The Canadian Journal of Statistics
Vol. 50, No. 4, 2022, Pages 1355–1386
La revue canadienne de statistique

Canadian contributions to environmetrics

Charmaine B. DEAN[1]*, Abdel H. EL-SHAARAWI[2], Sylvia R. ESTERBY[3], Joanna MILLS FLEMMING[4], Richard D. ROUTLEDGE[5], Stephen W. TAYLOR[6], Douglas G. WOOLFORD[7], James V. ZIDEK[8], and Francis W. ZWIERS[9]

[1]*Department of Statistics and Actuarial Science, University of Waterloo, 200 University Avenue West, Waterloo, Ontario, Canada N2L 3G1*
[2]*Department of Statistics, Faculty of Economics and Political Science, Cairo University, Cairo, Egypt*
[3]*Department of Computer Science, Mathematics, Physics and Statistics, University of British Columbia, Okanagan Campus, 3187, University Way, Kelowna, British Columbia, Canada V1V 1V7*
[4]*Department of Mathematics and Statistics, Dalhousie University, 6316 Coburg Road - PO BOX 15000, Halifax, Nova Scotia, Canada B3H 4R2*
[5]*Department of Statistics and Actuarial Science, Simon Fraser University, 8888 University Drive, Burnaby, British Columbia, Canada V5A 1S6*
[6]*Pacific Forestry Centre, 506 Burnside Road West, Victoria, British Columbia, Canada V8Z 1M5*
[7]*Department of Statistical & Actuarial Sciences, The University of Western Ontario, 1151 Richmond Street, London, Ontario, Canada N6A 5B7*
[8]*Department of Statistics, University of British Columbia, 2207 Main Mall, Vancouver, British Columbia, Canada V6T 1Z4*
[9]*Pacific Climate Impacts Consortium (PCIC), University of Victoria, University House 1, PO Box 1700 Stn CSC, Victoria, British Columbia, Canada V8W 2Y2*

Key words and phrases: Canadian contributions; climate; environmetrics; fire science; fisheries; monitoring networks.

MSC 2020: Primary 62-03; Secondary 01-02.

Abstract: This article focuses on the importance of collaboration in statistics by Canadian researchers and highlights the contributions that Canadian statisticians have made to many research areas in environmetrics. We provide a discussion about different vehicles that have been developed for collaboration by Canadians in the environmetrics context as well as specific scientific areas that are focused on environmetrics research in Canada including climate science, forestry, and fisheries, which are areas of importance for natural resources in Canada.

Résumé: Cet article souligne l'ampleur de la collaboration entre les scientifiques canadiens dans le domaine de la statistique et présente un survol des travaux réalisés par des spécialistes du sujet sur un ensemble de thèmes liés aux sciences de l'environnement. Les auteurs relatent différents moyens par lesquels cette collaboration s'est incarnée et a permis aux Canadiennes et Canadiens de contribuer à l'environnemétrie et à divers domaines connexes, notamment les sciences du climat, la foresterie et les pêches, dont l'importance est capitale pour la gestion des ressources naturelles du pays.

1. THE EMERGENCE OF ENVIRONMETRICS

This section provides a brief history of the emergence of environmetrics over the past half century, and contributions made by Canadians. Its origins lay in hydrology and geostatistics.

---

* *Corresponding author: cdean@uwaterloo.ca*

Much of that history can be found in Noel Cressie's classic (Cressie, 1993), where environmental spatial processes are emphasized.

1.1. Origins

The interest of statistical scientists in environmetrics was stimulated by the Clean Air Act (United States) of 1970, or rather by the United States Environmental Protection Agency (EPA), an organization created in 1971. The Act itself proclaimed that, while allowing for a "margin of uncertainty", enforceable primary and secondary national ambient air quality standards (NAAQS) needed to be set. The EPA was to be the creator and enforcer of the NAAQS, which in turn pointed to a need for both urban (health) and rural (welfare) ambient air quality monitoring networks. To create these networks and set those standards, there was a need for spatial and spatio-temporal models for air pollution fields, leading to EPA-funded research programmes. That is where the story begins.

1.2. Protecting Health and Welfare

Paul Switzer, a Canadian employed by Stanford University, and a group of his associates, set up a research/educational programme at Stanford, with funding from the EPA through the SIAM Institute of Mathematical Science (SIMS). It introduced statistical scientists to geostatistical theory and methods, and generally sparked interest in spatial statistics along with applications in that domain. This provided a foundation on which the NAAQS could be set while allowing for a margin of uncertainty.

1.3. Predicting Human Exposure to Environmental Hazards

The NAAQS were based on ground-level ambient standards. But the EPA recognized that indoor sources were also contributors to human exposure. Examples would be indoor smoking as well as improperly maintained stoves and fireplaces. So, the EPA commissioned the development of the probabilistic National Exposure Model (pNEM), a numerical simulator of human exposure based on surveys of human populations and the microenvironments in which respondents spent their time, depending on weather and outdoor (ambient) air pollution levels.

Canada could not set standards but it could, through Health Canada, create air quality criteria (AQC) for possible adoption by the provinces to protect human health. In addition, a pNEM for Canada was needed. Initially a variant was built for Health Canada by an American contractor and run on an expensive mainframe computer in the United States. But a made-in-Canada version was deemed necessary and a group at the University of British Columbia was formed by James Zidek to import the US version and modify it appropriately. The group was successful and during the 1994–1996 period built a Canadian version of pNEM that ran on the statistics department's multiuser computing system. Multiple simulation runs were completed under various scenarios for air pollution concentrations. In the end, Canada's first AQC were established.

Work continued at the University of British Columbia over the 1996–2000 period, in partnership with environmental epidemiologists at Harvard, on exposure estimation under a Cooperative Research Agreement with the EPA, obtained through SIMS. The result was an improved version of pNEM built with Python, which could be run remotely online with outputs downloaded to a client's spreadsheet on a desktop PC. It was named pCNEM, the pC to stand ambiguously for the Canadian version of pNEM and the PC version of pNEM. The EPA employed an American contractor to build a version of pCNEM, and employed Zidek in 2000–2001 as a consultant on that project. Now in 2021, Zidek is working on updating pCNEM for application by the Met Office in the United Kingdom, to predict exposure to the high temperatures that stem from global warming. Current research is underway that focuses on both updating pCNEM and determining how it must be modified.

1.4. New Environmental Hazards: Acid Deposition

In the 1980s, the US EPA and SIMS continued their support of environmental research through almost a decade of funding to study trends in acidic deposition, a newly identified hazard, which led to among other things a multi-centre research group at Harvard, Stanford, and the University of British Columbia over the 1984–1991 period. The University of British Columbia's portion of this large grant helped support the development of their new Department of Statistics, which was formed in 1983. Interest in the temporal trends in acid rain led beyond spatial statistics to spatio-temporal theory. Consequently, Sampson and Guttorp finished work on their celebrated spatial warping technique (Sampson & Guttorp, 1992) showing that non-stationary processes can be modelled as stationary. Then came a discovery that made feasible the application of the matric-t distribution for spatial fields with symmetric but heavy-tailed distributions (Caselton, Kan & Zidek, 1992; Le & Zidek, 1992). Trends in acidic deposition were assessed and published.

1.5. Environmetrics Emerges

By the end of the 1980s, a substantial body of work had been done on the design of spatial and spatio-temporal monitoring networks, the stochastic modelling of such fields including the multivariate case, and finally the application of that theory. But it took Canadian statisticians Abdel El-Shaarawi, Sylvia Esterby, and the late Ian MacNeill to recognize that a whole new field of statistical science had been born. They called it "environmetrics". A more detailed account of this historic development is found in Section 2. The subsequent sections of the article outline major developments in the fields of climate, fire, and fisheries research where Canadian statisticians and their collaborators have played a pivotal role. These topics, although important, only partly detail what is being done by Canadians in environmetrics, with research contributions in Canada encompassing other important fields such as forest ecology and monitoring networks.

1.6. Ensuring Data Quality

The SIMS program was the harbinger of other things to come. First, it sparked an awareness of the importance of good data and the need for methods for selecting monitoring sites. Canadians became involved on that front. They helped develop methods for selecting sampling sites to detect the potential environmental impacts of development, monitoring precipitation for flood control and irrigation management, and optimizing existing networks for air pollution monitoring as well as acid precipitation measurement.

1.7. The Changing Climate

Overarching the development of environmetrics was the growing world population and its associated change in the world's climate. This topic came into prominence in the 1980s but it was not until 1988 that the International Panel on Climate Change (IPCC) was formed to inform governments and policy makers. Climate models for the atmosphere and the oceans were built over large grid cells so that the impact of future scenarios could be explored. The output from these models (or simulators, as they are called), were datasets of such things as temperatures and precipitation. That simulated data could then be analyzed using spatio-temporal methods. One such dataset was entered into the case studies competition at an annual conference of the Statistical Society of Canada (SSC) by Francis Zwiers, and it led to informative analyses (e.g., Fu, Le & Zidek, 2003).

Concern about the world's food supply led to James Ramsey and Zidek forming a research programme in 2008 funded by the National Institute for Complex Data Structures (NICID). Those involved in the programme included scientists from Agriculture and Agri-Food Canada. Budgetary shortfalls led to the termination of NCIDS funding in just one year, but the work was subsumed by the Pacific Institute for the Mathematical Sciences (PIMS) programme. Among other products of the programme was a model for predicting annual crop yields as function of soil moisture content (Bornn & Zidek, 2012), a phenological model for bud bursting in Canadian orchards (Cai et al., 2014), and on the theoretical front, a new way of resolving nonstationarity in random spatio-temporal fields by adding additional, latent coordinates (Bornn, Shaddick & Zidek, 2012).

The following sections elaborate further on the substantial impact that Canadian statisticians, through important collaborations with scientists from other disciplines, have made in the areas of climate change, forest and fire science, and fisheries, and of monitoring and design.

2. ENVIRONMETRICS

A key element of environmetrics is collaboration. Formal structures of communication that fostered collaboration between statisticians and other scientists dealing with environmental issues were pivotal to the success of environmetrics research in Canada and are described here from a Canadian perspective. This includes the establishment of a journal, society, encyclopaedia, and research groups. Although the path from 1982 to the present is sketched out in the sections below, the description does not give recognition to all the individuals and organizations crucial to this development. The references provided will fill in some of these omissions.

2.1. The 1989 Conference and the Journal

Based on the 1970 report of the International Joint Commission (IJC), the governments of Canada and the United States signed the first Great Lakes Water Quality Agreement (GLWQA) in 1972, adopting common objectives for the control of phosphorus pollution. Later agreements expanded the scope of pollutants to be controlled. Surveillance programmes designed to assess the success of mitigation measures led to a need to handle very large datasets. In addition, a succession of emerging issues such as acid rain and toxic contaminants spawned data-rich research and operational programmes within Environment Canada and provincial agencies. This was the setting in which the need for a continuing venue for communication and a publication outlet for statisticians and other scientists collaborating on these issues became very clear.

The first environmetrics conference was built on the experience of three conferences organized by El-Shaarawi and colleagues at the Canada Centre for Inland Waters (CCIW) in Burlington, Ontario, which focused on methods for water-related issues (El-Shaarawi & Esterby, 1982; El-Shaarawi & Kwiatkowski, 1986; Chapman & El-Shaarawi, 1989). The conferences attracted international leaders (aided by the international reputation of CCIW) and spanned various disciplines, including work by Canadian statisticians from a number of Ontario universities (Western University, University of Waterloo, McMaster University, University of Guelph) and David Brillinger from UC Berkeley. Fortuitously these conferences led to the collaboration with MacNeill at Western University and the formation of a society and founding of a journal.

The announcement of the first conference, the International Conference on Statistical Methods for the Environmental Sciences, April 4–7, 1989 in Cairo, Egypt, emphasized the intent to start the journal Environmetrics. El-Shaarawi and MacNeill were conference cochairs and founding editors of Environmetrics. At a meeting of the participants of the Cairo conference, the decision was made to form a society called The International Environmetrics Society (TIES) with El-Shaarawi and MacNeill as President and Vice-President. They subsequently formed a six-member, five-country founding Board of Directors. The individuals involved in the initial committees and boards of the conference, journal, and society were from Canada, United States, Norway, Egypt, United Kingdom, Union of Soviet Socialist Republics, Saudi Arabia, Austria, France, Switzerland, and Australia (Esterby, 2018).

The vision for the first conference was that it should be interdisciplinary and to this end, the keynote speakers were J. Stuart Hunter, statistician, and Richard A. Vollenweider, limnologist, and the special lecturer was Donald A.S. Fraser (see *Environmetrics*, Issues 1–4, 1990–1993). Hunter spoke of the origins of the word environmetrics (see also El-Shaarawi & Hunter, 2006) and of the perspectives of data for the scientist and statistician, noting that the breadth of environmental topics associated with statistics in the conference programme confirmed statistics as the science of empiricism. Vollenweider embraced the purpose of the conference, that is, promotion of statistical methods in environmental assessment and establishment of a mechanism for regular contact between statisticians and environmental scientists, identifying data and data methods as key linkages between these two groups. Fraser spoke about statistical inference in science. A prominent environmental issue was the impact of acid rain. Sessions on turbulence models, a regular feature of the conferences in the early years, were organized by applied mathematician Paul Sullivan, Western University, and colleagues.

Although attendance numbers would be considered low relative to most conferences, participants were from 19 countries, with high Canadian attendance coming from Canadian environmental agencies and universities. High US participation reflected the strength of environmental statistics in that country, and the low numbers from other countries were at least partly due to environmental statistics being less well established in those countries.

2.2. TIES and Environmetrics Overview

The first issue of Environmetrics was composed of papers from the 1989 conference. Volume 1 was published by Environmetrics Press, Inc. and typeset by Scitex, Western University. Environmetrics is the official journal of TIES, The International Environmetrics Society. Volume 2 to the current volume 32 in 2021 have been published by John Wiley & Sons Ltd. El-Shaarawi and MacNeill were co-editors from 1990 to 1996, El-Shaarawi Editor-in-Chief from 1997 to 2009 and, among Deputy-Editors, Brillinger from 1997 to 2009. Since 2010, the Editors have also been individuals involved with TIES in other capacities: Peter Guttorp and Walter Piegorsch, 2009–2013; Piegorsch, 2014–2019; and Alessandro Fassò, 2020–present. Environmetrics has expanded from the initial four issues to six issues in 1995 and to the current eight issues in 2001. The other journals with comparable scope are: Environmental and Ecological Statistics founded in 1994 by Editor-in-Chief G.P. Patil, with current co-Editor Pierre Dutilleul, McGill University, and the Journal of Agricultural, Biological and Environmental Statistics (JABES) founded in 1996, a joint publication of the International Biometric Society and the American Statistical Association. Environmetrics has steadily increased its ranking and recognition, moving to a more statistical journal over time, but still ranking highly among environmental science journals.

