

Dissertation for the degree of doctor of philosophy

Statistical analysis of trends in data from ecological monitoring

Erla Sturludóttir



UNIVERSITY OF ICELAND

School of Engineering and Natural Sciences

Faculty of Physical Sciences

Reykjavík, May 2015

Dissertation submitted in partial fulfilment of a *Philosophiae Doctor* degree in
Statistics

Doctoral committee

Prof. Gunnar Stefánsson, advisor
University of Iceland

Dr. Helga Gunnlaugsdóttir
Matís ltd.

Dr. Ólafur K. Nielsen
Icelandic Institute of Natural History

Dr. Kristín Ólafsdóttir
University of Iceland

Opponents

Dr. Thor Aspelund
University of Iceland &
Icelandic Heart Association

Dr. Anders Bignert
Swedish Museum of Natural History

Statistical analysis of trends in data from ecological monitoring
© 2015 Erla Surludóttir

Printed in Iceland by Háskólaprent
ISBN 978-9935-9263-1-9

Abstract

The overall objective of this study was to develop statistical methods to detect trends with applications to two ecological monitoring programs, a) monitoring of contaminants in the marine environment around Iceland and b) monitoring of the population of the rock ptarmigan in Iceland. Polynomial models were used to account for trends with no consistent direction, mixed models were used to analyze data from multiple sites simultaneously and to describe correlations between observations. A changepoint (CP) model was investigated and a new method proposed which takes autocorrelation into account when detecting a CP in short time-series. A population reconstruction model was developed for the ptarmigan population in NE-Iceland which allows for the possibility of including a CP. The statistical analyses revealed that the concentration of the persistent organic pollutants have been decreasing both in mussel and cod over the recent years. However, there were signs of local pollution that could be traced back to a whaling station, aquaculture and waste incinerator. There was no consistent trend for the trace elements. A population reconstruction model was developed for the population of the rock ptarmigan in Iceland. It estimates the abundance, natural survival and hunting mortality for two age groups. This model allows for the possibility of modeling the natural survival as a function of density and the hunting mortality as functions of either density or hunting effort with a CP. A CP was included in the function for hunting mortality in 2003 when the hunting regulations were changed. The model indicates that changes in the hunting regulation did indeed have an effect in reducing the hunting mortality and also changing the harvest strategies of hunters. Still, management goal of reducing the total annual mortality to 37% has not been achieved and a further change in regulation may be needed.

Ágrip

Markmið verkefnisins var að þróa tölfræðiaðferðir til að finna breytingar í tímaröðum frá tveimur vöktunarverkefnum, a) vöktun á mengun í lífríki sjávar við Ísland og b) vöktun íslenska rjúpnastofnsins. Margliðulíkön voru notuð til að greina breytingar, blönduð líkön voru notuð til að greina gögn frá mörgum vöktunarstöðum samtímis og til að taka tillit til fylgni á milli mælinga. Aðferð til að greina breytipunkta í stuttum tímaröðum með sjálffylgni var þróuð. Stofnlíkan fyrir rjúpuna sem leyfir breytipunkta var aðlagð fyrir rjúpnastofninn á NA-landi. Tölfræðigreiningarnar leiddu í ljós að styrkur þrávirkra lífrænna efna sem mældur er í kræklingi og þorski hefur farið minnkandi síðastliðin ár. Þó sáust merki um staðbundna mengun sem hægt var að rekja til hvalveiða, fiskeldis og sorpbrennslu. Breytingar í styrk snefilefna voru mjög mismunandi eftir efnum. Stofnlíkan var þróað fyrir íslenska rjúpnastofninn og metur það fjölda ungfugla og fullorðinna fugla, náttúrulega lifun og veiðiafföll. Hægt er að líkja eftir lifun með falli af þéttleika og veiðiafföllum með föllum af annað hvort þéttleika eða fjölda veiðimanna, einnig er hægt að setja breytipunkt inn í föllin og var það gert þegar veiðireglum var breytt árið 2003. Líkanið sýndi fram á að breyting á veiðireglum hafði áhrif með því að minnka veiðaföll. Þó hefur markmiðum um að ná heildaraföllum niður í 37% ekki náðst og frekari breytingar á reglum gæti verið nauðsynleg.

Contents

List of Figures	xi
List of Tables	xv
List of Publications	xvii
Acknowledgements	xix
I Thesis	1
1 Introduction	3
1.1 Monitoring of ecosystems	3
1.2 Definition of a trend	4
1.3 Analyzing trends	4
1.4 Ecological monitoring programs	5
1.4.1 Monitoring of contaminants in the marine environment around Iceland	5
1.4.2 Monitoring of the rock ptarmigan in NE-Iceland	6
2 Objectives	9
3 Statistical analysis	11
3.1 Polynomial regression	11
3.2 Mixed models	13
3.2.1 Monitoring at multiple sites	13
3.2.2 Intra-class correlation	15
3.3 Changepoint model	16
3.4 Population reconstruction model	17

3.5	Statistical issues	20
3.5.1	The normal assumption	20
3.5.2	Autocorrelation	21
3.5.3	Statistical power	22
3.5.4	Covariates	24
3.5.5	Observations under limit of detection	24
4	Results	27
4.1	Trends in contaminant concentrations	27
4.1.1	Trends in contaminants measured in mussel	27
4.1.2	Trends in contaminants measured in cod	28
4.2	Trends in population parameters of the rock ptarmigan	31
4.2.1	Changepoint in annual mortality	31
4.2.2	Population dynamics	32
5	Conclusion and future perspectives	35
II	Papers	39
6	Paper I: Spatial and temporal trends of contaminants in mussel sampled around the Icelandic coastline	41
6.1	Introduction	43
6.2	Materials and methods	44
6.2.1	Sampling method and locations	44
6.2.2	Chemical analysis	46
6.2.3	Statistical analysis	47
6.3	Results	49
6.3.1	Spatial and temporal trends of POPs	49
6.3.2	Spatial and temporal trends of trace elements	53
6.4	Discussion	57
6.4.1	Concentrations of contaminants	57
6.4.2	Temporal trends of contaminants	58
6.4.3	Local sources	59
6.5	Conclusion	60
7	Paper II: Temporal trends of contaminants in cod from Icelandic waters	63
7.1	Introduction	65

7.2	Materials and Methods	66
7.2.1	Sampling method and locations	66
7.2.2	Chemical analysis	68
7.2.3	Statistical analysis	69
7.3	Results	71
7.3.1	Temporal trends of POPs	71
7.3.2	Temporal trends of trace elements	73
7.4	Discussion	77
7.4.1	Concentrations of contaminants	77
7.4.2	Temporal trends of contaminants	79
7.4.3	Effects of biological covariates	80
7.5	Conclusion	82
8	Paper III: Detection of a changepoint, a mean-shift accompanied with a trend change, in short time-series with autocorrelation	85
8.1	Introduction	87
8.2	Changepoint model	88
8.3	Critical values from the empirical distribution	89
8.4	Testing for autocorrelation	92
8.5	Power	94
8.6	Method proposed	95
8.7	Applications	96
8.7.1	Cadmium concentration in mussel	96
8.7.2	Mortality rate of the rock ptarmigan	98
8.8	Conclusion	99
9	Paper IV: Population reconstruction model for the rock ptarmigan in NE-Iceland	101
9.1	Introduction	103
9.2	Methods	104
9.2.1	The data	104
9.2.2	The population reconstruction model	104
9.3	Results	108
9.3.1	Inclusion of age in spring	108
9.3.2	Survival and hunting mortality as functions	110
9.3.3	Changepoint	111
9.3.4	The final model	111

9.3.5	The estimated population size, survival and hunting mortality	114
9.4	Discussion	117
9.4.1	The estimated abundance	117
9.4.2	The estimated natural survival	120
9.4.3	The estimated harvest and total mortality	120
9.5	Conclusion	122
Bibliography		125

List of Figures

1.1	Sampling sites for mussel and cod in the monitoring of contaminants in Icelandic waters.	6
1.2	The study area for the monitoring of rock ptarmigan in NE-Iceland and the 6 census plots.	7
3.1	Empirical cumulative distribution of the ρ estimated from the data and ρ estimated from simulated time-series with independent and autocorrelated errors ($\rho = 0, 0.1, 0.2, 0.3$) where a) No trend is assumed b) linear trend is assumed c) quadratic trend and d) cubic trend.	23
4.1	Predicted concentrations and trends of the POPs measured in mussels at the 11 locations.	29
4.2	Predicted concentrations and trends of the trace elements measured in mussels at the 11 locations (see Figure 4.1).	30
4.3	Mortality rate (Z_2) of the adult ptarmigan from 1982 to 2012.	32
6.1	Sampling site locations and average concentrations of the POPs at each location.	45
6.2	Sampling site locations and average concentrations of As, Cd and Hg at each location (note different axes are applied for each element).	50
6.3	Predicted concentration and pattern of change of the POPs (p,p' -DDE, HCB, α -HCH, PCB-153 and <i>trans</i> -nonachlor) at the 11 locations.	54
6.4	Predicted concentration and pattern of change of the trace elements (As, Cd, Cu, Hg, Se and Zn) at the 11 locations (see Figure 6.3).	56

7.1	Sampling site locations.	67
7.2	Predicted change in concentration of the POPs (PCBs, p,p'-DDE, HCB, HCHs, CHLs and Tox) from the final models (see Table 7.2) at the NE and NW location (see Figure 7.1).	74
7.3	Predicted change in concentration of the trace elements (As, Cd, Cu, Hg, Se and Zn) from the final models (see Table 7.2) at the NE and NW location.	76
8.1	Critical values from the empirical distributions for $N=\{10, 20, 30, 50, 100\}$ assuming autocorrelation from $\rho = 0$ to $\rho = 0.9$. . .	90
8.2	Error rate when ignoring autocorrelation for time-series of length $N = 10, 20, 30, 50$ and 100	90
8.3	The bias in the estimate of the autocorrelation parameter ($\hat{\rho}$) in the changepoint model for time-series of length $N = 10, 20, 30, 50$ and 100 . The thick black line shows unbiased estimates. . . .	91
8.4	Actual error rate when using critical values from the empirical distributions for $\rho = 0.0$ and $\rho = 0.2$ when using a nominal error rate of $\alpha = 0.05$ and assuming autocorrelation for time-series of length $N = 10, 20, 30, 50$ and 100	92
8.5	Power of detecting autocorrelation in time-series of length $N=10, 20, 30, 50$ and 100	93
8.6	Error rate when using the method of testing for autocorrelation in time-series of length $N = 10, 20, 30, 50$ and 100	94
8.7	Power of detecting a CP in a time-series with a step change of $\alpha_2 - \alpha_1 = 4$ where a) $c=N/4$ and b) $c=N/2$ and the power of detecting the correct CP where c) $c=N/4$ and d) $c=N/2$	95
8.8	Power of detecting a CP in a time-series with a trend change where $\beta_1 = 0, \beta_2 = 0.4, \alpha_1 = 0$ and $\alpha_2 = \alpha_1 + (\beta_1 - \beta_2) * c$ where a) $c=N/4$ and b) $c=N/2$ and the power of detecting the correct CP where c) $c=N/4$ and d) $c=N/2$	96
8.9	Change in cadmium concentration in mussel from 1991 to 2010. .	98
8.10	Mortality rate (Z_2) of the adult ptarmigan from 1982 to 2012. . .	99
9.1	The study area for the rock ptarmigan in NE-Iceland and the 6 census plots.	106
9.2	Estimated autumn abundance of juvenile and adult rock ptarmigan in NE-Iceland from 1998 to 2012.	116

9.3	Estimated total autumn abundance of rock ptarmigan in NE-Iceland from 1998 to 2012 compared with the spring density index.	117
9.4	Estimated natural survival for juvenile and adult rock ptarmigan in NE-Iceland from 1998 to 2012.	118
9.5	Estimated mortality of juvenile and adult rock ptarmigan in NE-Iceland from 1998 to 2012. a) Estimated hunting mortality (assumed equal for juveniles and adults) and b) estimated total mortality (see Equations 9.11 and 9.10).	119
9.6	Estimation of demographic parameters of rock ptarmigans in NE-Iceland from 1998 to 2012 from Model 9.8 and using previous method described in Magnússon et al. (2005) and Nielsen (2006) of a) total abundance b) hunting mortality c) annual adult mortality and d) annual juvenile mortality.	123
9.7	The proportion of juvenile ptarmigans in the harvest, in late summer and in spring in NE-Iceland from 1998-2013.	124

List of Tables

4.1	Change in the contaminant concentrations and median concentrations measured in cod sampled NE and NW of Iceland from 1990-2011.	31
4.2	Parameter estimates from the final model with 95% confidence intervals (CI) for rock ptarmigan in NE-Iceland 1998-2012. . . .	34
6.1	The final model for each contaminant.	49
7.1	Median (and range) of age, length, liver weight and liver fat of cod sampled at the NE and NW locations from 1991-2011.	68
7.2	Final model for each contaminant where y_{ijt} is the log-concentration of a contaminant in sub-sample i at location j in year t (a = age, le = length, f = liver fat content, lw = log liver weight, γ = random effect)	72
7.3	Change in the contaminant concentrations and median concentrations at NE and NW location.	73
7.4	Increase/decrease (%) in concentration of POPs with age, length, liver fat and weight, estimates $((e^\beta - 1) * 100)$ from the final models in Table 7.2.	75
7.5	Increase/decrease (%) in concentration of trace elements with age, length, liver fat and weight, estimates $((e^\beta - 1) * 100)$ from the final models in Table 7.2.	77
8.1	Critical values for time-series of length $N = 10$ to 100 at $\rho = 0.2$	97

9.1	The data used in the population model for the rock ptarmigan in northeast Iceland. Number of juveniles aged from harvest ($a_{i,1}^h$), number of adults aged from harvest ($a_{i,2}^h$), number of juveniles aged in spring ($a_{i,1}^s$), number of adults aged in spring ($a_{i,2}^s$), number of harvested rock ptarmigans (h_i), number of hunters (f_i) and the density index (I_i) for northeast Iceland from 1998 to 2013.	105
9.2	Fitted models with number of parameters (pm) and AIC (smaller is better).	112
9.3	Description of parameters in the final model for the rock ptarmigan in NE-Iceland 1998-2012.	114
9.4	Parameter estimates (see description in Table 9.3) from Model 9.8 with 95% confidence intervals (CI) for rock ptarmigan in NE-Iceland 1998-2012.	115

List of Publications

This thesis is based on four papers and references to them will be given by their Roman numerals. These papers are the following:

Paper I: Sturludottir, E., Gunnlaugsdottir, H., Jorundsdottir, H. O., Magnussdottir, E. V., Olafsdottir, K., & Stefansson, G. (2013). Spatial and temporal trends of contaminants in mussel sampled around the Icelandic coastline. *Science of the Total Environment*, 454, 500-509.

Paper II: Sturludottir, E., Gunnlaugsdottir, H., Jorundsdottir, H.O., Magnussdottir, E.V., Olafsdottir, K., & Stefansson, G. (2014). Temporal trends of contaminants in cod from Icelandic waters. *Science of the Total Environment*, 476-477, 181-188.

Paper III: Sturludottir, E., Gunnlaugsdottir, H., Nielsen, O.K. & Stefansson, G. (2015). Detection of a changepoint , a mean-shift accompanied with a trend change, in short time-series with autocorrelation. *Communications in Statistics - Simulation and Computation*. In press.

Paper IV: Sturludottir, E., Nielsen, O.K. & Stefansson, G. Population reconstruction model for the rock ptarmigan in NE-Iceland. To be submitted.

Acknowledgements

First, I would like to express my sincere gratitude to my supervisor professor Gunnar Stefánsson for his guidance, encouragement and kindness. I would also like to thank my doctoral committee Dr. Helga Gunnlaugsdóttir, Dr. Kristín Ólafsdóttir and Dr. Ólafur K. Nielsen for their expertise and good advice. I also thank my co-authors Dr. Hrönn Ó. Jörundsdóttir and Elín V. Magnúsdóttir for their valuable work.

I thank the Science Institute at the University of Iceland, Matís and the Icelandic Institute of Natural History for providing me with excellent working conditions. This project was financially supported by Matís, the Icelandic Research Fund (Rannís), the Icelandic Research Fund for Graduate Students and by the Icelandic Hunting Fund. The financial support is gratefully acknowledged.

I would like to thank my colleagues at Matís for making my stay there very enjoyable, special thanks to Natasa Desnica and Þuríður Ragnarsdóttir for their patience and information on the data. I thank my colleagues at the Icelandic Institute of Natural History for giving great working atmosphere for the last year of my project, special thanks go to Kjartan Birgisson for his technical expertise and for turning my computer into a super-computer and to Anette Theresia Meier for map making. I also thank my fellows at Tæknigarður for their good company, special thanks to Anna Helga Jónsdóttir and Bjarki Elvarsson for their help. I would like to thank Olga Sturludóttir for taking the time to proofread and to Davíð Sturluson for fixing my computer when needed.

Finally, thanks go to my friends and family for taking such good care of me.

Part I

Thesis

1

Introduction

1.1 Monitoring of ecosystems

Ecosystems are complex and dynamic systems of plants, animals, microorganism and the abiotic environment. They provide various services for people, such as food and fibers, they control the soil formation, photosynthesis and nutrient cycles. The ecosystems have influences on climate, floods, diseases, wastes and water quality and they also provide recreational and spiritual benefits. People are dependent on these services and changes in them can affect human well-being (Millennium Ecosystem Assessment, 2003).

Ecosystem degradation has become a world wide problem (Millennium Ecosystem Assessment, 2005). Increasing consumption and increasing human population has led to a change in land use and land cover to achieve greater production of food, fiber and timber. Wetlands and forests have been converted to agricultural lands which has led to a loss in biodiversity and ecosystem services (Lambrechts et al., 2009; Russi et al., 2013). Problems associated with contaminants and waste have been increasing with negative effects on the health of humans and wildlife (AMAP, 2009). Natural resources are being overexploited, including harvesting of wildlife that are already vulnerable because of habitat loss and pollution (Venter et al., 2006). These changes in the earth's ecosystems can be both of natural and anthropogenic origin and detection of changes are important to counteract further degradation.

Ecological monitoring is the long term act of measuring variables in the

ecosystems which provides data that can be used to determine if the ecosystems are changing, how they are changing and how fast. It has been used to assess the quality of the environment and to acquire knowledge about ecosystem processes. Monitoring is essential for sustainable management of resources and efficient conservation (Nichols and Williams, 2006).

An important part of monitoring programs is statistical analysis of the data they provide. Statistical analysis can help to answer questions by testing hypothesis, such as: has there been an increase in contaminant concentration over the last two decades? Has the biodiversity decreased? Is the forest cover changing? These changes are often called trends and a common practice in monitoring programs is to detect trends in time-series.

1.2 Definition of a trend

There is no consensus in the literature on what a trend is (Franzke, 2012; Wu et al., 2007) but the general definition of a trend is a long term change in the mean value over some period of time (Chandler and Scott, 2011). Trend has been defined in various ways: it has been defined as a linear change, monotone decreasing or increasing (Wu et al., 2007), cyclic and seasonal trend (Cryer and Chan, 2008) or as a change with no consistent direction. Some have distinguished a change with no consistent direction from a trend and called it fluctuations (Robson, 2002). A trend in the mean value of a time-series Y_1, Y_2, \dots, Y_T could be defined as $E[Y_t] = \mu_t$ as done in Diggle (1990) where μ_t is the mean at time t . If there is no trend in the time-series all of the μ_t are equal but if there is a trend they are not all equal. In this thesis the definition of a trend is taken as in Diggle (1990), therefore the trend can be monotone decreasing or increasing or with no consistent direction, which is often referred to as fluctuations or pattern of change.

1.3 Analyzing trends

Many statistical methods exist to detect trends in time-series from monitoring programs (Bignert, 2003; Thomas, 1996). What method to use depends on the aim of the study, questions asked and the nature of the time-series (Chandler and Scott, 2011). In some cases it may be adequate to use simple methods like linear regression or a Mann-Kendall test, but often more advanced methods are necessary to fully extract information from the available data. In complex

ecological studies a model of the ecosystem may be required before it is possible to analyze trends for certain factors in the system. Therefore, methods used for trend detection vary between monitoring programs and it is often necessary to make adjustments for each monitoring study.

1.4 Ecological monitoring programs

In this study, statistical analyses of trends were carried out for two different monitoring programs, monitoring of contaminants in the marine environment around Iceland and monitoring of the rock ptarmigan population in Iceland.

1.4.1 Monitoring of contaminants in the marine environment around Iceland

Contaminants are found all around the biosphere and can be of natural or anthropogenic origin but their output from anthropogenic sources increased during the 20th century (Järup, 2003). They can have negative effects on health, reproduction and survival of wildlife and humans (Fisk et al., 2005; Smith and Gangolli, 2002). In order to mitigate the emission of contaminants, international agreements, such as the Oslo/Paris convention (OSPAR) and the Stockholm conventions have been implemented.

National monitoring program for contaminants in the sea around Iceland has been running since 1989 (Jörundsdóttir et al., 2012). The program is under the auspices of the Environmental Agency of Iceland on behalf of Ministry for the Environment. The execution of the program is coordinated by Matis ltd. in cooperation with the Marine Research Institute and the Department of Pharmacology and Toxicology at the University of Iceland. The program is a part of the fulfillment of Iceland's obligations to the Stockholm Convention, OSPAR commission and the Arctic Monitoring and Assessment program (AMAP).

Contaminants have been measured in blue mussels (*Mytilus edulis*), sampled at 11 locations around the Icelandic coastline, and in cod (*Gadus morhua*), sampled NW and NE of Iceland (Figure 1.1). The persistent organic pollutants (POPs) *p,p'*-dichlorodiphenyl dichloroethene (*p,p'*-DDE), hexachlorobenzene (HCB), polychlorinated biphenyl (PCB), chlordanes (CHL) and hexachlorocyclohexane (HCH) have been analyzed both in the mussels and the cod livers, further, toxaphenes (Tox) were analyzed in the cod livers. The trace elements As, Cd, Cu, Hg, Se and Zn were analyzed in the mussels and cod livers

except Hg which was analyzed in the cod muscles (see Paper I Section 6.2 and Paper II Section 7.2 for details on sampling and chemical analysis).

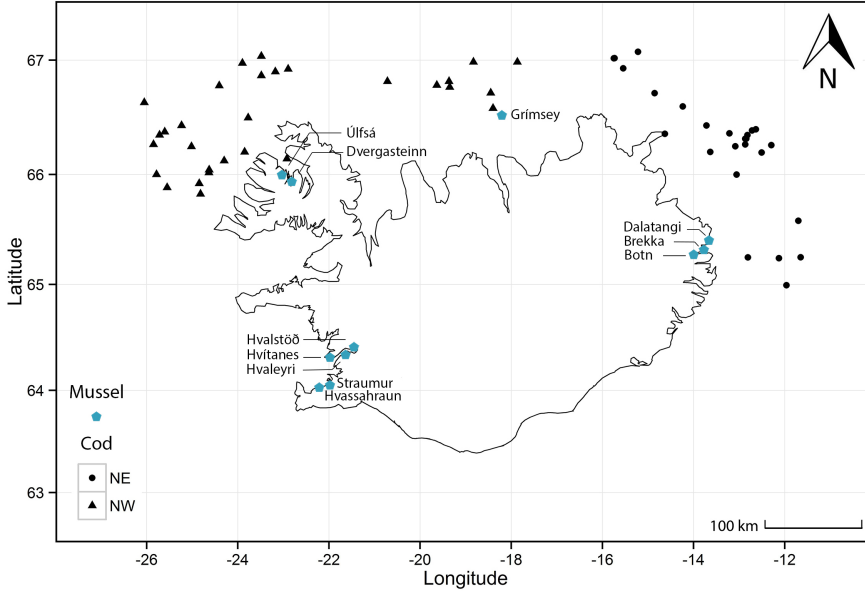


Figure 1.1: Sampling sites for mussel and cod in the monitoring of contaminants in Icelandic waters.

1.4.2 Monitoring of the rock ptarmigan in NE-Iceland

Monitoring of the population of rock ptarmigan (*Lagopus muta*) in Iceland has been carried out since 1963 and organized by the Icelandic Institute of Natural History (Nielsen, 1999). The population has cyclic fluctuations in numbers with a periodicity of 10-12 years (Gudmundsson, 1960; Nielsen and Petursson, 1995). It is a popular game bird in Iceland and market hunting was allowed before 2003 but that year a hunting ban was enforced after a long-term decline of the population (Brynjarsdóttir et al., 2003). The hunting ban lasted for two years and in 2005 hunting started again but with a shorter hunting season and a ban on market hunting.

The management goal for the ptarmigan population in Iceland has been to keep the total annual mortality at a level that will allow the population to exhibit natural fluctuations. This sustainable mortality rate has been esti-

mated to be 37% for adults (Magnússon et al., 2005; Nielsen, 2006). Hunting restrictions have been used in an attempt to reach this goal but without success. Knowledge of abundance, recruitment rate, survival and harvest mortality help wildlife managers to determine how hunting restrictions and regulations affect the population and to estimate whether the management goals have been achieved.

Ptarmigans have been counted on six census plots in NE-Iceland (Figure 1.2) and the sum of all cocks observed on these six plots is taken as a population index. Age ratios of juveniles and adults have been determined in spring and during the hunting season in autumn. The number of ptarmigans harvested and the number of hunters are also monitored, as hunters are obligated to turn in hunting reports to the Environmental Agency of Iceland (see Paper IV Section 9.2.1 for details).

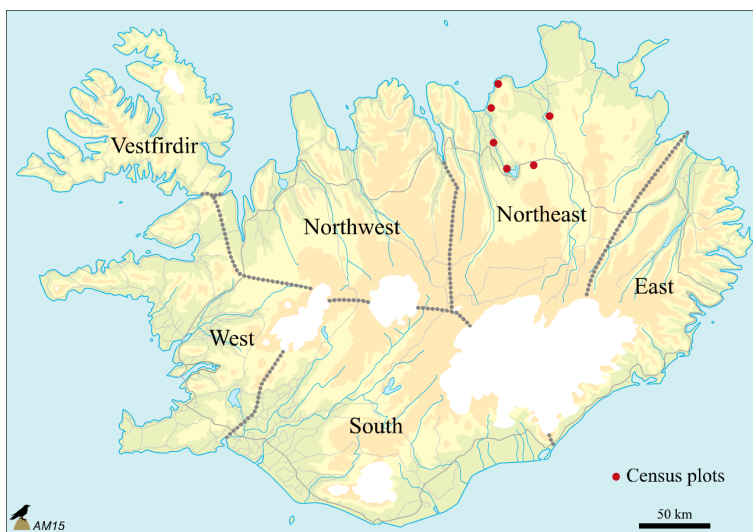


Figure 1.2: The study area for the monitoring of rock ptarmigan in NE-Iceland and the 6 census plots.

2

Objectives

The overall objective of this study was to develop statistical methods to detect trends in two ecological monitoring programs, a) monitoring of contaminants in the marine environment around Iceland and b) monitoring of the population of the rock ptarmigan in Iceland. The objectives for the individual papers, presented in part II of this thesis, were the following:

Paper I: The aim of the study presented in Paper I was to use the contaminant measurements from mussels sampled around the Icelandic coastline to answer the following questions: 1) Has there been a change in concentration of contaminants around the Icelandic coastline for the last two decades? 2) Are concentrations and changes, if present, consistent between locations?

Paper II: The aim of the study presented in Paper II was to determine temporal trends of POPs and trace elements measured in cod over the last two decades at two different locations in the Arctic Ocean north of Iceland. The relationship between the contaminant concentrations and biological covariates was also determined.

Paper III: The aim of the study presented in Paper III was to investigate a changepoint model which can detect either a mean shift and/or a trend change when accounting for autocorrelation in short time-series. A new method was proposed and applications of this new method were given using data from monitoring studies.

Paper IV: The aim of the study presented in Paper IV was to build a population reconstruction model for the rock ptarmigan in Iceland, to estimate the population size, natural survival and hunting mortality.

3

Statistical analysis

Statistical methods to detect trends in time-series from monitoring programs were developed in Papers I-IV. Time-series of different origin need different statistical methods to detect trends. For example, different methods need to be used to investigate possible trends in time-series of contaminant concentration and in the cyclic population of rock ptarmigan. The choice of method also depends on what kind of trends are being investigated. If there is an interest in testing for an increasing trend, then simple linear regression might be an appropriate test. However, if there is an interest in testing whether there has been any change in the time-series, fluctuations, then simple linear regression is not the appropriate method, instead polynomial regression would be more suitable to detect these kind of changes. In this chapter a summary is given of the statistical methods used and developed to detect trends in this study.

3.1 Polynomial regression

Trends in contaminant concentrations in the environment may not be linear, e.g. there can be increasing trend in contaminant concentration because of emission from sources but this trend can change to a decreasing trend if production of the contaminant stops. This process could also be in reverse, where stable or decreasing concentrations could start to increase because of global warming, e.g. contaminants that have accumulated in ice might be released again to the environment (Macdonald et al., 2005).

Polynomial regression can be used to model these trends and was used to

detect trends in contaminant concentrations in mussel and cod in the marine environment around Iceland (Papers I-II). Polynomial regression is actually a special case of multiple linear regression, used to fit a nonlinear relationship between two variables.

The order of the polynomial can be increased to make the functional form of the relationship more flexible. A linear trend can be modeled with a first-order polynomial (Equation 3.1).

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \quad (3.1)$$

A trend that shows e.g. increasing and then decreasing concentrations can be modeled with a second-order polynomial (Equation 3.2).

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \epsilon_i \quad (3.2)$$

More complex fluctuations can be modeled with higher order polynomials (Equation 3.3).

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_p x_i^p + \epsilon_i \quad (3.3)$$

The form of the trend is determined by the order of the polynomial, which can be chosen with a significance test or other model selection criteria such as the Akaike information criterion (AIC). The highest order is fitted first, order four was chosen in the analysis of trends in the time-series of contaminant concentrations. One can then test whether the coefficient for the variable of the highest order is significant. If it is not significant a model with one lower order is similarly evaluated, and the process continuous. Using this method could result in a linear model (Equation 3.1) or no trend at all (Equation 3.4).

$$y_i = \beta_0 + \epsilon_i \quad (3.4)$$

There are some disadvantages of using polynomial regression. For example polynomial models of higher order than three should only be fitted with caution as they can pose problems in both interpolation and extrapolation (Kutner et al., 2005), especially at the end points, where the polynomial function can become nonsensical and this gets worse for high order polynomials (Fornberg and Zuev, 2007). Also, a local change in the dependent variable can have a global effect on the form of the polynomial where this is also worse with high order polynomials (Magee, 1998).

The advantages of using polynomial regression may outweigh the disadvantages but they have to be kept in mind. The main advantage is that it is simple to use as it is just a special case of multiple linear regression and can be performed with most statistical softwares. Another advantage is that covariates can easily be included in the models and they can be extended to mixed models.

3.2 Mixed models

3.2.1 Monitoring at multiple sites

The method of mixed models can be useful when there is an interest in analyzing results from multiple sites simultaneously as was done in the analysis of contaminant concentrations in mussels (Paper I). A random coefficient model (RCM) is a special case of mixed models (Littell et al., 2006), which consists of a fixed component that describes the average trend over all sites and a random component that models how the trend at different sites varies from the average trend. A simple RCM with only an intercept and a slope can be written in the following way:

$$Y_{it} = (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})t + \epsilon_{it}$$

$$\mathbf{b} \sim N(0, \mathbf{G})$$

$$\epsilon \sim N(0, \sigma^2 \mathbf{I})$$

where

Y_{it} is the observation at site i and time t .

β_0 and β_1 are the fixed effects for intercept and slope.

b_{0i} and b_{1i} are the random coefficients in \mathbf{b} , which model how much the intercept and the slope for the i th site deviate from the mean of all sites.

Unknown parameters of the \mathbf{G} matrix are estimated using pre-specified covariance structure (e.g. a diagonal matrix where the random coefficients are assumed independent).

Using this method, it is possible to test the average trend in contaminant concentration over all sites and to test whether the trend and concentration are

different between sites. Verbeke and Molenberghs (2000) recommend starting with a saturated model, both fixed and random effects. Random effects are tested first using the restricted likelihood ratio test, which is known to be conservative (Pinheiro and Bates, 2000). Subsequently the fixed effects are tested using likelihood ratio tests. If fixed effects can be dropped the random effects are tested again. The modeling procedure can be carried out using the nlme package (Pinheiro et al., 2012) in the statistical software R (R Development Core Team, 2012).

If none of the random coefficients are significant then there is not a significant difference in concentration and trend between sites. If only the intercept b_{0i} is significant then there is no significant difference in the trend between sites but there is a significant difference in average concentration. If both b_{0i} and b_{1i} are significant then there is a significant difference in concentration and trend between sites. The expected values of the bs are zero so the fixed effects can be interpreted as the average concentration and trend of all sites. The best linear unbiased predictions (BLUPs) of random effects can be used to determine the trend at the individual sites.

In the case of the contaminants measured in mussels, which were sampled at 11 sites, an RCM was used to analyze the data from all sites simultaneously. The RCM can easily be extended by including additional polynomial terms and covariates. A polynomial model of order four was taken as a saturated model. The percentage of fat in the mussels was also included in the model as a covariate with a quadratic term, to reduce variability (see Section 3.5.4). The concentrations were log-transformed prior to analysis to meet assumptions of normality and homoscedasticity. The full model (3.5) was thus:

$$Y_{it} = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \beta_4 t^4 + \beta_5 f_{it} + \beta_6 f_{it}^2 \quad (3.5) \\ + b_{0i} + b_{1i} t + b_{2i} t^2 + b_{3i} t^3 + b_{4i} t^4 + b_{5i} f_{it} + b_{6i} f_{it}^2 + \epsilon_{it}$$

$$\mathbf{b} \sim N(0, \mathbf{G})$$

$$\epsilon \sim N(0, \sigma^2 \mathbf{I})$$

where Y_{it} is the log-concentration of a contaminant at site i and year t . The βs are fixed effect coefficients, the bs are coefficients describing random effects and

f_{it} is the percentage of fat in the sample at site i and year t . The G matrix was fitted as a diagonal matrix, i.e. the random effects were assumed independent but to have different variances.

