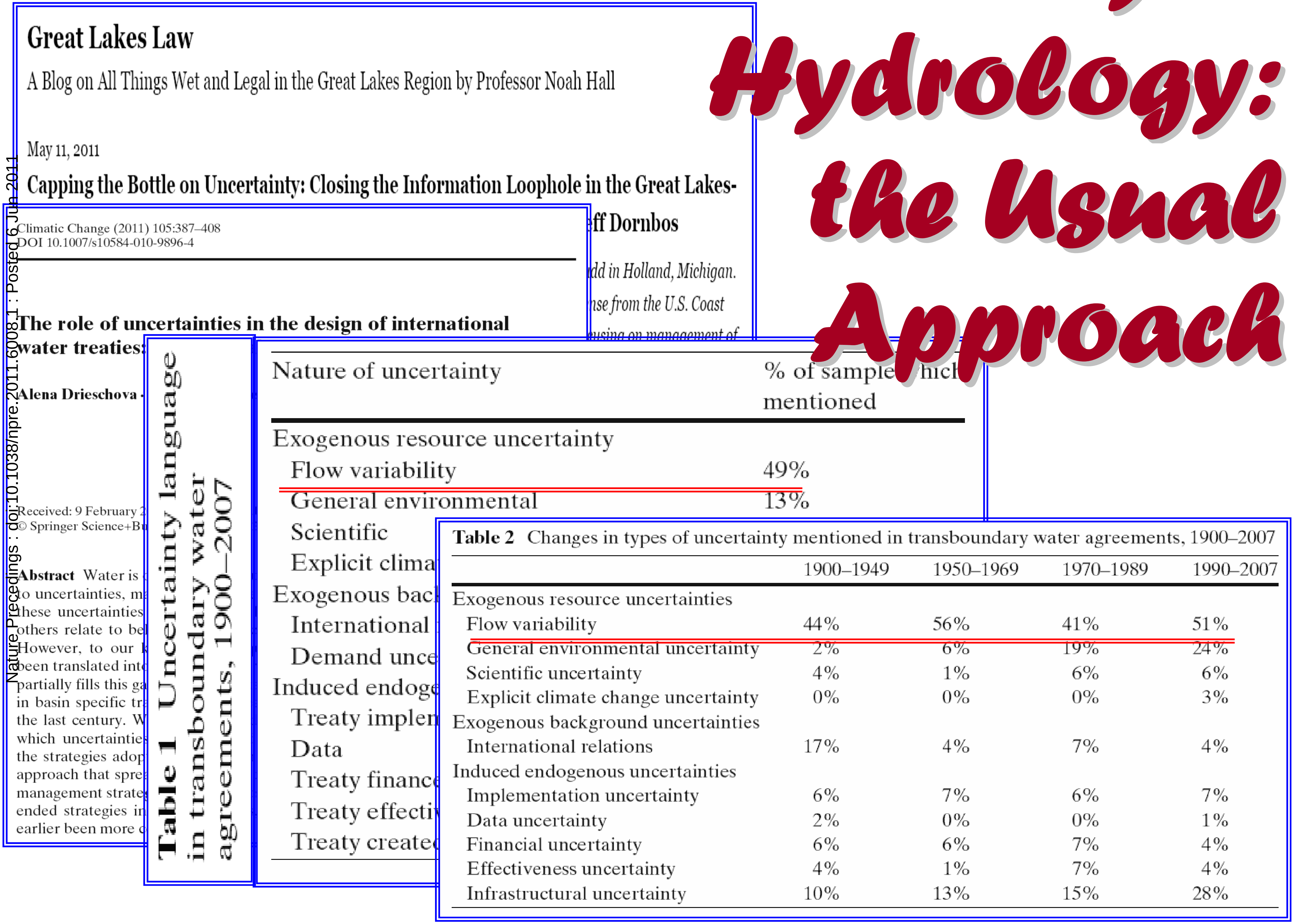
Computational Physics in Film

Numerical modeling of how objects and fluids move, collide, and break up underlies spellbinding video animations.

Robert Bridson[1,2,3]* and Christopher Batty[1]

www.sciencemag.org

The Uncertainty in Hydrology: the Usual Approach



Great Lakes Law

A Blog on All Things Wet and Legal in the Great Lakes Region by Professor Noah Hall

May 11, 2011

Capping the Bottle on Uncertainty: Closing the Information Loophole in the Great Lakes-

ff Dornbos

dd in Holland, Michigan.

nse from the U.S. Coast

using on management of

Climatic Change (2011) 105:387–408
DOI 10.1007/s10584-010-9896-4

The role of uncertainties in the design of international water treaties:

Alena Drieschova ·

Received: 9 February 2
© Springer Science+Bu

Abstract Water is
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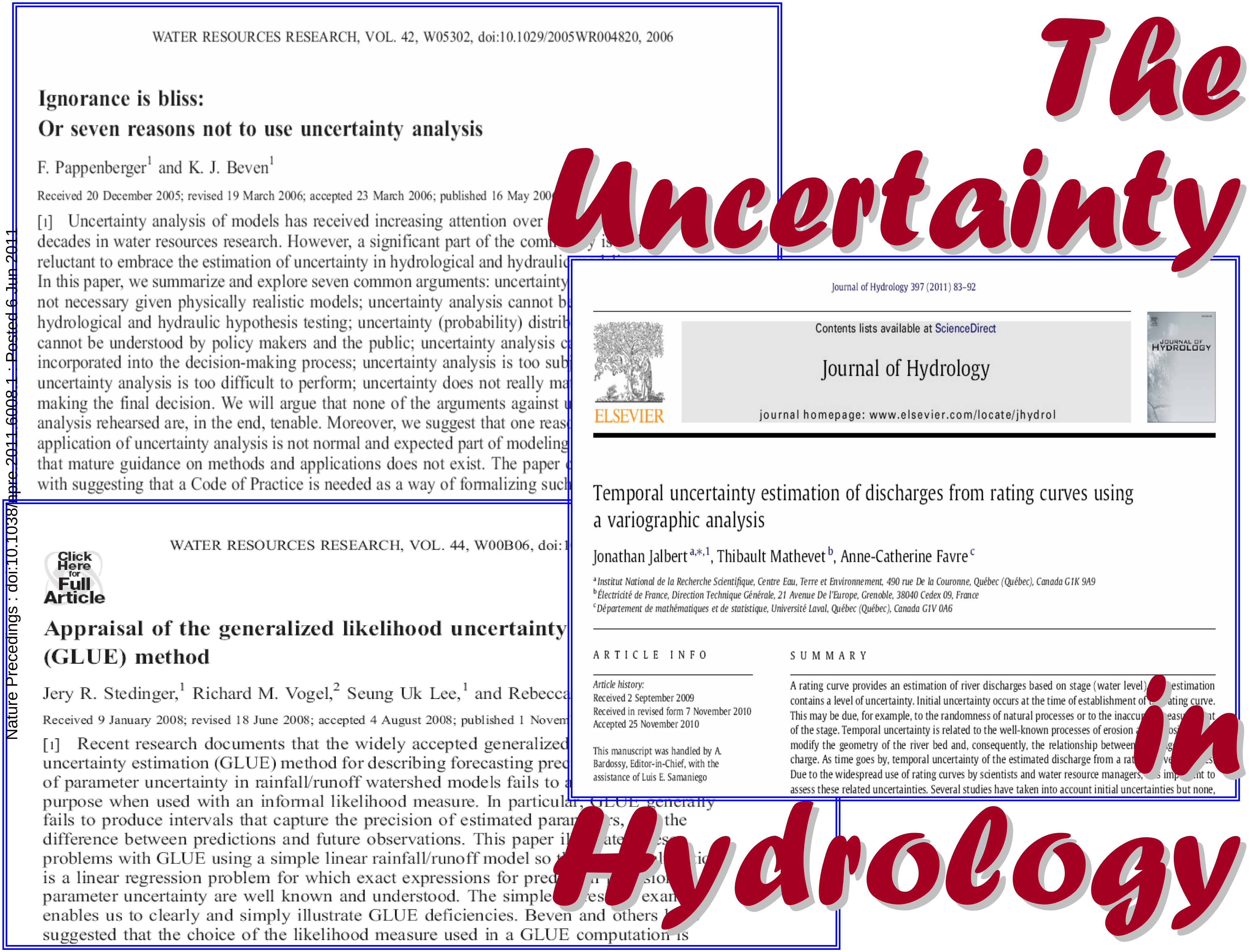
Table 1 Uncertainty langua in transboundary water agreements, 1900–2007

Nature of uncertainty	% of sample hich mentioned
Exogenous resource uncertainty	
Flow variability	49%
General environmental	13%
Scientific	
Explicit clima	
Exogenous bac	
International	
Demand unce	
Induced endoge	
Treaty implem	
Data	
Treaty finance	
Treaty effecti	
Treaty create	

Table 2 Changes in types of uncertainty mentioned in transboundary water agreements, 1900–2007

	1900–1949	1950–1969	1970–1989	1990–2007
Exogenous resource uncertainties				
Flow variability	44%	56%	41%	51%
General environmental uncertainty	2%	6%	19%	24%
Scientific uncertainty	4%	1%	6%	6%
Explicit climate change uncertainty	0%	0%	0%	3%
Exogenous background uncertainties				
International relations	17%	4%	7%	4%
Induced endogenous uncertainties				
Implementation uncertainty	6%	7%	6%	7%
Data uncertainty	2%	0%	0%	1%
Financial uncertainty	6%	6%	7%	4%
Effectiveness uncertainty	4%	1%	7%	4%
Infrastructural uncertainty	10%	13%	15%	28%

The Uncertainty in Hydrology



WATER RESOURCES RESEARCH, VOL. 42, W05302, doi:10.1029/2005WR004820, 2006

Ignorance is bliss:
Or seven reasons not to use uncertainty analysis

F. Pappenberger[1] and K. J. Beven[1]

Received 20 December 2005; revised 19 March 2006; accepted 23 March 2006; published 16 May 200

[1] Uncertainty analysis of models has received increasing attention over
decades in water resources research. However, a significant part of the comm
reluctant to embrace the estimation of uncertainty in hydrological and hydraulic
In this paper, we summarize and explore seven common arguments: uncertainty
not necessary given physically realistic models; uncertainty analysis cannot b
hydrological and hydraulic hypothesis testing; uncertainty (probability) distrib
cannot be understood by policy makers and the public; uncertainty analysis c
incorporated into the decision-making process; uncertainty analysis is too sub
uncertainty analysis is too difficult to perform; uncertainty does not really ma
making the final decision. We will argue that none of the arguments against u
analysis rehearsed are, in the end, tenable. Moreover, we suggest that one reas
application of uncertainty analysis is not normal and expected part of modeling
that mature guidance on methods and applications does not exist. The paper c
with suggesting that a Code of Practice is needed as a way of formalizing such

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WATER RESOURCES RESEARCH, VOL. 44, W00B06, doi:1

Click Here for Full Article

Appraisal of the generalized likelihood uncertainty (GLUE) method

Jery R. Stedinger,[1] Richard M. Vogel,[2] Seung Uk Lee,[1] and Rebecca

Received 9 January 2008; revised 18 June 2008; accepted 4 August 2008; published 1 Novem

[1] Recent research documents that the widely accepted generalized
uncertainty estimation (GLUE) method for describing forecasting prec
of parameter uncertainty in rainfall/runoff watershed models fails to a
purpose when used with an informal likelihood measure. In particular, GLUE generally
fails to produce intervals that capture the precision of estimated paran rs, the
difference between predictions and future observations. This paper il ate
problems with GLUE using a simple linear rainfall/runoff model so t
is a linear regression problem for which exact expressions for pred
parameter uncertainty are well known and understood. The simple exam
enables us to clearly and simply illustrate GLUE deficiencies. Beven and others h
suggested that the choice of the likelihood measure used in a GLUE computation is

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Journal of Hydrology 397 (2011) 83–92

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JOURNAL OF HYDROLOGY

Temporal uncertainty estimation of discharges from rating curves using a variographic analysis

Jonathan Jalbert[a,*,1], Thibault Mathevet[b], Anne-Catherine Favre[c]

[a] Institut National de la Recherche Scientifique, Centre Eau, Terre et Environnement, 490 rue De la Couronne, Québec (Québec), Canada G1K 9A9
[b] Électricité de France, Direction Technique Générale, 21 Avenue De l'Europe, Grenoble, 38040 Cedex 09, France
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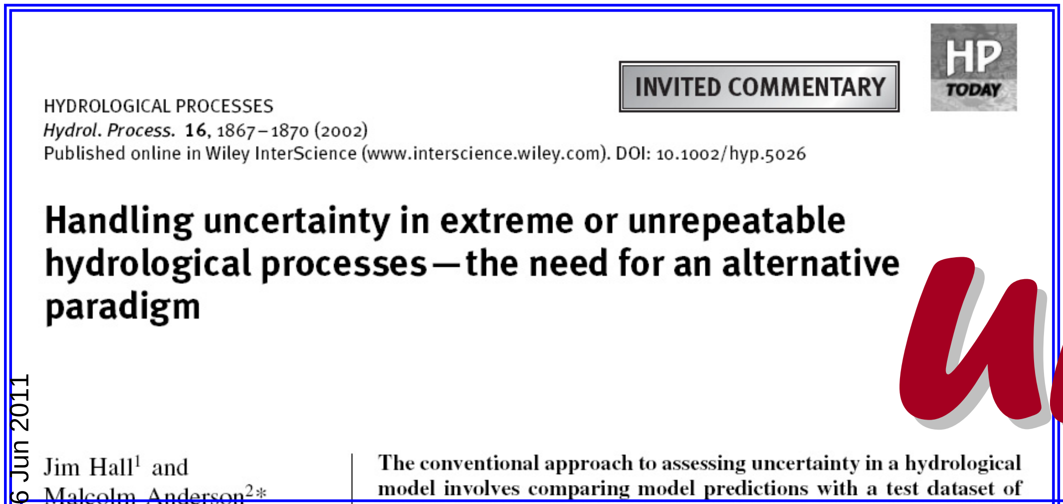
SUMMARY

A rating curve provides an estimation of river discharges based on stage (water level) estimation
contains a level of uncertainty. Initial uncertainty occurs at the time of establishment of ating curve.
This may be due, for example, to the randomness of natural processes or to the inaccur easu nt
of the stage. Temporal uncertainty is related to the well-known processes of erosion a osi
modify the geometry of the river bed and, consequently, the relationship between
charge. As time goes by, temporal uncertainty of the estimated discharge from a rat
Due to the widespread use of rating curves by scientists and water resource managers, imp nt to
assess these related uncertainties. Several studies have taken into account initial uncertainties but none,

The Uncertainty in Hydrology



INVITED COMMENTARY

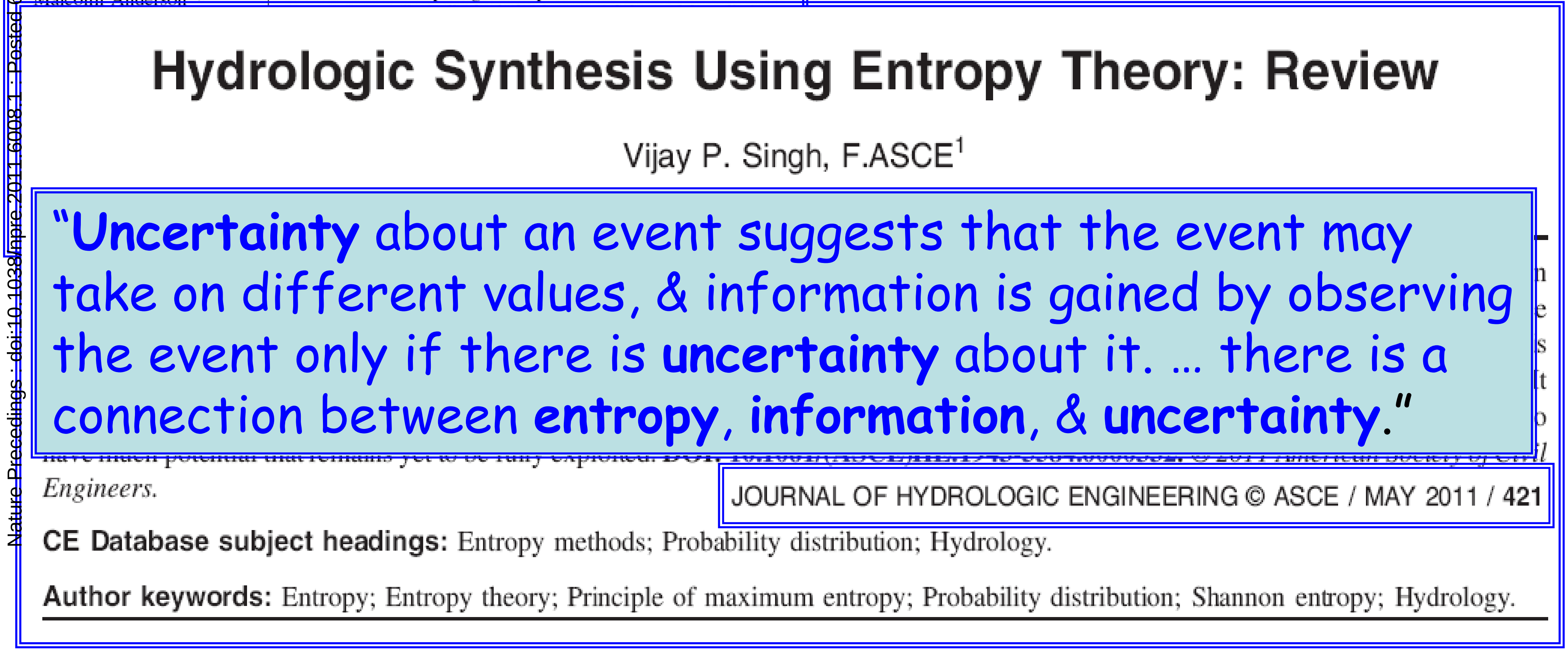
HP TODAY

HYDROLOGICAL PROCESSES
Hydrol. Process. **16**, 1867–1870 (2002)
Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/hyp.5026

Handling uncertainty in extreme or unrepeatable hydrological processes—the need for an alternative paradigm

Jim Hall[1] and
Malcolm Anderson[2]*

The conventional approach to assessing uncertainty in a hydrological model involves comparing model predictions with a test dataset of



Hydrologic Synthesis Using Entropy Theory: Review

Vijay P. Singh, F.ASCE[1]

Engineers.

JOURNAL OF HYDROLOGIC ENGINEERING © ASCE / MAY 2011 / 421

CE Database subject headings: Entropy methods; Probability distribution; Hydrology.

Author keywords: Entropy; Entropy theory; Principle of maximum entropy; Probability distribution; Shannon entropy; Hydrology.

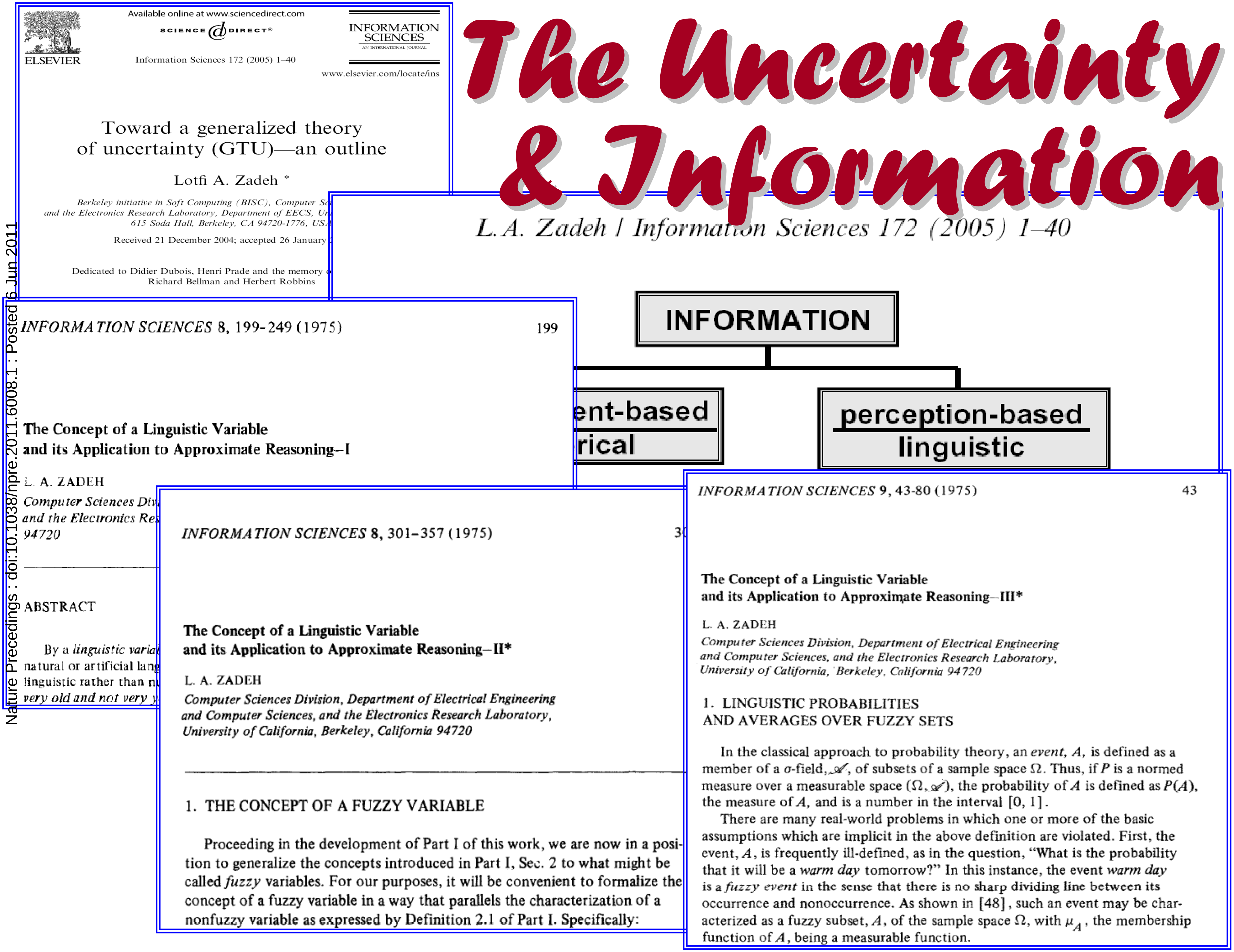
"**Uncertainty** about an event suggests that the event may take on different values, & information is gained by observing the event only if there is **uncertainty** about it. … there is a connection between **entropy**, **information**, & **uncertainty**."

The Uncertainty in Physics & Hydrology

In Physic,
the principle of Uncertainty is the base for consideration of locality, communication & time-symmetry for specifically determined systems & for proposing of new hypotheses.
In Hydrology,
the Uncertainty has to be defined with system specification, information & communication consideration for defined systems.

