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Spatial and temporal patterns of the industrial footprint in northeast Alberta, 1960-2000

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Abstract

We analysed landscape-scale statistical relationships between various components of cumulative industrial development within a 100,000km^2 study region of boreal forest in northeast Alberta, Canada. We measured the "industrial footprint" by the densities of drilled wells, seismic lines, pipelines and industrial and Provincial roads on ~10,000ha landscapes defined by the Provincial township grid. Densities of all feature classes were strongly intercorrelated. We developed univariate regression models of linear feature densities using well density as an independent variable, using various transformations to improve normality and linearity. The natural logarithm of drilled well density explained from 32 to 48% of the variance in the transformed densities of seismic lines, roads, and pipelines. The relationships between well and linear feature densities were highly non-linear. Dynamic models should not assume a constant of proportionality between feature densities. We used principal components analysis (PCA) of model residuals to explore linear dependency among the variables. No dependency was found but PCA proved to be a useful tool to uncover associations between the response variables. The PCA analysis revealed the following underlying linear combinations: (1) the total excess or deficit of scaled linear feature densities relative to well density; (2) a contrast between relative seismic line and pipeline densities; and (3) a contrast between relative road and pipeline densities. These components could be used in the design of landscape scale studies or in the analysis of landscape scale ecological datasets. We also present statistical and descriptive analysis of spatial and temporal patterns in well density in the study region over the interval 1960—2000, with applications to spatial dynamic modelling and the establishment of ecological benchmarks.

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1   Introduction

Schneider (2002) and Schneider et al (2003) characterized the cumulative regional effects of industrial activity in the boreal forests of northern Alberta, Canada. The primary regional actors are the forestry and energy sectors. The most conspicuous results of their combined activities are rapidly growing networks of so-called linear features, or long narrow openings in the forest, and an increasing density of clearings, or localized compact openings surrounding units of physical infrastructure. These openings have been collectively referred to as the "industrial footprint." Here we present a description and statistical analysis of the spatial and temporal pattern of this footprint, at a regional extent and landscape resolution (~10,0000 ha or 100 km^2). The study region was ~100,000 km^2 of boreal forest in northeast Alberta. In this case, the spatial units of analysis were townships. We considered four classes of linear features: seismic lines, pipelines, industrial and Provincial roads, and the most abundant class of industrial clearings, well sites.

Well sites are typically 1ha square clearings surrounding an active oil or natural gas well (Figure 1a, b). **Seismic lines** are narrow corridors (~5m in width) constructed as temporary access routes for the detection and delineation of subsurface hydrocarbon reservoirs by reflection seismology (Figure 1a). Wells and intermediate processing facilities (e.g. compressor stations) are connected by a dendritic network of **pipelines** that ultimately export the resources to markets in the south. Most pipelines are buried, but the surface rights-of-way are prevented from regenerating to forest in order to facilitate access for maintenance or emergencies. Pipeline rights-of-way are typically 25m in width. **Industrial roads** are a broad category of access corridors constructed for various purposes by both the energy and forestry sectors. Well sites and other remote installations require road access for periodic inspection and maintenance. The forestry sector must construct a pipeline-like network of primary and
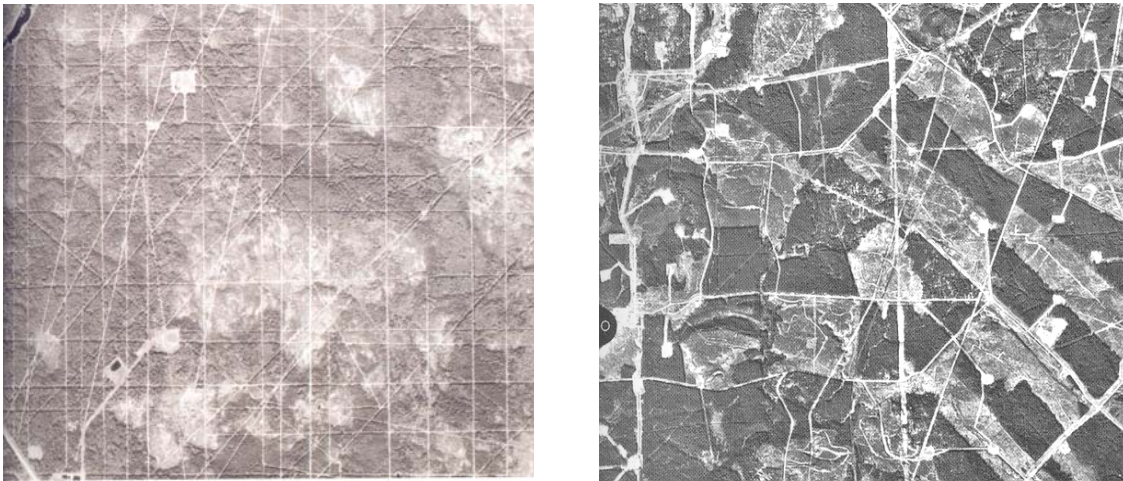
- Figure 1. Typical patterns of linear features in northeast Alberta. Left, a moderately dense network of seismic lines with 3 well sites connected by roads. Right, a more developed area with major roads and/or pipeline rights-of-way, overlain by forest harvesting. Both images are approximately 2km square. (Photos are property of the Province of Alberta, protected by the Copyright Act of Canada. Reproduced by permission of Alberta Sustainable Resources Development, Air Photo Distribution.)

lower-order haul roads terminating within individual cut-blocks (Figure 1b). The width, quality and notional permanence of industrial roads is highly variable. **Provincial roads** are permanent all-weather public highways. The density of these roads is low in the Alberta boreal forest because there are few towns or other permanent settlements. In northeastern Alberta, there are only four main highways, and two of these terminate near Ft. McMurray. For more complete descriptions of these features and the history of their development in Alberta, see the documents cited above. The World Resources Institute (2000) provides a continental perspective.