3.2.2 Intra-class correlation

Mixed models can be used when it is necessary to include correlation between some of the observations as was done when analyzing trends in the contaminant concentrations in cod (Paper II). It is well established that biological attributes of marine animals caught in close vicinity of each other tend to be more similar than attributes of animals caught at very different locations. In the context of general random effects models this is the intra-class correlation which, for marine surveys is termed the intra-haul correlation (Pennington and Volstad, 1994) and is typically taken into account by using the sampling location as a random effect.

In the case of contaminant concentrations in cod, one or two samples were taken annually from the NW location and one from the NE location (Figure 1.1). Each sample contained 25 individuals. Contaminants were determined in the livers except Hg which was determined in the muscles. The 25 muscles from each sample were homogenized and pooled together before the chemical analysis was performed while the 25 livers were divided into four to six sub-samples according to the weight of the livers (see Paper II Section 7.2.1 for details). Therefore, there were more than one observation from each location, each year that can be assumed to be more similar than observation from other years and locations.

To test whether the concentration of contaminants in cod had changed over time, a mixed model was fitted (Pinheiro and Bates, 2000), where the concentration over time was modeled as a polynomial. Monitoring of cod only took place at two locations and interactions were included in the model, instead of random coefficients as was done in the mussel example, to account for a possible difference between the locations. Interactions between location and the fixed effects were added to the model to test whether the change in concentration was different between the locations and to test whether the relationships between the concentrations and the covariates were different at the two locations. A random year-location interaction was included in the model to account for correlations between observations from the same year at each location.

The saturated model of the change in concentration of the contaminants in

cod was as follows:

$$Y_{ijt} = \beta_{0j} + \beta_{1j}t + \beta_{2j}t^2 + \beta_{3j}t^3 + \beta_{4j}t^4 \\ + \beta_{5j}a_{ijt} + \beta_{6j}le_{ijt} + \beta_{7j}f_{ijt} + \beta_{8j}lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$$

where Y_{ijt} is the log-concentration of a contaminant in sub-sample i at location j in year t . The average age (a_{ijt}), length (le_{ijt}), liver fat content (f_{ijt}) and liver weight (lw_{ijt}) of the sub-samples were used as covariates to adjust for biological variation. The γ_{jt} is the random effect for the intra-haul correlation and the G matrix was fitted as a diagonal matrix, i.e. the random effects were assumed independent. The model was fitted with restricted maximum likelihood (REML) using the nlme package (Pinheiro et al., 2013) in the statistical software R (R Development Core Team, 2012). Fixed effects were tested using the conditional t-test which is an approximate test (Pinheiro and Bates, 2000).

3.3 Changepoint model

As seen above, polynomial models can be used when there is an interest in modeling fluctuating trends. Sometimes there is an interest in knowing at what point in time a change in the trend took place, either a step change and/or a trend change. In this case a changepoint (CP) model can be applied. Such changes can occur e.g. in time-series of concentration of contaminants or in a time-series of wildlife population; a change in the analytical method can result in a step change in the contaminants and a change in the source of contaminants can result in a change in trend. Similarly, a change in time-series of a wildlife population can occur after a change in wildlife management practices. In Paper III a method was developed to detect an unknown CP, either step and/or trend change, while accounting for autocorrelation.

The CP model (3.6) allows for a CP in a time-series y_t , i.e. the intercept ($\alpha_1 \neq \alpha_2$) and/or the slope ($\beta_1 \neq \beta_2$) are different before and after the CP.

$$y_t = \begin{cases} \alpha_1 + \beta_1 t + \epsilon_t & 1 \leq t \leq c \\ \alpha_2 + \beta_2 t + \epsilon_t & c < t \leq N \end{cases} \quad (3.6)$$

The errors ϵ_t are assumed to be autocorrelated with an autoregressive structure of order one (AR(1)) with an autocorrelation parameter ρ , i.e. $\epsilon_t = \rho\epsilon_{t-1} + u_t$ and u_t is assumed to follow a normal distribution with mean 0 and variance σ_u^2 .

The time c is the unknown CP, assumed to lie in an interval $[n_0, N - n_0]$ where n_0 is the first possible CP and N is the length of the time-series. A reduced model with no CP would be a straight line (Equation 3.7).

$$y_t = \alpha + \beta t + \epsilon_t \quad (3.7)$$

To test the null hypothesis of no CP against an alternative hypothesis of unknown CP a likelihood ratio test is applied and the likelihood ratio statistic D_c is calculated for each c (Equation 3.8).

$$D_c = \left\{ -2 \ln \left(\frac{\text{likelihood for model (3.7)}}{\text{likelihood for model (3.6)}} \right) \right\} \quad (3.8)$$

The most likely CP is the point in time where these D s are at a maximum (Equation 3.9), this is the test statistic (D_{\max}) for the CP test.

$$D_{\max} = \max_c D_c \quad (3.9)$$

Unlike many likelihood ratios, the D_{\max} statistic does not follow a χ^2 distribution and critical values need to be extracted from simulated distribution which depends on the length of the time-series and the unknown autocorrelation structure. A simulation study was carried out in Paper III where it was observed that ignoring autocorrelation inflates the type I error. It was not possible to test if there was an autocorrelation in short time-series and the estimate of the autocorrelation parameter was biased. Therefore, the estimate of the autocorrelation parameter cannot be used when the distribution of D_{\max} is simulated. Instead, it was recommended to use a critical value for a fixed autocorrelation parameter $\rho = 0.2$ when positive autocorrelation is assumed to be present in the time-series. If critical values are chosen at the 5% nominal error rate then this method will keep the true error rate of the CP test below 10% when the autocorrelation does not exceed $\rho = 0.6$.

3.4 Population reconstruction model

Population reconstruction models can be used to estimate the population size, recruitment rate, natural survival and harvest mortality simultaneously. These models use harvest data, i.e. the number of harvested animals, age ratios from the harvest and the hunting effort. The precision of the models can be improved

by adding auxiliary data, e.g. data from radio telemetry studies or index data from count studies. The approach taken by Broms et al. (2010) was taken as a basis to develop a new population model for the rock ptarmigan in Iceland (see details in Paper IV Section 9.3). The model estimates demographic parameters for each age group but the age of the rock ptarmigan can only be determined as either juvenile (< 1 year) or adult (> 1 year).

The model consists of four likelihoods (see Model 3.10). The likelihood L_{catch} provides an estimate of the probability of catching a bird using the harvest data (h_i = number of harvested ptarmigans, f_i = number of hunters), and L_{AAH} provides an estimate of the probability that a harvested bird is juvenile using the age ratios from the harvest ($a_{i,j}^h$). L_{AAS} provides an estimate of the probability that a bird is juvenile at spring using the age ratios from spring ($a_{i,j}^s$), and L_{index} includes the relationship between the index (I) and total abundance (N). Maximizing the product of the likelihoods gives the maximum likelihood estimates for the demographic parameters of the model.

$$\begin{aligned}
 L_{joint} &= L_{catch} \cdot L_{AAH} \cdot L_{AAS} \cdot L_{index} \\
 L_{catch} &= \prod_{i=1}^{c-1} \binom{N_i}{h_i} \left(\frac{H_{b,i}(N_{i,1} + N_{i,2})}{N_{i,1} + N_{i,2}} \right)^{h_i} \\
 &\quad \left(1 - \frac{H_{b,i}(N_{i,1} + N_{i,2})}{N_{i,1} + N_{i,2}} \right)^{N_i - h_i} \\
 &\quad \prod_{i=c}^T \binom{N_i}{h_i} \left(\frac{H_{a,i}(N_{i,1} + N_{i,2})}{N_{i,1} + N_{i,2}} \right)^{h_i} \\
 &\quad \left(1 - \frac{H_{a,i}(N_{i,1} + N_{i,2})}{N_{i,1} + N_{i,2}} \right)^{N_i - h_i} \\
 L_{AAH} &= \prod_{i=1}^T \binom{a_{i,1}^h + a_{i,2}^h}{a_{i,1}^h} \left(\frac{N_{i,1}}{N_{i,1} + N_{i,2}} \right)^{a_{i,1}^h} \\
 &\quad \left(1 - \frac{N_{i,1}}{N_{i,1} + N_{i,2}} \right)^{a_{i,2}^h} \\
 L_{AAS} &= \prod_{i=1}^T \binom{a_{i+1,1}^s + a_{i+1,2}^s}{a_{i+1,1}^s} \left(\frac{N_{i,1}}{N_{i,1} + N_{i,2} \cdot S_{x,i}} \right)^{a_{i+1,1}^s} \\
 &\quad \left(1 - \frac{N_{i,1}}{N_{i,1} + N_{i,2} \cdot S_{x,i}} \right)^{a_{i+1,2}^s} \\
 L_{index} &= \prod_{i=1}^T \frac{1}{\sqrt{2\pi}\sigma} \exp \left[\frac{-(I_i - \alpha N_i)^2}{2\sigma^2} \right]
 \end{aligned} \tag{3.10}$$

The abundance of adult ptarmigans was calculated with Equation 3.11.

$$N_{i,2} = \begin{cases} (1 - H_{i-1})S_c(N_{i-1,1} + N_{i-1,2} \cdot S_{x,i-1}) & 1 \leq i < c \\ (1 - H_{i-1})S_c(N_{i-1,1} + N_{i-1,2} \cdot S_{x,i-1}) & c \leq i \leq T \end{cases} \tag{3.11}$$

where

$$H_i = 1 - e^{-a}, H_i = 1 - e^{-a+b \cdot I_i} \text{ or } H_i = 1 - e^{-b \cdot f_i} \tag{3.12}$$

and

$$S_{x,i} = 1, S_{x,i} = a \text{ or } S_{x,i} = a - b \cdot I_{i-1} \tag{3.13}$$

With this model it is possible to estimate the abundance of juveniles ($N_{i,1}$)

before the hunting season in year i , the abundance of adults in the first year ($N_{1,2}$), the excess winter survival ($S_{x,i}$) of adults in year i and annual survival of juveniles (S_c). Here it is possible to have $S_{x,i}$ fixed and if the natural survival of juveniles and adults is equal then $S_{x,i} = 1$. It is also possible to model the survival as a function of density (see Equation 3.13) but S_c is fixed in both cases. It is also possible to assume that the juvenile survival is density dependent and the adult survival fixed. The function for hunting mortality (H_i) is assumed common for juveniles and adults. If one wishes to assume a separate hunting mortality for the two age groups another likelihood needs to be included, e.g. a likelihood which includes age ratios from a telemetry study. The hunting mortality can be assumed fixed, it can also be assumed to be a function of either hunting effort or the prey density (see Equation 3.12), depending on the hunting strategy. The number of juveniles is estimated for every year and the number of adults is estimated for the first year only. These estimates along with the estimates of survival and hunting mortality are used to calculate the number of adults for each year after the first year (see Equation 3.11).

This modeling approach gives the possibility of including a CP in the model. For example if there has been a change in hunting regulations, the function for hunting mortality is allowed to be different before and after the CP. This can be used to test whether a change in hunting regulations had an actual effect, since models with and without a CP can be compared using either a likelihood ratio test or the AIC. If the inclusion of a CP improves the model one can conclude that the new hunting regulations did indeed have an effect.

3.5 Statistical issues

3.5.1 The normal assumption

Many statistical methods assume that the error terms follow the normal distribution. This is the case in the polynomial models, which are just a special case of multiple linear regression, the mixed models and the CP model. If this assumption is seriously violated the interpretation of the p-values is not meaningful. These methods are usually robust enough to handle small deviations from the normal distribution. Non-normal data are, however, common in ecological studies and right-skewed data is often encountered. In these cases a log-transformation can be helpful. Transforming the dependent variable will in many cases of right-skewed data make the error terms normal. The analysis

is then done on the log-transformed variables and the results can be back-transformed to the original scale, which facilitates interpretation of the trend, as was done with the contaminant concentrations in Papers I and II.

3.5.2 Autocorrelation

Most standard statistical methods assume that the observations are independent but in time-series this may not be the case. Observations close in time may be correlated, e.g. population size and mortality rates may be correlated through time because of density dependence. Such dependence between successive observations is called autocorrelation and is frequently observed in ecological time-series (Bence, 1995; Peres-Neto, 2009). If this autocorrelation is ignored in time-series analysis, e.g. when testing for a trend, the type I error rate gets inflated (Bence, 1995), i.e. one concludes that there is a significant trend too often when in truth there is no trend. It is very difficult to distinguish between a trend and autocorrelation as autocorrelated series can be observed to have a trend and series with a trend can be observed to be autocorrelated (Chandler and Scott, 2011; Kutner et al., 2005).

It is possible to account for autocorrelation in time-series and this can e.g. be done using the method of mixed models where the covariance structure allows for correlated observations (Verbeke and Molenberghs, 2000; Wolfinger, 1996). Autocorrelation greatly inflates the type I error rate, when detecting CP, if ignored and this was accounted for when the method of CP detection was developed, as seen in Paper III. Another way to account for autocorrelation is to study annual observations instead of e.g. monthly observations, which may be assumed independent in some cases.

To test if observations are independent a simulation study can be conducted where estimation of the autocorrelation from the data is compared to estimation from simulated time-series. To do this study a number of time-series must be available to get a distribution of the autocorrelation parameter from the data. The contaminant concentrations are annual observations and to test whether these time-series could be assumed to be independent, a simulation study was carried out. The simulated time-series were of length 14, which was the average length of the 118 time-series of contaminants. Four simulation studies were carried out, where time-series were simulated with a) no trend b) linear trend c) quadratic trend and d) cubic trend. In each study, independent and autocorrelated ($\rho = 0.0, 0.1, 0.2, 0.3$) time-series were simulated 1000 times. The

simulated distribution of ρ was compared to the empirical distribution of ρ from the data where the trend was assumed to be nonexistent, linear, quadratic or cubic using the Kolmogorov-Smirnov test (Marsaglia et al., 2003) (Figure 3.1). In the no trend study (a) all of the simulated distributions were significantly different from the distribution derived from the data ($p < 0.05$). In the study where a linear trend was assumed (b), all the simulated distributions were significantly different from the distribution from the data ($p < 0.05$) except where $\rho = 0.1$ ($p = 0.550$). In the third simulation study where a quadratic trend was assumed (c) the simulated distribution with $\rho = 0.0$ was not significantly different from the distribution from the data ($p = 0.088$) but the autocorrelated distributions were all significantly different from the data distribution ($p < 0.01$). The results were the same for the fourth simulation study where cubic trend was assumed. Therefore, it is most likely that there is no or very weak autocorrelation in the time-series of contaminant concentrations.

3.5.3 Statistical power

Statistical power is the probability of a test being significant, e.g. the probability of detecting a trend. The power increases with sample size and with significance level but it decreases with increasing variance. The power depends on the magnitude of the trend as time-series with large changes have higher power than time-series where the change is small. It can also depend on the pattern of the change (Nicholson and Fryer, 1992). It can be useful to think about statistical power when interpreting results from statistical tests. The absence of statistically significant trend may not imply that there has not been any change in the mean value, as this can be a consequence of low statistical power, typically that the sample size is too small to detect the trend.

The statistical power of detecting trends in time-series of contaminant concentration in the biota has been observed to be very low, probability of 24-47% of detecting annual change of 5% in 10 years of data (Rig  t et al., 2010). Many time-series from monitoring programs only have one observation per year but observations from multiple locations. Analyzing time-series from these locations simultaneously should give more power as the sample size has increased. This can be done with the method of mixed models (see Section 3.2 and Paper I).

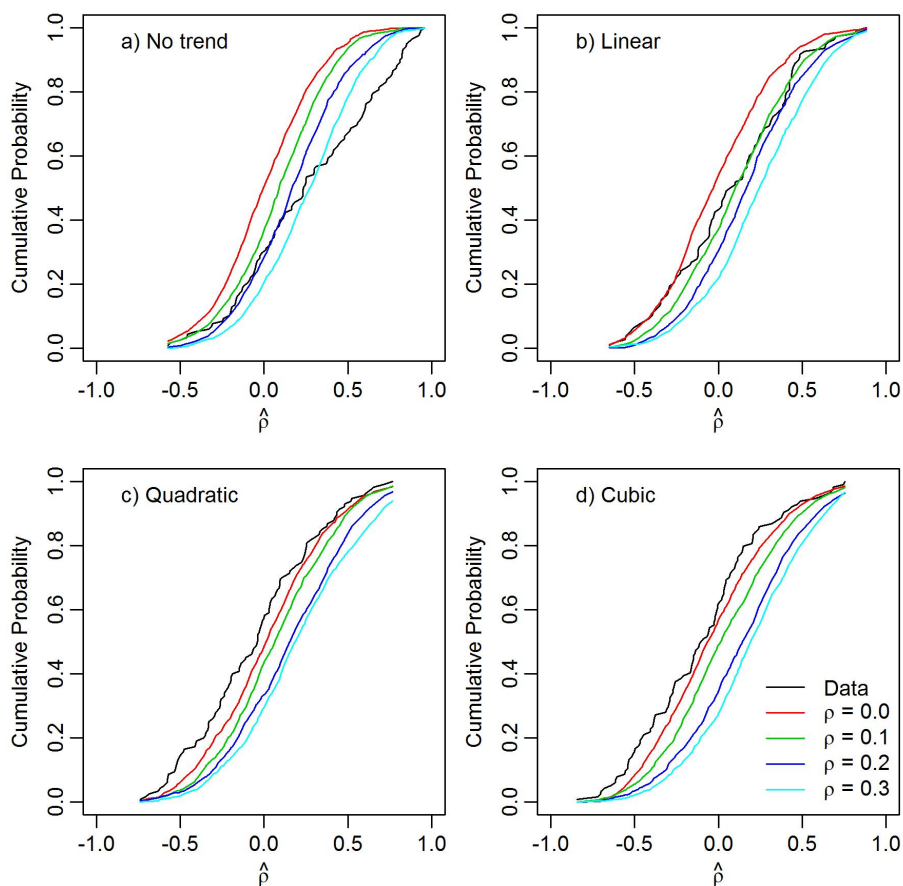


Figure 3.1: Empirical cumulative distribution of the ρ estimated from the data and ρ estimated from simulated time-series with independent and autocorrelated errors ($\rho = 0, 0.1, 0.2, 0.3$) where a) No trend is assumed b) linear trend is assumed c) quadratic trend and d) cubic trend.

3.5.4 Covariates

In a simple test for trend detection, e.g. in linear regression, the dependent variable is regressed against the explanatory variable time. In most cases other variables may affect and cause variation in the dependent variable. Including these variables as covariates in the analysis should then reduce the variability in the data and make trend detection more likely, i.e. increase the power for trend detection. This can easily be done using polynomial regression (see Section 3.1).

Covariates can also be confounding variables and a trend detected in one variable might be explained by a trend in another variable. For example, in the case of contaminant concentration, an increasing trend in concentration of a chemical component in cod liver might not necessary be because of increasing contaminant load in the environment but because of an increasing trend in fat content. POPs are known to be lipophilic and higher concentrations in wet weight are found in livers with higher fat content as discussed in Paper II.

3.5.5 Observations under limit of detection

Chemical analyses of contaminant concentrations are limited and low concentrations cannot always be accurately determined. In these cases the concentrations are reported to be under limit of detection (LOD). These values are then known to be somewhere between zero and the LOD. To be able to statistically analyze data with these values there are two options, either exclude these observations, replace them with values between zero and the LOD or use a maximum likelihood (ML) approach (Bignert, 2003; Chandler and Scott, 2011). If these observations are excluded the power of the statistical method applied will be reduced as the sample size has decreased. Replacing it with some value between zero and the LOD can introduce bias. The ML method would be the preferred method but it needs numerical techniques for maximization and is complicated to implement when using more advanced statistical methods such as mixed models. Observations below LOD have frequently be replaced by $\text{LOD}/2$ (Jörundsdóttir et al., 2006) or $\text{LOD}/\sqrt{2}$ (Nyberg et al., 2014) but was chosen to be at the LOD in this study (Paper I and II) because these observations were very close to the observations that were above the LOD. This was believed to introduce less bias than using the other methods. Bignert (2003) has suggest using the medians as they are not sensitive of outliers and observations below LOD. This was not possible in the mussel case as there was only one observation per year at each location. The medians were also not used in the cod case as it would reduce

the sample size and hence reduce the power of detecting a trend.

4

Results

The statistical methods described in Chapter 3 were used to analyze trends in two monitoring programs, monitoring of contaminants in the marine environment around Iceland and monitoring of the population of the rock ptarmigan in Iceland. The results are presented in Papers I-IV and will be summarized in this chapter.

4.1 Trends in contaminant concentrations

4.1.1 Trends in contaminants measured in mussel

Contaminant concentrations measured in mussel at 11 locations around the Icelandic coastline from 1991-2010 were analyzed for trend using the method of mixed models as described in Section 3.2.1 (see also Paper I). The method of mixed models revealed whether there was a significant change in concentration over the periods and whether the change and concentration were consistent at all locations. These results are shown in Figure 4.1 for the POPs and Figure 4.2 for the trace elements.

The concentration of p,p' -DDE did not have a consistent trend at all 11 locations, most locations showed decreasing or no trends in recent years except one location, Hvalstöð had a sudden increase which indicates a local source, possibly originating from a nearby whaling station which restarted operation in 2009 after a 20 year moratorium. HCB was observed to be decreasing at most locations but had an increasing trend at Úlfsá. A waste incinerator was operated

2 km from the sampling site which probably was the cause of the increasing HCB concentration at Úlfsá. The decreasing trend in α -HCH concentration was consistent at all locations where it started to decrease by -13% annually from 1999 to 2010. The concentration of PCB-153 has been decreasing around the Icelandic coastline except close to the whaling station and in a fjord on the east coast where aquaculture was carried out, which quite plausibly caused the elevated concentration. There was inconsistent trend between locations for trans-nonachlor concentration which showed again an increase close to the whaling station (Figure 4.1).

The change in As concentration was the same at all locations, a 2% annual increase followed by a -3% annual decrease. The concentration at Úlfsá was observed to be much higher than at the other locations, the cause of this is not known (see discussion in Paper I, Section 6.4.3). The Cd concentration showed fluctuating trends which was not the same at all locations. The concentration of Cu and Se was consistent at all locations and showed an increase followed by a decrease. There was no significant trend observed for Hg and Zn but there was a significant difference in the concentrations between locations (Figure 4.2).

4.1.2 Trends in contaminants measured in cod

Contaminant concentrations were measured in cod sampled at two locations, NW and NE of Iceland, from 1990 to 2011. Trends were analyzed using the method of mixed models as described in Section 3.2.2. Results of the trend analysis are given in Table 4.1 for both the POPs and the trace elements. More detailed results are presented in Paper II.

The concentration of all of the POPs measured in cod liver had a significant decreasing trend which was consistent at both the NW and NE locations. The decrease was -3 to -2% annually for PCB, p,p' -DDE, HCB, CHL and Tox but -9% for HCHs. No general trend was observed for the trace elements. The As concentration increased by 2% annually at both locations while the Zn concentration decreased significantly by -1% annually. Both the Cd and Cu showed fluctuating trends which were different between the two locations, while Hg and Se also showed fluctuating trends which were consistent at both locations (Table 4.1).

Biological covariates such as age, length, liver fat content and liver weight, were included in the analysis of trend in the cod. All of these covariates were significant except age. Interactions between the covariates and location were

4.1 Trends in contaminant concentrations

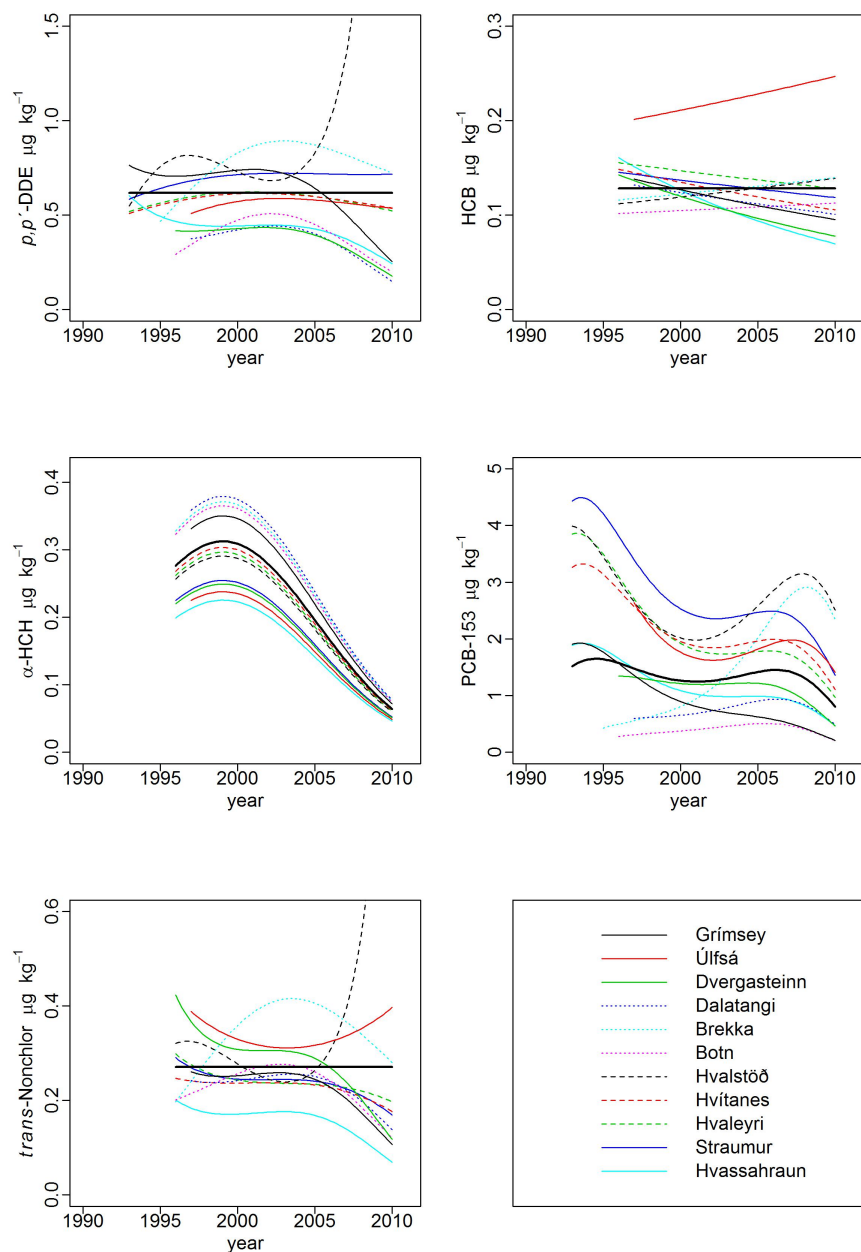


Figure 4.1: Predicted concentrations and trends of the POPs measured in mussels at the 11 locations.

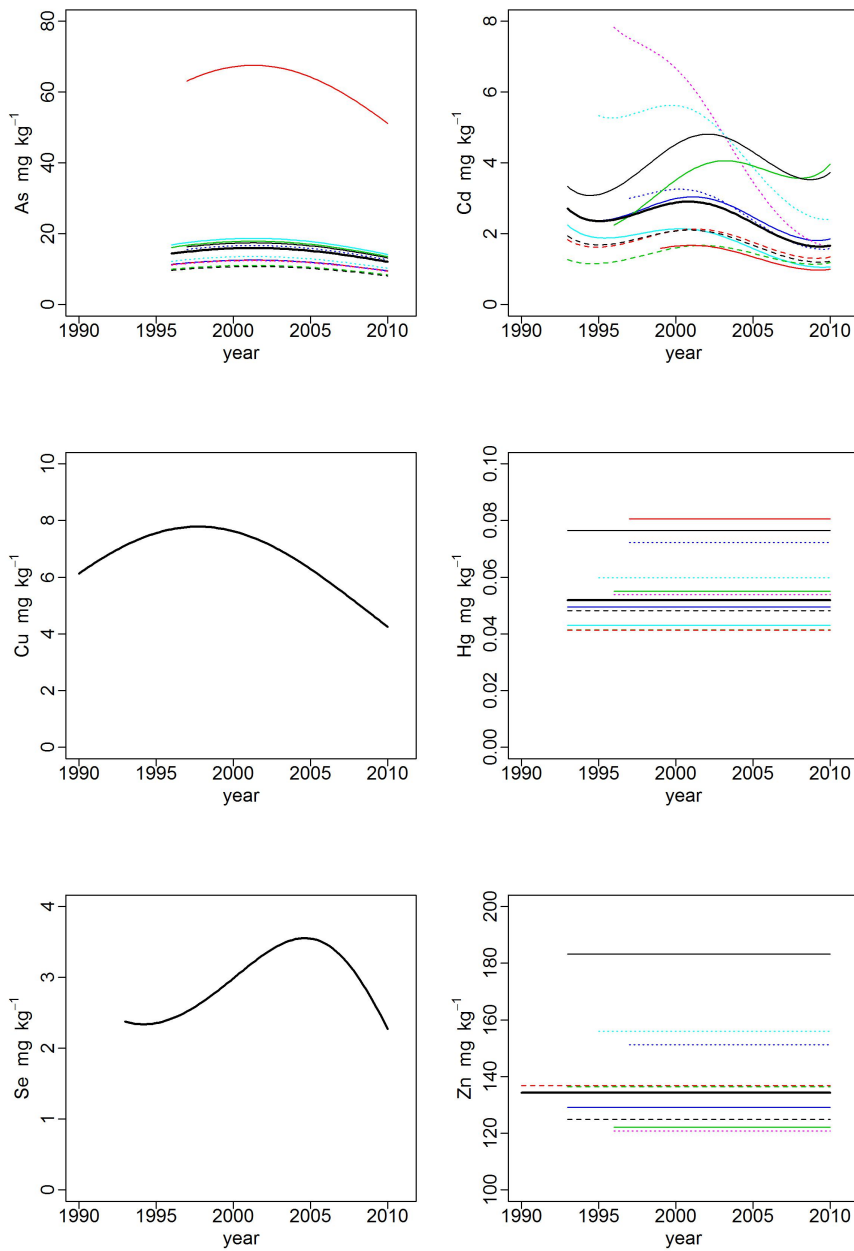


Figure 4.2: Predicted concentrations and trends of the trace elements measured in mussels at the 11 locations (see Figure 4.1).

included in the models to account for the possibility of different relationships between them and the contaminant concentrations at the two locations. This made the interpretation of the results more difficult as is discussed in detail in Paper II.

Table 4.1: Change in the contaminant concentrations and median concentrations measured in cod sampled NE and NW of Iceland from 1990-2011.

	Annual change (%)		P-value	Median concentration	
	NE	NW		NE	NW
				$\mu\text{g kg}^{-1}$	
PCB	-2	-2	0.0003	68	70
DDE	-2	-2	0.044	48	45
HCB	-3	-3	0.0007	19	18
HCH	-9	-9	<0.0001	5.9	4.9
CHL	-3	-3	0.0008	53	46
Tox	-3	-3	0.0009	77	65
				mg kg^{-1}	
As	2	2	0.0004	5.2	5.6
Cd	non-linear	non-linear	0.0065	0.14	0.24
Cu	non-linear	non-linear	0.0474	3.2	3.2
Hg	non-linear	non-linear	0.0143	0.022	0.03
Se	non-linear	non-linear	0.0276	0.85	0.85
Zn	-1	-1	0.0201	14	14

4.2 Trends in population parameters of the rock ptarmigan

4.2.1 Changepoint in annual mortality

The CP model (see Section 3.3) was used to test if there had been a change in the annual mortality ($1 - e^{-z_2}$, see Magnússon et al. (2005) for mortality calculations) of adult rock ptarmigans in NE-Iceland after a change in hunting regulations in 2003. There was a significant CP in 2002 indicating that something changed after that year but the test was only significant if the CP was known, i.e if only one point was tested for (see Paper III). The annual mortality had been increasing from 1982 to 2002 followed by a sudden drop in 2003 when it starting increasing again to 2012 (Figure 4.3).

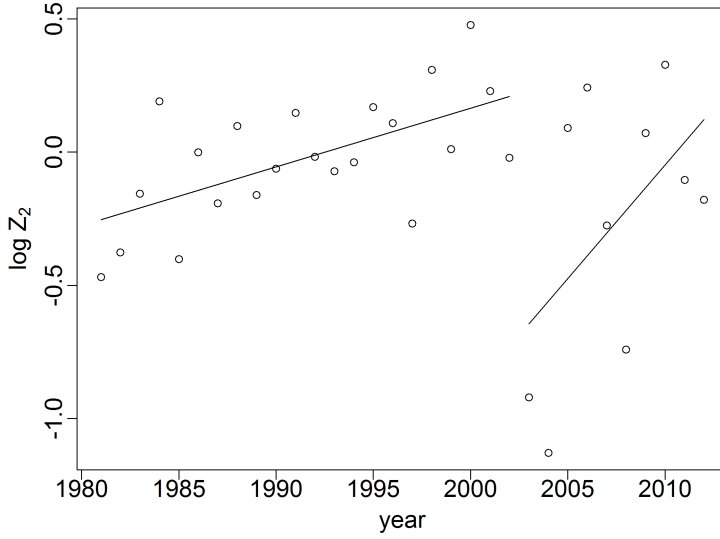


Figure 4.3: Mortality rate (Z_2) of the adult ptarmigan from 1982 to 2012.

4.2.2 Population dynamics

A population reconstruction model was done for the rock ptarmigan in NE-Iceland and the results are presented in Paper IV. Various models were fitted as suggested in Section 3.4 and the model which fitted the data best had a separate natural survival for adults and juveniles and the adult survival was modeled as a function of density with one year lag. The survival of the juveniles was taken as a constant as it was not possible to model survival of the two cohorts as a time-varying function and it gave a better fit to have the adult survival density-dependent rather than the survival of the juveniles. It was not possible to have a separate hunting mortality for juveniles and adults and it fitted the data best to include a CP in the hunting mortality. The CP was included when the hunting ban took place in 2003. The final model had different functions before and after the CP; before the hunting mortality was modeled as a function of density but after the CP as a function of hunter numbers. Therefore, the adult abundance was modeled in the following way:

$$N_{i,2} = \begin{cases} (1 - H_{b,i-1})S_c(N_{i-1,1} + N_{i-1,2} \cdot S_{x,i-1}) & 1998 \leq i < 2003 \\ (1 - H_{a,i-1})S_c(N_{i-1,1} + N_{i-1,2} \cdot S_{x,i-1}) & 2003 \leq i \leq 2012 \end{cases} \quad (4.1)$$

where $H_{b,i} = 1 - e^{-b+c_b \cdot I_i}$ and $H_{a,i} = 1 - e^{-c_a \cdot f_i}$ and $S_{x,i} = d - e \cdot I_{i-1}$

The maximum likelihood estimates from the final model are presented in Table 4.2. The abundance decreased from 1998 to a low in 2002, it increased again during the hunting ban years and reached a peak in 2005. It then decreased again to a low in 2007 and then increased again until it reached another peak in 2009 when it started decreasing again. The natural survival of adult rock ptarmigans ranged from 36% (95% CL 33 – 38%) in 1999 and 2011 to 65% (95% CL 60 – 70%) in 2003 and 2004. The survival for juveniles was taken as a constant and was estimated to be 19% (95% CL 18 – 20%). Before the hunting ban in 2003 the hunting mortality ranged from 32% (95% CI 28 – 35%) in 1998 to 54% (95% CI 49 – 60%) in 2002. After the hunting ban, the hunting mortality ranged from 11% (95% CI 9 – 13%) in 2007 to 17% (95% CI 14 – 20%) in 2009.