The Language, Information & Uncertainty for the Artificial Intelligence Creation

The Uncertainty & Information



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Toward a generalized theory
of uncertainty (GTU)—an outline

Lotfi A. Zadeh *

Berkeley initiative in Soft Computing (BISC), Computer Sc
and the Electronics Research Laboratory, Department of EECS, Un
615 Soda Hall, Berkeley, CA 94720-1776, USA

Received 21 December 2004; accepted 26 January

Dedicated to Didier Dubois, Henri Prade and the memory o
Richard Bellman and Herbert Robbins

L. A. Zadeh / Information Sciences 172 (2005) 1–40

INFORMATION

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INFORMATION SCIENCES 8, 199–249 (1975) 199

The Concept of a Linguistic Variable
and its Application to Approximate Reasoning–I

L. A. ZADEH

Computer Sciences Div
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ABSTRACT

By a *linguistic varia*
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INFORMATION SCIENCES 8, 301–357 (1975) 30

The Concept of a Linguistic Variable
and its Application to Approximate Reasoning–II*

L. A. ZADEH

Computer Sciences Division, Department of Electrical Engineering
and Computer Sciences, and the Electronics Research Laboratory,
University of California, Berkeley, California 94720

1. THE CONCEPT OF A FUZZY VARIABLE

Proceeding in the development of Part I of this work, we are now in a position to generalize the concepts introduced in Part I, Sec. 2 to what might be called *fuzzy* variables. For our purposes, it will be convenient to formalize the concept of a fuzzy variable in a way that parallels the characterization of a nonfuzzy variable as expressed by Definition 2.1 of Part I. Specifically:

INFORMATION SCIENCES 9, 43-80 (1975) 43

The Concept of a Linguistic Variable
and its Application to Approximate Reasoning–III*

L. A. ZADEH

Computer Sciences Division, Department of Electrical Engineering
and Computer Sciences, and the Electronics Research Laboratory,
University of California, Berkeley, California 94720

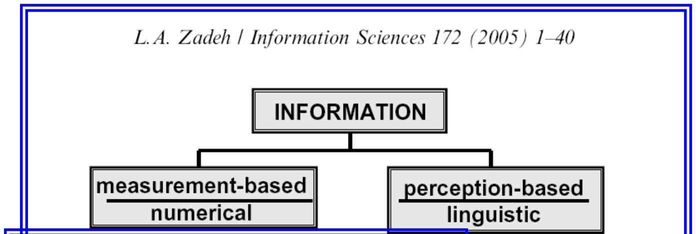
1. LINGUISTIC PROBABILITIES
AND AVERAGES OVER FUZZY SETS

In the classical approach to probability theory, an *event*, A, is defined as a member of a σ-field, $\mathscr{A}$, of subsets of a sample space Ω. Thus, if P is a normed measure over a measurable space $(\Omega, \mathscr{A})$, the probability of A is defined as $P(A)$, the measure of A, and is a number in the interval [0, 1].

There are many real-world problems in which one or more of the basic assumptions which are implicit in the above definition are violated. First, the event, A, is frequently ill-defined, as in the question, "What is the probability that it will be a *warm day* tomorrow?" In this instance, the event *warm day* is a *fuzzy event* in the sense that there is no sharp dividing line between its occurrence and nonoccurrence. As shown in [48], such an event may be characterized as a fuzzy subset, A, of the sample space Ω, with μ_A, the membership function of A, being a measurable function.

The Information

Natural & artificial languages dealing with information for Artificial Intelligence creation



L.A. Zadeh / Information Sciences 172 (2005) 1–40

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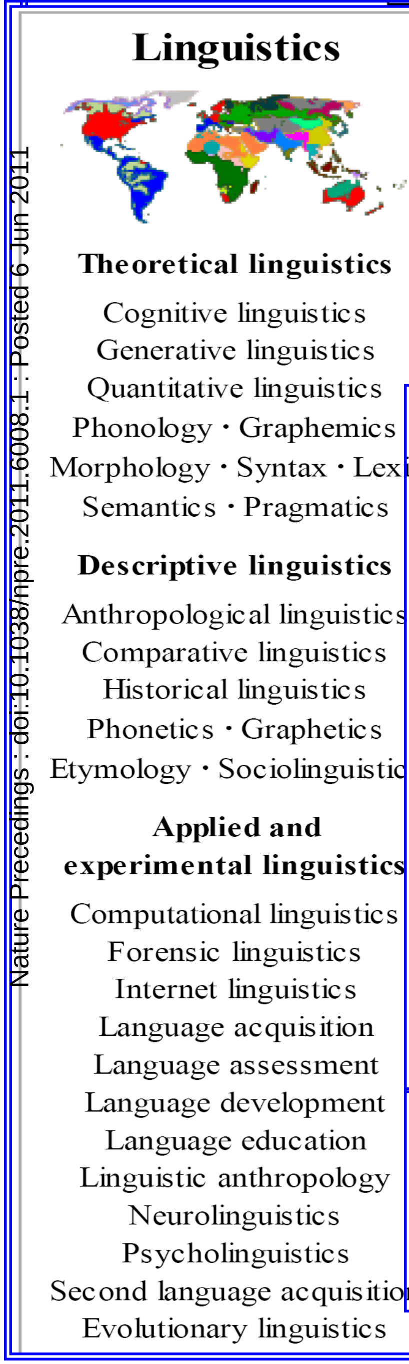


Linguistics

Theoretical linguistics

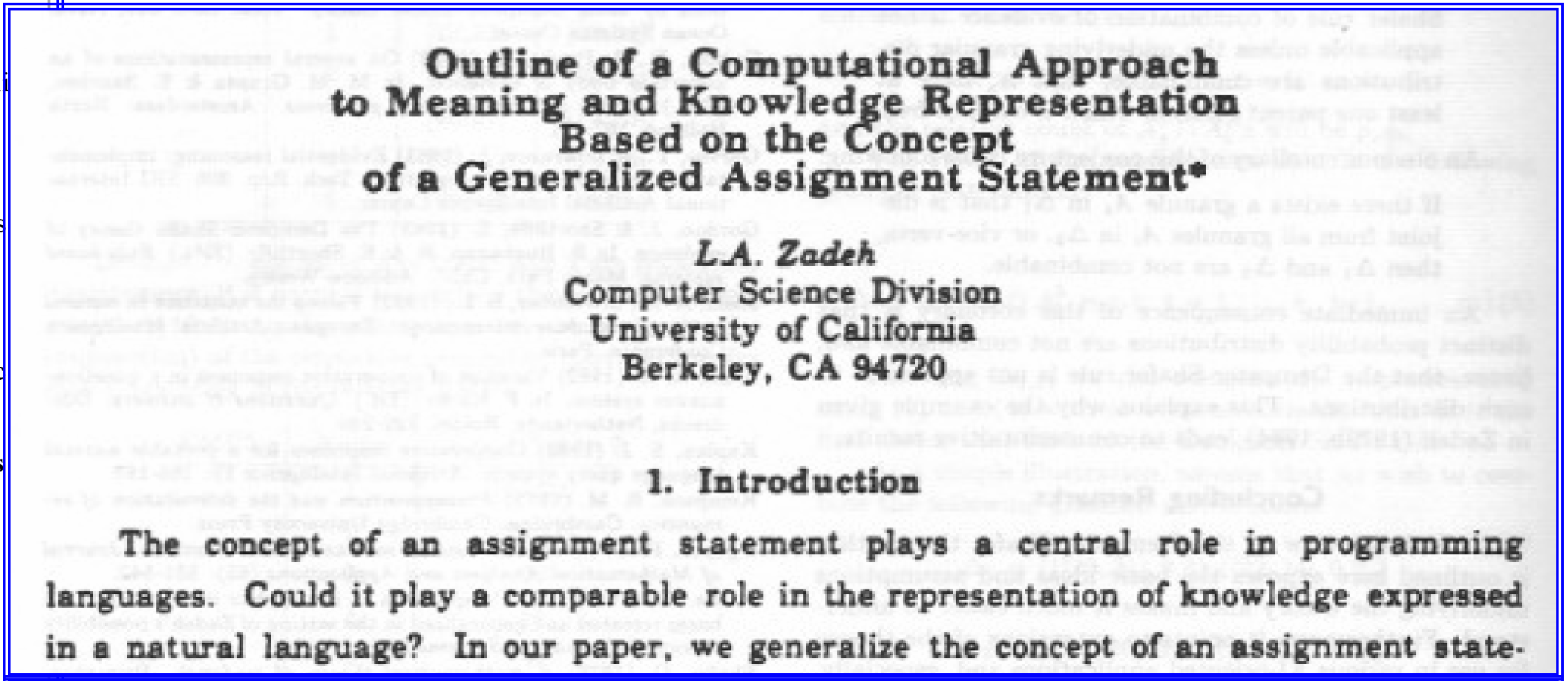
Cognitive linguistics
Generative linguistics
Quantitative linguistics
Phonology · Graphemics
Morphology · Syntax · Lexi
Semantics · Pragmatics

Descriptive linguistics

Anthropological linguistics
Comparative linguistics
Historical linguistics
Phonetics · Graphetics
Etymology · Sociolinguistic

Applied and experimental linguistics

Computational linguistics
Forensic linguistics
Internet linguistics
Language acquisition
Language assessment
Language development
Language education
Linguistic anthropology
Neurolinguistics
Psycholinguistics
Second language acquisitio
Evolutionary linguistics

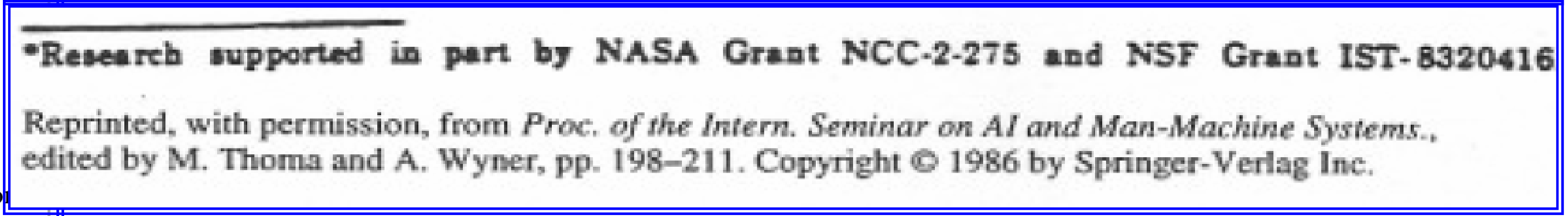


Outline of a Computational Approach to Meaning and Knowledge Representation Based on the Concept of a Generalized Assignment Statement*

L.A. Zadeh
Computer Science Division
University of California
Berkeley, CA 94720

1. Introduction

The concept of an assignment statement plays a central role in programming languages. Could it play a comparable role in the representation of knowledge expressed in a natural language? In our paper, we generalize the concept of an assignment state-



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*Research supported in part by NASA Grant NCC-2-275 and NSF Grant IST-8320416

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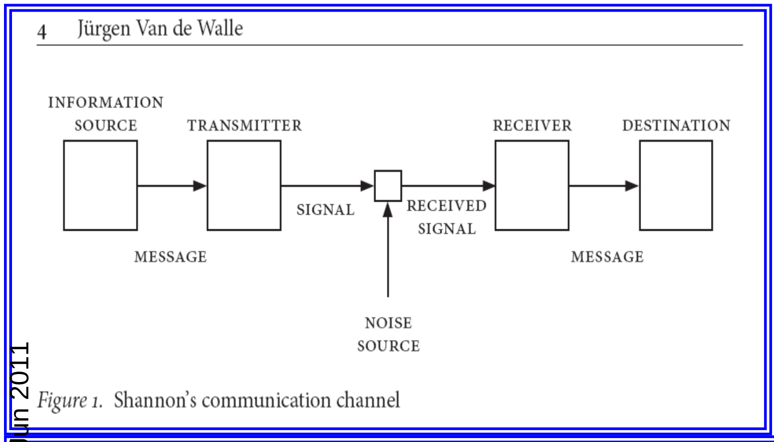
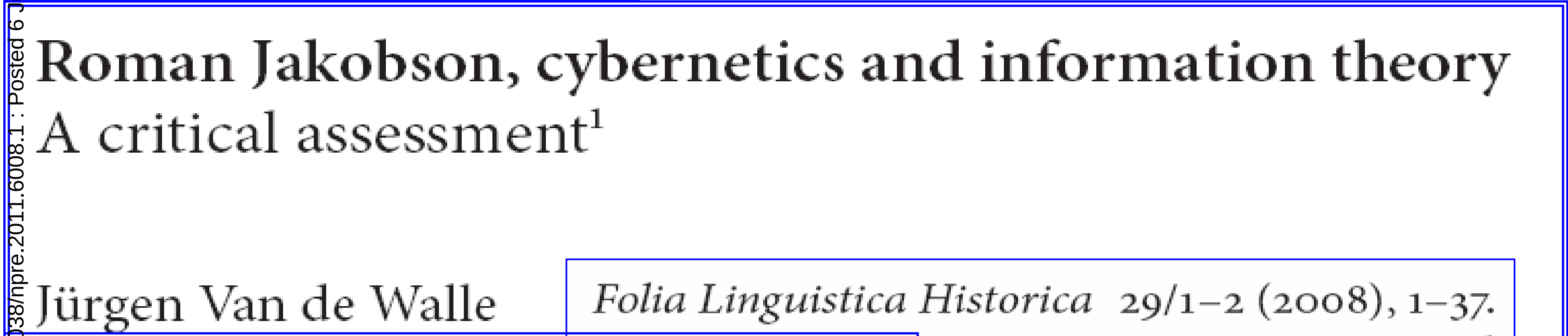
Information in the Language



4 Jürgen Van de Walle

Figure 1. Shannon's communication channel

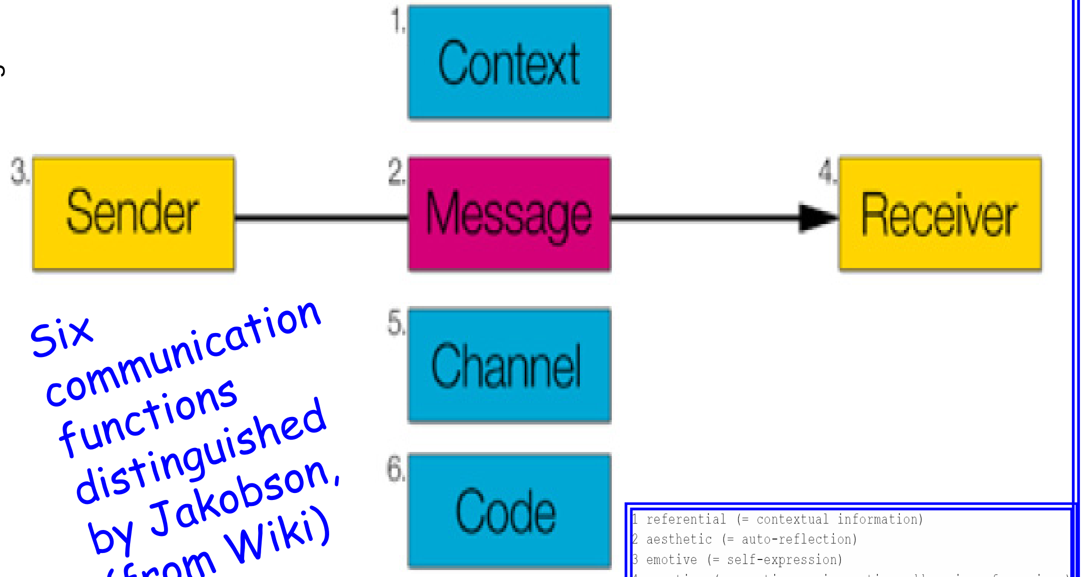


Roman Jakobson, cybernetics and information theory

A critical assessment[1]

Jürgen Van de Walle

Folia Linguistica Historica 29/1–2 (2008), 1–37.



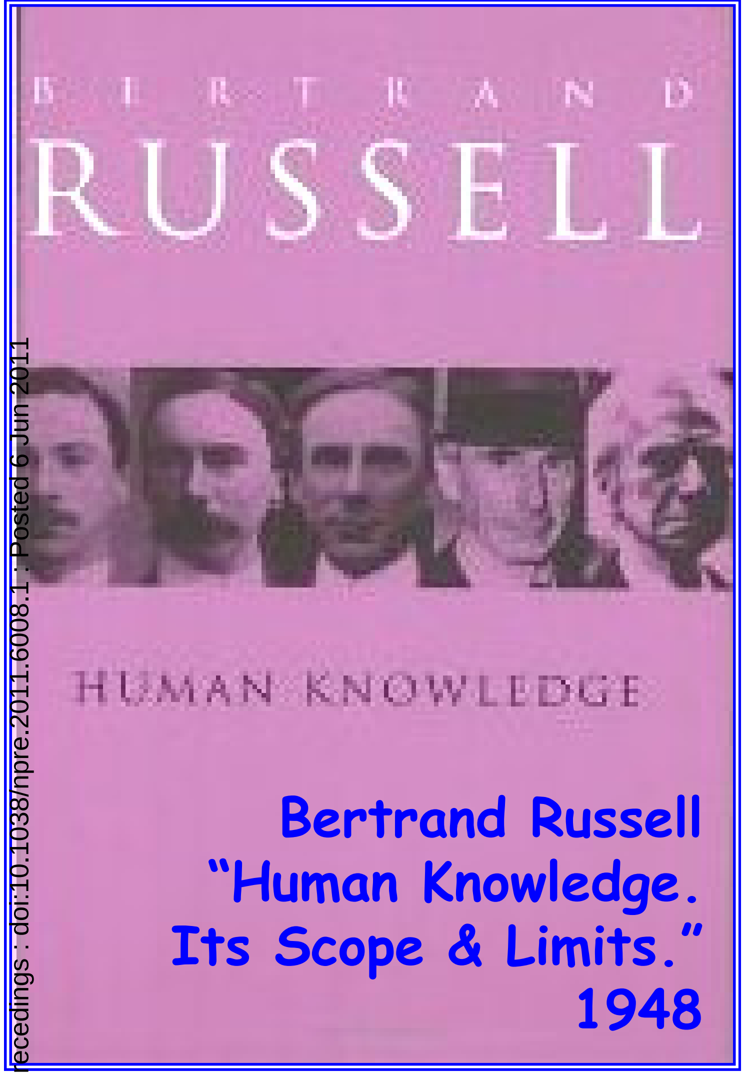
Six communication functions distinguished by Jakobson, (from Wiki)

1 referential (= contextual information)
2 aesthetic (= auto-reflection)
3 emotive (= self-expression)
4 conative (= vocative or imperative addressing of receiver)
5 phatic (= checking channel working)
6 metalingual (= checking code working)[2]

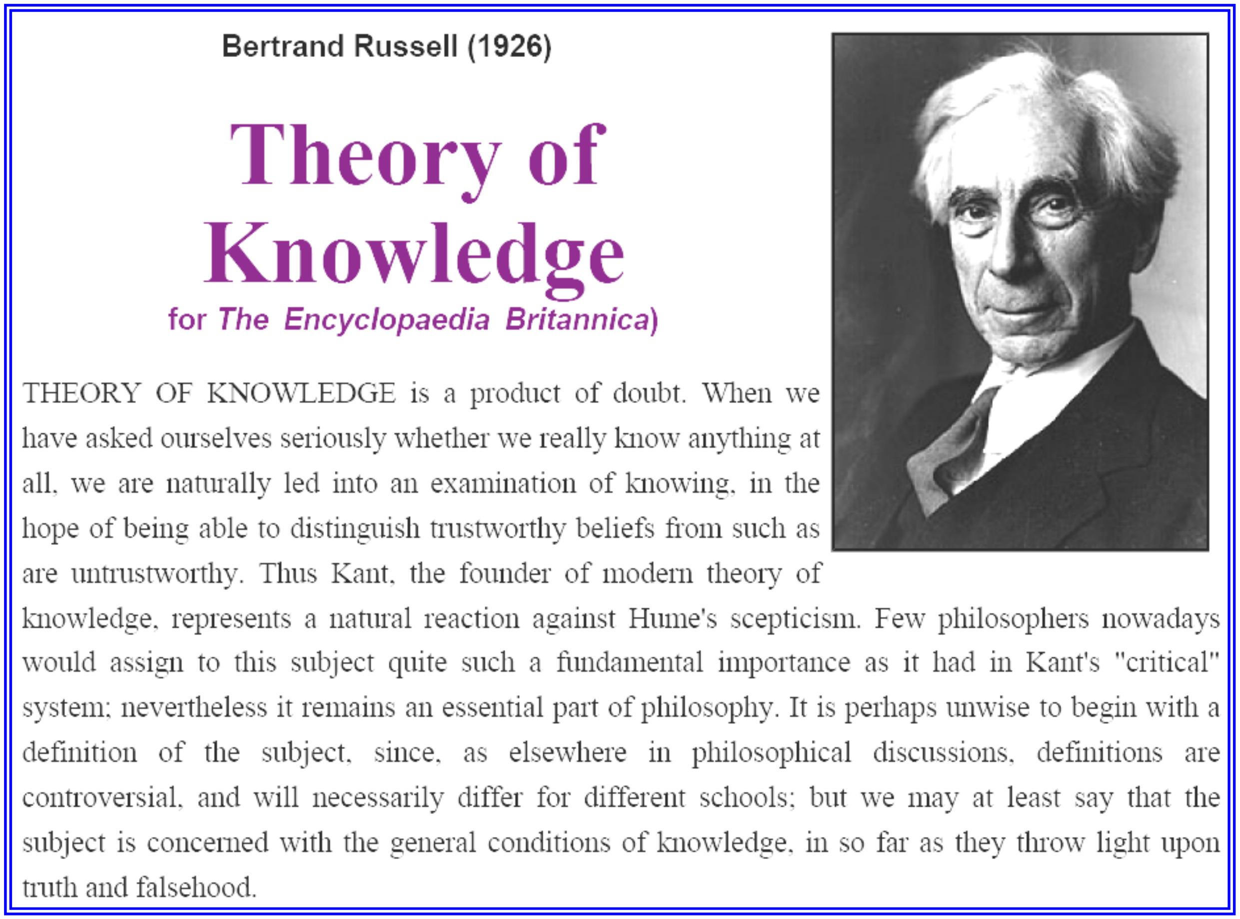
"In cognitive linguistics as in cognitive science, the human mind is considered to be an information-processing device (Stillings 1995), & language is viewed as a vehicle for communicating information."

From: J. Van de Walle, 2008

The Knowledge



Bertrand Russell
"Human Knowledge. Its Scope & Limits."
1948



Bertrand Russell (1926)

Theory of Knowledge

for *The Encyclopaedia Britannica*)

THEORY OF KNOWLEDGE is a product of doubt. When we have asked ourselves seriously whether we really know anything at all, we are naturally led into an examination of knowing, in the hope of being able to distinguish trustworthy beliefs from such as are untrustworthy. Thus Kant, the founder of modern theory of knowledge, represents a natural reaction against Hume's scepticism. Few philosophers nowadays would assign to this subject quite such a fundamental importance as it had in Kant's "critical" system; nevertheless it remains an essential part of philosophy. It is perhaps unwise to begin with a definition of the subject, since, as elsewhere in philosophical discussions, definitions are controversial, and will necessarily differ for different schools; but we may at least say that the subject is concerned with the general conditions of knowledge, in so far as they throw light upon truth and falsehood.

The book has six parts, & the part named "Language" is the biggest one with eleven chapters

"I. THE DEFINITION OF KNOWLEDGE

The question how knowledge should be defined is perhaps the most important and difficult of the three with which we shall deal. This may seem surprising: at first sight it might be thought that knowledge might be defined as belief which is in agreement with the facts. The trouble is that no one knows what a belief is, no one knows what a fact is, & no one knows what sort of agreement between them would make a belief true.

Belief. Words. Truth in Logic.