A summary of the first 25 TIES international conferences spanning 1989–2015 (Esterby, 2018) gives a viewpoint on how the conferences have developed to reflect the advances in the discipline of environmetrics while retaining the original character, which has helped to build an environmetrics community. Approximate attendance numbers by country (Table 2, Esterby, 2018) show that Canadian support has been strong. The text of the paper and tables published as supplementary to Esterby (2018) identify some of the Canadian supporters and their areas of contribution. The intention of the founders was to take the conference around the world to expand the discipline. By the ninth conference, held in Australia in 1998, conferences had been convened on all continents except the Antarctic and the conference location continued to rotate among the five continents until cancellation of the Oxford University 2020 conference due to COVID-19.

Regional conferences began in 2007 (see the list on TIES webpage) and there are several reasons such conferences are held, but in general they provide the type of meeting described for the International Conference. The first regional conference was organized by Peter Guttorp at the University of Washington and there have been three regional conferences in the United States (2007, 2009, 2011). Collaboration with other environmental statistics groups leading to regional conferences included several with GRASPA (Gruppo di Ricerca per le Applicazioni della Statistica ai Problemi Ambientali), and one with the Royal Statistical Society (RSS) Environmental Statistics Section and the RSS panel on Statistics for Ecosystem Change (2008) held in London, United Kingdom. Joint international conferences were held in: 1993 in Australia with the Modelling and Simulation Society of Australia and two other societies; 1999 in Greece with the Bernoulli Society's Committee on Probability and Statistics in the Physical Sciences; 2000 in the United Kingdom with Statistics in Public Resources, Utilities and in Care of the Environment (SPRUCE); 2003 in South Africa with South African Statistical Association; 2004 in the United States with Spatial Accuracy Assessment in Natural Resources and Environmental Sciences; 2009 and 2017 in Italy with GRASPA; and 2014 in China with Division of Resource and Environmental Statistics, Chinese Association for Applied Statistics.

A constitution for TIES, drafted by the eight individuals comprising the founding Board, drew upon the features of the SSC, TIES being regional as is the SSC. In 1993, TIES was incorporated in Canada as a not-for-profit Canadian corporation with three Regions, and a Board comprising an executive of five members and six regional representatives. The legal home shifted to the Netherlands after TIES became an Association of the International Statistical Institute (ISI) in 2008. Canadian statisticians who have served on the Board, in addition to the founders (El-Shaarawi, President; MacNeill, Vice-President; Esterby, Secretary-Treasurer, Treasurer, President-Elect, President) are Brillinger (President-Elect, President), Yulia Gel (Treasurer, President-Elect, President), Ayesha Ali (Publications Officer), Jeannette O'Hara Hines, Ying Zhang, and ecosystem modeller Nathaniel Newlands (North American Regional Representative). Board members who have trained in Canada include Krishna Jandahyla (North American Regional Representative) and Leticia Ramírez Ramírez (Treasurer). Grace Chan and Ramírez Ramírez also served as Web Master and Michael Dowd as Newsletter Editor.

Like most societies, TIES has a Newsletter (first issue in 1994), web page, and a number of continuing special conference lectures and awards. The J. Stuart Hunter Lecture has been given by Brillinger (inaugural lecture, 1996), Switzer (2001), and Zidek (2003). The President's Invited Lecture has been given by Agnes Herzberg (inaugural lecture, 2001) and El-Shaarawi (2007). There have been 17 recipients of the Abdel El-Shaarawi Early Investigator's Award since its inception in 2002, including Alexandra Schmidt (2008), Joanna Mills Flemming (2013), and Gel (2014); to recognize researchers at an earlier stage in their careers, a Best Student Paper Award was established in 1998 to be given at each international conference, and a Best Poster Award was also created. Two other presentation awards were established in 2018. TIES and ASA's Section on Statistics and the Environment (ENVR) were started at nearly the same time and have many members in common. Recipients of ENVR awards also include several Canadians: Young Investigator Award, Grace Chiu (2012), and Distinguished Achievement Award, Switzer (1993), MacNeil (1995), El-Shaarawi (1996), Zidek (2000), Esterby (2016), Schmidt (2017), Gel (2018).

2.3. Encylopedia of Environmetrics

Following publication in 1998 of the first edition of the Encyclopedia of Biostatistics by John Wiley & Sons Ltd, co-edited by Peter Armitage and Theodore Colton, environmetrics was considered a discipline mature enough to warrant a similar encyclopaedia. The first edition of the Encyclopedia of Environmetrics was published in 2002 by Wiley with El-Shaarawi and Piegorsch as Editors-in-Chief. It consisted of 4 volumes with 2800 pages and had a 9-page list of contributors including many Canadians. An Advisory Board oversaw the contributions in 12 broad categories and 3 of these were Hydrological and Physical Processes (P.C. Chatwin and Paul Sullivan), Stochastic Modelling and Environmental Change (Brillinger), and Statistical Theory and Methods (Zidek). An online version was released by Wiley in 2006. The second edition was published in 2012 as a 6-volume, 3510 pages print version and an online version again with El-Shaarawi and Piegorsch as Editors-in-Chief. The list of contributors expanded to 14 pages with many Canadian contributors, and the Advisory Board acted as section editors for contributions in 14 broad categories with two new ones being Ecological Statistics (Charmaine Dean) and Environmental Policy and Regulations (Esterby). The Wiley encyclopedias transitioned to a comprehensive online reference resource, StatsRef, first published in 2014, covering the fundamentals and applications of statistics in all fields, with articles selected from the eight encyclopaedias covering statistical topics including the Encyclopedia of Environmetrics. Two of the six founding co-editors were Piegorsch and another long-time TIES member, Jef Teugels.

2.4. Environmetrics Collaborative Research Group

Environmetrics—Georisk and Climate Change (2007–2010) was a Collaborative Research Group (CRG) of PIMS with group leaders Zidek (University of British Columbia), Dean (Simon Fraser University), Esterby (University of British Columbia Okanagan), and Guttorp (University of Washington) and with participants from these institutions as well as from other Western provinces, Ontario, Quebec, the United States, and internationally (see further information at https://www.pims.math.ca/scientific/collaborative-research-groups/past-crgs/environmetrics-2007-2010). The research themes involved statistical and deterministic models dealing with risk, quality assessment, and changes in water, forests, and species at risk, including relationships to climate change. The primary aim was to strengthen statistical research and training in the Pacific Northwest on topics relevant to environmental issues. Support was given for graduate and postdoctoral training.

Ten events were held during the period of the CRG. Two workshops concentrated on the CRG itself: the inaugural workshop (January 2007) introduced the themes and aided planning, and the final workshop reviewed the accomplishments and looked to the future (April 2010). CRG members participated in three summer schools: Modeling Environmental Space-Time Processes, University of Washington, July 2007; Perceiving, Measuring, and Managing Risk, University of British Columbia, June-July 2008; Statistics and Climate Modelling, National Center for Atmospheric Research, August 2008. Three events were sponsored by the CRG: TIES North American Regional Conference, University of Washington, June 2007; TIES International Conference at University of British Columbia Okanagan, June 2008; and Workshop on Applications of Climate Statistics in Agriculture, Regina, 2007. The CRG organized the workshop Climate Change Impacts on Ecology and the Environment at the Banff International Research Station (BIRS), May 2008, and co-organized, with the National University of Singapore, the 3-week programme Data-driven and Physically-based Models for Characterization of Processes in Hydrology, Hydraulics, Oceanography and Climate Change, January 2008. These events and the CRG itself were critical to building bridges across scientific disciplines and many participants continued lengthy collaborations, some of which are discussed in other sections below.

3. SPATIAL SAMPLING FOR MONITORING AND ASSESSMENT IN ENVIRONMETRICS

In this section, we explore Canadian contributions on the topic of measuring environmental spatio-temporal fields.

3.1. Environmental Sampling

Although there is extensive literature on the optimal model-based design of experiments, the design of spatial and spatio-temporal monitoring networks presents special contextual features, which must be accounted for. Such designs are needed to ensure adequate data quality for an intended application in environmetrics. Green at Western University made important early contributions in biology and ecology to this subject, which are well recognized (e.g., Green & Young, 1993). General reviews on this subject are available (Zimmerman, 2006; Zidek & Zimmerman, 2010).

The quality of a sampling plan depends on how well it serves its intended purpose. Concerns about the impact of climate change on Canadian forests (e.g., the mountain pine beetle) led the National Lumber Grading Association of Canada to employ Zidek and Carolyn Taylor working with an industrial testing lab in Vancouver to design a long-term program for monitoring the strength of Canadian lumber. Their rotating panel design still in use today tests annual samples of lumber. Moreover, the complex design and the need to monitor the 5th percentile of the strength distribution led to joint funding by FPInnovations and an NSERC Collaborative Research and Development Grant to solve theoretical problems that arose (Wong & Zidek, 2019). Zidek served as the PI and Taylor as the Research Coordinator and Scientific Research Associate. In the 11 years of this research programme, which ended in 2021, more than 50 investigators were involved including graduate students and faculty, structural engineers, and wood scientists.

As a second example, Zidek designed a plan for sampling benthic organisms in the seabed of Harrison Bay in Alaska, which was meant to yield data on the impact of exploratory drilling for oil. Work, which began in Seattle, was completed at University of British Columbia with theoretical solutions to some challenging problems that arose (Schumacher & Zidek, 1993).

More challenging problems arise when a proposed network has competing, changing, or unforeseen objectives. Instruments for acidic deposition were replaced/augmented by ones that collected data on air pollution concentrations. Data from urban monitoring networks set up to detect noncompliance with NAAQS came to be used to estimate human health effects. In this latter example, the primary objective leads to citing monitors where the pollution levels are expected to be the highest. But these same data yield underestimates when used to estimate health impacts of a criterion air pollutant. What is needed in this case are monitoring sites in a representative set of locations.

In British Columbia, a network was seen to be needed by hydrologists to measure the spatio-temporal field of precipitation (rain and snow). The data were needed for managing the levels of water in provincial reservoirs for irrigation in summer on the one hand and reducing the risk of flooding on the other. William Caselton, a civil engineer who had reviewed the literature on optimal design, approached Zidek to design a network given these competing objectives. Their collaboration ultimately led to a new criterion for situations like this, where some future objectives were even unknown. Simply put, it stipulated that sites be selected to optimize the amount of information the monitoring network would yield. While the resulting network may not be optimal for any one specific objective, it would be robust when competing objectives presented themselves. This new objective could alternatively be interpreted as selecting the sites where the degree of uncertainty measured by Shannon's entropy about the random spatio-temporal field is greatest.

3.2. Designs to Optimally Reduce Uncertainty

More precisely, assume the spatio-temporal process is indexed by a discrete domain of points so that a future realization of the process may be represented by a random vector **Y**. Selecting a spatial design amounts to partitioning **Y,** which, after a permutation of its coordinates, becomes $\mathbf{Y} = (\mathbf{U}, \mathbf{G})$. Here **G** stands for spatio-temporal responses at which measurements are to be taken, that is, at sites that are "gauged". Its companion **U** represents the ungauged sites. Finally, **D** denotes the set of all currently available spatio-temporal process data on the discrete grid that indexes the process. The joint process vector's distribution is conditional on a parameter θ for which a prior distribution has been selected to represent its uncertainty. Then Shannon's entropy can be decomposed as

$$\mathrm{TOT} = \mathrm{PRED} + \mathrm{MODEL} + \mathrm{MEAS}, \tag{1}$$

where

$$\mathrm{TOT} = H(Y,\ \theta),$$

$$\mathbf{PRED} = E[-\log\left(f(U \mid G,\ \theta,\ D)\right) \mid D],$$

$$\mathbf{MODEL} = E[-\log\left(f(\theta \mid G,\ D)\right) \mid D],\ \text{and}$$

$$\mathbf{MEAS} = E[-\log\left(f(\ G|D)\right) \mid D].$$

Thus, the Caselton–Zidek approach amounts to selecting a partition for which **MEAS** is maximized so that the sum of the remaining two terms in Equation 3.1 is minimized.

This approach was initially implemented in Caselton & Zidek (1984) when $\mathbf{Y}$ had a multivariate normal distribution. However, the acid precipitation program encountered species for which that distribution, even when symmetrized after a suitable transformation, had heavier than normal tails. Furthermore, the covariance structure is not always stationary. Finally, the multiplicity of chemical species made $\mathbf{Y}$ a matrix rather than a vector, which led to an extension of the original theory (Caselton, Kan & Zidek, 1992; Le, Sun & Zidek, 2002). A computer package, Envirostat (Le et al., 2015), published in the CRAN library embraces this optimal design theory as well as the associated theories for spatial prediction and future forecasting within a matric-t context.

The theory described above was successfully applied to redesign the air pollution network monitoring Metro Vancouver's air shed (Ainslie et al., 2009). Some monitoring sites were terminated and replaced by others as a result.

3.3. Preferential Sampling

However, networks designed for one purpose may well yield data that are biased when used for another purpose. For example, preferentially selected monitoring sites where air pollution is expected to be high (to detect non-compliance with air quality standards) have been used by environmental epidemiologists to estimate the effect of air pollution on human health. These data would lead to underestimates of that effect. To see this, suppose for simplicity that the health effect (Y) of the amount of air pollution (X) was modelled by $\mathrm{Y} = \mathrm{a} + \mathrm{b}\ \mathrm{X}$. If X were typically too large, the fitted b would be too small. The perceived risk of X, as quantified by b, would be too small, with potentially serious consequences.

Preferential sampling was demonstrated by a case study of a network in the United Kingdom for measuring black smoke during the period 1966–1996. The study provided evidence that during that period, sites were removed, added, or maintained, according to whether the levels of black smoke were high or low (Shaddick & Zidek, 2014). A method for reducing that bias when computing official statistics followed (Zidek, Shaddick & Taylor, 2014).