The density and prevalence of linear features and related disturbances are projected to increase rapidly throughout the western boreal forest, if industrial development continues (Schneider et al. 2003). This is of serious concern for the following reasons. The total area of productive forest alienated by these features may become large enough to threaten the sustainability of present levels of timber harvest (Schneider et al. 2003). Direct negative effects of linear features have been demonstrated for e.g. woodland caribou (Dyer et al 2001). Linear features have been shown to effect dispersal or other behaviours of several species of forest songbird, with potentially negative population-level consequences (St. Clair, 2003 and references therein). Recent landscape-scale studies in the Alberta boreal forest have found significant negative correlations between the density of the industrial footprint and the relative abundances of fisher and some forest songbirds (Schneider et al. 2002, Figs 5.10-11). Linear features facilitate human access to formerly remote areas, exposing game species to increased hunting or fishing pressure, both legal and illegal. Landscape road density has also been correlated with the frequency of human-caused fires in northern Alberta (S. Cumming, unpublished). All parties in the management of boreal forests recognise the need to predict the effects of a growing industrial footprint on such indicators. When the individual or cumulative effects of linear features are imprecisely known, they must first be estimated from existing conditions. For many indicators, this can be done by observational or manipulative landscape-scale studies. Such studies need maps of appropriate covariates.

Mapping the present-day spatial distribution of linear features in Alberta is a major undertaking because no central authority maintains the necessary records in any convenient form. For the same reason, and also because of the sheer rate of new developments, such maps are difficult to maintain once built. Reconstructing a time series of maps from the pre-industrial era (c. 1950) to the present day may well be infeasible. In comparison, maps of well site density are easy to develop and maintain, and time series maps can be assembled from published data (e.g. SRD 2003). Also, the abundance and distribution of well sites may prove to be key state variables in simulations of energy sector behaviour (e.g. Schneider et al. 2003). Statistical relations between the densities of well sites and other feature classes could be of value for retrospective studies and for simulation modelling.

Multiple feature classes are already present at some density in most landscape units in the study area, and their densities are strongly correlated at the landscape scale. The ecological effects of individual feature classes are therefore difficult to disentangle. A set of independent, but interpretable variables might be useful in the design and analysis of landscape-scale studies. The specific objectives of this study were to:

- Describe the spatial distribution of various classes of linear features, and well sites, in northeast Alberta;

- Evaluate the nature and strengths of univariate statistical relations between the densities of well sites and linear features;

- Develop a set of independent measures of linear feature density that are also independent of well site density.

As a second component of the study, we undertook a preliminary exploration and analysis of the spatial and temporal patterns in drilled well abundances, from 1960 to 2000.
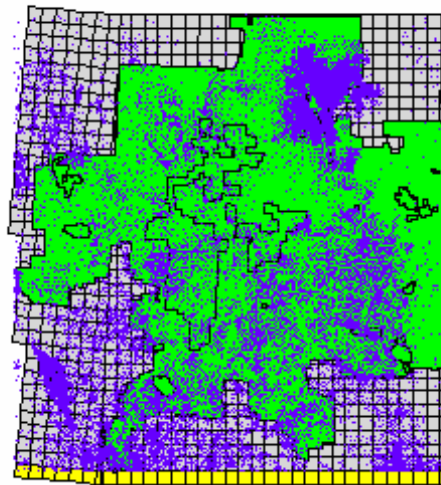
- Figure 2. Area containing townships selected for this study (NW corner: 100.07.5; NE corner: 100.01.4; SW corner: 065.06.5; SE corner: 065.03.4). From O'Neill 2001.

2 Data and Methods

2.1 Study region, data sources, exclusions, and transformations

The dataset for this study was derived from a spatial coverage of various classes of linear features over a large study area in northeast Alberta, assembled by or on behalf of Alberta Pacific Forest Industries Inc. The data are considered valid and complete as of no later than October 1998 (O'Neill 2001). The spatial data were intersected with the Alberta Township grid (Figure 2). After this intersection, the total length of each linear feature class in each township was determined by GIS analysis and then divided by total township surface area. The results were exported as densities of seismic lines (s), industrial roads ($r.i$), provincial roads ($r.p$), and pipelines ($p.i$) in units of km/km^2. The raw densities of the four linear feature classes are mapped in Figure 3. In some applications it may not be possible to distinguish the two road classes. Therefore we defined an additional variable for total road density, $r = r.i + r.p$. We note that estimated densities of industrial roads and seismic lines are confounded since some roads are created from upgraded or improved seismic lines (O'Neill 2001). Where the GIS attributes allowed, the data were post-processed to eliminate such over-representation of features, but these corrections are known to be incomplete.

The locations and year of origin of all drilled wells were assembled from Provincial archives and linked to the township grid. Well densities were exported as cumulative counts per township at five-year intervals from 1960 through 2000 (Figure 3e). Total well counts and annual increments over the entire study region were computed for the interval 1960—2000.

