DEVELOPMENT AND TUNING OF A 3D STOCHASTIC INVERSION METHODOLOGY TO THE EUROPEAN ARCTIC

Juerg Hauser[1], Kathleen M. Dyer[2], Michael E. Pasyanos[2], Hilmar Bungum[1], Jan Inge Faleide[3], and Stephen A. Clark[3]

NORSAR[1], Lawrence Livermore National Laboratory[2], and University of Oslo[3]

Sponsored by the National Nuclear Security Administration

Award Nos. DE-AC52-08NA28651 and DE-AC52-07NA27344
BAA08-38

ABSTRACT

The development of three-dimensional (3D) seismic models for the crust and upper mantle has traditionally focused on finding one model that provides the best fit to the data, while observing some regularization constraints. Such deterministic models, however, ignore a fundamental property of many inverse problems in geophysics: nonuniqueness. It is likely that if a model can be found to satisfy given datasets, an infinite number of alternative models will exist that satisfy the datasets equally well. Our solution to the inverse problem of developing a seismic model for the Barents Sea, given various datasets, is therefore a probabilistic model, a posterior distribution of models that satisfy the data to the same degree. We use a Markov Chain Monte Carlo algorithm to sample the unknown posterior distribution, which describes the ensemble of models that are in agreement with prior information and the datasets. An example of prior information used in this work is the extent of regions with limited sediment coverage. The datasets we use are thickness constraints, velocity profiles, gravity data, surface-wave group velocities, and body-wave travel times. The model introduced here for the crust and upper mantle structure of the European Arctic is parameterized by a set of one-dimensional (1D) models positioned at the nodes of an arbitrary mesh. Two linear functions in the sediment layer, three in the crystalline crust, and three in the mantle are used to describe the seismic parameters (i.e., Vp, Vs, and density) as a function of depth. This allows changes of seismic parameters within the sediments, the crystalline crust, and the upper mantle without introducing artificial discontinuities that would result from parameterizing the structure using layers with constant seismic parameters. The samples drawn from the posterior distribution using a Markov Chain Monte Carlo technique form our probabilistic model. Analyzing this ensemble of models that fit the data allows us to estimate a mean model and the standard deviation for the model parameters, i.e., their uncertainty. Maps of sediment thickness and thickness of the crystalline crust derived from the posterior distribution are in good agreement with knowledge of the regional tectonic setting. The predicted uncertainties, which are equally important as the absolute values, correlate well with the variation in data coverage and data quality in the region. The real power of a probabilistic model, however, lies in predicting observables and their uncertainties. A probabilistic model allows estimation of seismic-event location uncertainties that take into account uncertainties in the velocity model and the inability to absolutely identify the onset of the arrival associated with a phase.

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **SEP 2010**	2. REPORT TYPE	3. DATES COVERED **00-00-2010 to 00-00-2010**

4. TITLE AND SUBTITLE **Development and Tuning of a 3D Stochastic Inversion Methodology to the European Arctic**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **NORSAR,Gunnar Randers vei 15,N-2007 Kjeller Norway,**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR’S ACRONYM(S)
	11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
Published in Proceedings of the 2010 Monitoring Research Review - Ground-Based Nuclear Explosion Monitoring Technologies, 21-23 September 2010, Orlando, FL. Volume I. Sponsored by the Air Force Research Laboratory (AFRL) and the National Nuclear Security Administration (NNSA). U.S. Government or Federal Rights License

14. ABSTRACT

The development of three-dimensional (3D) seismic models for the crust and upper mantle has traditionally focused on finding one model that provides the best fit to the data, while observing some regularization constraints. Such deterministic models, however, ignore a fundamental property of many inverse problems in geophysics nonuniqueness. It is likely that if a model can be found to satisfy given datasets, an infinite number of alternative models will exist that satisfy the datasets equally well. Our solution to the inverse problem of developing a seismic model for the Barents Sea, given various datasets, is therefore a probabilistic model, a posterior distribution of models that satisfy the data to the same degree. We use a Markov Chain Monte Carlo algorithm to sample the unknown posterior distribution, which describes the ensemble of models that are in agreement with prior information and the datasets. An example of prior information used in this work is the extent of regions with limited sediment coverage. The datasets we use are thickness constraints, velocity profiles, gravity data, surface-wave group velocities, and body-wave travel times. The model introduced here for the crust and upper mantle structure of the European Arctic is parameterized by a set of one-dimensional (1D) models positioned at the nodes of an arbitrary mesh. Two linear functions in the sediment layer, three in the crystalline crust, and three in the mantle are used to describe the seismic parameters (i.e., Vp, Vs, and density) as a function of depth. This allows changes of seismic parameters within the sediments, the crystalline crust, and the upper mantle without introducing artificial discontinuities that would result from parameterizing the structure using layers with constant seismic parameters. The samples drawn from the posterior distribution using a Markov Chain Monte Carlo technique form our probabilistic model. Analyzing this ensemble of models that fit the data allows us to estimate a mean model and the standard deviation for the model parameters, i.e., their uncertainty. Maps of sediment thickness and thickness of the crystalline crust derived from the posterior distribution are in good agreement with knowledge of the regional tectonic setting. The predicted uncertainties, which are equally important as the absolute values, correlate well with the variation in data coverage and data quality in the region. The real power of a probabilistic model, however, lies in predicting observables and their uncertainties. A probabilistic model allows estimation of seismic-event location uncertainties that take into account uncertainties in the velocity model and the inability to absolutely identify the onset of the arrival associated with a phase.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**10**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

OBJECTIVES

The area of interest for this study is the European Arctic, in particular the Barents Sea and surrounding regions such as the Norwegian-Greenland Sea, the Southern Eurasian Basin, Novaya Zemlya, the Kara Sea, the East European Lowlands, the Kola Peninsula, and the Arctic plate boundary (Figure 1). The complex geology of the region, encompassing oceanic crust, continental shelf regions, rift basins, and old cratonic crust and the nonuniform coverage of the region by data with varying levels of uncertainty, makes the European Arctic a challenging setting for any imaging technique and therefore an ideal environment for the development and application of a probabilistic approach to seismic imaging.

