FINAL REPORT

FUGITIVE GAS MIGRATION DATABASE DEVELOPMENT AND STATISTICAL ANALYSIS TOWARD ENHANCING THE UNDERSTANDING OF OCCURRENCE, ATTRIBUTES, AND POTENTIAL CAUSES OF GAS MIGRATION AT BC OIL AND GAS ACTIVITIES ACT (OGAA) WELLS.

Prepared for:
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Prepared by:
Elyse Sandl, Roger Beckie, Laurie Welch, Aaron Cahill, and Bethany Ladd
The University of British Columbia Energy and Environment Research Initiative

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EXECUTIVE SUMMARY

Oil and gas wells are engineered with barriers to prevent fluid movement along the wellbore. If the integrity of one or more of these barriers fails, it may result in subsurface leakage of natural gas outside the well casing, a process termed fugitive gas migration (GM). Knowledge of the occurrence and causes of GM is essential for effective management of the potential risks of GM. In the province of British Columbia, Canada (BC), oil and gas producers are required to report well drilling, completion, production, and abandonment records for all oil and gas wells to the British Columbia Oil and Gas Commission (BCOGC). These well data provide a unique opportunity to identify well characteristics with higher probabilities for GM to develop. Here we conduct statistical analyses to identify the associations between various well attributes and occurrences of GM, which have been reported at 0.6% of the 25,000 oil and gas wells in BC.

A study database was developed by compiling data for relevant well attributes, selected based on the availability of data, theory presented in the GM literature, inclusion in previous studies and interviews with regulators and industry members. Additional data attributes were added to the study database for a subset of 1,456 wells located to the east of Fort Nelson, BC, in an area we refer to as the Jean Marie Area. Two sets of statistical modeling analyses were conducted: (1) the regional analysis included all 23,859 wells in the regional database, located across Northeast BC, and (2) the localized analysis included the 1,456 wells in Jean Marie Area database, which had additional data attributes to use as explanatory variables.

The probability of the presence or absence of GM was modeled using Bayesian multilevel logistic regression. In multilevel models, observations are assigned categorical group membership, and the models identify effects at both the population-level, based on all observations (i.e., all wells), and the group-level, based on groups or clusters of wells. During the regional analysis, we considered distinct geographical regions by grouping wells into oil and gas areas with unique geological environments. By considering group-level model effects that varied between areas, we allowed for (1) comparison of GM occurrence between areas/geological environments, (2) interaction between areas/geology and other effects, and (3) reduced adverse effects of spatial correlation. The imbalance between the number of GM occurrences and wells without reported GM created challenges for the model fitting. The databases were balanced with respect to the number of wells with and without GM to a ratio of 1:1 through a combination of random undersampling and random oversampling, which improved some aspects of the model fits. Overall the relationships between GM and individual well attributes were consistent between models fit to the balanced dataset and the unbalanced dataset.

Based on the results of the statistical models, along with descriptive statistics, data exploration and Gm theory, we made interpretations and hypotheses regarding the occurrence of GM in BC. The main findings, implications and recommendations of the project are:

1. Rigorous statistical analysis did not reveal strong predictors of GM in the oil and gas well data analyzed in this study. The presented statistical models were not able to discriminate known individual cases of GM from similar or adjacent wells, with high likelihood, as the attributes or combinations of attributes associated with GM are not unique to GM wells. Therefore, a statistical model will have a low likelihood of successfully predicting unidentified GM cases using data in the study databases. Field inspections will be the most effective approach for detecting GM cases and reducing uncertainty around GM occurrence.

2. The statistical models identified the strongest association between GM and other indicators of compromised well integrity such as surface casing vent flow (SCVF), remedial treatments (cement squeeze or remedial casing), or blowouts. For prioritizing sites for field inspections, this study supports putting a higher priority on wells with SCVF, blowouts, or remedial treatments.

3. Sub-regional areas of higher GM occurrence have been observed across North American jurisdictions, which may warrant geographically targeted monitoring for indicators of GM presence. This study found that in BC there is spatial clustering of wells with GM in the Fort Nelson Plains area, including the local area we referred to as the Jean Marie Area. We have inferred that this geographic clustering has underlying geological influences, which increase the likelihood of GM. Systematic monitoring for GM in this area may be beneficial.
4. Based on available reservoir gas pressure data we estimated that the gas in the intermediate Lower Debolt and Elkton Formations is locally overpressured relative to hydrostatic pressure in the Jean Marie Area. We speculate that these formations represent possible local sources of GM and SCVF gas. These hypotheses could be further investigated through isotopic and compositional analyses of the gases.
5. Most of GM wells in the Jean Marie Area have fully cemented surface and intermediate casings, suggesting that uncemented well annulus intervals or low cement tops are not likely contributing to higher GM occurrence. There was limited digital information available to evaluate the quality of cement in well annuli in BC. An academic review of cement bond logs, cement bond log interpretations, or other potential cement quality indicators relevant to GM may be useful to identify specific cement-related indicator data useful in supporting future analysis of GM (and SCVF) occurrence.

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INTRODUCTION

Although there is a long history of oil and gas development in North America, the relatively recent increase in unconventional production has provoked questions about the effects of the unintentional release of gas into the subsurface (Council of Canadian Academies, 2014). If a well's initial construction is inadequate or it later suffers a failure of integrity, natural gas may be unintentionally mobilized and has the potential to reach the shallow subsurface. When gas migrates outside of the well casing the process is referred to as gas migration (GM) which can impact the critical zone including potable groundwater resources and contribute to greenhouse gas emissions. A comprehensive understanding of the causes and conditions that lead to GM is important to inform the detection, monitoring, and management of GM and to assess the associated potential risks. In this study, we use public well records to assess potential factors associated with known occurrences of GM at oil and gas wells in the Province of British Columbia, Canada (BC).

For GM to occur there needs to be a migration pathway, a gas source, and a pressure imbalance (Bonett and Pafitis, 1996; T. Watson and Bachu, 2009; Zare Bezgabadi, 2018), and it is hypothesized that some wells are inherently more susceptible to GM than others. The susceptibility of a given well to developing GM is controlled by a complex interplay of factors related to drilling, cementing and completion, gas properties, geology, intermediate or shallow gas sources, among others. Previous studies have provided analyses of well integrity failures using public well records in Alberta, Pennsylvania and Colorado (Bachu, 2017; Considine et al., 2013; Ingraffea et al., 2014; Lackey et al., 2017; Montague et al., 2018; Vidic et al., 2013; T. Watson and Bachu, 2009; Watson and Bachu, 2008; Wisen et al., 2019; Appendix A). However, no conclusive causal relationships were identified and there appear to be regional variations in the factors associated with GM such as local, geology, drilling practices or operational practices. Consequently, further research is needed to understand the general and local causes and GM in oil and gas producing regions across North America, including BC (Cahill et al., 2019).

As of January 2018, GM had been identified and reported in 145 (0.6%) of approximately 25,000 oil and gas wells in BC. To date, there has been little research investigating the occurrence of GM in the province, and no rigorous statistical data analysis of the factors associated with GM has been conducted (Cahill et al., 2019). There is a need to identify and evaluate the factors associated with the highest likelihood of GM in BC, as it is fundamental to inform future research needs and regulatory enhancements.

In BC, oil and gas producers are required to submit well drilling, completion, production, and abandonment records to the provincial regulator, the British Columbia Oil and Gas Commission (BCOGC). We were able to access and mine this valuable public dataset to identify well conditions that pose the highest likelihood for GM in BC. Here, we aim to identify the associations between observed occurrences of GM and various local well constructions, geological environments, and operational practices. This study included a compilation of public wellbore records into a database, data exploration and description, and development of statistical models to explain the presence or absence of GM at wellbores in BC. A contemporary approach was taken to statistical modeling; drawing on Bayesian inference and hierarchical model structures. This approach allowed us to reduce the effects of spatial correlation within the data, as well as investigate the variations in effects between different groups of wells, rather than making generalized conclusions at the provincial scale.

This report is intended to provide a brief project overview. A more detailed discussion can be found in:

1. Our submitted journal publication [Sandl, E., Cahill, A.G., Welch, L., Beckie, R., Submitted. Investigating factors associated with fugitive gas migration at oil and gas wells in Northeast British Columbia, Canada. Science of the Total Environment.]

2. The master thesis of Elyse Sandl [Sandl, E., 2020. Investigating factors associated with fugitive gas migration in Northeast British Columbia, Canada. University of British Columbia, Vancouver, Canada, https://open.library.ubc.ca/collections/24/items/1.0389605.]

METHODS

STUDY DATABASE DEVELOPMENT

BC oil and gas well data was obtained from both the IHS Markit database accessed through the software AccuMap (IHS Markit, 2018) and from the BCOGC data downloads online portal (BCOGC, 2018). A study well population was selected to include 24,911 production, injection, disposal, and observation wells located in Northeast BC, cased or completed between 1948 and January 2018.

We obtained records of GM and surface casing vent flows (SCVF) through personal communication with the BCOGC. As of January 2018, the BCOGC had records of GM at 145 wells or 0.6% of wells drilled. For every well in the study well population, GM was recorded as present or absent, with the assumption that GM was absent at wells without associated GM reports. Although 12 cases of GM were repaired, we assumed that GM was "present" at all wells that have developed GM at any time.

A study database was then developed for the study well population by compiling data for selected relevant well attributes (Table 1). Attributes were selected based on the availability of data, the theory presented in the GM literature, inclusion in previous studies and interviews with regulators and industry members (Appendix A). Following data compilation and quality control, the final study database included 23,859 wells with complete data, including 143 wells with GM.

Additional data attributes were added to the study database for a subset of 1,456 wells located to the east of Fort Nelson, BC, within BC NTS 250K Mapsheet 94I. We refer to the area as the Jean Marie Area, which was selected because of the higher density of GM wells and the availability of bedrock topography data (Figure 1). Additional drilling and cementing related attributes (Table 1) were manually retrieved from original drilling records on file with the BCOGC for wells in the Jean Marie Area. We refer to two subsets of the study database (1) the regional database containing complete data for the base set of attributes for all 23,859 wells, and (2) the Jean Marie Area database containing complete data for all base and additional attributes for the subset of 1,456 wells in the Jean Marie Area.