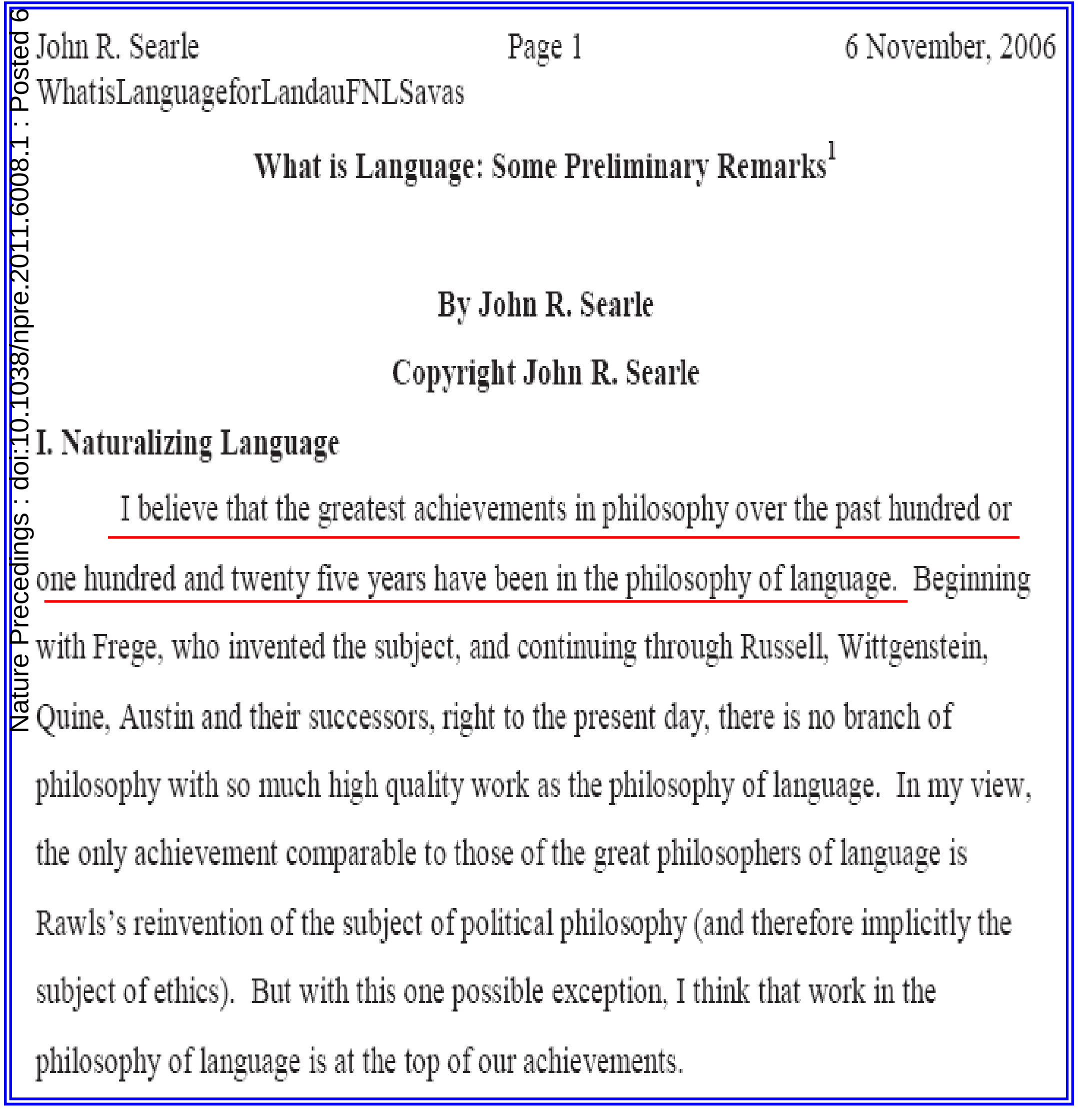
II. THE DATA

Animal Inference. Mental & Physical Data.

III. METHODS OF INFERENCE

Induction. Probability. Limitation of Variety. Grades of Certainty."

The Science & the Language



John R. Searle Page 1 6 November, 2006
WhatisLanguageforLandauFNLSavas

What is Language: Some Preliminary Remarks[1]

By John R. Searle

Copyright John R. Searle

I. Naturalizing Language

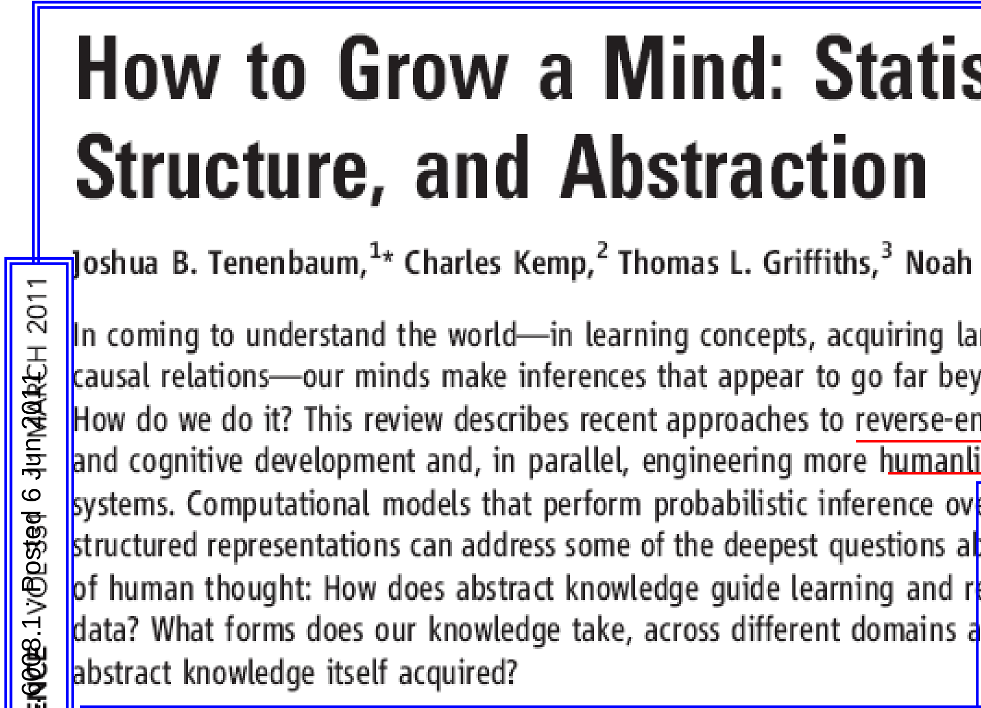
I believe that the greatest achievements in philosophy over the past hundred or one hundred and twenty five years have been in the philosophy of language. Beginning with Frege, who invented the subject, and continuing through Russell, Wittgenstein, Quine, Austin and their successors, right to the present day, there is no branch of philosophy with so much high quality work as the philosophy of language. In my view, the only achievement comparable to those of the great philosophers of language is Rawls's reinvention of the subject of political philosophy (and therefore implicitly the subject of ethics). But with this one possible exception, I think that work in the philosophy of language is at the top of our achievements.

"Chomsky argues that no science has a mechanical procedure for discovering the truth anyway"

[In linguistic] ...
"the proper object of study was **the speaker's underlying knowledge of the language**, his "linguistic competence" that enables him to produce & understand sentences he has never heard before"

From: **"Chomsky's Revolution in Linguistics" by John R. Searle**
The New York Review of Books, June 29, 1972

Learning Concept

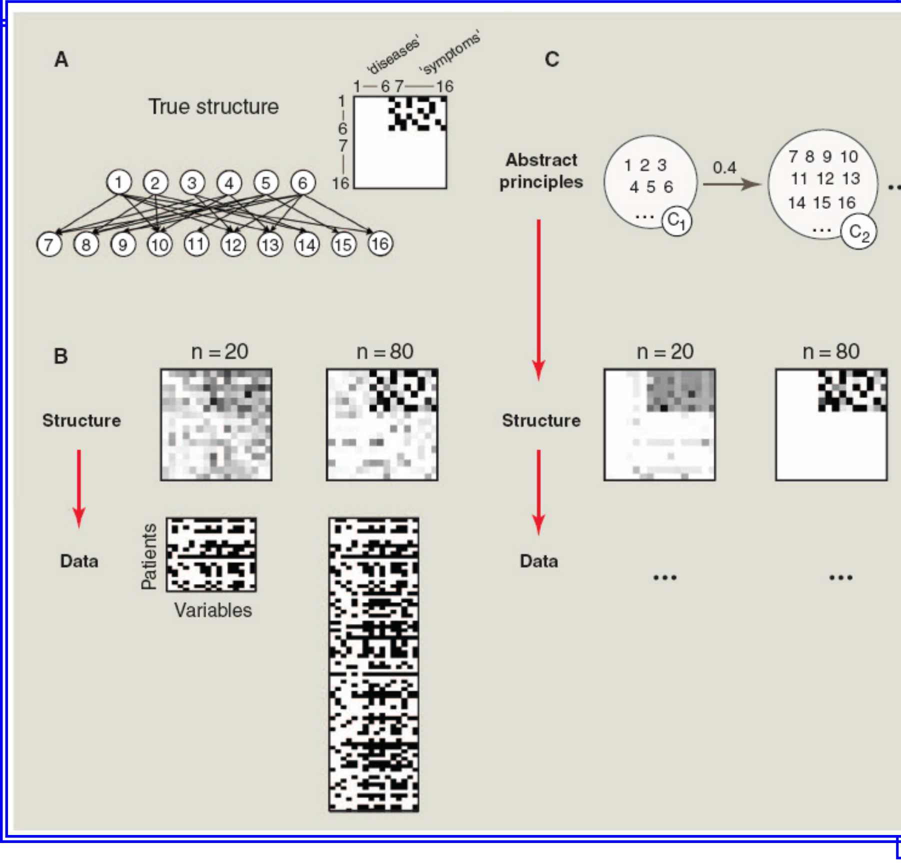


How to Grow a Mind: Statistics, Structure, and Abstraction

Joshua B. Tenenbaum,[1]* Charles Kemp,[2] Thomas L. Griffiths,[3] Noah D. Goodman[4]

In coming to understand the world—in learning concepts, acquiring language, and grasping causal relations—our minds make inferences that appear to go far beyond the data available. How do we do it? This review describes recent approaches to reverse-engineering human learning and cognitive development and, in parallel, engineering more humanlike machine learning systems. Computational models that perform probabilistic inference ov structured representations can address some of the deepest questions ab of human thought: How does abstract knowledge guide learning and r data? What forms does our knowledge take, across different domains a abstract knowledge itself acquired?

SCIENCE MARCH 2011



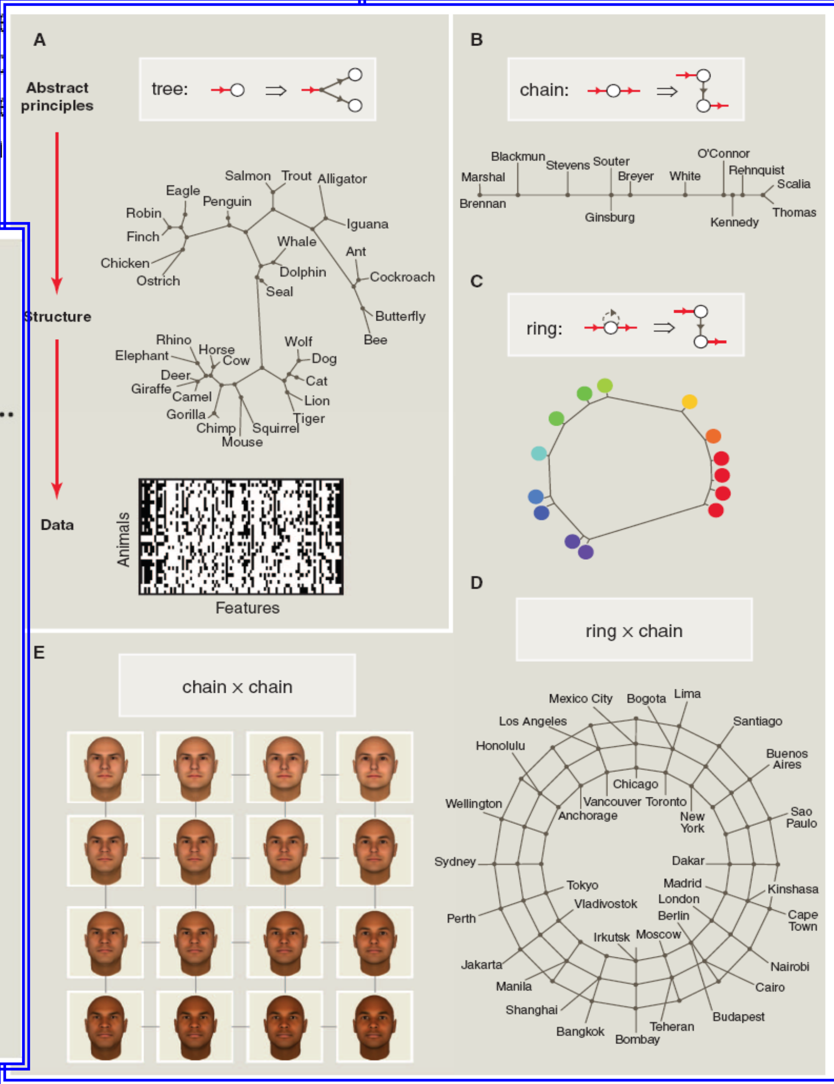
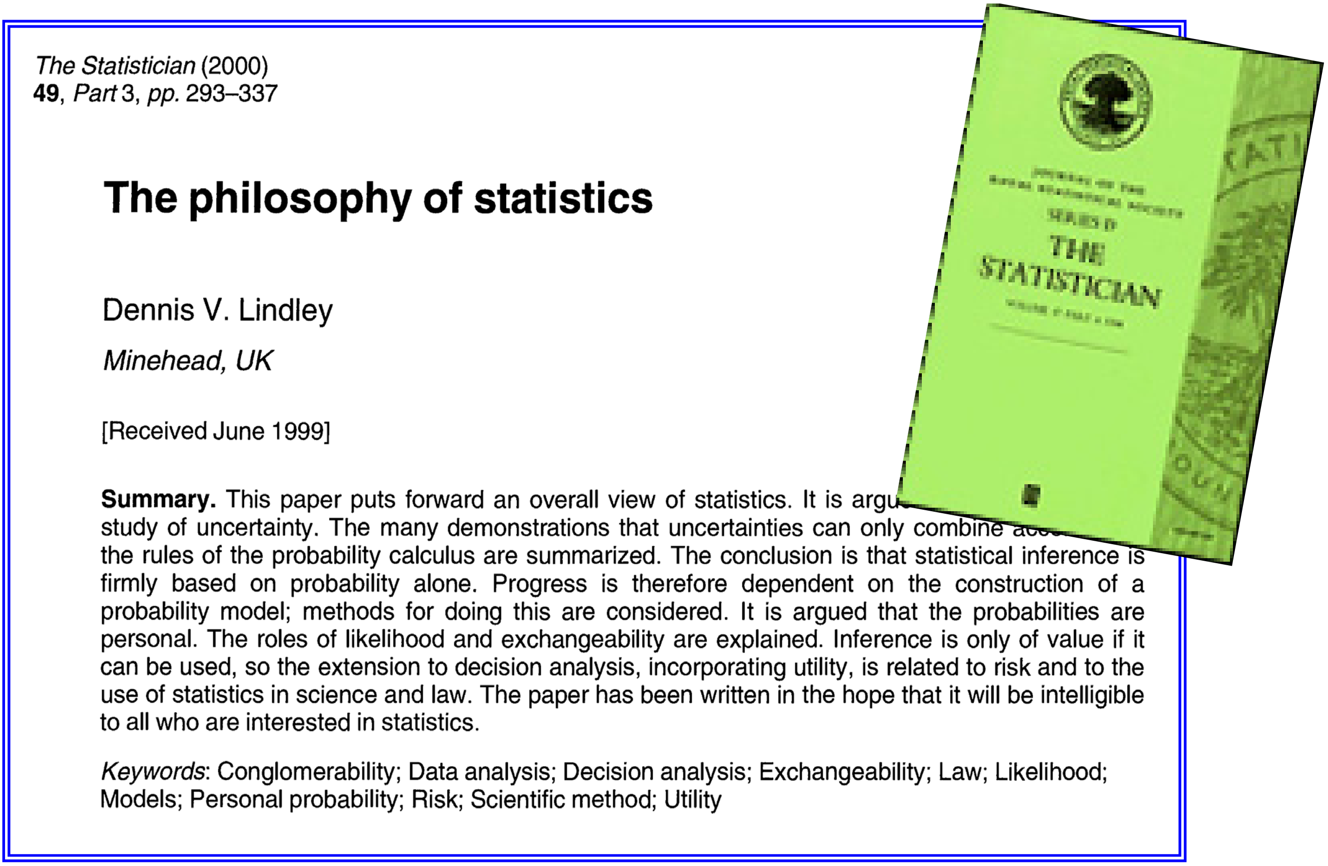


Fig. 2. Kemp and Tenenbaum (47) showed how the form of structure in a domain can be discovered by using a HBM defined over graph grammars. At the bottom level of the model is a data matrix *D* of objects and their properties, or similarities between pairs of objects. Each square of the matrix represents whether a given feature (column) is observed for a given object (row). One level up is the structure *S*, a graph of relations between objects that describes how the features in *D* are distributed. Intuitively, objects nearby in the graph are expected to share similar feature values; technically, the graph Laplacian parameterizes the inverse covariance of a gaussian distribution with one dimension per object, and each feature is drawn independently from that distribution. The highest level of abstract principles specifies the form *F* of structure in the domain, in terms of grammatical rules for growing a graph *S* of a constrained form out of an initial seed node. Red arrows represent $P(S|F)$ and $P(D|S)$, the conditional probabilities that each level specifies for the level below. A search algorithm attempts to find both the form *F* and the structure *S* of that form that jointly maximize the posterior probability $P(S,F|D)$, a function of the product of $P(D|S)$ and $P(S|F)$. **(A)** Given as data the features of animals, the algorithm finds a tree structure with intuitively sensible categories at multiple scales. **(B)** The same algorithm discovers that the voting patterns of U.S. Supreme Court judges are best explained by a linear "left-right" spectrum. **(C)** Subjective similarities among colors are best explained by a circular ring. **(D)** Given proximities between cities on the globe, the algorithm discovers a cylindrical representation analogous to latitude and longitude: the cross product of a ring and a ring. **(E)** Given images of realistically synthesized faces varying in two dimensions, race and masculinity, the algorithm successfully recovers the underlying two-dimensional grid structure: a cross product of two chains.

Statistics & Uncertainty



The Statistician (2000)
49, *Part* 3, *pp.* 293–337

The philosophy of statistics

Dennis V. Lindley
Minehead, UK

[Received June 1999]

Summary. This paper puts forward an overall view of statistics. It is argu study of uncertainty. The many demonstrations that uncertainties can only combine acc the rules of the probability calculus are summarized. The conclusion is that statistical inference is firmly based on probability alone. Progress is therefore dependent on the construction of a probability model; methods for doing this are considered. It is argued that the probabilities are personal. The roles of likelihood and exchangeability are explained. Inference is only of value if it can be used, so the extension to decision analysis, incorporating utility, is related to risk and to the use of statistics in science and law. The paper has been written in the hope that it will be intelligible to all who are interested in statistics.

Keywords: Conglomerability; Data analysis; Decision analysis; Exchangeability; Law; Likelihood; Models; Personal probability; Risk; Scientific method; Utility

"… **uncertainty should be described solely in terms of your probability**. The statistician's task is to articulate the scientist's uncertainties in the language of probability… A model is merely your reflection of reality &, like probability, it describes neither you nor the world, but only a relationship between you & that world." (p. 303)

"… **data analysis assists in the formulation of a model** & is an activity that precedes the formal probability calculations that are needed for inference." (p. 305)

"Karl Pearson said 'The unity of all science consists alone in its method, not in its material' (Pearson, 1892). **It is not true to say that physics is science whereas literature is not**." (p. 316)

"**Statisticians are not masters in their own house.** Their task is to help the client to handle the uncertainty that they encounter. The **'you'** of the analysis is the client, not the statistician." (p. 318)

The Complex Models

ADDRESSING THE COMPLEXITY OF THE EARTH SYSTEM

BY CARLOS NOBRE, GUY P. BRASSEUR, MELVYN A. SHAPIRO, MYANNA LAHSEN, GILBERT BRUNET, ANTONIO J. BUSALACCHI, KATHY HIBBARD, SYBIL SEITZINGER, KEVIN NOONE, AND JEAN P. OMETTO

al, and societal processes would accelerate
th system prediction.

OCTOBER 2010 BAMS

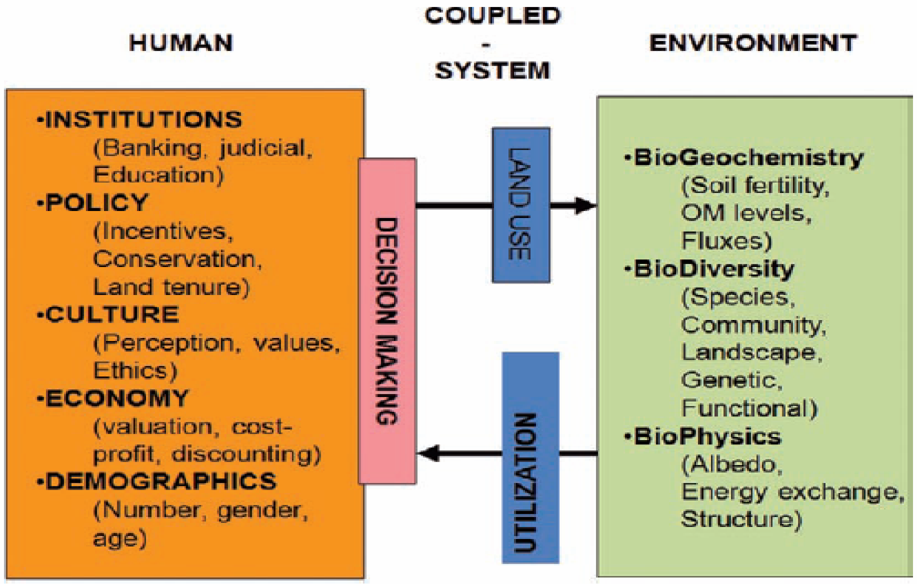
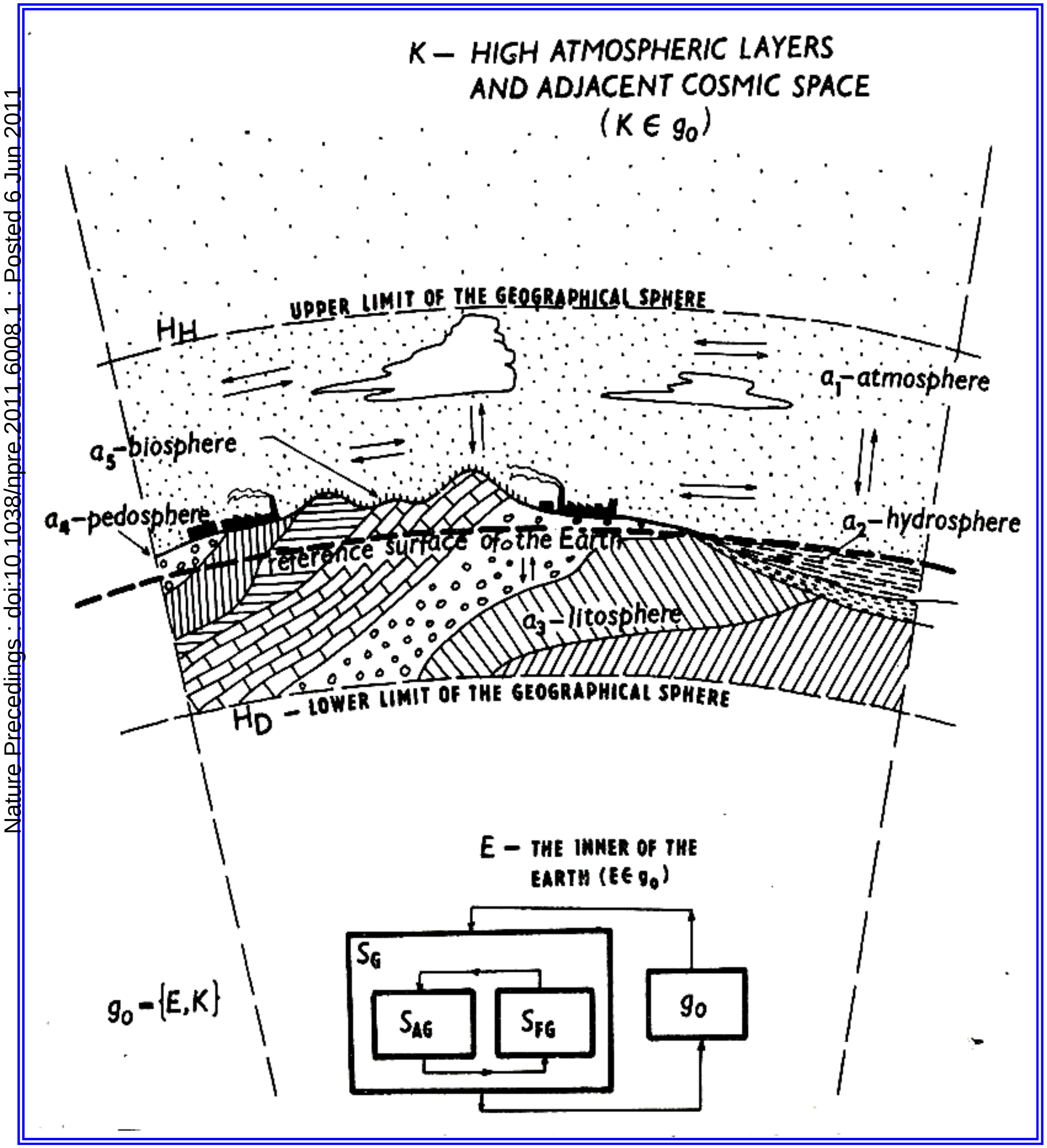


FIG. 4. An example of a model of a coupled human–environmental system that accounts for the influences of one subset of human actions (land use) on the natural systems and for the role of environmental goods and services for human welfare (utilization). [While "culture" is listed as a separate factor in this list, it is worth emphasizing that culture is a pervasive factor that also shapes institutions, economy, science, etc. (Proctor 1998).]