The study area (Figure 2) was approximately rectangular, bounded on the southeast at 54°30'N 110°W and on the northwest at 57°40'N 115°W. It included 1,171 townships. We excluded townships in the "white zone" or agricultural land on the southern edge of the study region. These landscapes have a relatively high density of provincial roads (e.g. bottom centre of Figure 3c) and represent a distinct population where the main surface activity is agriculture, not forestry. We also excluded a small number of forested townships that had a total terrestrial surface area less than 2000ha, based on total township surface area and area of permanent water bodies estimated from Alberta Phase 3 Forest Inventory data. After these exclusions, 1,053 townships remained with a total area 100,003 km^2 of which 3,748 km^2 was open water. The total area of dry land was 96,549 km^2 and the mean proportion of dry land per township was 0.962. The distribution of this proportion was skewed (q^{75}=0.996, q^{50}=0.985, q^{25}=0.961, q^{10}=0.909). We renormalized the raw linear feature densities as lengths per unit area of dry land, in units of km/km^2. Raw well counts per township were converted to densities with units of wells/10,000ha dry land. We use the symbol 'w' to refer to the normalized well densities.
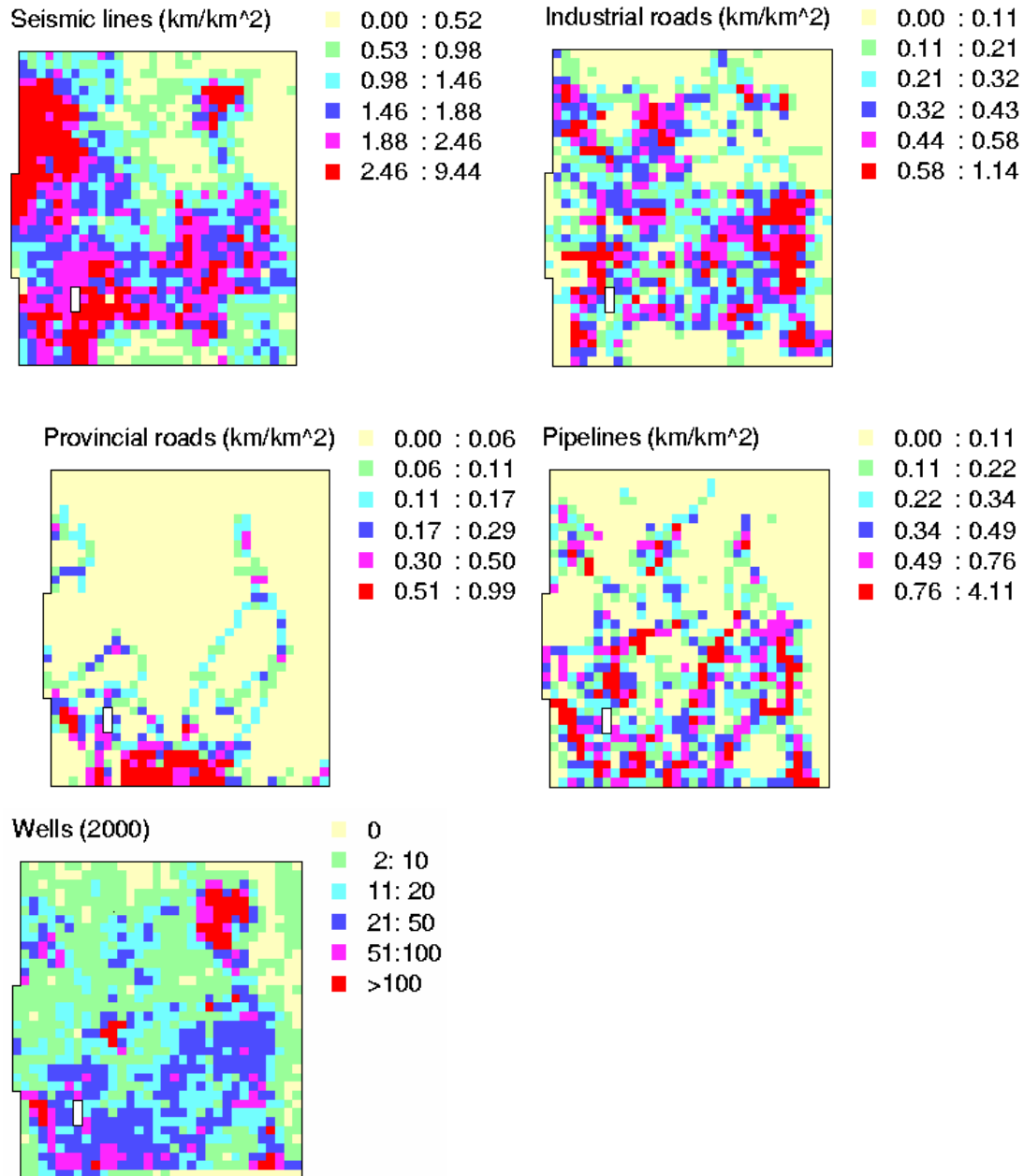
- Figure 3. Approximate densities per township of a) seismic lines, b) industrial roads, c) provincial roads, d) pipelines, and e) wells, as of 2000. Note that scales differ.

The variables display varying levels of skew (Figure 4), mainly due to the large number of townships that had true zero densities of one or more feature (Table 1). To allow for logarithmic transformations, true zeros were replaced with small positive values as indicated in the table. Log-transformation of well densities removed much of the skewness (Figure 4). The transformed value $\log(w)$ is used in all subsequent analyses. The summaries of the distributions (Table 2) indicate that there may be outliers for seismic lines, provincial roads, and pipelines since the maximum values are noticeably far away from their respective medians. Also of note is that log-transformed pipeline density has a high variance.

- Table 1. Number of townships with true zero densities, by feature class. The value Zero is substituted for true zeroes when taking logs.

Variable	True zero densities	Proportion	Zero
Well density	104	9.9%	0.5
Seismic line density	24	2.3%	0.0020
Industrial road density	172	16.3%	0.0005
Provincial road density	829	78.7%	0.0005
Pipeline density	444	42.2%	0.0005

- Table 2. Summary of the distributions of well and linear feature densities and the transformed values used in the statistical analysis.