To handle larger networks an alternative approach to modelling the effect of preferential sampling was developed (Watson, Zidek & Shaddick, 2019). That approach showed a more complex pattern of network modifications over time in the United Kingdom, with sequential selection favouring lower emission levels of black smoke levels in the early 1970s followed by higher emission sites being favoured in the 1980s. A simple and very general method of detecting preferential selection was subsequently developed (Watson, 2021). That method was applied in a case study of the Southern California air shed, with results being reported in a manuscript under development (Jones, Zidek & Watson, 2022).

4. GLOBAL CLIMATE CHANGE

Climate science is an important area of activity in Canada and one fundamental to many fields in environmetrics. Earth's temperature is determined by how the balance is maintained between the energy Earth receives from the Sun in the form of sunlight and the energy that it radiates back to space in the form of heat. Fourier (1827), of Fourier transform fame, first described the basic physical processes that maintain that balance and thus the mechanism by which the greenhouse gas effect operates (Pierrehumbert, 2004). The potential impact of atmospheric CO2 concentration changes on that balance, and thus on global temperatures, was first considered by Svante Arrhenius (1896). Serious investigation of the potential impacts of rising greenhouse gas concentrations using complex numerical models of the Earth's systems came much later with the pioneering work of Suki Manabe (Manabe & Wetherald, 1967), who was recently recognized as a co-recipient of the 2021 Nobel Prize for Physics. Canada began to focus attention on the modelling of the climate system in the late 1970s, with the establishment by George Boer of a climate modelling group at what was then known as the Atmospheric Environment Service of Environment Canada. That group, which evolved into the internationally recognized Canadian Centre for Climate Modelling Analysis, published its first climate model in 1984 (Boer et al., 1984). That model, while simple by comparison with today's models, nevertheless reproduced many of the basic aspects of the global climate well (Boer, McFarlane & Laprise, 1984).

4.1. Global Climate Science Assessments

At about the same time, the first assessment of global climate models and the potential for increasing atmospheric greenhouse gases to warm the climate was published (National Research Council, 1979). The Charney report, as it came to be known, concluded that the eventual warming that would occur if the CO2 concentration stabilized at double the preindustrial level was likely about 3°C with a probable error of +/− 1.5°C. Subsequent assessments by the IPCC, including the recent report released in August 2021 (IPCC, 2021), have not materially changed this assessment of the equilibrium climate sensitivity (ECS) to CO2 doubling; the IPCC's best estimate of the ECS remains 3°C, with the value likely between 2.5 and 4°C (>66% probability; see Zwiers and Zhang, 2022, for a discussion of the IPCC calibrated uncertainty terms), and very likely between 2 and 5°C (>90% probability).

The IPCC was established in 1988 as the culmination of a complex political process that took place in the context of growing international awareness of climate issues and the potential threat posed by climate change (Agrawala, 1998). The Toronto Climate Conference (WMO, 1988) and some key Canadian actors, such as Howard Ferguson and James Bruce, played an important early role in promoting the IPCC. The unique "intergovernmental" structure of the IPCC has, arguably, allowed it to evolve into one of the most comprehensive, intensely reviewed, and influential scientific assessment processes in existence, even if progress on obtaining international climate action via the UN Framework Convention on Climate Change (UNFCCC) is frustratingly slow. Each IPCC assessment report culminates in a Summary for Policy Makers (SPM) that is the result of an intense negotiation process in which the science is pitted against the perceptions and policy objectives of governments from around the world. While this process is anathema to most scientists, the result is that one can be confident that the SPM and the underpinning report can withstand those tests. Canadian scientists have been influential in each assessment, particularly in the detection and attribution of the causes of historical changes in the global climate (Mitchell et al., 2001; Hegerl et al., 2007; Bindoff et al., 2013; Eyring et al., 2021), the assessment of our understanding of observed and projected changes in extreme events (Seneviratne et al., 2021), and the assessment of climate models (Flato et al., 2013).

4.2. Application of Statistical Concepts in Climate Studies

The study of climate involves the application of both physical and statistical concepts. Canadians have made substantial contributions from both perspectives, with work from a statistical perspective dominantly being published in subject matter journals rather than in journals directed to the statistically minded. Some aspects of climate change science to which Canadians have made particularly strong contributions include the attribution of observed changes in the climate system to causes like the accumulation of greenhouse gases in the atmosphere, the extension of these studies to the consideration of extremes, the analysis of projected changes in extremes, and estimation of the quantiles in the deep upper tail of precipitation distribution. Canadians have also been influential in informing generations of graduate students and postdocs in the application of statistical methods to climate research problems (e.g., via the monograph of von Storch & Zwiers, 1999, which has been cited more than 5000 times according to Google Scholar; accessed 1 June 2022) and through the leading role that they have played in the International Meetings on Statistical Climatology, which is a series of meetings at the interface between climatology and statistics that have occurred periodically since 1979 (Murphy & Zwiers, 1993).

4.3. Detection and Attribution of Climate Change: Mean State and Extremes

Canadian strength in the detection and attribution of climate change is reflected by the contributions that Canadians have made to successive IPCC assessments. Zwiers & Zhang (2021) describe the progression of assessments on the causes of the warming that has occurred since the preindustrial era and discuss the role that the consistent use of calibrated language for describing uncertainties has played in that process. Key accomplishments in the area of climate change detection and attribution include the first study to detect a human imprint in observed changes in the global distribution of precipitation (Zhang et al., 2007) and a quantification of the influence of the urban heat island effect, which is not a direct result of greenhouse gas increases, on temperatures recorded in China (Sun et al., 2016), where most meteorological stations are near population centres.

In addition to contributing importantly to our understanding of changes in mean climate conditions, Canadians have also played a leading role in the study of changes in weather and climate extremes. Hegerl et al. (2004) first demonstrated the feasibility of posing questions about the causes of changes in temperature and precipitation extremes, and Min et al. (2011) first demonstrated that human influence on the climate was also affecting precipitation extremes. Subsequent studies, such as Zhang et al. (2013) and Sun et al. (2022), have substantially strengthened the body of evidence concerning human influence on precipitation extremes, including extensions that consider the impacts on extreme precipitation in continental and subcontinental regions.

A considerable challenge with the study of precipitation extremes is that it involves a change of support problem. Our most reliable long-term precipitation observations are collected by rain gauges at weather stations, which make point measurements that are only representative of the immediate area surrounding the station. By contrast, climate models simulate grid box average precipitation amounts for grid boxes that, in modern climate models, are about 100 km on each side (i.e., have a surface area of about 10,000 km^2 each). Studies of extreme precipitation initially dealt with this problem by applying a probability integral transform to observed and model simulated precipitation amounts (e.g., Min et al., 2011; Zhang et al., 2013) and then applied more or less standard detection and attribution formalisms (e.g., Ribes, Planton & Terray, 2013) to the transformed data. Typically, these studies also process the transformed data heavily by calculating spatial and temporal averages to reduce the complexity of the signal detection problem and filter out as much natural unforced variability as possible. Recently, however, Sun et al. (2022) have demonstrated that station data and model output can be used directly for the detection and attribution of changes in extremes. This was achieved by casting the problem as a multivariate nonstationary extreme value analysis problem, where marginal generalized extreme value (GEV) distributions are fitted to observed annual maximum precipitation amounts at weather stations across a domain of interest by means of a weighted sum of marginal GEV score equations (Wang et al., 2020). In contrast to the profile likelihood approach used in Zwiers, Zhang & Feng (2011), the approach of Wang et al. (2020) is sufficiently computationally efficient that it becomes possible to simultaneously consider the effects of more than one type of climate forcing agent, such as the combined effect of anthropogenic forcing factors (greenhouse gas increases, changes in aerosol loading, and land use change) and simultaneously, the combined effect of natural external forcing factors (changes in solar output and variations in volcanic activity).

4.4. Projected Changes in Extremes

Canadians have also led in analyses of projected changes in extremes, bringing extreme value theory to bear on the analysis of climate model output, starting with Zwiers & Kharin (1998) who considered projected changes in temperature and precipitation extremes in an early version of the Canadian global climate model. Subsequent papers, including Kharin et al. (2007, 2013) and Li et al. (2021), have been extremely influential in IPCC reports. Recent work in this area has taken advantage of the large initial conditions ensembles of climate model simulations that are increasingly becoming available—think of sampling realizations of entire space-time stochastic processes as opposed to sampling in space and time from an individual realization of such a process. Essentially these simulation experiments produce a sample of independent realizations of the evolution of climate that is consistent with a specified combination of external forcing factors. An early example of such an ensemble, which consists of 50 simulations of the evolution of climate from 1950 to 2100, was produced with the CanESM2 global climate model of the Canadian Centre for Climate Modelling and Analysis (see Kushner et al., 2018, and https://open.canada.ca/data/en/dataset/aa7b6823-fd1e-49ff-a6fb-68076a4a477c; accessed 1 June 2022). Each of these simulations was subsequently "downscaled" to a finer resolution over North America using the CanRCM4 regional climate model as described in Scinocca et al. (2016); see also https://open.canada.ca/data/en/dataset/83aa1b18-6616-405e-9bce-af7ef8c2031c accessed 1 June 2022). Among other applications, the latter ensemble has been used extensively to study the amount of information that is needed to constrain nonstationary models of extreme precipitation (Li et al., 2019b), consider how the intensification of precipitation extremes depends on tail location and why there is such a variation in intensification (Li et al., 2019a), upper tail stability (Ben Alaya, Zwiers & Zhang, 2020a), and the possibility of better representing the deep upper tail of the extreme precipitation distribution by applying a bivariate conditional extremes model (Ben Alaya, Zwiers & Zhang, 2020b) based on the conditional extremes model of Heffernan & Tawn (2004). The latter study demonstrates that by accounting for a basic aspect of the physics that govern the generation of extreme precipitation, it may be possible to increase confidence in estimates of the quantiles deep in the upper tail of the extreme precipitation distribution, of the type that are required for critical infrastructure (such as dams) that must be built to perform reliably under truly rare extreme meteorological conditions.

4.5. Extreme Event Attribution

An additional area in which Canadian expertise is internationally recognized concerns extreme event attribution (NAS, 2016), which deals with questions about the extent to which human influence on the climate has affected high-impact extreme events. This is a question that emerges soon after the occurrence of any extreme event that draws our attention, including the "heat dome" event that affected British Columbia in late June of 2021, which is estimated to have caused the deaths of 570 people (https://www.cbc.ca/news/canada/british-columbia/ubcm-heat-dome-panel-1.6189061), and the flooding events in southwestern British Columbia in mid-November 2021 that essentially severed the surface transportation network connecting Vancouver and its port to the rest of Canada. Allen (2003) first proposed that such studies might be possible, which was followed by Stott, Stone & Allen (2004), who analyzed the role of human influence in altering the likelihood and intensity of the extremely warm European summer that set the background conditions for the 2003 European heatwave, which reportedly caused

70,000 deaths (https://en.wikipedia.org/wiki/2003_European_heat_wave). A key contribution to the development of this aspect of climate science is the seminal paper of Hannart et al. (2015) that describes the causal inference framework that underpins extreme event attribution. Canadian scientists have performed their fair share of studies of extreme events, including the record-low Arctic sea-ice extent observed in 2013 (Kirchmeier-Young, Zwiers & Gillett, 2017), wildfires (Kirchmeier-Young et al., 2017, 2019), floods (Teufel et al., 2016, 2018; Gillett et al., 2022), and the recent heat-dome event (Philip et al., 2021).

5. THE AQUATIC DOMAIN

5.1. Dawn of a New Science

In Canada, statistics on commercial fishery catches date back to the 16th century for Northwest Atlantic cod and to the late 19th century for Pacific salmon. By contrast, the more daunting task of estimating, not just what is taken out of the vast oceans, but what is left behind, began only after the Second World War. From the outset of this era, Canadian researchers have played a leading role.

Just two years after the war ended, Daniel Delury, then head of the Mathematics Department at the University of Toronto, published a seminal paper (Delury, 1947) on how one might estimate the number of "fish" (or in his leading example, lobsters) solely from a time series of numbers caught in the fishery. Lobster fishing in Atlantic Canada used to take place in an intense, short-term opening each spring, during which the lobster population was likely relatively constant—except for fishing mortality. Delury's basic idea was that if on each day of fishing, the fishery caught the same fraction of the remaining fish, then the catch would decline exponentially. On a logarithmic scale, the decline would be linear–at least until it hit 0, when only 1 lobster would be left. He used the method of least squares to fit the line from which the remaining population could then be estimated (by the sum of the predicted subsequent catch numbers until the population would have been depleted).

Delury used real data collected by personnel at St. Andrews Biological Station (SABS) in New Brunswick. This was Canada's first marine biological research station, having been established in 1899 as a temporary floating laboratory that researchers from across Canada would come to visit in the summer months to do field research. His proposed methodology represented a solution to an identified need. He further identified the need for an underlying statistical model—a model with stringent conditions that future researchers would later extend. His paper sparked the development of a major field associated with catch-per-unit-effort modelling. Interestingly, the paper is also a testament to changing publication standards: it contained no references whatsoever.

5.2. Ricker's Curve and Beyond: Methodologies for Fisheries Management

A decade later, Bill Ricker, at the Pacific Biological Station (PBS) in Nanaimo, British Columbia, laid the foundations for stock-recruitment analysis (Ricker, 1954, 1958). Ricker had been studying a sockeye salmon population that spawned in Cultus Lake, BC. Most of these fish returned to spawn (if they survived) at age 4. Ricker modelled the number of adults returning to spawn (recruits) as a function of the number of spawners in the parent generation, 4 years earlier. He proposed that this would, for small populations, resemble a straight line through the origin, but that for larger populations, he proposed that the number of recruits per spawner would fall off. Hence, the graph would curve downward (in fact, for his model, now called Ricker's Curve, the slope eventually became negative). The model that he proposed had the highly valuable property that it too could be reduced to a simple linear regression model—a feature of prime importance before the advent of high-powered electronic computers. He then proposed using such models to calculate the catch rate that would maximize the sustainable yield of the fishery.

Although the notion of maximal sustainable yield has since been recognized as far too risky in a world of rapidly escalating extinction risks, the need for more sophisticated versions of Ricker's fundamental stock-recruitment analysis has become even more important. The Pacific Salmon Commission still uses models based on Ricker's Curve in its annual assessments of the plight of declining Fraser sockeye salmon populations. Indeed, it remains a highly useful model for monitoring the viability of fish populations around the world. Ricker also published three editions of a widely used overview of statistical methodology for fish populations (Ricker, 1975). The winding access road down to the PBS where Ricker spent his career is now named Ricker's Curve in his honour.