Table 4.2: Parameter estimates from the final model with 95% confidence intervals (CI) for rock ptarmigan in NE-Iceland 1998-2012.

Parameter	Estimate	LCI	UCI
$N_{1998,1}$	121000	107000	138000
$N_{1999,1}$	82000	78000	94000
$N_{2000,1}$	57000	55000	64000
$N_{2001,1}$	38000	36000	42000
$N_{2002,1}$	31000	30000	34000
$N_{2003,1}$	58000	43000	79000
$N_{2004,1}$	96000	37000	73000
$N_{2005,1}$	90000	73000	127000
$N_{2006,1}$	71000	57000	87000
$N_{2007,1}$	58000	47000	72000
$N_{2008,1}$	80000	66000	99000
$N_{2009,1}$	109000	89000	133000
$N_{2010,1}$	95000	78000	116000
$N_{2011,1}$	51000	41000	62000
$N_{2012,1}$	55000	45000	68000
$N_{1998,2}$	32000	28000	37000
c_b	0.0029	0.0021	0.0038
b	0.93	0.75	1.11
c_a	1.36	1.09	1.70
S_c	0.19	0.18	0.20
d	4.01	3.41	4.65
e	0.011	0.008	0.014
α	0.0013	0.0011	0.0015
σ^2	464	220	1100

5

Conclusion and future perspectives

Statistical methods have been adapted to detect trends in two monitoring programs. Polynomial models were used to account for trends with no consistent direction, mixed models were used to analyze data from multiple sites simultaneously and to include correlation between observations. A CP model was investigated and a new method proposed which takes autocorrelation into account when detecting a CP in short time-series. A population reconstruction model was developed for the ptarmigan population in Iceland which allows for the possibility of including a CP.

The method of mixed models was used to analyze trends in contaminant concentrations in mussel and cod. The trends were not simply assumed to be increasing or decreasing but permitted to have no consistent direction. To account for the possibility of an increasing trend followed by a decreasing trend a polynomial model was used in the analysis. There was a sudden increase in the POP concentrations at some of the mussel sampling sites which the polynomial models detected, while linear models would in some cases not be able to detect these sudden increases. The sudden increases in *p,p'*-DDE, PCB-153 and *trans*-nonchlor concentrations could be explained by anthropogenic activity such as aquaculture and whale processing that were carried out for some time close to the sampling sites. A gradual linear increase in HCB was also detected that could be traced back to a waste incinerator (see Paper I Section 6.4.3 for

further discussion). Only linear decreasing trends were detected for the POPs measured in cod. The cod is sampled in the open sea and minor sources of pollution do not have as much effect on the contaminant concentration in cod as they do in mussel sampled closer to the sources. However, non-linear trends were detected for some of the trace elements measured in cod as well as in the mussel. The reason for the non-linear trends in the trace elements is not known as no local sources of these elements are known in Iceland. There was however a sign of a local pollution with respect to As at one of the mussel sampling sites as the concentration was much higher at that location, the reason for this is not known but a possible source could be an oil storage facility. The waste incinerator and the oil storage facility have now been closed down and continued monitoring and statistical analysis of the data should reveal decreasing trends for the contaminants if those were the source. These kind of trends can be detected with polynomial models or with a CP model.

The CP model detects a point in time where there is a step change and/or a trend change. The CP model was investigated with simulations and a new method proposed. The simulation study revealed the effect of ignoring autocorrelation when detecting a CP. The type I error rate gets inflated even for low autocorrelation so there has to be strong evidence of no autocorrelation if the test is to be carried out assuming independent data. The new method was able to detect a CP in two different time-series while accounting for autocorrelation, one where no point was assumed more likely *a priori*, i.e. the CP was unknown, and in the other where the CP was known (see Paper III, Section 8.7). As expected, the test has more power when only one point in time is tested for, i.e. one tests whether a change occurs at the true CP. On the other hand, testing for one point in time should only be done when there is evidence that something may have caused a change in the time-series at a particular point in time. This method could for example be used to test if the close down of the waste incineration and the oil storage facility did in fact have an effect on contaminant concentrations. In this case the CP would be known, i.e. the time when the facilities were closed, and a test where the CP is known would be used as it has more power than when the CP is unknown. It may also be appropriate to assume independent data in the time-series of contaminant concentrations as was shown in Section 3.5.2 as this would increase the power further.

A population reconstruction model was adjusted to fit the rock ptarmigan in NE-Iceland. The model estimates the juvenile and adult abundance, separate natural survival for juveniles and adults and a common hunting mortality for

both age groups. All the parameters are estimated simultaneously which should give better estimates than when parameters are estimated separately as in the population model proposed by Magnússon et al. (2005). This model also allows for the possibility of adding a CP to the model, e.g. in the hunting mortality. By the inclusion of a CP it is possible to test if a hunting regulation had an effect on the hunting mortality.

The population model was used to estimate the demographic parameters for the ptarmigan in NE-Iceland but it could also be used for the ptarmigan in other parts of the island and for the entire country. It is possible that the ptarmigan has higher natural survival in other parts of the island and can therefore withstand higher hunting mortality in some areas. The model could also be used for other species that are hunted, e.g. the arctic fox (*Vulpes lagopus*) in Iceland.

It may be possible to improve the model further, by the inclusion of random survival and hunting mortality parameters to account for stochasticity in environmental conditions (Gast et al., 2013). The population of the gyrfalcon (*Falco rusticolus*) and the arctic fox are monitored and these are the main predators of the ptarmigan, it may be possible to model the effects of these predators by adding parameters in the survival function. Addition of parameters would however make the model computationally unstable and it is possible that other parts of the model would have to be simplified or more data would have to be included in order to be able to estimate all the parameters of the model.

The results of this thesis showed that human activity can have impact on the ecosystems. Elevated contaminant concentrations were found at some locations along the coastline that can most likely be traced back to aquaculture, whale processing, waste incineration and an oil storage facility. Hunting was found to affect the annual mortality of the rock ptarmigan and the hunting regulation did have an effect on the hunting strategy and the mortality.

Monitoring programs are essential to assess the changes that take place in the ecosystems and statistical analyses are an important part of that assessment. The information that these programs provide is important for decision and policy makers to carry out efficient conservation and to be able to ensure environmental quality, food safety and public health.

Part II

Papers

6

Paper I

Spatial and temporal trends of contaminants in mussel sampled around the Icelandic coastline.

Erla Sturludottir, Helga Gunnlaugsdottir, Hronn O. Jorundsdottir,
Elin V. Magnusdottir, Kristin Olafsdottir, Gunnar Stefansson

Abstract

Contaminants have been determined in blue mussels (*Mytilus edulis*) at 11 locations around the Icelandic coastline from 1990-2010. The aim of the present study was to investigate if there has been a change in concentration of contaminants around the Icelandic coastline for the last two decades and if the concentrations and changes, if present, were consistent between locations. Concentrations of the persistent organic pollutants, *p,p'*-dichlorodiphenyl dichloroethene (*p,p'*-DDE), hexachlorobenzene (HCB), α -hexachlorocyclohexane (α -HCH), polychlorinated biphenyl (PCB-153) and trans-nonachlor, have decreased at most of the sampling locations in Iceland in recent years. However, an increasing trend was found at few locations that could be explained by anthropogenic activity. The concentration levels of the persistent organics were much lower than found at the Norwegian, USA and Chinese coasts, especially levels of *p,p'*-DDE. The concentration of copper and selenium had a consistent pattern of change and concentration between locations over the period which showed a decreasing trend in recent years. The trace elements arsenic, cadmium, mercury and zinc showed more variation in concentration between locations, the concentration of arsenic, mercury and zinc was fairly stable over the period, whereas there were fluctuations in cadmium concentrations. The concentrations of cadmium and zinc were observed to be somewhat higher than found in mussels from Norway, USA and China but values of mercury and lead were much lower in the mussel sampled in Iceland. The higher concentrations of cadmium and zinc can be explained by the volcanic activity in Iceland but no major anthropogenic sources of trace elements are known in Iceland.

6.1 Introduction

Trace elements, such as metals in the Arctic have both natural geological and anthropogenic sources. Their output from anthropogenic sources increased during the 20th century (Järup, 2003). In order to mitigate the emission of trace elements, international agreements, such as the OSPAR convention have been implemented. This is considered a necessary action since trace elements, especially arsenic, cadmium, lead and mercury, can cause adverse health effects (Järup, 2003). Unlike the trace elements, persistent organic pollutants (POPs) mainly come from anthropogenic sources. They have been used extensively in agriculture and industry in the past. However, most countries have signed the Stockholm convention and have consequently banned or restricted the use of POPs due to their persistence and negative effects on the health, reproduction and survival of wildlife and humans (Fisk et al., 2005; Smith and Gangolli, 2002).

POPs and trace elements can migrate from lower latitudes to higher ones by long-range transport (Pacyna et al., 1985; Wania and Mackay, 1993). The contaminants are mainly transported to the Arctic with air, ocean currents and rivers (AMAP, 1998) and these main pathways can be affected by climate change (Macdonald et al., 2005). These changes can make interpretation from time-series difficult as trends may also arise from climate change but not only change in emission (Macdonald et al., 2005). Results from spatial and temporal analysis of POPs in Arctic air indicate that the reducing ice cover, increasing temperature of the sea and biomass burning may affect trends in POP concentrations in the Arctic (Hung et al., 2010).

A meta-analysis was carried out by Rigét et al. (2010) on temporal trends of POPs in the Arctic biota. Their results revealed that POPs in the Arctic have mostly been decreasing the last two to three decades, even if increasing trends were observed in some cases. The same results were reported from trend analysis of POPs in the Arctic air (Hung et al., 2010). Research on spatial and temporal trends of metals in the Arctic area has mainly focused on mercury (Hg). Temporal trends of Hg in the Arctic biota have shown no consistent pattern of change over the last 30 years (Rigét et al., 2011). Nevertheless, a spatial trend for Hg was observed, higher proportion of time-series from Canada and Greenland showed increasing trends than time-series from eastern regions (Rigét et al., 2011). Less is known regarding trends of other trace elements in the Arctic such as arsenic (As), cadmium (Cd), copper (Cu), lead (Pb),

selenium (Se) and zinc (Zn). Analysis of time series from the marine biota around Greenland and Norway showed no consistent pattern of change for Cd concentration (Green et al., 2011; Riget et al., 2004). The metal Pb was found to decrease in concentration during the period 1990-2010 in the marine biota at the Norwegian coast, and some of the Norwegian time-series of Cu and Zn had either increasing or decreasing trends (Green et al., 2011).

National monitoring programs for environmental conditions in the sea around Iceland have been running since 1989. The program is under the auspices of the Environmental Agency of Iceland on the behalf of Ministry for the Environment. The execution of the program is coordinated by Matís ltd. in cooperation with the Marine Research Institute and the Department of Pharmacology and Toxicology at the University of Iceland. The program is part of the fulfillment of Iceland's obligations to the Stockholm Convention, OSPAR commission and the Arctic Monitoring and Assessment program (AMAP). Contaminants have been measured in blue mussels (*Mytilus edulis*) for 15 to 21 years at 11 locations around the Icelandic coastline (depending on contaminant and location). Blue mussels are common around the Icelandic coast, they are filter feeding organisms that live in intertidal areas attached to secure substrates and are therefore a good biomonitoring species, indicating local pollution at the sampling site. The aim of the present study was to use the monitoring data collected in Iceland to answer the following questions: 1) Has there been a change in concentration of contaminants around the Icelandic coastline for the last two decades? 2) Are concentrations and changes, if present, consistent between locations?

6.2 Materials and methods

6.2.1 Sampling method and locations

Blue mussels (*Mytilus edulis*) with shell length of 4-6 cm have been sampled in autumn (August to October) since 1990 in Iceland and contaminants in the mussels have been measured for 15-21 years at 11 locations (depending on contaminant and location) around the Icelandic coastline by the Marine Research Institute. Each sample contained 50 individuals which were deshelled, pooled and homogenized, making one sample per location each year. The samples were kept frozen at -20°C until analysis was performed.

The sampling sites are shown in Figure 6.1. Two of these sampling sites are located close to villages on the Westfjord peninsula, a village of 145 residents is

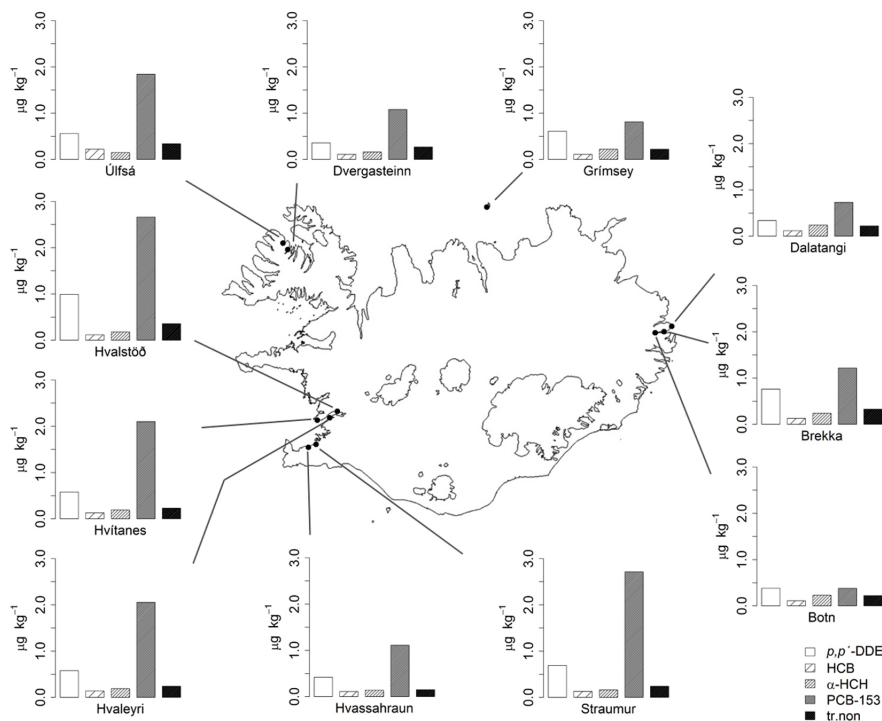


Figure 6.1: Sampling site locations and average concentrations of the POPs at each location.

located 4 km from Dvergasteinn and a village of 2600 people is 2 km from Úlfarsá. A small waste incineration plant was in operation from 1994 to 2010 about 2 km from Úlfarsá. Hvalstöð, Hvalleyri and Hvítanes are all located in the same fjord, Hvalfjörður, in western Iceland, where an aluminum factory started its operation in 1998, a ferro-silicon plant was in operation for the whole period and a whaling station, located close to the site Hvalstöð restarted operation in 2009 and 2010 after a 20 year cease. The sampling sites Dalatangi, Brekka and Botn are in a fjord in the eastern part of Iceland called Mjóifjörður with a population of about 40 people. Salmon aquaculture was carried out in the fjord from 2001 to 2007 and there is a small fish factory at Brekka. Straumur is located beside an aluminum factory not far from the capital area and Hvassahraun is 6 km southwest from Straumur. Grímsey is a remote island in the north with around 80 residents.

6.2.2 Chemical analysis

Chemical analysis of POPs

POPs were analyzed at the Department of Pharmacology and Toxicology at the University of Iceland. The mussels were extracted wet, basically according to the method of Jensen et al. (1983) as described earlier (Ólafsdóttir et al., 1995). In short, the tissue was extracted with hexane/acetone/diethyl ether, solvents evaporated at 40° C under N₂, the residue resuspended in isooctane containing 1,2,3,4-tetrachloronaphthalene (the internal standard) and cleaned with concentrated sulfuric acid. Recovery was checked and corrected for by the addition of ϵ -HCH, *op'*-DDD, PCB #112 and PCB #198 (no. according to IUPAC) to all samples at the first step of the extraction. The fat content was determined gravimetrically.

The individual polychlorinated biphenyls (PCBs) and pesticides were determined by gas chromatography (HP6890) against a six level standard curve (0.5-200 pg/ μ l) made from the corresponding individual standards and the internal standard from Promochem, Wesel, Germany and Accustandard, USA. Twelve chlorinated pesticides or their metabolites, hexachlorobenzene (HCB), α -, β - and γ -hexachlorocyclohexane (HCH), α - and γ -chlordane, *trans*-nonachlor, oxychlordane, *p,p'*-dichlorodiphenyl dichloroethene (*p,p'*-DDE), *p,p'*-dichlorodiphenyl dichloroethane (*p,p'*-DDD), *p,p'*-dichlorodiphenyl trichloroethane (*p,p'*-DDT) and *o,p'*-DDT and 11 PCB-congeners (#28, 31, 52, 101, 105, 118, 138, 153, 156, 170, 180) were determined using two different capillary columns from JW Scientific (DB5, 60 m, 0.25 mm inside diameter, 0.25 μ m film thickness and DB1701, 60 m, 0.25 mm inside diameter, 0.25 μ m film thickness) and an ECD detector. Helium was used as the carrier gas (25 cm/s) and nitrogen as a make-up gas, splitless injection of 2.5 min, injector temperature 270°C. Temperature program for DB5: 85°C for 2 min, 30°C/min to 200°C, hold for 29 min, 1.5°C/min to 246°C, 10°C/min to 310°C, hold for 8 min; and for DB1701: 85°C for 1.5 min, 30°C/min to 200°C, hold for 28 min, 2°C/min to 250°C, 7°C/min to 290°C, hold for 8 min. The limit of quantification was at least 0.01-0.1 μ g/kg ww (wet weight) (0.05-0.25 μ g/kg dw (dry weight)) for the pesticides and the individual PCB congeners.

Quality assurance was ascertained in the laboratory participating twice annually in QUASIMEME (Quality Assurance of Information for Marine Environmental Monitoring in Europe) BT2 and BT5 exercises, the use of blank samples and a mussel reference sample from QUASIMEME was extracted and run with

every analysis. The standard solutions were checked by comparison to certified reference material (NIST1493, Promochem, Germany).

Chemical analysis of trace elements

The analysis of trace elements (As, Cd, Cu, Hg, Pb, Se and Zn) was carried out at Matis ltd. The samples analyzed before 2007 were analyzed using cold vapor atomic absorption (Hg), FAA/impact bead using D2-background correction (Cd, Cu, Zn, Pb) and hydride generation atomic absorption (As, Se) as described by Yngvadóttir et al. (2006) after sample digestion in 50 ml Parr digestion bombs as described by Rabieh et al. (2007). Samples analyzed in the year 2007 and later were analyzed with microwave digestion (Mars5, CEM, Matthews, USA) and inductively coupled plasma mass spectrometer (ICP-MS, Agilent 7500ce, Agilent Technologies, Waldbronn, Germany). All samples were freeze dried before analysis and dry weight content calculated. Matis ltd. is accredited for analysis of trace elements and detailed description of the analytical method is found in Reykdal et al. (2011).

Blank samples and certified reference samples were treated and analyzed simultaneously with the samples to ensure the quality and accuracy of the analyses. Mussel tissue (ERM-CE278, DG, JRC, IRMM, Geel, Belgium) was used as certified reference material. Further, the laboratory participates in the QUASIMEME interlaboratory performance program BT-1 twice annually.

6.2.3 Statistical analysis

The data used for the statistical analysis was retrieved from the ICES database and can be accessed at <http://dome.ices.dk/>. To test for an overall pattern of change of concentration of the contaminants and to test whether the pattern of change and concentration was different between locations, analyses with random coefficient models were carried out using a method by Verbeke and Molenberghs (2000). They recommend starting with a saturated model, both fixed and random effects. A polynomial model of order four was considered to be a saturated model. The percentage of fat in the mussels was also included in the model with a quadratic term to reduce variability. The concentrations were log-transformed prior to analysis to meet the normal assumption. The full model was thus:

$$Y_{it} = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \beta_4 t^4 + \beta_5 f_{it} + \beta_6 f_{it}^2 \\ + b_{0i} + b_{1i} t + b_{2i} t^2 + b_{3i} t^3 + b_{4i} t^4 + b_{5i} f_{it} + b_{6i} f_{it}^2 + \epsilon_{it}$$

$$\mathbf{b} \sim N(0, \mathbf{G})$$

$$\epsilon \sim N(0, \sigma^2 \mathbf{I})$$

where Y_{it} is the log-concentration of a contaminant at location i and year t . The β s are fixed effect coefficients, the b s are coefficient describing random effects and f_{it} is the percentage of fat in the sample at location i and year t . The \mathbf{G} matrix was fitted as a diagonal matrix, i.e. the random effects were assumed independent. Random effects were tested first using the restricted likelihood ratio test, which is known to be conservative (Pinheiro and Bates, 2000). Subsequently the fixed effects were tested using likelihood ratio tests. Terms not significant at $\alpha = 0.05$ were removed from the model. If fixed effects could be dropped the random effects were tested again. The modeling procedure was done using the nlme package (Pinheiro et al., 2012) in the statistical software R (R Development Core Team, 2012).

The random effects indicate whether and how much variation exists between locations in concentration and pattern of change with time. If none of the random effects are significant then there is not a significant difference in concentration between locations or in the pattern of change. If for example only the intercept, b_{0i} is significant then there is no significant difference in the pattern of change between locations but there is a significant difference in average concentration. The expected values of the b s are zero so the fixed effects can be interpreted as the average concentration and pattern of change of all locations. The best linear unbiased predictions (BLUPs) of random effects were used to determine the pattern of change at the individual locations. The average concentration for each individual sampling location was calculated from the predicted values for the years sampled, adjusted for average fat percentage (0.41%). All values are given on a dry weight basis.

Of the PCBs, only the highest congener, PCB-153 was statistically analyzed, to avoid uncertainties accompanying lower levels. Similarly, p,p' -DDE was chosen for the DDT-compounds, *trans*-nonachlor for the chlordanes and α -HCH for

Table 6.1: The final model for each contaminant.

Contaminant	Model
<i>p,p'</i> -DDE	$Y_{it} = \beta_0 + \beta_5 f_{it} + b_{0i} + b_{1i}t + b_{2i}t^2 + b_{3i}t^3 + \epsilon_{it}$
HCB	$Y_{it} = \beta_0 + \beta_5 f_{it} + b_{0i} + b_{1i}t + \epsilon_{it}$
α -HCH	$Y_{it} = \beta_0 + \beta_1t + \beta_2t^2 + \beta_5 f_{it} + b_{0i} + \epsilon_{it}$
PCB-153	$Y_{it} = \beta_0 + \beta_1t + \beta_2t^2 + \beta_3t^3 + \beta_4t^4 + \beta_5 f_{it} + \beta_6 f_{it}^2 + b_{0i} + b_{1i}t + b_{2i}t^2 + \epsilon_{it}$
<i>trans</i> -Nonach.	$Y_{it} = \beta_0 + \beta_5 f_{it} + b_{0i} + b_{1i}t + b_{2i}t^2 + b_{3i}t^3 + \epsilon_{it}$
As	$Y_{it} = \beta_0 + \beta_1t + \beta_2t^2 + \beta_5 f_{it} + b_{0i} + \epsilon_{it}$
Cd	$Y_{it} = \beta_0 + \beta_1t + \beta_2t^2 + \beta_3t^3 + \beta_4t^4 + \beta_5 f_{it} + b_{0i} + b_{1i}t + \epsilon_{it}$
Cu	$Y_{it} = \beta_0 + \beta_1t + \beta_2t^2 + \epsilon_{it}$
Hg	$Y_{it} = \beta_0 + \beta_5 f_{it} + \beta_6 f_{it}^2 + b_{0i} + \epsilon_{it}$
Se	$Y_{it} = \beta_0 + \beta_1t + \beta_2t^2 + \beta_3t^3 + \beta_5 f_{it} + \beta_6 f_{it}^2 + \epsilon_{it}$
Zn	$Y_{it} = \beta_0 + \beta_5 f_{it} + b_{0i} + \epsilon_{it}$

the HCHs. Values under the limit of detection (LOD) were taken as being at the LOD. The series of α -HCH had the most frequent <LOD values or 8% and the Hg series had 4% of its values <LOD, other series had 2% or less <LOD values. Statistical analysis of Pb was not included because over 35% of the values were <LOD which ranged between 0.06 to 1.1 mg kg⁻¹ for Pb with median of 0.13 μ g kg⁻¹.

6.3 Results

Results for both POPs and trace elements are interpreted from the final model for each contaminant (Table 6.1). All concentrations are predicted from the model adjusted for the average fat percentage in the samples. The average concentration at each location is shown in Figure 6.1 for the POPs and Figure 6.2 for As, Cd and Hg and patterns of change for POPs are presented in Figure 6.3 and in Figure 6.4 for trace elements.

6.3.1 Spatial and temporal trends of POPs

p,p'-DDE

The average concentration of *p,p'*-DDE over all locations was 0.60 μ g kg⁻¹ and on average there was no significant change in the concentration over the period. However, the year effect had a significant random cubic term indicating that

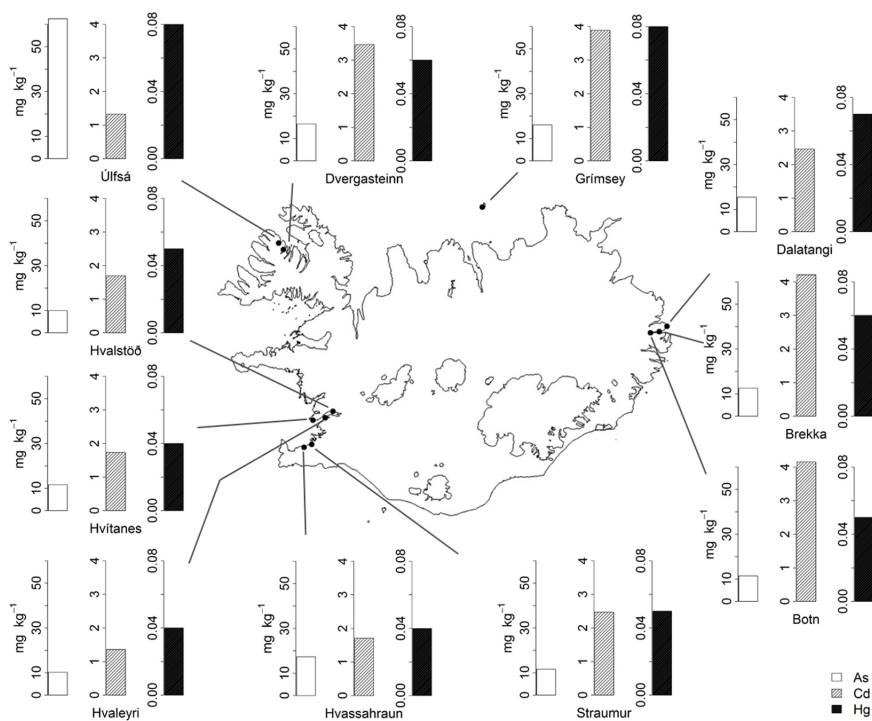


Figure 6.2: Sampling site locations and average concentrations of As, Cd and Hg at each location (note different axes are applied for each element).

although there was no change on average, there was some change at individual locations. Three locations in the same fjord, Botn, Brekka and Dalatangi, had a similar pattern of change, seen as an increase followed by a decrease. The increase was largest at Botn (10% annually from 1996 to 2002) but less at Brekka (8% annually from 1995 to 2003) and Dalatangi (2% annually from 1997 to 2002). The concentration started decreasing 2002-2003 by 11 and 13% annually at Botn and Dalatangi, respectively but only by 2% at Brekka. Mussels collected at Brekka had the highest average *p,p'*-DDE concentration ($0.76 \mu\text{g kg}^{-1}$) of the three sites (Figure 6.1). Hvaleyrri and Hvítanes, which are both located in Hvalfjörður at the west coast, had a consistent pattern of change, which was fairly constant, and an average concentration of $0.58 \mu\text{g kg}^{-1}$. Hvalstöð, which is located at the head of the same fjord, had a very different pattern from Hvaleyrri and Hvítanes. There was a sudden increase in concentration in 2009 at Hvalstöð (Figure 6.3), the average concentration before 2009 was $0.82 \mu\text{g kg}^{-1}$ but after 2009 it was $4.52 \mu\text{g kg}^{-1}$. Dvergasteinn and Úlfsá are located in two parallel fjords next to each other (Figure 6.1). The average concentration at Úlfsá ($0.56 \mu\text{g kg}^{-1}$) was higher than at Dvergasteinn ($0.36 \mu\text{g kg}^{-1}$) and no decrease was observed there, as was the case at Dvergasteinn (annual decrease of -11% from 2002 to 2010). Straumur and Hvassahraun are located close to each other, but Straumur is closer to an industrial area. A higher concentration was found at Straumur ($0.69 \mu\text{g kg}^{-1}$) than at Hvassahraun ($0.42 \mu\text{g kg}^{-1}$). Furthermore, no decrease was observed at Straumur while at Hvassahraun a -7% average annual decrease from 2002 to 2010 was noted. The *p,p'*-DDE concentration at Grímsey ($0.61 \mu\text{g kg}^{-1}$), an island north of the mainland, was stable in the beginning but started to decrease around 2001 (average annual decrease of -11% from 2001 to 2010).

HCB

There was no change in HCB concentration when averaged over all locations ($0.13 \mu\text{g kg}^{-1}$), but the year effect had a significant random term indicating different trends between the locations. Hvassahraun, Dvergasteinn, Grímsey, Hvítanes, Dalatangi, Straumsvík and Hvaleyrri all had a decreasing trend ranging from -6 to -1% a year (Hvassahraun with the highest trend and Hvaleyrri the lowest). Úlfsá, Hvalstöð, Brekka and Botn had an increasing trend from 1 to 2% a year. There was a difference in concentration between the locations, with Úlfsá having the highest concentration ($0.22 \mu\text{g kg}^{-1}$) which was 1.5-2 times more than found at the other locations ($0.11\text{-}0.14 \mu\text{g kg}^{-1}$).

α -HCH

The year effect did not have a significant random term, suggesting a consistency in the pattern of change of α -HCH between the locations. The concentration decreased on average by -13% annually from 1999 to 2010. There was a significant difference in concentration between the locations. The three locations with the highest concentration were all from the same fjord system at the east coast, Botn, Brekka and Dalatangi, with average concentrations from 0.23 to 0.24 $\mu\text{g kg}^{-1}$. The three locations with the lowest concentration were Dvergasteinn (0.16 $\mu\text{g kg}^{-1}$), Úlfsá (0.15 $\mu\text{g kg}^{-1}$) and Hvassahraun (0.14 $\mu\text{g kg}^{-1}$). The concentration at Hvassahraun was about 60% of the highest concentration.

PCB-153

There was a significant difference in the pattern of change in PCB-153 concentration between locations. Dalatangi and Botn which are located in the same fjord had a consistent pattern of change, in the form of slight increase followed by a decrease but the average concentration at Dalatangi (0.73 $\mu\text{g kg}^{-1}$) was higher than at Botn (0.22 $\mu\text{g kg}^{-1}$). Brekka, located in the same fjord as Botn and Dalatangi, had an increase in PCB-153 concentration of 16% a year on average from 1995 to 2008 and an average concentration of 1.22 $\mu\text{g kg}^{-1}$. Hvalstöð, Hvaleyrri and Hvítanes (all in the same fjord) had a similar decreasing trend until 2001 when the concentration at Hvalstöð started to increase by 7% a year on average until 2008. At other locations there was a decreasing trend between -8 to -5% annually and a decreasing trend of -12% a year at Grímsey from 1993 to 2010. There was a considerable difference in concentrations at some locations that are not located far apart (Figure 6.1) e.g. Straumur (2.71 $\mu\text{g kg}^{-1}$) had 2.4 times higher concentrations than Hvassahraun (1.11 $\mu\text{g kg}^{-1}$) and Úlfsá (1.84 $\mu\text{g kg}^{-1}$) had 1.7 times higher concentrations than Dvergasteinn (1.08 $\mu\text{g kg}^{-1}$).

***trans*-Nonachlor**

Averaged over all locations there was no pattern of change in the *trans*-nonachlor concentration in the last 14 years (0.26 $\mu\text{g kg}^{-1}$). There was, however, a significant difference in pattern of change between locations. Hvaleyrri and Hvítanes had very similar concentrations (0.23-0.24 $\mu\text{g kg}^{-1}$) that were fairly stable over the period. The pattern of change was similar at the locations, Botn, Brekka and Dalatangi, located in the eastern part of Iceland, where an increase was observed until 2003-2004 when the concentration started decreasing again. The

increase was largest at Brekka, 10% a year and less at Botn and Dalatangi, 1 and 5% a year respectively. The decrease at Brekka (-6% a year from 2003 to 2010) was not as large as at the other two locations where it was -11% a year at Botn and -10% at Dalatangi. Dvergasteinn, Hvassahraun and Straumur showed a decreasing trend of -9, -7 and -4% a year, respectively. At Úlfsá there was a decreasing trend of -4% a year until 2003 when it started increasing by 4% a year. There was a sudden increase in *trans*-nonachlor concentration at Hvalstöð in 2009, where the average concentration was $0.30 \mu\text{g kg}^{-1}$ before 2009 but $1.18 \mu\text{g kg}^{-1}$ after 2009.