The aim of this study was to develop a probabilistic seismic model, i.e., sample the posterior distribution consisting of the ensemble of models that are all in agreement with the data. The datasets used in this work are thickness constraints, velocity profiles, gravity data, surface-wave group velocities, and body-wave travel times. The stochastic inversion methodology that has been further developed in this study has been used previously by Pasyanos et al. (2006) to derive a geophysical model for the Yellow Sea and Korean Peninsula region, given surface-wave group velocities, body-wave travel times, receiver functions, and gravity data.

The project has achieved three objectives. First, we have developed a probabilistic seismic model for the European Arctic that not only harnesses the information available in more datasets than used in previous models but also employs an improved model parameterization. Second, we have shown how a probabilistic model can be used in seismic monitoring to estimate location uncertainties that are caused by model uncertainties. Third, the introduction of improved forward solvers, an arbitrary mesh, and linear transitions to represent structure will facilitate the application of the methodology to other regions.

RESEARCH ACCOMPLISHED

The development of a probabilistic seismic model for the European Arctic involved improving the methodology employed by Pasyanos et al. (2006). The introduction of a new model parameterization (Figure 2) that allows for an arbitrary mesh and uses two linear transitions in the sediments and three in the crystalline crust and upper mantle to represent the seismic parameters (Vp, Vs, and density) made it necessary to develop new forward solvers for the various datasets. The parameterization of structure associated with every 1D model represents a trade-off between trying to describe the structure as accurately as possible and limiting the number of parameters to avoid having to search a model space that is unnecessarily large. The parameters are not completely independent of each other due to the constraints imposed on the prior distribution (see below). The node spacing of 83 km was chosen based on the expected resolution of the data and the computational resources available.

When developing regional seismic models, one often uses layers with constant seismic parameters to represent structure (e.g. Pasyanos et al., 2006 and Ritzmann et al., 2007). For deep sedimentary basins like the East Barents Sea Basin, however, the rate of increase of Vp, Vs, and density decreases with depth, and the seismic parameters at the bottom of the basin are comparable to those of the underlying basement. Two layers that allow for a linear increase of the seismic parameters allow us to model this behavior better than two layers with constant seismic parameters.

The datasets used in this study were described in a previous MRR contribution (Hauser et al., 2009). We therefore focus here on the probabilistic model, its application, and the inversion methodology.

Markov Chain Monte Carlo Algorithm

The Markov Chain Monte Carlo (MCMC) algorithm employed here is a derivative of the Metropolis algorithm by Metropolis et al. (1953) as described by Mosegaard and Tarantola (1995). MCMC algorithms sample the model space at a rate proportional to the posterior probabilities, a process known as importance sampling, thereby empirically reconstructing the unknown posterior distribution. They achieve this by moving through model space according to the posterior probabilities for these models, thereby performing a guided search and focusing on regions that better fit the prior information and the data. In contrast, a Monte Carlo algorithm samples the model space purely randomly. The definition of which models are accessible from a given model when constructing the Markov Chain is critical for the success of a probabilistic inversion. If we perturb the model too much, we will be sampling the model space randomly instead of performing a guided search. On the other hand, if we perturb the model too little, we might not explore the model space sufficiently.

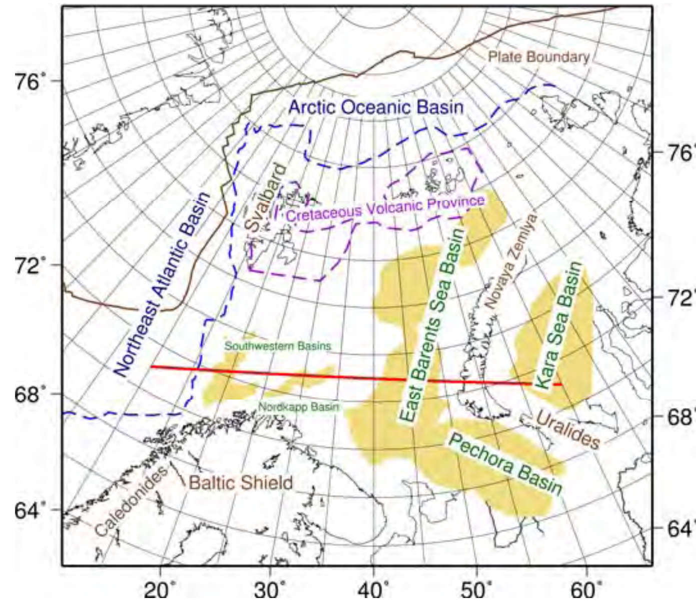

Figure 1. Simplified tectonic map of the region after Ritzmann et al. (2007) and Bird (2003). The plate boundary is given by the brown line and the continent-ocean boundary by the dashed blue line. Beige areas represent the major sedimentary basins in the region. The cross section along which we will examine our probabilistic model in Figure 5 is outlined in red.