Table 1 List of well attributes in the Regional and Jean Marie Area well attribute databases used as explanatory variables in statistical models.

Regional Database Base Attributes	Jean Marie Area Additional Attributes
Well Orientation	Surface Casing Cement Returns at Surface
Fluid Type	Intermediate Casing Cement Returns at Surface
Well Age	Cement Location
Well Status	Underbalanced Drilling (UBD)
Well Type	Location within Paleovalley
Hydraulically Fractured	Distance to Paleovalley Centerline
Acid Treatments	Lost Circulation
SCVF	Intersection of the Lower Debolt Formation
Remedial Treatments	
Number of Drilling or Completion Events	
Number of Potentially Gas-bearing Formations Intersected (Gas-bearing Formations)	
Number of Potentially Overpressured Gas-bearing Formations Intersected (Overpressured Formations)	
Kicks	
Blowouts	
Surface Casing Depth	
Well True Vertical Depth	
Well Total Depth (Length)	
Well Density	
Oil and Gas Areas	

DATA ANALYSIS AND STATISTICAL MODELLING

Statistical model building is an iterative, multistep exercise that begins with exploratory data analysis (Tong, 2019). Prior to statistical modelling, exploratory data analysis was used to:

- Screen the data;
- Identify collinearity in the data;
- Examine the spatial distribution of data;
- Assist in the selection of relevant attributes to be used as explanatory variables in the statistical models; and
- Develop hypotheses.

Initial data exploration indicated that there is a spatial cluster of GM wells in the Fort Nelson Plains Area and 79 of these GM cases are located within the Jean Marie Area, which was therefore selected for a localized analysis (Figure 1). Data exploration revealed correlations among several well attributes, often referred to as collinearity. Several of the attributes in the study database were also spatially correlated (e.g., wells tend to be deeper to the east and shallower to the west based on the geological structure of the WCSB). Wells within a given field tend to be drilled by a limited number of operators, during a regulatory or operational era, using methods suited to the resource and geology. These types of correlations can be misleading in a regional-scale analysis. The observed spatial correlation in attributes motivated the Bayesian, multilevel logistic regression model for our analysis. Further discussion of the challenges and limitations associated with the correlations identified during the data exploration are included in the Challenges and Limitations section below.

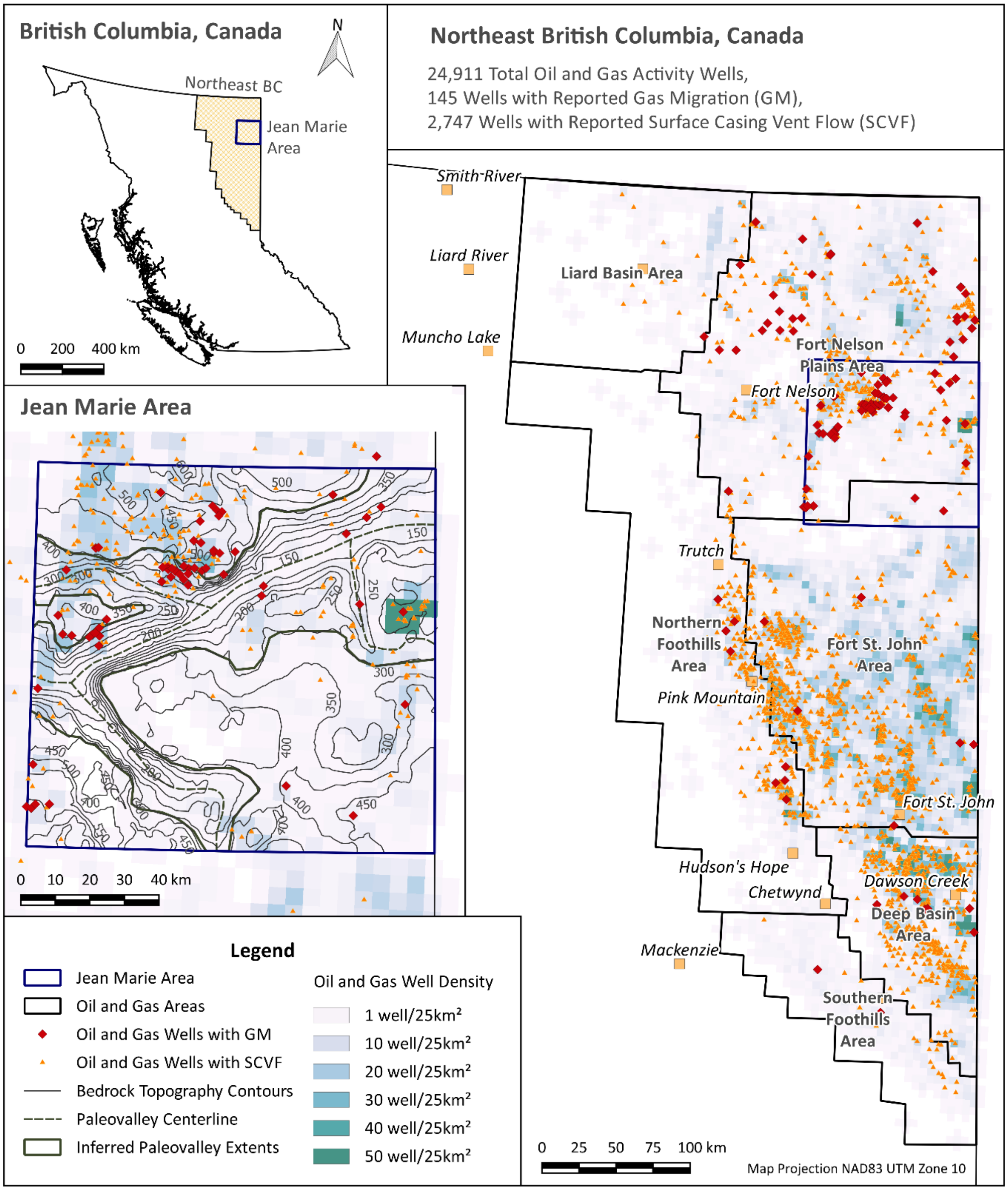

Figure 1 Map of oil and gas well distribution and locations of reported occurrences of GM and SCVF in Northeast BC. Oil and gas areas modified from British Columbia Ministry of Energy, Mines and Petroleum Resources (2006). Interpolated bedrock contours and paleovalley centerlines from Hickin et al. (2008). Base map features retrieved from the Province of British Columbia (2018). Source Sandl et al. (Submitted).

Statistical Modelling

The probability of the presence or absence of GM was modeled using multilevel logistic regression, with the statistical package Rethinking (McElreath, 2016) in the R programming language. Logistic regression is appropriate when the model outcome is binary – here the presence of GM. Model explanatory variables were selected from the attributes in the study database, and probabilistic models were proposed and fit to the data. Model parameters were fit to the data using Hamiltonian Markov Chain Monte Carlo (MCMC) from the Bayesian inference package Stan (Stan Development Team, 2018). A comprehensive discussion of the Bayesian underpinnings of the approach and the mechanics of the model fitting are in McElreath's text (McElreath, 2015).

Bayesian inference allows for the fitting of multilevel models, where observations are assigned categorical group membership, and the models identify effects at both the population-level, based on all observations (i.e., all wells), and the group-level, based on groups or clusters of wells (Gelman and Hill, 2007, p. 237). We followed an iterative approach to statistical modelling, gradually increasing model complexity from single variate logistic regression to multivariate logistic regression and then multilevel logistic regression. Interaction terms were added to the models systematically to explore the interactions between different explanatory variables.

Two sets of statistical modeling analyses were conducted: (1) the regional analysis included the base attributes for all 23,859 wells in the regional database, located across Northeast BC, and (2) the localized analysis included the 1456 wells in Jean Marie Area database, which had additional data attributes to use as explanatory variables. During the regional analysis, we considered distinct geographical regions by grouping wells into oil and gas areas with unique geological environments as defined by British Columbia Ministry of Energy, Mines and Petroleum Resources (2006) (Figure 1). By considering group-level model effects that varied between areas, we allowed for (1) comparison of GM occurrence between areas/geological environments, (2) interaction between areas/geology and other effects, and (3) reduced adverse effects of spatial correlation (Zuur et al., 2009, p. 481).

The imbalance between the number of GM occurrences and wells without reported GM creates challenges for the model fitting (Kubat et al., 1998; Montague et al., 2018). This is a common difficulty in data analysis aimed at predicting/understanding a rare but important event, such as well integrity failure. The databases were balanced with respect to the number of wells with and without GM through a combination of random undersampling and random oversampling (Fernández et al., 2018). As a large number of the database attributes are categorical variables, this method was selected over generation of synthetic GM wells using a nearest neighbors method such as synthetic minority oversampling (SMOTE, Chawla et al., 2002), which is most applicable to continuous variables. A comparison of random oversampling and synthetic sample generation through SMOTE-NC, a SMOTE variant which accommodates some categorical variables, indicated that the random oversampling preserved the original structure of the data better than SMOTE-NC. Sensitivity analysis was used to select the final balance and sample size of the datasets. A ratio of 1:1 GM well to wells without GM was selected. The regional database was randomly under- and oversampled to a final sample size of 20, 000 wells (10,000 GM wells and 10,000 wells without GM). The localized database was randomly under- and oversampled to a final sample size of 2 000 wells (1000 GM wells and 1000 wells without GM).

A more detailed discussion of the statically modelling methodology is included in Appendix B.

RESULTS AND DISCUSSION

Following contemporary statistical modeling (Tong, 2019) and model comparison (Appendix B, e.g., Johnson and Omland, 2004; McElreath, 2015, p. 196; Vehtari et al., 2017; Watanabe, 2010) we selected several models as the "best" models from each analysis. For the regional analysis which included all 23,859 wells in the regional database, three top models were selected (*NEBC_1* through *NEBC_3*). Model *NEBC_1* included the variables: oil and gas areas; well status; SCVF; treatments; blowouts; well age; well density; and number of potentially overpressured gas-bearing formations intersected (overpressured formations). Model *NEBC_2* had the well type variables removed, and model *NEBC_3* had well orientation variables added (Table 2).