6.3.2 Spatial and temporal trends of trace elements

Arsenic

There was not a significant difference in pattern of change in the As concentration between locations (Figure 6.4). There was an increase in concentration of 2% a year on average from 1996 to 2001 when it started decreasing by 3% a year. There was a significant difference in concentration between locations. Úlfsá had a much higher As concentration (62 mg kg^{-1}) than was observed at any other location investigated ($10\text{-}17 \text{ mg kg}^{-1}$), furthermore the concentration at Úlfsá was 3.7 times higher than at Dvergasteinn which is located in the next fjord (Figure 6.2).

Cadmium

There was a significant difference in pattern of change of Cd concentration between locations. Hvassahraun, Hvalstöð, Hvaleyri, Hvítanes and Úlfsá all had similar concentration ($1.3\text{-}1.7 \text{ mg kg}^{-1}$) and pattern of change, which was fairly constant. All the locations in the fjord in the east had a decrease in concentration of -11, -8 and -8% at Botn, Brekka and Dalatangi, respectively. Increasing trend of 6% was observed at Grímsey from 1994 to 2002 when it started to decrease by 4% a year. The pattern was similar at Dvergasteinn where the concentration increased from 1996 to 2003 by 9% a year and then decreased by 2% a year. The highest concentrations were found at Botn, Brekka and Grímsey ($3.9\text{-}4.2 \text{ mg kg}^{-1}$).

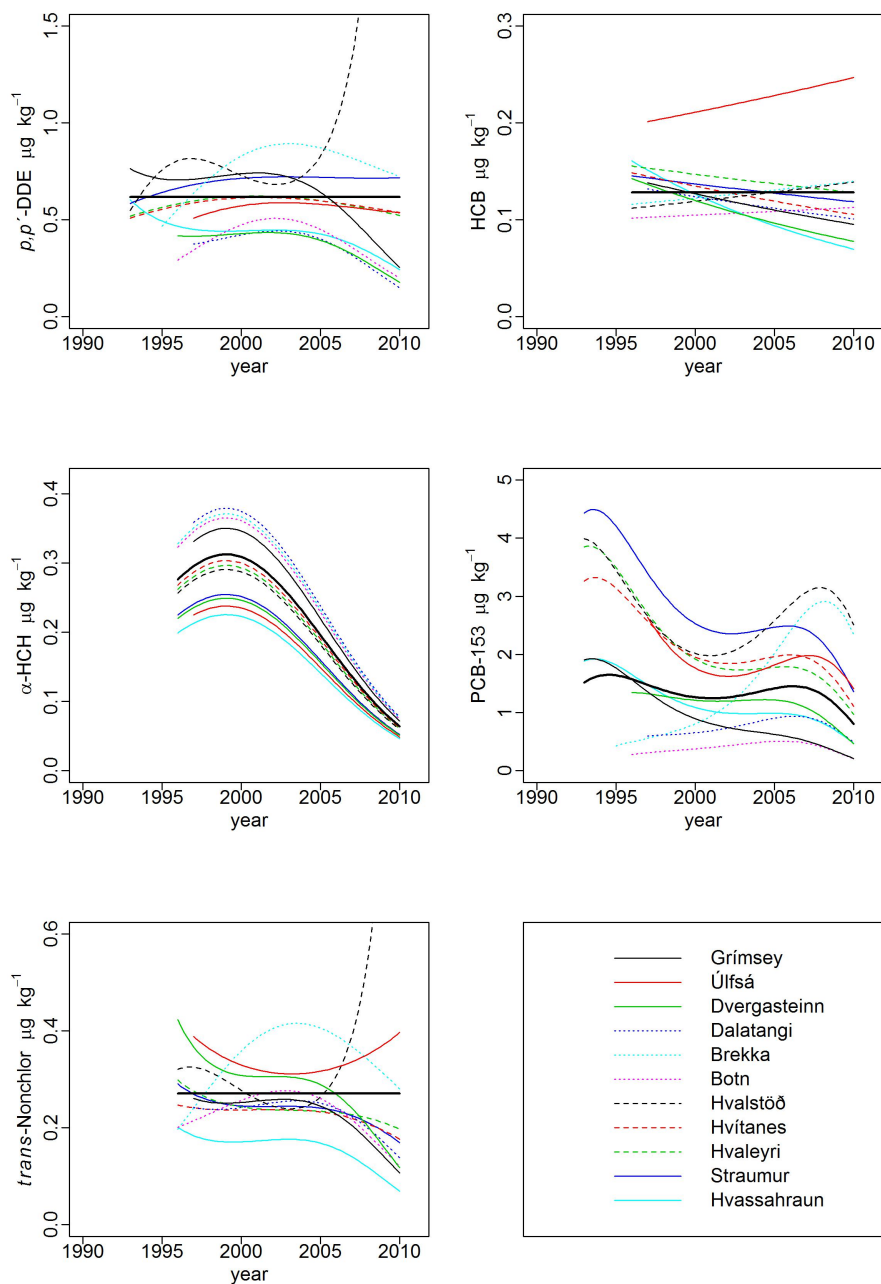


Figure 6.3: Predicted concentration and pattern of change of the POPs (p,p' -DDE, HCB, α -HCH, PCB-153 and *trans*-nonachlor) at the 11 locations.

Copper

There was no significant difference of pattern of change and concentration of Cu between locations. There was an increasing trend from 1990 to 1998 of 3% a year on average when it started decreasing by -5% a year. The average concentration was 6.6 mg kg^{-1} the last two decades.

Mercury

There was no significant change in Hg concentration. There was, however, a significant difference in average concentration between the locations (Figure 6.2 and 6.4). Hvítanes, Hvaleyrri, Hvalstöð, Hvassahraun and Straumur had similar concentrations ($0.041\text{-}0.049 \text{ mg kg}^{-1}$). Brekka and Botn had similar concentrations ($0.054\text{-}0.060 \text{ mg kg}^{-1}$) while the concentration at Dalatangi was 0.072 mg kg^{-1} and at Grímsey 0.077 mg kg^{-1} . The highest concentration was found at Úlfsá (0.081 mg kg^{-1}) which was twice as high as the concentration at Hvítanes where it was lowest.

Selenium

There was no significant difference in pattern of change and of Se concentration between locations. The concentration of Se had been increasing by 4% a year on average from 1993 to 2005 when it reached 3.5 mg kg^{-1} . Then it started decreasing again by -9% a year on average.

Zinc

There was no significant change in Zn concentrations and the average concentration was 130 mg kg^{-1} . There was, however, a significant difference in Zn concentration between locations. The lowest concentration was found at Botn, 120 mg kg^{-1} , but the two other locations, Dalatangi and Brekka, in the same fjord had 25-29% higher concentrations ($150\text{-}160 \text{ mg kg}^{-1}$) and in fact the second and third highest concentration of all the locations. The highest concentration was observed at Grímsey (180 mg kg^{-1}).

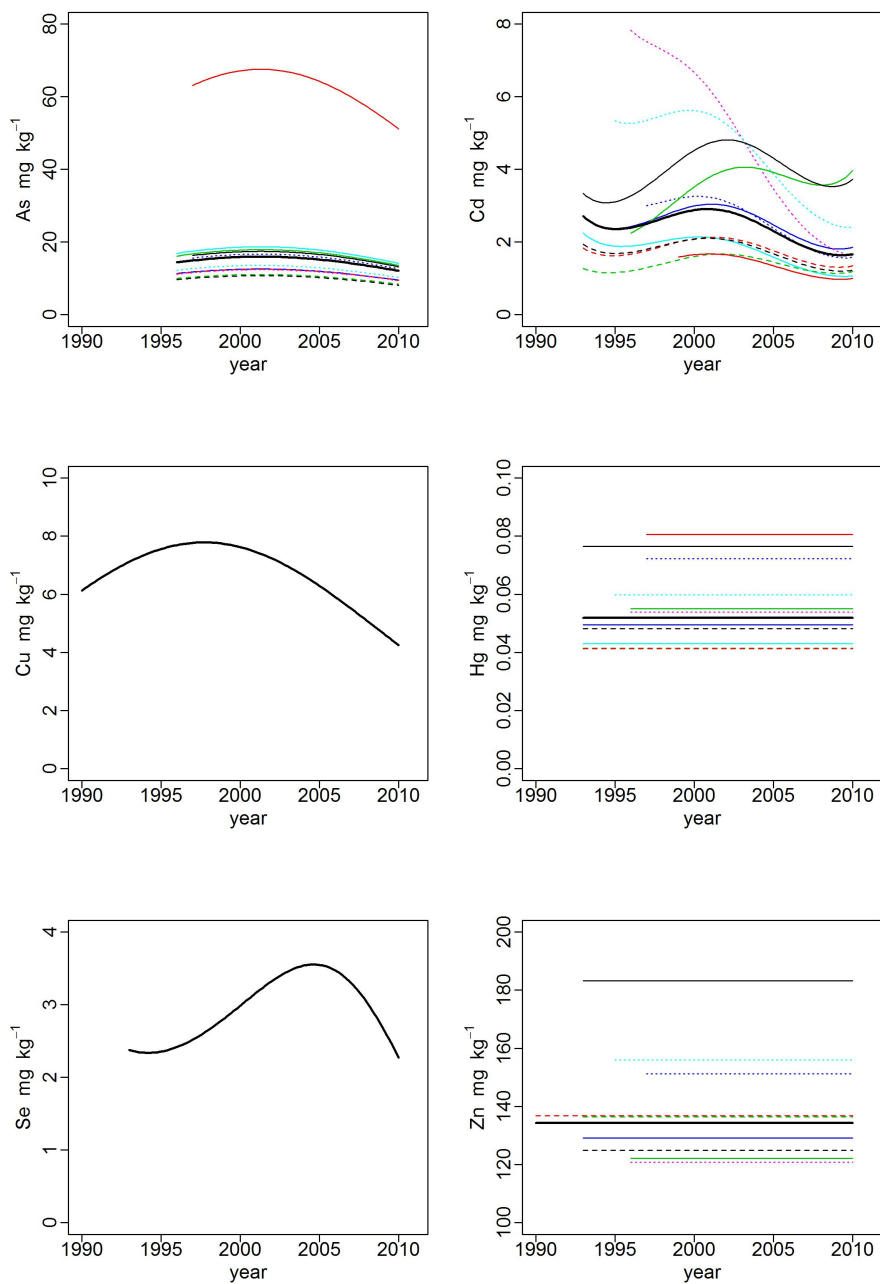


Figure 6.4: Predicted concentration and pattern of change of the trace elements (As, Cd, Cu, Hg, Se and Zn) at the 11 locations (see Figure 6.3).

6.4 Discussion

6.4.1 Concentrations of contaminants

The levels of POPs in mussels collected at the Icelandic coast are generally very low, even compared to pristine sites. The results from this study can be compared to results from the monitoring programs in Norway (Green et al., 2011), northeastern USA (Kimbrough et al., 2008) and in China (conversion from wet weight assuming 10% dry weight) (Fung et al., 2004; Monirith et al., 2003). Median values were used in these comparisons. The concentration of Σ DDTs (Σ DDTs: *o,p'*-DDD+*o,p'*-DDE+*o,p'*-DDT+*p,p'*-DDD+*p,p'*-DDE+*p,p'*-DDT in USA, *p,p'*-DDD+*p,p'*-DDE+*p,p'*-DDT in China and *p,p'*-DDD+*p,p'*-DDE+*p,p'*-DDT+*o,p'*-DDT in Iceland (median of $1.2 \mu\text{g kg}^{-1}$, not shown in results)) was 20 and 1000 times higher in mussel from USA and China, respectively, than in the ones from Iceland. The concentration of *p,p'*-DDE was about 10 times higher in Norway compared to Iceland. The concentration of HCB was five times higher both in mussels from China and in Norway compared to Iceland, but was not reported for the US mussels. The PCB-7 was calculated (sum of PCBs#28, 52, 101, 118, 138, 153, 180, not shown in results) to compare to the values from Norway. The concentration of PCB-7 in mussels from Norway was about two times higher than found in the ones sampled in Iceland ($5.8 \mu\text{g kg}^{-1}$). PCBs reported in the US and Chinese mussels could not be compared to PCB-7.

The median concentration of As was similar in mussels sampled in Iceland, Norway, USA and China ($10\text{-}16 \text{ mg kg}^{-1}$). However, the highest concentration was found in Iceland at Úlfsá which was approximately two times higher than the second highest which was observed in Norway. The concentration of Cd was two times higher in Iceland compared to Norway and USA but very similar compared to China. The concentration of Zn was also found to be higher in mussels from Iceland than from Norway, USA and China of about 20-30%. However, higher values were observed at few locations from both Norway and USA than at any of the Icelandic sites for both Cd and Zn. The concentration of Cu was in the same range in mussel from Iceland, Norway, USA and China ($6\text{-}10 \text{ mg kg}^{-1}$). The concentration of Hg was two times and three times higher in mussels from Norway and USA, respectively, than in mussels from Iceland but the concentration of Hg in China was about 700 times higher than observed in Iceland. The concentration of Pb was found to be 5, 15 and 19x higher in mussels in China, Norway and USA, respectively, than the median concentra-

tion in mussels sampled in Iceland (0.15 mg kg^{-1} , not shown in results) which was frequently below the LOD. There are no major anthropogenic sources of trace elements known in Iceland that could explain the high concentration observed in the Icelandic mussels. Iceland is a volcanic island where there are 20-25 eruptions per century (Thordarson and Larsen, 2007) and eruptions are known sources of metals (AMAP, 2005; Hong et al., 1996). Krause-Nehring et al. (2012) concluded that the Pb concentration in northern Atlantic bivalves (*Arctica islandica*) sampled near Iceland had volcanic origin but not anthropogenic like the ones sampled in the USA and Europe. It is likely that other trace elements have the same origin in Iceland as Pb.

6.4.2 Temporal trends of contaminants

The concentration of *p,p'*-DDE has been decreasing around Iceland in recent years which is consistent with what has been found elsewhere in the Arctic region (Green et al., 2011; Rigét et al., 2010). There was, however, a substantial increase after 2009 at Hvalstöð suggesting a local source, most likely the whale-processing at the whaling station but whales are known to have high concentrations of POPs compared to the mussels. There was not much change observed in HCB concentration, although seven of the 11 sample locations investigated in Iceland had decreasing trends which is consistent with results from Norway (Green et al., 2011) and other locations in the Arctic (Rigét et al., 2010). Four of the Icelandic locations showed signs of increasing trend of HCB. Out of the forty time-series of HCB concentration analyzed by Rigét et al. (2010), no significant increasing trends were observed while Green et al. (2011) found a significant increase in one time-series. The decrease found in α -HCH was consistent with what has been found elsewhere in the Arctic where 59% of time-series were found to have a decreasing trend (-7.4% annual decrease on average) and none with increasing trends (Rigét et al., 2010). In our study most time-series of PCB-153 had a decreasing trend but two locations showed increasing trends. In the meta-analysis carried out by Rigét et al. (2010) only three out of forty time-series of PCB-153 concentration had increasing trends and one of those time series was from Iceland. Of the 33 locations where Σ PCB-7 concentration was measured in blue mussel in Norway no significant increasing trends were found (Green et al., 2011). There was no consistent pattern of change in *trans*-nonachlor concentrations in our study but other studies have in general shown a decreasing trend of 1% on average (Rigét et al., 2010).

In our study the Cd concentration was unstable at most locations. This is in agreement with the results from Norway where no general trend in Cd concentration in blue mussel was observed (Green et al., 2011). Decrease in Cu concentration was found in our study while no trends out of the 25 time-series were observed in Norway (Green et al., 2011). Meta-analysis of 83 Hg time-series from the Arctic carried out by Rigét et al. (2011) showed trends ranging from -8.6 to 10% annual change and most of the time-series did not show a significant trend, which is consistent with what was found at the Icelandic locations where no trend could be detected. No trends in Zn concentration were found at any of the Icelandic locations which is consistent with results from most of the Norwegian locations (Green et al., 2011). The trend in As concentration could not be compared to the Norwegian data because the Norwegian time-series were too short for trend analysis.

6.4.3 Local sources

There appears to be some local sources of pollution around the Icelandic coastline. There was an increase in PCB-153 concentration at Brekka, located in the middle of a fjord on the east coast, although no increase was observed at the location at the head of the fjord, Botn, or at the mouth of the fjord, Dalatangi. Furthermore, elevated concentrations of *p,p'*-DDE, HCB and *trans*-nonachlor were observed at Brekka. Salmon aquaculture was carried out from 2001 to 2008 close to Brekka which could be the explanation for the increased concentrations since higher levels of PCBs have been observed in fish from aquaculture than in wild fish and the elevated levels have been traced back to the fish feed (Sapkota et al., 2008).

In 1986 commercial whaling was banned in Iceland but permitted again in 2006 and in 2009 the cutting of fin whale started again at the whaling station close to the sampling site Hvalstöð. The same year a sudden increase was observed in *p,p'*-DDE and *trans*-nonachlor concentration in the mussels collected at that site. The ratio of PCB-153:*p,p'*-DDE in the mussels sampled in 2010 at Hvalstöð was 0.4 but this ratio was usually between 2 and 3.5 at other locations. The ratio in whale cut at the station at the same time was 0.2-0.4 (G.A. Auðunsson, unpublished data) suggesting that the elevated values could be explained by waste from the station.

The results showed that there was much higher concentration of As and HCB at Úlfsá than at any other location. A waste incinerator was operated

from 1994 approximately 2 km from the sampling site. It is well known that HCB is produced by combustion (Bailey, 2001) and this might explain the elevated value of HCB at this location. The elevated level of As, but not for any of the other trace elements, is however difficult to explain. Measurements of both ash and water from the incinerator did not reveal high values of As (G.S. Jónsson, Environment Institute of Iceland, personal communication) suggesting that the As may have a different origin. Iceland is a volcanic island and eruptions are sources of inorganic compounds. The As at Úlfsá does, however, not seem to have volcanic origin as mussels were also sampled in the next fjord, at Dvergasteinn, where the concentration of As was much lower. Other possible sources of As is an old landfill that a part of the village is built on or an oil storage facility located 2 km from the sampling location which has been running on an exemption from operating license for some years. A study carried out by Wainipiee et al. (2010) showed that absorption of As by the mineral goethite was reduced in water with high oil loads. Oil polluted water could therefore have an effect on the cycling and biogeochemistry of As and raise the As concentration. The waste incinerator has now been shut down and a new oil storage facility will be operating next year. If the oil storage facility and the waste incinerator were the sources for elevated levels of As and HCB at Úlfsá, continued monitoring should show decreasing concentrations of HCB and As over the next years.

6.5 Conclusion

There has been a decreasing trend in the concentration of POPs at most of the sampling locations in Iceland in recent years, consistent with observations elsewhere in the North. Nevertheless, an increasing trend was found at a few locations that could be explained by anthropogenic activity. The Cu and Se concentrations have been consistent between locations with decreasing trends in recent years. The concentrations of As, Hg and Zn have been fairly stable in the last 15 years at all locations but no general pattern of change was observed for Cd concentration. The decrease in the levels of some contaminants can be traced to banned or restricted usage but some changes in concentration could be due to climate change in recent years. The climate change could affect wind fields and sea currents which would lead to change in transport pathways of the contaminants. Increase in sea temperature could also have some effect on the growth of the mussels and influence bioaccumulation of the contaminants. The concentrations of the POPs were generally found to be lower in Iceland

compared to Norway, China and the northeastern coast of USA. However, the concentration of Cd and Zn were observed to be somewhat higher than found in Norway, USA and China but values of Hg and Pb were much lower in the mussel sampled in Iceland. The higher concentrations of Cd and Zn can probably be explained by the volcanic activity in Iceland since no major anthropogenic sources of trace elements are known in Iceland, such as e.g. mining. The results further show that human activity can have impact on the environment, elevated concentration of contaminants found at some locations in Iceland can most likely be traced back to aquaculture, whale processing, waste incineration and an oil storage facility. Monitoring is therefore essential to identify and prevent contamination from human activity.

Acknowledgement

The national monitoring program is run by funding from the Ministry for the Environment with contribution from the institutions involved. This study was financially supported by the Icelandic research fund and the Icelandic research fund for graduate students.

7

Paper II

Temporal trends of contaminants in cod from Icelandic waters

Erla Sturludottir, Helga Gunnlaugsdottir, Hronn O. Jorundsdottir,
Elin V. Magnusdottir, Kristin Olafsdottir, Gunnar Stefansson

Abstract

Contaminants have been analyzed in cod (*Gadus morhua*) since 1990 as part of the national monitoring program for the environmental conditions in the sea around Iceland. The aim of this study was to determine the temporal trends of persistent organic pollutants (POPs: polychlorinated biphenyls (PCBs), p,p'-dichlorodiphenyl dichloroethene (p,p'-DDE), hexachlorobenzene (HCB), hexachlorocyclohexanes (HCHs), chlordanes (CHLs) and toxaphenes (Tox)) and trace elements (As, Cd, Cu, Hg, Pb, Se and Zn) in cod over the last two decades at two different locations in the Arctic Ocean north of Iceland. The relationship between the contaminant concentrations and biological covariates was also determined. All of the POPs showed decreasing trends but the trace elements showed no clear signs of trend except arsenic which showed an increasing trend and zinc which showed a decreasing trend. The concentration of the POPs were lower or similar in the Icelandic cod compared to cod sampled in Norway, the Barents Sea and in the Baltic Sea, except for HCB which was higher in the Icelandic cod compared to the Norwegian cod. The concentration of the trace elements As, Cu, Hg and Zn were similar in the Icelandic cod compared to cod sampled in Norway and Greenland but the concentration of Cd was higher in the Icelandic cod. The inclusion of the biological covariates was found to be important for the statistical analysis. The POPs had a positive relationship with liver fat content but negative relationship with liver weight. The trace elements had a negative relationship with liver fat and liver weight except As which had positive relationship with liver weight. Only positive relationships were observed between the contaminant concentrations and length.

7.1 Introduction

The Arctic is sparsely populated with very limited industrial activity and is therefore considered a pristine area. However, contaminants like persistent organic pollutants (POPs) which have anthropogenic origin are found all over the Arctic and sub-Arctic (Ólafsdóttir et al., 2005; Rigét et al., 2010) although they have rarely been used there. The POPs are transported from sources at lower latitudes, to higher ones by long-range transport (Pacyna et al., 1985; Wania and Mackay, 1993). Most time-series of POPs in the Arctic have shown decreasing trends, nonetheless, a few series have shown increasing trends (Rigét et al., 2010). Although trace elements occur naturally in the environment a significant amount comes from human activity such as from fossil fuel combustion, non-ferrous metal production and waste incineration (AMAP, 2005). The analysis of POP and metal concentrations in mussels (*Mytilus edulis*) around the coastline of Iceland mostly indicated reducing levels from 1990-2010, but revealed three minor local sources of the contaminants (Sturludóttir et al., 2013). Increased levels of mercury in the Arctic biota have been observed in the Canadian Arctic and in Greenland (Muir et al., 1999; Rigét et al., 2011). The concentration of mercury in some Arctic species such as pilot whales and beluga exceed the toxicological threshold limits and increasing concentrations are alarming (Dietz et al., 2013).

Fish liver is often used as a monitoring matrix for POPs and metals in the marine environment as their concentrations are elevated in the liver either due to high lipid content (POPs) or certain organ affinity (trace elements) and thus give more reliable results of the usually low levels. The livers can be very variable in size and composition depending on the nutritional status of the individual which has great influence on the concentration of contaminants in the livers (Auðunsson, 1999). The contaminants are either lipophilic or lipophobic and the fat content of the liver is therefore considered an important covariate when determining temporal or spatial trends. Other biological factors are also expected to affect the concentration of contaminants such as: age, length, dry and total weight of the liver (Auðunsson, 1999; Green and Knutzen, 2003; Rigét et al., 2000).

Contaminants have been analyzed in cod (*Gadus morhua*) liver and muscle since 1990 as a part of the national monitoring program for the environmental conditions in the sea around Iceland (Jörundsdóttir et al., 2012). The cod studied in the national monitoring program has mainly been caught north of

Iceland where the ocean can be divided into two areas with different types of waters, relatively warm and saline Atlantic water to the west and mixture of Atlantic water and cold and low-salinity Polar water to the east (Valdimarsson and Malmberg, 1999). Cod caught in these two areas may also have different genetic structures. A study by Pampoulie et al. (2006) on the genetic variability of the Icelandic cod showed a significant difference in the genetic structure in cod that spawned at the main fishing grounds at the SW coast and at the NE coast of Iceland. Marteinsdottir et al. (2000) have shown that first year cod caught off the NE coast are younger (born later in the year) than the ones caught off the NW coast. This indicates that juveniles in the NE area are mainly from local spawning areas whereas more of the juveniles at the NW area come from the spawning grounds to the SW of Iceland.

The cod feeds mainly on capelin (*Mallotus villosus*) and other fish but the northern shrimp (*Pandalus borealis*) and other decapods are also important in the cod diet (Jaworski and Ragnarsson, 2006). Regional differences in cod diets have been observed where the northern shrimp is more common in the diet of cod in the NW area than at the NE area and small crustaceans of the order Euphausiacea are more common at the NE than at the NW area (Pálsson, 1983). Temporal changes in the cod diet have been observed from 1988 to 2010 where the consumption of capelin and northern shrimp has fluctuated (Pálsson and Björnsson, 2011). Diet preferences may influence biomagnifications of contaminants (Ruus et al., 1999; Skarphedinsdottir et al., 2010) and therefore factors such as season, location and fish size can affect the concentrations of contaminants as feeding depends on these factors and fish becomes a larger proportion of the cod diet as the cod grows (Jaworski and Ragnarsson, 2006).

The aim of this study was to use the data collected as a part of the national monitoring program to determine temporal trends of POPs and trace elements in cod liver and mercury in cod muscle over the last two decades at two different locations in the Arctic Ocean north of Iceland. The relationship between the contaminant concentrations and biological covariates is also determined.

7.2 Materials and Methods

7.2.1 Sampling method and locations

Sampling of cod (*Gadus morhua*) was carried out from 1990-2011 using sampling guidelines from OSPAR/ICES. Cod of length 30-45 cm were collected in March

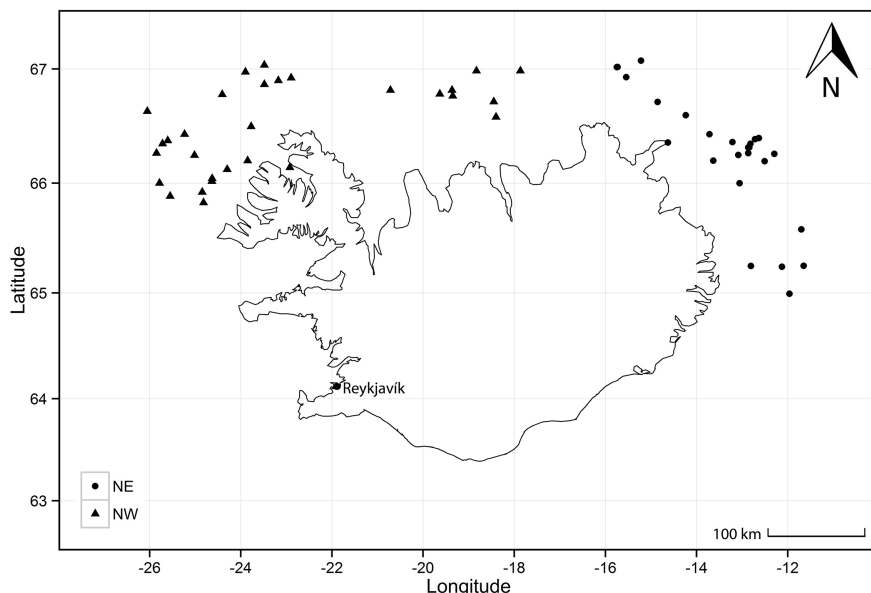


Figure 7.1: Sampling site locations.

in the annual bottom trawl survey carried out by the Icelandic Marine Research Institute. Samples were taken from two locations NW and NE of Iceland (Figure 7.1). One or two samples were taken each year from the NW location and one from the NE location. Each sample contained 25 individuals which were gutted at time of sampling and the livers were put in a pre-weighed and pre-cleaned glass jars and both the livers and the fish were frozen at -20°C until sample preparation. Further handling of the samples was carried out in the laboratory. Each individual was weighed, the length of the fish measured, the gender determined, otoliths were removed for age determination, the fish was filleted, skinned and the muscle weighed (Table 7.1). The 25 muscles from each sample were homogenized and kept frozen until chemical analysis was performed. The 25 livers were divided into four to six sub-samples according to the weight of the livers, livers with similar weight were pooled together, except in 1992 and 1995 when all the livers were pooled into one group. The liver samples were then homogenized and kept frozen until chemical analysis took place.

Table 7.1: Median (and range) of age, length, liver weight and liver fat of cod sampled at the NE and NW locations from 1991-2011.

	NE	NW
Age (years)	3.0 (2.0-5.0)	3.0 (2.0-5.0)
Length (cm)	38 (31-45)	39 (31-45)
Liver weight (g)	23 (4-79)	17 (2-80)
Liver fat (%)	55 (19-69)	53 (9-74)

7.2.2 Chemical analysis

Chemical analysis of POPs

The homogenized cod livers were extracted wet, basically according to the method of Jensen et al. (1983) as described earlier (Ólafsdóttir et al., 1995). In short, approx. 3 g of tissue were extracted with hexane/acetone/diethyl ether, solvents evaporated at 40°C under N₂, the residue or a fraction of it, re-suspended in isooctane containing 1,2,3,4-tetrachloronaphthalene (the internal standard) and cleaned with concentrated sulfuric acid. Recovery was checked and corrected for by the addition of ϵ -HCH, *o,p'*-DDD, PCB #112 and PCB #198 (no. according to IUPAC) to all samples at the first step of the extraction. The fat content was determined gravimetrically.

The individual polychlorinated biphenyl (PCB) congeners and pesticides were determined by gas chromatography (HP6890) against a six level standard curve (0.5-200 pg/ μ l) made from the corresponding individual standards and the internal standard from Promochem, Wesel, Germany and Accustandard, USA. Fifteen chlorinated pesticides or their metabolites; i.e. hexachlorobenzene (HCB), α -, β - and γ - hexachlorocyclohexane (HCH), α - and γ - chlordane, *trans*-nonachlor, oxychlordane, three toxaphene congeners (Parlar no. 26, 50 and 62), *p,p'*- dichlorodiphenyl dichloroethene (*p,p'*-DDE), *p,p'*- dichlorodiphenyl dichloroethane (*p,p'*-DDD), *p,p'*- dichlorodiphenyl trichloroethane (*p,p'*-DDT) and *o,p'*-DDT and 11 PCB-congeners (#28, 31, 52, 101, 105, 118, 138, 153, 156, 170, 180), were determined using two different capillary columns from JW Scientific (DB5, 60 m, 0.25 mm inside diameter, 0.25 μ m film thickness and DB1701, 60 m, 0.25 mm inside diameter, 0.25 μ m film thickness) and an ECD detector. Helium was used as the carrier gas (25 cm/s) and nitrogen as a make-up gas, splitless injection of 2.5 min, injector temperature 270°C. Temperature program for the DB5 column: 85°C for 2 min, 30°C/min to 200°C, hold for 29 min, 1.5°C/min to 246°C, 10°C/min to 310°C, hold for 8 min;

and for the DB1701 column: 85°C for 2 min, 30°C/min to 200°C, hold for 28 min, 1.5°C/min to 250°C, 7°C/min to 290°C, hold for 8 min. The limit of quantification was at least 0.1-0.5 µg/kg wet weight (ww) for the pesticides and the individual PCB congeners.

Quality assurance was ascertained in the laboratory participating bi-annually in QUASIMEME (Quality Assurance of Information for Marine Environmental Monitoring in Europe), BT2 and occasionally BT5 exercises and the use of blank samples and a cod liver reference sample from QUASIMEME was extracted and run with every analysis. The standard solutions were checked by comparison to certified reference material (NIST1493).

Chemical analysis of trace elements

The trace elements As, Cd, Cu, Pb, Se and Zn were analyzed in cod liver and Hg in cod muscle. Before 2007, Hg was analyzed using cold vapor atomic absorption, Cd, Cu, Zn and Pb were analyzed using FAA/impact bead using D2-background correction and As and Se were analyzed with hydride generation atomic absorption as described by Yngvadóttir et al. (2006) after sample digestion in 50 ml Parr digestion bombs as described by Rabieh et al. (2007). Samples analyzed in the year 2007 and later were analyzed with microwave digestion (Mars5, CEM, Matthews, USA) and inductively coupled plasma mass spectrometer (ICP-MS, Agilent 7500ce, Agilent Technologies, Waldbronn, Germany). The laboratory is accredited for analysis of trace elements and a detailed description of the analytical method can be found in Reykdal et al. (2011). To assure the validity of the new analytical method when the method was changed in 2007, the results of the two analytical methods were compared by analyzing a range of samples and certified reference material with both methods as well as participate in interlaboratory comparison studies such as QUASIMEME with the new method. The difference in the results between the two methods was within set criteria of $|Z|$ score ≤ 2 . Results for all samples are presented on wet weight bases (w.w.).

7.2.3 Statistical analysis

The data used for the statistical analysis were retrieved from the ICES database and can be accessed at <http://dome.ices.dk/>. The contaminant concentrations are all on wet weight basis. Some of the POPs were statistically analyzed together; PCBs (sum of PCB-congeners #28, 52, 101, 118, 138, 153, 180),

HCHs (sum of α -, β - and γ -HCH), CHLs (sum of α - and γ -chlordane and *trans*-nonachlor) and Tox (sum of three toxaphene congeners, Parlar no. 26, 50 and 62). The time-series are variable of length as analysis of some of the contaminants started after 1990. Analysis of HCH began in 1994 with missing observations from 1997-98. Analysis of CHLs started in 1997, analysis of Tox in 2000, of As in 1996 and of Se in 1994. Other time-series are from 1990. In 1990 the fish was frozen whole and the livers were damaged, therefore data from that year was not used in the statistical analysis. Values of β -HCH from 1994 and 1995 were unusually high and because of missing observations from 1997-98 the time-series of HCH was analyzed from 1999. The concentration of Pb was not used in the statistical analysis because 90% of the data was below the limit of detection (LOD) which ranged from 0.02 to 0.1 mg kg⁻¹ wet weight. For other contaminants 0-7% of the data was <LOD and these values were treated as equal to the LOD in the statistical analysis.