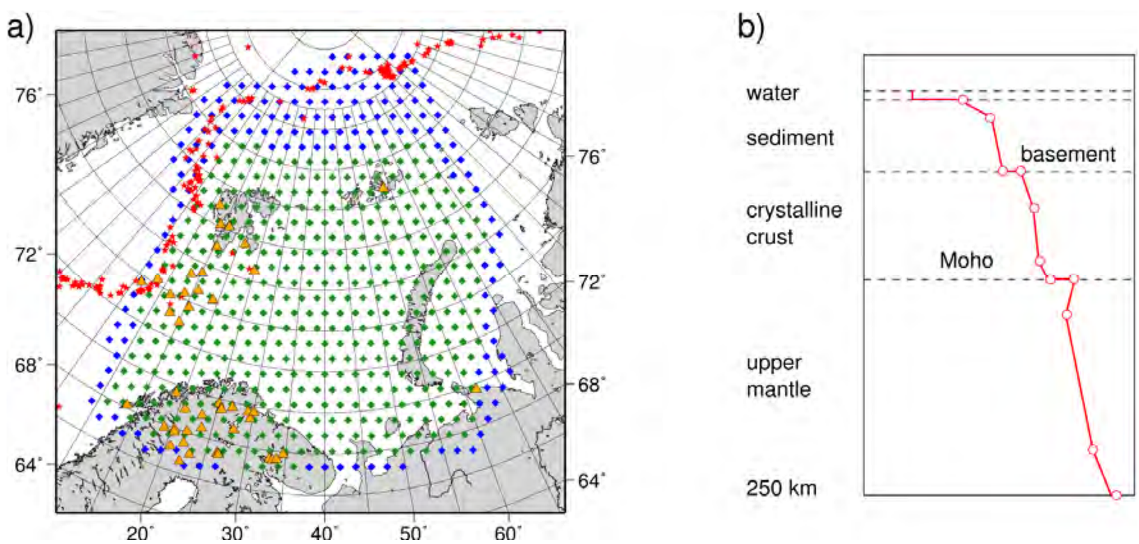

Figure 2. Parameterization of the target region for this study. (a) The red stars are the earthquakes in the target region, according to the Global CMT catalog (1971–2008), and seismic stations used in this study are marked by orange triangles. The blue and green diamonds show the distribution of the 1D profiles used to describe the structure. For the blue diamonds, the starting model is based on CRUST 2.0 (Bassin et al., 2000); for the green diamonds, it is based on the crustal model of Ritzmann et al. (2007) and the mantle model of Levshin et al. (2007). (b) Diagram showing the constant gradient parameterization used to describe the seismic parameters as a function of depth.

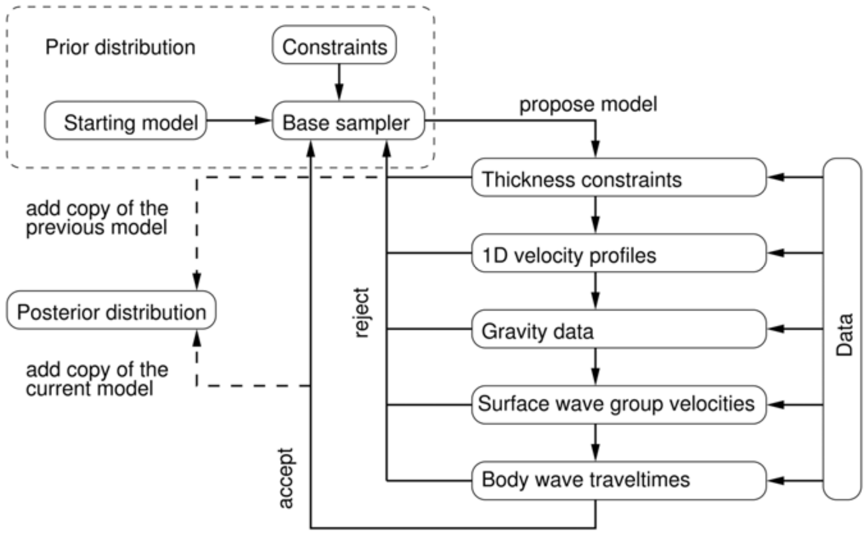

Figure 3. Flowchart showing the MCMC inversion methodology used to derive the probabilistic model.

As mentioned before, the success of an MCMC methodology relies partly on a mechanism for generating plausible models based on the prior information. In a Bayesian formulation, this process is known as sampling the prior distribution. The prior distribution is given by the starting model and constraints for the individual parameters. The most-basic constraints are the upper and lower limits and the standard deviation for the normal distribution, from which we randomly draw new model parameters when perturbing the model. More sophisticated constraints employed in this study are ranges for acceptable Vp/Vs and Vp/density ratios, a positive velocity contrast imposed across the Moho interface and across the interface between the sediments and the crystalline crust, and a limit on the maximum decrease of seismic parameters with increasing depth. Plausible ranges for seismic parameters in the area of interest and the relationship between them were derived from previous studies covering the region, in particular from Breivik et al. (2002).

Our MCMC algorithm shown in Figure 3 has two major components: (1) the base sampler, which proposes new models by randomly perturbing the current model, while observing the rules for the prior distribution; and (2) the datasets against which proposed models are tested. If all the models proposed by the base sampler are accepted, one recovers the prior distribution. The aim is to recover the posterior distribution, and proposed models are therefore tested against data. The datasets are tested in sequence, and a proposed model is added to the posterior set if it fits the data equally well or better for all the stages than the previous model that was added to the posterior set. A model with a worse fit to the data might also be accepted to the posterior set but with a probability dependent on the decrease in fit relative to the previous accepted model. In other words, the worse the fit to the data the more likely it is that the model is rejected. Accepting models with a worse fit to the data with a certain probability means that an MCMC algorithm can avoid a situation where the guided search might get trapped in a local minimum. For each chain we also randomly swap a subset of nodes in the starting model to ensure that we are exploring the model space sufficiently.