Four models were selected as the "best" models from the localized analysis of the Jean Marie Area (*JMA_1* through *JMA_4*). All four models included explanatory variables for SCVF, remedial treatments, number of potentially gas-bearing formations intersected (gas-bearing formations), well status, underbalanced drilling (UBD), and location within a paleovalley. Models *JMA_3* and *JMA_4* also included the intersection of the Lower Debolt Formation and models *JMA_2* and *JMA_4* included an interaction term between remedial treatments and suspended well status (Table 2).

A qualitative description of each model variables relationship to the probability of GM occurring at a well is summarized in Table 2. For quantitative results of the probability distributions of model coefficients, including means (most likely value representing the relationship) and width (describing the uncertainty of the relationship) see Sandl, (2020) for the unbalanced data results and Sandl et al. (Submitted) for the balanced data results.

Table 2 Summary of statistical relationships between GM and well attributes identified by statistical modelling.

Category	Variable	Results	
		Regional Analysis	***Jean Marie Area Analysis***
N/A	SCVF	Significant positive relationship. Effects vary between well statuses	Significant positive relationship
	Remedial Activities	Significant positive relationship	Significant positive relationship
	Acid Treatments	Significant negative relationship	-
	Hydraulic Fracturing	Significant negative relationship	-
	Overpressured Formations	Significant positive relationship	-
	Gas-bearing Formations	-	Significant positive relationship
	Well Density	Significant negative relationship Effects vary between oil and gas areas**	-
	Age	Negative relationship. Effects vary between oil and gas areas and well statuses**	-
	Blowouts	Positive relationship. Effects vary between oil and gas areas and well statuses**	-
	UBD	-	Significant positive relationship
	Paleovalleys	-	Significant positive relationship
	Lower Debolt Formation	-	Positive relationship
Well Types	Undefined	Reference level	-
	Producing	No relationship relative to undefined well type	-

Category	Variable	Results	
		Regional Analysis	***Jean Marie Area Analysis***
	Injection	Negative relationship relative to undefined well type	-
	Disposal	Significant negative relationship relative to undefined well type	-
	Observation	Positive relationship relative to undefined well type	-
Well Orientation	Vertical	Reference level	-
	Horizontal	Positive relationship relative to vertical wells	-
	Deviated	No relationship relative to vertical wells	-
	Multiple	Significant positive relationship relative to vertical wells	-
Oil and Gas Area*	Liard Basin	Negative relationship	-
	Fort Nelson Plains	Significant positive relationship	-
	Fort St. John	Negative relationship	-
	Deep Basin	Negative relationship	-
	Southern Foothills	No relationship	-
	Northern Foothills	Negative relationship	-
Well Status*	Active	No relationship	Reference level
	Abandoned	Negative relationship	Significant negative relationship relative to active status
	Suspended	Positive relationship	Negative relationship relative to active status
	Completed	Negative relationship	Negative relationship relative to active status

Notes: Significant relationships indicate stronger associations where posteriors distributions that do not include zero within 95% of the high probability density interval (McElreath, 2015, p 56), but are not necessarily causal relationships.
* Group-level variables assigned to wells grouped by area or well status in multilevel models.
** Interactions with group-level variables, where effects of a variables well age, well density, SCVF and blowouts vary between groups of wells, divided by oil and gas area or well status.

Despite grouping data into oil and gas areas some spatial autocorrelation of covariates remained within areas during the regional analysis. For example, the regional association between GM and well density and well age were opposite of what was expected; that is, well density had a negative association rather than a positive one. This is likely the effect of spatial correlation and clustering of the GM wells rather than a causal effect, highlighting the need for caution when assigning causality in observational datasets. Spatial overlap of well attributes and collinearity was also a challenge during the Jean Marie Area analysis. For example, there is some redundancy between the Lower Debolt Formation explanatory variable and the gas-bearing formations variable such that the effect of the Lower Debolt Formation variable is less significant (posterior probability distribution of the coefficient is closer to zero) when both variables are included in the model. Over 50% of the GM wells in the area intersect 12 gas-bearing formations, including the production zone. Typically, these wells produce gas from the Jean Marie Formation and intersect the Lower Debolt Formation. The Lower Debolt Formation is discussed in greater detail below.

MODEL PREDICTIVE CHECKS

The statistical models take as input the values of various attributes and output a probability that a well with those attributes would have GM. To assess model fits, the model-averaged predicted probability of

GM was generated for every well in the dataset. Ideally, the predicted probabilities for wells with GM would approach 1. Consistent with the discussion of Montague et al. (2018), models fit to the unbalanced dataset effectively predicted the low probability of GM at wells without observed GM but were less effective at predicting a high probability at wells with observed GM.

Models fit to the balanced dataset had produced increased predicted probabilities of GM and overall greater difference in predicted probabilities between wells with and without GM, i.e. higher predictive accuracy. The relationships between GM and individual well attributes were consistent between models fit to the balanced dataset and the unbalanced dataset. We felt that the statistical models, along with descriptive statistics, data exploration and theoretical relationships, were suitable to support the interpretations and speculations made about GM in BC discussed below.

GENERAL INTERPRETATION OF RESULTS

Appendix A includes findings from statistical modelling and comparison to previous research, including assessment of each of the strongest explanatory variables relationship to GM, both on statistical and physical grounds.

The inspection of the model coefficients shows that several variables are correlated with GM. However, as the attributes or combinations of attributes (i.e. explanatory variables) associated with GM are not unique to GM wells, the models have limited power to predict individual occurrences of GM in BC. Regional models effectively assigned an increased probability of GM to many wells within the Fort Nelson Plains Area and Jean Marie Area. However, as many of the wells in the Jean Marie Areahave similar characteristics it was challenging for models to discriminate individual GM wells from the adjacent wells.

Our analysis shows that typical GM wells in the Jean Marie Area tend to be active gas production wells that are less than 20 years old. They typically produce from the Jean Marie Formation by horizontal legs drilled with UBD. The wells most often intersect 12 gas-bearing formations, of which two or more are potentially overpressured (locally the Elkton and Lower Debolt Formations). Within Jean Marie Area, the wells' surface casings are typically 250 m to 300 m deep and fully cemented. The intermediate casings are also fully cemented to surface and around 1440 m deep (down to the producing zone). The wells may have SCVF or remedial treatments and are unlikely to be hydraulically fractured or acid treated. A graphical representation of an average Jean Marie Area GM well is presented in Figure 2.

The analyses identified the strongest association between GM and other indicators of compromised well integrity such as SCVF, remedial treatments (cement squeeze or remedial casing), or blowouts. Approximately 50% of the wells with GM also have reported SCVF. Forde et al. (2019) found that 9/10 inspected well pads in the Fort Nelson Plains/Jean Marie Area had GM isotopic signatures matching SCVF gas with variable degrees of oxidation. To exhibit both GM and SCVF from the same source, the gas source is most likely located below the surface casing. The statistical models also identified significant correlations between oil and gas areas and the occurrence of GM. Although the data does not explicitly explain this spatial variation, we hypothesize that it is related to local geological conditions.

INFERENCES REGARDING JEAN MARIE AREA GM CLUSTER

There is spatial overlap between the Jean Marie Area GM wells, paleovalleys, the use of UBD, the occurrence of the Lower Debolt Formation, and other well attributes. We hypothesize that the statistical association between paleovalleys, UBD, and GM may be an artifact of spatial correlations rather than a causal relationship, and we speculate that the intersection of the Lower Debolt Formation may have a causal relationship with GM occurrence.

The review of original drilling records for the subset of wells in the Jean Marie database indicated that most often UBD is only used to drill the horizontal leg of a well, typically through the Jean Marie Formation around 1400 m to 1500 m depth. Therefore, we hypothesize that the use of UBD is unlikely to influence the integrity of the vertical section of the well, which is of the highest interest for the formation of GM (Figure 2). The locations of paleovalleys were included in the analysis as a proxy for shallow gas occurrence. The occurrence of both GM and SCVF suggests a gas source is present below the surface casing, which is required to extend into competent bedrock in BC (*Drilling and Production Regulation, B.C. Reg. 282/2010, Last amended by B.C. Reg. 103/2019*, 2010). Therefore, we believe that potential shallow gas within paleovalleys is not likely the gas source for the wells with both GM and SCVF.

Using initial reservoir pressure data, we estimated the local gas pressure in the formations intersected by the Jean Marie Area wells relative to hydrostatic pressure (Appendix C). Although GM wells in the Jean Marie Area typically intersect 12 gas-bearing formations, according to our estimates many of them are underpressured relative to hydrostatic (Appendix C). Locally, the Lower Debolt and Elkton Formations have gas pressures exceeding hydrostatic, and the overlying Bullhead Group hosts normally pressured to overpressured gas (Appendix C). We propose that this sequence of formations (Bullhead Group, Lower Debolt, and Elkton) presents a potential intermediate gas source in the Jean Marie Area, based on gas pressures and formation depth below the surface casing shoe, typically between 500 and 650 m.

Overpressured gas in the Lower Debolt Formation not only represents a potential source of GM, but it also poses a theoretical risk to cement quality during well construction as discussed below. The review of original drilling records indicated gas kicks and lost circulation during drilling have been reported associated with the Lower Debolt Formation in the Jean Marie Area. Local karstic porosity within the Lower Debolt Formation (British Columbia Ministry of Energy, Mines and Petroleum Resources, 2006) could make the formation susceptible to lost circulation. With higher formation gas pressures, even a small loss of annular pressure through volume reduction or loss of cement to the formation can allow invasion of gas into the cement (kick) (e.g., Bannister et al., 1984; Bonett and Pafitis, 1996; Sabins et al., 1982). Gas invasion can lead to channels, micro–annuli, and poor zonal isolation, making the well more susceptible to GM (e.g., Bannister et al., 1984; Bonett and Pafitis, 1996; Dusseault and Jackson, 2014; Kiran et al., 2017). Based on the identified statistical association, the formation depth below the surface casing, gas pressures and karstic porosity, we speculate that the Lower Debolt Formation (and overlying Bullhead Group and underlying Elkton Formation) may be potential intermediate gas source(s) for the GM and SCVF in the Jean Marie Area, warranting further investigation. The source of GM in these cases can be constrained through isotopic fingerprinting.