To test whether the concentration of contaminants in cod had changed over the periods a method of mixed models was applied (Pinheiro and Bates, 2000). The change in concentration over time was modeled as a polynomial and a polynomial model of order four was considered a saturated model. The average age, length, liver fat content and liver weight of the sub-samples were used as covariates to adjust for biological variation. Interactions between location and the fixed effects were added to the model to test whether the change in concentration was different between the locations and to test whether the relationship between the concentrations and the covariates were different at the two locations. It is well established that biological attributes of marine animals caught in close vicinity of each other tend to be more similar than attributes of animals caught at very different locations. In the context of general random effects model this is the intra-class correlation or, for marine surveys, the intra-haul correlation (Pennington and Volstad, 1994) and is typically taken into account by using the discrete sampling location as a random effect. Therefore, a random year-location interaction was also included in the model to account for correlation between observations from the same year at each location.

The saturated model of the change in concentration of the contaminants (PCBs, DDE, HCB, HCHs, CHLs, Tox, As, Cd, Cu, Se and Zn in cod liver) is as follows.

$$y_{ijt} = \beta_{0j} + \beta_{1j}t + \beta_{2j}t^2 + \beta_{3j}t^3 + \beta_{4j}t^4 \\ + \beta_{5j}a_{ijt} + \beta_{6j}l_{ijt} + \beta_{7j}f_{ijt} + \beta_{8j}lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$$

where y_{ijt} is the log-concentration of a contaminant in sub-sample i at location j in year t , a_{ijt} is the average age, le_{ijt} is the average length, f_{ijt} is the average fat content of the livers and lw_{ijt} is the log of the average liver weight in the sub-samples. The γ_{jt} is the random effect for the intra-haul correlation and the G matrix was fitted as a diagonal matrix, i.e. the random effects were assumed independent. The model for Hg in cod muscle was different because of the different data structure, it did not have a random term and it only had age and length as covariates. The models were fitted with restricted maximum likelihood (REML) using the nlme package (Pinheiro et al., 2013) in the statistical software R (R Development Core Team, 2012). Fixed effects were tested using the conditional t-test which is an approximate test (Pinheiro and Bates, 2000), terms not significant at $\alpha = 0.05$ were removed from the model.

7.3 Results

The change in concentration and median concentrations of the contaminants were predicted from the final models (Table 7.2) adjusted for the median of the significant covariates, age (3 years), length (39 cm), liver fat content (53%) and liver weight (19 g). The changes in the POP concentrations are shown in Figure 7.2 and for the trace elements in Figure 7.3, where all concentrations are on wet weight basis.

7.3.1 Temporal trends of POPs

A significant change in concentration of all of the POPs was observed (see Table 7.3). The concentration decreased by -3 to -2% for PCB, p,p' -DDE, HCB, CHL and Tox but by -9% for HCHs (Figure 7.2). The annual decrease was the same at both locations and the median concentration of the POPs over the periods were similar or higher at the NE location compared to the NW location (Table 7.3).

The biological covariates, except age were found to have a significant relationship with the POP concentrations. Length had a significant and positive relationship with all the POPs except with HCH where it was not significant. This relationship was not the same at both locations; the concentration increased significantly more with length at the NE location (PCB: $p = 0.0121$, DDE: $p = 0.0344$, HCB: $p = 0.0403$, CHL: $p = 0.0098$) and it was found to have a negative relationship with HCB at the NW location. The relationship

Table 7.2: Final model for each contaminant where y_{ijt} is the log-concentration of a contaminant in sub-sample i at location j in year t (a = age, le = length, f = liver fat content, lw = log liver weight, γ = random effect)

Contaminant	Model
PCBs	$y_{ijt} = \beta_{0j} + \beta_1 t + \beta_{6j} le_{ijt} + \beta_{8j} lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
DDE	$y_{ijt} = \beta_{0j} + \beta_1 t + \beta_{6j} le_{ijt} + \beta_7 f_{ijt} + \beta_{8j} lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
HCB	$y_{ijt} = \beta_{0j} + \beta_1 t + \beta_7 f_{ijt} + \beta_{8j} lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
HCHs	$y_{ijt} = \beta_{0j} + \beta_1 t + \beta_7 f_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
CHLs	$y_{ijt} = \beta_{0j} + \beta_1 t + \beta_{6j} le_{ijt} + \beta_7 f_{ijt} + \beta_{8j} lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
Tox	$y_{ijt} = \beta_{0j} + \beta_1 t + \beta_6 le_{ijt} + \beta_7 f_{ijt} + \beta_{8j} lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
As	$y_{ijt} = \beta_{0j} + \beta_1 t + \beta_7 f_{ijt} + \beta_{8j} lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
Cd	$y_{ijt} = \beta_{0j} + \beta_{1j} t + \beta_{2j} t^2 + \beta_{3j} t^3 + \beta_7 f_{ijt} + \beta_8 lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
Cu	$y_{ijt} = \beta_{0j} + \beta_{1j} t + \beta_{2j} t^2 + \beta_{3j} t^3 + \beta_4 t^4$ $+ \beta_6 le_{ijt} + \beta_7 f_{ijt} + \beta_8 lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
Hg	$y_{ijt} = \beta_{0j} + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \gamma_{jt} + \epsilon_{ijt}$
Se	$y_{ijt} = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_6 le_{ijt} + \beta_7 f_{ijt} + \beta_8 lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$
Zn	$y_{ijt} = \beta_0 + \beta_1 t + \beta_6 le_{ijt} + \beta_7 f_{ijt} + \beta_8 lw_{ijt} + \gamma_{jt} + \epsilon_{ijt}$

between length and Tox concentration ($p = 0.0001$) was, however, consistent at both locations (Table 7.4). Liver fat content had a significant and positive relationship that was consistent at both locations with DDE, HCH, CHL and Tox ($p = 0.0002$, $p < 0.0001$, $p = 0.0002$, $p < 0.0001$, respectively). Liver fat also had a positive relationship with HCB but there was a significant difference between the locations ($p = 0.0009$) and PCB did not have a significant relationship with liver fat (Table 7.4). All the POP concentrations had a significant and negative relationship with liver weight, except HCB and HCH where significance was not detected. This relationship was however not consistent between the locations (Table 7.4), the concentration decreased significantly more with liver weight at the NE location compared to the NW location (PCB: $p = 0.0044$, DDE: $p = 0.0008$, CHL: $p = 0.0002$, Tox: $p = 0.0058$).

The interactions between the covariates and location make interpretation more difficult as the difference in concentration between the two locations depends on the covariates. The interactions between location and length for the PCB, DDE, HCB and CHL resulted in a higher concentration at the NW location compared to the NE location for short fish but higher concentration at the NE location for longer fish. The interactions between liver weight and location had opposite effects for PCB, DDE and CHL, fish with small livers had higher concentration at the NE location but fish with larger livers had higher

Table 7.3: Change in the contaminant concentrations and median concentrations at NE and NW location.

	Annual change (%)		P-value	Median concentration	
	NE	NW		NE	NW
				$\mu\text{g kg}^{-1}$	
PCB	-2	-2	0.0003	68	70
DDE	-2	-2	0.044	48	45
HCB	-3	-3	0.0007	19	18
HCH	-9	-9	<0.0001	5.9	4.9
CHL	-3	-3	0.0008	53	46
Tox	-3	-3	0.0009	77	65
				mg kg^{-1}	
As	2	2	0.0004	5.2	5.6
Cd	non-linear	non-linear	0.0065	0.14	0.24
Cu	non-linear	non-linear	0.0474	3.2	3.2
Hg	non-linear	non-linear	0.0143	0.022	0.03
Se	non-linear	non-linear	0.0276	0.85	0.85
Zn	-1	-1	0.0201	14	14

concentration at the NW location. The concentrations of HCB and Tox were higher at the NE location but this difference decreased as the livers got smaller because of the interactions between liver weight and location. The relationship between liver fat content and the POP concentrations was consistent for all the POPs except for HCB where the concentration increased more with increasing fat content at the NW location compared to the NE location. Therefore, the concentration of HCB was higher at the NE location for livers with low fat content but higher at the NW location for livers with high fat content.

7.3.2 Temporal trends of trace elements

No general trend was observed for the trace elements. The concentration of As increased significantly by 2% annually at both the NE and NW location while the Zn concentration decreased significantly by -1% annually (see Table 7.3 and Figure 7.3). There were significant changes in the other trace elements, the concentration of Cd and Cu showed fluctuations over time that were not consistent at both locations. The Hg and Se concentrations also fluctuated with time but the change was consistent at both the NE and NW location (Figure 7.3). The median concentration of the trace elements were the same for Cu, Se

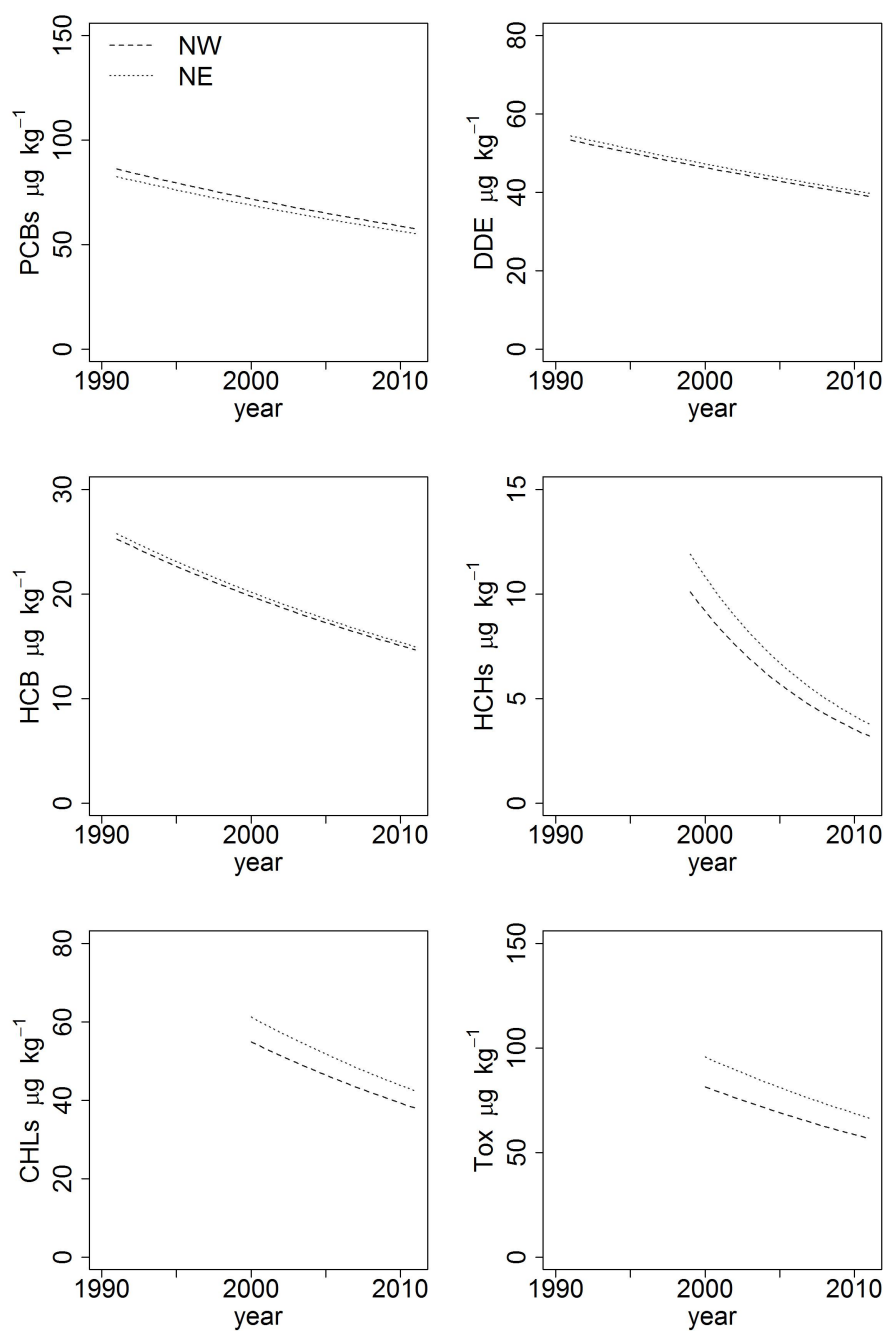


Figure 7.2: Predicted change in concentration of the POPs (PCBs, p,p'-DDE, HCB, HCHs, CHLs and Tox) from the final models (see Table 7.2) at the NE and NW location (see Figure 7.1).

Table 7.4: Increase/decrease (%) in concentration of POPs with age, length, liver fat and weight, estimates $((e^\beta - 1) * 100)$ from the final models in Table 7.2.

		PCB	DDE	HCB	HCH	CHL	Tox
Age	NE	0	0	0	0	0	0
	NW	0	0	0	0	0	0
Length	NE	5.5	7.2	0.9	0	6.1	3
	NW	1.8	2.6	-1	0	1.4	3
Liver fat	NE	0	1.3	1.4	2.2	1.1	2.1
	NW	0	1.3	2.5	2.2	1.1	2.1
Log liver weight	NE	-34.5	-51.8	0	0	-38.9	-31.6
	NW	-18.3	-29.4	0	0	-13.5	-21.7

and Zn at the both locations but higher for As, Cd and Hg at the NW location compared to the NE location (Table 7.3).

The biological covariates, except age were found to have a significant relationship with the trace elements concentrations. Length had a significant and positive relationship with the Cu, Se and Zn concentrations ($p < 0.0001$, $p = 0.0045$, $p < 0.0001$, respectively) which was consistent at both locations but significant relationships were not detected with As, Cd and Hg (Table 7.5). Liver fat content had a significant and negative relationship with all concentration measured in the liver (Cd: $p < 0.0001$, Cu: $p = 0.0044$, Se: $p < 0.0001$ and Zn: $p < 0.0001$) which was consistent at both location for all the trace elements except As where the concentration decreased significantly ($p < 0.0001$) more with increasing fat content at the NE location (Table 7.5). The relationship between liver weight and the trace elements concentrations were found to be significant and negative for all the elements at both locations (Cd: $p = 0.0141$, Cu: $p < 0.0001$, Se: $p < 0.0001$ and Zn: $p < 0.0001$), except for As where the difference was significant between locations ($p = 0.0012$), it was positive at the NE location but negative at the NW location (Table 7.5). This interaction between the liver and location for the As concentration resulted in higher concentration of As at the NE location for livers with a low fat content and weight compared to the NW location.

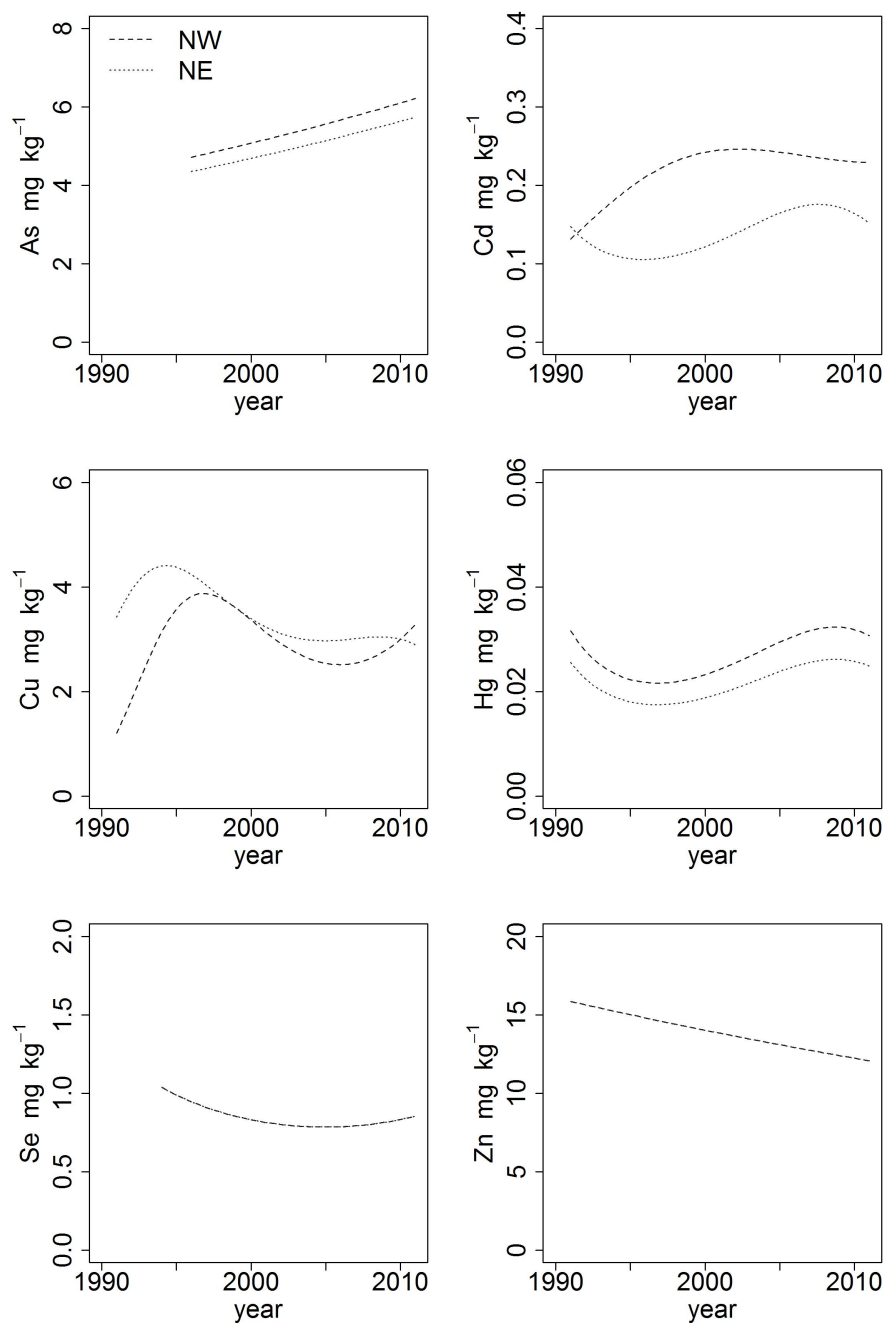


Figure 7.3: Predicted change in concentration of the trace elements (As, Cd, Cu, Hg, Se and Zn) from the final models (see Table 7.2) at the NE and NW location.

Table 7.5: Increase/decrease (%) in concentration of trace elements with age, length, liver fat and weight, estimates $((e^\beta - 1) * 100)$ from the final models in Table 7.2.

		As	Cd	Cu	Hg	Se	Zn
Age	NE	0	0	0	0	0	0
	NW	0	0	0	0	0	0
Length	NE	0	0	5.2	0	1.8	2.5
	NW	0	0	5.2	0	1.8	2.5
Liver fat	NE	-3.3	-2.5	-0.9	-	-2.2	-1.5
	NW	-1.4	-2.5	-0.9	-	-2.2	-1.5
Log liver weight	NE	23.9	-12.2	-32.4	-	-18.5	-18.4
	NW	-3.4	-12.2	-32.4	-	-18.5	-18.4

7.4 Discussion

7.4.1 Concentrations of contaminants

The concentrations of the POPs in cod were similar or higher at the NE location than at the NW location but the concentration of Cd and Hg was higher at the NW location than at the NE location for the average fish (age = 3 years, length = 39 cm, liver fat content = 53% and liver weight = 19 g). The ocean at the NW location is mainly relatively warm and saline Atlantic water, while the ocean at the NE location is mixed with cold and low salinity Polar water (Valdimarsson and Malmberg, 1999). The chemical composition may not be same in the different waters (Hafrannsóknastofnun, 2008), consequently causing some of the difference in the contaminant concentrations. Different diets at the two locations (Pálsson, 1983) probably have the greatest influence on the contaminant concentrations and the liver fat.

Three minor local sources of contaminants have been found at the Icelandic coastline (Sturludottir et al., 2013). These sources are a small waste incineration plant, a whale processing station and aquaculture; these sources are too small to significantly contribute to contamination at the open sea where the cod was sampled. The similar PCB/DDE ratios at both locations and the correlation between individual POP levels indicate that the source of the POPs is the same at both locations, most likely long range transport.

It can be difficult to compare concentrations between locations because of the influence of biological covariates such as age, length, liver fat and weight. In many studies on concentration of contaminants information on the covariates is missing. The concentrations of the contaminants in this study were com-

pared to results from Norway (Green et al., 2011), the Barents Sea (Stange and Klungsøyr, 1997), the Baltic Sea (Fromberg et al., 2000; Szlinder-Richert et al., 2009) and West Greenland (Riget et al., 2003) using median values as follows.

The median concentration of PCBs was observed to be four times higher in cod liver sampled in Norway from 2000 to 2010 ($288 \mu\text{g kg}^{-1}$) than in Iceland. The cod in Norway is sampled both off the open coast and in the fjords where it can be affected by local pollution which may result in higher contaminant concentrations than in cod sampled at the open sea. The cod sampled in Norway is also larger (37-70 cm) than the one sampled in Iceland which could explain higher concentrations in Norway. The concentration of *p,p'*-DDE was very similar in the Icelandic and the Norwegian cod ($40 \mu\text{g kg}^{-1}$). The concentration of HCB was, however, three times higher in the Icelandic cod than in the cod sampled in Norway ($7.2 \mu\text{g kg}^{-1}$). This is in contrast with results of air levels of HCB at the S-Icelandic coast which were an order of magnitude lower than at the Zeppelin station at Svalbard, Norway (Hung et al., 2010). PCBs concentration was six times higher in cod in the Barents Sea in 1992-1993 (sum of 13 PCBs, $392 \mu\text{g kg}^{-1}$) than in the Icelandic cod. The concentration of DDTs (sum of *p,p'*-DDD, *p,p'*-DDE and *p,p'*-DDT, $114 \mu\text{g kg}^{-1}$) and the HCH concentration ($12 \mu\text{g kg}^{-1}$) were about two times higher in cod sampled in the Barents Sea compared to cod sampled in Iceland. The concentration of HCB and CHLs were in the same range in the Icelandic cod and the cod from the Barents Sea (HCB = $23 \mu\text{g kg}^{-1}$, CHLs (sum of *trans*-nonachlor, oxychlordan, *cis*-chlordan and *trans*-chlordan) = $75 \mu\text{g kg}^{-1}$). The PCB concentration was also much lower in cod sampled in Icelandic waters than reported in cod caught in the Baltic Sea from 1998 to 2003 ($640 \mu\text{g kg}^{-1}$, converted to w.w. assuming 50% liver fat). The *p,p'*-DDE concentration was nine times higher in cod in the Baltic Sea ($439 \mu\text{g kg}^{-1}$) compared to the Icelandic cod but Tox concentration was two times higher in the Icelandic cod compared to the concentration in 1996 in the Baltic Sea ($33 \mu\text{g kg}^{-1}$). All this difference in POP levels and ratios indicate the variable sources or pathways for the persistent contaminants to the Arctic and sub-Arctic as discussed by Li and Macdonald (2005).

The concentration of As was similar in cod sampled in Iceland and Norway (4.7 mg kg^{-1}). The concentration of Cu (5.7 mg kg^{-1}), Zn (23 mg kg^{-1}) and Hg (0.06 mg kg^{-1}) measured in Norwegian cod were about two times higher than in the Icelandic cod. The Cd concentration was on the other hand six times higher in the Icelandic cod than what was found in cod from most monitoring stations in Norway (0.03 mg kg^{-1}). The concentration of Se was similar in

cod in West Greenland (0.78 mg kg^{-1} mean of five individuals) and Iceland. The concentration of Cd and Hg was observed to be four and two times higher in cod sampled in Icelandic waters than in cod from West Greenland (Cd = 0.05 mg kg^{-1} mean of five individuals, Hg = 0.014 mg kg^{-1} mean of nine individuals). Similar observations were seen in mussels collected on the eastern coast of Iceland (Sturludottir et al., 2013) where high Cd concentrations, in the absence of any known anthropogenic sources, were believed to be due to the volcanic nature of Icelandic rock. Comparison of the Pb levels could not be done, since 90% of the Icelandic cod had levels <LOD in the livers.

7.4.2 Temporal trends of contaminants

Due to worldwide efforts to reduce the use and control waste management of POPs over extended periods, decreasing trends were expected. In the present study significant decreasing trends were detected in PCB, HCB, *p,p'*-DDE, HCHs, CHLs and Tox at both the NE and NW location. These results are consistent with results from Riget et al. (2010) and Green et al. (2011). HCB have been found to be decreasing in many time-series from the Arctic, Green et al. (2011) found decreasing trends in six out of eight time-series of HCB in cod liver and Rigét et al. (2010) found decreasing trends in 14 out of 40 time series from the Arctic biota. No increasing trends were observed in either of these studies. HCB has also been observed to be decreasing in the atmosphere, by 90% from 1990 to 2011 (Gusev et al., 2011). Green et al. (2011) also found decreasing trends in most of the *p,p'*-DDE time series and in all eight time series of γ -HCH. Rigét et al. (2010) found decreasing trends in half of the HCH time series analyzed but only in 28% of the 40 time series of *p,p'*-DDE. Rigét et al. (2010) analyzed 17 time series of CHLs and ten of Tox and found two decreasing trends for each.

There were fluctuations in the concentration of the metals Cd, Cu and Hg in this study at both locations (Figure 7.3). Green et al. (2011) reported both decreasing and increasing trends in Hg in cod muscles and in Cd and Cu in cod liver sampled in Norway. No general trend was found in Hg concentration in the Arctic biota (Rigét et al., 2011; Riget et al., 2004) or in Cd concentration in the Greenland biota (Riget et al., 2004). The results in this study showed decreasing trends for Zn at both locations which is consistent with results from Norway where only decreasing trends were observed in Zn in cod liver (Green et al., 2011). Increasing concentration of As was observed in the presents study

but the reason for the increase remains unknown. The literature study did not provide any time series for As from other monitoring activities for comparisons.

Temporal trend analysis done by Sturludottir et al. (2013) on contaminant values in mussel around the Icelandic coast revealed that the concentration of POPs had decreased in recent years at most locations. In that study, α -HCH had decreased by -13% annually from 1999 to 2010 which is consistent with results from the present study where HCH decreased by -9% annually. There were no signs of decreasing trends of Zn and increasing trends of As in the mussel study as was observed in this study.

7.4.3 Effects of biological covariates

Care must be taken before drawing conclusions from observed relationships between the contaminant concentrations and biological covariates. Correlations between many of the biological covariates, i.e. positive log-linear correlation between length and liver weight ($r = 0.7, p < 0.001$) and between liver fat content and weight ($r = 0.7, p < 0.001$), have to be considered in order to be able to make meaningful predictions from the models obtained.

Excluding important biological variables from the models can change the observed relationship between the concentrations and covariates, i.e. excluding liver weight from the models resulted in a negative relationship between liver fat content and some of the POP concentrations. In addition, ignoring the effect of the biological covariates can result in a different final statistical model of the change in concentration over the period. For example, if the covariates are excluded from the model for the As concentrations the predicted change in the concentration becomes different, resulting in an apparently decreasing concentration at the NW location instead of an increasing one. One sub-sample is measured with high concentration in the first year, this sub-sample also has low liver fat and weight and if those covariates are ignored this measurement acts as an influential observation, i.e. deleting this observation changes the regression slope. Including biological covariates also reduces the error of the models making it more likely to detect significant changes in the concentration of contaminants.

A temporal change in the biological covariates can look like a temporal change in the concentrations, i.e. if the fat content of the liver has increased with time the concentration of the POPs may appear to have increased because of the positive relationship between liver fat content and POP concentrations.

It is therefore important to include biological covariates and also to check if there are temporal changes in the covariates. The liver weight was observed to be increasing in time at the NW location but it was stable at the NE location. The concentrations of the PCB and DDE were observed to be decreasing at the NW location with and without the covariates but there was no significant change at the NE location without the covariates included in the model. If the decrease in the POP concentrations at the NW location were only due to the change in liver size, this decrease should not be detected when the liver covariates were included in the models as was done in this study. Decrease in the POP concentrations was also detected at the NE location where the livers were stable, which further supports that the decrease seen in PCB and DDE at the NW location are not a result of the change in liver size.

The relationship between contaminant concentration in cod liver and covariates has often been described with log-log linear relationship (Auðunsson, 1999; Nicholson et al., 1991). Log transforming the variables liver fat content, fish length and age did not result in a better fit in this study but transforming liver weight did. Age was not found to have a significant relationship with any of the contaminant concentrations. The range of age was very narrow and the cod was in most cases three to four years old and very few were two and five years old. This limited age range may be the reason why effects of age were not detected for any of the contaminants but other studies have for example shown positive correlation between age and Cd concentration (Auðunsson, 1999). However, Nicholson et al. (1991) did not find a significant relationship between Cd concentration and age and Riget et al. (2000) concluded that fish length was more important than age. Livers from a few individuals were homogenized into one sub-sample, which also reduces the power to detect significant relationships between age and contaminant concentrations.

A positive relationship was observed between some of the contaminant concentrations (Cu, Se, Zn, PCB, DDE, CHLs and Tox) and length (Table 7.4 and 7.5). Green and Knutzen (2003) and Nicholson et al. (1991) also observed a positive correlation between length and PCBs concentration. No significant relationship was observed in this study between Hg concentration and length as has been observed in other studies (Riget et al., 2000; Rigét et al., 2011), which is probably due to the limited length range of the cod samples investigated in this study. Also, Hg was measured in pooled samples of muscle of the 25 individuals which made only one sample a year per location. Therefore there are fewer observation in the Hg time-series compared to the other time-series

which comes from the livers (which were grouped according to weight), making it more difficult to detect significance in the Hg time-series.

A positive relationship was observed between all of the POP concentrations and liver fat, except PCBs and a negative relationship between all of the POP concentrations and liver weight, except HCB and HCHs which only had a significant relationship with liver fat. High fat content in the liver indicates that the fish is well fed and has consequently ingested more POPs than fish which is not well fed. When feed availability is low the fat content in the liver decreases and the concentrations of the POPs increases as they remain in the cod. This factor should however, be avoided due to the consistent seasonal sampling done in this study.

A negative relationship was observed between the As, Cd, Cu, Se and Zn concentrations and liver fat and a negative relationship between all of those concentrations and liver weight, except the As concentration had a positive relationship with liver weight which may be because of the special properties of As. Sele et al. (2012) has for example reported that As is transformed to both lipophilic and lipophobic organic compounds in marine organisms and that arsenolipids can be up to 77% of the total As in cod liver, which is different from the other trace elements which are lipophobic.

Significant interactions between the locations and the covariates were frequently observed and many factors can cause these interactions. It is for example possible that the different waters at the two locations i.e. Atlantic water at the NW location and Polar water at the NE location (Valdimarsson and Malmberg, 1999) can have an effect as the temperatures are different with colder water to the NE. This can influence food availability which has been observed to be diverse at the two locations (Pálsson, 1983) which consequently leads to different biomagnification rate at these two locations. The genetic structure of the cod at these two locations may be different (Pampoulie et al., 2006) and this may also have an effect on the biomagnifications of the contaminants in the liver.

7.5 Conclusion

Biological covariates such as age, length, liver fat and weight need to be considered before making inference about contaminant concentration, both when comparing concentrations and when analyzing temporal trends. In the present study all covariates, except age were found to influence the contaminant con-

concentrations and were adjusted for, before conclusions were drawn. The concentration of the POPs were lower or similar in the Icelandic cod compared to cod sampled in Norway, the Baltic Sea and in the Barents Sea, except for HCB which was higher in the Icelandic cod compared to the Norwegian cod. The concentration of the trace elements As, Cu, Hg and Zn were similar in the Icelandic cod compared to cod sampled off Norway and Greenland but the concentration of Cd was found to be higher in the Icelandic cod. All of the POPs showed decreasing trends but the trace elements showed no clear signs of trend except As which showed an increasing trend and Zn which showed a decreasing trend. It is important for regulators and policy makers to have information regarding trends of environmental pollutants in order to forecast their future behavior and distribution to ensure environmental quality, food safety and public health. The information presented in this paper shows the trends of several major environmental pollutants in the North Atlantic and is an important contribution for international monitoring programs such as the Arctic Monitoring and Assessment Programme (AMAP) and the Oslo-Paris convention (OSPAR) for comparison of the global pollution load.

Acknowledgement

The national monitoring program is funded by the Ministry for the Environment with contribution from the institutions involved. The Marine Research Institute of Iceland is acknowledged for the collection of samples. This study was financially supported by the Icelandic Research Fund (Rannís) and the Icelandic Research Fund for Graduate Students.

8

Paper III

**Detection of a changepoint, a mean-shift
accompanied with a trend change, in
short time-series with autocorrelation**

Erla Sturludottir, Helga Gunnlaugsdottir, Olafur K. Nielsen and
Gunnar Stefansson

Abstract

In this study a changepoint model, which can detect either a mean shift or a trend change when accounting for autocorrelation in short time-series, was investigated with simulations and a new method proposed. The changepoint hypotheses were tested using a likelihood ratio test. The test statistic does not follow a known distribution and depends on the length of the time-series and the autocorrelation. The results imply that it is not possible to detect autocorrelation and that the estimate of the autocorrelation parameter is biased. It is therefore recommended to use critical values from the empirical distribution for a fixed autocorrelation.

8.1 Introduction

Short time-series are frequent in environmental studies and in such programs it is often of interest to detect when a change has taken place. This time of change is called a changepoint (CP) and is a point in time-series when there is either a step change, i.e. a mean shift in the response variable or a trend change. These changes can occur e.g. in time-series of concentration of contaminants or in a time-series of wildlife population; a change in the analysis method can result in a step change in the contaminants and a change in source of contaminants can result in a change in trend. A change in time-series of wildlife population can for example occur after a modification in wildlife management.

A number of methods exist to detect CP, back to Quandt (1958) who developed a method using the likelihood ratio test where the test statistic was assumed to follow the χ^2 distribution. Later, Quandt (1960) published another article which showed that the approximation of the χ^2 distribution was poor. Approximation methods have been developed using the likelihood ratio test (Kim and Siegmund, 1989; Liu and Qian, 2009). All of these methods assume independent and normally distributed errors. However, an autocorrelation is common in time-series which inflate the type I error rate if ignored when testing for a trend (Yue et al., 2002) or a CP (Lund et al., 2007). It can be difficult to estimate autocorrelation in short time-series. Further, the estimate is biased and the bias is greater for shorter time-series and stronger autocorrelation (Bence, 1995). This bias also needs to be considered when testing for a CP. The test statistic for an unknown CP does not follow a known distribution (Lund and Reeves, 2002) and the critical value of an empirical distribution depends both on the length of the time-series and the unknown true autocorrelation parameters (Wang, 2008a). Changepoint analyses have been carried out in long time-series, e.g. in climate time-series (Lund and Reeves, 2002; Lund et al., 2007; Reeves et al., 2007; Wang, 2008b). Methods for detecting a mean shift in long time-series have been developed both as a parametric (Lund et al., 2007; Wang, 2008a) and as a non-parametric test (Dehling et al., 2012). The focus has been on a step change rather than a change in trend (Lund et al., 2007; Wang, 2008b) and also many of the methods assume independent errors (Lund and Reeves, 2002; Reeves et al., 2007; Wang, 2008b).