PBS also attracted John Schnute, a mathematician from Texas State University, who worked there for nearly 30 years. He was one of the early proponents and developers of key statistical approaches to fisheries questions (Schnute, 1985) and helped champion the development of Automatic Differentiation Model Builder (ADMB), a statistical application that implements automatic differentiation using C++ classes and a native template language. It was created by Canadian Dave Fournier in the late 1980s for fish stock assessments with hundreds of parameters and highly nonlinear objective functions, with its use having since spread within the broader ecological community and other scientific fields. Fournier also contributed directly to stock assessment methodology, notably pioneering integrated analysis (Fournier & Archibald, 1982).

Other fisheries scientists on the west coast of Canada, including Carl Walters at the University of British Columbia and Randall Peterman at Simon Fraser University, have made extensive use of the Ricker model in studying the dynamics of Pacific salmon populations. In addition, Walters' career-long work with Ray Hilborn resulted in a seminal textbook (Hilborn & Walters, 1992). Peterman held a Canada Research Chair in "Fisheries Risk Assessment and Management" from 2001 through 2012 and specialized in quantitative methods to improve fisheries management.

5.3. Mark–Recapture and Adaptive Sampling

Numerous Canadians have also made major, substantive contributions to the development of mark–recapture methodology. In contrast to a commercial fishery, in mark–recapture studies, captured individuals are marked and then released back into the population where they are available to be recaptured. For example, Howard Smith developed a method for live-capturing juvenile sockeye salmon departing from Babine Lake in northern BC on their seaward migration. He then marked the fish and released them back into the lake where they were then available for potential recapture as they tried to leave the lake for a second time. If a second sample were in fact a simple random sample of the population, then the proportion of marked fish in the sample would roughly equal the proportion of fish in the population. This provides an equation that can be used to estimate the unknown population size. Smith recruited Peter MacDonald of McMaster University to extend the existing capture–recapture methodology to accommodate the novel aspects of this new application (MacDonald & Smith, 1980).

Neil Arnason (University of Manitoba) and his PhD graduate, Carl Schwarz (University of Manitoba and Simon Fraser University) made extensive, internationally significant contributions to mark–recapture methodology over several decades. Not only did they develop foundational methodology (Schwarz & Arnason, 1996), they also facilitated applications through the development of their software package, POPAN, that provided a convenient interface for their FORTRAN subroutines. POPAN is now incorporated as a module into the leading mark–recapture package, MARK. Furthermore, early in his career, Schwarz arranged to spend a sabbatical at PBS where he developed strong, lasting collaborations with leading fisheries biologists. Later, he became the go-to person for training courses in statistical methodology (including mark–recapture methodology) for resource management scientists throughout British Columbia. Schwarz also co-authored, with George Seber, an update to Seber's classic overview text (Schwarz & Seber, 1999).

Schwarz and Arnason also left a remarkable legacy of younger researchers who have made their own contributions to the field including Simon Bonner (now at Western University), Laura Cowen (now at the University of Victoria), and Audrey Béliveau (now at the University of Waterloo). Other Simon Fraser University faculty and adjuncts have also made notable contributions to fisheries statistics (e.g., Banneheka, Routledge & Schwarz, 1997, on stratified mark–recapture estimation; and Ainsworth, Routledge & Cao, 2011, on functional data analysis in environmental research with specific reference to a long-term study coordinated by Routledge on a collapsed sockeye salmon population in British Columbia).

Finally, Louis-Paul Rivest and Nathalie Plante (Université Laval), with Gilles Tremblay (Canadian Wildlife Service), also made considerable contributions to stratified mark–recapture methodology (e.g., Plante, Rivest & Tremblay, 1998).

In 2005, Simon Fraser University recruited Steve Thompson to Canada. Thompson pioneered the method of adaptive sampling, of special value in sampling highly clustered populations such as spawning aggregations of pelagic fish. Traditional sample surveys of such populations typically come up empty most of the time. Thompson's methodology provided the opportunity to capitalize on the sporadic discoveries of hotspots. He not only had the practical sense to recognize the importance of such an innovation, he backed it up with high-level statistical theory, using the Rao-Blackwell theorem to help derive some of his estimators. While in Canada, he also further developed insight based on common properties of his adaptive sampling technique and network sampling of marginalized human populations. Thompson's innovative ideas have had a major impact far beyond the confines of fisheries statistics.

5.4. New Methodology for an Uncertain Future

Many important developments in fisheries statistics also occurred on the east coast of Canada. While at Fisheries and Oceans Canada's (DFO) Bedford Institute of Oceanography (BIO) in Dartmouth, Nova Scotia, Stratos Gavaris wrote the ADAPT package, which implemented an age-structured estimation model, it was the gold standard for stock assessment modelling in the 1980s and 1990s. Bob Mohn was the first graduate student in Dalhousie University's nascent computer science program, after which he joined BIO, where he rapidly developed his expertise in fish stock modelling and proposed Mohn's rho (Mohn, 1999) to measure the severity of retrospective patterns. This metric has been highly cited and is often used to adjust estimates of biomass and quotas. He was one of the first researchers to truly address methodological issues in stock assessment related to diagnostics and the quantification of uncertainty.

In the early 1990s, American-born Ram Myers, who had earned a PhD in Biology at Dalhousie, became profoundly concerned about the collapse of the northern cod while working as a research scientist at DFO's Northwest Fisheries Center in St. John's, Newfoundland. He and colleague Jeff Hutchings issued warnings about global overfishing (Hutchings & Myers, 1994). Ultimately, both returned to Dalhousie in 1997, Myers as the first Killam Chair in Ocean Studies. Before his premature death in 2007, at the age of 54, Myers had co-authored more than 100 papers, and in the October 2005 issue of Fortune Magazine, he was listed among the world's 10 people to watch for "working to develop new and better ways to husband the wealth beneath the sea." One of Myers' most important contributions to fisheries statistics was to stock recruitment: collection and analysis of data and the subsequent development of models to predict the survival rate for fish larvae.

Noel Cadigan (Marine Institute of the Memorial University of Newfoundland), a former DFO colleague of Myers', developed a state-space stock-assessment model for the severely depressed northern cod. This would provide him with a uniquely valuable perspective in the following initiative.

In 2013, a Dalhousie-led consortium received funding from the Canadian Statistical Sciences Institute (CANSSI) for collaborative research in state-space modelling for fisheries science. Led by Joanna Mills Flemming (Dalhousie) with collaborators Chris Field (Dalhousie), Noel Cadigan (Memorial University of Newfoundland), Rick Routledge (Simon Fraser University), and Dave Campbell (Simon Fraser University), the project brought together academic and government quantitative scientists to develop and apply statistical methodology for addressing well-identified scientific and management needs. This project laid the foundation for a second CANSSI-funded project led by Flemming in 2018. Once again, funding for such collaborations paid rich dividends as demonstrated below.

Steve Smith of DFO's BIO formed a close collaboration with the Dalhousie group, which provided excellent training for the junior researchers and generated a solid illustration of the value of state-space modelling in stock assessment (Yin et al., 2019). This Dalhousie-BIO collaboration continues to flourish with Dave Keith and Jessica Sameoto assuming Smith's role (McDonald et al., 2021a,b). The team also engaged international partners, notably Anders Neilsen who was instrumental in the development of Template Model Builder (TMB), an R package for fitting random effects models that is strongly inspired by ADMB. These efforts produced valuable methodological advances in state-space modelling (Aeberhard, Mills Flemming & Nielsen, 2018; Aeberhard et al., 2020). William Aeberhard is now Senior Data Scientist, Swiss Data Science Center, ETH Zurich, Switzerland; another postdoctoral fellow in the group, Marie Auger-Méthé (Auger-Méthé et al., 2021), now holds a CRC Tier 2 Chair at the University of British Columbia.

6. THE FORESTS

6.1. Introduction

Canadian statisticians have been heavily involved in work related to wildland fire science and management, leading to joint collaborations with scientists from other disciplines and fire management practitioners. These collaborations launched the development of large-scale networks to study issues that threaten resource sectors or that can be used to spur efficiency and enrich our natural environment. A key player in the initiation of these collaborations was Brillinger, an influential Canadian statistical scientist who, as discussed here and the sections above, maintained strong ties with Canadian researchers. David Martell, a leading fire management researcher, noted that a chance encounter with Brillinger often acted as a catalyst—not only would it spark a career-changing trajectory for early statistical scientists, but also make waves outside of our discipline. Martell recalls being contacted by Brillinger for fire data out of the blue, a conversation that subsequently led to very productive relationships between many Canadian statistical and fire scientists. It also resulted in a then-novel approach to postgraduate training, such as the first enlistment of a postdoc (Doug Woolford) to receive "hybrid" training, working out of both the Firelab at the University of Toronto and a department of statistics at Simon Fraser University, under the co-supervision of Martell and two statisticians (Dean and John Braun). Martell noted how essential it is for statisticians to experience fieldwork and interact with fire researchers and management practitioners, where statisticians directly learn the terminology and processes they are modelling, as well as the complicated nature of fire science. Indeed, he observed that once a common language of communication is established between statisticians and fire scientists, problem-solving escalates. Steve Cumming, an applied forestry researcher from Université Laval, recalls struggling to tune percolation models to reproduce some features of empirical data, namely the mean size of wildfires. After working to explain the problem, Reg Kulperger brightened up and said "Oh, you mean calibration". In due course, Woolford utilized a technique on shape-constrained GAMs that led to the required solution, now widely used in simulation studies across Canada. Not a very complicated problem, as it turned out, once collaborators had managed to understand each other.

A very important characteristic and challenge to understanding, predicting, and managing wildfires is the high spatio-temporal variability in the fire environment, namely the weather, vegetation, and topographic conditions in which a fire is burning. This, in turn, is reflected in variability in fire events, processes, and features at different temporal and spatial scales (e.g., fire ignitions, rates of spread, intensity, and size over time, and ultimately in fire size and the area burned, and fire frequency in a region). Predicting these and other fire characteristics is important to fire management decisions at many scales, from anticipating the national fire load and resource requirements to responding to individual incidents.

Although fire is fundamentally a chemical reaction producing energy that is governed by physical principles (e.g., conservation of energy/mass, angular momentum), fire science in Canada has taken an empirical rather than a physically based approach. Comprehensive data have accrued on the hundreds of thousands of wildland fires that have occurred across Canada over the decades, along with detailed environmental observations (fuel/vegetation maps, weather, fire-weather codes and indices, and lightning activity) and information about key anthropogenic features (roads, railways, and powerlines). Productive analyses of such data have largely been a result of collaborative enterprises bringing together a broad range of expertise including statisticians, fire managers, fire scientists, forest ecologists, engineers, and operations researchers.

6.2. Modelling Fire Ignition and Rate of Spread Processes

Much of the fire research in Canada prior to 2000 was carried out in government laboratories using simple statistical methods to characterize variability in the fire environment and to predict important fire processes from observations made in field experiments. Beginning in 1929, federal fire researchers James Wright and Herb Beall correlated the moisture content of needle and leaf litter to weather elements (evaporation rate, relative humidity, wind speed), and the inflammability of surface fuels with fuel moisture content based on field observations and burn trials at the Petawawa Research Forest. These methods resulted in the first fire hazard tables in Canada. Beall also produced some of the first predictions of fire occurrence from the empirical frequency of human-caused fires in the Petawawa district in different hazard classes. During the following 40 years, a series of regional hazard tables were developed from analysis of over 20,000 ignition tests that were carried out in a variety of forest types at 10 other field stations from Newfoundland to British Columbia to the Northwest Territories.

In the 1970s, Charles Van Wagner developed models of fuel moisture that use a negative exponential model to represent the fuel drying rate in relation to weather properties. These models were incorporated in a nationally cohesive Fire Weather Index (FWI) System (VanWagner, 1987) that replaced the regional hazard tables. Towards the end of the 20th century, a group of federal fire researchers fit the Chapman-Richards growth equation (Richards, 1959) to observations of fire spread rate, fine fuel moisture, and wind speed observed in dozens of large-scale experimental fires that they carried out in important forest and vegetation types in Ontario, Alberta, British Columbia, and the Northwest Territories. These rate of spread (ROS) equations are the backbone of the Fire Behavior Prediction System used across Canada (Stocks et al., 1989), and along with the FWI System, have been adopted by several other countries.

6.3. Modelling Fire Occurrence and Fire Frequency

Although wildland fires are rare events on a fine space-time scale, predicting when, where, and how many fires may occur is a crucial component to wildland fire management. It provides data-driven, evidence-based support for short-term fire management decisions, such as the planning of organized detection efforts (e.g., McFayden et al., 2019) and resource positioning.

Statistical contributions to methods and advancements for fire occurrence prediction (FOP) are highlighted in the historical review of human-caused FOP in North America in Woolford et al. (2021), the human and lightning-caused FOP modelling presented in Nadeem et al. (2019) and Magnussen & Taylor (2012), and the methods for modelling lightning-caused FOP as a two-stage process involving ignition and eventual detection after a period of smouldering by Wotton & Martell (2005). Arrival of smouldering fires can lead to large clusters of lightning-caused fires (Woolford & Braun, 2007) that stress fire management agencies. FOP modelling in the context of wildland fire management is discussed by Taylor et al. (2013). See Xi et al. (2019) and Johnston et al. (2020) for discussions of FOP in the context of fire risk.

Early FOP research in the Canadian context included the human-caused modelling by Cunningham & Martell (1973) and the lightning-caused modelling of Kourtz & Todd (1991). The first known use of a probability-based model for fire occurrence in North America is generally accepted to be Bruce (1963), who used a negative binomial framework to model daily human-caused fire occurrences in Louisiana and Missouri, United States, as a function of a fire danger rating class. Bruce's work recognized the rareness of fire occurrence at a fine scale and the issue of overdispersion because of too many zeros in the response. This need to handle the large class imbalance when modelling occurrences remains, especially when developing fine-scale, spatially explicit FOP models over large extents, leading to very large datasets.

The theoretical underpinnings of fine-scale, spatially explicit fire occurrence prediction appeared in seminal work led by Brillinger, Preisler & Benoit (2003), who discussed spatio-temporal point processes with inhomogeneous conditional intensity functions for fire occurrence modelling and outlined a discretization method for approximating its likelihood that uses response-dependent sampling to create data that are of a reasonable size for modelling, which was connected to case–control methodology in Woolford et al. (2011).