The localized Jean Marie Area analysis did not identify a significant relationship between GM and cement location or cement returns at surface (a potential indicator of a low cement top). The majority of GM wells in the Jean Marie Area have fully cemented surface and intermediate casings, suggesting that uncemented well annulus intervals or low cement tops are not likely contributing to higher GM occurrence, such as was suggested for other regions (Lackey et al., 2017; T. Watson and Bachu, 2009). The occurrence of GM and SCVF is, therefore, more likely attributed to cement quality than cement location. In future analyses, including additional cement related data, unavailable in the current digital records, may improve understanding of cement failures or microannulus formation related to GM and SCVF.

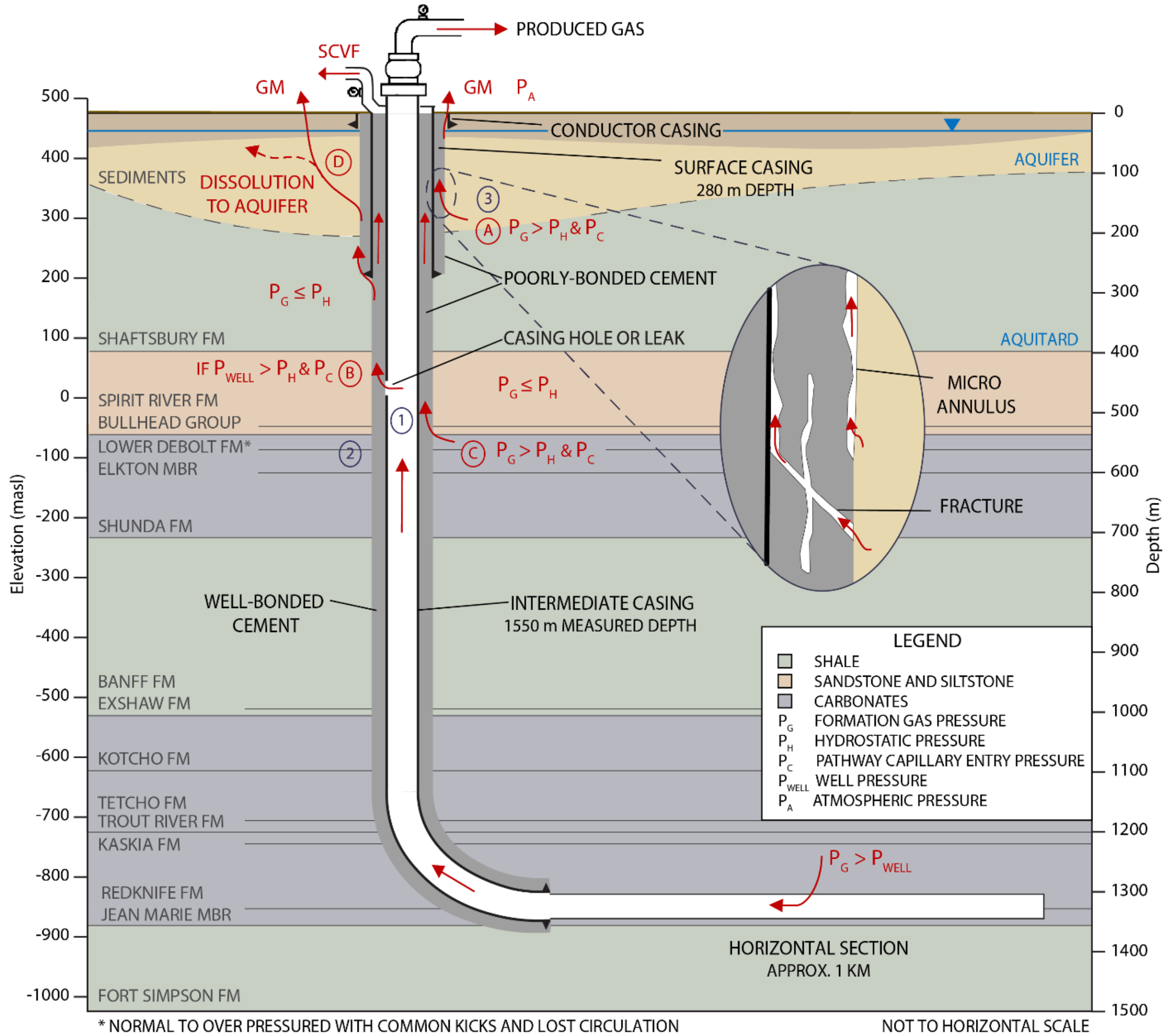

Figure 2 Typical stratigraphy and well construction in Jean Marie Area. Stratigraphy based on well logs and British Columbia Ministry of Natural Gas Development (2011). Conceptual model of pressure conditions for fluid movement (red) that can lead to GM and / or SCVF. A) a shallow gas source intersected by the surface casing enters and migrates through a permeable outer surface casing annulus B) casing leak (e.g., due to a hole or leaking casing connection) allows production gas to leak into and migrate through the outer annulus C) an intermediate gas source is intersected by the well casing, gas enters and migrates through a permeable outer annulus, and D) gas migrating in an outer well annulus enters an aquifer in gas phase or dissolved phase. Potential gas sources include 1) production gas, 2) intermediate-depth gas-bearing formation, and 3) shallow depth gas-bearing formation. Source Sandl et al. (Submitted).

CONCLUSION AND RECOMMENDATIONS

To date, there has been little research investigating the occurrence or attributes associated with GM in BC (Cahill et al., 2019). Wisen et al. (2019b) provide a descriptive analysis of fugitive gas cases in BC, with a focus on SCVF. However, to date, no rigorous statistical data analysis of the factors associated with GM in BC has been conducted. This study included a compilation of public wellbore records into a database, rigorous data exploration and description, and development of robust statistical models to provide insights for describing and explaining the presence or absence of GM at wellbores in BC. We used a contemporary statistical modeling methodology, drawing on Bayesian inference and hierarchical model structures, to evaluate those attributes associated with the highest likelihood for GM. This approach allowed us to reduce the effects of spatial correlation within the data, as well as investigate the variations between different groups of wellbores, rather than making generalized conclusions at the provincial scale. The main findings, challenges and limitations, and conclusions and recommendations of this study are described below.

FINDINGS

Detailed findings from statistical models and comparison to previous research are presented in Appendix A, Sandl (2020), and Sandl et al. (Submitted). The main findings of this research are summarized below.

1. Rigorous statistical analysis did not reveal strong predictors of GM in the oil and gas well data analyzed in this study. The presented statistical models, based upon available data, were not able to discriminate known individual cases of GM from similar or adjacent wells, with high likelihood, as the attributes or combinations of attributes (i.e. explanatory variables) associated with GM are not unique to GM wells. Therefore, a statistical model will have a low likelihood of successfully predicting unidentified GM cases using data in the study databases.
2. The statistical models identified the strongest association between GM and other indicators of compromised well integrity such as SCVF, remedial treatments (cement squeeze or remedial casing), or blowouts. The statistical models also identified a significant relationship between oil and gas areas and the occurrence of GM. The Fort Nelson Plains area has the highest occurrence of GM and therefore the highest statistical probability of GM at a well. Although the data does not explicitly explain this spatial variation, we hypothesized that it is related to local geological conditions.
3. Within the Fort Nelson Plains area, there is a higher occurrence of GM in wells located to the east of Fort Nelson, in an area we have referred to as the Jean Marie Area (Figure 1). Within this area, GM wells tend to be active gas production wells that are less than 20 years old. They typically produce from the Jean Marie Formation by horizontal legs drilled with UBD. These wells most often intersect 12 gas-bearing formations, of which two or more are potentially overpressured. Within Jean Marie Area, the wells' surface casings are typically 250 m to 300 m deep and fully cemented. The intermediate casings are also fully cemented to surface and around 1440 m deep (down to the producing zone). The wells may have SCVF or remedial treatments and are unlikely to be hydraulically fractured or acid-treated (Figure 2).
4. Both regionally and within the Jean Marie Area, over 50% of the wells with GM also have reported SCVF, suggesting, where isotopic signatures of the gas match, that the gas source originates below the surface casing for many GM cases. Based on available reservoir pressure data, we estimated that the gas in the intermediate Lower Debolt and Elkton Formations is locally overpressured relative to hydrostatic pressure, and we speculate that these formations represent possible sources of GM and SCVF gas in the Jean Marie Area. These hypotheses could be further investigated through isotopic and compositional analyses of the gases.

5. The localized Jean Marie Area analysis did not identify a significant relationship between GM and cement location or cement returns at surface (a potential indicator of a low cement top). The majority of GM wells in the Jean Marie Area have fully cemented surface and intermediate casings, suggesting that uncemented well annulus intervals or low cement tops are not likely contributing to higher GM occurrence, as suggested for other regions (Lackey et al., 2017; T. Watson and Bachu, 2009). The occurrence of GM and SCVF is, therefore, more likely attributed to cement quality than cement location.
6. Multilevel models are an effective tool for analyzing large complex data sets. In this study, dividing wells into hierarchical groups aided the analysis by reducing some of the correlation within a data set and by comparing effects between groups (McElreath, 2015, p 14; Zuur et al., 2009, p 313).

CHALLENGES AND LIMITATIONS

1. In BC and many other jurisdictions, GM inspections and monitoring are done only when there is observed evidence of GM. Further, records and results of the inspections are typically only reported when results indicate the presence of GM. Due to the dataset uncertainty with respect to the number of inspections and the rate of GM detection, it is difficult to estimate or constrain the true rate of GM occurrence in BC.
2. A challenge in the analysis of observational datasets, such as public records for existing oil and gas wells, is that explanatory variables cannot been controlled or randomized, which has the effect that collinearity and spatial autocorrelation are commonly encountered. This can lead to coefficients that are hard to interpret as independent effects, underestimation of standard errors, and increased false positives (Legendre, 1993; Ramsey and Schafer, 2013; Zuur et al., 2009, p 21). Consequently, cause and effect relationships generally cannot be determined (Kutner, 2005). Despite grouping data into oil and gas areas in our analysis, some spatial autocorrelation of covariates remained within areas, which can lead to inaccurate model results (Legendre, 1993; Zuur et al., 2009, p 21). For example, the regional association between GM and well density and well age were opposite of the expected effects (i.e., well density had a negative association rather than positive). This is likely the effect of spatial correlation and clustering of the GM wells rather than a causal effect, highlighting the need for caution when analyzing observational datasets.
3. The imbalance between the number of GM occurrences (145) and wells without reported GM (23,859) creates challenges for the model fitting. This is a common challenge in data analysis aimed at predicting/understanding a rare but important event, such as well integrity failure (Kubat et al., 1998). Data balancing with random oversampling and random undersampling improved some aspects of the model fits and increased the predictive probabilities of GM. However, random oversampling can lead to overfitting in some cases (Fernández et al., 2018). The relationships between GM and individual well attributes were consistent between models fit to the balanced dataset and the unbalanced dataset.