Probabilistic Seismic Model

Two separate runs of our MCMC algorithm with different seeds for the random number generator were used to generate our probabilistic model. In practice this means that we have explored the model space with two different chains starting at different points in model space. Once convergence is reached, however, the two chains are statistically similar. Our probabilistic model is based on a combination of the last 1/3 of the two chains, with each consisting of 12,000 iterations. Our samples of the posterior distribution are given by 4,000 models, where every second model is taken from the same chain, thus we are mixing the chains. We determined an average model to compare the results of this study to other studies of the same region. The real power of a probabilistic model lies however in the fact that it describes the distribution of models that fit the data, as we will see later in the location example.

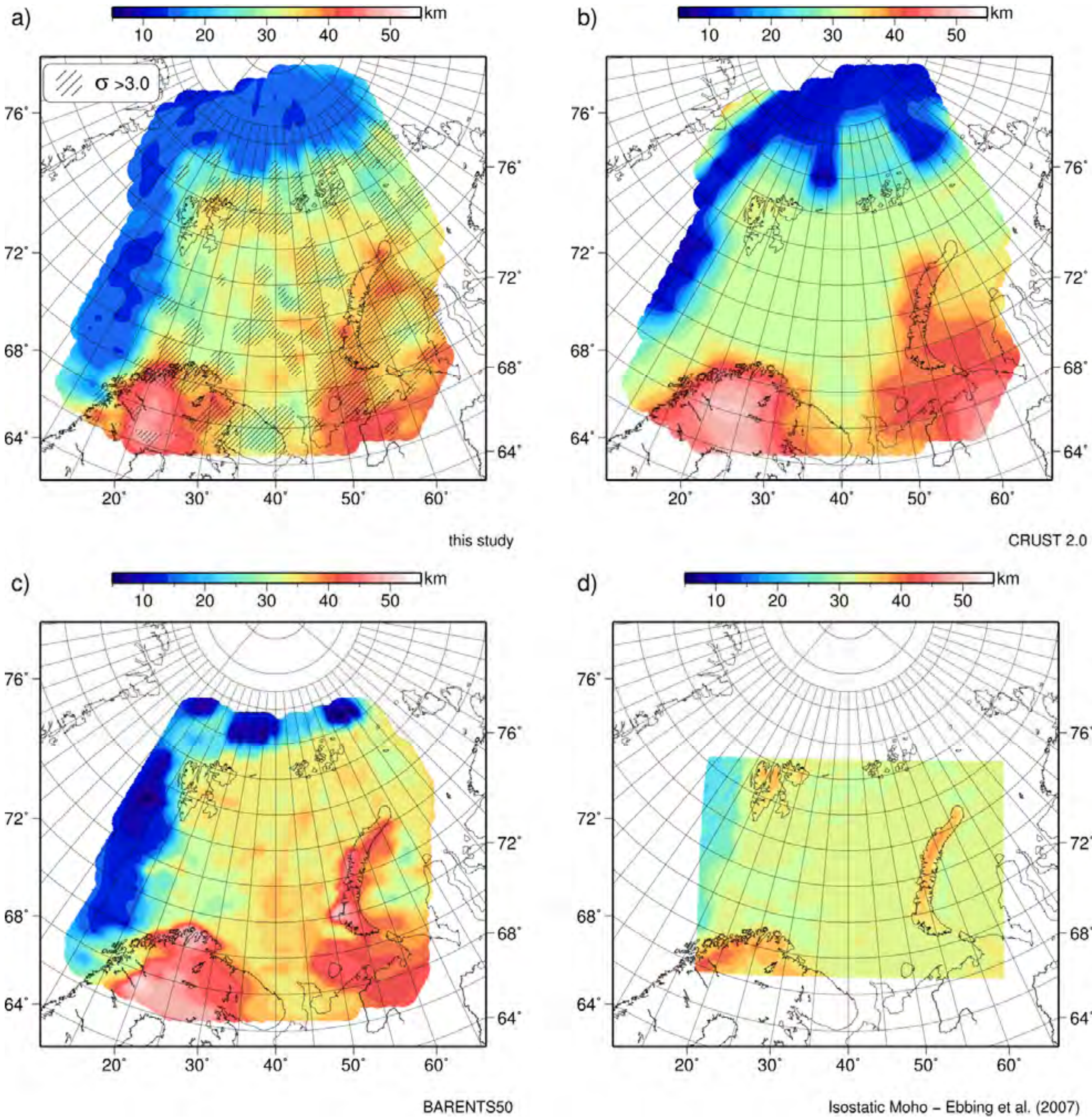

Figure 4. Depth to Moho: (a) Mean model obtained in this study, (b) CRUST 2.0 after Bassin et al. (2000), (c) BARENTS50 after Ritzmann et al. (2007), and (d) isostatic Moho of Ebbing et al. (2007).

Figure 4 shows the depth to Moho in this study, CRUST 2.0 (Bassin et al., 2000), BARENTS50 (Ritzmann et al., 2007) and for an isostatic Moho computed by Ebbing et al. (2007). It is important to keep in mind that the different models have different spatial resolutions; our model, for example, has a node spacing of 83 km, while CRUST 2.0 uses a 2-by-2–degree grid. This makes it necessary to resample the models for this comparison. Unlike the other models, our probabilistic model also provides estimates for the uncertainties, thus we can compute a standard deviation in addition to the mean of our samples of the posterior distribution. We have hatched the areas where the standard deviation on the Moho exceeds 3 km, indicating where this parameter is poorly constrained. The models are generally similar, with some notable differences. For example, most models see more complexity within the major tectonic provinces than the relatively simple CRUST 2.0 model. Also, the Moho recovered by BARENTS50 appears more detailed than the Moho recovered in the present study. This comes as no surprise when one takes into

account that BARENTS50 has a spatial resolution of 50 km. The models differ the most from each other around Novaya Zemlya and in the Kara Sea. It is interesting that this is also where the uncertainties in the depth to Moho are generally larger than 3 km in our study. The isostatic modeling of Ebbing et al. (2007) suggests, as expected, a shallower and smoother Moho than the other, seismically based models.