	Min.	Median	Mean	Max.	Var.
$\log(w)$	-0.689	2.402	2.182	6.780	2.384
s	0.002	1.442	1.563	9.496	1.231
$r.p.$	0.000	0.000	0.029	0.754	0.006
$r.i.$	0.000	0.242	0.273	1.157	0.055
$p.i.$	0.000	0.064	0.219	4.058	0.140
$\mathrm{sqrt}(s)$	0.045	1.201	1.161	3.082	0.217
$r=(r.p+r.i)$	0.001	0.259	0.302	1.286	0.065
$\log(p.i.)$	-7.601	-2.744	-4.077	1.401	9.905
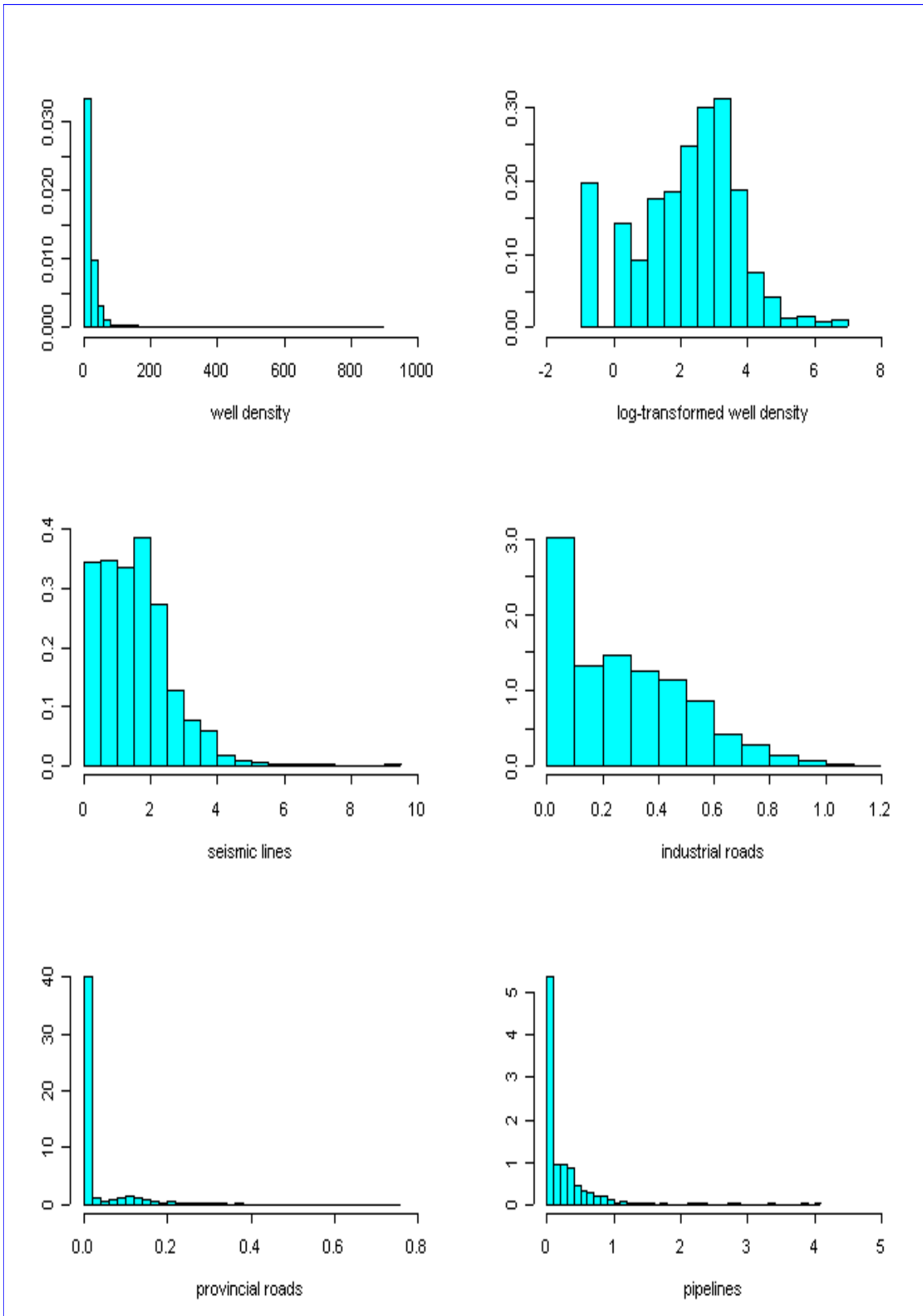
- Figure 4. Histograms of well density, log-transformed well density, seismic line density, industrial road density, provincial road density, and pipeline density. All densities are normalized as explained in the text.

2.1.1   Outliers

We had initially assumed that most recorded wells were associated with individual well sites, or 1 ha clearings, as in Figure 1. The density of well sites is limited by regulation to a maximum of 1 per quarter section (Bauwens 1999), so the maximum number of well sites per township is 144. However, some well sites may contain multiple drilled wells. Moreover, not all wells are for the purpose of extracting conventional oil or gas reserves. Wells are also drilled for the extraction of heavy oil deposits, or the delineation of oil sand deposits. These wells are not necessarily associated with permanent clearings and can occur at very high densities. We could not distinguish the different types of wells given the data available. Townships with high well counts might be outliers with respect to the desired statistical relations between well and linear feature densities. Of the 21 townships with the highest well counts (from 154 to 728), 15 were clustered around Ft. McKay, in the northeast of the study region (Figure 5). The primary GIS consultant overlaid well locations on recent orthophotos for seven of these townships, and we closely examined three of these (e.g. Figure 6). The main conclusions were:

1)   Many wells in the northeast of the study region were established to delineate reserves of heavy oil or tar sands for surface or subsurface mining:

2)   Most of the these wells are not associated with 1ha clearings, or well-sites;

3)   The density of linear features associated with these wells is relatively high.

We therefore assumed that our analysis would not be invalidated by measurement error in the number of wells-sites per township.
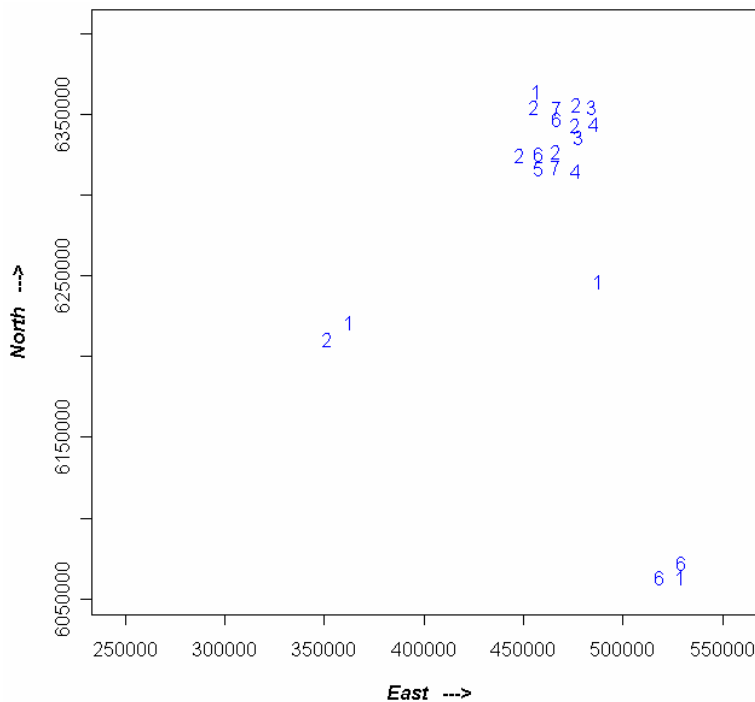
• Figure 5. Townships with more than 144 wells: codes are multiples of 100 wells.

• Figure 6. The southwest quarter of township 096.10.4 showing the industrial footprint. Wellheads are represented by yellow dots. The township has a total of 749 wells. (Photo: Alberta Pacific Forest Industries Inc.)