IMPLICATIONS AND RECOMMENDATIONS

1. Negative Inspection Results

In many jurisdictions, GM monitoring is done only when there is observed evidence of GM, and negative results may not be reported. The collection and reporting of both positive and negative GM detection results would strengthen certainty in the general statistics related to the occurrence rate for cases of GM and the effectiveness of GM detection. Further, these additional data would support improvements for future statistical data analysis and other GM research initiatives. This knowledge gap could be supported by a dedicated study with pre-registration involving random sampling with rigorous detection methods, to assess the GM detection error in BC oil and gas fields.

2. Targeted Monitoring

Rigorous statistical analysis did not reveal strong predictors of GM in the oil and gas well data analyzed in this study. Therefore, a statistical model will have a low likelihood of successfully predicting unidentified GM cases using data in the study databases. As the attributes for this study were selected based on a solid foundation of previous research, theoretical associations, and insights from the regulator, these results suggest that for NEBC, field inspections will be the most effective approach for detecting GM cases and reducing uncertainty around GM occurrence. For prioritizing sites for field inspections, which may be necessary for remote areas of NEBC, this study supports putting a higher priority on wells with SCVF, blowouts, or remedial treatments, and wells in areas of high GM occurrence.

3. Intermediate Geology and Gas Characterization

Sub-regional areas of higher GM occurrence have been observed across North American jurisdictions (Bachu, 2017; Ingraffea et al., 2014; Lackey et al., 2017), which may warrant geographically targeted monitoring for indicators of GM presence. This study found that in BC there is spatial clustering of wells with GM in the Fort Nelson Plains area, including the local area we referred to as the Jean Marie Area (Figure 1). We have inferred that this geographic clustering has underlying geological influences, which increase the likelihood of GM. Systematic monitoring for GM in this area may be beneficial.

It may be possible to further define GM risks in this area through additional research focusing on potential shallow and intermediate gas sources, including the Lower Debolt and Elkton Formations. These formations are locally overpressured (Appendix C) and speculated that they are potential local fugitive gas sources. Comparison of GM, SCVF, and intermediate formation gas samples and isotopic analysis may provide additional insights into the sources and pathways of fugitive gas in the Jean Marie Area.

4. Cement Data

A good quality cement seal is critical to preventing pathway formation in a well annulus (e.g., Davies et al., 2014; King, 2012; Kiran et al., 2017). We found that wells in the Jean Marie Area typically have fully cemented surface casings and intermediate casings. Therefore, the occurrence of GM and SCVF is more likely attributed to cement quality than to uncemented intervals of the well annulus or low cement tops. There was limited digital information available to evaluate the quality of cement in well annuli in BC, consequently, it was not considered in this analysis. An academic review of cement bond logs, cement bond log interpretations, or other potential cement quality indicators relevant to GM may be useful to identify specific cement-related indicator data useful in supporting future analysis of GM (and SCVF) occurrence.

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Appendix A Attributes Rational, Findings or Previous Data Analysis and Comparison to Current Results

Table 3 Summary statistical model findings and comparison to previous research

	Rational	Findings of Previous Studies	Model Result	Discussion
Well Orientation	It has been proposed that wellbore deviation can create more challenging conditions for cementing and well completion due to eccentricity and drill mud filter cake (Kiran et al., 2017; T. Watson and Bachu, 2009). The effect of orientation would be dependent on the depth of the deviation and the location of cement; however, this data is not digitally available for BC (personal communication BCOGC).	Watson and Bachu (2009) and Montague et al. (2018) found deviated wellbores in Alberta exhibit GM and SCVF more frequently than vertical wells. However, Bachu (2017) found that deviation was not conclusively associated with GM. In Colorado, Lackey et al. (2017) found a correlation between SCP and deviated and horizontal wells.	Well orientation was not a strong predictor of GM but including coefficients did improve deviance (WAIC) of some models. When orientation was included, model results indicated that horizontal, deviated, and multiple orientations all have an increased probability of GM over vertical wells.	Initial hypotheses developed during data exploration predicted that well orientation might be a strong predictor or GM. Results did not confirm this expectation. Consistent with previous studies, which found that directionally drilled wells experience well integrity issues more frequently than vertical wells.
Well Status	Well barriers such as cement undergo strength reduction and chemical degradation over time (Ingraffea et al., 2014; Kiran et al., 2017). It is hypothesized that aged or abandoned wells may have a higher frequency of integrity issues. However, it is noted in other jurisdictions that older or abandoned wells often received significantly fewer well integrity inspections, which may bias results (Ingraffea et al., 2014; T. Watson and Bachu, 2009; Wisen et al., 2019).	Bachu (2017) identified that abandoned wells in Alberta frequently exhibit GM, which he attributed to older well construction and abandonment practices.	Including group-level effects for well status significantly improved the performance of regional models. Wells with active and suspended status, had a higher probability of GM occurrence than wells with abandoned or completed statuses. (As our study considered repaired GM wells to have GM occurrence, the well status variable is considered unaffected by whether GM was previously repaired). The effects of other variables also vary depending on the status of the well.	The lower probability of GM for wells abandoned status, may be related to detection bias due to less frequent inspections of abandoned wells. In 2017, the BCOGC instituted an aerial monitoring program for abandoned wells (BCOGC, 2019b, 2019c, 2017), and found that 1% to 3% of surveyed decommissioned wells were emitting methane however, previously systematic monitoring of abandoned wells was not conducted (Wisen et al., 2019).

	Rational	Findings of Previous Studies	Model Result	Discussion
Well Age		In Colorado, well era (pre/post-2010) was found to be more significant for predicting SCP than well age (Lackey et al., 2017). Whereas, Ingraffea et al. (2014) found that the influence of well era varied geographically within Pennsylvania.	Regionally, a negative relationship between well age and GM was identified, indicating that younger wells have a higher probability of exhibiting GM than older wells. The negative relationship between well age and GM varied across oil and gas areas and well statuses. Conventional resource areas such as the Southern Foothills host older wells, and the negative relationship is less significant. For abandoned and suspended wells well statuses, which tend to include older wells, the negative relationship is less significant.	The negative relationship is counterintuitive based on the theory that cement and well components degrade over time, leading to a higher risk of failure in older wells. In addition to the potential detection bias mentioned above, this effect may also be driven by the spatial clustering of GM cases within fields that were developed primarily between 2000 and 2010 in the Fort Nelson Plains Area.
Well Type	The operational application of wells may influence the risk of well integrity failures due to the variations in temperatures, pressure regimes, treatments, and downhole procedures. Duguid et al. (2017) predicted that injection wells have the highest risk due to high-pressure gradients. However, the operation of each well type may vary between jurisdictions.	In Alberta, Watson and Bachu (2009) noted that well type did not have a strong effect on wellbore leakage, but Bachu (2017) found that thermal wells leak most frequently.	Well type was not a strong predictor of GM, but including coefficients did improve deviance (WAIC) of some models. When well type was included in models, observation wells had the strongest association with GM, and injection and disposal wells have the lowest probability of GM.	Our findings are consistent with those of Watson and Bachu (2009). In BC, injection and disposal wells are held to higher construction standards than other wells types for this reason (personal communication, BCOGC).
Hydraulically Fractured and Acid Treatments	Hydraulic fracturing and acidizing are the two treatments with the greatest potential to affect well integrity (Watson and Bachu, 2008). Hydraulic fracturing induces severe downhole pressure conditions and commonly used acids, such as hydrochloric and hydrofluoric, can be damaging to cement (Kiran et al., 2017).	Lackey et al. (2017) found no relationship between SCP and the degree of hydraulic fracturing. Watson and Bachu (2008) identified a minor effect of hydraulic fracturing and acidizing on SCVF and GM.	Regionally there is a negative association between GM and hydraulic fracturing and acid treatments. As wells in the Jean Marie tend not to be hydraulically fractured, no significant relationship was identified during the localized analysis.	Hydraulic fracturing and acid treatments usually occur in the producing formations at the bottom of the well and are not linked to the outer annulus permeability and gas movement in the shallow vertical portion of the well (Dusseault and Jackson, 2014). My findings were consistent with the findings of Lackey et al. (2017).
SCVF	It is anticipated that wells with GM may exhibit other indicators of well integrity loss such as SCVF or remedial workovers such as cement squeezes, remedial casing, or casing patches.	Bachu (2017) found that a significant number of wells with GM in Alberta also exhibited SCVF.	Both regionally and within Jean Marie Area, there was a strong positive association between SCVF and GM. Over 50% of the wells which have reported GM also have reported SCVF. The predicted probability of GM is greater for active and completed wells with SCVF than suspended and abandoned wells.	Consistent with the findings of Bachu (2017). This relationship is likely not causal, rather paired symptoms of the same underlying well integrity issues. The relationship is likely meaningful for detection as SCVF is more readily observed than GM.