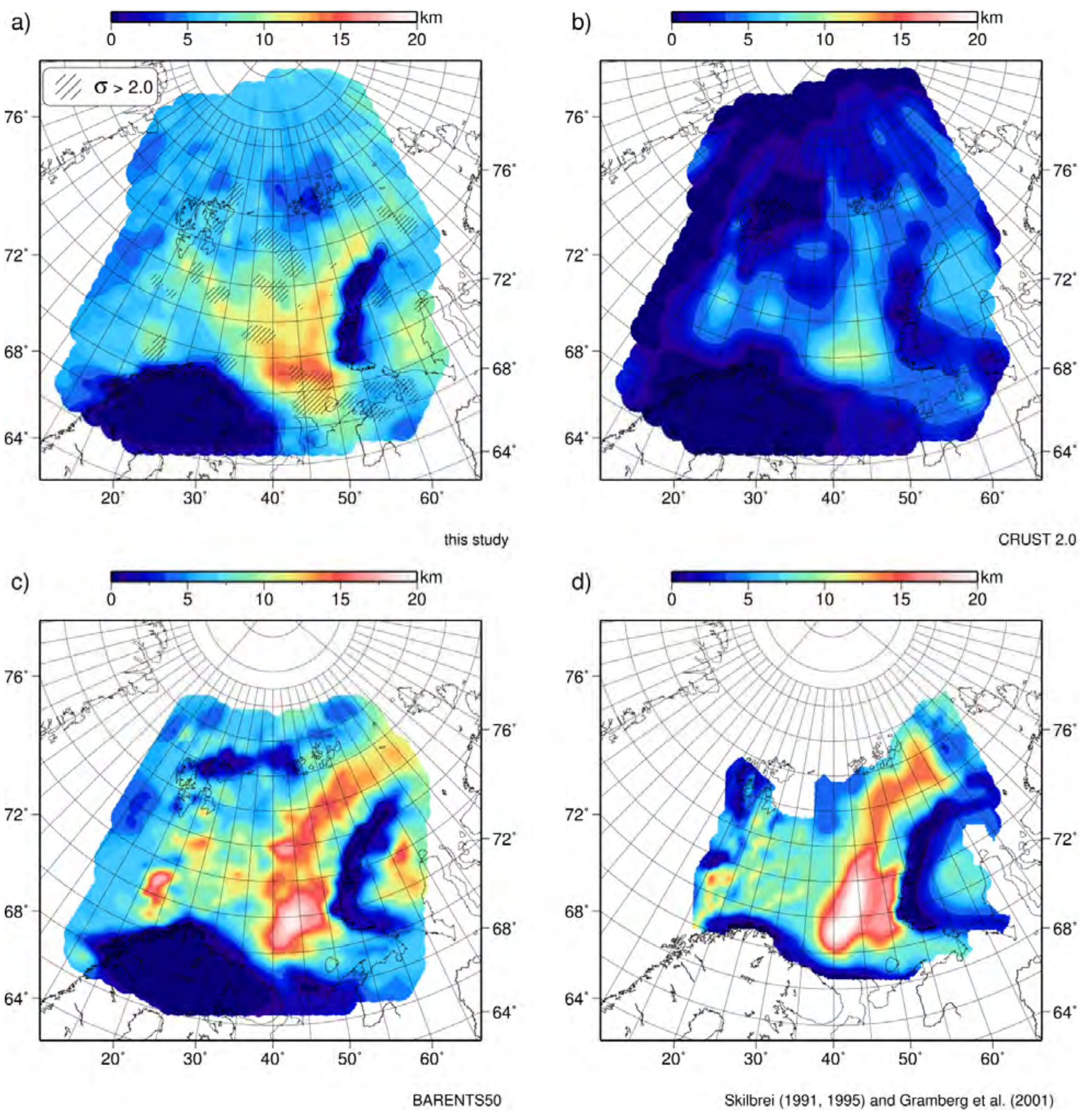

Figure 5. Depth to basement: (a) Mean model obtained in this study, (b) CRUST 2.0 after Bassin et al. (2000), (c) BARENTS50 after Ritzmann et al. (2007), and (d) compilation of depth to basement by Smelror et al. (2009), based on the work by Skilbrei (1991,1995) and Gramberg et al. (2001).

A similar comparison among the models for the depth to basement is given in Figure 5. Here we compare the mean of our probabilistic model with CRUST 2.0 (Bassin et al., 2000), BARENTS50 (Ritzmann et al., 2007) and a compilation of depth to basement by Smelror et al. (2009) derived from magnetic and seismic data based on the work by Skilbrei (1991,1995) and Gramberg et al. (2001). We have again hatched areas in our map indicating

regions with poor constraint, where the standard deviation in depth to basement exceeds 2.0 km. In contrast to the different Moho results, the depth-to-basement topography varies significantly among the studies. There are differences in the overall depth and shape for the major basins between our study and the other studies. In a deep basin the sediments at the bottom of the basin become chemically compacted or weakly metamorphosed, making their seismic parameters comparable to those of the underlying basement. This means that datasets used in this study are not very sensitive to the position of this interface between the sediments and the crystalline crust. This also correlates with the relatively large uncertainties for the southern end of the East Barents Sea Basin.