Recently, there has been increased interest in the use of machine learning (ML) methods for fire occurrence prediction (Jain et al., 2020). However, many machine learning classification tools require training data where the response variable is balanced and many ML models for FOP are not properly calibrated to produce true probabilities because the subsampling of nonfire events for training data leads to overprediction (Phelps & Woolford, 2021a). Canadian statistical scientists have played a key role here to ensure that properly calibrated models—whether they are model-based or algorithm-based methods—are employed, that they are properly assessed, and that the interpretability of the various approaches is discussed with fire management practitioners should the goal be operational implementation (Phelps & Woolford, 2021b) where visualization of model output plays a key role (Boychuk et al., 2021).

Another promising avenue for FOP research where Canadian statisticians have contributed is smoke plume identification from digital images. This requires sophisticated data fusion, processing, and modelling techniques. Research identifying smoke is also important for respiratory health applications (e.g., Wan et al., 2011; Wolters & Dean, 2017).

William Reed, a very early Canadian statistical scientist to work on fire, clearly recognized the connection to forest management in the light of the uncertainty and risk posed by wildland fire, studying topics such as the chances of stand replacing fires (Reed, 1994), and designing the optimal rotation period in fire prone forest stands (Reed, 1984, Reed & Errico, 1986). Reed (1998, 2000) made key contributions to fire frequency analyses, showing how to reconstruct the frequency of fires and identify change points in the underlying hazard; he asserted that the fire cycle should be redefined as "the expected time between fires at any given location in the study area" (Reed, 2006).

6.4. Modelling Fire Size, Growth, and Duration

Another key characteristic of a wildland fire regime is its size distribution, which, of course, depends on how fires spread and how long they "survive". Canadian contributions to parametric models for size distributions include Cumming (2001) and Schoenberg, Peng & Woods (2003). Reed & McKelvey (2002) examined the claim of power-law behaviour for fire sizes (e.g., Malamud, Morein & Turcotte, 1998), developing methodology for modelling both the spread and extinguishment of fires, introducing the concept of an extinguishment growth rate ratio to identify when and where power-law behaviour was present. Reed & Hughes (2003) demonstrated that power-law behaviour could result from "interplay" between exponential growth and stopping times.

Contributions to wildland fire growth/spread modelling began in earnest at a 2006 BIRS Forests, Fires, and Stochastic Modelling Workshop. The Alberta Wildfire Management Branch actively pursued and engaged the mathematics and statistics academic community to collaboratively resolve technical issues encountered during the development of the Prometheus Canadian Wildland Fire Growth Model (Tymstra et al., 2010). For example, the marker method for front propagation used in Prometheus requires vertex management. During the 10th PIMS Industrial Problem Solving Workshop (June 26–30, 2006), Dean organized that the problem be brought forward, and an unwinding routine based on the two-colour theorem for planar curves was proposed as a feasible solution to resolve tangles and singularities. Chris Bose worked collaboratively with software engineer Robert Bryce to implement the new algorithm in the Prometheus model. Garcia et al. (2008) developed a Prometheus R version, proposed improving the Prometheus model through parameter smoothing, and evaluated introducing stochasticity using a residual-based bootstrap. Han & Braun (2014) demonstrated that a Monte Carlo approach was not necessary to incorporate randomness into Prometheus, illustrating how an empirical modelling approach could be used to quantify the distribution of the spreading fire front.

Boychuk et al. (2007, 2009) developed an interacting particle system model for fire spread, constructed using a continuous-time Markov chain on a grid where state transitions were governed by local covariate information. Their model also incorporated the impact of spotting, where burning material can be carried by winds ahead of the fire front over fuel breaks. A variant of the Boychuk et al. model was introduced by Wang et al. (2019) who showed how such a model could be calibrated using data from "micro-fires" conducted in an experimental setting. An analysis of micro-fires was also conducted by Thompson & Braun (2020), who introduced a consistent estimator for fire spread that used anisotropic local constant regression.

Modelling the duration of fires informs fire management because fire load (the number of fires active on the landscape) can limit the availability of suppression resources. Morin et al. (2015) illustrated the use of survival analysis methods for the time to control a suppressed fire. This was extended in Morin et al. (2019), who employed a shared frailty approach to explore spatial patterns in control times. Tremblay, Duchesne & Cumming (2018) presented a novel application of survival analysis, considering size as the response. However, the duration of a fire and its final size are not independent and different methods are needed when considering both outcomes.

6.5. Joint Modelling Approaches

Oftentimes in fire science and in environmetrics in general, multiple data types are collected, and multiple outcomes on individuals are interrelated. A so-called joint modelling framework allows the analysis of correlated responses simultaneously, reducing biases that are sometimes present when modelling the outcomes separately. In addition to realizing efficiencies in analysis, it allows a quantification of how correlated the outcomes are, providing further understanding of related processes (Dean & Renouf, 2021). This framework has become increasingly popular in environmetrics research, and Canadian leadership in this area has led to modelling species distribution where competition from other species can affect survival, incorporating outcomes with different time scales, or jointly modelling spatial data from a collection of sites resulting in a collection of correlated spatial maps. The joint modelling framework has demonstrated flexibility in analyzing multiple data types from vast and increasingly complex datasets collected in environmetrics research, including fire science. In collaborative work, this framework has been used to jointly model the duration and size of extended attack wildfires as dependent outcomes (Xi, Dean & Taylor, 2020), with a further extension to joint mixture models (Xi, Dean & Taylor, 2021). Becker, Woolford & Dean (2021) developed visualization tools for joint models of the spatial location of wildland fires with the total burn area of each of the fires, rather than treating occurrence and size as separable as was done in the compound modelling approach of Podur, Martell & Stanford (2010). Other outcomes that will be interesting to explore jointly in the context of fire science include occurrence and human behaviour, occurrence and intensity in relation to climate changes, and smoke density and respiratory disease outcomes.

6.6. Modelling Climate Change Impacts on Fire

Key components of many fire occurrence models include temporal (seasonal and/or long-term trends) and spatial effects, referred to as "baselines" by Brillinger, Preisler & Benoit (2003), which quantify how occurrence is changing over time and space, after accounting for key drivers such as weather, fuel moisture, and land-use patterns. Studying how these or other similar components change has been used to monitor and/or forecast changes in Canada that may be due to a warming climate, such as lengthening fire seasons (e.g., Albert-Green et al., 2013; Hanes et al., 2019), and increases to occurrences and their association with climate anomalies (e.g., Beverly et al., 2011; Woolford et al., 2014). Other important work has been done in attributing the influence of anthropogenic forcings on characteristics of fire regimes (e.g., Kirchmeier-Young, Zwiers & Gillett, 2017, Kirchmeier-Young et al., 2019; Gillett et al., 2004), and the forecasting of potential changes to future fire regimes (e.g., Wang et al., 2016, 2017; Wotton, Flannigan & Marshall, 2017). Statistical methods for process monitoring/quality control have shown potential here (e.g., Podur, Martell & Knight, 2002). This is an interesting avenue for additional research in this context and in other areas of wildland fire science and management (e.g., Becker et al., 2019).

6.7. Interdisciplinary Initiatives

As noted throughout this section, one key element related to the impact of statistics arises because of the close-knit collaboration between statisticians and scientists from other disciplines. Of course, statistics is inherently an interdisciplinary field, and we should note that important contributions have been made by scientists who have substantive quantitative expertise in the applied areas related to forestry and fire science. Researchers have long recognized that opportunities for effective collaboration are needed to build a strong research programme that encourages interdisciplinary work.

Several key mechanisms to support collaboration in the Canadian context related to environmetrics in general were mentioned earlier. It is important to note that specific initiatives were also at play in developing the field. An important collaborative initiative in the fire science context, for example, began in 2005 with the National Program for Complex Data Structures (NPCDS, directed by James Stafford, University of Toronto), which then evolved into the NICDS. This initiative partnered statisticians with government agencies and fire resource managers, contributing vital in-person training events and internships and encouraging international collaborations. A specialized initiative called Forests, Fires and Stochastic Modelling advanced tools and methods for modelling and predicting the spread of forest fires based on modelling of biological and physical processes. The primary aim was to encourage and enable interaction between students and postdoctoral fellows, and those working in applied forestry research and resource management. This successful initiative resulted in numerous publications and allowed development of new tools for government agencies to manage forestry resources and predict forest fires. This project served as the foundation for other team projects described below.

Major networks also supported various efforts. With a view to open communication and removing barriers and delays between knowledge development and subsequent application (Dean et al., 2012), the GEOmatics for Informed DEcisions (GEOIDE) Network was born in 1998 (Wachowicz & Chrisman, 2012). This network was part of the National Research and Engineering Council's Networks for Centres of Excellence. These networks fostered collaborations among different arms of scientific communities to solve complex problems, made impact through engagement with industrial and agency partners who would implement solutions, and importantly provided a unique training environment for the next generation of statistical researchers working in fire science. With the primary goal of crossing interdisciplinary boundaries and connecting academic researchers with industry and government agencies (Dean et al., 2012), this network approach has been instrumental in facilitating beneficial collaborations with measurable impact. The result has been decades of useful applied research that is translated into valuable practical application through a collaboration of statisticians and applied researchers. The GEOIDE network group on Stochastic Modelling of Forest Dynamics was a successful collaborative endeavour that trained students with teams of researchers and agency scientists, and brought together substantial expertise from agency stakeholders, fire managers, and industry to work on appropriate and valuable solutions for fire science challenges. Indeed, training was the most important part of the GEOIDE network: training the next generation of researchers in a collaborative environment is essential for solving many of the complex problems facing the world, requiring involvement of multiple disciplines. International and collaborative scientific training is essential, teaching students to set common goals, providing background knowledge of related disciplines, fostering a safe environment for communication and asking questions, setting a common language for technical terms, accepting others' terminology and making the effort to understand a problem from multiple perspectives before applying modelling solutions. Diplomacy, graciousness, and interest in other perspectives and related fields of research were also important training skills (Dean et al., 2012). Another important network for fire science collaboration was set up through a CANSSI Collaborative Research Team in 2015 for "Evolving Marked Point Processes with Application to Wildland Fire Regime Modeling". This network was very important for training highly qualified personnel and is described further here: http://www.canssi.ca/news-events/data-driven-models-for-wildland-fire-management/. Establishing future collaborative support networks for scientific exchange should remain a priority in Canada.

Den Boychuk, a Forest Fire Science and Technology Program Officer with the Ontario Ministry of Northern Development, Mines, Natural Resources and Forestry, and a collaborator with Canadian Statistical scientists working in this area, reflects that the knowledge, perspectives, and methods of the research and practice worlds are very different. Having worked in both academia and fire management, he notes that he has made the mistake of working without close collaboration. "I understood the system incompletely and incorrectly via the narrow filters of other researchers, literature, and limited data, and I produced impractical work that missed relevant factors. Practitioners working in isolation understand their data and system but are limited in being able to answer important questions. Researchers working closely with practitioners in periodic meetings and with frequent communication can develop an increasingly deep understanding of the complexity and dynamics of the system, the meaning of its data and the important questions to address."

6.8. Final Notes

This reflection of contributions focused on wildland fire science and management; however, there are many other fields where statisticians have had an impact. Of note, we mention the important field of forest ecology, with leadership in research provided by Marie-Josée Fortin and important contributions by Ainsworth & Dean (2008) and Feng & Dean (2012) in zero-heavy spatial modelling, and Dean, Nathoo & Nielsen (2007) in mixture models for pine weevil studies. With such a large field of research in forestry and much work to be done, there is a need for continued training and talent to engage in these areas. This is especially critical because of the importance of forests as a resource for Canada.

7. CURRENT AND FUTURE DIRECTIONS

There is much research in a variety of areas for which Canadians are contributing to future directions. Here we will focus on four particular areas as reflective of the focus of this article.

7.1. Future for TIES and Environmetrics

The need for communication avenues for quantitative environmental research and practice seems to be even more urgent in this time of environmental crises we are facing. The maturation of the subject and the record of modes of communication discussed above are important to the collaborative effort needed to solve pressing environmental problems. Statistics is becoming more computational, and environmetrics seems to be one manifestation of what data science is all about. Regardless of the term used for the practice of solving real-world problems where solutions involve extracting information from data, environmetrics has as crucial a role now as it did back in 1971 when the term was used by Philip Cox (El-Shaarawi & Hunter, 2006), adding it to counterparts such as biometrics and econometrics. Entities such as TIES, the American Statistical Association's Section on Statistics and the Environment, GRASPA, the Royal Statistical Society environmental endeavours, and the Section on Environmental Sciences of the International Society for Bayesian Analysis (EnviBayes) and the journals mentioned in previous sections (although not exhaustive lists) have a key role in the future. The sections below discuss some of the science and contributions fostered by collaborations and various communication vehicles.

7.2. Monitoring and Assessment in Environmetrics: Health Impacts of Hazardous Fields and Extreme Temperature Fields

Approaches for adjusting bias on estimated health effects for preferential sampling have been developed (Liu, Shaddick & Zidek, 2016; Shaddick, Zidek & Liu, 2016). However, more refined approaches are needed and the search for these methods is the subject of current research in environmental epidemiology. The importance of the health impacts of extreme temperatures has emerged as a new research area (Song et al., 2021).

Issues about the design of temperature monitoring networks raised in Section 3 arise anew and a search for optimal fields of monitors has begun (Resende-Casquilho, Le & Zidek, 2016, Resende-Casquilho et al., 2017). Current work is addressing the important issue of predicting exposures to high temperatures, based on ambient temperature fields and the effect on human behaviour. In other words, high outdoor temperatures may induce people to stay indoors and thus avoid an adverse health impact. Current research is both updating pCNEM and determining how it must be modified. Its adaptation for estimating the health impacts of extreme temperature is complicated by the numerous changes in the computing systems that have occurred in the intervening years.

7.3. Charting a Course Through Turbulent Waters: Future Fisheries Research

For more than 70 years, Canadian researchers have played a leading role in the development and implementation of fisheries statistics. Key aspects contributing to this remarkable success include (1) close collaboration between academic statisticians and both academic and government fisheries biologists; (2) availability of targeted funding for promoting such collaborations including Fisheries and Oceans Canada's Science Subvention Grants, CANSSI's Collaborative Research Team program, and into the future possibly NSERC Alliance partnerships; (3) promoting the use of novel methodology through software development and training courses; (4) the existence of a base for government scientists to conduct fundamental research; and (5) the maintenance of research expertise through graduate supervision and training programmes.