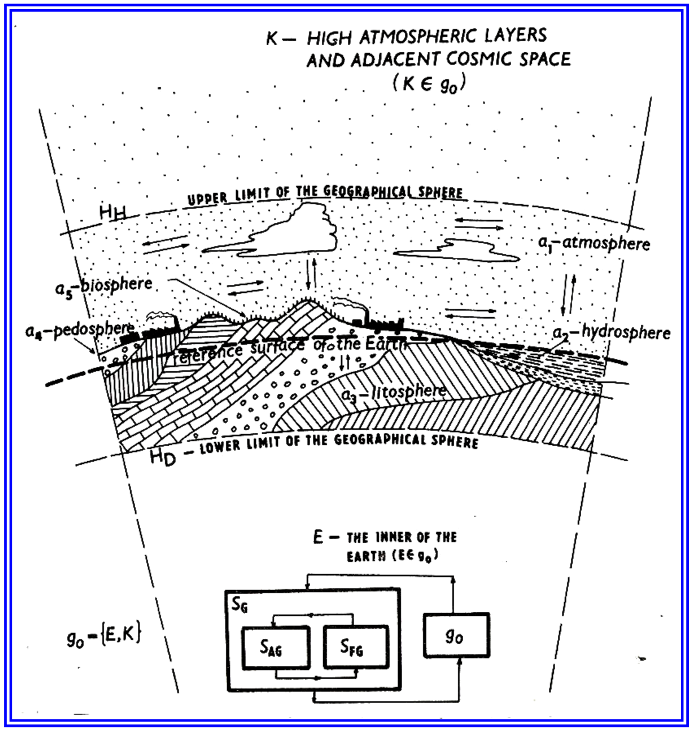
& of the Watershed

The Cybernetic Model of the Geosphere



Vertical slice of the Geographical Sphere with two independent elements: System of Anthropological Geography (S_{AG}) & System of Physical Geography (S_{FG}). Arrows indicate vertical & horizontal components of matter, energy & information circulation (after Krcho, 1978)

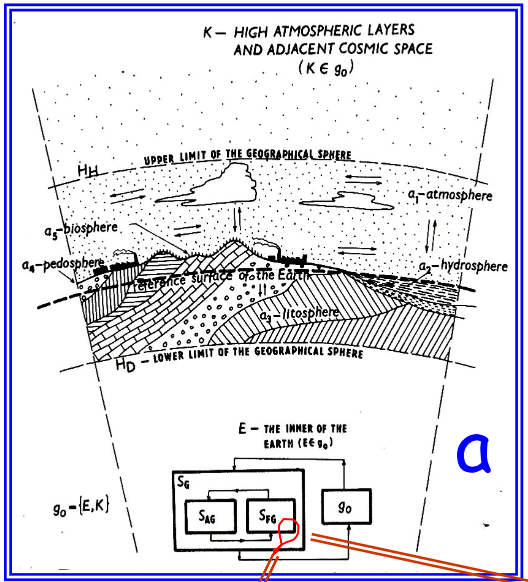
The Cybernetic Model for the Landscape

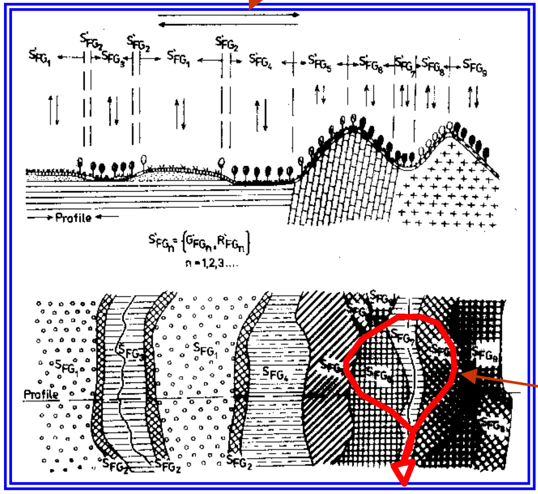


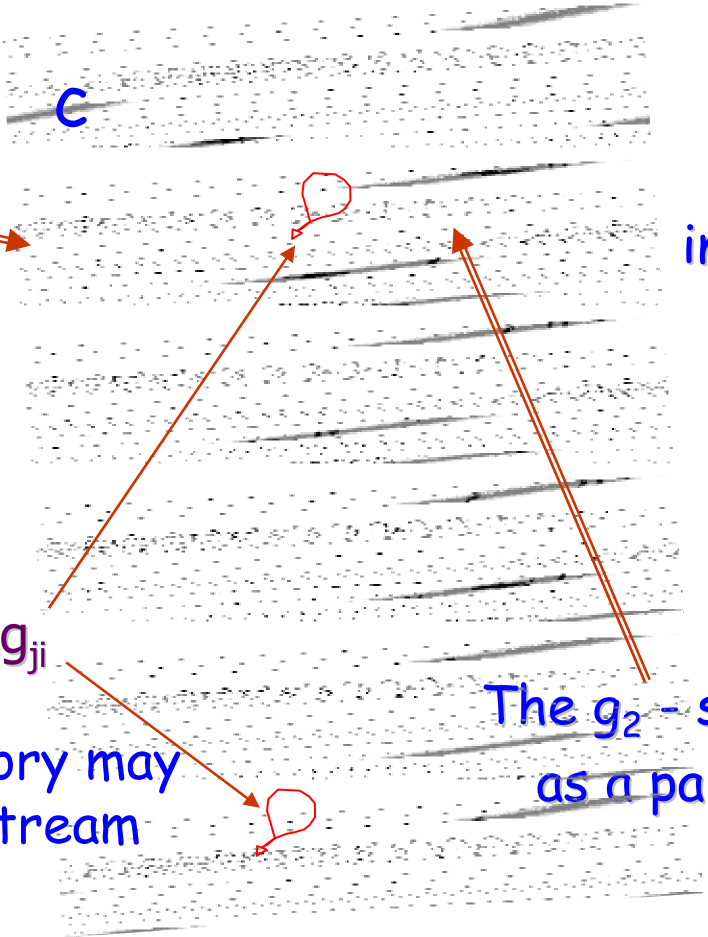
System of Physical Geography Sphere (S_{FG}) with five independent elements:
a_1- atmosphere,
a_2- hydrosphere,
a_3- lithosphere,
a_4- pedosphere,
a_5- biosphere
(after J. Krcho, 1978).

Each of these components may be characterized by matrix of input {Wi}, matrix of output {Qi}, & matrix of states {Hi}.

System Model (a) for Watershed in Landscape, with Map of Conditions (b) & Multilayer Map (c)







System of Physical Geography Sphere (S_{FG}) with five independent elements:

a_1- atmosphere,

a_2- hydrosphere,

a_3- lithosphere,

a_4- pedosphere,

a_5- biosphere

(after Krcho, 1978)

g_{ji}

The g_2 - stream runoff system as a part of a_2- hydrosphere may be presented as:

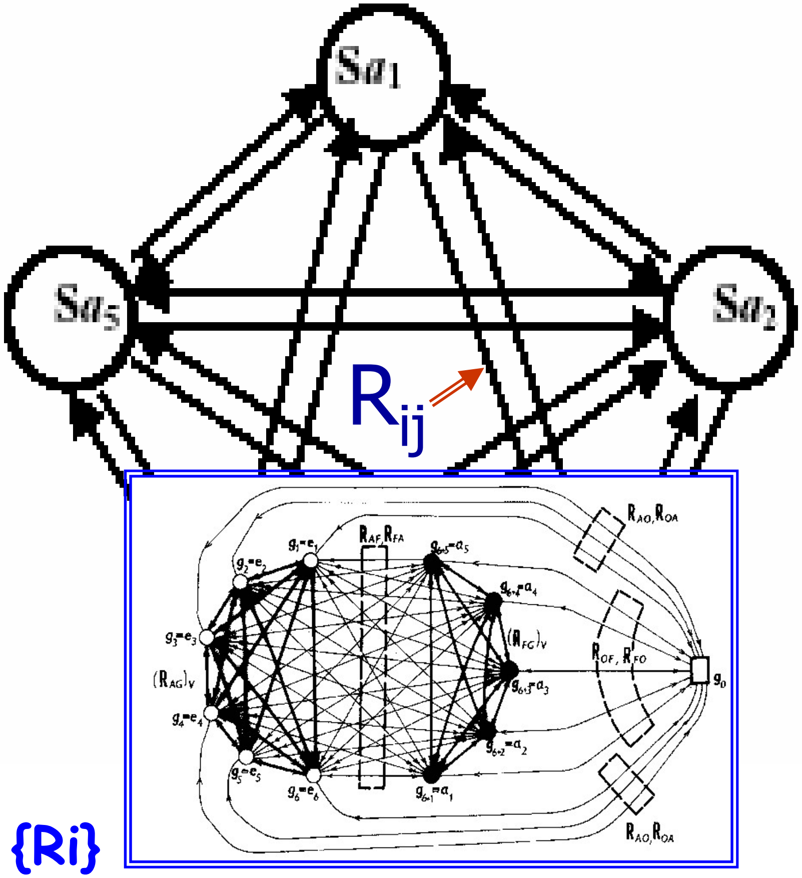
$Sg_2 = \{ g_{ji}, R_{ji} \}$,

where g_{Ji}- watershed

Any watershed g_{ji} for territory may be considered as a part of stream runoff system Sg_2.

Each of these components may be characterized by matrix of input {Wi}, matrix of output {Qi}, & matrix of states {Hi}.

The Multidimensional Structure of the Relations



{Ri}
is a matrix of relations between parts of landscape (after Krcho, 1978)

Entering the codes & numbers for initial matrix $\{X_{n*p}\}$ we open the way to recovery connections those exist in landscape

The number of characteristics for elements of landscape & watershed is unlimited but for stable landscape the set of watersheds or stations with data allows to obtain statistical description of connections

Axis for hydrological space – factors (principal components) of initial data matrixes $\{X_{n*p}\}$, allow consider {Ri} as a time spatial structure

The Cases of Cyber Model Application

Results for Watershed's Modeling

e.com/documents/3289/version/1

http://precedings.nature.com/documents/1371/version/1

Spatiotemporal Regime of Climate & Streamflow in the US Great Lakes Basin

Boris Shmagin &
Carol Johnston,
South Dakota State University,
Nir Y. Krakauer,
City College of New York

52nd Annual Conference
Research
May 18-22, 2009
Toledo, Ohio
BRIDGING Lakes
Ecosystems & Environmental Health across our Great Lakes

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ScienceD

journal homepage: www.elsevie

Multidimensional structure of streamflow regime in a hierarchy of landscapes within the U.S. Great Lakes basin

Boris Shmagin &
Carol Johnston, SDSU,
& Scott Bridgham, UO

This research is funded by
U.S. EPA - Science To Achieve Results (STAR) Program
Grant #

IAGLR '05
Great Lakes Ecosystem Forecasting
Improving Understanding & Prediction
University of Michigan
Ann Arbor, Mich.
May 23-27, 2005

Regionalization, seasonality, and trends of streamflow in the US Great Lakes Basin

Carol A. Johnston [a,*], Boris A. Shmagin [b,1]

[a] Department of Biology and Microbiology, South Dakota State University, Box 2207B, Brookings, SD 57007, United States
[b] Water Resources Institute, South Dakota State University, Box 2120, Brookings, SD 57007, United States

Received 28 February 2008; received in revised form 13 August 2008; accepted 14 August 2008

Philosophy of Data Analysis & Natural Structures

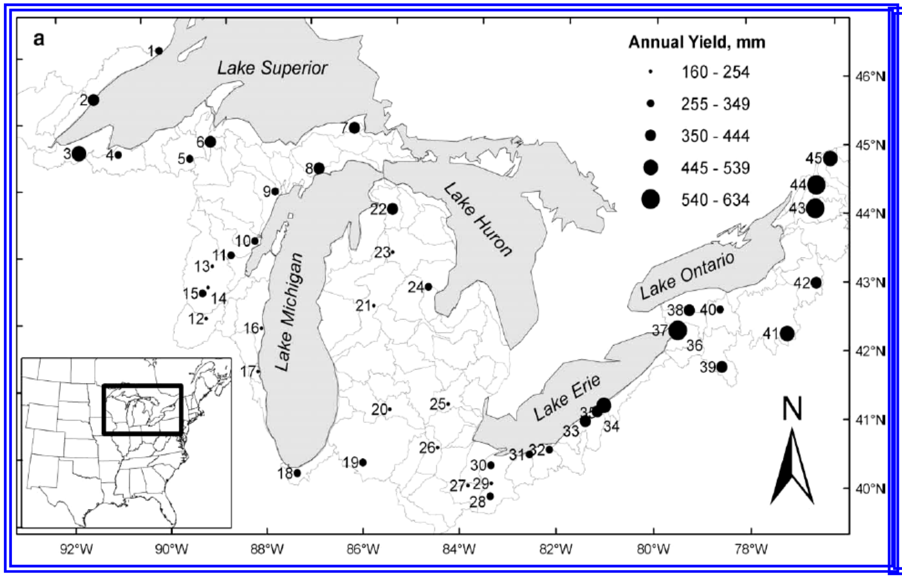
Factor analysis is method for **extraction** that are regarded as the **basic variables that account for the interrelations observed in the data**

A **factor** is a portion of a quantity, usually an integer or polynomial that, when multiplied by other factors, gives the entire quantity

The main applications of factor analytic techniques are:

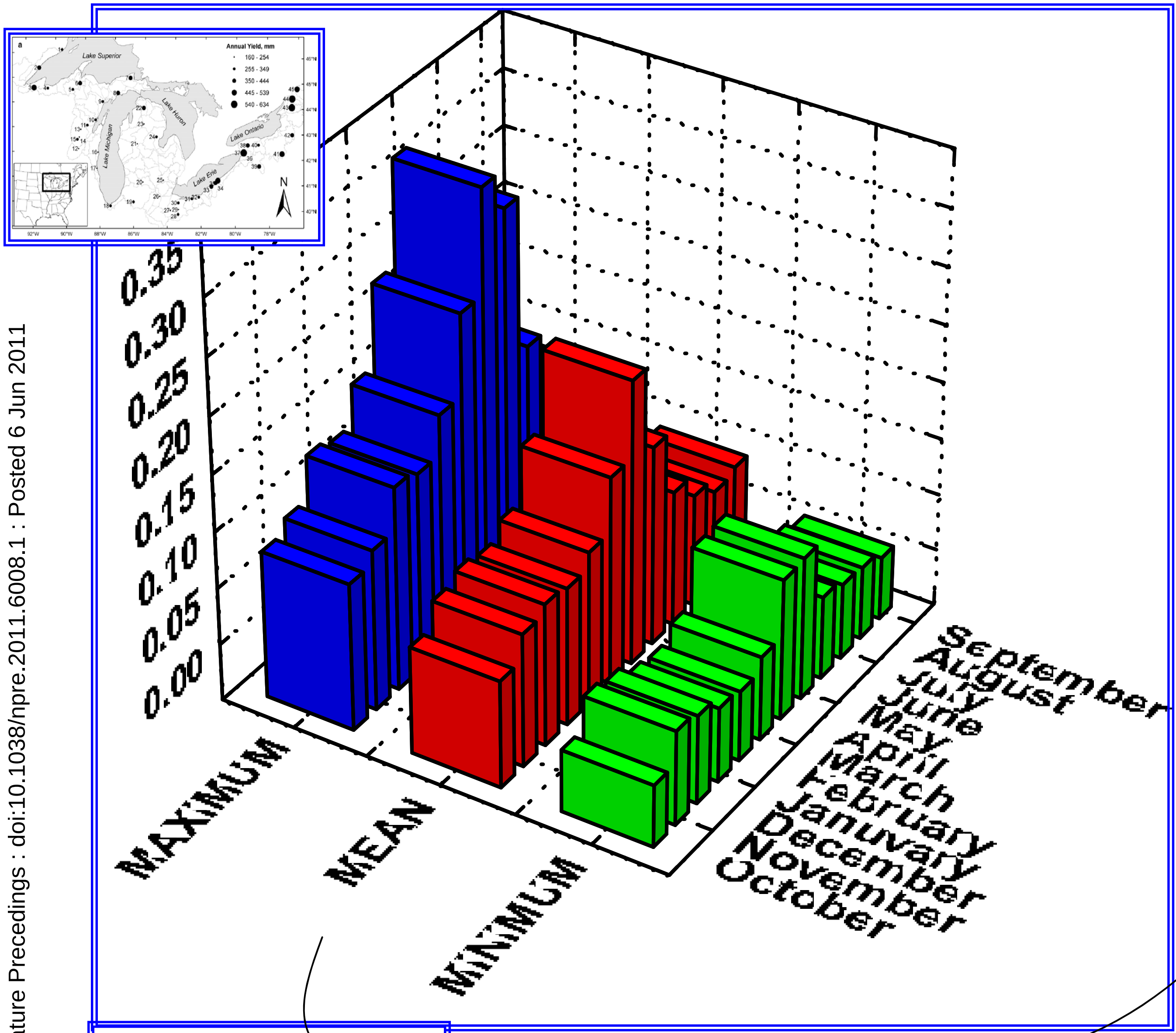
- (1) to **reduce the number** of variables and
- (2) to **detect structure** in the relationships between variables, that is to **classify variables**.

(From: Wolfram *MathWorld*)

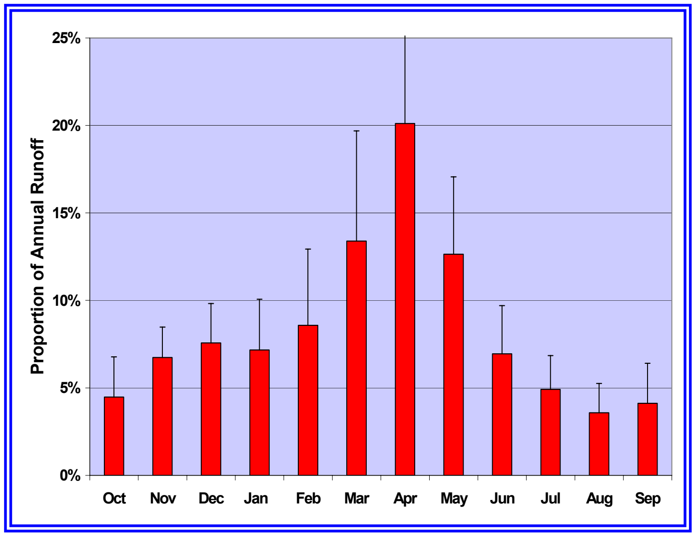


From: Johnston & Shmagin, 2008

The **variables selected** after factor analysis are considered as typical & may be used for time-series analysis



Average for 1956-70:
blue – MAXIMUM;
red – MEAN;
green - MINIMUM



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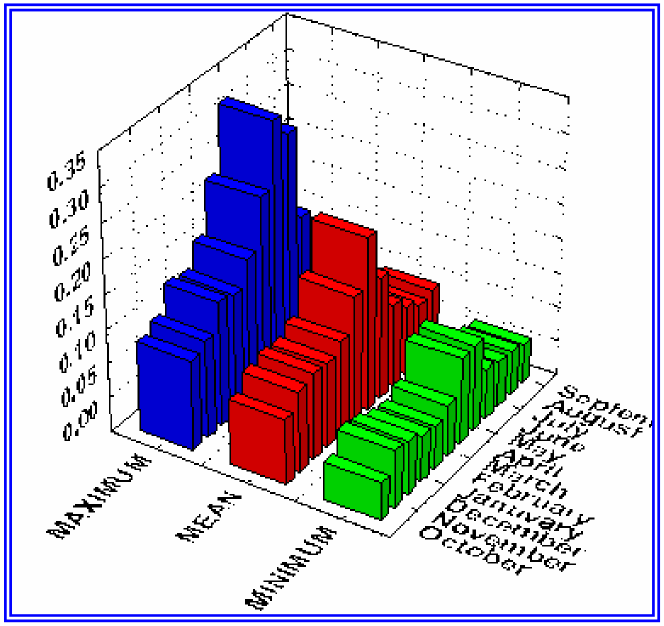
Monthly Proportions of Annual Streamflow for 45 Watersheds

Table of Factor Loadings for Monthly Proportions of Annual Streamflow (1956-70)

Month	Factor 1	Factor 2	Factor 3
October	0.43	0.39	**0.80**
November			**0.97**
December	-0.25	**-0.91**	
January		**-0.88**	-0.40
February		**-0.77**	***-0.60***
March	-0.40	***-0.63***	***-0.58***
April	***-0.68***	***0.69***	
May		**0.91**	
June	***0.60***	**0.70**	
July	**0.89**	0.28	
August	**0.80**		0.53
September	***0.53***	0.41	***0.69***
Explained Variability	3.01 (25.8%)	4.85 (40.4%)	3.26 (27.2)