In this study a CP model which can detect either a mean shift or a trend change when accounting for autocorrelation in short time-series will be investigated with simulations and a new method of analysis proposed. Applications

of the new method will be given using data from monitoring studies.

8.2 Changepoint model

Model (1) allows for a CP in a time-series y_t , i.e. the intercept ($\alpha_1 \neq \alpha_2$) and/or the slope ($\beta_1 \neq \beta_2$) are different before and after the CP.

$$y_t = \begin{cases} \alpha_1 + \beta_1 t + \epsilon_t & 1 \leq t \leq c \\ \alpha_2 + \beta_2 t + \epsilon_t & c < t \leq N \end{cases} \quad (8.1)$$

The errors ϵ_t are autocorrelated with autocorrelation parameter ρ , i.e. $\epsilon_t = \rho\epsilon_{t-1} + u_t$ and u is assumed to follow normal distribution with mean 0 and variance σ_u^2 . Time c is the unknown CP in the interval $[n_0, N - n_0]$ where n_0 is the first possible CP and N is the length of the time-series. This model is designed to detect both step and trend type CP. A reduced model with no CP would be.

$$y_t = \alpha + \beta t + \epsilon_t \quad (8.2)$$

To test the null hypothesis of no CP (H_0) against an alternative hypothesis of unknown CP (H_1) a likelihood ratio test is applied. The full model (1) and the reduced model (2) where $\alpha_1 = \alpha_2$ and $\beta_1 = \beta_2$ are fitted using maximum likelihood and the likelihood ratio statistic D is calculated for each c . The most likely CP is the point in time where these D are at a maximum (D_{\max}), this is the test statistic for the CP test.

$$H_0 : \alpha_1 = \alpha_2 \text{ and } \beta_1 = \beta_2$$

$$H_1 : \alpha_1 \neq \alpha_2 \text{ or } \beta_1 \neq \beta_2$$

$$D_c = \left\{ -2 \ln \left(\frac{\text{likelihood for model (2)}}{\text{likelihood for model (1)}} \right) \right\}$$

$$D_{\max} = \max_c D_c$$

The D_{\max} statistic does not follow a χ^2 distribution. To test whether the CP is significant, the empirical distribution needs to be simulated and D_{\max} tested against the critical values of the simulated distribution. The empirical distribution of D_{\max} depends on both the length of the time-series and on the

structure of the autocorrelation. The test statistic also depends on n_0 , where the first CP is allowed to take place. In this study $n_0 = 4$ and the errors will be assumed to be normally distributed and with an autoregressive of order 1 structure (AR(1)).

8.3 Critical values from the empirical distribution

The empirical distribution of D_{\max} under the null hypothesis was simulated with Monte Carlo simulations for time-series of length $N = \{10, 20, 30, 50, 100\}$ with autocorrelation parameters $\rho = \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$. The critical values were the 95th percentiles of the empirical distributions and shown in Figure 8.1. Each combination of N and ρ were simulated 50,000 times, all together 2.5 million time-series were simulated.

The critical values of the empirical distribution depended both on N and ρ (Figure 8.1) as Wang (2008a) had shown before when testing for a mean shift. The critical values became larger as the autocorrelation increased and also as the time-series became shorter. The difference in the critical values was large between short time-series, e.g. the difference between the critical values for $N = 10$ and $N = 20$ with $\rho = 0.5$ was 3.85 but between $N = 20$ and $N = 30$ this difference was 1.35. This difference reduced further for longer time-series. It is therefore important to use critical values from the empirical distributions, approximated with the correct length for short time-series.

It is well known that the type I error rate is inflated when autocorrelation is ignored (Lund et al., 2007; Yue et al., 2002). The error rate in the test for a CP was inflated when the test was applied and no autocorrelation assumed although present in the time-series. The error rate was larger for longer time-series and increased fast as the autocorrelation became stronger in the time-series (Figure 8.2). The error rate was about 20% for time-series of length $N = 20$ with an autocorrelation of $\rho = 0.3$ but close to 30% in time-series of length $N = 50$.

To keep the type I error rate at 5% it would be necessary to use the critical values for each autocorrelation parameter ρ . To do this the ρ needs to be estimated in the time-series and the critical value chosen according to the estimated ρ . Estimating the autocorrelation in short time-series is however very difficult (Bence, 1995). As shown in Figure 8.3, the estimate of the autocorrelation in the CP model was observed to be negatively biased. This bias increased as the time-series became shorter and with increasing autocorrelation. The estimated autocorrelation for time-series of length $N = 10$ was negative even when

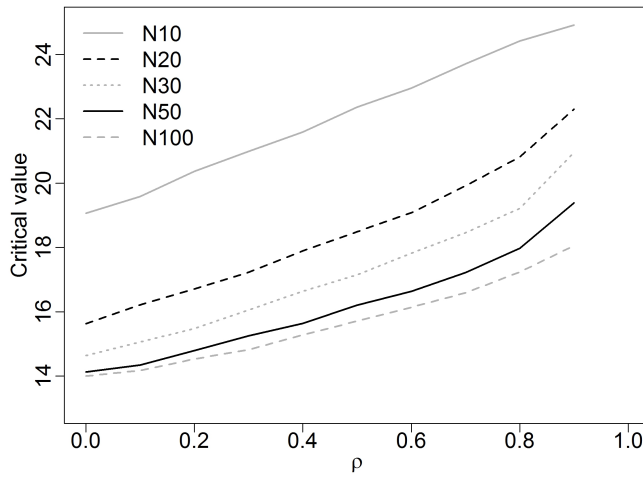


Figure 8.1: Critical values from the empirical distributions for $N=\{10, 20, 30, 50, 100\}$ assuming autocorrelation from $\rho = 0$ to $\rho = 0.9$.

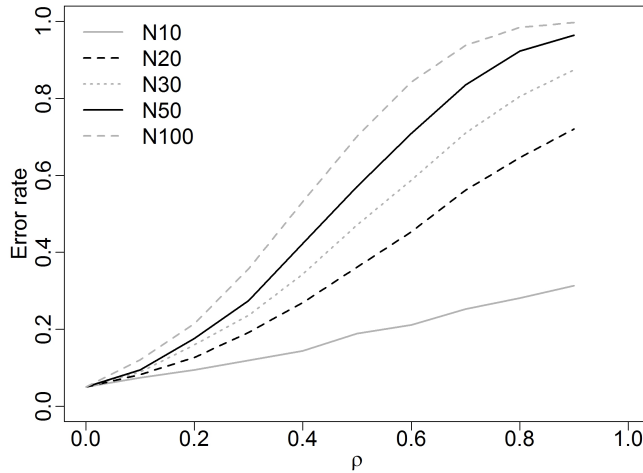


Figure 8.2: Error rate when ignoring autocorrelation for time-series of length $N = 10, 20, 30, 50$ and 100 .

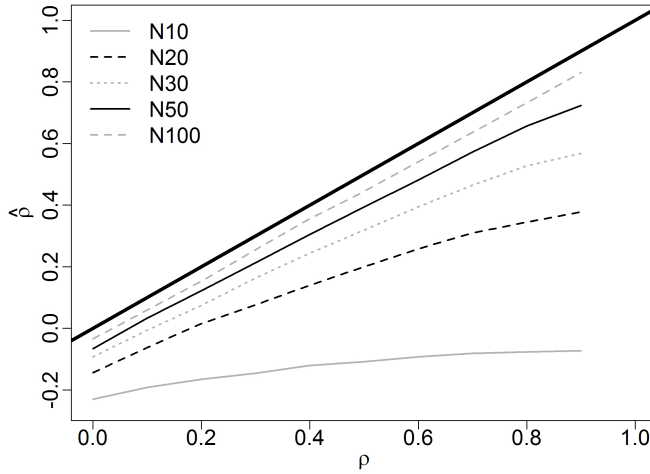


Figure 8.3: The bias in the estimate of the autocorrelation parameter ($\hat{\rho}$) in the changepoint model for time-series of length $N = 10, 20, 30, 50$ and 100 . The thick black line shows unbiased estimates.

the true autocorrelation was $\rho = 0.9$. Using the critical values based on estimated autocorrelation would lead to inflated error rate and is therefore not the appropriate method for detecting CP.

Choosing a critical value using a model where autocorrelation is assumed to exist greatly reduces the type I error rate even though the percentiles for $\rho = 0$ are used as the critical values (autocorrelation is assumed when the empirical distribution of D_{\max} was simulated but the simulated time-series were not autocorrelated). When the autocorrelation parameter ρ is equal to 0.5 the error rate is 0.10 for time-series of length 50 (Figure 8.4) but 0.60 when the autocorrelation is ignored (Figure 8.2). The difference is even larger for longer time-series; it is 0.09 for time-series of length 100 but 0.70 when the autocorrelation is ignored. The error rate is reduced even further if percentiles for $\rho = 0.2$ is used as the critical values, e.g. time-series with autocorrelation lower than $\rho = 0.6$ have error rate below 10%. A critical value for $\rho = 0$ or $\rho = 0.2$ can be used when testing for a CP in short time-series with positive autocorrelation which is assumed to be low or moderate and an error rate of 10% is acceptable.

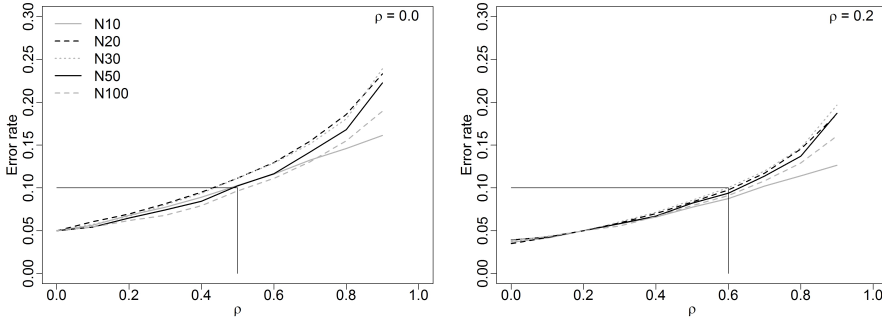


Figure 8.4: Actual error rate when using critical values from the empirical distributions for $\rho = 0.0$ and $\rho = 0.2$ when using a nominal error rate of $\alpha = 0.05$ and assuming autocorrelation for time-series of length $N = 10, 20, 30, 50$ and 100 .

8.4 Testing for autocorrelation

It is well known that assuming autocorrelation when there is none reduces the power of statistical tests. Therefore, it would be ideal to test for an autocorrelation in the CP model and if it turned out to be significant, then do the test assuming autocorrelation, otherwise assume independence. To test this method 5000 time-series for each combination of $N = \{10, 20, 30, 50, 100\}$ and $\rho = \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$ were simulated under the null hypothesis of no CP. First, the time of the most likely changepoint was estimated assuming autocorrelation and then compared to a model with the same changepoint but without autocorrelation. The autocorrelation was tested using a restricted likelihood ratio test (Wolfinger, 1993), where the test statistic was assumed to follow the χ^2 distribution with one degree of freedom. If the test was significant at $\alpha = 0.05$ the model with autocorrelation was fitted again using maximum likelihood and D_{\max} compared to a critical value from the empirical distribution assuming $\rho = 0.2$. If however, the test was not significant, D_{\max} from the model without autocorrelation was compared to a critical values from the empirical distribution where independence was assumed.

Autocorrelation rarely became significant in short time-series even though they were strongly autocorrelated (Figure 8.5). In time-series of length $N = 10$ autocorrelation was significant in less than 5% of the time-series, even when the true autocorrelation was $\rho = 0.9$. Even when the time-series were of length $N = 50$, detection of autocorrelation did not reach 80% until the autocorrelation became stronger than $\rho = 0.6$. For time-series of length $N = 100$ autocorrelation

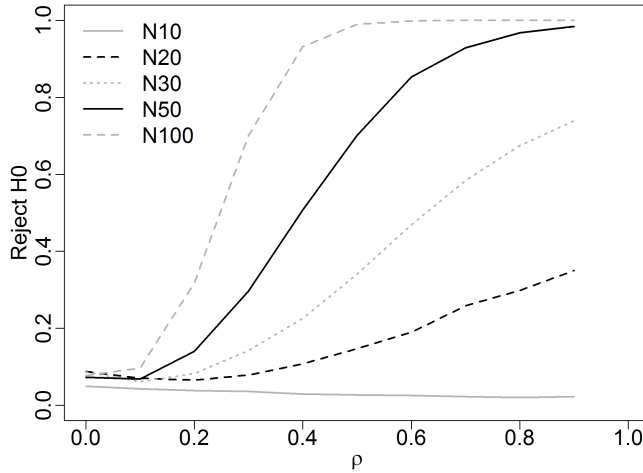


Figure 8.5: Power of detecting autocorrelation in time-series of length $N = 10, 20, 30, 50$ and 100 .

became significant in more than 80% of the time-series when the autocorrelation was $\rho = 0.3$ or higher. As was shown in Figure 8.3 the autocorrelation is seriously underestimated and this has influence when testing for autocorrelation.

The type I error rate of CP detection at the 5% significance level when using the method of testing for autocorrelation, as described earlier in this section, was over 10% for all the time-series when the autocorrelation exceeded $\rho = 0.2$ except for time-series of length $N = 100$ (Figure 8.6). The error rate increased with stronger autocorrelation for time-series of length $N = 10$ and $N = 20$ and the error rate was higher for the $N = 20$ time-series, especially for strong autocorrelation. The pattern was different for time-series of length $N = 30$ and $N = 50$, where the error rate increased until the autocorrelation reached $\rho = 0.4$ to $\rho = 0.5$ when it decreased and then it increased again for very strong autocorrelation. The error rate for the $N = 100$ time-series was very close to 10% for all values of ρ . This different error rate pattern for time-series of different length comes from the ability of detecting whether there is autocorrelation in the time-series or not, which is very different for the time-series as can be seen in Figure 8.5. This method of testing for autocorrelation is not acceptable in short time-series ($N < 100$) as the error rate becomes higher than 10% even when the autocorrelation is weak.

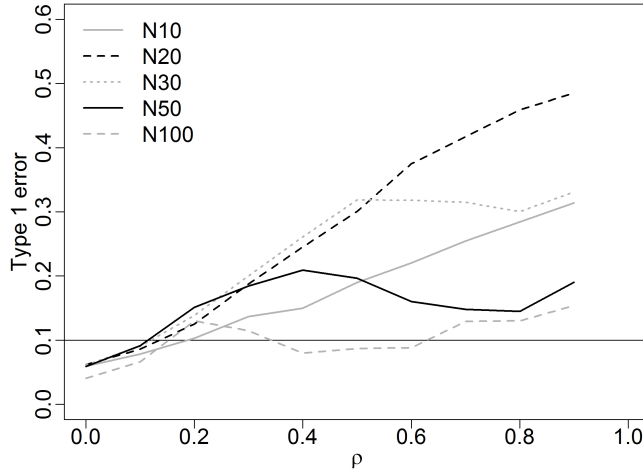


Figure 8.6: Error rate when using the method of testing for autocorrelation in time-series of length $N = 10, 20, 30, 50$ and 100

8.5 Power

The power of the CP model was studied with simulation of 1000 time-series for each combination of N and ρ as described above. The variance was fixed at $\sigma^2 = 1$ for each ρ by setting $\sigma_u^2 = 1 - \rho^2$. The power was tested for time-series where a step change occurred, $\alpha_2 - \alpha_1 = 4$ and a trend change, where the trend was $\beta_1 = 0$ before the CP and $\beta_2 = 0.4$ after. The trend change was a continuous change and no step occurred, i.e. the α_2 was constrained to be $\alpha_2 = \alpha_1 + (\beta_1 - \beta_2) * c$. The power was investigated for two different CP, at quarter ($c = N/4$, except for $N = 10$) and in the middle ($c = N/2$) of the time-series. Further, the power of detecting a CP and the power of detecting the "correct" CP was documented, where the CP was deemed "correct" if it was within $0.1 * N$ of the true CP.

The power of detecting a step change was higher at the quarter in the time-series than in the middle. The difference was the largest in time-series of length $N = 20$ and it was larger when the autocorrelation was weak. The power was for example 64% for time-series of length $N = 20$ with $\rho = 0.2$ when the CP was at the quarter but 51% when it was in the middle (Figure 8.7a and 8.7b). The power was stable in all the time-series when the autocorrelation was weak and started to increase when autocorrelation reached $\rho = 0.4$ as well as the error rate (Figure 8.4). The test did detect the "correct" CP ($0.1 * N$ of the true CP)

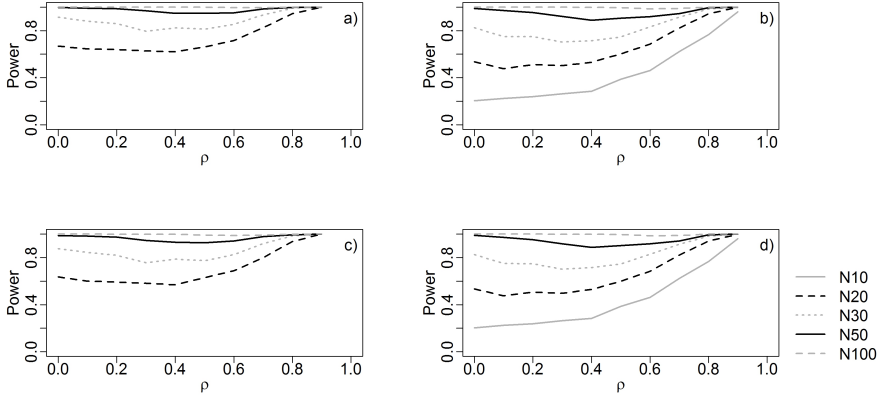


Figure 8.7: Power of detecting a CP in a time-series with a step change of $\alpha_2 - \alpha_1 = 4$ where a) $c=N/4$ and b) $c=N/2$ and the power of detecting the correct CP where c) $c=N/4$ and d) $c=N/2$.

in most cases when it did detect a CP (Figure 8.7c and 8.7d). The power of the CP model increased with increasing length of the time-series and reached 80% in time-series of length $N = 30$.

The power of detecting a trend change of $\beta_2 - \beta_1 = 0.4$ was higher when the CP was in the middle compared to when it was at the quarter but it was the other way around when detecting step change. This difference was highest in time-series of $N = 30$, where the power was 21% when the CP was at the quarter (Figure 8.8a) and 66% when it was in the middle (Figure 8.8b) for $\rho = 0.2$. The power decreased with increasing autocorrelation in time-series of length $N = 50$ and in time-series of length $N = 30$ where the CP was in the middle. The "correct" CP was detected in over 50% of the occurrences when a CP was detected for time-series of length $N = 20$ and $N = 30$ but over 70% for the longer time-series (Figure 8.8c and 8.8d).

8.6 Method proposed

When testing for a CP in time-series, i.e. a mean shift accompanied with a trend change, autocorrelation must be accounted for to reduce the type I error rate. As was shown previously testing for autocorrelation is not feasible in time-series which have less than 100 observations. Also, the estimation of the autocorrelation parameter is heavily biased in short time-series and therefore

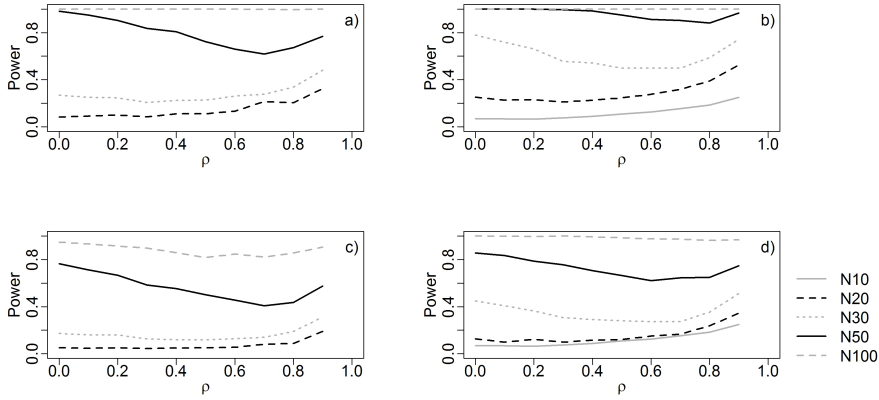


Figure 8.8: Power of detecting a CP in a time-series with a trend change where $\beta_1 = 0, \beta_2 = 0.4, \alpha_1 = 0$ and $\alpha_2 = \alpha_1 + (\beta_1 - \beta_2) * c$ where a) $c=N/4$ and b) $c=N/2$ and the power of detecting the correct CP where c) $c=N/4$ and d) $c=N/2$.

it is not possible to use the estimated parameters to choose the critical value to use to test the hypothesis of a CP. For detection of a mean shift that is accompanied with a trend change, we recommend that a critical value for $\rho = 0.2$ will be used when positive autocorrelation is assumed in the time-series and the autocorrelation is not assumed to exceed $\rho = 0.6$. Critical values for time-series of length $N = 10$ to $N = 100$ are available in Table 8.1.

8.7 Applications

The method described above was used to test for a CP in two different time-series, both originating from monitoring programs. The first example is a time-series of the trace element cadmium measured in mussel (*Mytilus edulis*) and the second example is a time-series of mortality rate in the bird species rock ptarmigan (*Lagopus muta*).

8.7.1 Cadmium concentration in mussel

Cadmium concentration in mussel has been monitored around the Icelandic coastline for two decades. Time-series of 18 observations, from 1991 to 2010, from Hvalstod at the west coast of Iceland (Sturludottir et al., 2013) was used to test for a CP.

Table 8.1: Critical values for time-series of length $N = 10$ to 100 at $\rho = 0.2$.

N	Critical Value	N	Critical Value
10	20.37	26	15.84
11	19.77	27	15.80
12	19.14	28	15.69
13	18.78	29	15.64
14	18.34	30	15.58
15	17.97	32	15.39
16	17.70	34	15.31
17	17.32	36	15.26
18	17.12	38	15.15
19	16.97	40	15.03
20	16.70	45	14.90
21	16.55	50	14.80
22	16.37	60	14.63
23	16.18	80	14.54
24	16.08	100	14.53
25	15.92		

To test if there has been a CP in the time-series, D_{\max} was calculated and compared to the critical value from the empirical distribution from time-series with length $N = 18$ and $\rho = 0.2$ (Table 8.1). Using maximum likelihood and assuming AR(1) covariance structure the CP was estimated to be in the year 2004 and $D_{\max} = 23.2$, which exceeded the critical value of 17.12. The cadmium concentration was increasing until 2004 when there was a sudden drop in the concentration and it started to decrease (Figure 8.9). It is not known what caused this drop in concentration, most likely it was natural fluctuations as cadmium has shown fluctuations at other locations around the Icelandic coastline (Sturludottir et al., 2013). This method could be very useful when monitoring contaminants to detect when a change in concentration has taken place and to locate a possible source to prevent further contamination. The error rate using this method can be as high as 10% but in cases like this that may well be an acceptable rate.

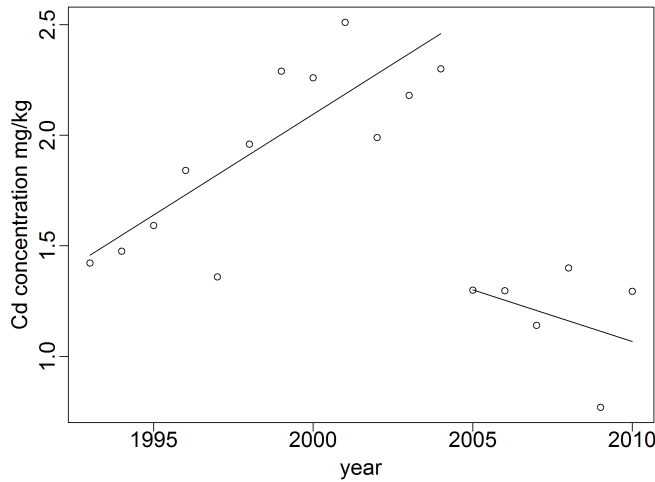


Figure 8.9: Change in cadmium concentration in mussel from 1991 to 2010.

8.7.2 Mortality rate of the rock ptarmigan

Indexes of population abundance and age ratios of the rock ptarmigan in Iceland were used to calculate the mortality rate of adult birds as described in Magnússon et al. (2005). The mortality rates were calculated for each year from 1982 to 2012.

To test if a CP could be detected the method previously described was applied. Using maximum likelihood and assuming AR(1) covariance structure the CP was estimated to be in the year 2002 and $D_{\max} = 13.0$ which did not exceed the critical value of 15.39. If however, autocorrelation was ignored then $D_{\max} = 14.8$ which exceeded the critical value of 12.8 from the empirical distribution when independence is assumed. It has to be kept in mind that the type I error rate when autocorrelation is ignored can be as high as 50%. Both methods revealed a CP in the year 2002. The rock ptarmigan is a popular game bird in Iceland and in 2003 a hunting ban was enforced because of a decline in the population, the ban lasted two years and in 2005 the hunting started again but with different regulations, this included a ban to market hunting and shortening of the hunting season. The method described above is used when there is an interest to test if there has been a CP in the time-series and no point is assumed *a priori* to be more likely than any other, i.e. the CP is unknown. In this case we knew something had changed at a particular point in time that could have caused either a step or trend change. Therefore, we could test if that

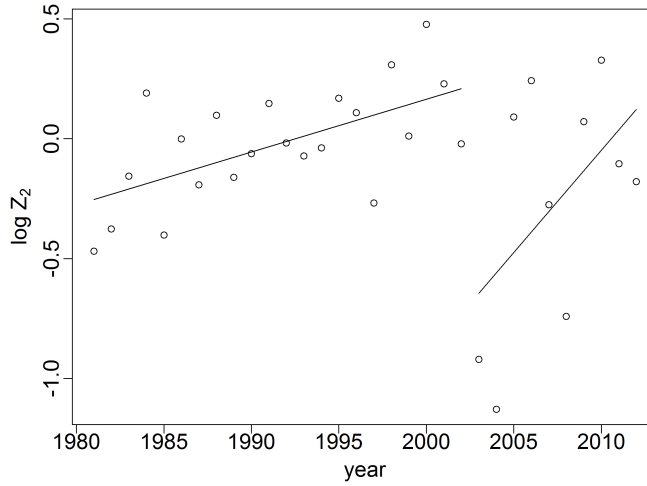


Figure 8.10: Mortality rate (Z_2) of the adult ptarmigan from 1982 to 2012.

CP was significant. In that case only one point would be chosen and tested for and in that case the CP is known and the critical value is lower than when an unknown CP is tested. In this case the critical value would be 8.4 for $\rho = 0.2$ and the test statistic from the likelihood ratio test was 13.0 which is higher than the critical value and the CP would be significant (Figure 8.10).

8.8 Conclusion

A new method has been proposed to detect CP in time-series when accounting for autocorrelation. This study has shown that accounting for autocorrelation is important in time-series when detecting CP to reduce the error rate which is high when autocorrelation is ignored, even when the autocorrelation is weak. It was not possible to test for autocorrelation in the time-series as the power was very low. Also, the estimate of the autocorrelation was negatively biased and could not be used to choose the right critical value for the CP test. It is therefore recommended to use a critical value for a fixed autocorrelation and a critical value for $\rho = 0.2$ was chosen to keep the true error rate below 10% (using a nominal error rate of 5%). The new method was able to detect a CP in two different time-series while accounting for autocorrelation, one where no point was assumed more likely *a priori*, i.e. the CP was unknown, and in the other where the CP was known. Also, as seen in the case study on ptarmigan

mortality, the test has more power when only one predefined point in time is tested for being a CP, i.e. one tests whether a change occurs at the true CP. On the other hand, testing for a CP at a fixed point in time should only be done when there is *priori* evidence that something may have caused a change in the time-series at a particular point in time.

Acknowledgment

This study was funded by the Icelandic Research Fund and the Icelandic Research Fund for Graduate Students.

9

Paper IV

Population reconstruction model for the rock ptarmigan in NE-Iceland

Erla Sturludottir, Olafur K. Nielsen and Gunnar Stefansson

Abstract

The rock ptarmigan (*Lagopus muta*) is found all over Iceland but has the highest density in the northeastern part of the island. It is a popular game bird but the hunting regulation was changed in 2003. The aim of this study was to build a population reconstruction model for the rock ptarmigan in NE-Iceland, to estimate the population size, recruitment, natural survival and hunting mortality. The total abundance at the beginning of the hunting season was estimated to have ranged from 38,000 birds in 2002 to 153,000 birds in 1998. The natural survival of adult rock ptarmigans was assumed to be density dependent, it ranged from 36% in 1999 and 2011 to 65% in 2003 and 2004. The survival of juveniles was taken as a constant and was estimated to have been 19%. A changepoint was included in the model to account for a change in the hunting mortality that could have occurred with the changes in the hunting regulations. Before 2003 the hunting mortality was modeled as a function of ptarmigan density and ranged from 32% to 54%. After the hunting ban, the hunting mortality was modeled as a function of the number of hunters and ranged from 11% to 17%. This model indicates that changes in the hunting regulation did have an effect in reducing the hunting mortality and also changing the harvest strategies of hunters. Still, management goal of reducing the total annual mortality to 37% has not been achieved and a further change in regulation may be needed.

9.1 Introduction

The rock ptarmigan (*Lagopus muta*) is the only grouse (Tetraoninae) that breeds in Iceland. It is found all over Iceland but has the highest densities in the north-eastern part of the island. The population has cyclic fluctuations in numbers with a periodicity of 10-12 years (Gudmundsson, 1960; Nielsen and Petursson, 1995). It is a popular game bird and market hunting was allowed prior to 2003 but that year a hunting ban was enforced after a long-term decline of the population (Brynjarsdóttir et al., 2003). The hunting ban lasted for two years and in 2005 hunting started again but with shortening of the hunting season and market hunting was not allowed.

The winter mortality of the rock ptarmigan accounts for the greatest part of the total annual mortality and is the main demographic factor influencing the size of the breeding population the following spring (Gardarsson, 1988). The total mortality of adults increased from 1981 to 2002, it was estimated to be 47% in 1981 but had risen to 62% in 2002 (Magnússon et al., 2005). The winter mortality of juveniles was observed to be density dependent with a delay of 2-4 years (Magnússon et al., 2005), it was 80% when the population was increasing and 94-97% when the population was decreasing (Gardarsson, 1988).

The rock ptarmigan is an important prey to a number of predators, including the gyrfalcon (*Falco rusticolus*), the raven (*Corvus corax*), the mink (*Mustela vison*) and the arctic fox (*Vulpes lagopus*). Of those predators only the gyrfalcon is specialized on ptarmigan and the two species show a coupled predator-prey cycle in Iceland (Nielsen, 2011). The ptarmigan is especially vulnerable for predation in spring and in early autumn (Gardarsson, 1988; Nielsen and Cade, 1990).

The management goal for the ptarmigan population in Iceland has been to keep the total annual mortality at a level that will allow the population to have natural fluctuations. The sustainable mortality rate was estimated to be 37% for adults (Magnússon et al., 2005; Nielsen, 2006). Knowledge of abundance, recruitment rate, survival, harvest mortality, age and sex ratios of populations can be helpful to wildlife managers to determine how regulations affect the population and to estimate whether management goals have been achieved. Different methods have been used to estimate these demographic parameters (Skalski et al., 2005; Williams et al., 2002). Most of them only estimate one or a few of these parameters so a different approaches have to be applied to estimate all of them. Also, many methods do not provide uncertainty of parameter

estimation. Population reconstruction models can be used to estimate these parameters simultaneously using age-at-harvest data and auxiliary data (Broms, 2007; Broms et al., 2010; Gove et al., 2002; Skalski et al., 2005).

The aim of this study was to build a population reconstruction model for the rock ptarmigan in NE-Iceland, to estimate the population size, recruitment, natural survival and hunting mortality.

9.2 Methods

9.2.1 The data

The data used in the population model was a spring population index, age ratios measured in both autumn and spring, the number of hunters and the number of harvested rock ptarmigans (Table 9.1). Ptarmigans were counted on six plots in the study area, total size 26.8 km² (Figure 9.1), and the sum of all cocks observed on these six plots is the population index (Nielsen, 2011). The age ratios were determined in spring and in the autumn using the pigmentation of the primary feathers (Weeden and Watson, 1967). The bird age can only be determined to be either juvenile (< 1 year) or adult (> 1 year). The age ratios in spring were derived from ptarmigans found dead during field work (mostly killed by gyrfalcons), birds trapped for ringing and from birds flushed and photographed. The age ratios in the autumn were estimated from samples (wings) that hunters send in after the hunting season. Hunters must buy an annual hunting card issued by the Environmental Agency of Iceland (EAI) to have a hunting license. After the hunting season the hunters turn in a report stating how many ptarmigans were caught, in what part of the country and since 2005 how many days were spent hunting. The number of hunters that hunted ptarmigans in NE-Iceland, 21,000 km² (Figure 9.1), was used and the number of harvested ptarmigans. The number of hunters was missing for 1998 and 1999 and these values were estimated by regressing the number of hunters in NE-Iceland on total number of hunters in 2000-2012. The estimated values for both years were 1,106 hunters.

9.2.2 The population reconstruction model

Gove et al. (2002) and Skalski et al. (2005) suggested using a statistical population reconstruction model for modeling populations of game species. Population

Table 9.1: The data used in the population model for the rock ptarmigan in northeast Iceland. Number of juveniles aged from harvest ($a_{i,1}^h$), number of adults aged from harvest ($a_{i,2}^h$), number of juveniles aged in spring ($a_{i,1}^s$), number of adults aged in spring ($a_{i,2}^s$), number of harvested rock ptarmigans (h_i), number of hunters (f_i) and the density index (I_i) for northeast Iceland from 1998 to 2013.