	Rational	Findings of Previous Studies	Model Result	Discussion
Remedial Treatments	It is anticipated that wells with GM may exhibit other indicators of well integrity loss such as SCVF or remedial workovers such as cement squeezes, remedial casing, or casing patches.	Ingraffea et al. (2014) investigated records of remedial treatments as indicators of well integrity failures.	Regionally and within Jean Marie Area, remedial treatments represent one of the strongest predictors of GM.	The majority of the remedial treatments reported for GM wells are remedial cement squeezes, with some remedial casings. As some remedial treatments may be associated with GM or SCVF repair, there is some redundancy between these variables (collinearity in statistical parlance). Only 12 GM wells in the dataset have a repaired status (BCOGC, Personal Communication, 2018); however, BCOGC data about remedial treatments associated with SCVF repair was not retrieved for this study.
Number of Potentially Gas-bearing Formations	Intermediate and shallow gas-bearing formations are commonly the sources of gas for GM (Bachu, 2017; King and King, 2013). Overpressured formations (gas pressure exceeding hydrostatic) can create vertical pressure gradients that drive fluid flow (Davies et al., 2014; Kiran et al., 2017) and hydrostatically pressured formations can source leaking wells through buoyancy and diffusion-driven migration (Davies et al., 2014).	Lackey et al. (2017) found an association between high formation pressures and SCP. They hypothesized that high-pressure gradients across the cement make installation more challenging. Bachu (2017) identified that the source gas for GM is Alberta was above the producing reservoir in 95% of cases investigated.	Regionally, there is a positive relationship between the overpressured formations and GM. Regionally the highest occurrence of GM was associated with the intersection of two potentially overpressured formations. Within Jean Marie Area there was a positive association between gas formations and GM.	Over 50% of the GM wells in the Jean Marie area intersect 12 gas formations. Typically, these wells produce from the Jean Marie Formation.
Lower Debolt Formation Intersected:			Within Jean Marie Area, there is a positive association between GM and the intersection of the Lower Debolt Formation. There is some redundancy between the Lower Debolt Formation explanatory variable and the gas formations variable such that the effect of the Lower Debolt Formation variable is less significant (posterior probability distribution of the coefficient is closer to zero) when both variables are included in the model.	The karstic porosity in the Lower Debolt Formation presents a drilling challenge, which may also create cementing challenges. In the Jean Marie Area, we estimate that gas pressures in the Lower Debolt Formation exceed hydrostatic, suggesting that it could be a potential source of migrating gas. Based on localized analysis model results and other observational data, we predict that the Lower Debolt Formation may be a potential gas source for some of the GM cases in the Jean Marie Area and warrants further investigation.
Blowouts	Blowouts are the results of overpressured formation fluids that have invaded the wellbore during drilling or cementing. Blowouts generate elevated subsurface pressures, which may damage the borehole and surrounding formations, resulting in enhanced vertical pathways along the well (Schout et al., 2018; Walters, 1991).	Schout et al. (2018) identified ongoing gas migration from the reservoir to the subsurface in a well with a previous underground blowout.	Regional modeling identified a positive relationship between blowouts and GM; however, due to the low sample size of wells with reported blowouts, there is a wide predicted posterior probability distribution, indicating high uncertainty in this estimate. In the Deep Basin Area, there was a stronger association with blowouts, as there are only 8 GM wells and one of them had a reported blowout.	The positive relationship identified between blowouts and GM was consistent with hypothesized results and findings of Schout et al. (2018).

	Rational	Findings of Previous Studies	Model Result	Discussion
Well Density	It is hypothesized that the probability of interwellbore communication (IWC) increases with a higher density of nearby wells. IWC can create a source of pressurized fluids which could migrate along a wellbore with compromised integrity (Montague and Pinder, 2015).	Watson and Bachu's (2009) results indicated that there was little correlation between GM and well density in Alberta. This finding was supported by the work of Lackey et al. (2017) and Montague et al. (2018).	Regional models identified a negative association between well density and GM. The effects of well density varied between oil and gas areas. The effect of well density was more strongly negative in the Fort St. John Area, which has very high well density and few cases of GM, with less of an effect in the Fort Nelson Plains Area, which has lower well density.	The identified negative relationship is counterintuitive based on the theory that higher well density increases the probability of IWC. The results are likely attributable to spatial clustering of GM cases in a lower well density area, rather than being a causal association. This is supported by the findings of Lackey et al. (2017, Montague et al. (2018), and Watson and Bachu (2009), who did not identify significant relationships between well density and well integrity.
Oil and Gas Areas	There may be variation in the occurrence of known GM between areas of BC due to geologic factors and potential variation in the operational factors, which may be influenced by local geology and geography, the era of development, or local operators. Previous work found geographic clustering of well integrity issues.	Previous work by Bachu (2017), Ingraffea et al. (2014), Lackey et al. (2017) found geographic clustering of well integrity issues	Including group-level effects for oil and gas areas significantly improved the performance of models during the regional analysis. The wells in the Fort Nelson Plains Area have the highest probability of GM, after accounting for the other variables in the model.	These group-level effect terms account for variations between areas that are not accounted for by other data attributes, such as localized geological effects. This is consistent with previous studies that found local geology are correlated with GM/well integrity (Bachu, 2017; Ingraffea et al., 2014; Lackey et al., 2017).
Underbalanced Drilling	UBD is a technique that intentionally designs the hydrostatic head of drilling fluids to be lower than the pressure of the formation being drilled by using compressed gases or aerated fluids (Ojha et al., 2019). UBD has disadvantages that can prove detrimental to the outcome of the drilling process, including a higher risk of blowout or explosion (Ojha et al., 2019). The use of low-density drilling fluids may reduce the cushioning between the drill pipe and the casing, potentially damaging the cement (BCOGC, 2013). Additionally, the well casing may be exposed to repeated pressure fluctuations during drilling, which could weaken the cement bond (BCOGC, 2013).	The BCOGC (2013) identified that a high proportion of the GM wells in the Fort Nelson Plains of BC were drilled using UBD.	Within Jean Marie Area, models identified a positive association between GM and UBD. It was noted in several scanned well reports that UBD was typically only used to drill the horizontal leg of the wells.	The use of UBD in this area appears to be correlated with production from the Jean Marie Formation, and UBD methods are therefore typically employed between 1400 m and 1500 m depth. It is difficult to draw conclusions about these relationships.
Location Relative to Paleovalleys	Paleovalleys are known to be a source of artesian groundwater and pressurized shallow gas (Hickin et al., 2008). Shallow gas in the valley-fill sediments may be associated with GM in BC. A well in northeast BC blew out as the result of a gas kick from quaternary gravel deposits at 140 m depth (BCOGC, 2005).	NA	During the localized analysis, models identified a positive association with the location of paleovalleys, indicating an increased probability of GM for wells located within the paleovalleys.	The locations of paleovalleys are roughly delineated by interpolating the bedrock surface between available borehole logs and included in the model as a proxy for shallow gas, which likely does not extend throughout the paleovalleys. Further, there is spatial overlap between paleovalleys, the use of UBD, the overpressured Lower Debolt Formation, and other well attributes.

	Rational	Findings of Previous Studies	Model Result	Discussion
Kicks	Kicks are the results of overpressured formation fluids that have invaded the wellbore during drilling or cementing. As gas invasion during cement setting can compromise cement quality (Kiran et al., 2017), we expect there may be a correlation between kicks and GM.	NA	Not a significant predictor of GM in BC.	NA
Number of Drilling or Completion Events	I hypothesize that it is more complex to complete and operate wells with multiple producing/perforated intervals, which may increase the risk of reduced well integrity. It has also been hypothesized that multiple completions or perforated intervals provide a higher potential for crossflow between discrete geologic zones (Watson and Bachu, 2009).	Lackey et al. (2017) found that the relationship between SCP and multiple completions was not significant in Colorado.	Not a significant predictor of GM in BC.	Consistent with the findings of Lackey et al. (2017).
Surface Casing Depth	Deeper surface casing increases the probability that shallow or intermediate gas-bearing formations, if present, will be intersected above the surface casing shoe. Any mobile fluid would not be captured by the surface casing and could migrate as GM.	Watson and Bachu (2009) found that in Alberta, "generally as the surface casing depth increases the occurrence of SCVF decreases and the occurrence of GM increases."	Not a significant predictor of GM in BC.	Consistent with the findings of Watson and Bachu (2009).
Well True Vertical Depth	Deeper wells experience higher temperature and pressure conditions and potentially intersect a greater number of intermediate gas-bearing formations.	Lackey et al. (2017) found that the relationship between well depth and SCP was not significant.	Not a significant predictor of GM in BC.	Consistent with the findings of Lackey et al. (2017).
Well Total Depth (Length)	Well completion may be challenging for deeper wells with longer annuli and cement intervals (Watson and Bachu, 2009).	Watson and Bachu (2009) found that total depth had a minor association with GM and SCVF in Alberta.	Not a significant predictor of GM in BC.	Consistent with the findings of Watson and Bachu (2009).
Fluid Type	Although not anticipated to be a strong predictor of GM, the fluid type was included in the analysis. As a source of gas is required for GM, we expect that wells that produce gas may have a higher occurrence of GM.	Montague et al. (2018) found that fluid properties did not significantly improve the predictive accuracy of their models.	Not a significant predictor of GM in BC.	Consistent with the findings of Montague et al. (2018).

	Rational	Findings of Previous Studies	Model Result	Discussion
Cement Returns at Surface and Cement Location	As cement is one of the primary barriers to fluid movement in the well annulus, the presence and quality of cement are expected to be linked to the probability of GM. Cement returns at surface serve as visual indicators of downhole conditions. If full and good quality cement is not returned at the completion of the cement job, it indicates losses to the formation and there is typically an open, uncemented interval above the thief zone (Lavrov, 2017). For the surface casing, this zone is typically filled with cement by a top job, where cement is filled into the open annulus from the surface, which has some challenges and disadvantages such as water getting trapped between the two cement intervals.	Watson and Bachu (2009) found that a low cement top or exposed casing was the most important factor for predicting SCVF and GM in Alberta.	Not a significant predictor of GM in Jean Marie Area.	The localized Jean Marie Area analysis did not identify a significant relationship between GM and cement location or cement returns at surface (a potential indicator of a low cement top). The majority of GM wells in the Jean Marie Area have fully cemented surface and intermediate casings, suggesting that uncemented well annulus intervals or low cement tops are not likely contributing to higher GM occurrence, such as was suggested for other regions (Lackey et al., 2017; Watson and Bachu, 2009).
Lost Circulation	When fluids are lost to the formation, the bottom-hole pressure may be insufficient to balance the fluid pressure in the formation. This may lead to difficulties such as blowouts or wellbore collapse (Feng and Gray, 2017). Further, if a so-called thief zone is not adequately sealed during drilling, circulation also can be lost during cementing, and the height of the cement column may be shorter than expected, compromising quality (Lavrov, 2017).	NA	Not a significant predictor of GM in Jean Marie Area.	NA

Appendix B Statistical Modelling Methods

To determine factors recorded in public data associated with GM, we took a contemporary approach to the statistical analysis, which relies on Bayesian inference and multilevel model structures. My approach allowed us to reduce the effects of spatial correlation within the data, as well as investigate the variations in effects between different groups of wellbores, rather than making generalized conclusions at the provincial scale.