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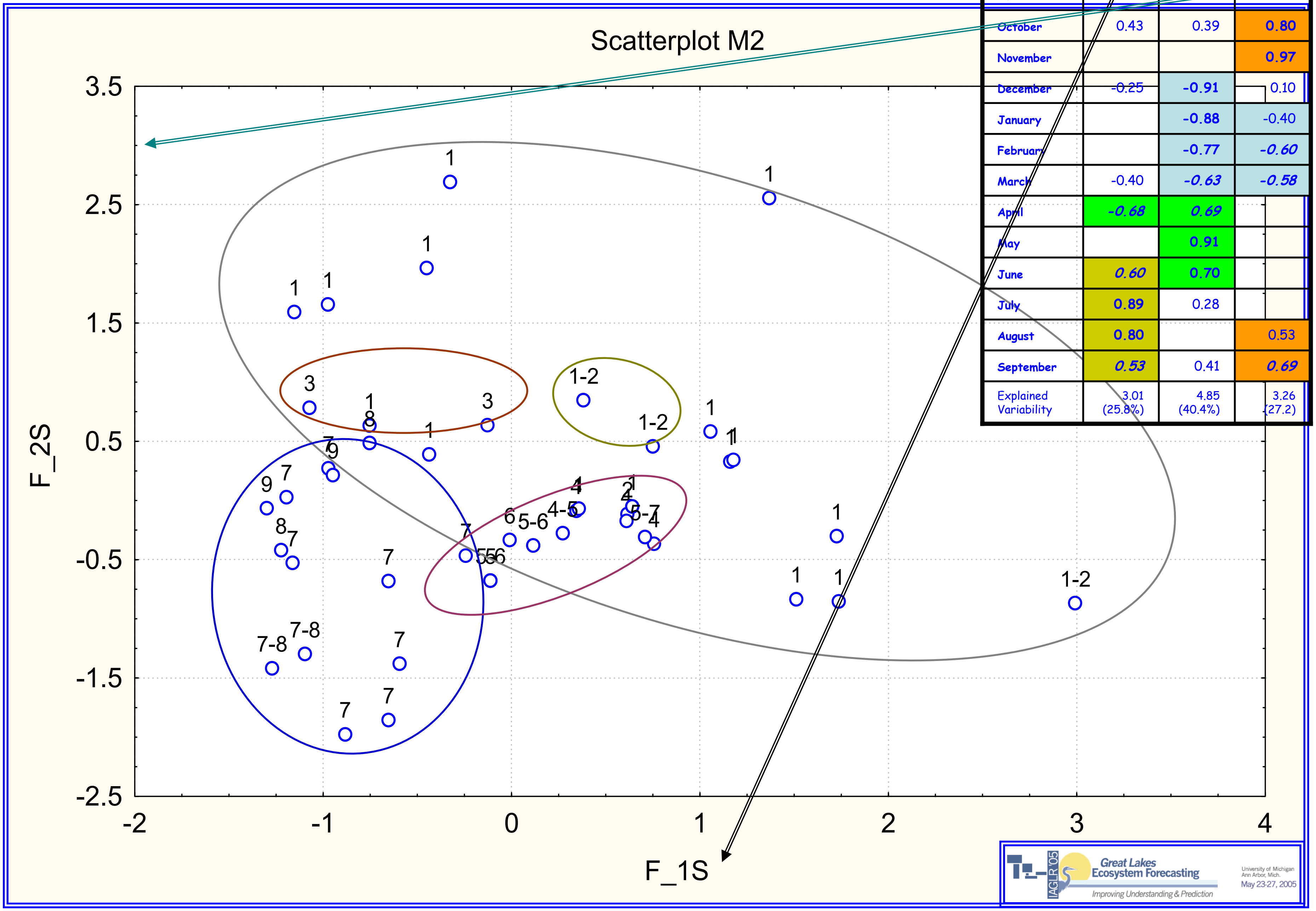
Factor Scores for 45 Watersheds in Plane of First & Second Factors Axis



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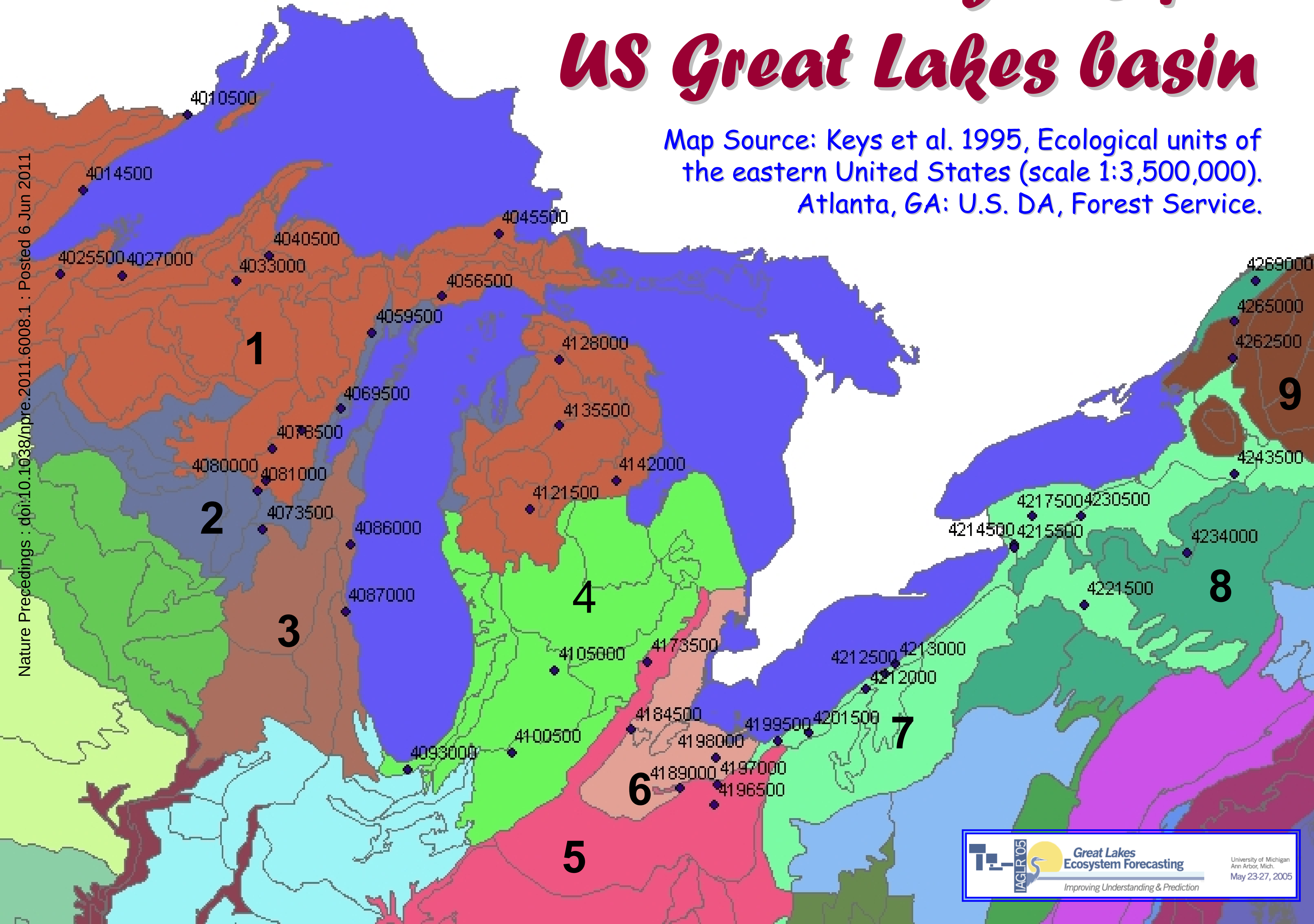
Ecoregions for US Great Lakes basin

Map Source: Keys et al. 1995, Ecological units of the eastern United States (scale 1:3,500,000). Atlanta, GA: U.S. DA, Forest Service.



Great Lakes Ecosystem Forecasting

Improving Understanding & Prediction

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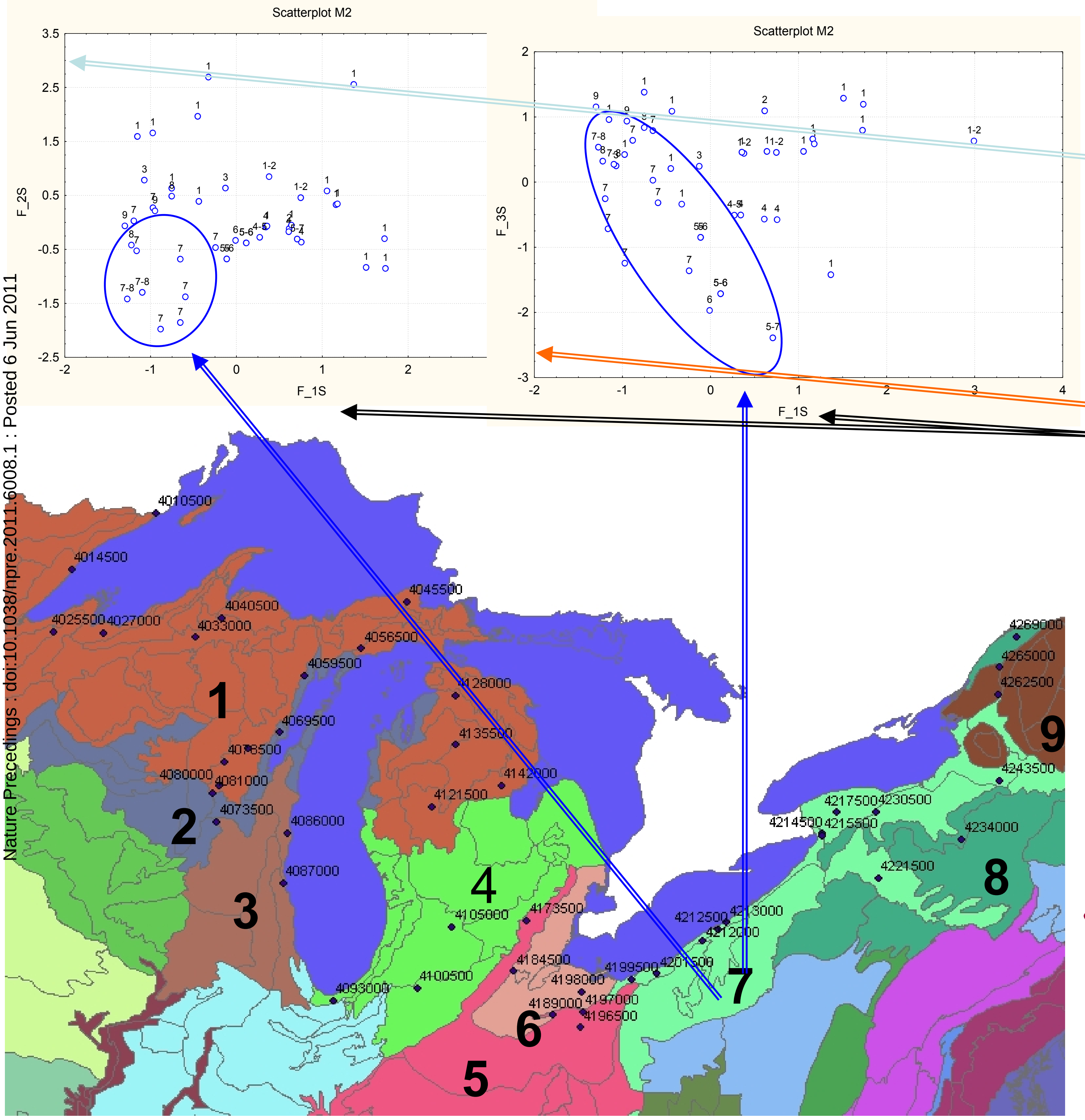

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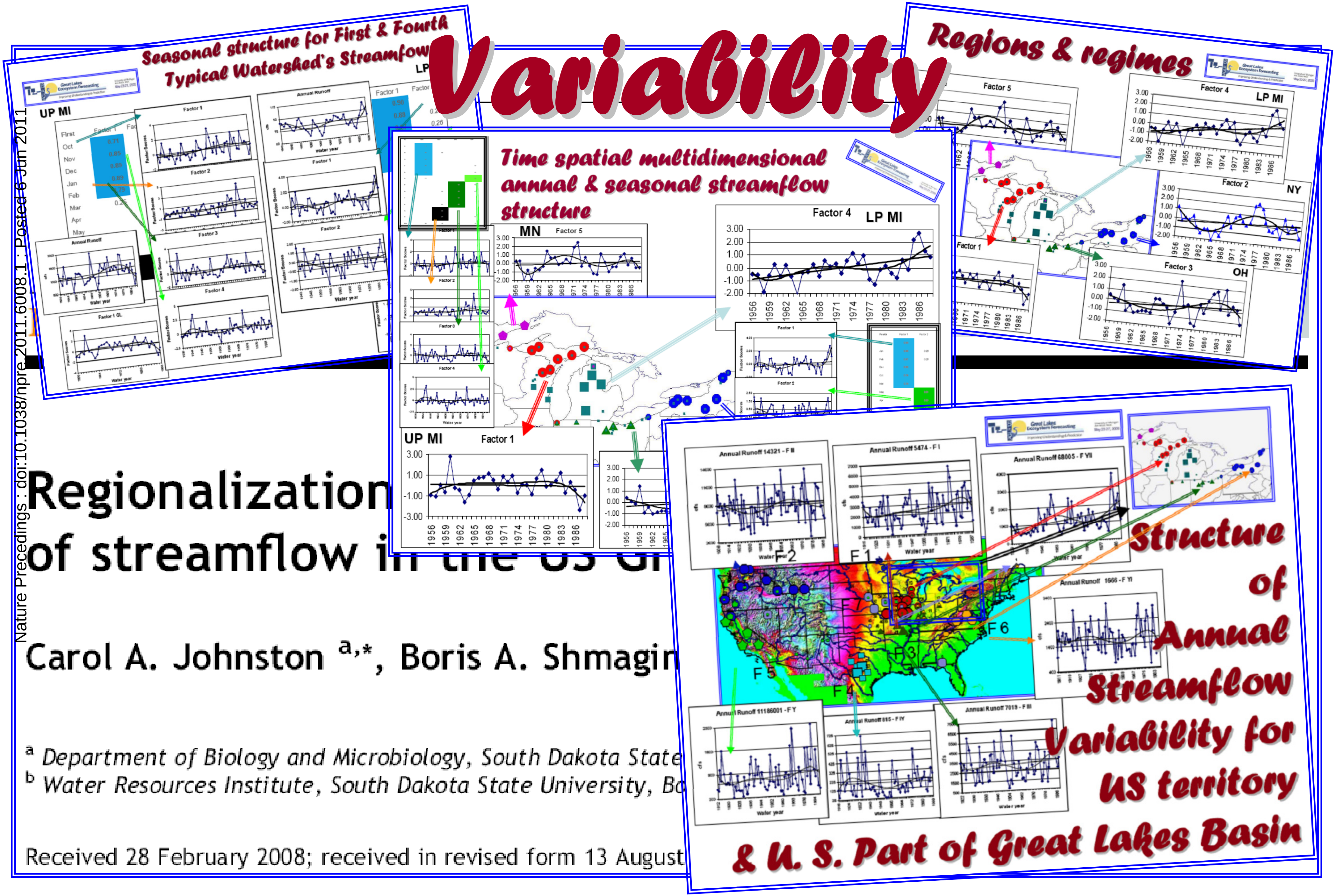
Ecoregions & Seasonality of Annual Streamflow

Structures of Streamflow Variability



Seasonal structure for First & Fourth Typical Watershed's Streamflow

Regions & regimes

Time spatial multidimensional annual & seasonal streamflow structure

Structure of Annual Streamflow Variability for US territory & U. S. Part of Great Lakes Basin

Regionalization of streamflow in the US Gr

Carol A. Johnston [a],*, Boris A. Shmagin

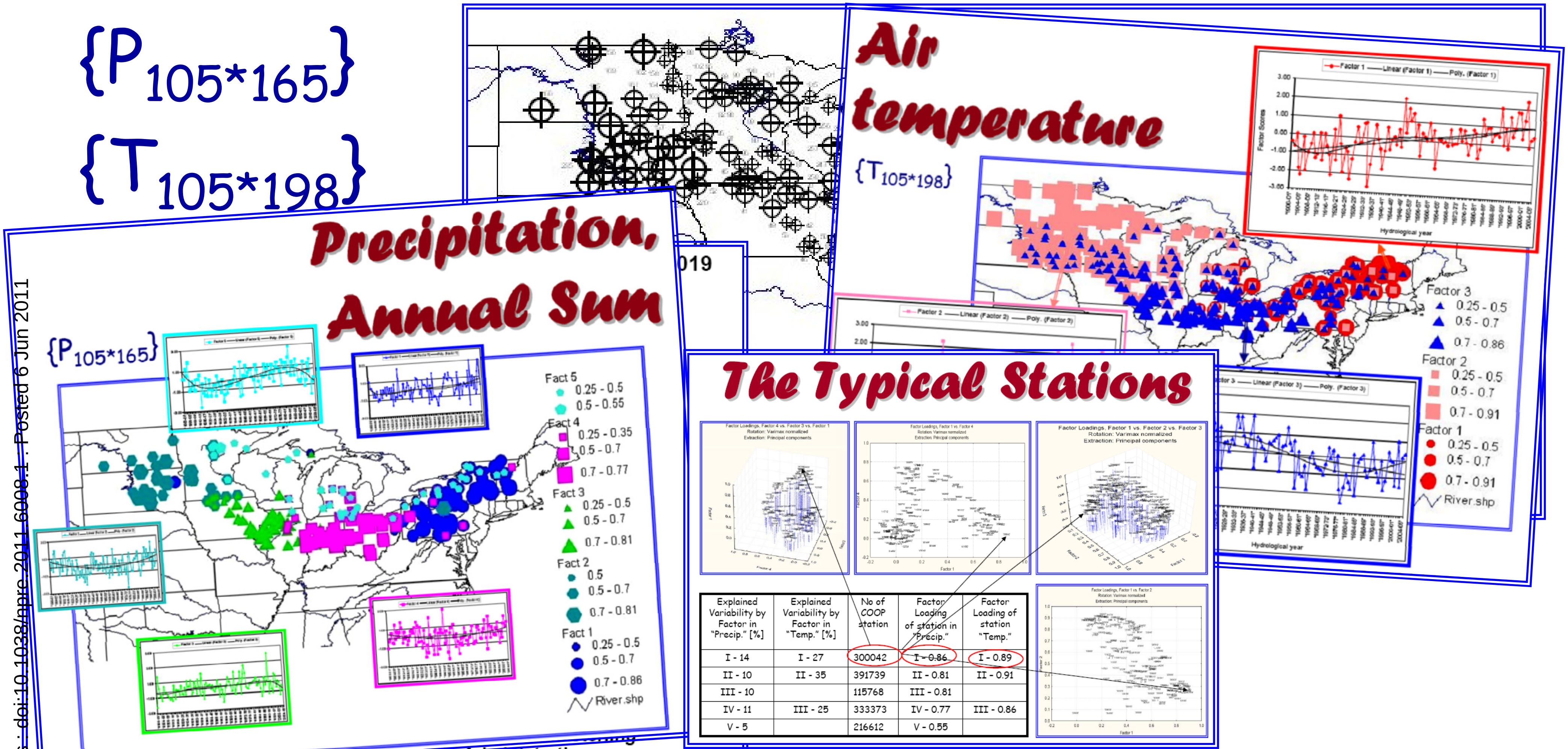
[a] Department of Biology and Microbiology, South Dakota State

[b] Water Resources Institute, South Dakota State University, Bo

Received 28 February 2008; received in revised form 13 August

$\{P_{105*165}\}$

$\{T_{105*198}\}$



Explained Variability by Factor in "Precip." [%]	Explained Variability by Factor in "Temp." [%]	No of COOP station	Factor Loading of station in "Precip."	Factor Loading of station "Temp."
I - 14	I - 27	300042	I - 0.86	I - 0.89
II - 10	II - 35	391739	II - 0.81	II - 0.91
III - 10		115768	III - 0.81	
IV - 11	III - 25	333373	IV - 0.77	III - 0.86
V - 5		216612	V - 0.55	

Administration,
National Climatic Data Center,
Asheville, North Carolina

Prepared for on-line distribution by:
B.L. Jackson, L.M. Olsen, D.P. Kaiser, and T.A.
Carbon Dioxide Information Analysis Center
Environmental Sciences Division
Oak Ridge National Laboratory
Ridge, Tennessee 3783 35
managed by
see-
the
ENT OF
der contract DE-AC05-00OR22725

Data & Structures for Climate Variability Characterization

Hydrology with Structure

- Number of factor's axis create annual & seasonal structure of hydrologic space
- Distribution of watersheds in this space depends upon their hydrologic characteristics
- Groups of watersheds in hydrological space may provide a base for regionalization & creation of hydrological map
- The factor model characteristics present the part of information used from empirical data
- The use of Cyber Model & Data Analysis allows communicate the knowledge of hydrologic structures

The Beginning of the Earth Sciences

HISTORY OF SCIENCE

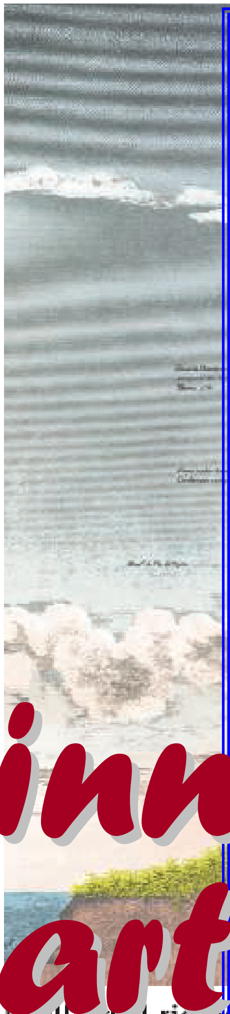
Alexander von Humboldt and the General Physics of the Earth

In the early 19th century, Alexander von Humboldt laid the foundations for today's Earth system sciences.

Stephen T. Jackson

As scientists are celebrating the 200th anniversary of Charles Darwin's birth and the 150th anniversary of the publication of his *On the Origin of Species*, Darwin's ideas continue to shape and enrich the sciences (*1*). 6 May 2009 marks the 150th anniversary of the death of another 19th-century figure—Alexander von Humboldt—whose scientific legacy also flourishes in the 21st century. Humboldt helped create the intellectual world Darwin inhabited, and his writings inspired Darwin to embark on *H.M.S. Beagle*. More pertinent to our time, Humboldt established the foundation for the Earth system sciences: the integrated system of knowledge on which human society may depend in the face of global climate change.

Like Darwin, Humboldt undertook a [illegible]or[illegible]ge that wo[illegible]s[illegible]e his ideas [illegible]l th[illegible]g[illegible]boldt[illegible] y[illegible](1[illegible] [illegible]180[illegible]ist A[illegible]e B[illegible] ing Venezuela, the north[illegible]ndes, and [illegible]tral Mexic[illegible], with v[illegible]its to Tenerife, Cuba, a[illegible] th[illegible]Uni[illegible]State[illegible]he[illegible]lect[illegible]botan[illegible] [illegible]oo[illegible]g[illegible] geol[illegible]cal[illegible]gical [illegible]s, [illegible]ade ext[illegible]iv[illegible]ic and [illegible] physic[illegible] measurements, and recorded the [illegible]raphic l[illegible]cation of their thousands of [illegible]cime[illegible]te[illegible]f[illegible]nd[illegible]f[illegible] [illegible]m[illegible]s[illegible]um[illegible]22[illegible]a[illegible] most of his inherited fortune in Paris, p



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On the Origin of Ecological Structure

RINE SUTLIFF/SCIENCE; WIKIPEDIA/GEORGE RICHMOND, FROM ORIGINS, RICHARD LEAKEY AND ROBERT LEWIN

ON 23 JUNE 1802, PRUSSIAN NATURALIST Alexander von Humboldt attempted to reach the summit of Mount Chimborazo, the highest peak in the northern Andes. Bleeding, his beard c[illegible]ed with ice, the 33-year-old Humboldt [illegible]ed his way along a 12-centimeter-wide [illegible]e o[illegible] to be blocke[illegible] cliff some [illegible]ne[illegible] to[illegible]'s barometer [illegible]ca[illegible]e[illegible]a[illegible]ing record [illegible]ea[illegible] brought him [illegible]erna[illegible]nal fa[illegible].

The lasting impac[illegible]trip, however, came [illegible]m his explorat[illegible] of somewhat less lo[illegible]n. Having studied Mount Chimbo[illegible] [illegible]earby peaks for months, Humboldt [illegible] the first comprehensive treatise—[illegible]he Geography of Plants*—on how [illegible]varies with altitude, climate, soil, and [illegible]er fa[illegible]s. The work was a groundbreaking exploration of the physical underpinnings of ecological structure: what determines the species that make up a community and their relative abundance.

More than a half-century later, Charles Darwin quietly conducted experiments in his garden at Down House that were even more albeit a controversial one, for community structure, and Darwin included the experiment in *On the Origin of Species*. "What a wondrous problem it is," Darwin wrote to the botanist Joseph Hooker in 1857, "what a play of forces, determining the kind and proportion of each plant in a square yard of turf!"