Year _{<i>i</i>}	$a_{i,1}^h$	$a_{i,2}^h$	$a_{i,1}^s$	$a_{i,2}^s$	h_i	f_i	I_i
1998	859	213			48,269		189
1999	400	109	109	87	48,343		110
2000	345	61	68	69	36,203	1,047	80
2001	320	82	34	9	24,236	968	76
2002	332	99	21	14	20,194	886	54
2003	0	0	59	37	0	0	52
2004	0	0	97	54	0	0	97
2005	911	369	121	79	14,680	963	180
2006	614	155	65	50	11,342	893	140
2007	625	192	93	70	8,407	829	91
2008	817	200	109	53	13,080	1,047	129
2009	1534	464	85	70	21,894	1,337	178
2010	1651	424	178	84	18,482	1,221	190
2011	516	207	148	127	9,858	1,045	103
2012	459	129	143	149	7,581	840	82
2013			159	92			

reconstruction is a method that utilizes harvest data, i.e. the number of harvested animals, age ratios from the harvest and the hunting effort, which can be measured as the number of hunters. The precision of the model can be improved by adding auxiliary data, e.g. data from radio telemetry studies or index data from count studies. The method was developed for animals where the age could be determined to years but Broms et al. (2010) adjusted the method of Gove et al. (2002) and Skalski et al. (2005) for small game species where the age can only be determined into two classes, juveniles and adults.

The model as defined by Broms et al. (2010) consists of four likelihoods, three likelihoods of the binomial distribution and one of the normal distribution (see Model 9.1). The likelihood L_{catch} provides an estimate of the probability of catching a bird using the harvest data, and L_{AAH} provides an estimate of the probability that a harvested bird is a juvenile using the age ratio from the harvest. Auxiliary data is used to construct the likelihoods L_{radio} and

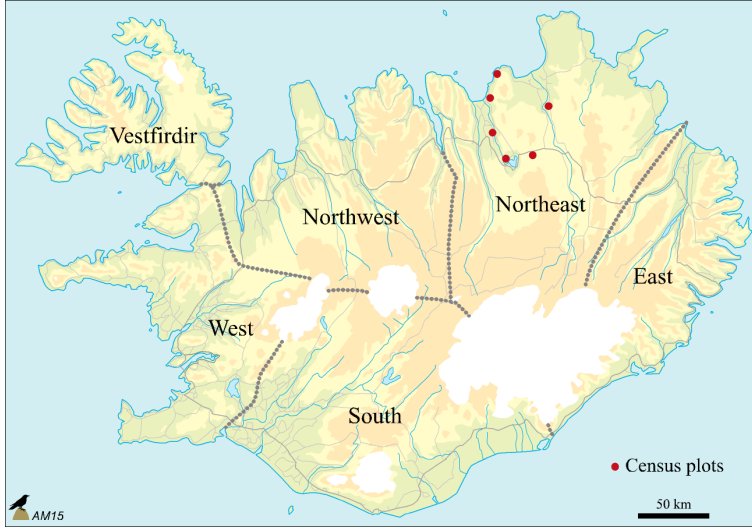


Figure 9.1: The study area for the rock ptarmigan in NE-Iceland and the 6 census plots.

L_{index} . L_{radio} provides an estimate of the probability of harvesting a juvenile of all marked juveniles by using the number of all radiomarked birds ($R_{i,j}$) and the number of marked birds harvested ($r_{i,j}$), for age group j ($j = \{1, 2\}$, $1 = \text{juvenile}$, $2 = \text{adult}$). L_{index} includes the relationship between the index and total abundance. The maximum likelihood of the joint likelihoods gives the estimates for the demographic parameters of the model.

The likelihoods can contribute differently to the joint likelihood as they include different data sources and weighting of the likelihoods will make the model fit the data better. However, Gove et al. (2002) recommend using unweighted likelihood model for the population reconstruction model.

$$\begin{aligned}
 L_{\text{joint}} &= L_{\text{catch}} \cdot L_{\text{AAH}} \cdot L_{\text{radio}} \cdot L_{\text{index}} \\
 L_{\text{catch}} &= \prod_{\text{year}=i=1}^Y \binom{N_i}{h_i} \left(\frac{N_{i,1}H_{i,1} + N_{i,2}H_{i,2}}{N_{i,1} + N_{i,2}} \right)^{h_i} \\
 &\quad \left(1 - \frac{N_{i,1}H_{i,1} + N_{i,2}H_{i,2}}{N_{i,1} + N_{i,2}} \right)^{N_i - h_i} \\
 L_{\text{AAH}} &= \prod_{\text{year}=i=1}^Y \binom{a_{i,1}^h + a_{i,2}^h}{a_{i,1}^h} \left(\frac{N_{i,1}H_{i,1}}{N_{i,1}H_{i,1} + N_{i,2}H_{i,2}} \right)^{a_{i,1}^h} \\
 &\quad \left(1 - \frac{N_{i,1}H_{i,1}}{N_{i,1}H_{i,1} + N_{i,2}H_{i,2}} \right)^{a_{i,2}^h} \\
 L_{\text{radio}} &= \prod_{\text{year}=i=1}^Y \binom{R_{i,1}}{r_{i,1}} H_{i,1}^{r_{i,1}} (1 - H_{i,1})^{R_{i,1} - r_{i,1}} \\
 &\quad \binom{R_{i,2}}{r_{i,2}} H_{i,2}^{r_{i,2}} (1 - H_{i,2})^{R_{i,2} - r_{i,2}} \\
 L_{\text{index}} &= \prod_{\text{year}=i=1}^Y \frac{1}{\sqrt{2\pi}\sigma} \exp \left[\frac{-(I_i - \alpha N_i)^2}{2\sigma^2} \right]
 \end{aligned} \tag{9.1}$$

$$N_{i,2} = N_{i-1,1} \cdot (1 - H_{i-1,1}) \cdot S_1 + N_{i-1,2} \cdot (1 - H_{i-1,2}) \cdot S_2 \tag{9.2}$$

$$H_{i,j} = 1 - e^{-c_j \cdot f_i} \tag{9.3}$$

With this model it is possible to estimate the abundance of juveniles ($N_{i,1}$) before the hunting season in year i , the abundance of adults before the hunting season for the first year in the time period ($N_{1,2}$), natural survival (S_j), from hunting season to hunting season, for age group j , the hunting vulnerability coefficient (c_j) for age group j , the relationship (α) between the index (I) and total abundance (N). The number of juveniles is estimated for every year but the number of adults is estimated for the first year. These estimates along with the estimates of S_j and c_j are used to calculate the number of adults for each year after the first year (see Equation 9.2). The hunting mortality rate ($H_{i,j}$) is assumed to be a function of the number of hunters (f_i) (see Equation 9.3).

There are four variations of this model: 1) juveniles and adults have a common S and c (1c1s); 2) juveniles and adults have a different S but a common

c (1c2s); 3) juveniles and adults have a common S but a different c (2c1s); 4) juveniles and adults have a different S and c (2c2s).

When there are 15 years of data as in our case the number of parameters that needs to be estimated in the simplest model (1c1s) is 20 and 22 for the most complex model (2c2s). It can be very difficult to estimate all of those parameters, especially separate survival and vulnerability parameters for adults and juveniles.

9.3 Results

The model of Broms et al. (2010) was adjusted to fit the rock ptarmigan in Iceland. We did not use data from radio telemetry studies as they only existed for one year, but age ratios had been estimated in spring and a likelihood using these age ratios was included in the model. Also, variations of how to model the hunting mortality was proposed along with the possibility of adding a changepoint (CP) to the model (Sturludottir et al., 2015).

9.3.1 Inclusion of age in spring

A likelihood with the age ratios in spring (Equation 9.4) was added to the model of Broms et al. (2010). With this addition it becomes easier to estimate separate survival parameters for adults and juveniles. This likelihood is based on the binomial distribution and uses the spring age ratios to estimate the proportion of juveniles in the population during spring and the winter survival ($S_{w,j}$). This proportion can be simplified, so instead of estimating a separate $S_{w,j}$ for adults and juveniles one survival parameter $S_{w,x}$ is sufficient. This parameter is the excess winter survival of adults, i.e. the survival ratio of adults and juveniles $S_{w,x} = \frac{S_{w,2}}{S_{w,1}}$.

$$\begin{aligned}
 L_{\text{AAS}} &= \prod_{\text{year}=i=1}^Y \left(\frac{a_{i+1,1}^s + a_{i+1,2}^s}{a_{i+1,1}^s} \right) \\
 &\quad \left(\frac{N_{i,1}(1 - H_{i,1})S_{w,1}}{N_{i,1}(1 - H_{i,1})S_{w,1} + N_{i,2}(1 - H_{i,2})S_{w,2}} \right)^{a_{i+1,1}^s} \\
 &\quad \left(1 - \frac{N_{i,1}(1 - H_{i,1})S_{w,1}}{N_{i,1}(1 - H_{i,1})S_{w,1} + N_{i,2}(1 - H_{i,2})S_{w,2}} \right)^{a_{i+1,2}^s} \\
 &= \prod_{\text{year}=i=1}^Y \left(\frac{a_{i+1,1}^s + a_{i+1,2}^s}{a_{i+1,1}^s} \right) \\
 &\quad \left(\frac{S_{w,1}N_{i,1}(1 - H_{i,1})}{S_{w,1}(N_{i,1}(1 - H_{i,1}) + N_{i,2}(1 - H_{i,2})S_{w,x})} \right)^{a_{i+1,1}^s} \\
 &\quad \left(1 - \frac{S_{w,1}N_{i,1}(1 - H_{i,1})}{S_{w,1}(N_{i,1}(1 - H_{i,1}) + N_{i,2}(1 - H_{i,2})S_{w,x})} \right)^{a_{i+1,2}^s} \\
 &= \prod_{\text{year}=i=1}^Y \left(\frac{a_{i+1,1}^s + a_{i+1,2}^s}{a_{i+1,1}^s} \right) \\
 &\quad \left(\frac{N_{i,1}(1 - H_{i,1})}{N_{i,1}(1 - H_{i,1}) + N_{i,2}(1 - H_{i,2})S_{w,x}} \right)^{a_{i+1,1}^s} \\
 &\quad \left(1 - \frac{N_{i,1}(1 - H_{i,1})}{N_{i,1}(1 - H_{i,1}) + N_{i,2}(1 - H_{i,2})S_{w,x}} \right)^{a_{i+1,2}^s}
 \end{aligned} \tag{9.4}$$

If the hunting vulnerability coefficient is assumed to be equal for juveniles and adults the likelihood can be simplified further (see Equation 9.5).

$$\begin{aligned}
 L_{\text{AAS}} &= \prod_{\text{year}=i=1}^Y \left(\frac{a_{i+1,1}^s + a_{i+1,2}^s}{a_{i+1,1}^s} \right) \left(\frac{N_{i,1}}{N_{i,1} + N_{i,2}S_{w,x}} \right)^{a_{i+1,1}^s} \\
 &\quad \left(1 - \frac{N_{i,1}}{N_{i,1} + N_{i,2}S_{w,x}} \right)^{a_{i+1,2}^s}
 \end{aligned} \tag{9.5}$$

The calculation of $N_{i,2}$ has to be simplified accordingly (see Equation 9.6 and 9.7).

$$\begin{aligned}
N_{i,2} &= N_{i-1,1} \cdot (1 - H_{i-1,1}) \cdot S_{w,1} \cdot S_s + N_{i-1,2} \cdot (1 - H_{i-1,2}) \cdot S_{w,2} \cdot S_s \\
&= S_{w,1} \cdot S_s (N_{i-1,1} \cdot (1 - H_{i-1,1}) + N_{i-1,2} \cdot (1 - H_{i-1,2}) \cdot S_{w,x}) \quad (9.6) \\
&= S_c (N_{i-1,1} \cdot (1 - H_{i-1,1}) + N_{i-1,2} \cdot (1 - H_{i-1,2}) \cdot S_{w,x})
\end{aligned}$$

If the hunting mortality is equal for adults and juveniles Equation 9.6 simplifies to Equation 9.7.

$$N_{i,2} = S_c(1 - H_{i-1})(N_{i-1,1} + N_{i-1,2} \cdot S_{w,x}) \quad (9.7)$$

When we added the spring ratios, we had the survival of juveniles ($S_{w,1}$) and adults ($S_{w,2}$) over the winter (from hunting season to spring) and the survival over the summer (S_s) which is assumed to be equal for adults and juveniles (the second summer of the juveniles, the first four months in the life of juveniles are excluded in this approach). Instead of having these three survival parameters two are sufficient, the excess adult survival ($S_{w,x}$) and juvenile survival from hunting season to hunting season ($S_c = S_{w,1} \cdot S_s$). The adult survival from hunting season to hunting season can then be calculated as $S_{w,x} \cdot S_c$.

9.3.2 Survival and hunting mortality as functions

The hunting mortality can be modeled as a function of the number of hunters as suggested by Gove et al. (2002) and Broms et al. (2010) (see Equation 9.3), but it could also be assumed fixed or modeled as a function of the size of the population or the abundance index, i.e. $H_{i,j} = 1 - e^{(-b_j + c_j I_i)}$. The relationship between hunting mortality and population size depends on the harvest strategy (Deroba and Bence, 2008). When the hunting mortality is assumed fixed the harvest increases when the population increases but when the harvest is assumed to be constant the hunting mortality is a function of the population and the hunting mortality decreases with increasing population size.

The natural survival can be assumed fixed and equal for all age groups in the simplest case but it may be more fitting to model the survival as a function of density $S_{i,j} = e^{(d_j - e_j I_i)}$ if e.g. the survival is higher when the density is low and lower when the density is high.

9.3.3 Changepoint

A CP can occur if there is a change in the management of the population (Sturludottir et al., 2015), and in particular if the hunting regulations are changed it may be better to allow the function of the harvest mortality ($H_{i,j}$) to change. The vulnerability coefficients (c_j) may not be the same before and after the change or the function of the harvest mortality might change, e.g. it might be a function of the population size before the change but a function of the number of hunters after the change. It may also be appropriate to assume a CP in the natural survival if there was a point in time when the environmental conditions for the population changed permanently, i.e. the changes were not attributed to a random changes which frequently take place in the environment.

9.3.4 The final model

Five variations of the model were used to fit the data (Table 9.2). The maximum likelihood of the joint likelihoods with equal weights was found using the `nlminb` function in the statistical software R (R Development Core Team, 2012). These models were compared using the AIC. It was not possible to estimate separate vulnerability coefficient for adults and juveniles and the number of hunters was scaled with 1/10,000 to aid in the numerical optimization. Model (a) with a common survival parameter for both juveniles and adults was compared with a model (b) with a CP, where the vulnerability coefficient c was allowed to be different before and after the hunting ban in 2003. The model (b) with a CP included fitted the data better. Model (b) was compared to model (c) with a CP and a separate survival parameter for juveniles and adults. The model (c) fitted the data better than model (b). In model (d) the survival was assumed different for juveniles and adults but the excess winter survival of the adults was assumed to be a function of the density with a one year-lag. This model (d) had a better fit than model (c) where the survival was assumed to be constant. The fifth model (e) had the survival parameters as model (d) but the function for the hunting mortality was assumed to be a function of the density before 2003 but a function of the number of hunters after 2003. This addition gave a better fit than model (d) where the hunting mortality was assumed to be a function of the number of hunters both before and after 2003 but with a different vulnerability coefficient. The model that fitted the data best of the five models was model (e) which can be seen in details in Model 9.8 and description of the parameters in the model are in Table 9.3.

Table 9.2: Fitted models with number of parameters (pm) and AIC (smaller is better).

Model	Description	pm	AIC
a)	$N_{i,2} = S_c(N_{i-1,1} \cdot (1 - H_{i-1}) + N_{i-1,2} \cdot (1 - H_{i-1}))$ $H_i = 1 - e^{-cf_i}$	20	1063
b)	$N_{i,2} = S_c(N_{i-1,1} \cdot (1 - H_{i-1}) + N_{i-1,2} \cdot (1 - H_{i-1}))$ $H_{(i < 2003)} = 1 - e^{-c_b f_i}$ and $H_{(i \geq 2003)} = 1 - e^{-c_a f_i}$	21	1043
c)	$N_{i,2} = S_c(N_{i-1,1} \cdot (1 - H_{i-1}) + N_{i-1,2} \cdot (1 - H_{i-1}) \cdot S_{w,x}^\dagger)$ $H_{(i < 2003)} = 1 - e^{-c_b f_i}$ and $H_{(i \geq 2003)} = 1 - e^{-c_a f_i}$	22	730
d)	$N_{i,2} = S_c(N_{i-1,1} \cdot (1 - H_{i-1}) + N_{i-1,2} \cdot (1 - H_{i-1}) \cdot S_{x,i-1}^{\dagger\dagger})$ $H_{(i < 2003)} = 1 - e^{-c_b f_i}$ and $H_{(i \geq 2003)} = 1 - e^{-c_a f_i}$	23	721
e)	$N_{i,2} = S_c(N_{i,1} \cdot (1 - H_{i-1}) + N_{i,2} \cdot (1 - H_{i-1}) \cdot S_{x,i-1})$ $H_{(i < 2003)} = 1 - e^{-b+c_b I_i}$ and $H_{(i \geq 2003)} = 1 - e^{-c_a f_i}$	24	690

[†] $S_{w,x}$ = constant, excess winter survival of adults.

^{††} $S_{x,i}$ = $d - e \cdot I_{i-1}$, excess winter survival of adults.

$$\begin{aligned}
 L_{\text{joint}} &= L_{\text{catch}} \cdot L_{\text{AAH}} \cdot L_{\text{AAS}} \cdot L_{\text{index}} \\
 L_{\text{catch}} &= \prod_{i=1998}^{2002} \binom{N_i}{h_i} \left(\frac{H_{b,i}(N_{i,1} + N_{i,2})}{N_{i,1} + N_{i,2}} \right)^{h_i} \\
 &\quad \left(1 - \frac{H_{b,i}(N_{i,1} + N_{i,2})}{N_{i,1} + N_{i,2}} \right)^{N_i - h_i} \\
 &\quad \prod_{i=2003}^{2012} \binom{N_i}{h_i} \left(\frac{H_{a,i}(N_{i,1} + N_{i,2})}{N_{i,1} + N_{i,2}} \right)^{h_i} \\
 &\quad \left(1 - \frac{H_{a,i}(N_{i,1} + N_{i,2})}{N_{i,1} + N_{i,2}} \right)^{N_i - h_i} \\
 L_{\text{AAH}} &= \prod_{i=1998}^{2012} \binom{a_{i,1}^h + a_{i,2}^h}{a_{i,1}^h} \left(\frac{N_{i,1}}{N_{i,1} + N_{i,2}} \right)^{a_{i,1}^h} \\
 &\quad \left(1 - \frac{N_{i,1}}{N_{i,1} + N_{i,2}} \right)^{a_{i,2}^h} \\
 L_{\text{AAS}} &= \prod_{i=1998}^{2012} \binom{a_{i+1,1}^s + a_{i+1,2}^s}{a_{i+1,1}^s} \left(\frac{N_{i,1}}{N_{i,1} + N_{i,2} \cdot S_{x,i}} \right)^{a_{i+1,1}^s} \\
 &\quad \left(1 - \frac{N_{i,1}}{N_{i,1} + N_{i,2} \cdot S_{x,i}} \right)^{a_{i+1,2}^s} \\
 L_{\text{index}} &= \prod_{i=1998}^{2012} \frac{1}{\sqrt{2\pi}\sigma} \exp \left[\frac{-(I_i - \alpha N_i)^2}{2\sigma^2} \right]
 \end{aligned} \tag{9.8}$$

The abundance of adult ptarmigans was calculated with Equation 9.9.

$$N_{i,2} = \begin{cases} (1 - H_{b,i-1})S_c(N_{i-1,1} + N_{i-1,2} \cdot S_{x,i-1}) & 1998 \leq i < 2003 \\ (1 - H_{a,i-1})S_c(N_{i-1,1} + N_{i-1,2} \cdot S_{x,i-1}) & 2003 \leq i \leq 2012 \end{cases} \tag{9.9}$$

where $H_{b,i} = 1 - e^{-b+c_b \cdot I_i}$ and $H_{a,i} = 1 - e^{-c_a \cdot f_i}$ and $S_{x,i} = d - e \cdot I_{i-1}$

The model estimates the natural survival and hunting mortality from autumn to autumn which can be used to calculate the total annual mortality ($M_{i,j}$) for juvenile (Equation 9.10) and adult (Equation 9.11) ptarmigans.

$$M_{i,1} = \begin{cases} 1 - (1 - H_{b,i})S_c & 1998 \leq i < 2003 \\ 1 - (1 - H_{a,i})S_c & 2003 \leq i \leq 2012 \end{cases} \tag{9.10}$$

$$M_{i,2} = \begin{cases} 1 - (1 - H_{b,i}) \cdot S_c \cdot S_{x,i} & 1998 \leq i < 2003 \\ 1 - (1 - H_{a,i}) \cdot S_c \cdot S_{x,i} & 2003 \leq i \leq 2012 \end{cases} \quad (9.11)$$

Table 9.3: Description of parameters in the final model for the rock ptarmigan in NE-Iceland 1998-2012.

Data	Description
$N_{i,1}$	Abundance of juveniles.
$N_{i,2}$	Abundance of adults.
N_i	Total abundance $N_{i,1} + N_{i,2}$.
c_b	Coefficient in the function for hunting mortality.
b	Coefficient in the function for hunting mortality.
c_a	Vulnerability coefficient.
d	Coefficient in the function of excess winter survival of adults.
e	Coefficient in the function of excess winter survival of adults.
S_c	Survival of juveniles.
α	Index to abundance ratio.
σ^2	Variance associated with the index abundance ratio.

9.3.5 The estimated population size, survival and hunting mortality

The maximum likelihood estimates of Model 9.8 are presented in Table 9.4 with 95% confidence intervals (CI) which were found using the profile likelihood method (Stryhn and Christensen, 2003).

The autumn abundance of juvenile and adult rock ptarmigans from 1998 to 2012 can be seen in Figure 9.2. The abundance of juveniles ranged from 31,000 (95% CI 30,000 – 34,000) in 2002 to 121,000 (95% CI 107,000 – 138,000) in 1998 and the abundance of adults ranged from 6,500 in 2002 to 32,000 in 1998. The abundance decreased from 1998 to a low in 2002, it increased again in the hunting ban and reached a peak in 2005. It then decreased again to a low in 2007 and then increased again until it reached another peak in 2009 when it started decreasing again. The total abundance followed the fluctuations in the density index but did not reach the peaks of the index in 2005 and 2010 (Figure

Table 9.4: Parameter estimates (see description in Table 9.3) from Model 9.8 with 95% confidence intervals (CI) for rock ptarmigan in NE-Iceland 1998-2012.

Parameter	Estimate	LCI	UCI
$N_{1998,1}$	121000	107000	138000
$N_{1999,1}$	82000	78000	94000
$N_{2000,1}$	57000	55000	64000
$N_{2001,1}$	38000	36000	42000
$N_{2002,1}$	31000	30000	34000
$N_{2003,1}$	58000	43000	79000
$N_{2004,1}$	96000	73000	127000
$N_{2005,1}$	90000	72000	111000
$N_{2006,1}$	71000	57000	87000
$N_{2007,1}$	58000	47000	72000
$N_{2008,1}$	80000	66000	99000
$N_{2009,1}$	109000	89000	133000
$N_{2010,1}$	95000	78000	116000
$N_{2011,1}$	51000	41000	62000
$N_{2012,1}$	55000	45000	68000
$N_{1998,2}$	32000	28000	37000
c_b	0.0029	0.0021	0.0038
b	0.93	0.75	1.11
c_a	1.36	1.09	1.70
S_c	0.19	0.18	0.20
d	4.01	3.41	4.65
e	0.011	0.008	0.014
α	0.0013	0.0011	0.0015
σ^2	464	220	1100

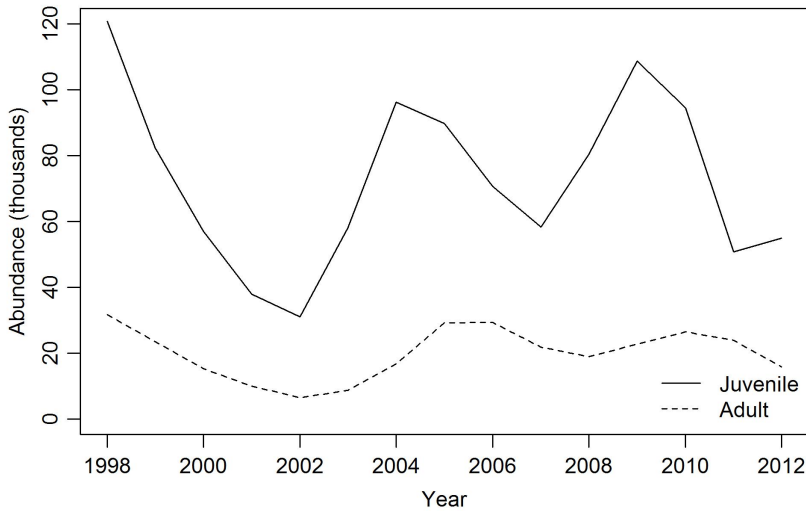


Figure 9.2: Estimated autumn abundance of juvenile and adult rock ptarmigan in NE-Iceland from 1998 to 2012.

9.3).

It was not possible to estimate both the juvenile and adult survival as a function of density but only either one. It fitted the data better to assume constant survival for the juveniles. The natural survival of adult rock ptarmigans was assumed to be a function of the density with a one year lag, it ranged from 36% (95% CL 33 – 38%) in 1999 and 2011 to 65% (95% CL 60 – 70%) in 2003 and 2004. The survival for juveniles was taken as a constant and was estimated to be 19% (95% CL 18 – 20%) (Figure 9.4).

The hunting mortality was assumed to be equal for juvenile and adult rock ptarmigans (Figure 9.5a). A CP was included in the model to account for a change in the hunting mortality that could have occurred with the hunting ban and changes in the hunting regulations. Before the hunting ban in 2003 the hunting mortality was modeled as a function of density and ranged from 32% (95% CI 28 – 35%) in 1998 to 54% (95% CI 49 – 60%) in 2002. After the hunting ban, the hunting mortality was modeled as a function of the number of hunters and ranged from 11% (95% CI 9 – 13%) in 2007 to 17% (95% CI 14 – 20%) in 2009 when the number of hunters peaked.

The total mortality of the juveniles (Equation 9.10) was higher before the

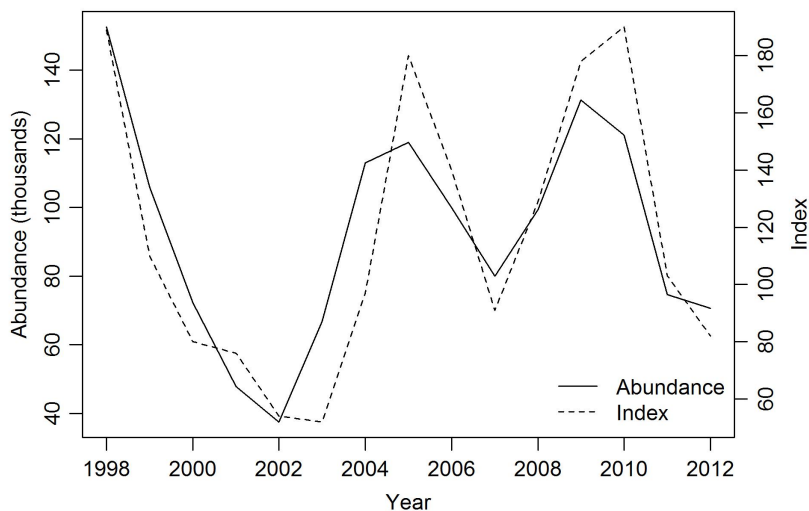


Figure 9.3: Estimated total autumn abundance of rock ptarmigan in NE-Iceland from 1998 to 2012 compared with the spring density index.

hunting ban than after the ban or around 90% and 83%, respectively. The total mortality of adults (Equation 9.11) was lowest during the hunting ban in 2003 and 2004 when it was 35%. It was higher before the hunting ban than after, or 67% to 81% and 51% to 69%, respectively (Figure 9.5b).

9.4 Discussion

9.4.1 The estimated abundance

The population of rock ptarmigan in Iceland has previously shown 10-12 year cycles in numbers (Gudmundsson, 1960; Nielsen and Petursson, 1995). The estimated abundance in this study did not show a 10 year cycle. Instead, there was a peak in 1998, then in 2005 and again in 2009. Hunting ban was in effect in 2003 and 2004 which might explain this different pattern. The hunting ban resulted in greatly reduced mortality rates which probably lead to the peak in 2005. The estimated abundance did follow the density index which also showed an increase in density after the hunting ban.

The total estimated abundance was around 120,000-150,000 in the peak

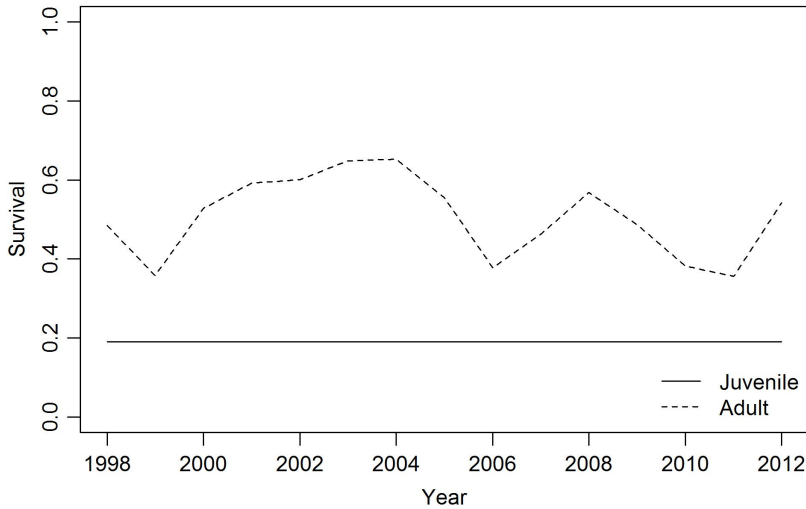


Figure 9.4: Estimated natural survival for juvenile and adult rock ptarmigan in NE-Iceland from 1998 to 2012.

years and around 40,000 when it was lowest in 2002. The population in NE-Iceland has not been estimated before but the spring population has been estimated for the whole country. Using the method of Magnússon et al. (2005) the total spring population in 2005 was estimated as 219,000 birds (Nielsen, 2006). From this number the total population in autumn 2005 was estimated using a method described in Nielsen (2006) as 765,000 birds.

The method described in Magnússon et al. (2005) involves estimating the relationship between the spring abundance and the density index ($N = 1/q \cdot I$) along with the natural survival. Using data from 1998-2012 for NE-Iceland (Table 9.1) gives an estimate of $1/q = 345$ and calculated spring population of 62,000 birds in 2005. This would then make a total population in autumn of 216,000 birds, assuming 68.5% annual survival and juvenile age ratio of 76% as was done in Nielsen (2006). This estimate is twice the estimated population size using the model from the present study (Figure 9.6a). The confidence limits are very wide when this method is used. For example, Magnússon et al. (2005) estimated $1/q = 1207$ with 95% confidence interval of 628-15667 which makes total autumn population for the entire country of 393,000 to 9,816,000 birds. The method used to estimate q includes highly autocorrelated data and this

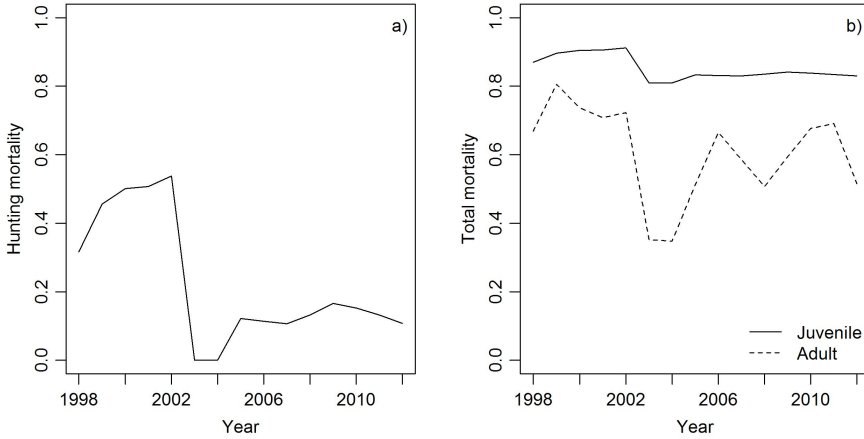


Figure 9.5: Estimated mortality of juvenile and adult rock ptarmigan in NE-Iceland from 1998 to 2012. a) Estimated hunting mortality (assumed equal for juveniles and adults) and b) estimated total mortality (see Equations 9.11 and 9.10).

needs to be taken into account which widens the intervals. The estimate of q is also highly variable with respect to the time-period chosen. If the period is 1998-2004 $1/q = 256$ and for 2003-2012 $1/q = 79$ which gives a total autumn population for NE-Iceland in 2005 of 161,000 and 49,000 birds, respectively.

The method of Magnússon et al. (2005) has high uncertainty which has to be kept in mind if used. The confidence limits obtained from the population reconstruction model are much narrower, e.g. the 95% confidence interval for the juvenile abundance in 2005 is 72,000-111,000 birds. However, it is possible that the confidence intervals from the model are too narrow. Gast et al. (2013) showed that the confidence intervals of a population reconstruction model only covered the true abundance in <40% of simulated cases and the estimates were biased in some cases. The coverage of the confidence intervals improved and the bias was reduced with addition of auxiliary data such as age ratios from telemetry study. The model tested in Gast et al. (2013) is not exactly the same as the model in the present study and further Broms (2007) showed that the model which the present model is built on had accurate abundance estimates when hunting mortality was between 20-50%. A separated simulation study is needed to determine whether the estimates from the present model are unbiased and if the confidence intervals have 95% coverage.