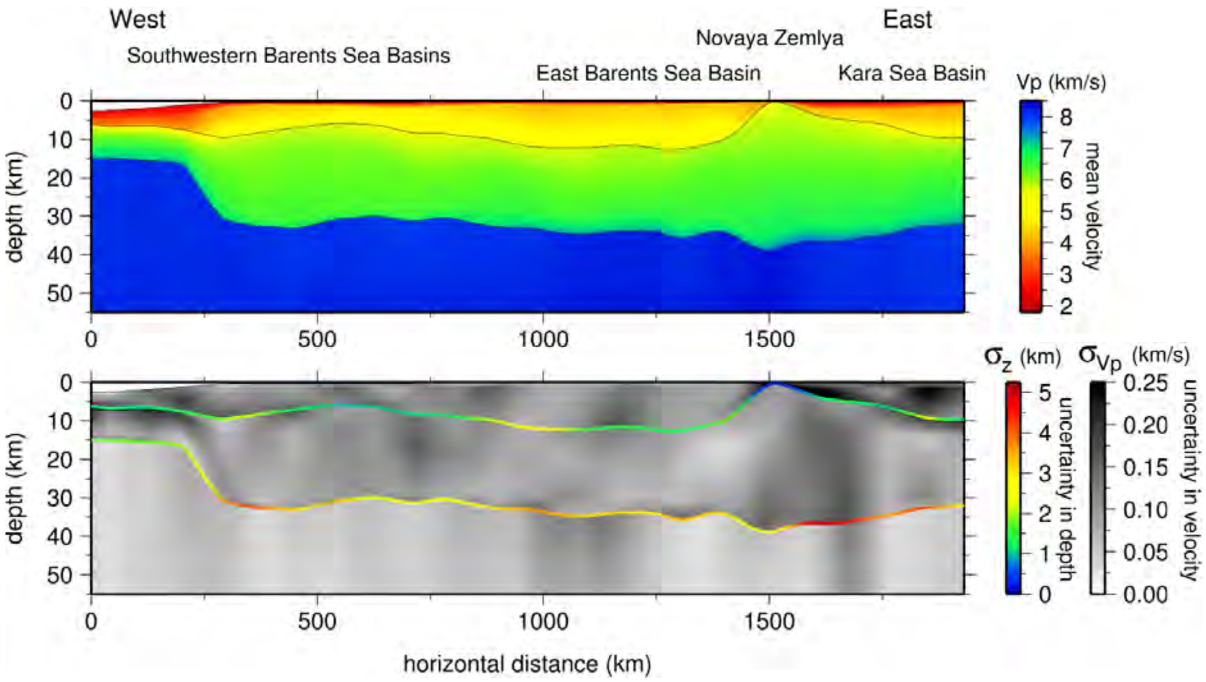

Figure 6. West-east cross section along the great circle path shown in Figure 1. The top panel shows Vp, and the bottom panel shows the uncertainty in Vp. In the bottom panel, interfaces are colored according to the uncertainty in depth.

Figure 6 shows a west-to-east cross section through our probabilistic model. Unlike cross sections farther north across the western continental margin, we find a relatively rapid transition in crustal thickness and see an increase in crustal thickness associated with Novaya Zemlya. The highest uncertainty in depth to Moho lies below the Kara Sea. This is related to the weak constraints on the Moho here: gravity data and a velocity profile with a relatively high uncertainty, with no body waves sampling the Moho. We clearly recover the East Barents Sea and Kara Sea basin. The sedimentary basins in the southwestern Barents Sea, on the other hand, are only 10s of kilometers wide. The node spacing of 83 km used in this study means that we cannot recover these basins. What we are able to recover is the fact that the sedimentary layer is on average thicker if there are several sedimentary basins a few 10s of kilometers wide.

The sediments on the epicontinental Barents Shelf have significantly higher velocities than sediments covering the oceanic crust. This feature of our model can be linked to the uplift of the region in the Neogene and the repeated phases of glaciation in the Barents Sea during the late Pliocene and Pleistocene (Smelror et al., 2009). Uplift and glaciation cause erosion of the sediments covering the Barents Shelf and the deposition of large amounts of young sediments into major submarine fans along the western and northern margin. These young sediments are less consolidated and have, as a consequence, lower seismic velocities when compared to the older sediments covering the Barents Shelf. The uppermost sediments in the Kara Sea Basin show slightly lower velocities than the uppermost sediments in the East Barents Sea Basin. This correlates with the interpretation that only during the maximum extent of glaciation in the late Pleistocene did the ice sheet reach into the Kara Sea (Smelror et al., 2009). Sediments in the Kara Sea have therefore experienced less erosion, leaving less compacted sediment exposed at the seafloor, possibly together with deposits from other periods of glaciation.

Probabilistic Earthquake Location

The nonlinear problem of seismic event location using body-wave travel times is often solved using nonlinear iterative approaches. However, a poor station distribution and a complex 3D velocity structure contribute to the nonlinearity of the location problem and create potential instabilities. The potential failure of linearization, together with the need for more comprehensive location uncertainty information in the form of a probability density function, has led to the formulation of numerous probabilistic approaches (e.g., Kennett and Sambridge, 1992; Billings, 1994; Lomax et al., 2000). Location uncertainty is caused by pick uncertainties (i.e., the inability to accurately estimate onset time for a phase) and uncertainties in the velocity models. Most estimates for location uncertainty do not however take into account the uncertainties in the model used to predict the travel times. They are solely based on pick uncertainties. A probabilistic model, on the other hand, allows a prediction of observables and their uncertainties.

The distribution of an observable (i.e., its value and uncertainty), given a probabilistic model, can be recovered by calculating its values for every model belonging to the posterior set that defines the probabilistic model. Similarly, it is possible to obtain an estimate for the location uncertainty of a seismic event due to model uncertainty by locating the event for all the models that compose the posterior set. Here we use an MCMC approach to approximate the posterior distribution for the origin time and location of an earthquake. The maximum of the posterior distribution then defines the hypocenter location and origin time.