Ever since, ecologists have wrestled with understanding what dictates the kinds and proportions of organisms in communities ranging from meadows to montane forests. How these forces set up communities has "arguably been one of the most primary questions driving ecological science since its origins," says Brian Enquist of the University of Arizona, Tucson. Competition, predation, disturbance, and other factors have a heavy hand, and new research is showing the influential role of evolution as well. "You can't understand the assembly process if you don't think about evolution," says Jeannine Cavender-Bares of the University of Minnesota, Twin Cities.

Despite these achievements, there is still no consensus on the relative importance of the various forces. Darwin and many later ecologists emphasized competition among species, but proponents of a controversial theory of biodiversity that assumes competition has no impact argue that immigration and other random demographic events can account for much of the apparent makeup of communities. As a result, ecologists have a long way to go to come up with formulas that predict how communities might arise and change. Yet the ability to make predictions is important for the restoration and management of ecosystems impacted by invasive species or climate change.

Many forces

Species abundance and composition—i.e., structure—may be the

THE YEAR OF DARWIN

This essay is the 10th in a monthly series. For more on evolutionary topics online, see the Origins blog at **blogs.sciencemag.org/origins**. For more on ecological structure, listen to a podcast by author Erik Stokstad at **www.sciencemag.org/multimedia/podcast**.

to place, wet tropical forests still exist as recognizable entities on four continents. A combination of physical and biological forces organizes species into these predictable communities.

Following Humboldt's lead, scientists in the 19th century assembled evidence that the composition of communities depends on physical factors such as climate and soil chemistry. Today, ecologists call these factors "environmental filters" that broadly determine which species can live where. For example, forests in the eastern United States are rich in sugar maples in the north but gradually become dominated by oaks and hickories to the south as temperature rises. Hemlock and beech trees disappear to the west as conditions generally become drier.

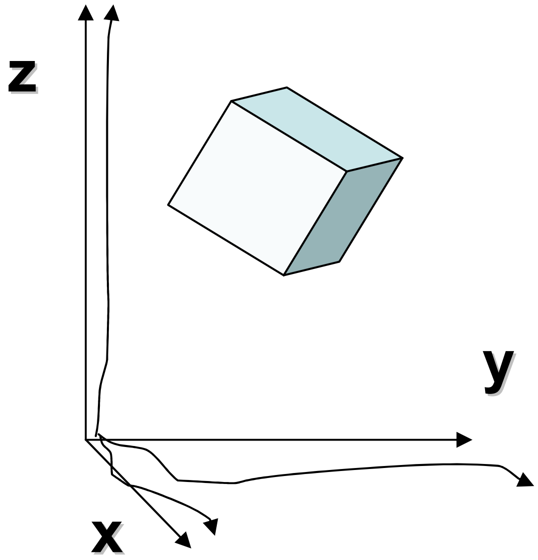
On a global scale, the importance of physical factors varies with latitude, according to conventional thinking, popularized by Theodore Dobzhansky in 1950. Stress from cold and freezing limits diversity at high latitudes, according to this widely established view, whereas species diversity in the tropics is capped by another major driver, biological interactions.

But to what degree are local patterns driven by the direct influence of climate versus biological interactions such as competition? "Answering this question is critical for our ability to predict shifts in natural communities due to global climate change," says Nicholas Gotelli of the University of Vermont, Burlington.

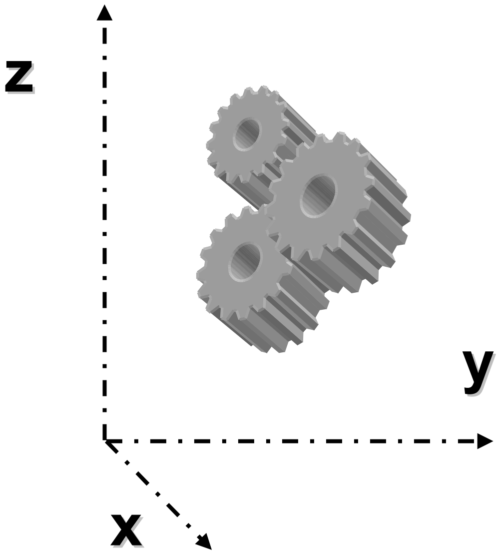
It's long been clear that biological interactions—competition, predation, and so on—can be big players. In the 1930s, Soviet microbiologist Georgii Gause conducted influential research into how competition sets up communities. Gause studied mixtures of three species of the protist *Paramecium* that were provided with one or two kinds of food: yeast, bacteria, or both. The experiments revealed that one species of *Paramecium* would always drive the others extinct if they had to compete for the same resource. This led to the principle of competitive exclusion and eventually to the idea that species

The Coordinates for the River Watershed

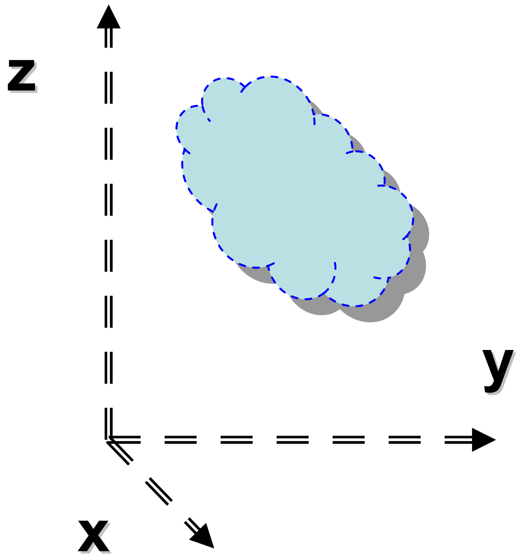
The Uncertainty & Different Systems of Coordinates



Mathematical & physical objects “have” the principle of uncertainty

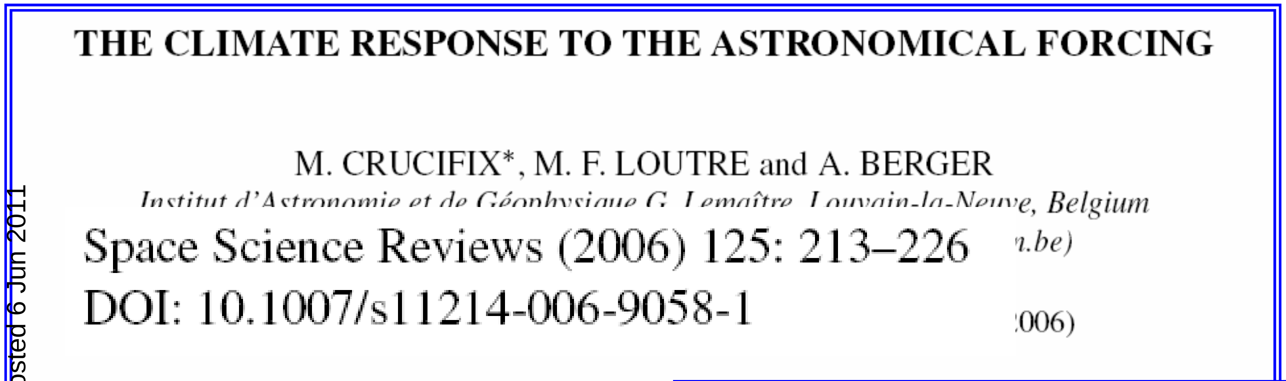


Technological objects have the errors of measurement



Natural objects have fuzzy boundaries in their own coordinates of multi-dimensional process

The Coordinates for the Earth



THE CLIMATE RESPONSE TO THE ASTRONOMICAL FORCING

M. CRUCIFIX*, M. F. LOUTRE and A. BERGER
Institut d'Astronomie et de Géophysique G. Lemaître, Louvain-la-Neuve, Belgium
.be)

Space Science Reviews (2006) 125: 213–226
DOI: 10.1007/s11214-006-9058-1
006)

Abstract. Links between climate and Earth's orbit
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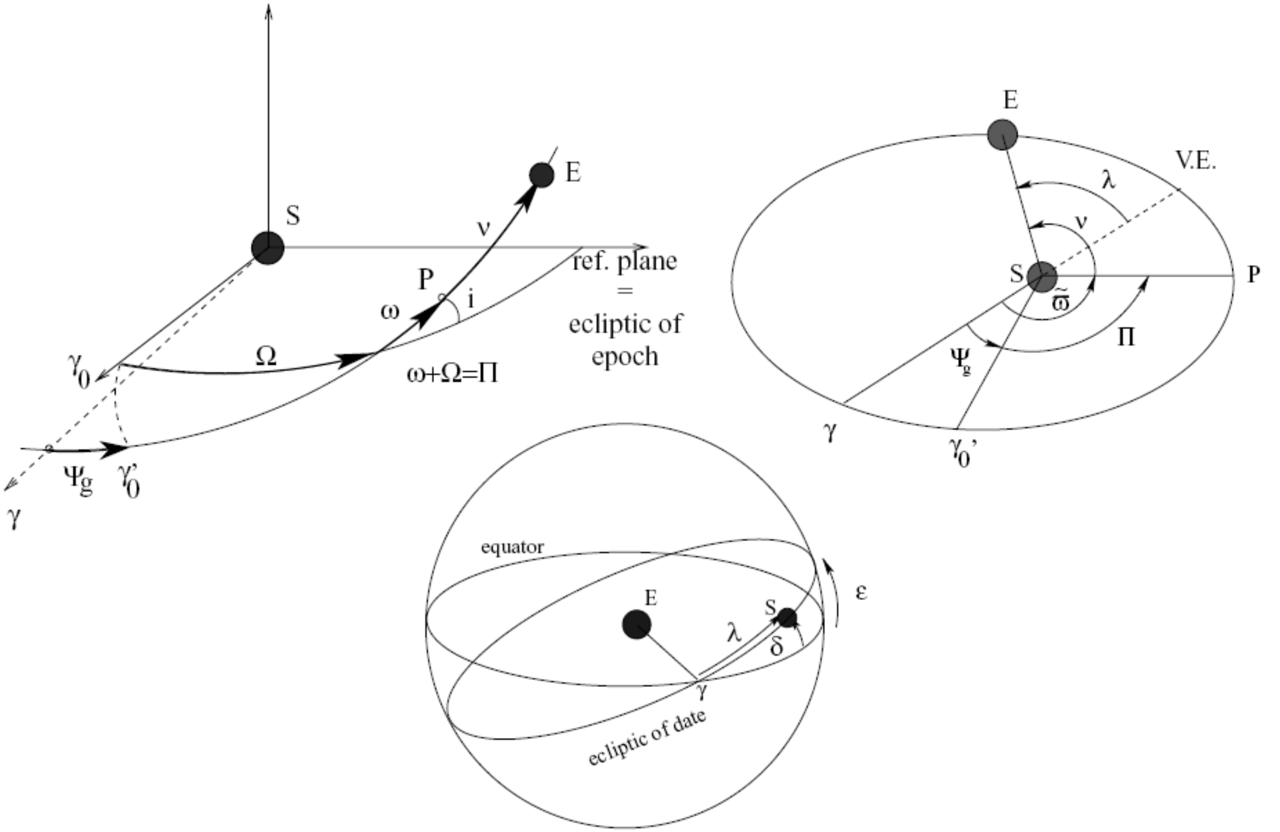
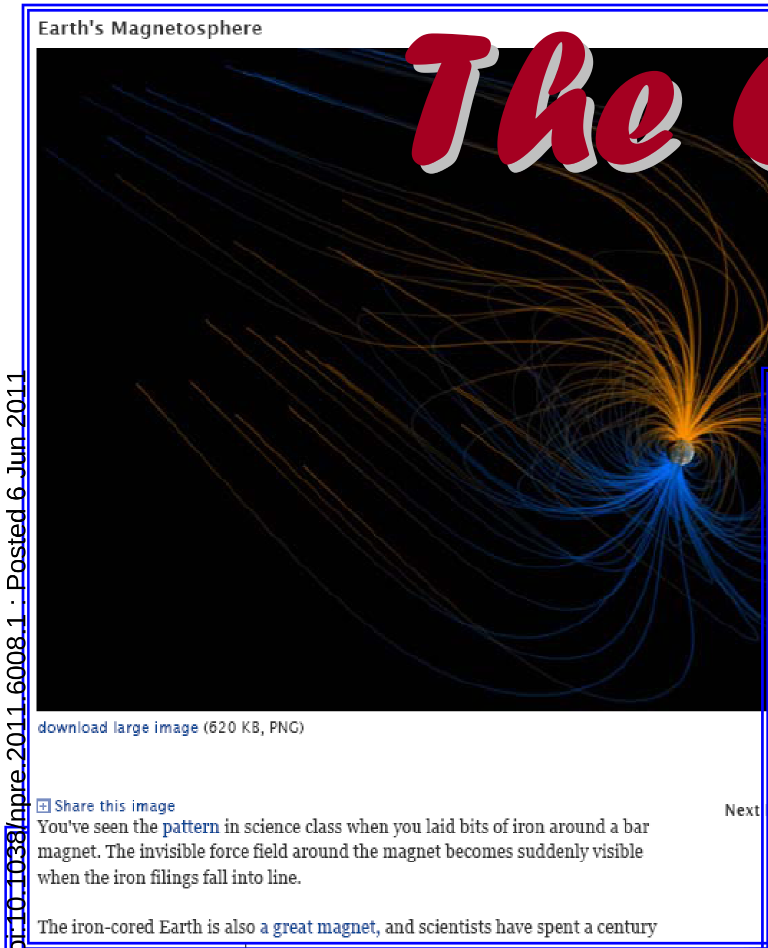


Figure 1. Angles relevant for the astronomical theory of climate, represented on *(left)* the ecliptic plane of epoch, *(right)* the actual orbit plane, also called ecliptic of date, and *(middle)* in geocentric coordinates. P is perihelion and V.E., vernal equinox.

The Coordinates for the Earth



Earth's Magnetosphere Posted April 23, 2011

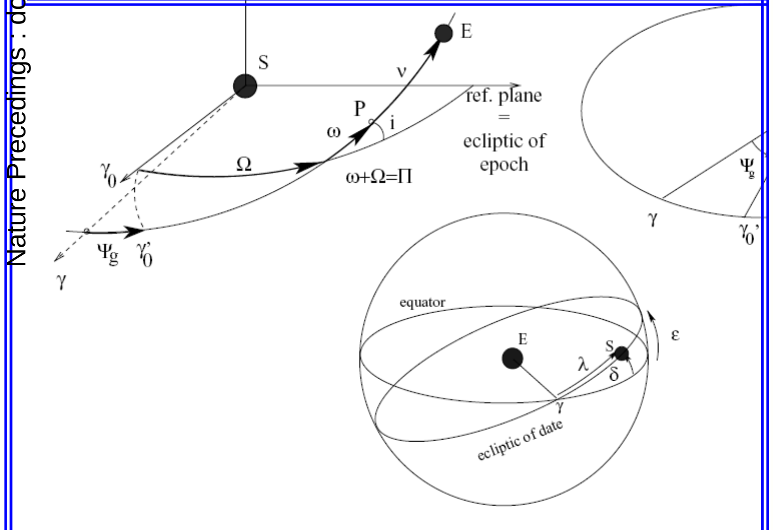
download large image (620 KB, PNG)

Share this image

Next

You've seen the pattern in science class when you laid bits of iron around a bar magnet. The invisible force field around the magnet becomes suddenly visible when the iron filings fall into line.

The iron-cored Earth is also a great magnet, and scientists have spent a century



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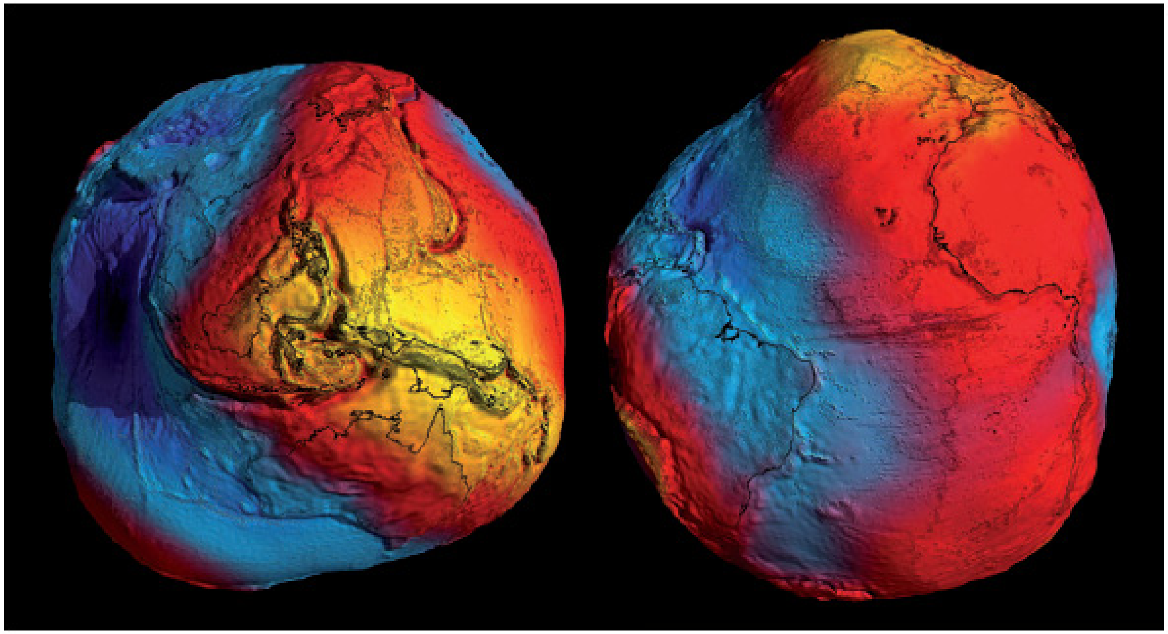
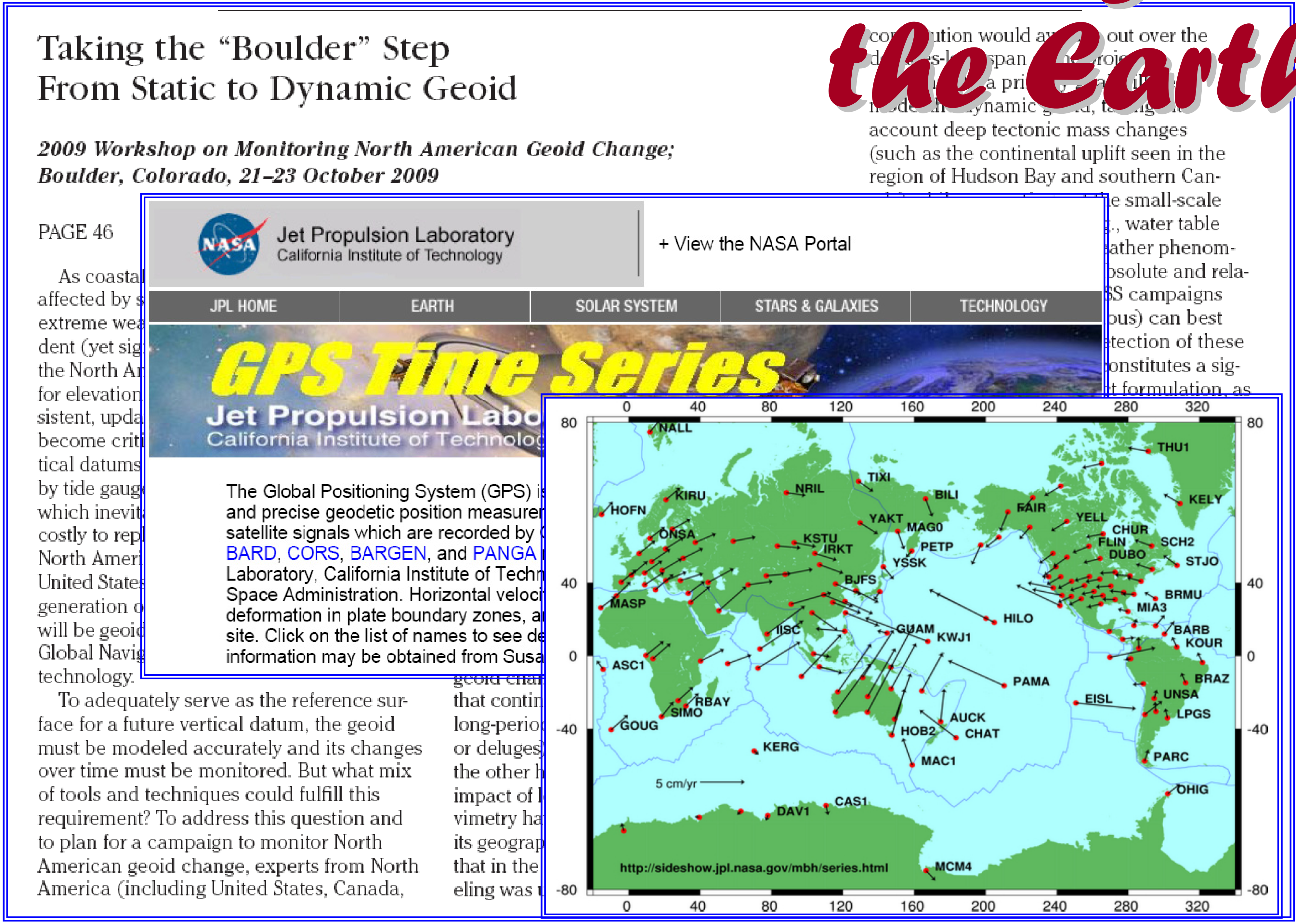


The pull of the planet

The most detailed map of Earth's gravity ever made was unveiled last week in Munich, Germany, when researchers presented eight months' worth of data from the European Space Agency's Gravity Field and Steady-State Ocean Circulation Explorer (GOCE), a satellite launched in 2009. GOCE maps subtle variations in Earth's gravitational field that arise from the planet's uneven distribution of mass. The result is a 'geoid' (pictured — variations exaggerated 10,000 times), showing the world if it were covered by an ocean whose height was influenced only by gravity. This reference allows geoscientists to precisely measure the heights of shifting oceans and continents. GOCE will continue mapping until the end of 2012.

The Coordinates on the Earth



Taking the “Boulder” Step
From Static to Dynamic Geoid

***2009 Workshop on Monitoring North American Geoid Change;
Boulder, Colorado, 21–23 October 2009***

PAGE 46

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To adequately serve as the reference surface for a future vertical datum, the geoid must be modeled accurately and its changes over time must be monitored. But what mix of tools and techniques could fulfill this requirement? To address this question and to plan for a campaign to monitor North American geoid change, experts from North America (including United States, Canada,

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GPS Time Series

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The Global Positioning System (GPS) i
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Laboratory, California Institute of Techn
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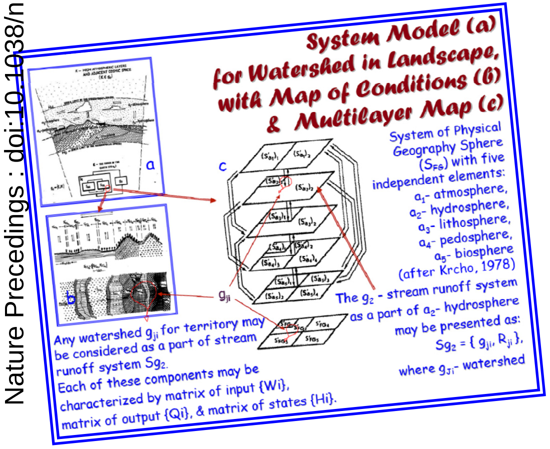
The Knowledge & the Uncertainty about the Great Lakes Watershed

The Uncertainty & The Knowledge through Modeling: Object, Data, Analysis & Results

Photo picture as presentation of the natural object

The knowledge (K)= 0, about a new object for the consideration the uncertainty (U)= 1



System Model (a) for Watershed in Landscape, with Map of Conditions (b) & Multilayer Map (c)

System of Physical Geography Sphere (S_{FG}) with five independent elements:
a_1- atmosphere,
a_2- hydrosphere,
a_3- lithosphere,
a_4- pedosphere,
a_5- biosphere
(after Krcho, 1978)

The g_2 - stream runoff system as a part of a_2- hydrosphere may be presented as:
$Sg_2 = \{ g_{ji}, R_{ji} \}$,
where g_{Ji}- watershed

Any watershed g_{ji} for territory may be considered as a part of stream runoff system Sg_2.
Each of these components may be characterized by matrix of input {Wi}, matrix of output {Qi}, & matrix of states {Hi}.