With continued support, Canada can maintain its leading role in this field. Yet such support can never be taken for granted. The quasi-independent Fisheries Research Board of Canada that supported Ricker's fundamental research was disbanded in 1973 (Anderson, 1984) to promote research "more in line with the broad Management Operations of the Fisheries and Marine Service [DFO precursor]". Support for fundamental research is unavoidably at the whim of fickle political winds. These need to be countered by steady, ongoing demonstrations of the value of such research to the sustainability of Canada's fisheries resources.

Nor can we rest on our laurels. We indeed have much to learn from others' successes. In particular, we need more formalized fisheries training programmes, much like the graduate programmes currently offered by the School of Aquatic and Fisheries Sciences at the University of Washington.

Has the research area run its course? Far from it. Widespread collapses of major fish populations like Northwest Atlantic cod and Pacific salmon call for urgent attention. Traditional estimation methods like catch per unit effort lose their value when the denominator of this fraction declines to near zero. Moreover, it is now clear that merely monitoring the abundance of such populations, waiting for them to rebuild on their own, is insufficient. We urgently need to learn more about their reproduction and survival in an underwater environment that has become increasingly unstable and often highly variable in space. New technologies such as ocean tracking networks and remotely operated underwater vehicles will need to be deployed to address this emergency, and this will in turn create an ongoing stream of exciting new statistical challenges.

7.4. Some Current Challenges in Climate Research

The application of statistical concepts and reasoning in climate research continues to present an abundance of challenges that are of critical importance for enhancing our ability to adapt to future climate change. One such challenge is to quantify the uncertainty in the projections of future climate change that is due to climate model uncertainty. Models are developed from physical principles at roughly 20 climate modelling centres around the globe, with more than 40 models participating in recent phases of the Coupled Model Intercomparison Project (CMIP; see https://www.wcrp-climate.org/wgcm-cmip), which provides the bulk of the climate change simulations that are used in climate research and IPCC assessments. Although the differences between the projections from different models provide an indication of the effect of choices that are made by modellers in the course of developing their models, the interpretation of that variation is difficult because it is not known how the available ensemble of opportunity (Tebaldi & Knutti, 2007) samples the space of all plausible representations of the climate system or whether exchangeability assumptions (e.g., Rougier, Goldstein & House, 2013) are valid. Recognizing that there are differences between models, and that they may not all be equally skilful, a second group of challenges is therefore to identify emergent constraints that can be used to narrow uncertainty in the projection of future change (e.g., Brient, 2020). A third challenge is that climate change adaptation activities, such as designing infrastructure so that it is resilient to the projected changes in climate, are place-specific and thus require information at very fine spatial scales. The ability to provide this kind of information with dynamical climate models is still very limited due to their extraordinarily high computational cost, and thus statistical downscaling schemes (e.g., Cannon, Sobie & Murdock, 2015, Cannon, 2018; Hiebert et al., 2018) are often used. Improving and further developing these methods, particularly so that they represent extreme events at fine spatial scales as effectively as possible, remains a high priority. A fourth challenge is to be able to undertake the detection and attribution of small-amplitude signals in the noisy climate record. Initially, the climate response to greenhouse gas emissions reductions will be small, and yet it seems inevitable that scientists are going to be asked to pronounce on whether there is evidence that greenhouse gas abatement is having its intended effect. Finally, the acute impacts of climate change to society almost always occur as a result of a confluence of factors. For example, the likelihood and magnitude of a flooding event in a given watershed that is associated with the occurrence of extreme precipitation may have been altered by antecedent events that preconditioned the watershed for the occurrence of flooding and landslides. Climate scientists are beginning to consider compound extreme events, sometimes in collaboration with statisticians (e.g., Huang, Monahan & Zwiers, 2021), but we are still only at the early stages of being able to effectively apply the tools for multivariate extreme value analysis to which Canadians (e.g., Genest & Rivest, 1989; Genest & Favre, 2007; Joe, Li & Nikoloulopoulos, 2010) have made key foundational contributions. Some very impressive advances are also being made in the area of spatial extremes, such as Beck et al. (2020).

7.5. Ongoing Challenges in Wildland Fire Science

Fostering approaches for true knowledge exchange is critical. The successes of forestry teams who have previously contributed in the Canadian context discussed here stem from the true, interdisciplinary collaborations that occurred. Statistical scientists need to engage with fire management practitioners and researchers from other areas to understand their business, its needs, and how statistical data science can inform decisions. It is up to statistical scientists, as researchers, to engage the end users/practitioners regularly to ensure two-way knowledge exchange. It does not work if we simply find out what their problem is, secure data, and then work on it in isolation. Moreover, that approach does not build trust in a tool that may be used operationally for decision support. Recruitment of the next generation of researchers for forestry research is also important. Many bright young statisticians and data scientists may not fully appreciate the complex problems and data available for research in this field, and environmetrics broadly, and instead are more attracted to business, medical, or technology research areas. Given the need to work together for a sustainable planet, opening doors for our emerging statisticians through a variety of venues at society meetings, and through collaborations, will support the gap in expertise available in Canada for this area of research.

REFERENCES

Aeberhard, W., Cantoni, E., Field, C., Kuensch, H., & Mills Flemming, J. (2020). Robust estimation for discrete-time state space models. *Annual Review of Statistics and its Application*, 5, 215–235.

Aeberhard, W., Mills Flemming, J., & Nielsen, A. (2018). Review of state-space models for fisheries science. *Annual Review of Statistics and its Application*, 5, 215–235.

Agrawala, S. (1998). Context and early origins of the Intergovernmental Panel on Climate Change. *Climatic Change*, 39, 605–620.

Ainslie, B., Reuten, C., Steyn, D., Le, N. D., & Zidek, J. V. (2009). Application of an entropy-based Bayesian optimization technique to the redesign of an existing monitoring network for single air pollutants. *Journal of Environmental Management*, 90(8), 2715–2729.

Ainsworth, L., Routledge, R., & Cao, J. (2011). Functional data analysis in ecosystem research: The decline of Oweekeno lake sockeye salmon and Wannock river flow. *Journal of Agricultural, Biological, and Ecological Statistics*, 16, 282–300.

Ainsworth, L. M. & Dean, C. B. (2008). Detection of local and global outliers in mapping studies. *Environmetrics*, 19, 21–37. https://doi.org/10.1002/env.851

Albert-Green, A., Dean, C. B., Martell, D. L., & Woolford, D. G. (2013). A methodology for investigating trends in changes in the timing of the fire season with applications to lightning-caused forest fires in Alberta and Ontario. *Canada. Canadian Journal of Forest Research*, 43(1), 39–45.

Allen, M. (2003). Liability for climate change. *Nature*, 421, 891–892.

Anderson, F. (1984). The demise of the Fisheries Research Board of Canada: A case study of Canadian research policy. *HSTC Bulletin*, 8(2), 151–156. https://doi.org/10.7202/800193ar

Arrhenius, S. (1896). On the influence of carbonic acid in the air upon the temperature of the ground. *Philosophical Magazine and Journal of Science Series*, 5(41), 237–276.

Auger-Méthé, M., Newman, K., Cole, D., Empacher, F., Gryba, R., King, A., Leos-Barajas, V. et al. (2021). A guide to state-space modeling of ecological time series. *Ecological Monographs*, 91(4), p.e01470. https://doi.org/10.1002/ecm.1470

Banneheka, S., Routledge, R., & Schwarz, C. (1997). Stratified two-sample tag recovery census of closed populations. *Biometrics*, 53, 1212–1224.

Beck, N., Genest, C., Jalbert, J., & Mailhot, M. (2020). Predicting extreme surges from sparse data using a copula-based hierarchical Bayesian spatial model. *Environmetrics*, 31, p.e2616. https://doi.org/10.1002/env.2616

Becker, D. G., Braun, W. J., Dean, C. B., & Woolford, D. G. (2019). Visualizing multivariate time series of aerial fire fighting data. *Journal of Environmental Statistics*, 9(1), 1–15.

Becker, D.G., Woolford, D.G. & Dean, C.B. (2021). Visualization of joint spatio-temporal models via feature recognition with an application to wildland fires. In *Proceedings of the 16th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2021) - Volume 3: IVAPP*, 233–239.

Ben Alaya, M. A., Zwiers, F. W., & Zhang, X. (2020a). An evaluation of block-maximum based estimation of very long return period precipitation extremes with a large ensemble climate simulation. *Journal of Climate*, 33, 6957–6970. https://doi.org/10.1175/JCLI-D-19-0011.1

Ben Alaya, M. A., Zwiers, F. W., & Zhang, X. (2020b). A bivariate approach to estimating the probability of very extreme precipitation events. *Weather and Climate Extremes*, 30, 100290. https://doi.org/10.1016/j.wace.2020.100290

Beverly, J. L., Flannigan, M. D., Stocks, B. J., & Bothwell, P. (2011). The association between Northern Hemisphere climate patterns and interannual variability in Canadian wildfire activity. *Canadian Journal of Forest Research*, 41, 2193–2201.

Bindoff, N. L., Stott, P. A., AchutaRao, K. M., Allen, M. R., Gillet, N., Gutzler, D., Hansingo, K. et al. (2013). Detection and attribution of climate change: From global to regional. In Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., & Midgley, P. M. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Boer, G. J., McFarlane, N. A., & Laprise, R. (1984). The climatology of the Canadian Climate Centre general circulation model as obtained from a five-year simulation. *Atmosphere-Ocean*, 22(4), 430–473.

Boer, G. J., McFarlane, N. A., Laprise, R., Henderson, J. D., & Blanchet, J.-P. (1984). The Canadian Climate Centre spectral atmospheric general circulation model. *Atmosphere-Ocean*, 22, 397–429.

Bornn, L., Shaddick, G., & Zidek, J. V. (2012). Modeling nonstationary processes through dimension expansion. *Journal of the American Statistical Association*, 107(497), 281–289.

Bornn, L. & Zidek, J. V. (2012). Efficient stabilization of crop yield prediction in the Canadian Prairies. *Agricultural and Forest Meteorology*, 152, 223–232.

Boychuk, D., Braun, W. J., Kulperger, R. J., Krougly, Z. L., & Stanford, D. A. (2007). A stochastic model for forest fire growth. *INFOR: Information Systems and Operational Research*, 45, 9–16.

Boychuk, D., Braun, W. J., Kulperger, R. J., Krougly, Z. L., & Stanford, D. A. (2009). A stochastic forest fire growth model. *Environmental and Ecological Statistics*, 16(2), 133–151.

Boychuk, D., McFayden, C. B., Woolford, D. G., Wotton, M., Stacey, A., Evens, J., Hanes, C. C., & Wheatley, M. (2021). Considerations for categorizing and visualizing numerical information: A case study of fire occurrence prediction models in the province of Ontario, Canada. *Fire*, 4(3), 50.

Brient, F. (2020). Reducing uncertainties in climate projections with emergent constraints: Concepts, examples and prospects. *Advances in Atmospheric Sciences*, 37, 1–15. https://doi.org/10.1007/s00376-019-9140-8

Brillinger, D. R., Preisler, H. K., & Benoit, J. W. (2003). Risk assessment: A forest fire example. In *Statistics and Science: A Festschrift for Terry Speed*, Institute of Mathematical Statistics Lecture Notes, Monograph Series 40, IMS, Beachwood, Ohio, 177–196.

Bruce, D. (1963). How many fires? *Fire Control Notes*, 24(2), 45–50.

Cai, S., Zidek, J. V., Newlands, N. K., & Neilsen, D. (2014). Statistical modeling and forecasting of fruit crop phenology under climate change. *Environmetrics*, 25(8), 621–629.

Cannon, A. J. (2018). Multivariate quantile mapping bias correction: An N-dimensional probability density function transform for climate model simulations of multiple variables. *Climate Dynamics*, 50, 31–49. https://doi.org/10.1007/s00382-017-3580-6

Cannon, A. J., Sobie, S. R., & Murdock, T. Q. (2015). Precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *Journal of Climate*, 28, 6938–6959. https://doi.org/10.1175/JCLI-D-14-00754.1

Caselton, W., Kan, L., & Zidek, J. V. (1992). Quality data networks that minimize entropy. In Walden, A. T. & Guttorp, P. (Eds.), *Statistics in the Environmental and Earth Sciences*, Elsevier Science, London, 10–38.

Caselton, W. & Zidek, J. (1984). Optimal monitoring network designs. *Statistics & Probability Letters*, 2(4), 223–227.

Chapman, D. & El-Shaarawi, A. (1989). *Statistical Methods for the Assessment of Point Source Pollution*, Kluwer Academic Publishers, Dordrecht.

Cressie, N. (1993). *Statistics for Spatial Data*, Revised ed., John Wiley, New York.

Cumming, S. G. (2001). A parametric model of the fire-size distribution. *Canadian Journal of Forest Research*, 31(8), 1297–1303.

Cunningham, A. A. & Martell, D. L. (1973). A stochastic model for the occurrence of man-caused forest fires. *Canadian Journal of Forest Research*, 3(2), 282–287.

Dean, C. B., Braun, W. J., Martell, D., & Woolford, D. (2012). Interdisciplinary training in a collaborative research environment. In Wachowicz, M. & Chrisman, N. (Eds.), *The Added Value of Scientific Networking: Perspectives from the GEOIDE Network Members 1998-2012*, GEOIDE Network, Québec. https://doi.org/10.7939/R3ZS2KK4T

Dean, C. B., Nathoo, F., & Nielsen, J. D. (2007). Spatial and mixture models for recurrent event processes. *Environmetrics*, 18(7), 713–725.

Dean, C. B. & Renouf, E. M. (2021). Joint outcome modeling in environmetrics. *Environmetrics*, 32(6), https://onlinelibrary.wiley.com/doi/toc/10.1002/(ISSN)1099-095X.Joint-Outcome-Modeling.

Delury, D. B. (1947). On the estimation of biological populations. *Biometrics*, 3(4), 145–167.

El-Shaarawi, A. & Hunter, J. (2006). Environmetrics overview. In El-Shaarawi, A. H. & Piegorsch, W. W. (Eds.), *Encyclopedia of Environmetrics*, 2nd ed., John WIley & Sons, West Sussex, England.

El-Shaarawi, A. & Kwiatkowski, R. (1986). Statistical aspects of water quality monitoring: Proceedings of a workshop held at Canada Centre for Inland Waters, October 7-10, 1985. *Developments in Water Science*, 27.

El-Shaarawi, A. H. & Esterby, S. R. (1982). Time series methods in hydrosciences, proceedings of an international conference held at Canada Centre for Inland Waters, Burlington, Ontario, Canada, October 6-8, 1981. *Developments in Water Science*, 17.