2.1.2 Relationship between well counts and well sites.

We estimated the number of well sites in each township by counting the number cl of small clearings (<2 ha) mapped by the Alberta Phase 3 forest inventory. Although not all well sites are assigned a Phase 3 polygon, and not all small mapped clearings are in fact well sites, no other estimates of well-site abundances were readily available. There was a significant linear relationship between w and cl on a log-log scale:

$$\log(w) = 1.75 + 0.70 \log(cl + 0.5)$$

($R^2 = 0.27$, $w < 144$, n = 1030; Figure 7). A linear model fit poorly in comparison ($R^2 = 0.15$). As the Phase 3 inventory was interpreted from aerial photography flown mostly between 1978 and 1984, we also evaluated the relation between cl and the per-township well counts as of 1980 ($w80$, not log-transformed). As expected, these two variables were more highly correlated and adequate linear models could be fit after values in the 9th decile of $w80$ (>50) were excluded, e.g.,

$$w80 = 1.52 + 1.19\ cl$$

($R^2 = 0.38$, $w80 < 50$, n=1021). We concluded that the densities of drilled wells and well sites are approximately equal at the landscape scale for most of the study region.
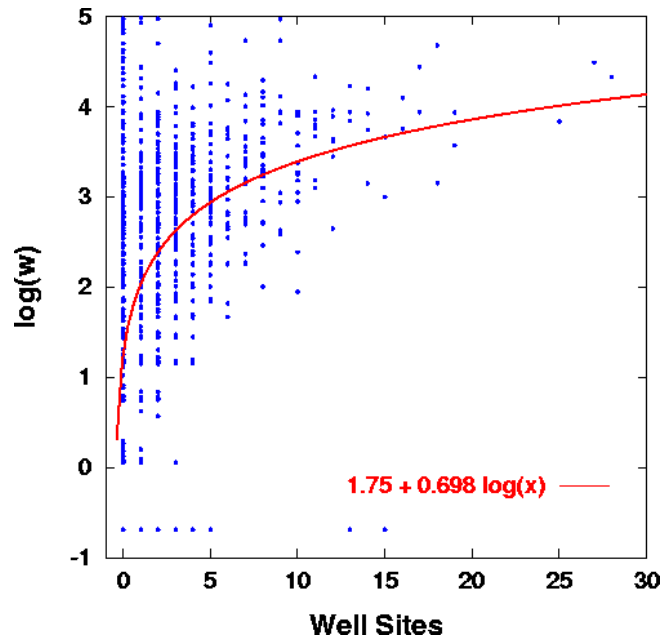
- Figure 7. Relation between log (*w*) and the number of well sites/township (*cl*) as estimated from Phase 3 inventory data.

2.2   Univariate statistical models

The densities of linear features and drilled wells are strongly inter-correlated at landscape scales (Table 3). The reported correlation coefficients are all significant ($p < 0.001$) after accounting for the effects of spatial autocorrelation. Total road density *r* was more strongly correlated with log(w), *s*, and *p.i.* than either *r.i* or *r.p* alone. It is important to remember that the correlations between *s* and *r* or *r.i.* are inflated as some industrial roads are created from modified seismic lines. In many cases, Spearman rank correlation coefficients were higher that the Pearson correlation coefficients (Table 3), indicating that the relations between linear feature density and log(*w*) are non-linear.

We developed univariate linear regression models relating the densities of each linear feature class to log(*w*). Because of the evidence of non-linearity we evaluated a number of common transformations of the dependent variables (e.g. square-root, log, inverse). In some cases, when bivariate scatter plots indicated more complex relationships, we fit polynomial models (e.g., y $\sim \beta_0 + \beta_1 * x + \beta_2 * x^2$). We evaluated model fit by R^2, residual plots, and normality plots. Model residuals are obtained by subtracting the fitted values $\hat{y}$ from the observed values (i.e., $y - \hat{y}$). Positive residuals signify that there is a higher density of the linear feature than predicted by the model, given the well density. We examined residuals plotted against fitted values to see if variance increased or decreased with increased $\hat{y}$ or if the sign of the residuals changed with $\hat{y}$. Because model errors must be normally distributed for ordinary least squares regression, we examined normality plots of residuals for deviations from the line that passes through the first and third quartiles. The R software system (Leisch 2003) was used for all statistical analysis.

- Table 3 Pair-wise correlation coefficients of linear feature and well densities.

Pearson correlation coefficients					
	log(w)	s	$r.p.$	$r.i.$	$p.i.$
S	0.487				
$r.p.$	0.312	0.220			
$r.i.$	0.612	0.419	0.115		
$p.i.$	0.492	0.244	0.516	0.464	
R	0.657	0.452	0.406	0.955	0.581
Spearman correlation coefficients					
	log(w)	s	$r.p.$	$r.i.$	$p.i.$
S	0.532				
$r.p.$	0.379	0.364			
$r.i.$	0.674	0.507	0.218		
$p.i.$	0.740	0.434	0.421	0.650	
R	0.721	0.549	0.408	0.966	0.709

2.2.1 Marginal increments in linear feature densities

The marginal increase in linear feature density is the increase that results from adding one additional well to a township. The marginals can be interpreted as development costs. Given a univariate regression model $y = f(w)$, where y is linear feature density and w is well density, the marginal increase is the derivative d $f(w)$/d w of the regression equation f with respect to w. If f is a linear function of w, then the marginal increase is constant, independent of the initial value of w. For example, if $y = a + bw$, the constant marginal increase is the coefficient b and b units of feature are added to a landscape per additional well. However, our models are non-linear in w because of our use of the logarithmic and other transformations. One would expect that as e.g. landscape road and pipeline density increases, the length of additional feature required to service new wells would decline. We calculated the derivatives of the final univariate models, mapped the present spatial distributions of marginal increases over the study region, and estimated the present regional averages for landscapes in various stages of development.

2.3 Principal components analysis of model residuals

The residuals of correctly specified models are linearly independent of the independent variable. Thus, the residuals of the univariate statistical models should measure excesses or deficits in landscape linear feature densities, given log(w). However, the model residuals are not necessarily independent of each other. Moreover, simply taking residuals does not reduce the number of variables (here 4 or 5) required to measure the industrial footprint. A reduced set of independent variables could be of value e.g. in landscape-scale studies where samples sizes are usually small. We therefore conducted a principal components analysis (PCA) on the model residuals for seismic line, pipeline and total road densities. The

resulting 3 principle components are independent linear combinations of the residuals. The analysis should reveal secondary structures or sub-dimensions within the data if these are present (Linacre 1999). A reduced set of variables may emerge if the residuals are strongly inter-correlated. In that case, 1 or 2 principle components may adequately describe joint variation in the residuals. Alternatively, interpretation of the variable loadings might identify a subset of components that are most relevant to a particular study.