K_p = 1 & we have the direction for the research, the task, U = 0, but the knowledge is previous (K_p)

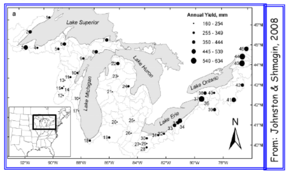
Philosophy of Data Analysis & Natural Structures

Factor analysis is method for **extraction** that are regarded as the **basic variables that account for the interrelations observed in the data**

A **factor** is a portion of a quantity, usually an integer or polynomial that, when multiplied by other factors, gives the entire quantity

The main applications of factor analytic techniques are:
- (1) to **reduce the number** of variables and
- (2) to **detect structure** in the relationships between variables, that is to **classify variables**.

(From: Wolfram *MathWorld*)

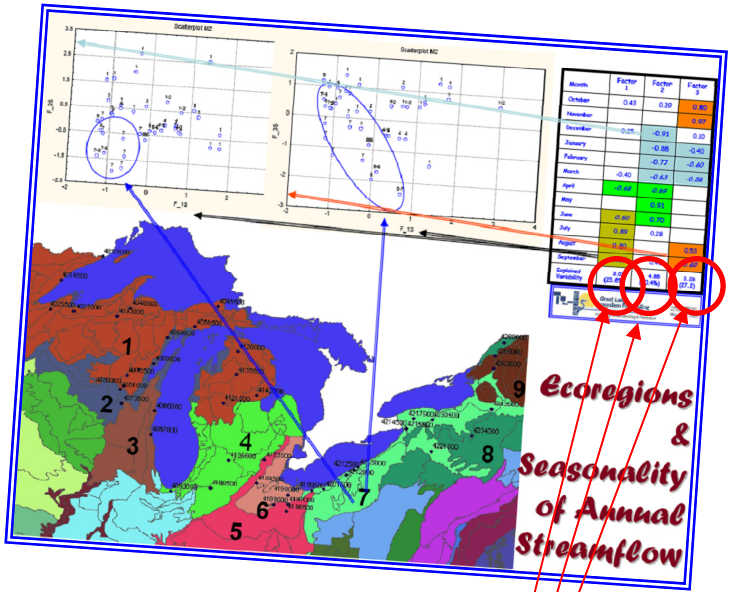


From: Johnston & Shmagin, 2008

The **variables selected** after factor analysis are considered as typical & may be used for time-series analysis

The Data Analysis is the way to “extract” (obtain) the structure of a natural object

The conceptual model (Cyber Model) is the way to use previously obtained knowledge



Month	Factor 1	Factor 2	Factor 3
October	0.43	0.39	0.80
November			0.97
December	0.25	-0.91	0.10
January		-0.88	-0.40
February		-0.77	-0.60
March	-0.40	-0.63	-0.58
April	-0.68	0.69	
May		0.91	
June	0.60	0.70	
July	0.89	0.28	
August	0.80		0.53
September	[illegible]	[illegible]	0.69
Explained Variability	[illegible]	4.85 ([illegible])	3.26 (27.2)

Ecoregions & Seasonality of Annual Streamflow

The Uncertainty from Analysis =
1- explained variability

After Data Analysis
K > U

Communicating the Knowledge for the Watershed

The Uncertainty & The Knowledge through Modeling: Object, Data, Analysis & Results

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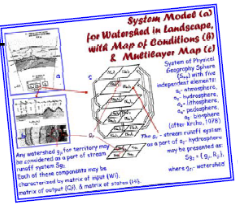

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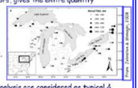

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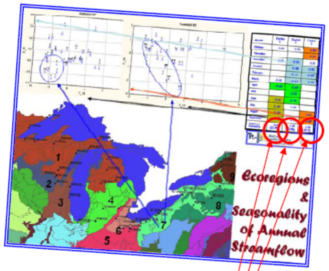

Ecoregions & Seasonality of Annual Streamflow

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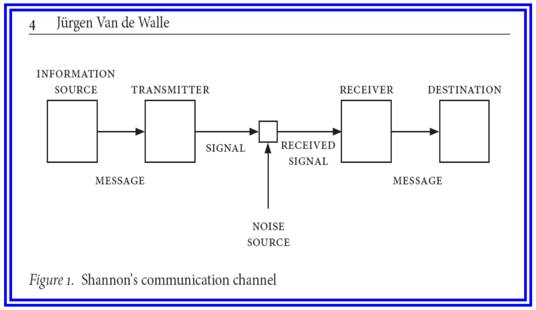
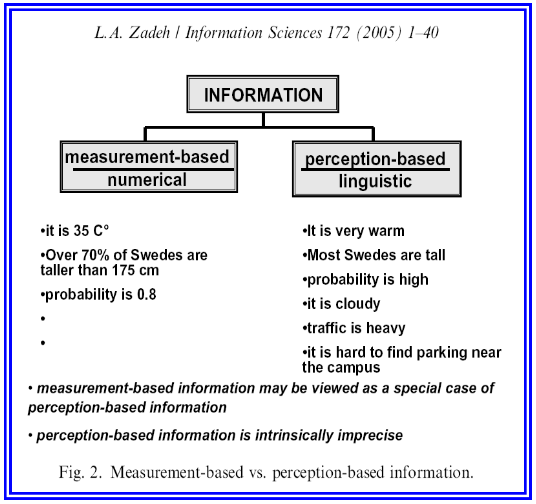
After Data Analysis K > U



4 Jürgen Van de Walle

Figure 1. Shannon's communication channel



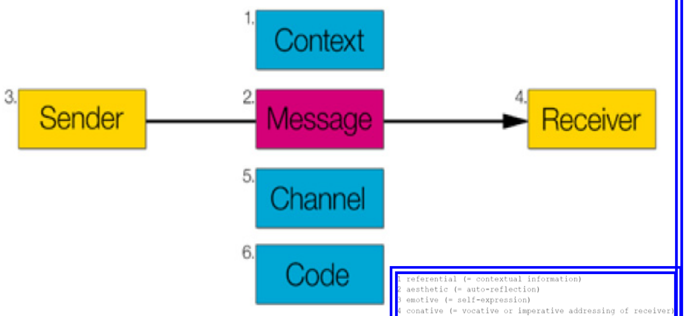
L.A. Zadeh / Information Sciences 172 (2005) 1–40

INFORMATION

measurement-based numerical	perception-based linguistic
•it is 35 C°	•It is very warm
•Over 70% of Swedes are taller than 175 cm	•Most Swedes are tall
•probability is 0.8	•probability is high
•	•it is cloudy
•	•traffic is heavy
	•it is hard to find parking near the campus

- ***measurement-based information may be viewed as a special case of perception-based information***
- ***perception-based information is intrinsically imprecise***

Fig. 2. Measurement-based vs. perception-based information.



```
1 referential (= contextual information)
2 aesthetic (= auto-reflection)
3 emotive (= self-expression)
4 conative (= vocative or imperative addressing of receiver)
5 phatic (= checking channel working)
6 metalingual (= checking code working)[2]
```

Scientists working in Hydrology have to develop principles to handle the Uncertainty & communicate the Knowledge about time-spatial variability of the Watershed

The Scientists
& the
Knowledge

The Scientist

"In questions
of science,
the authority of a thousand
is not worth
the humble reasoning of
a single individual."
Galileo Galilei

"A model is merely your
reflection of reality &,
like probability,
it describes neither you
nor the world,
but only a relationship
between you & that world"
Dennis Lindley

The New York Times

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Vladimir Nabokov

From Wikipedia, the free encyclopedia

This article is about the novelist. For his father, the politician, see Vladimir Dmitrievich Nabokov.

This name uses Eastern Slavic naming customs; the patronymic is Vladimirovich *and the family name is* Nabokov.

Vladimir Vladimirovich Nabokov (Russian: Влади́мир Влади́мирович Набо́ков, pronounced [vlɐ ˈdʲimʲɪr nɐˈbokəf]; 22 April [O.S. 10 April] 1899[c] – 2 July 1977) was a multilingual Russian novelist and short story writer. Nabokov wrote his first nine novels in Russian, then rose to international prominence as a master English prose stylist. He also made contributions to entomology and had an interest in chess problems.

Nabokov's *Lolita* (1955) is frequently cited as among his most important novels and is his most widely known, exhibiting the love of intricate word … that characterised all his works. The novel was ranked at #4 in the list of the … *Pale Fire* (1962) was ranked at #53 on the same list. His memoir, … nonfiction list.[2]

Contents [hide]
1 Life and career
1.1 Russia
1.2 Emigr…
1.3 Berl…
1.4 Ame…
1.5 Montreu…
2 Work
3 Nabokov's …
4 Entomology

Vladimir Nabokov

Born: Vladimir Vladimirovich Nabokov
22 April [O.S. 10 April] 1899[a]
Saint Petersburg, Russian Empire
Died: 2 July 1977 (aged 78)
Montreux, Switzerland
Occupation: Novelist, lepidopterist, professor
Literary movement: Modernism, Postmodernism

The Scientist

January 25, 2011

Nonfiction: Nabokov Theory on Butterfly Evolution Is Vindicated

By **CARL ZIMMER**

Vladimir Nabokov may be known to most people as the author of classic novels like "Lolita" and "Pale Fire." But even as he was writing those books, Nabokov had a parallel existence as a self-taught expert on butterflies.

He was the curator of lepidoptera at the Museum of Comparative Zoology at Harvard University, and he collected the insects across the United States. He published detailed descriptions of hundreds of species. And in a speculative moment in 1945, he came up with a sweeping hypothesis for the evolution of the butterflies he studied, a group known as the Polyommatus blues. He envisioned them coming to the New World from Asia over millions of years in a series of waves.

Results for Discussion

- Knowledge about natural systems (watershed in our case) may be only obtained by the analysis of the empirical data (instrumental observations)
- Uncertainty starts from the research task unveiled by the scientist
- The cyber model of watershed applied to landscape allows for formulating research tasks, developing methods of analysis, & presenting results as a map
- The main sources of the uncertainty come from the natural system “extraction” (the first is the unit’s boundaries) for modeling & from the unavoidable limitations of data representing both time & space variability
- The math model does not have the criteria to verify itself (Gödel's incompleteness theorems) & multi-scale studies with empirical data have to be completed
- The uncertainty has to be considered in the context of time & space of the watershed in natural coordinates
- The watershed has the formal determined boundary - this property places hydrology in the center of regional climate research

Questions?

View from
south shore
of Lake Superior
in Michigan's
Upper Peninsula
46°31'N 86°24'W
08/03/10 9:27

Appendix
in Case
of Questions

Structures of Streamflow Regimes

Journal of Hydrology (2008) 362, 69–88

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journal homepage: www.elsevier.com/locate/jhydrol

Regionalization, seasonality, and trends of streamflow in the US Great Lakes Basin

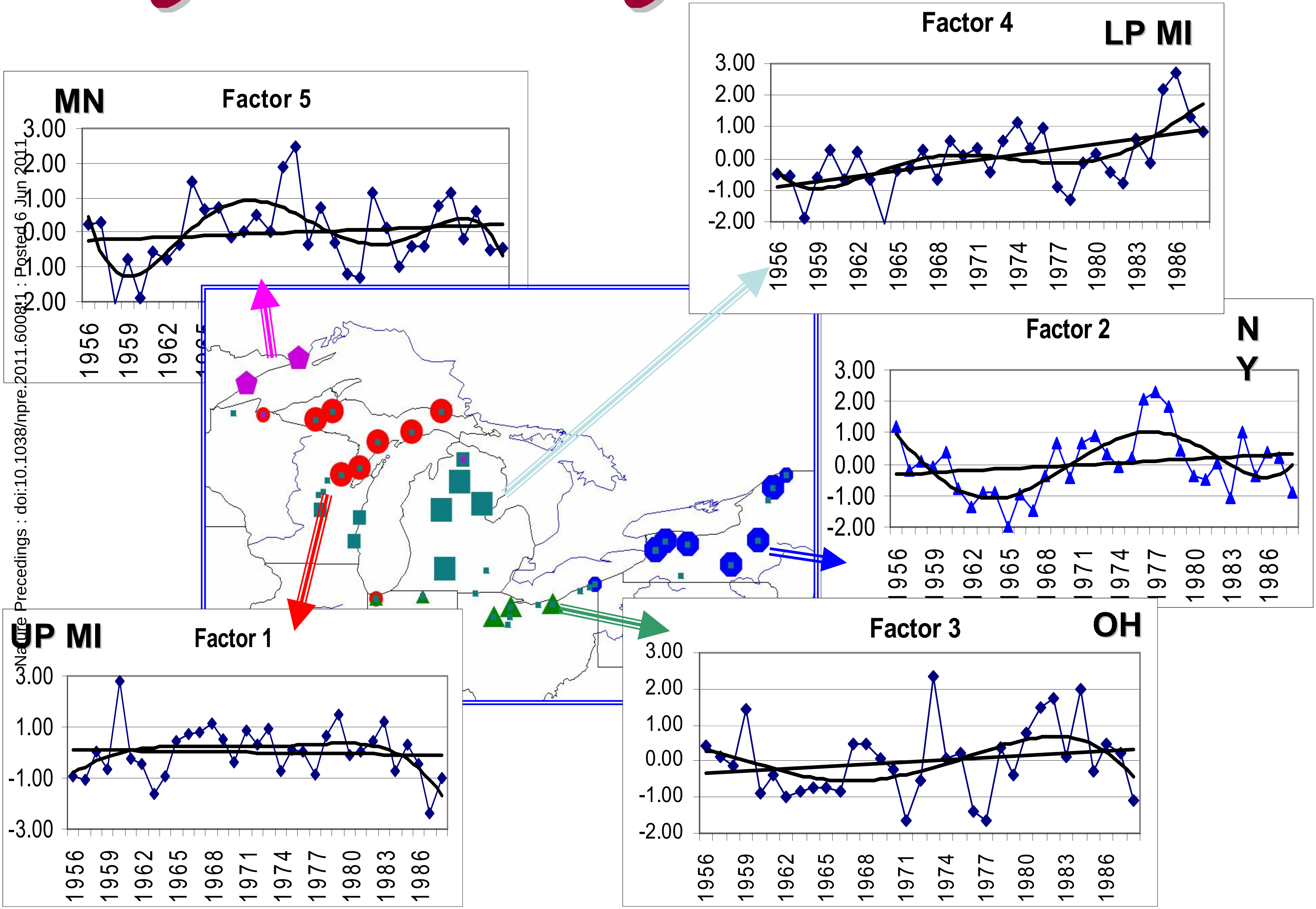
Carol A. Johnston [a,*], Boris A. Shmagin [b,1]

[a] Department of Biology and Microbiology, South Dakota State University, Box 2207B, Brookings, SD 57007, United States
[b] Water Resources Institute, South Dakota State University, Box 2120, Brookings, SD 57007, United States

Received 28 February 2008; received in revised form 13 August 2008; accepted 14 August 2008

Regions & regimes

IAGLR '05
Great Lakes Ecosystem Forecasting
Improving Understanding & Prediction
University of Michigan
Ann Arbor, Mich.
May 23-27, 2005



IAGLR '05
Great Lakes Ecosystem Forecasting
Improving Understanding & Prediction
University of Michigan
Ann Arbor, Mich.
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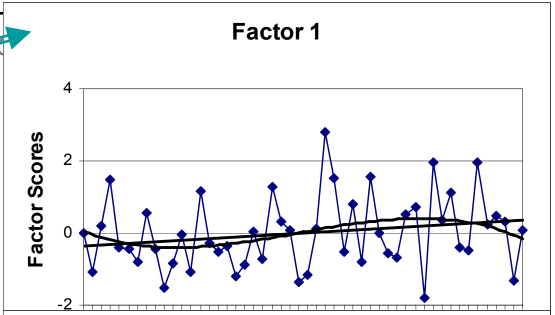
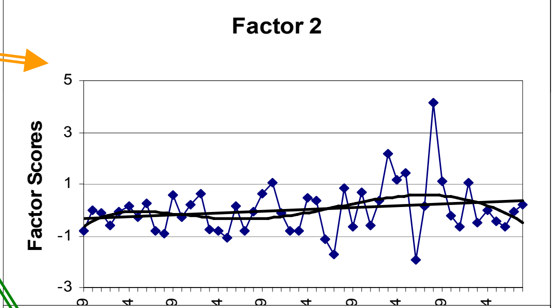
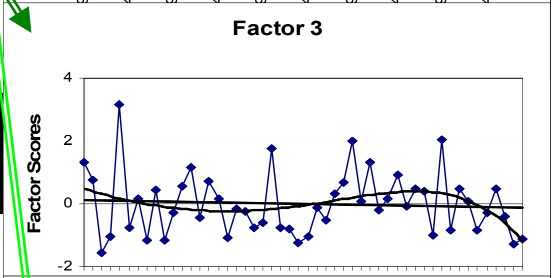
Seasonal Structure for First & Fourth Typical Watershed's Streamfow

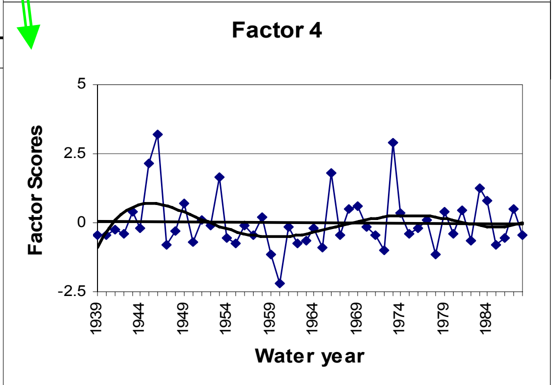
UP MI

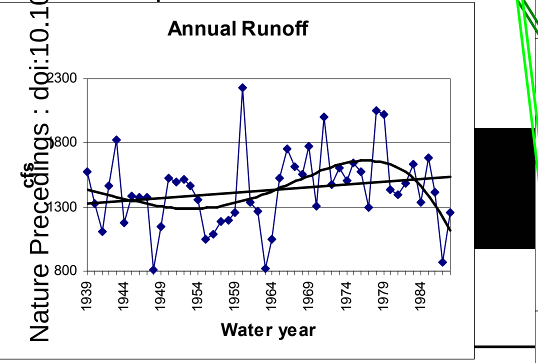
First	Factor 1	Fac 2
Oct	0.71	
Nov	0.85	
Dec	0.89	
Jan	0.89	
Feb	0.79	
Mar	0.25	
Apr		
May		

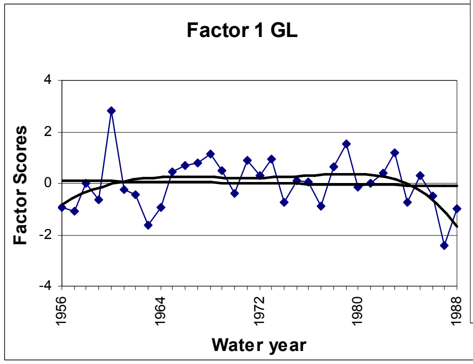






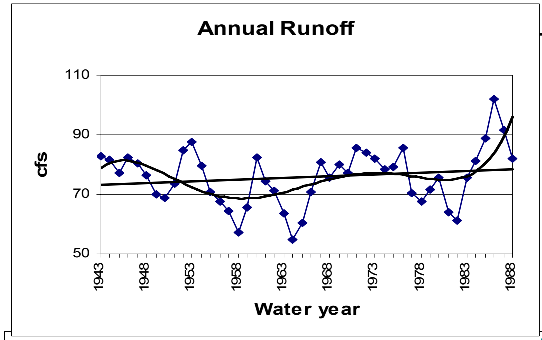


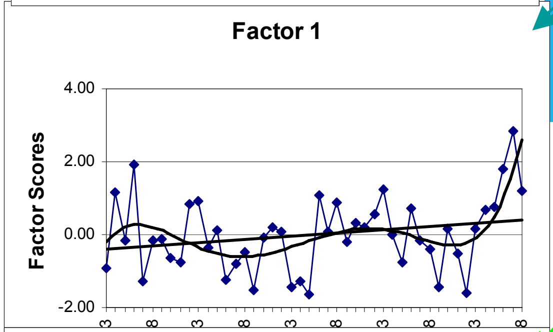


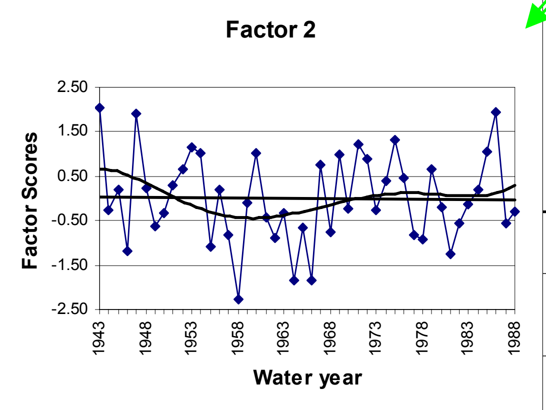


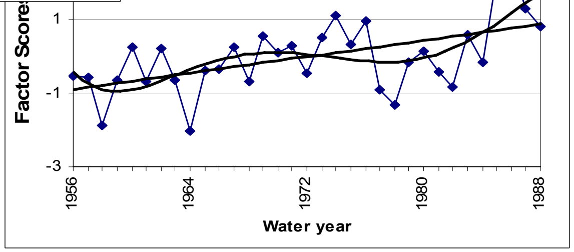
LP MI

Factor 1	Factor 2
0.90	
0.88	0.28
0.87	0.26
0.82	
0.78	
0.70	
	0.81
	0.80
	0.80
0.27	0.77
0.31	0.67
0.26	0.51
4.37	3.49