BACKGROUND

The Bayesian approach to statistical inference focusses on probability as a subjective degree of belief, which can be updated as new data is acquired (Lambert, 2018; Tong, 2019). A Bayesian analysis includes the specification of prior probability distributions for the model parameters, then updating these probabilities in light of the data (Tong, 2019). The result is a posterior probability distribution, which is used to make predictions on new observations and evaluate the model against the current data (Gelman, 2014). This process is referred to as Bayesian updating (McElreath, 2015. p. 29)

Bayesian Updating: Prior Probability + Data → Posterior Probability

Bayesian inference is based on probability theory. In simplified terms, it is a way of estimating the probability of an event by adding up all the ways something can happen, relative to all of the possible things that could happen, conditional on the assumptions. Events that can happen in more ways have a higher probability of occurrence (McElreath, 2015). In Bayesian statistics, explicitly describing uncertainty is central and done through probability distributions, diverging from the conventional frequentist approaches of hypothesis testing and p-values (Lambert, 2018). Several concepts and terms that are found in Bayesian statistics are described below:

1. **Likelihood Function** – The is a mathematical formula that expresses the plausibility of parameter values given the data sample. Many conventional likelihood functions may be used, such as Gaussian or binomial, to express the plausibility of the data (McElreath, 2015, p 33).
2. **Prior Probability Distribution (or "the prior")** – The prior states the initial set of plausibilities for every parameter. The prior may be flat, indicating that there is an equal probability for any possibility. More preferably, it may be regularizing or weakly informative, which gently nudges the model towards and more reasonable range of values. The goal of a regularizing prior is to spread the probability density over the widest distribution (least informative) to reduce overfitting, while staying consistent with any particular existing knowledge about the parameter (McElreath, 2015, p 186).
3. **Posterior Probability Distribution –** The posterior distribution represents the updated, current understanding about the parameters and is the product of the prior and the likelihood function, conditional on the data (Hosmer et al., 2013, p 411; McElreath, 2015, p 36).
4. **Markov Chain Monte Carlo –** MCMC is the most popular computational method used to compute posterior distributions in Bayesian statistics (Hosmer et al., 2013, p. 409). MCMC can be described as a 'random walk' around the posterior distribution of parameters, where a sequence of values are selected in sequence from an approximate

distribution, with each selection depending on the previous value. The approximate distributions are improved at each step in the simulation, in the sense of converging to the target distribution (Gelman, 2014). It is only through a robust solver such as MCMC that most multilevel regression and Bayesian inference is possible (Hosmer et al., 2013, p 409; McElreath, 2015, p 360).

5. **Logistic Regression –** A form of regression model where the response variable to be explained or predicted is discrete and takes a binary or dichotomous form. The methods for logistic regression follow the same general principle as linear regression, with changes to the form of the model and its assumptions. For example, a binomial distribution rather than a Gaussian distribution describes the distribution of the errors. The link function for logistic regression is the logit link function or logistic transform (Equation 2which maps the binomially distributed probability density (p_i) onto a linear model by taking the log of the odds of the event.

6. **Multilevel Model –** Multilevel or hierarchical models are not unique to Bayesian statistics, but they are easily implemented under a Bayesian approach. They allow for analysis of hierarchical data by including parameters to model variations at different levels of data. Observations are assigned categorical group membership, and the models identify effects at both the population-level, based on all observations, and the group-level, based on groups or clusters of wells (Gelman and Hill, 2007, p 237). Some of the benefits of multilevel models include their ability to adjust estimates for repeated or imbalanced sampling, and to study variation between groups of individuals to avoid averaging across groups (McElreath, 2015, p 14).

7. **Information Criteria –** Information criteria metrics such as AIC, DIC, and WAIC, are used to compare the predictive accuracy of several models trained on the same data, by estimating their out of sample deviance (Gelman, 2014, p 173; Vehtari et al., 2017). Information criteria are commonly used for model selection or model averaging. During model selection, the model with the lowest information criteria is typically selected as the "best" model (McElreath, 2015, p. 196). Model averaging means using information criteria to construct a posterior distribution based on several models and knowledge of their relative accuracy Model averaging involves averaging of predictions, rather than averaging parameter values (McElreath, 2015, p. 196). This method allows the uncertainty of each model to be carried through, avoiding overconfidence in results. By using information criteria to focus on the relative accuracy of models, Bayesian statistics are able to move away from traditional methods of model evaluation such as significance testing or goodness of fit tests.

MODEL DESCRIPTION

A logit link function was used to estimate the binomially distributed probability (p_i) of the presence of GM (y_i) at a given well (i) (Equation 1). The response was modeled with a multilevel linear model, which included population-level intercepts (α), group level-intercepts (α_k), population-level effects (β_j) for each exploratory variable (j), and group-level effects $(\beta_{j,k})$ for select explanatory variables (j) and each group (k). The group-level effects $(\alpha_k, \beta_{j,k})$ are defined by a multivariate Gaussian distribution, and covariance defined by a matrix including variances $(\sigma_{\alpha,k}, \sigma_{\beta,k})$ and a correlation matrix with the correlation between the intercepts and slopes (ρ). The logit link function maps the probability density onto the linear model by taking the log of the odds of the event, the odds being the ratio of the probability of an event occurring to the probability of it not occurring (Equation 2).

Equation 1. Example of a generic multilevel model with a two-dimensional covariance matrix (for one group-level explanatory variable)

$$y_i \sim Binomial(1; p_i) \tag{2.1.1}$$

$$logit(p_i) = \alpha + \alpha_k + (\beta_j + \beta_{j,k})x_{i,k} \tag{2.1.2}$$

$$\begin{bmatrix} \alpha_{k[i]} \\ \beta_{k[i]} \end{bmatrix} \sim MVNormal(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, S) \tag{2.1.3}$$

$$S = \begin{pmatrix} \sigma_{\alpha,k} & 0 \\ 0 & \sigma_{\beta,k} \end{pmatrix} \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \begin{pmatrix} \sigma_{\alpha,k} & 0 \\ 0 & \sigma_{\beta,k} \end{pmatrix} \tag{2.1.4}$$

Equation 2. Logit link function

$$logit(p_i) = log \frac{p_i}{1 - p_i} \tag{2.2}$$

Weakly informative or regularizing prior probability distributions were assigned to each model parameter, to help constrain the parameter estimates within a reasonable range and improve the efficiency of the MCMC sampling process. Continuous variables were centered and scaled prior to analysis so that coefficients could be interpreted on the same scale. Markov chains were run with 5000 samples each, including 1000 warmup samples. MCMC convergence was assessed based on diagnostic parameters and visual inspection of plotted chains.

To assess and compare different models of GM, we used the Widely Accepted Information Criterion (WAIC; (Watanabe, 2010)). A model's WAIC value is a measure of its expected out of sample deviance, which is a widely adopted model comparison metric in Bayesian analysis (Gelman, 2014, p. 173; Vehtari et al., 2017). Model fits were compared using WAIC values, and the mean and 95% prediction intervals of the coefficients' posterior probability distributions were reviewed and plotted to assess effects and significance.

Based on the WAIC values, an Akaike weight was determines for the preferable models, which is interpreted as an estimate of the likelihood that a given model makes the best predictions on new data. Akaike weights are normalized across the set of candidate models to sum to one and are interpreted as probabilities (Johnson and Omland, 2004; McElreath, 2015, p 199). Rather than selecting a single final model, the information and uncertainty from several models was maintained by generating model-averaged predictions (Dunson, 2006; McElreath, 2015, p. 203). The model-averaged predictions of the probability of GM were generated by sampling from the posterior probability distributions of each of the best models in proportion to their assigned Akaike weights using the inverse logit-link function. Predictions were used (1) to compare the observed proportion of wells with GM to the predicted probability of GM for each explanatory variable (2) to predict the probability of GM for each well in the dataset to compare to its reported GM status.

Weakly informative or regularizing prior probability distributions were assigned to each model parameter, to help constrain the parameter estimates within a reasonable range (Table 4). Examples provided in McElreath's text (McElreath, 2015) were used to inform the selection of prior probability distributions. Priors that center the probability around zero are considered weak, and when posterior distributions have non-zero probabilities, it indicates that the empirical data provides contravening evidence to the weak prior. When the posterior distributions are close to zero, reflecting the weak prior, it indicates that the data is not informative about the parameters (Koster and McElreath, 2017). Priors also improve the efficiency of the MCMC sampling process by preventing the MCMC from considering highly implausible values (Koster and McElreath, 2017).

Table 4 Summary of Prior Probability Distributions assigned to Model Parameters

Model Parameter	**Type of Distribution**	**Prior Parameterization**	**Prior Probability Distribution**
Population-level intercept (α)	Normal or Gaussian	Mean (μ_α) = 0 Variance (σ_α) = 5	**Generic:** $\alpha \sim Normal(\mu_\alpha, \sigma_\alpha)$ **Final:** $\alpha \sim Normal(0,5)$
Population-level effects (β_j)	Normal or Gaussian	Mean (μ_β) = 0 Variance ($\sigma_{\beta,j}$) = 5	**Generic:** $\beta_j \sim Normal(\mu_\beta, \sigma_{\beta,j})$ **Final:** $\beta_j \sim Normal(0,5)$
Standard deviations within covariance matrix ($\sigma_{\alpha,k}$, $\sigma_{\beta,k}$)	Half Cauchy	Location ($x\|x_0$) = 0 Scale (γ) = 2	**Generic:** $\sigma_{\alpha,k}, \sigma_{\beta,k} \sim HalfCauchy(x\|x_0, \gamma)$ **Final:** $\sigma_{\alpha,k}, \sigma_{\beta,k} \sim HalfCauchy(0,2)$
Correlation matrix R = $\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$	LKJ Correlation	Shape (η) = 2	**Generic:** $R \sim LKJcorr(\eta)$ **Final**: $R \sim LKJcorr(2)$

Appendix C Reservoir Gas Pressure Data

Reservoir pressure test data was obtained from Accumap, and data was filtered for pressure tests performed within a single unit, with complete information, shut-in time greater than 36 hours, and the first test performed in each well completion (indicating the initial reservoir pressure at that location).