2.4   Spatial and temporal dynamics of well density

We explored spatial and temporal patterns in the total abundance and distribution of drilled wells at both regional and landscape scales, using a variety of graphical and statistical methods. At regional scale and annual resolution, we examined trends in cumulative total well counts and in annual increments and per-capita rates of increase for the interval 1960-1999. Preliminary analysis suggested that standard models of population dynamics could describe the data. Accordingly, we fit variants of the discrete exponential growth model

$$W(t+1) = r\ W(t)$$

where $W(t)$ is the total number of drilled wells in year t and r is the per-capita rate of increase. To allow for random variation, we fit stochastic models by Poisson regression on the observed annual increments in $W(t)$.

To gain some insight into the underlying processes of exploration and development, we mapped per-landscape total well counts at 10yr intervals from 1960-2000. We also mapped per-landscape 10yr and 5yr increments over the same period. The maps distinguish periodic increments to landscapes initially with and without wells, to allow for visual comparison between patterns of initial exploration and subsequent development activity. We summarised these dynamics at a regional scale by measuring the number and proportion of townships with and without wells, the periodic loss rates of well-free townships, and the periodic activity rates, or the proportion of townships with wells to which new wells were added. Townships that remained well free c. 2000 or that had been inactive for long periods (e.g. 20yr) might be candidates for new protected areas or landscape scale ecological benchmarks, if the probability of future exploration and development there is low. To assess this, we modelled 5yr loss and activity rates from 1960—2000 using logistic regression (or binomial GLMs). We also compared the industrial footprint in active, inactive and well free townships as of c.2000, using various measures of well and linear feature density.

Finally, we examined temporal trends in well counts at the landscape scale. We assumed that the number of potential drilled wells per township was limited and hypothesised that, after initial access, the cumulative totals would follow an approximately logistic function in time. We plotted cumulative total well counts for over the interval 1950-1999 for 20 randomly selected townships, to check for evidence of logistic growth and of decreasing increments at high well densities. To test for a unimodal relationship between periodic increments and initial well density, we fit a Poisson GLM to 5yr increments and initial counts to data from 1004 townships with 1990 well counts $\leq$ 144. Initial well counts >144 were removed because they were outliers that greatly influenced model fit.

3   Results

3.1   Linear models

3.1.1   Seismic lines and well density

The relationship between normalised seismic line and well densities is clearly non-linear (Figure 8 upper left). A linear regression model explained relatively little variance ($R^2 = 23.7\%$) and a normality plot revealed moderate violation of the normality assumption. A model using $\log(s)$ as the dependent variable had an R^2 of 30.7% but the normality plot indicated severe violation of the assumption of normal distribution of errors. A linear regression of $\sqrt{s}$ against $\log(w)$ (Figure 8. upper right, Table A.1) fit slightly better ($R^2 = 31.7\%$) but the residuals were much more evenly distributed. Higher fitted values seemed to be associated with negative residuals (Figure 8, lower left), suggesting that these data points might be outliers. The normality plot (Figure 8, lower right) shows the model residuals to be approximately normally distributed. We explored other transformations of s, but these did not result in improved models. To test for possible outliers, we refit the model using only data where $w \leq 144$: the intercept was not changed and the slope coefficient increased only marginally to 0.18. Model selection and parameter estimates were not strongly influenced by landscapes with high well counts.

3.1.2   Roads and well density

Total road density r was more highly correlated with well density than either industrial or provincial roads alone (Table 4, $R^2 = 43.15\%$). The relationship between r and $\log(w)$ was approximately to be linear (Figure 9, upper right, Table A.2) and linear model residuals evenly and approximately normally distributed. A third-order polynomial in $\log(w)$ significantly improved the fit ($R^2 = 48.26\%$, Figure 9, upper right, Table A.3). As above, appropriateness of this model was supported by residual and normality plots (Figure 9). Other transformations on r yield improved models. Landscapes with raw well counts > 144 did not affect model selection and had negligible influence on parameter estimates. The best model of industrial road and well densities was also a cubic polynomial in $\log(w)$, but explained less of the variance ($R^2 = 43.12\%$, Table A.4).