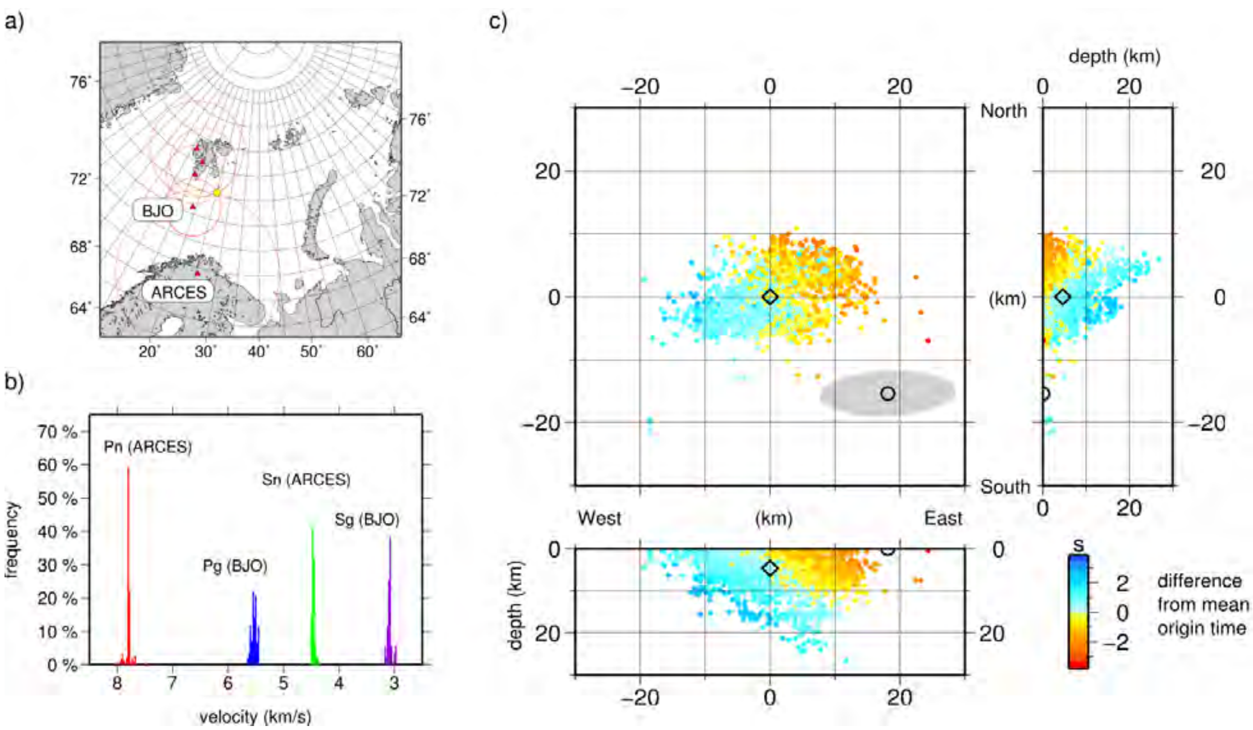

Figure 7. Probabilistic location of an earthquake, taking model uncertainties into account: (a) station distribution, (b) distribution of average path velocities for regional phases for two stations used in the location example, and (c) hypocenter and origin time of the earthquake computed for each of the 4,000 models forming our probabilistic model. The mean location is given by the black diamond. The points are colored according to the deviation from the mean origin time of our set of locations. The black circle marks the location of the event computed using a 1D velocity model and a fixed depth of 0 km, and the error ellipse is given by the gray shaded area.

We use an earthquake in the western Barents Sea to investigate the influence of model uncertainties on location uncertainties. Figure 7a shows the station distribution, and Figure 7b shows the distribution of the mean path velocities, between the event and two selected stations. For longer paths that reside primarily in the mantle, the mean velocity is less influenced than for shorter paths that reside in the crust. We have located the earthquake for each of

the 4,000 models in the posterior distribution. Figure 7c shows the 4,000 locations obtained and thereby provides an estimate for the location uncertainty from model errors alone, together with an event location obtained using a regional 1D velocity model. All stations available for the location of this event lie to the west of the earthquake. This results in both the error ellipse for the 1D velocity model solution and the cloud of locations being elongated in the west-east direction. We observe a linear trend between late deep-event locations to the southwest and early shallow locations to the northeast. Bondár et al. (2004) showed that for excellent station coverage, depth and origin time are more sensitive to the velocity model than the epicenter location. We find that for an uneven station distribution as shown here, the epicenter location seems to be equally sensitive to the velocity model as to the origin time and depth.

CONCLUSIONS AND RECOMMENDATIONS

We have successfully employed a probabilistic approach for the development of a data-driven regional seismic model for the European Arctic. We have compared the mean model of our posterior distribution with other models that cover the region and find that it captures the features that can be resolved with a node spacing of 83 km. Our probabilistic model not only provides images of the subsurface, together with estimates of uncertainties, it also allows for the prediction of observables and uncertainties. This can be used to derive seismic event location uncertainties from model uncertainties and can in the future be used for location algorithms that take model uncertainties in addition to uncertainties in onset time into account.

The introduction of an arbitrary mesh to represent structure means that future applications of the methodology could include optimizing the mesh as part of the inversion. Trans-dimensional MCMC algorithms (e.g., Green, 1995) provide a framework for situations where the optimum number and distribution of model parameters is unknown. Such an algorithm would allow optimizing the distribution and number of nodes used to describe structure as part of the inversion and thereby account for the differences in data quality and data density between the eastern and western part.