The test depth was used to establish the pressure gradient from the formation to the ground surface in kPa/m. Initial pressure gradient estimates were summarized by formation and oil and gas area are plotted in Figure 3 below. Initial pressure gradient estimates for wells within the Jean Marie Area are plotted in Figure 4 below. Initial Pressure gradient estimates for individual wells in the Jean Marie Area and the surrounding area are plotted in Figure 5 below. Formation codes can be found in

Under the assumption that the groundwater table is near the ground surface, formations that had more than one test in each area and mean pressure gradients above 9.8 kPa/m were considered overpressured, relative to hydrostatic pressure, in that area.

The potentially overpressured formations identified in each oil and gas area were:

- Liard Basin: Besa River, Evie Lake, Kotcho, Muskwa, Otter Park.
- Fort Nelson Plains: Elkton, Evie Lake, Klua, Lower Debolt, Muskwa, Otter Park.
- Fort St. John: Banff, Montney, Slave Point, Shunda.
- Deep Basin: Doig, Montney.
- North Foothills: Doig, Charlie Lake, Montney.
- South Foothills: Doig, Kiskatinaw, Montney.

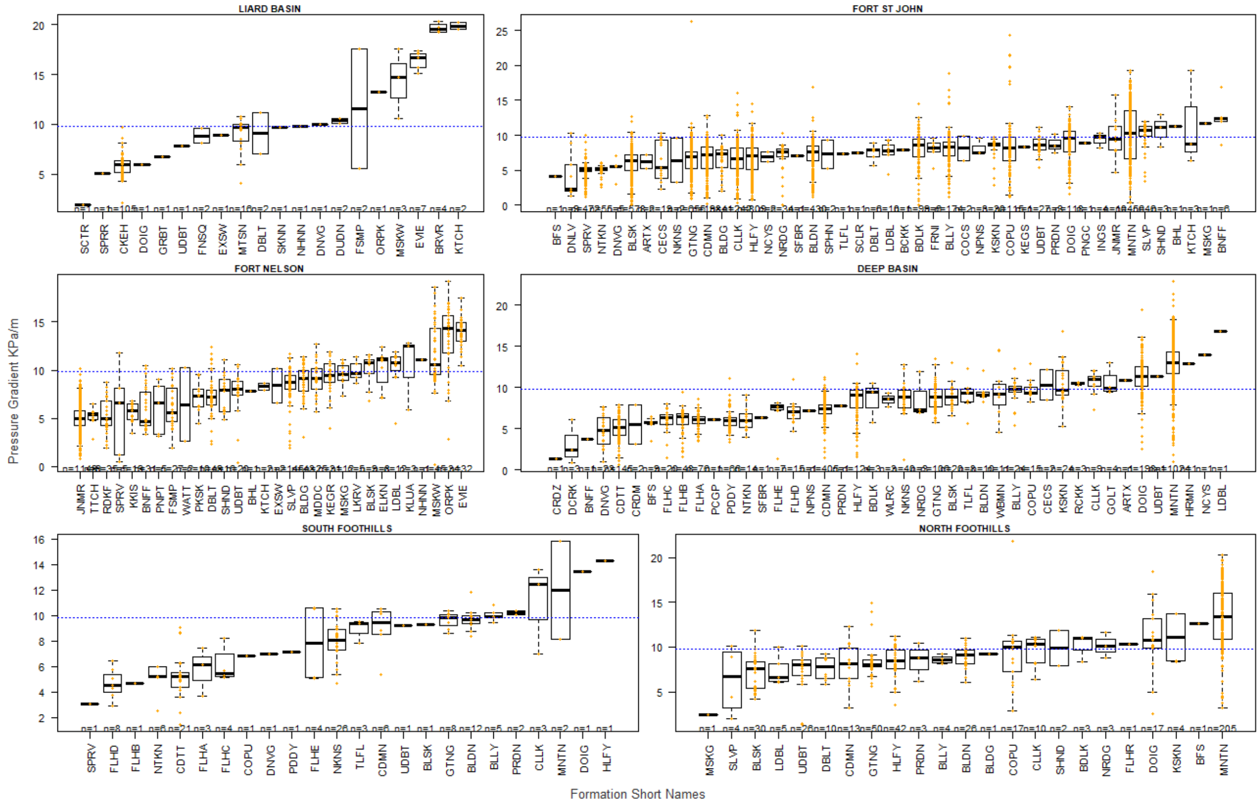

Figure 3 Formation Pressure Gradients to Ground Surface in Each Oil and Gas Area. Formation abbreviations correspond to formations in British Columbia Oil and Gas Commission, (2018b).

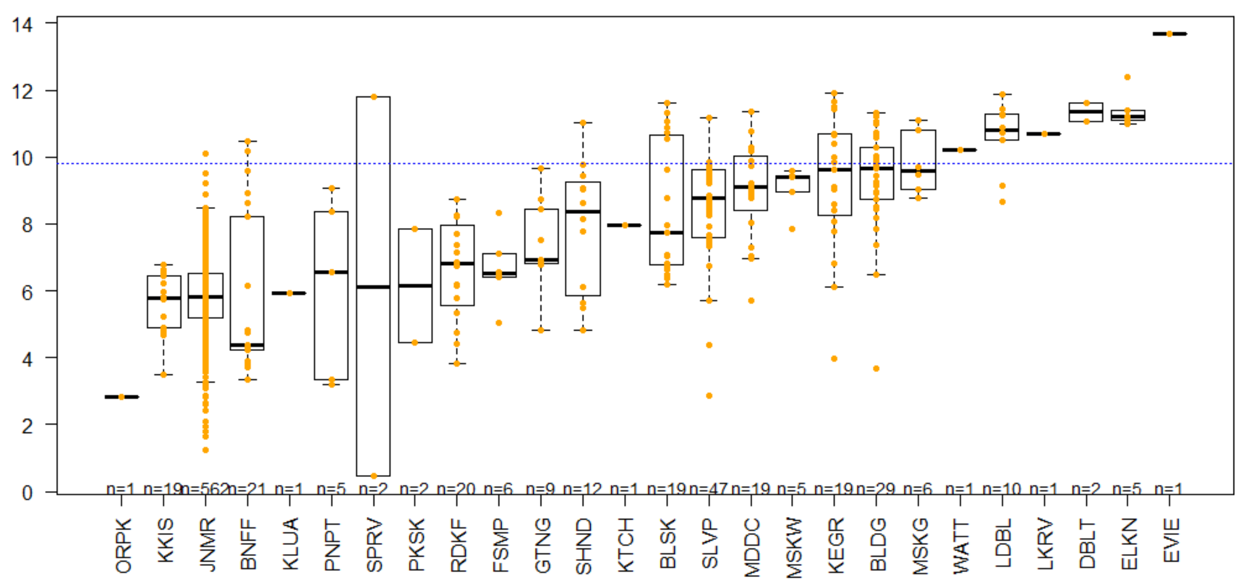

Figure 4 Formation Pressure Gradients to Ground Surface in the Jean Marie Area. Formation abbreviations correspond to formations in British Columbia Oil and Gas Commission (2018b).

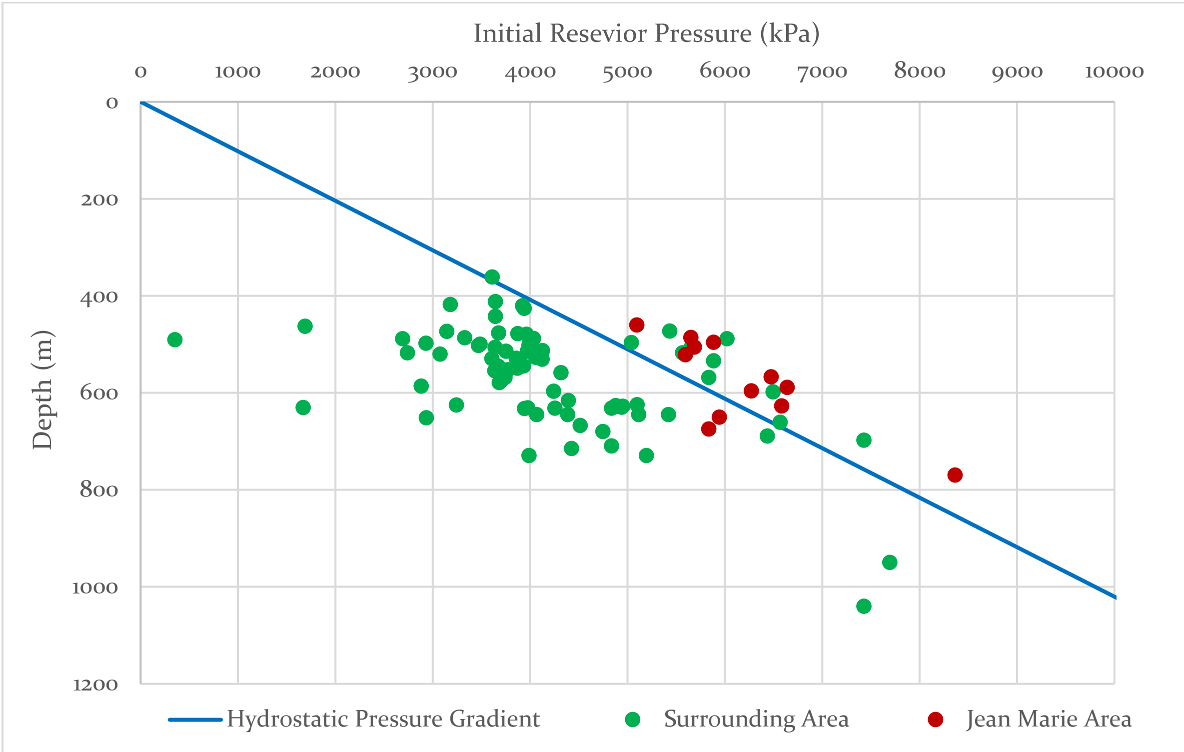

Figure 5 Lower Debolt Formation initial reservoir gas pressure measurements in the Jean Marie Area and the surrounding area.