3.1.3   Pipelines and well density

Pipeline density pi was not linearly related to $\log(w)$ (Figure 10, upper left, $R^2 = 24.19\%$) and linear residuals were non-normal. A linear regression of $\log(pi)$ against $\log(w)$ was a better fit ($R^2 = 46.37\%$, $p < 0.001$, Figure 10, upper right). Alternate transformations of pi and polynomial models did not improve model fits and/or degraded regression diagnostics. Again, the residual plot (Figure 10; lower left) hi-lighted northeast townships with high well counts but few or no pipelines (see e.g. Figure 11c, below). In this case, these points may be influential: they decreased the slope coefficient from 1.53 to 1.39.
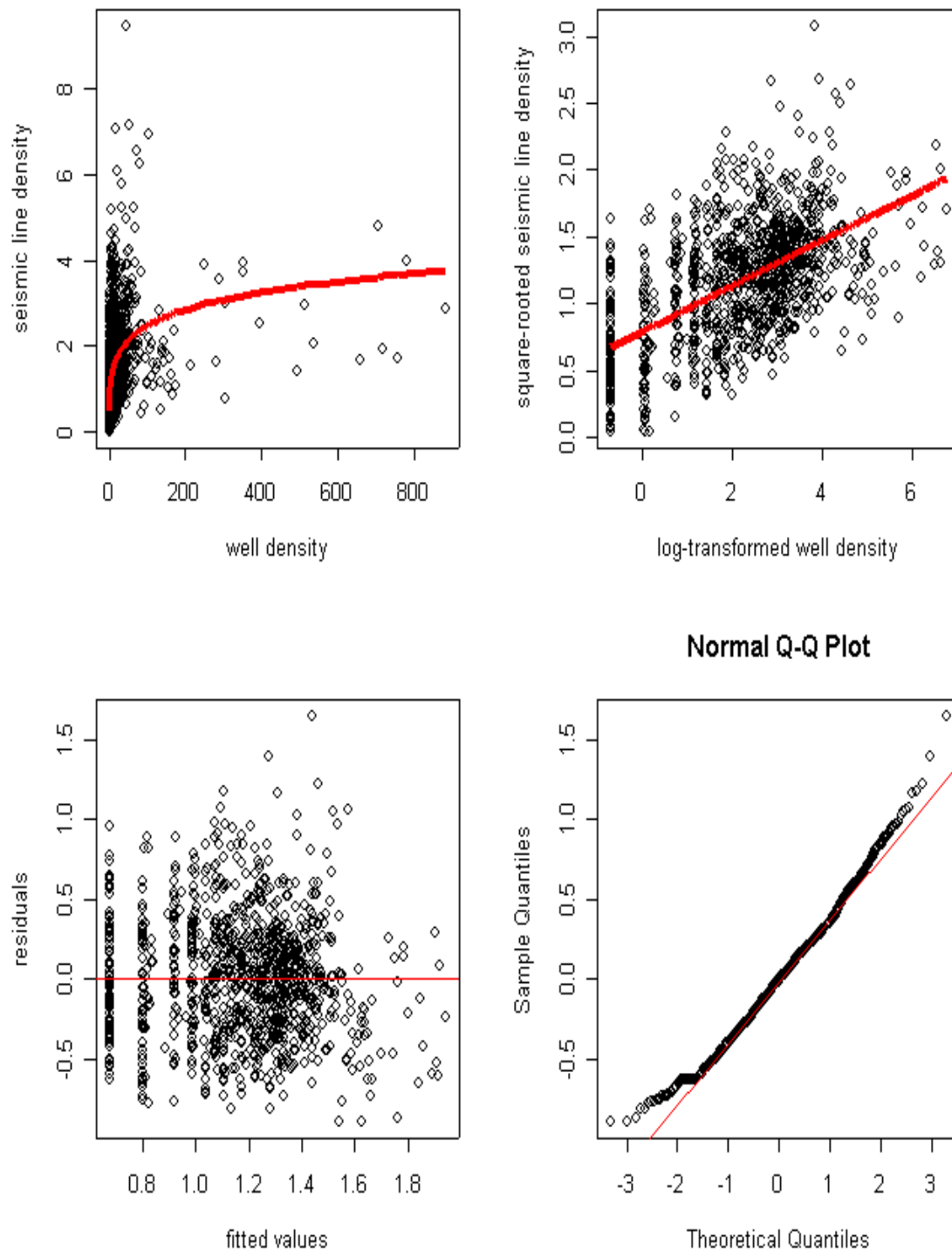
Figure 8. Upper left: scatterplot of seismic line vs. well densities with final model plotted in red; Upper right: scatter- plot of the Ös against log(w); Lower left: residual plot of the linear model Ö(s) = b0 + b1*log(w); Lower right: normality plot of model residuals.
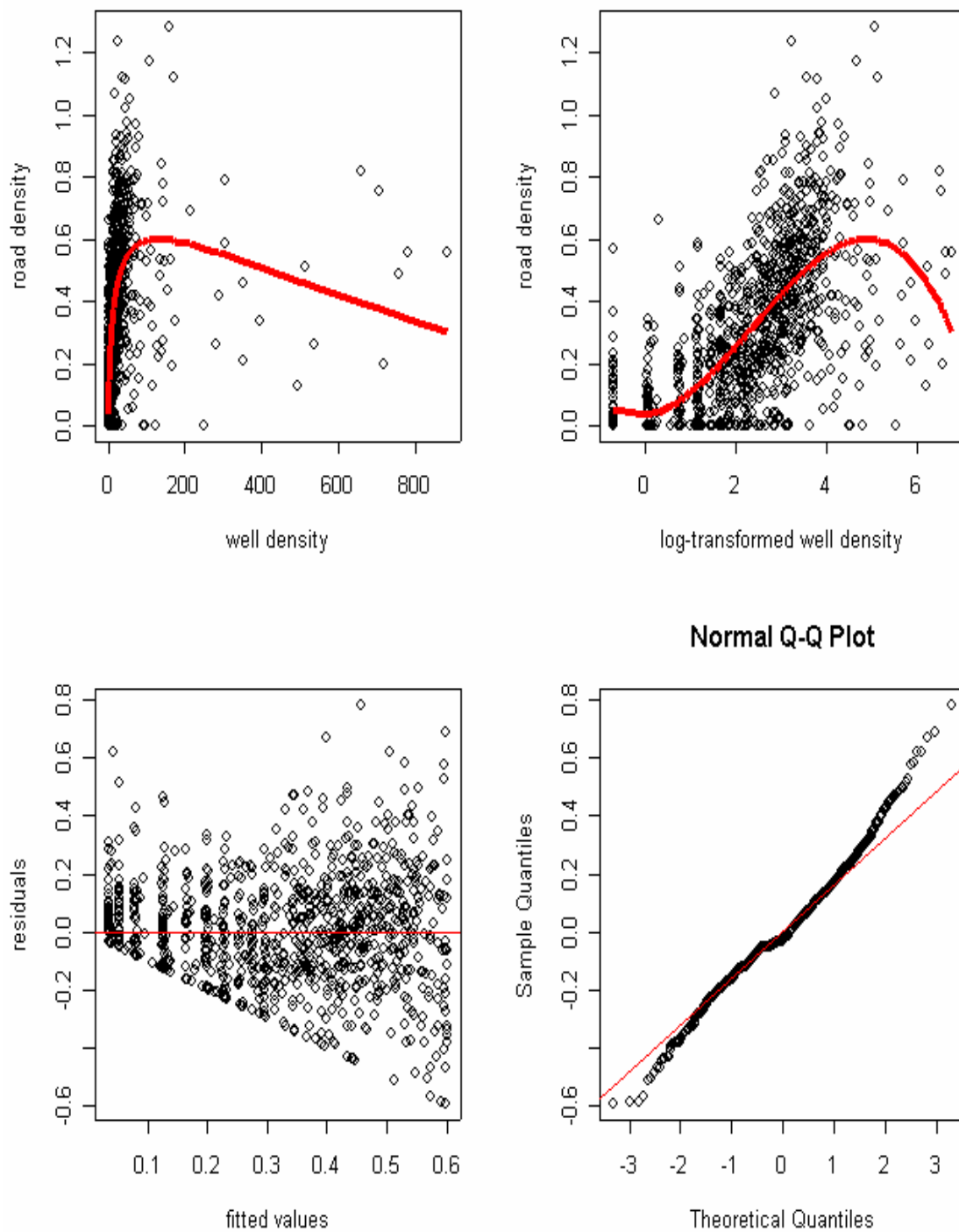
Figure 9. Upper left: scatter plot of total road density r and well density (final model shown in red); upper right: scatter plot of r against log(w); lower left: residual plot of linear model $r = b0 + b1*log(w) + b2*log(w)2 + b3*log(w)3$; lower right: normality plot of model residuals.
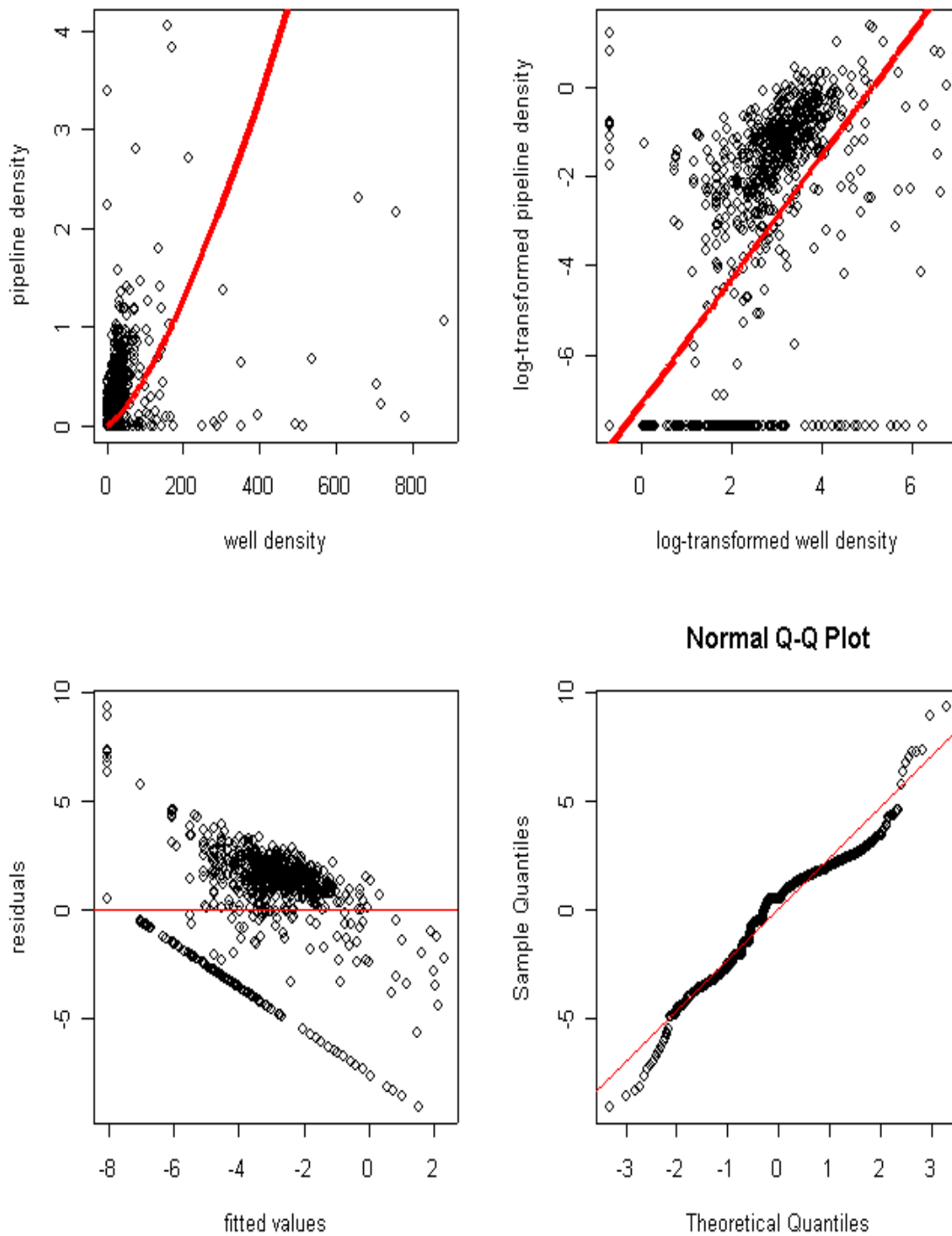
- Figure 10. Upper left: relationship between pipeline and well densities; upper right: relationship between log-pipeline and log-well densities; lower left: residual plot of the linear model log(p.i) = b0 + b1*log(w); lower right: normality plot of model residuals.