Esterby, S. (2018). A window on The International Environmetrics Society: The first 25 international conferences. *Environmetrics*, 29, 5–6.

Eyring, V., Gillett, N. P., Achuta Rao, K. M., Barimalala, R., Barreiro Parrillo, M., Bellouin, N., & Cassou, C. et al. (2021). Human influence on the climate system. In Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N. et al. (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, UK, New York, USA, 423–552.

Feng, C. X. & Dean, C. B. (2012). Joint analysis of multivariate spatial count and zero-heavy count outcomes using common spatial factor models. *Environmetrics*, 23(6), 493–508.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W., & Cox, P. (2013). Evaluation of climate models. In Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Doschung, J., Nauels, A., Xia, Y., Bex, V., & Midgley, P. M. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, New York.

Fourier, J.-B. J. (1827). Mémoire sur les Températures du Globe Terrestre et des Espaces Planétaires. *Mémoires d l'Académie Royale des Sciences de l'Institute de France VII*, Paris, 570–604.

Fournier, D. & Archibald, C. (1982). A general theory for analyzing catch at age data. *Canadian Journal of Fisheries and Aquatic Sciences*, 39, 1195–1203.

Fu, A., Le, N.D. & Zidek, J.V. (2003). *A statistical characterization of a simulated Canadian annual maximum rainfall field*. Technical report, TR 2003-17, Statistical and Mathematical Sciences Institute, RTP, NC.

Garcia, T., Braun, W. J., Bryce, R., & Tymstra, C. (2008). Smoothing and bootstrapping the PROMETHEUS fire growth model. *Environmetrics*, 19(8), 836–848.

Genest, C. & Favre, A.-C. (2007). Everything you always wanted to know about copula modeling but were afraid to ask. *Journal of Hydrologic Engineering*, 12, 347–368.

Genest, C. & Rivest, L.-P. (1989). A characterization of Gumbel's family of extreme value distributions. *Statistics and Probability Letters*, 8, 207–211.

Gillett, N. P., Cannon, A. J., Malinina, E., Schnorbus, M., Anslow, F., Sun, Q., Kirchmeier-Young, M. et al. (2022). Human influence on the 2021 British Columbia floods. *Weather and Climate Extremes*, 36, 100441. https://doi.org/10.1016/j.wace.2022.100441

Gillett, N. P., Weaver, A. J., Zwiers, F. W., & Flannigan, M. D. (2004). Detecting the effect of climate change on Canadian forest fires. *Geophysical Research Letters*, 31(18), L18211.

Green, R. H. & Young, R. C. (1993). Sampling to detect rare species. *Ecological Applications*, 3(2), 351–356.

Han, L. & Braun, W. J. (2014). Dionysus: A stochastic fire growth scenario generator. *Environmetrics*, 25(6), 431–442.

Hanes, C. C., Wang, X., Jain, P., Parisien, M. A., Little, J. M., & Flannigan, M. D. (2019). Fire-regime changes in Canada over the last half century. *Canadian Journal of Forest Research*, 49(3), 256–269.

Hannart, A., Pearl, J., Otto, F. E. L., Naveau, P., & Ghil, M. (2015). Causal counterfactual theory for the attribution of weather and climate-related events. *Bulletin of the American Meteorological Society*, 97(1), 99–110. https://doi.org/10.1175/BAMS-D-14-00034.1

Heffernan, J. E. & Tawn, J. A. (2004). A conditional approach for multivariate extreme values (with discussion). *Journal of the Royal Statistical Society, Series B*, 66, 497–546.

Hegerl, G. C., Zwiers, F. W., Braconnot, P., Gillett, N., Marengo, J., Nicholls, N., Penner, J., Stott, P., & Lou, Y. (2007). Understanding and attributing climate change. In Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., & Miller, H. L. (Eds.), *Climate Change 2007: The physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Washington, DC.

Hegerl, G. C., Zwiers, F. W., Stott, P. A., & Kharin, V. V. (2004). Detectability of anthropogenic changes in temperature and precipitation extremes. *Journal of Climate*, 17, 3683–3700.

Hiebert, J., Cannon, A., Schoeneberg, S., Sobie, S., & Murdock, T. (2018). ClimDown: Climate downscaling in R. *Journal of Open Source Software*, 3, 360. https://doi.org/10.21105/joss.00360

Hilborn, R. & Walters, C. (1992). *Quantitative Fisheries Stock Assessment: Choice, Dynamics & Uncertainty*, Springer Science & Business Media, Dordrecht.

Huang, W., Monahan, A., & Zwiers, F. W. (2021). Estimating concurrent climate extremes: A conditional approach. *Weather and Climate Extremes*, 33, 100332. https://doi.org/10.1016/j.wace.2021.100332

Hutchings, J. & Myers, R. (1994). What can be learned from the collapse of a renewable resource? Atlantic cod, Gadus morhua, of Newfoundland and Labrador. *Canadian Journal of Fisheries and Aquatic Sciences*, 51(9), 2126–2146.

IPCC (2021). Summary for policymakers. In Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N. et al. (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jain, P., Coogan, S. C., Subramanian, S. G., Crowley, M., Taylor, S., & Flannigan, M. D. (2020). A review of machine learning applications in wildfire science and management. *Environmental Reviews*, 28(4), 478–505.

Joe, H., Li, H., & Nikoloulopoulos, A. K. (2010). Tail dependence functions and vine copulas. *Journal of Multivariate Analysis*, 101, 252–270. https://doi.org/10.1016/j.jmva.2009.08.002

Johnston, L. M., Wang, X., Erni, S., Taylor, S. W., McFayden, C. B., Oliver, J. A., Stockdale, C. et al. (2020). Wildland fire risk research in Canada. *Environmental Reviews*, 28(2), 164–186.

Jones, A., Zidek, J. V. & Watson, J. (2022). Preferential monitoring site location in the Southern California Air Quality Basin (in preparation).

Kharin, V. V., Zwiers, F. W., Zhang, X., & Hegerl, G. C. (2007). Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations. *Journal of Climate*, 20, 1419–1444.

Kharin, V. V., Zwiers, F. W., Zhang, X., & Wehner, M. (2013). Changes in temperature and precipitation extremes in the CMIP5 ensemble. *Climatic Change*, 119(2), 345–357.

Kirchmeier-Young, M. C., Gillett, N. P., Zwiers, F. W., Cannon, A. J., & Anslow, F. S. (2019). Attribution of the influence of human-induced climate change on an extreme fire season. *Earth's Future*, 7(1), 2–10.

Kirchmeier-Young, M. C., Zwiers, F. W., & Gillett, N. P. (2017). Attribution of extreme events in Arctic sea-ice extent. *Journal of Climate*, 30, 553–571. https://doi.org/10.1175/JCLI-D-16-0412.1

Kirchmeier-Young, M. C., Zwiers, F. W., Gillett, N. P., & Cannon, A. J. (2017). Attributing extreme fire risk in Western Canada to human emissions. *Climatic Change*, 144(2), 365–379.

Kourtz, P. H. & Todd, J. B. (1991). Predicting the daily occurrence of lightning-caused forest fires. In *Forestry Canada, Petawawa National Forestry Institute*, Information Report PI-X-112, Chalk River, Ontario.

Kushner, P. J., Mudryk, L. R., Merryfield, W., Ambadan, J. T., Berg, A., Bichet, A., Brown, R. et al. (2018). Assessment of snow, sea ice, and related climate processes in Canada's Earth System Model and Climate Prediction System. *The Cryosphere*, 12, 1137–1156. https://doi.org/10.5194/tc-2017-157

Le, N., Sun, W., & Zidek, J. (2002). Bayesian multivariate spatial interpolation with data missing by design. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 59(2), 501–510.

Le, N. & Zidek, J. (1992). Interpolation with uncertain spatial covariances: A Bayesian alternative to kriging. *Journal of Multivariate Analysis*, 43, 351–374.

Le, N., Zidek, J., White, R., Cubranic, D., Sampson, P.D. & Guttorp, P. (2015). *Envirostat: Statistical analysis of environmental space-time processes*. R package version 0.4-2. Available online at: https://CRAN.R-project.org/package=EnviroStat

Li, C., Zwiers, F. W., Zhang, X., Chen, G., Lu, J., Li, G., Norris, J., & Tan, Y. (2019a). Larger increases in more extreme local precipitation events in a warming climate. *Geophysical Research Letters*, 46(12), 6885–6891. https://doi.org/10.1029/2019GL082908

Li, C., Zwiers, F. W., Zhang, X., & Li, G. (2019b). How much information is required to well-constrain local estimates of future precipitation extremes? *Earth's Future*, 7(1), 11–24. https://doi.org/10.1029/2018EF001001

Li, C., Zwiers, F. W., Zhang, X., Li, G., Sun, Y., & Wehner, M. (2021). Changes in annual extremes of daily temperature and precipitation in CMIP6 models. *Journal of Climate*, 34(9), 3441–3460. https://doi.org/10.1175/JCLI-D-19-1013.1

Liu, Y., Shaddick, G., & Zidek, J. V. (2016). Incorporating high-dimensional exposure modelling into studies of air pollution and health. *Statistics in Biosciences*, 9(2), 559–581. https://doi.org/10.1007/s12561-016-9150-3

MacDonald, P. D. M. & Smith, H. D. (1980). *Mark-Recapture Estimation of Salmon Smolt Runs*, Biometrics, September, 401–417.

Magnussen, S. & Taylor, S. W. (2012). Prediction of daily lightning-and human-caused fires in British Columbia. *International Journal of Wildland Fire*, 21(4), 342–356.

Malamud, B. D., Morein, G., & Turcotte, D. L. (1998). Forest fires: An example of self-organized criticality. *Science*, 281, 1840–1842.

Manabe, S. & Wetherald, R. T. (1967). Thermal equilibrium of the atmosphere with a given distribution of relative humidity. *Journal of the Atmospheric Sciences*, 24, 241–259.

McDonald, R., Keith, D., Sameoto, J., Hutchings, J., & Mills Flemming, J. (2021a). Explicit incorporation of spatial variability in a biomass dynamics assessment model. *ICES Journal of Marine Science*, 78(9), 3265–3280.

McDonald, R., Keith, D., Sameoto, J., Hutchings, J., & Mills Flemming, J. (2021b). Incorporating intra-annual variability in fisheries abundance data to better capture population dynamics. *Fisheries Research*, 246, 106152.

McFayden, C. B., Woolford, D. G., Stacey, A., Boychuk, D., Johnston, J. M., Wheatley, M. J., & Martell, D. L. (2019). Risk assessment for wildland fire aerial detection patrol route planning in Ontario. *Canada. International Journal of Wildland Fire*, 29(1), 28–41.

Min, S.-K., Zhang, X., Zwiers, F. W., & Hegerl, G. C. (2011). Human contribution to more intense precipitation events. *Nature*, 470, 378–381. https://doi.org/10.1038/nature09763

Mitchell, J. F. B., Karoly, D. J., Hegerl, G. C., Zwiers, F. W., Allen, M. R., & Marengo, J. (2001). Detection of climate change and attribution of causes. In Houghton, J. T., Ding, Y., Griggs, D. J., Noguer, M., van der Linden, P., Dai, X., Maskell, M., & Johnson, C. A. (Eds.), *Climate Change 2001: The Physical Science Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Mohn, R. (1999). The retrospective problem in sequential population analysis: An investigation using cod fishery and simulated data. *ICES Journal of Marine Science*, 56(4), 473–488.

Morin, A. A., Albert-Green, A., Woolford, D. G., & Martell, D. L. (2015). The use of survival analysis methods to model the control time of forest fires in Ontario, Canada. *International Journal of Wildland Fire*, 24(7), 964–973.

Morin, A. A., Albert-Green, A., Woolford, D. G., & Martell, D. L. (2019). Frailty models for the control time of wildland fires in the former intensive fire management zone of Ontario, Canada. *Journal of Environmental Statistics*, 9(5), 1–16.

Murphy, A. H. & Zwiers, F. W. (1993). International meetings on statistical climatology, meeting review. *Bulletin of the American Meteorological Society*, 79, 1721–1727.

Nadeem, K., Taylor, S. W., Woolford, D. G., & Dean, C. B. (2019). Mesoscale spatiotemporal predictive models of daily human-and lightning-caused wildland fire occurrence in British Columbia. *International Journal of Wildland Fire*, 29(1), 11–27.

NAS (2016). *Attribution of Extreme Weather Events in the Context of Climate Change*, National Academies Press, Washington, DC. https://doi.org/10.17226/21852 (Zwiers was a committee member).

National Research Council (1979). *Carbon Dioxide and Climate: A Scientific Assessment*, The National Academies Press, Washington, DC. https://doi.org/10.17226/12181

Phelps, N. & Woolford, D. G. (2021a). Guidelines for effective evaluation and comparison of wildland fire occurrence prediction models. *International Journal of Wildland Fire*, 30(4), 225–240.

Phelps, N. & Woolford, D. G. (2021b). Comparing calibrated statistical and machine learning methods for wildland fire occurrence prediction: A case study of human-caused fires in Lac La Biche, Alberta, Canada. *International Journal of Wildland Fire*, 30, 850–870.

Philip, S. Y., Kew, S. F., van Oldenborgh, G. J., Anslow, F. S., Seneviratne, S. I., Vautard, R., Coumou, D. et al. (2021). Rapid attribution analysis of the extraordinary heatwave on the Pacific Coast of the US and Canada June 2021. *Earth System Dynamics Discussion*, 12, 1–34. https://doi.org/10.5194/esd-2021-90

Pierrehumbert, R. T. (2004). Warming the world. *Nature*, 432, 677. https://doi.org/10.1038/432677a

Plante, N., Rivest, L. P., & Tremblay, G. (1998). Stratified capture-recapture estimation of the size of a closed population. *Biometrics*, 54, 47–60.

Podur, J. J., Martell, D. L., & Knight, K. (2002). Statistical quality control analysis of forest fire activity in Canada. *Canadian Journal of Forest Research*, 32(2), 195–205.

Podur, J. J., Martell, D. L., & Stanford, D. (2010). A compound Poisson model for the annual area burned by forest fires in the province of Ontario. *Environmetrics*, 21(5), 457–469.

Reed, W. J. (1984). The effects of the risk of fire on the optimal rotation of a forest. *Journal of Environmental Economics and Management*, 11(2), 180–190.

Reed, W. J. (1994). Estimating the historic probability of stand-replacement fire using the age-class distribution of undisturbed forest. *Forest Science*, 40(1), 104–119.