The success of a probabilistic technique for the development of a regional seismic model relies on a mechanism to propose plausible models. In this context, choosing plausible ranges for the ratios between seismic parameters is as important as the ranges for individual values. Ultimately, one is only interested in testing models for their fit to the data if they are plausible from a geological, geodynamical, and compositional point of view. The primary application of the type of models developed here is the location of seismic events. On the other hand, a probabilistic framework where we would invert for composition and temperature instead of velocity and density is feasible and could be a valuable tool for understanding the nature of the upper mantle in the European Arctic and in particular of the eastward-dipping high-velocity anomaly under the Barents Sea and Kara Sea (Ritzmann and Faleide, 2009).

ACKNOWLEDGEMENTS

We thank NOTUR (The Norwegian Metacenter for Computational Science) and the University of Oslo for providing the computational resource on the Titan III high-performance computing facilities. We thank Stephen Myers (Lawrence Livermore National Laboratory) for contributing the ground-truth data and NGU (The Geological Survey of Norway) for providing the depth-to-Moho and depth-to-basement data shown in Figures 4d and 5d. We also thank Johannes Schweitzer (NORSAR) for contributing the P observation from deep seismic experiments.

REFERENCES

Bassin, C., G. Laske, and G. Masters (2000). The current limits of resolution for surface wave tomography in North America, *EOS Trans. AGU* 81: F897.

Billings, S. (1994). Simulated annealing for earthquake location, *Geophys. J. Int.* 118: 680–692.

Bird, P. (2003). An updated digital model of plate boundaries, *Geochem. Geophys. Geosyst.* 4: 1027, doi:10.1029/2001GC000252.

Bondár, I., S. Myers, E. Engdahl, and E. Bergman (2004). Epicentre accuracy based on seismic network criteria, *Geophys. J. Int*., 156: 483–496, doi:10.1111/j.1365-246X.2004.570 02070.x.

Breivik, A., R. Mjelde, P. Grogan, H. Shimamura, Y. Murai, Y. Nishimura, and A. Kuwano (2002). A possible Caledonide arm through the Barents Sea imaged by OBS data, *Tectonophys.* 355: 67–97.

Ebbing, J., C. Braitenberg ,and S. Wienecke (2007). Insights into the lithospheric structure and the tectonic setting of the Barents Sea region by isostatic considerations, *Geophys. J. Int.* 171: 1390–1403, doi:10.1111/j.1365-246X.2007.03602.x.

Gramberg, I. S., V. Y. Glebovsky, G. E. Grikurov, V. L Ivanov, E. A. Korago, M. K. Kos'ko, S. P. Maschenkov, A. L. Piskarev, Y. E. Pogrebitsky, Y. V. Shipelkevitch, and O. I. Suprunenko (2001). Eurasian arctic margin: Earth science problems and research challenges, *Polarforschung* 69: 3–25.

Green, P. (1995). Reversible jump Markov chain Monte Carlo computation and Bayesian model determination, *Biometrika* 82: 711–732.

Hauser, J., K. Dyer, M. E. Pasyanos, H. Bungum, J. I. Faleide, and S. A. Clark (2009). Development and tuning of a 3-D stochastic inversion methodology to the European Arctic, in *Proceedings of the 2009 Monitoring Research Review*: *Ground-Based Nuclear Explosion Monitoring Technologies*, LA-UR-09-05276, Vol. 1, pp. 73–83.

Kennett, B. L. N. and M. Sambridge (1992). Earthquake location—Genetic algorithms for teleseismic location, *Phys. Earth Planet. Inter.* 75: 103–110.

Levshin, A., J. Schweitzer, C. Weidle, N. Shapiro, N. Maercklin, and M. Ritzwoller (2007). Surface wave tomography for the Barents Sea and surrounding regions, *Geophys. J. Int*. 170: 441–459, doi:10.1111/j.1365-246X.2006.03285.x.

Lomax, A., J. Virieux, P. Volant, and C. Berge (2000). Probabilistic earthquake location in 3D and layered models: Introduction of a Metropolis-Gibbs method and comparison with linear locations, in *Advances in Seismic Event Location*, C. H. Thurber and N. Rabinowits, Eds. Dordrecht, Netherlands: Kulwer.

Metropolis, N., A. Rosenbluth, M. Rosenbluth, A. Teller, and E. Teller (1953). Equation of state calculations by fast computing machines, *J. Chem. Phys*. 21: 1087–1092.

Mosegaard, K. and A. Tarantola (1995). Monte Carlo sampling of solutions to inverse problems, *J. Geophys. Res*. 100: B7, 2,431–12,447.

Pasyanos, M. E., G. A. Franz, and A. L. Ramirez (2006). Reconciling a geophysical model to data using a Markov Chain Monte Carlo algorithm: An application to the Yellow Sea-Korean Peninsula region, *J. Geophys. Res.* 111: B03313, doi:10.1029/2005JB003851.

Ritzmann, O. and J. Faleide (2009). The crust and mantle lithosphere in the Barents Sea/Kara Sea region, *Tectonophys.* 470: 89–104, doi:10.1016/j.tecto.2008.06.018.

Ritzmann, O., N. Maercklin, J. I. Faleide, H. Bungum, W. D. Mooney, and S. T. Detweiler (2007). A 3D geophysical model for the crust in the greater Barents Sea region: Model construction and basement characterization. *Geophys. J. Int*. 170: 417–435, doi: 10.1111/j.1365-246X.2007.03337.x.

Skilbrei, J. (1991). Interpretation of depth to the magnetic basement in the northern Barents Sea (south of Svalbard), *Tectonophys.* 200: 127–141.

Skilbrei, J. (1995). Aspects of the geology of the southwestern Barents Sea from aero-magnetic data, *NGU Bull.* 427, 64–67.

Smelror, M. O., O. Petrov, G. B. Larsen, and S.Werner (2009). *Geological History of the Barents Sea*. Geological Survey of Norway.