9.4.2 The estimated natural survival

The excess natural survival of adults was modeled as a function of density with a lag of one year. The survival was estimated to be highest one year after the population was the lowest and lowest one year after the peak in population number. This is in accordance with theory on density-dependence (Skalski et al., 2005; Turchin, 1999). Magnússon et al. (2005) calculated excess winter mortality of juvenile ptarmigan in NE-Iceland and observed a relation between the mortality of juveniles and density but not for adults. The data they used were from 1981 to 2004. If the mortality for juveniles and adults is calculated using the method of Magnússon et al. (2005) for 2005 to 2012, the pattern changes, the mortality of juveniles no longer follows the density but the adult mortality seems to be density dependent after 2002. Density dependence has been observed to be more common for juvenile survival for many animals but density dependent adult survival has also been observed (Gaillard et al., 1998).

The survival of juveniles was assumed constant as it was not possible to estimate both the adult and juvenile survival as a function. It is however possible to estimate the juvenile survival as a function of density and the adult survival as a constant. This was done in the present study (results not shown) but it did not improve the model to assume the juvenile survival as a function of density over a constant. It did however improve the model to model the adult survival as a function of density. The connection between survival and density can change in the future and inclusion of a CP can improve the fit of the model by allowing the function for survival to be different before and after the CP.

9.4.3 The estimated harvest and total mortality

The hunting mortality of juveniles and adults was assumed to be equal but this may not be the case. If this was the case and the juveniles were for example more vulnerable for hunting than adults then the proportion of juveniles should be higher in the harvest than in the population. Age ratios are also recorded in late summer and they do not support this theory as they are in the same range as age ratios from the harvest. The age ratios from spring are however different from both the harvest and late summer where the proportion of juveniles is much lower indicating higher mortality rates of juveniles than adults over the winter (Figure 9.7).

Including a CP in the function of the hunting mortality improved the model and indicates that the hunting ban and the changes in hunting regulations did

have an effect. The hunting mortality was modeled as a function of density before 2003, this should be more appropriate than to model it as a function of hunter numbers that is to say if the hunters show a saturation effect (Van Deelen and Etter, 2003), i.e. hunters harvest a smaller proportion as the population increases. Prior to 2003 the hunters had 69 days to hunt and might have used more time hunting when the population was low to achieve same harvest as when the population numbers were high. The time spent hunting before 2003 is not known as data on hunting effort was not registered until 2005. After the hunting ban the hunting mortality was modeled as a function of hunter numbers as the reduced length of the hunting season limited the ability of the hunters to compensate for low catch. Also, the ban to market hunting should have reduced the drive to catch many birds. It might be better to model the harvest mortality as a function of days spent hunting. This was not done as this data has only been available since 2005. The data shows that the average number of the hunting days has been relatively stable 2005-2012 or between three and four days (Steinar Rafn Beck Baldursson in litt. 6.3.2015).

Before the hunting ban in 2003 and 2004 the hunting season was 69 days and market hunting was allowed. Hunting was allowed again in 2005 but there was a ban to market hunting and the hunting season was reduced to 47 days in 2005 and then to 26 days in 2006. Later, the hunting season was reduced further, and has been 9-18 days since. This change has led to a decrease in hunting mortality, still the management goal of keeping the total annual adult mortality below 37% has not been reached. The total annual mortality of adults was only below this limit during the hunting ban when it was 35% but after the hunting began again it has always been above 50%. To achieve this goal the harvest mortality may not be higher than 3% (2000-3000 birds) when the natural mortality is the lowest (natural survival the highest) which was one year after the population was the lowest but the natural mortality was 64% when the population was the highest which does not support any hunting as it is then already higher than the set goal of 37%.

The reduced hunting mortality after the hunting ban has not led to an increase in the population as would have been expected. The adult population shows an increase in 2004 and 2005 but decreases again when hunting started in 2005 and the peak abundance in 2010 is not higher than in 1998. The density index does also not show higher peaks after the hunting ban than in 1998.

The harvest mortality was estimated to be as high as 54% in 2002 and was always higher than the estimated mortality from the previous method (Figure

9.6b). It was assumed to be a function of density, this may not be correct though this gave a better fit than to assume it as fixed or a function of hunter numbers. It is possible that the estimated harvest mortality is biased upwards and the abundance biased downwards. This needs to be investigated further with simulations. However, the estimated total mortality, which consists of both the natural mortality and the hunting mortality, of adults was consistent with the calculated adult mortality using the method of Magnússon et al. (2005) as can be seen in Figure 9.6c (note that the calculation of the total annual mortality by Magnússon et al. (2005) is independent of the estimation of the abundance discussed in Section 9.4.1). The total annual mortality of juveniles from autumn to autumn can be calculated using the method of Magnússon et al. (2005) as the adult mortality plus the excess winter mortality of juveniles. This calculated mortality is in the same range as the juvenile mortality from Model 9.8 as seen in Figure 9.6d.

9.5 Conclusion

A population reconstruction model for the rock ptarmigan in NE-Iceland has been developed. The model estimates the juvenile and adult abundance and separate survival for juveniles and adults, where the adult survival is modeled as a function of the density with a one year lag. The hunting mortality rate is assumed to be equal for both juveniles and adults. A CP was included in the model when hunting regulations were altered and allowed a change in the function for hunting mortality which improved the model. This indicates that the regulation did reduce the hunting mortality and also changed the harvest strategy of hunters. Still, management goal of reducing total mortality to 37% has not been achieved and a further change in regulation may be needed. This model can then be used to estimate what effect new regulations have on the population dynamics of the rock ptarmigan.

Acknowledgment

The Environment Agency of Iceland is acknowledged for providing the data on hunters number and harvested ptarmigans. This study on the population model was financially supported by the Icelandic Research Fund for Graduate Students and the Icelandic Hunting Fund.

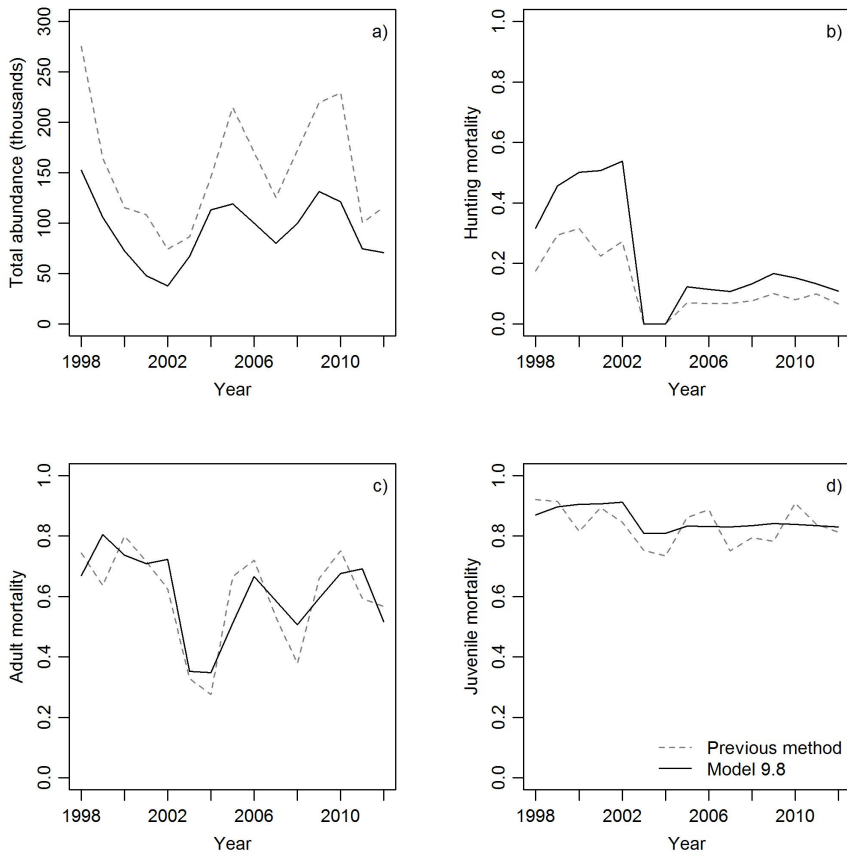


Figure 9.6: Estimation of demographic parameters of rock ptarmigans in NE-Iceland from 1998 to 2012 from Model 9.8 and using previous method described in Magnússon et al. (2005) and Nielsen (2006) of a) total abundance b) hunting mortality c) annual adult mortality and d) annual juvenile mortality.

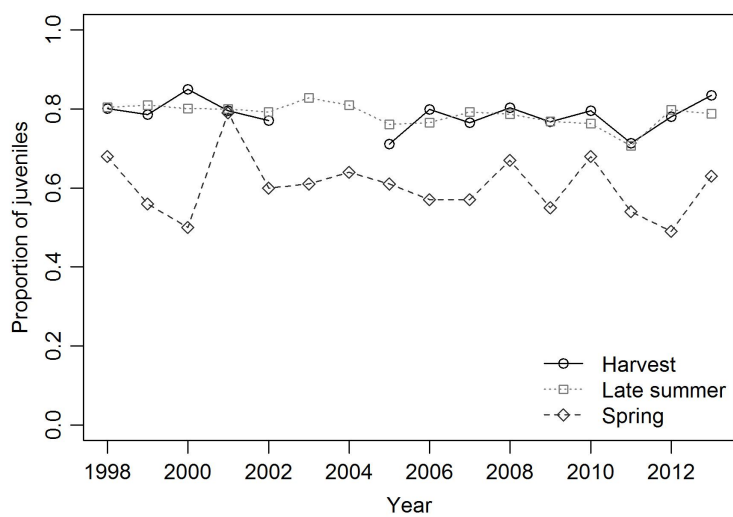


Figure 9.7: The proportion of juvenile ptarmigans in the harvest, in late summer and in spring in NE-Iceland from 1998-2013.

Bibliography

- AMAP (1998). *AMAP assessment report: Arctic pollution issues*. Arctic Monitoring and Assessment Programme (AMAP), Oslo, Norway.
- AMAP (2005). *AMAP assessment 2002: heavy metals in the Arctic*. Arctic Monitoring and Assessment Programme (AMAP), Oslo, Norway.
- AMAP (2009). *AMAP Assessment 2009: Human health in the Arctic*. Arctic Monitoring and Assessment Programme (AMAP), Oslo, Norway.
- Auðunsson, G. A. (1999). The effect of nutritional status of icelandic cod (*Gadus morhua*) on macroconstituents and trace elements in the liver. *Journal of the Marine Research Institute*, 16:111–129.
- Bailey, R. E. (2001). Global hexachlorobenzene emissions. *Chemosphere*, 43(2):167–182.
- Bence, J. R. (1995). Analysis of short time series: correcting for autocorrelation. *Ecology*, 76(2):628–639.
- Bignert, A. (2003). *Biological aspects and statistical methods to improve assessments in environmental monitoring*. PhD thesis, Stockholm University, Department of Zoology.
- Broms, K. (2007). *Small game population reconstruction: model development and applications*. MS thesis, University of Washington.
- Broms, K., Skalski, J. R., Millsbaugh, J. J., Hagen, C. A., and Schulz, J. H. (2010). Using statistical population reconstruction to estimate demographic trends in small game populations. *The Journal of Wildlife Management*, 74(2):310–317.
- Brynjarsdóttir, J., Lund, S. H., Magnússon, K. G., and Nielsen, Ó. K. (2003). *Analysis of time series for rock ptarmigan and gyrfalcon populations in north-east Iceland*. Science Institute, University of Iceland.
- Chandler, R. and Scott, M. (2011). *Statistical methods for trend detection and analysis in the environmental sciences*. John Wiley & Sons, United King-

- dom.
- Cryer, J. D. and Chan, K.-S. (2008). *Time series analysis: with applications in R*. Springer, New York.
- Dehling, H., Rooch, A., and Taqqu, M. S. (2012). Non-parametric change-point tests for long-range dependent data. *Scandinavian Journal of Statistics*, 40(1):153–173.
- Deroba, J. J. and Bence, J. R. (2008). A review of harvest policies: understanding relative performance of control rules. *Fisheries Research*, 94(3):210–223.
- Dietz, R., Sonne, C., Basu, N., Braune, B., O’Hara, T., Letcher, R. J., Scheuhammer, T., Andersen, M., Andreasen, C., Andriashek, D., et al. (2013). What are the toxicological effects of mercury in Arctic biota? *Science of the Total Environment*, 443:775–790.
- Diggle, P. (1990). *Time series: a biostatistical introduction*. Oxford University Press, New York.
- Fisk, A. T., De Wit, C. A., Wayland, M., Kuzyk, Z. Z., Burgess, N., Letcher, R., Braune, B., Norstrom, R., Blum, S. P., Sandau, C., et al. (2005). An assessment of the toxicological significance of anthropogenic contaminants in Canadian Arctic wildlife. *Science of the Total Environment*, 351:57–93.
- Fornberg, B. and Zuev, J. (2007). The Runge phenomenon and spatially variable shape parameters in RBF interpolation. *Computers & Mathematics with Applications*, 54(3):379–398.
- Franzke, C. (2012). Nonlinear trends, long-range dependence, and climate noise properties of surface temperature. *Journal of Climate*, 25(12):4172–4183.
- Fromberg, A., Cederberg, T., Hilbert, G., and Büchert, A. (2000). Levels of toxaphene congeners in fish from Danish waters. *Chemosphere*, 40(9):1227–1232.
- Fung, C., Lam, J., Zheng, G., Connell, D., Monirith, I., Tanabe, S., Richardson, B., and Lam, P. (2004). Mussel-based monitoring of trace metal and organic contaminants along the east coast of China using *Perna viridis* and *Mytilus edulis*. *Environmental Pollution*, 127(2):203–216.
- Gaillard, J.-M., Festa-Bianchet, M., and Yoccoz, N. G. (1998). Population dynamics of large herbivores: variable recruitment with constant adult survival. *Trends in Ecology & Evolution*, 13(2):58–63.
- Gardarsson, A. (1988). Cyclic population changes and some related events in Rock Ptarmigan in Iceland. In Bergerud, A. and Gratson, M., editors, *Adaptive strategies and population ecology of northern grouse*, pages 300–

329. University of Minnesota Press, Minneapolis, USA.
- Gast, C., Skalski, J. R., and Beyer, D. E. (2013). Evaluation of fixed-and random-effects models and multistage estimation procedures in statistical population reconstruction. *The Journal of Wildlife Management*, 77(6):1258–1270.
- Gove, N. E., Skalski, J. R., Zager, P., and Townsend, R. L. (2002). Statistical models for population reconstruction using age-at-harvest data. *The Journal of Wildlife Management*, 66(2):310–320.
- Green, N., Schøyen, M., Øxnevad, S., Ruus, A., Høgåsen, T., Beylich, B., Håvardstun, J., Rogne, Å., and Tveiten, L. (2011). *Hazardous substances in fjords and coastal waters-2010. Levels, trends and effects. Long-term monitoring of environmental quality in Norwegian coastal waters*. Norwegian Institute for Water Research, Oslo, Norway.
- Green, N. W. and Knutzen, J. (2003). Organohalogens and metals in marine fish and mussels and some relationships to biological variables at reference localities in Norway. *Marine Pollution Bulletin*, 46(3):362–374.
- Gudmundsson, F. (1960). Some reflections on ptarmigan cycles in Iceland. In Bergman, G., Donnet, K. O., and Haartman, L., editors, *Proceedings of the XIIth International Ornithological Congress*, volume 1, pages 259–265, Helsinki.
- Gusev, A., Mantseva, E., Rozovskaya, O., Shatalov, V., Vulykh, N., Aas, W., and Breivik, K. (2011). *Persistent organic pollutants in the environment*, volume 3. Meteorological Synthesizing Centre - East, Moscow, Russia and Norwegian Institute for Air Research (NILU), Kjeller, Norway.
- Hafrannsóknastofnun (2008). Ástand sjávar og svífsamfélög (environmental conditions and plankton communities). In *Þættir úr vísfræði sjávar 2007 (Environmental conditions in Icelandic waters 2007)*. Hafrannsóknastofnun (The Marine Research Institute of Iceland), Reyjavík, Iceland.
- Hong, S., Candelone, J. P., and Boutron, C. F. (1996). Deposition of atmospheric heavy metals to the Greenland ice sheet from the 1783–1784 volcanic eruption of Laki, Iceland. *Earth and Planetary Science Letters*, 144(3):605–610.
- Hung, H., Kallenborn, R., Breivik, K., Su, Y., Brorström-Lundén, E., Olafsdottir, K., Thorlacius, J. M., Leppänen, S., Bossi, R., Skov, H., et al. (2010). Atmospheric monitoring of organic pollutants in the Arctic under the Arctic Monitoring and Assessment Programme (AMAP): 1993–2006. *Science of the Total Environment*, 408:2854–2873.

- Järup, L. (2003). Hazards of heavy metal contamination. *British Medical Bulletin*, 68(1):167–182.
- Jaworski, A. and Ragnarsson, S. Á. (2006). Feeding habits of demersal fish in Icelandic waters: a multivariate approach. *ICES Journal of Marine Science: Journal du Conseil*, 63(9):1682–1694.
- Jensen, S., Reutergardh, L., and Jansson, B. (1983). Analytical methods for measuring organochlorines and methyl mercury by gas chromatography. *FAO Fish Technical Paper*, 212:21–33.
- Jörundsdóttir, H., Desnica, N., Ragnarsdóttir, Þ., and Gunnlaugsdóttir, H. (2012). *Monitoring of the marine biosphere around Iceland 2010 and 2011*. Matís ltd., Reykjavík, Iceland.
- Jörundsdóttir, H., Norström, K., Olsson, M., Pham-Tuan, H., Hühnerfuss, H., Bignert, A., and Bergman, Å. (2006). Temporal trend of bis (4-chlorophenyl) sulfone, methylsulfonyl-DDE and-PCBs in Baltic guillemot (*Uria aalge*) egg 1971–2001—a comparison to 4,4'-DDE and PCB trends. *Environmental pollution*, 141(2):226–237.
- Kim, H.-J. and Siegmund, D. (1989). The likelihood ratio test for a change-point in simple linear regression. *Biometrika*, 76(3):409–423.
- Kimbrough, K. L., Lauenstein, G., Christensen, J., and Apeti, D. (2008). *An assessment of two decades of contaminant monitoring in the Nation's Coastal Zone*. NOAA, Silver Spring, MD.
- Krause-Nehring, J., Brey, T., and Thorrold, S. R. (2012). Centennial records of lead contamination in northern Atlantic bivalves (*Arctica islandica*). *Marine Pollution Bulletin*, 64(2):233–240.
- Kutner, M. H., Nachtsheim, C. J., Neter, J., and Li, W. (2005). *Applied linear statistical models*, volume 5. McGraw Hill, New York.
- Lambrechts, C., Wilkie, M., Rucevska, I., and Sen, M. (2009). *Vital forest graphics*. Food and Agriculture Organization of the United Nations (FAO).
- Li, Y. and Macdonald, R. (2005). Sources and pathways of selected organochlorine pesticides to the Arctic and the effect of pathway divergence on HCH trends in biota: a review. *Science of the Total Environment*, 342(1-3):87–106.
- Littell, R. C., Milliken, G. A., Stroup, W. W., Wolfinger, R. D., and Schabenberger, O. (2006). *SAS for mixed models*. SAS institute Inc., Cary, NC.
- Liu, Z. and Qian, L. (2009). Changepoint estimation in a segmented linear regression via empirical likelihood. *Communications in Statistics-Simulation and Computation*, 39(1):85–100.

- Lund, R. and Reeves, J. (2002). Detection of undocumented changepoints: A revision of the two-phase regression model. *Journal of Climate*, 15(17):2547–2554.
- Lund, R., Wang, X. L., Lu, Q. Q., Reeves, J., Gallagher, C., and Feng, Y. (2007). Changepoint detection in periodic and autocorrelated time series. *Journal of Climate*, 20(20):5178–5190.
- Macdonald, R. W., Harner, T., and Fyfe, J. (2005). Recent climate change in the Arctic and its impact on contaminant pathways and interpretation of temporal trend data. *Science of the Total Environment*, 342(1-3):5–86.
- Magee, L. (1998). Nonlocal behavior in polynomial regressions. *The American Statistician*, 52(1):20–22.
- Magnússon, K. G., Brynjarsdóttir, J., and Nielsen, Ó. K. (2005). *Population cycles in rock ptarmigan *Lagopus muta*: modelling and parameter estimation*. Science Institute, University of Iceland, Reykjavík, Iceland.
- Marsaglia, G., Tsang, W. W., and Wang, J. (2003). Evaluating Kolmogorov’s distribution. *Journal of Statistical Software*, 8(18):1–4.
- Marteinsdottir, G., Gunnarsson, B., and Suthers, I. M. (2000). Spatial variation in hatch date distributions and origin of pelagic juvenile cod in Icelandic waters. *ICES Journal of Marine Science*, 57(4):1182–1195.
- Millennium Ecosystem Assessment (2003). *Ecosystems and Human Well-being: A Framework for Assessment*. Island Press, Washington, DC.
- Millennium Ecosystem Assessment (2005). *Ecosystems and Human Well-being: Current State and Trends*, volume 1. Island Press, Washington, DC.
- Monirith, I., Ueno, D., Takahashi, S., Nakata, H., Sudaryanto, A., Subramanian, A., Karuppiah, S., Ismail, A., Muchtar, M., Zheng, J., et al. (2003). Asia-Pacific mussel watch: monitoring contamination of persistent organochlorine compounds in coastal waters of Asian countries. *Marine Pollution Bulletin*, 46(3):281–300.
- Muir, D., Braune, B., DeMarch, B., Norstrom, R., Wagemann, R., Lockhart, L., Hargrave, B., Bright, D., Addison, R., Payne, J., et al. (1999). Spatial and temporal trends and effects of contaminants in the Canadian Arctic marine ecosystem: a review. *Science of the Total Environment*, 230(1-3):83–144.
- Nichols, J. D. and Williams, B. K. (2006). Monitoring for conservation. *Trends in Ecology & Evolution*, 21(12):668–673.
- Nicholson, M. and Fryer, R. (1992). The statistical power of monitoring programmes. *Marine Pollution Bulletin*, 24(3):146–149.

- Nicholson, M., Green, N., and Wilson, S. (1991). Regression models for assessing trends in cadmium and PCBs in cod livers from the Oslofjord. *Marine Pollution Bulletin*, 22(2):77–81.
- Nielsen, Ó. K. (1999). *Fjölrit Náttúrufræðistofnunar: Vöktun rjúpnastofnsins*, volume 39. Náttúrufræðistofnun Íslands, Reykjavík, Iceland.
- Nielsen, Ó. K. (2006). *Ráðgjöf Náttúrufræðistofnunar vegna rjúpnaveiða 2006*. Náttúrufræðistofnun Íslands.
- Nielsen, Ó. K. (2011). Gyrfalcon population and reproduction in relation to rock ptarmigan numbers in Iceland. In Watson, R. T., Cade, T. J., Fuller, M., Hunt, G., and Potapov, E., editors, *Gyrfalcons and Ptarmigans in a Changing World*, volume II, pages 21–48, Boise, Idaho, USA. The Peregrine Fund.
- Nielsen, Ó. K. and Cade, T. J. (1990). Seasonal changes in food habits of gyrfalcons in NE-Iceland. *Ornis Scandinavica*, 21(3):202–211.
- Nielsen, O. K. and Petursson, G. (1995). Population fluctuations of gyrfalcon and rock ptarmigan: analysis of export figures from Iceland. *Wildlife Biology*, 1(2):65–71.
- Nyberg, E., Danielsson, S., Eriksson, U., Faxneld, S., Miller, A., and Bignert, A. (2014). Spatio-temporal trends of PCBs in the Swedish freshwater environment 1981–2012. *Ambio*, 43(1):45–57.
- Ólafsdóttir, K., Petersen, A., Thordardóttir, S., and Jóhannesson, T. (1995). Organochlorine residues in Gyrfalcons (*Falco rusticolus*) in Iceland. *Bulletin of Environmental Contamination and Toxicology*, 55(3):382–389.
- Ólafsdóttir, K., Petersen, Æ., Magnúsdóttir, E. V., Björnsson, T., and Jóhannesson, T. (2005). Temporal trends of organochlorine contamination in Black Guillemots in Iceland from 1976 to 1996. *Environmental Pollution*, 133(3):509–515.
- Pacyna, J. M., Ottar, B., Tomza, U., and Maenhaut, W. (1985). Long-range transport of trace elements to Ny Ålesund, Spitsbergen. *Atmospheric Environment (1967)*, 19(6):857–865.
- Pálsson, Ó. K. and Björnsson, H. (2011). Long-term changes in trophic patterns of Iceland cod and linkages to main prey stock sizes. *ICES Journal of Marine Science*, 68:1488–1499.
- Pampoulie, C., Ruzzante, D. E., Chosson, V., Jörundsdóttir, T. D., Taylor, L., Thorsteinsson, V., Daniëlsdóttir, A. K., and Marteinsdóttir, G. (2006). The genetic structure of Atlantic cod (*Gadus morhua*) around Iceland: insight from microsatellites, the Pan I locus, and tagging experiments.

- Canadian Journal of Fisheries and Aquatic Sciences*, 63(12):2660–2674.
- Pennington, M. and Volstad, J. H. (1994). Assessing the effect of intra-haul correlation and variable density on estimates of population characteristics from marine surveys. *Biometrics*, 50:725–732.
- Peres-Neto, P. R. (2009). A unified strategy for estimating and controlling spatial, temporal and phylogenetic autocorrelation in ecological models. *Oecologia Australis*, 10(1):105–119.
- Pinheiro, J. C. and Bates, D. M. (2000). *Mixed-effects models in S and S-PLUS*. Springer Verlag, New York.
- Pinheiro, J. C., Bates, D. M., DebRoy, S., Sarkar, D., and the R Development Core Team (2012). *nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1-103*.
- Pinheiro, J. C., Bates, D. M., DebRoy, S., Sarkar, D., and the R Development Core Team (2013). *nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1-109*.
- Pálsson, I. K. (1983). The feeding habits of demersal fish species in Icelandic waters. *Journal of the Marine Research Institute*, 7:1–60.
- Quandt, R. E. (1958). The estimation of the parameters of a linear regression system obeying two separate regimes. *Journal of the American Statistical Association*, 53(284):873–880.
- Quandt, R. E. (1960). Tests of the hypothesis that a linear regression system obeys two separate regimes. *Journal of the American Statistical Association*, 55(290):324–330.
- R Development Core Team (2012). *A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria.
- Rabieh, S., Schmeisser, E., Yngvadóttir, E., Jónsdóttir, I., Ragnarsdóttir, T., and Gunnlaugsdóttir, H. (2007). *Monitoring of the marine biosphere around Iceland in 2005-2006*. Mátis ltd., Reykjavík, Iceland.
- Reeves, J., Chen, J., Wang, X. L., Lund, R., and Lu, Q. Q. (2007). A review and comparison of changepoint detection techniques for climate data. *Journal of Applied Meteorology and Climatology*, 46(6):900–915.
- Reykðal, O., Rabieh, S., Steingrimsdóttir, L., and Gunnlaugsdóttir, H. (2011). Minerals and trace elements in Icelandic dairy products and meat. *Journal of Food Composition and Analysis*, 24(7):980–986.
- Riget, F., Asmund, G., and Aastrup, P. (2000). Mercury in Arctic char (*Salvelinus alpinus*) populations from Greenland. *Science of the Total Environment*, 245(1):161–172.

- Rigét, F., Bignert, A., Braune, B., Stow, J., and Wilson, S. (2010). Temporal trends of legacy POPs in Arctic biota, an update. *Science of the Total Environment*, 408(15):2874–2884.
- Rigét, F., Braune, B., Bignert, A., Wilson, S., Aars, J., Born, E., Dam, M., Dietz, R., Evans, M., Evans, T., et al. (2011). Temporal trends of Hg in Arctic biota, an update. *Science of the Total Environment*, 409(18):3520–3526.
- Riget, F., Dietz, R., Vorkamp, K., Johansen, P., and Muir, D. (2004). Levels and spatial and temporal trends of contaminants in Greenland biota: an updated review. *Science of the Total Environment*, 331(1):29–52.
- Riget, F., Johansen, P., Glasius, M., Vorkamp, K., Dahlgaard, H., Muir, D., Asmund, G., and Born, E. W. (2003). Chapter 4. marine environment. In Riget, F., Christensen, J., and Johansen, P., editors, *AMAP Greenland and the Faroe Islands 1997-2001. Vol. 2: The Environment of Greenland*. Ministry of Environment, Denmark.
- Robson, A. J. (2002). Evidence for trends in UK flooding. *Philosophical Transactions of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, 360(1796):1327–1343.
- Russi, D., ten Brink, P., Farmer, A., Badura, T., Coates, D., Förster, J., Kumar, R., and Davidson, N. (2013). *The economics of ecosystems and biodiversity for water and wetlands*. IEEP, London and Brussels.
- Ruus, A., Ugland, K., Espeland, O., and Skaare, J. (1999). Organochlorine contaminants in a local marine food chain from Jarfjord, Northern Norway. *Marine Environmental Research*, 48(2):131–146.
- Sapkota, A., Sapkota, A. R., Kucharski, M., Burke, J., McKenzie, S., Walker, P., and Lawrence, R. (2008). Aquaculture practices and potential human health risks: current knowledge and future priorities. *Environment International*, 34(8):1215–1226.
- Sele, V., Sloth, J. J., Lundebye, A.-K., Larsen, E. H., Berntssen, M. H., and Amund, H. (2012). Arsenolipids in marine oils and fats: A review of occurrence, chemistry and future research needs. *Food Chemistry*, 133(3):618–630.
- Skalski, J. R., Ryding, K. E., and Millsaugh, J. (2005). *Wildlife demography: analysis of sex, age, and count data*. Academic Press, USA.
- Skarphedinsdottir, H., Gunnarsson, K., Gudmundsson, G. A., and Nfon, E. (2010). Bioaccumulation and biomagnification of organochlorines in a marine food web at a pristine site in Iceland. *Archives of Environmental*

- Contamination and Toxicology*, 58(3):800–809.
- Smith, A. and Gangolli, S. (2002). Organochlorine chemicals in seafood: occurrence and health concerns. *Food and Chemical Toxicology*, 40(6):767–779.
- Stange, K. and Klungsøyr, J. (1997). Organochlorine contaminants in fish and polycyclic aromatic hydrocarbons in sediments from the Barents Sea. *ICES Journal of Marine Science*, 54(3):318–332.
- Stryhn, H. and Christensen, J. (2003). Confidence intervals by the profile likelihood method, with applications in veterinary epidemiology. In *Proceedings of the 10th International Symposium on Veterinary Epidemiology and Economics, Vina del Mar*, page 208.
- Sturludottir, E., Gunnlaugsdottir, H., Jorundsdottir, H. O., Magnúsdottir, E. V., Olafsdottir, K., and Stefansson, G. (2013). Spatial and temporal trends of contaminants in mussel sampled around the Icelandic coastline. *Science of the Total Environment*, 454:500–509.
- Sturludottir, E., Gunnlaugsdottir, H., Nielsen, O. K., and Stefansson, G. (2015). Detection of a changepoint, a mean shift accompanied with a trend change, in short time-series with autocorrelation. *Communications in Statistics - Simulation and Computation*. In press.
- Szlinder-Richert, J., Barska, I., Mazerski, J., and Usydus, Z. (2009). PCBs in fish from the southern Baltic Sea: levels, bioaccumulation features, and temporal trends during the period from 1997 to 2006. *Marine Pollution Bulletin*, 58(1):85–92.
- Thomas, L. (1996). Monitoring long-term population change: why are there so many analysis methods? *Ecology*, 77(1):49–58.
- Thordarson, T. and Larsen, G. (2007). Volcanism in Iceland in historical time: volcano types, eruption styles and eruptive history. *Journal of Geodynamics*, 43(1):118–152.
- Turchin, P. (1999). Population regulation: a synthetic view. *Oikos*, 84:153–159.
- Valdimarsson, H. and Malmberg, S.-A. (1999). Near-surface circulation in Icelandic waters derived from satellite tracked drifters. *Journal of the Marine Research Institute*, 16:23–40.
- Van Deelen, T. and Etter, D. (2003). Effort and the functional response of deer hunters. *Human Dimensions of Wildlife*, 8(2):097–108.
- Venter, O., Brodeur, N. N., Nemiroff, L., Belland, B., Dolinsek, I. J., and Grant, J. W. (2006). Threats to endangered species in Canada. *Bioscience*, 56(11):903–910.
- Verbeke, G. and Molenberghs, G. (2000). *Linear mixed models for longitudinal*

- data*. Springer Verlag, New York.
- Wainippee, W., Weiss, D. J., Sephton, M. A., Coles, B. J., Unsworth, C., and Court, R. (2010). The effect of crude oil on arsenate adsorption on goethite. *Water Research*, 44(19):5673–5683.
- Wang, X. L. (2008a). Accounting for autocorrelation in detecting mean shifts in climate data series using the penalized maximal t or F test. *Journal of Applied Meteorology and Climatology*, 47(9):2423–2444.
- Wang, X. L. (2008b). Penalized maximal F test for detecting undocumented mean shift without trend change. *Journal of Atmospheric and Oceanic Technology*, 25(3):368–384.
- Wania, F. and Mackay, D. (1993). Global fractionation and cold condensation of low volatility organochlorine compounds in polar regions. *Ambio*, 22:10–18.
- Weeden, R. B. and Watson, A. (1967). Determining the age of rock ptarmigan in Alaska and Scotland. *The Journal of Wildlife Management*, 31:825–826.
- Williams, B. K., Nichols, J. D., and Conroy, M. J. (2002). *Analysis and management of animal populations*. Academic Press, USA.
- Wolfinger, R. D. (1993). Covariance structure selection in general mixed models. *Communications in Statistics-Simulation and Computation*, 22(4):1079–1106.
- Wolfinger, R. D. (1996). Heterogeneous variance: covariance structures for repeated measures. *Journal of Agricultural, Biological, and Environmental Statistics*, 1(2):205–230.
- Wu, Z., Huang, N. E., Long, S. R., and Peng, C.-K. (2007). On the trend, detrending, and variability of nonlinear and nonstationary time series. *Proceedings of the National Academy of Sciences*, 104(38):14889–14894.
- Yngvadóttir, E., Mikaelisdóttir, A., Jónsdóttir, I., and Ragnarsdóttir, Þ. (2006). *Monitoring of the marine biosphere around Iceland in 2004-2005*. Rannsóknastofnun fiskiðnaðarins, Reykjavík, Iceland.
- Yue, S., Pilon, P., and Cavadias, G. (2002). Power of the Mann–Kendall and Spearman’s rho tests for detecting monotonic trends in hydrological series. *Journal of Hydrology*, 259(1):254–271.