Reed, W. J. (1998). Determining changes in historical forest fire frequency from a time-since-fire map. *Journal of Agricultural, Biological, and Environmental Statistics*, 1, 430–450.

Reed, W. J. (2000). Reconstructing the history of forest fire frequency: Identifying hazard rate change points using the Bayes information criterion. *Canadian Journal of Statistics*, 28(2), 353–365.

Reed, W. J. (2006). A note on fire frequency concepts and definitions. *Canadian Journal of Forest Research*, 36(7), 1884–1888.

Reed, W. J. & Errico, D. (1986). Optimal harvest scheduling at the forest level in the presence of the risk of fire. *Canadian Journal of Forest Research*, 16(2), 266–278.

Reed, W. J. & Hughes, B. D. (2003). Power-law distribution from exponential processes: An explanation for the occurrence of long-tailed distributions in biology and elsewhere. *Scientiae Mathematicae Japonicae*, 58(2), 473–484.

Reed, W. J. & McKelvey, K. S. (2002). Power-law behaviour and parametric models for the size-distribution of forest fires. *Ecological Modelling*, 150(3), 239–254.

Resende-Casquilho, C., Le, N. & Zidek, J. (2016). Spatio-temporal modelling of temperature fields in the Pacific Northwest. arXiv preprint, arXiv:1604.00572.

Resende-Casquilho, C., Le, N., Zidek, J. V., & Wang, W. (2017). Design of monitoring networks using K-Determinantal point processes. *Environmetrics*, 29, e2483.

Ribes, A., Planton, S., & Terray, L. (2013). Application of regularized optimal fingerprinting to attribution. Part I: Method, properties and idealized analysis. *Climate Dynamics*, 4, 2817–2836. https://doi.org/10.1007/s00382-013-1735-7

Richards, F. J. (1959). A flexible growth function for empirical use. *Journal of Experimental Botany*, 10(2), 290–301.

Ricker, W. (1954). Stock and recruitment. *Journal of the Fisheries Board of Canada*, 11(5), 559–623.

Ricker, W. (1958). Maximum sustained yields from fluctuating environments and mixed stocks. *Journal of the Fisheries Board of Canada*, 5(5), 991–1006.

Ricker, W. (1975). Computation and interpretation of biological statistics of fish populations. *Bulletin of the Fisheries Research Board of Canada*, 191, 1–382.

Rougier, J., Goldstein, M., & House, L. (2013). Second-order exchangeability analysis for multimodel ensembles. *Journal of the American Statistical Association*, 108, 852–863. https://doi.org/10.1080/01621459.2013.802963

Sampson, P. & Guttorp, P. (1992). Nonparametric estimation of nonstationary spatial covariance structure. *Journal of the American Statistical Association*, 87, 108–119.

Schnute, J. (1985). A general theory for analysis of catch and effort data. *Canadian Journal of Fisheries and Aquatic Sciences*, 42(3), 414–429.

Schoenberg, F. P., Peng, R., & Woods, J. (2003). On the distribution of wildfire sizes. *Environmetrics*, 14(6), 583–592.

Schumacher, P. & Zidek, J. (1993). Using prior information in designing intervention detection experiments. *The Annals of Statistics*, 1, 447–463.

Schwarz, C. & Seber, G. (1999). A review of estimating animal abundance III. *Statistical Science*, 14(4), 427–456.

Schwarz, C. J. & Arnason, A. N. (1996). A general methodology for the analysis of capture-recapture experiments in open populations. *Biometrics*, 52, 860–873.

Scinocca, J. F., Kharin, V. V., Jiao, Y., Qian, M. W., Lazare, M., Solheim, L., Flato, G. M. et al. (2016). Coordinated global and regional climate modeling. *Journal of Climate*, 29, 17–35. https://doi.org/10.1175/JCLI-D-15-0161.1

Seneviratne, S., Zhang, X., Hauser, M., Kirchmeier-Young, M., Alexander, L. V., Allan, R. P., Almazroui, M. et al. (2021). Weather and climate extreme events in a changing climate. In Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N. et al. (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Shaddick, G. & Zidek, J. V. (2014). A case study in preferential sampling: Long term monitoring of air pollution in the UK. *Spatial Statistics*, 9, 951–965.

Shaddick, G., Zidek, J. V., & Liu, Y. (2016). Mitigating the effects of preferentially selected monitoring sites for environmental policy and health risk analysis. *Spatial and Spatio-temporal Epidemiology*, 18, 44–52.

Song, J., Pan, R., Yi, W., Wei, Q., Qin, W., Song, S., Tang, C. et al. (2021). Ambient high temperature exposure and global disease burden during 1990–2019: An analysis of the Global Burden of Disease Study 2019. *Science of The Total Environment*, 787, 147540. https://doi.org/10.1016/j.scitotenv.2021.147540

Stocks, B. J., Lawson, B. D., Alexander, M. E., VanWagner, C. E., McAlpine, R. S., Lynham, T. J., & Dube, D. E. (1989). The Canadian forest fire danger rating system: An overview. *The Forestry Chronicle*, 65, 450–457.

Stott, P. A., Stone, D. A., & Allen, M. R. (2004). Human contribution to the European heatwave of 2003. *Nature*, 432, 610–614.

Sun, Q., Zhang, X., Zwiers, F. W., & Yan, J. (2022). Quantifying the human influence on the intensity of extreme 1- and 5-day precipitation amounts at global, continental, and regional scales. *Journal of Climate*, 35, 195–210. https://doi.org/10.1175/JCLI-D-21-0028.1

Sun, Y., Zhang, X., Ren, G., Zwiers, F. W., & Hu, T. (2016). Contribution of urbanization to warming in China. *Nature Climate Change*, 6(7), 706–709. https://doi.org/10.1038/NCLIMATE2956

Taylor, S. W., Woolford, D. G., Dean, C. D., & Martell, D. L. (2013). Wildfire prediction to inform fire management: Statistical science challenges. *Statistical Science*, 28(4), 586–615.

Tebaldi, C. & Knutti, R. (2007). The use of the multi-model ensemble in probabilistic climate projections. *Philosophical Transactions of the Royal Society A*, 365, 2053–2075. https://doi.org/10.1098/rsta.2007.2076

Teufel, B., Diro, G. T., Whan, K., Milrad, S. M., Jeong, D. I., Ganji, A., Huziy, O. et al. (2016). Investigation of the 2013 Alberta flood from a weather/climate perspective. *Climate Dynamics*, 48(9), 2881–2899. https://doi.org/10.1007/s00382-016-3239-8

Teufel, B., Sushama, L., Huzly, O., Diro, G. T., Jeong, D. I., Winger, K., Garnaud, C. et al. (2018). Investigation of the mechanisms leading to the 2017 Montreal flood. *Climate Dynamics*, 52(7), 4193–4206. https://doi.org/10.1007/s00382-018-4375-0

Thompson, J. R. & Braun, W. J. (2020). Anisotropic local constant smoothing for change-point regression function estimation. arXiv preprint arXiv:2012.00180.

Tremblay, P. O., Duchesne, T., & Cumming, S. G. (2018). Survival analysis and classification methods for forest fire size. *PLoS one*, 13(1), e0189860.

Tymstra, C., Bryce, R. W., Wotton, B. M., Taylor, S. W., & Armitage, O. B. (2010). *Development and Structure of Prometheus: The Canadian Wildland Fire Growth Simulation Model*, Information Report NOR-X-417, *Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre*, Edmonton, Alberta.

VanWagner, C. E. (1987). *The Development and Structure of the Canadian Forest Fire Weather Index System*, Forestry Technical Report-35, *Canadian Forest Service, Petawawa National Forestry Institute*, Chalk River, Ottawa.

von Storch, H. & Zwiers, F. W. (1999). *Statistical Analysis in Climate Research*, Cambridge University Press, Cambridge, England.

Wachowicz, M. & Chrisman, N. (2012). The added value of scientific networking. In *Perspectives from the GEOIDE Network Members 1998-2012*. GEOIDE Network, Québec. https://doi.org/10.7939/R3ZS2KK4T

Wan, V., Braun, W. J., Dean, C. B., & Henderson, S. (2011). A comparison of classification algorithms for the identification of smoke plumes from satellite images. *Statistical Methods in Medical Research*, 20(2), 131–156.

Wang, X., Parisien, M.-A., Taylor, S. W., Candau, J.-N., Stralberg, D., Marshall, G., Little, J., & Flannigan, M. D. (2017). Projected changes in daily fire spread across Canada over the next century. *Environmental Research Letters.*, 12(2), 025005. https://doi.org/10.1088/1748-9326/aa5835

Wang, X., Parisien, M.-A., Taylor, S. W., Perakis, D. D., Little, J. M., & Flannigan, M. D. (2016). Future burn probability in south-central British Columbia. *International Journal of Wildland Fire*, 25, 200–212.

Wang, X. J., Thompson, J. R., Braun, W. J., & Woolford, D. G. (2019). Fitting a stochastic fire spread model to data. *Advances in Statistical Climatology, Meteorology and Oceanography*, 5(1), 57–66.

Wang, Z., Jiang, Y., Wan, H., Yan, J., & Zhang, X. (2020). Toward optimal fingerprinting in detection and attribution of changes in climate extremes. *Journal of the American Statistical Association*, 116(533), 1–13. https://doi.org/10.1080/01621459.2020.1730852

Watson, J. (2021). A perceptron for detecting the preferential sampling of locations and times chosen to monitor a spatio-temporal process. *Spatial Statistics*, 43, 100500. https://doi.org/10.1016/j.spasta.2021.100500

Watson, J., Zidek, J., & Shaddick, G. (2019). A general theory for preferential sampling in environmental networks. *Annals of Applied Statistics.*, 13, 2682–2700.

WMO, 1988 *Proceedings, World conference, Toronto, Canada June 27-30, 1988: The Changing Atmosphere: Implications for Global Security*. World Meteorological Organization, WMO/710. Available from: https://digitallibrary.un.org/record/106359?ln=en

Wolters, M. A. & Dean, C. B. (2017). Classification of large-scale remote sensing images for automatic identification of health hazards. *Statistics in Biosciences*, 9(2), 622–645.

Wong, S. W. & Zidek, J. V. (2019). The duration of load effect in lumber as stochastic degradation. *IEEE Transactions on Reliability*, 68(2), 410–419.

Woolford, D. G., Bellhouse, D. R., Braun, W. J., Dean, C. B., Martell, D. L., & Sun, J. (2011). A spatio-temporal model for people-caused forest fire occurrence in the Romeo Malette Forest. *Journal of Environmental Statistics*, 2, 2–16.

Woolford, D. G. & Braun, W. J. (2007). Convergent data sharpening for the identification and tracking of spatial temporal centers of lightning activity. *Environmetrics*, 18(5), 461–479.

Woolford, D. G., Dean, C. B., Martell, D. L., Cao, J., & Wotton, B. M. (2014). Lightning-caused forest fire risk in northwestern Ontario, Canada, is increasing and associated with anomalies in fire weather. *Environmetrics*, 25(6), 406–416.

Woolford, D. G., Martell, D. L., McFayden, C. B., Evens, J., Stacey, A., Wotton, B. M., & Boychuk, D. (2021). The development and implementation of a human-caused wildland fire occurrence prediction system for the province of Ontario, Canada. *Canadian Journal of Forest Research*, 51(2), 303–325.

Wotton, B. M., Flannigan, M. D., & Marshall, G. (2017). Potential climate change impacts on fire intensity and key wildfire suppression thresholds in Canada. *Environmental Research Letters*, 12, 095003. https://doi.org/10.1088/1748-9326/aa7e6e

Wotton, B. M. & Martell, D. L. (2005). A lightning fire occurrence model for Ontario. *Canadian Journal of Forest Research*, 35(6), 1389–1401.

Xi, D. D., Taylor, S. W., Woolford, D. G., & Dean, C. B. (2019). Statistical models of key components of wildfire risk. *Annual Review of Statistics and its Application*, 32(6), 197–222.

Xi, D. D. Z., Dean, C. B., & Taylor, S. W. (2020). Modeling the duration and size of extended attack wildfires as dependent outcomes. *Environmetrics*, 31(5), e2619.

Xi, D. D. Z., Dean, C. B., & Taylor, S. W. (2021). Modeling the duration and size of wildfires using joint mixture models. *Environmetrics*, e2685.

Yin, Y., Aeberhard, W., Smith, S., & Mills Flemming, J. (2019). Identifiable state-space assessment models, a case study of the Bay of Fundy sea scallop fishery. *Canadian Journal of Statistics*, 47(1), 27–45.

Zhang, X., Wan, H., Zwiers, F. W., Hegerl, G. C., & Min, S. K. (2013). Attributing intensification of precipitation extremes to human influence. *Geophysical Research Letters*, 40, 5252–5257. https://doi.org/10.1002/grl.51010

Zhang, X., Zwiers, F. W., Hegerl, G. C., Lambert, F. H., Gillett, N. P., Solomon, S., Stott, P. A., & Nozawa, T. (2007). Detection of human influence on twentieth-century precipitation trends. *Nature*, 448, 461–465. https://doi.org/10.1038/nature06025

Zidek, J. V., Shaddick, G., & Taylor, C. G. (2014). Reducing estimation bias in adaptively changing monitoring networks with preferential site selection. *Annals of Applied Statistics*, 3, 1640–1670.

Zidek, J. V. & Zimmerman, D. L. (2010). Monitoring network design. In *Handbook of Spatial Statistics*, CRC Press Boca Raton, Florida, 131–148.

Zimmerman, D. L. (2006). Optimal network design for spatial prediction, covariance parameter estimation, and empirical prediction. *Environmetrics*, 17(6), 635–652.

Zwiers, F. W. & Kharin, V. V. (1998). Changes in the extremes of the climate simulated by CCC GCM2 under CO2 doubling. *Journal of Climate*, 11, 2200–2222.

Zwiers, F. W. & Zhang, X. (2021). Translating science into actionable policy information–a perspective on the IPCC process. In Woolford, D., Kotsopoulos, D., & Samuels, B. (Eds.), *Applied Data Science: Data Translators Across the Disciplines*, Springer, Interdisciplinary Applied Sciences.

Zwiers, F. W., Zhang, X., & Feng, Y. (2011). Anthropogenic influence on long return period daily temperature extremes at regional scales. *Journal of Climate*, 24, 881–892. https://doi.org/10.1175/2010JCLI3908.1

Received 9 February 2022
Accepted 29 June 2022