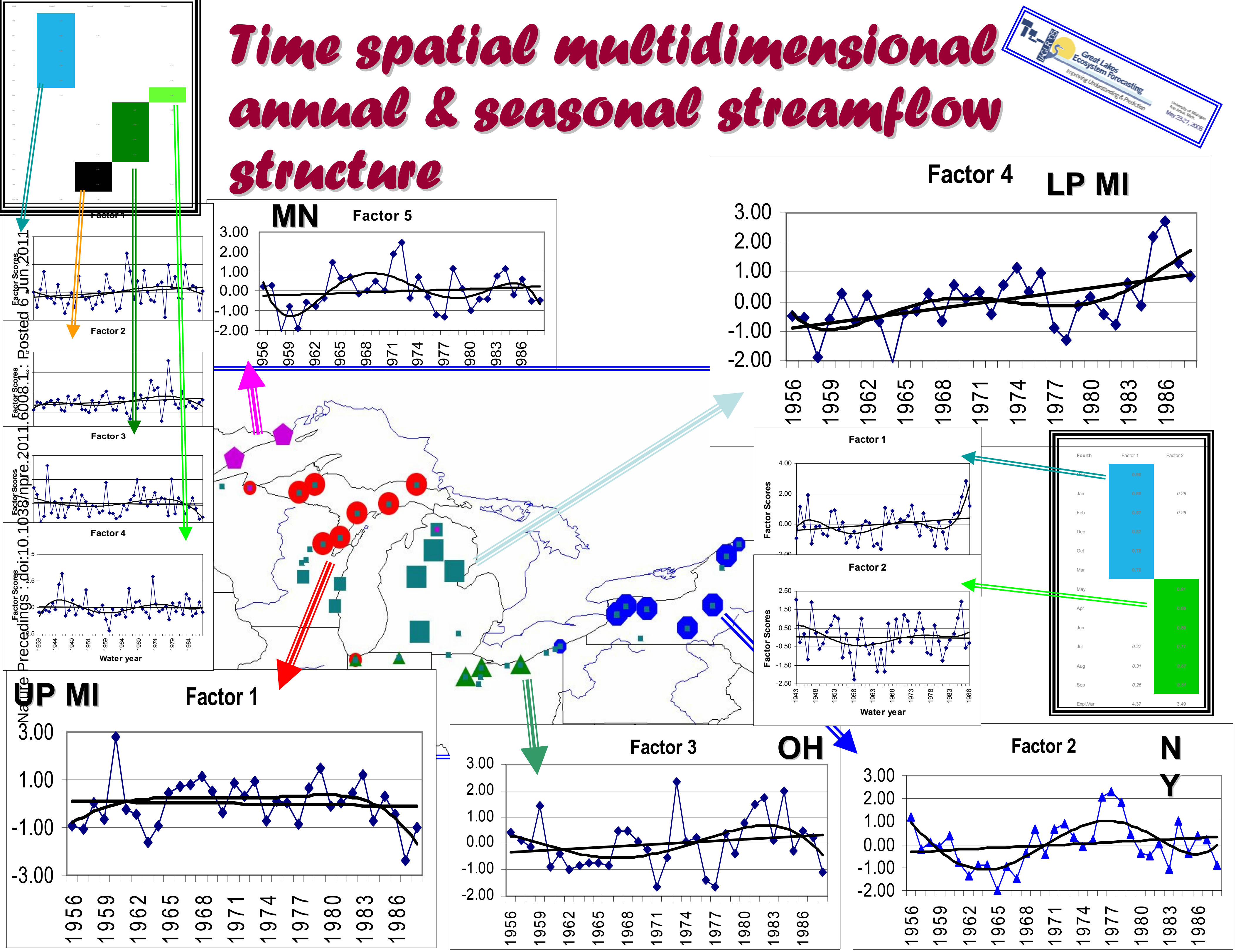






Time spatial multidimensional annual & seasonal streamflow structure

IAGLR '05
Great Lakes Ecosystem Forecasting
Improving Understanding & Prediction
University of Michigan
Ann Arbor, Mich.
May 23-27, 2005



Fourth	Factor 1	Factor 2
Nov	0.90	
Jan	0.88	0.28
Feb	0.87	0.26
Dec	0.82	
Oct	0.78	
Mar	0.70	
May		0.81
Apr		0.80
Jun		0.80
Jul	0.27	0.77
Aug	0.31	0.67
Sep	0.26	0.51
Expl.Var	4.37	3.49

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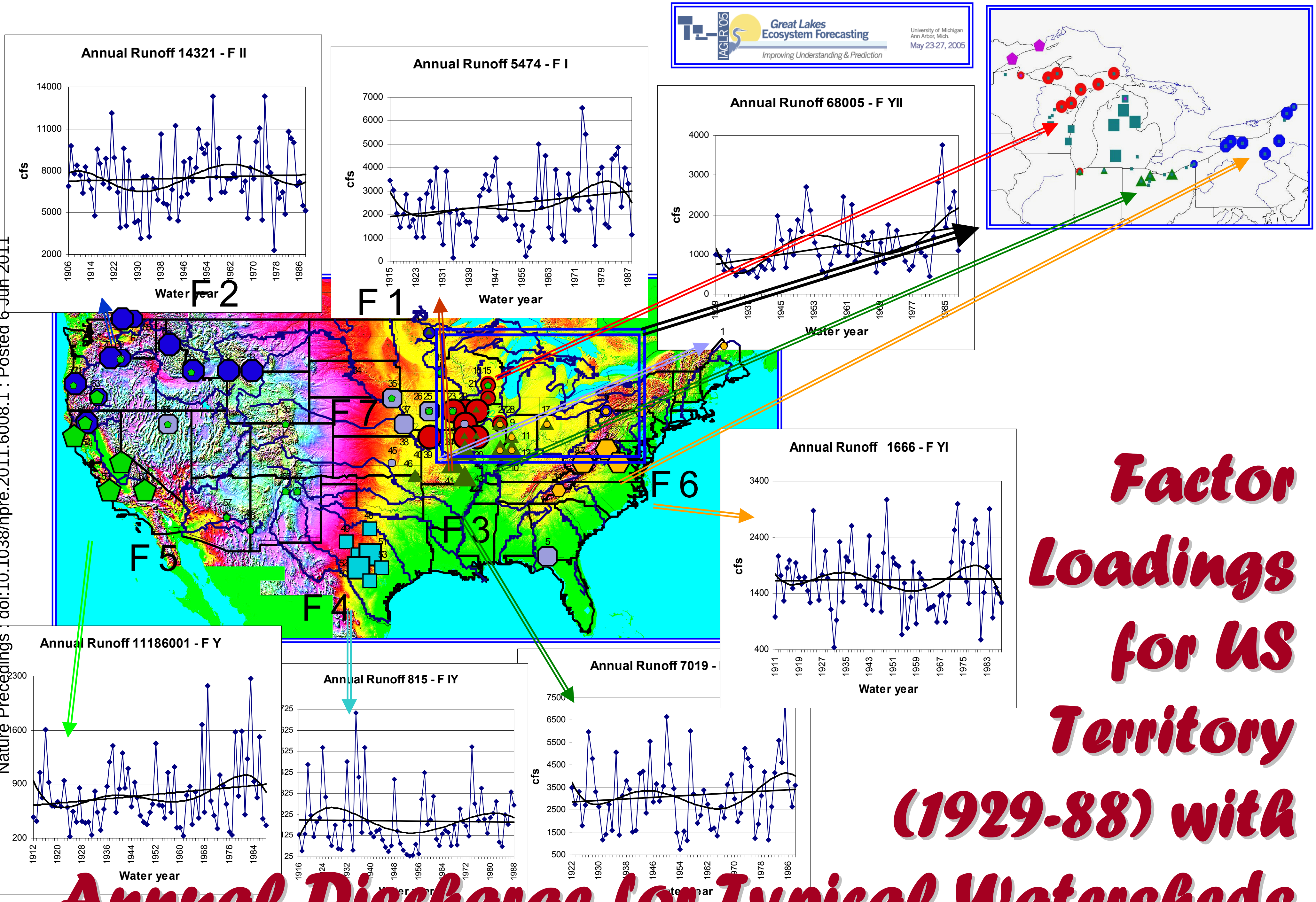
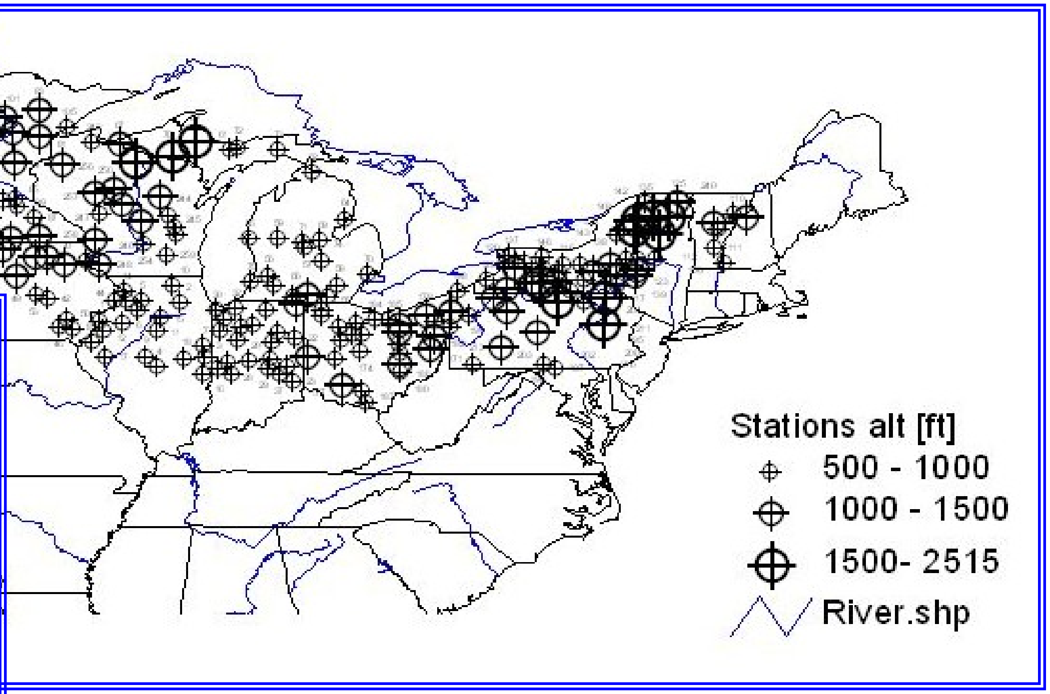
Factor Loadings for US Territory (1929-88) with Annual Discharge for Typical Watersheds & U. S. part of Great Lakes Basin



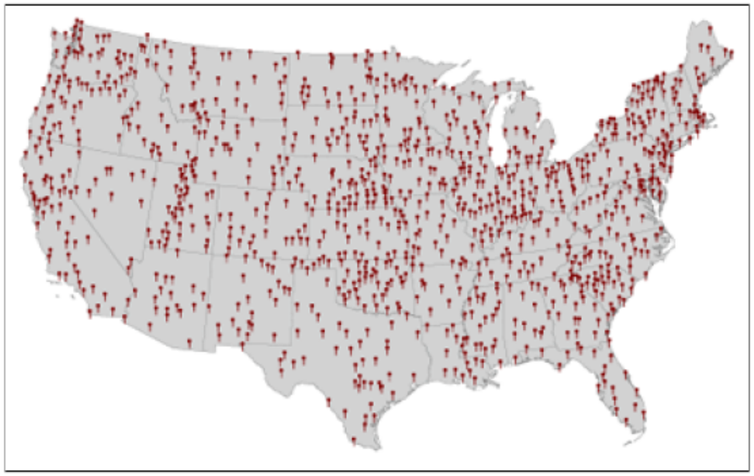
$\{P_{105*165}\}$

$\{T_{105*198}\}$



U.S. HISTORICAL CLIMATOLOGY NETWORK (USHCN) - NDP-019

Monthly Temperature and Precipitation Data



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Environmental Sciences Division
Oak Ridge National Laboratory
Oak Ridge, Tennessee 37831-6335
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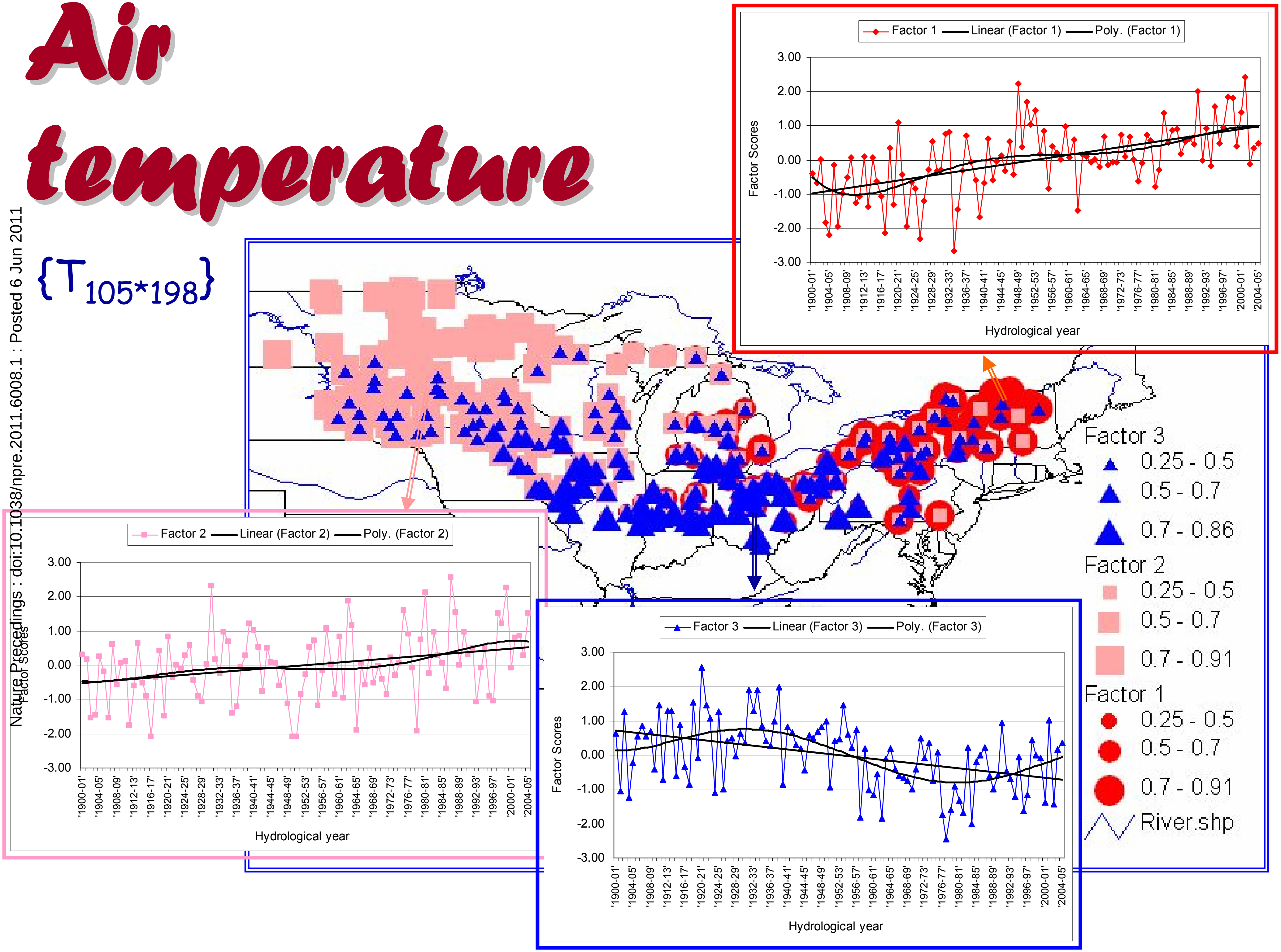
University of Tennessee-Battelle, LLC
for the
U.S. DEPARTMENT OF ENERGY
under contract DE-AC05-00OR22725

Data for Characteristics of Climate Variability

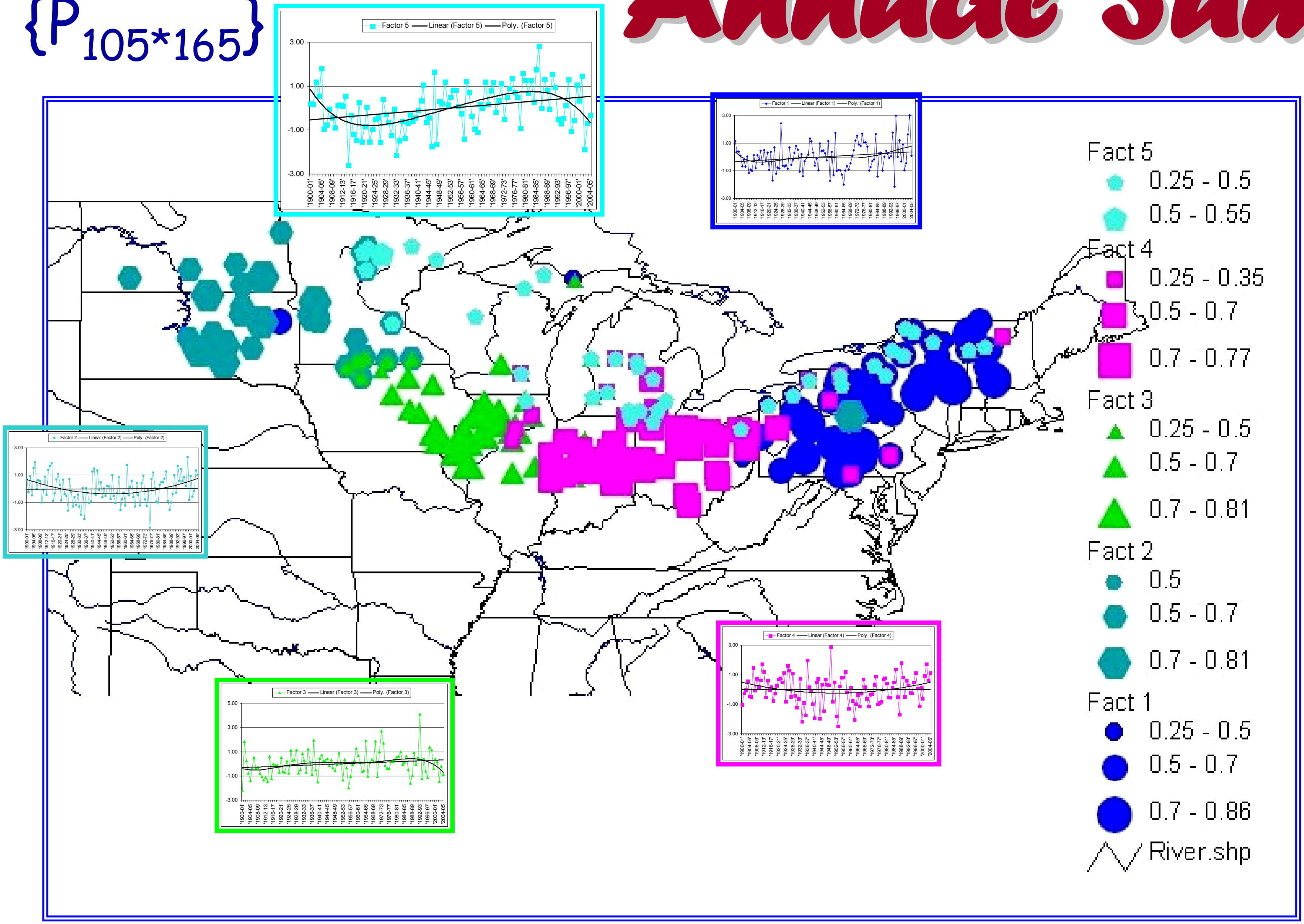
Air temperature

$\{T_{105*198}\}$

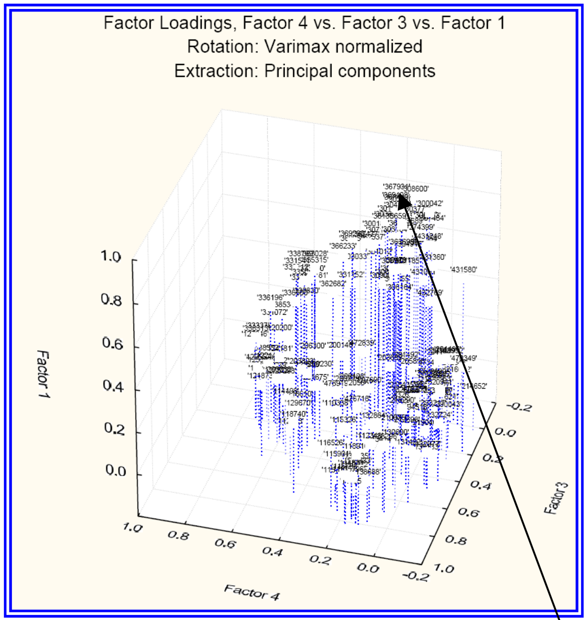


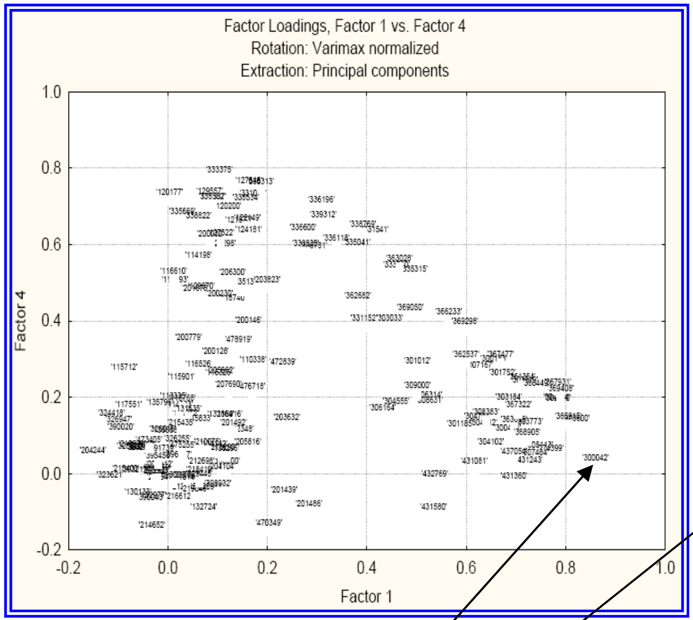
Precipitation, Annual Sum

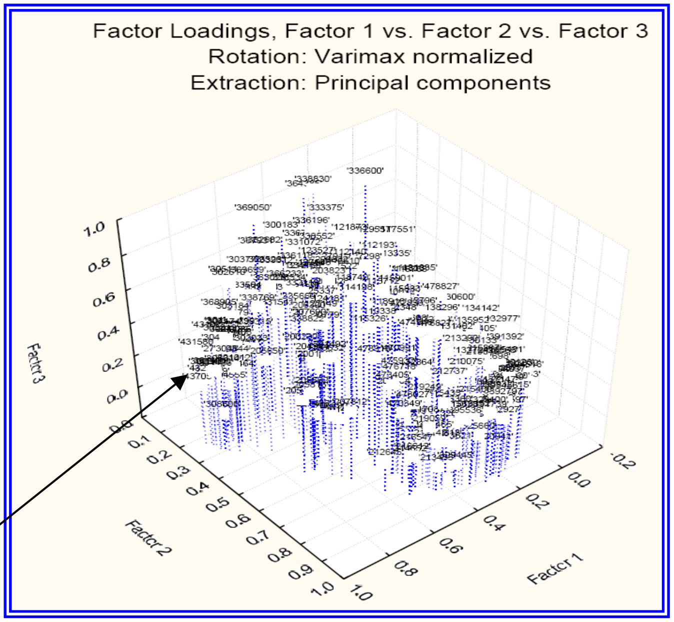
$\{P_{105*165}\}$

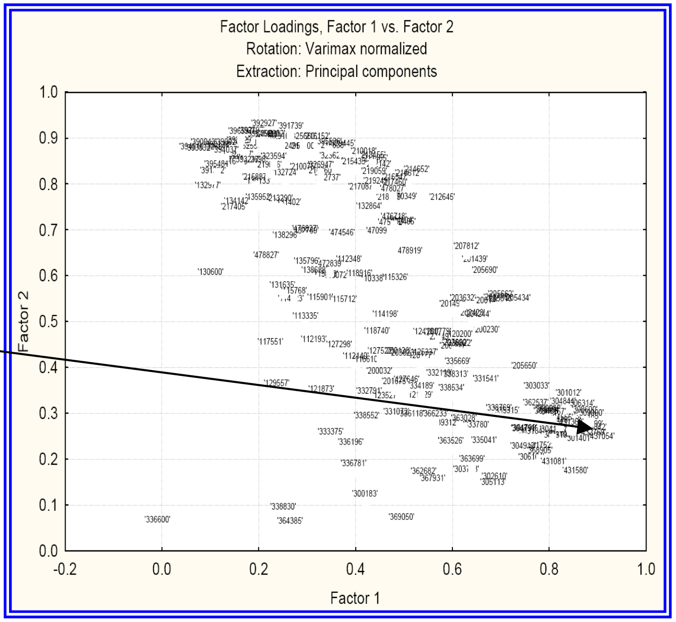


The Typical Stations









Explained Variability by Factor in "Precip." [%]	Explained Variability by Factor in "Temp." [%]	No of COOP station	Factor Loading of station in "Precip."	Factor Loading of station "Temp."
I - 14	I - 27	300042	I - 0.86	I - 0.89
II - 10	II - 35	391739	II - 0.81	II - 0.91
III - 10		115768	III - 0.81	
IV - 11	III - 25	333373	IV - 0.77	III - 0.86
V - 5		216612	V - 0.55	