3.2   Summary of linear models

From sections 3.1.1, 3.1.2, 3.1.3, the best models for the data ($R^2 = 31.7\%, 48.3\%, 46.4\%$, respectively) are:

$$\sqrt{s} = 0.790 + 0.17\log(w)$$

$$r = 0.034 + 0.018\log w + 0.063\log w^2 - 0.009\log w^3$$

$$\log pi = -7.106 + 1.388\log w$$

Residuals of these models measure the excess or deficit in scaled linear feature densities after the effect of well density has been removed (i.e., densities are higher or lower then predicted from the number of wells). These residuals were much less inter-correlated than were the transformed variables (Table 4). For example, the correlation between road and pipeline density was 0.67 (p < 0.001) compared to 0.302 (p <0.001) for their model residuals. Maps of the residuals (Figure 11) reveal some spatial structures in the intensity and nature of the industrial footprint that are obscured in the raw data (Figure 3), and de-emphasise others. For example, residuals point out the relative deficit of linear features in the vicinity of Ft. McMurray and of seismic lines in the Cold Lake Air Weapons Range.

- Table 4. Correlations of transformed linear features (seismic lines sqrt(*s*), total roads *r*, and pipelines log(*pi*) and the model residuals *rsqs*, *rr3*, and *rlpi*).

Variables	sqrt(*s*)	*r*	log(pi)		rsqs	rr3	rlpi
sqrt(s)	1.000	0.504	0.438	rsqs	1.000	0.222	0.090
r	0.504	1.000	0.670	rr3	0.222	1.000	0.302
log(*pi*)	0.438	0.670	1.000	rlpi	0.090	0.302	1.000

3.2.1   Marginal increases in linear feature lengths

The marginal rates of increases in the lengths of seismic lines and roads, based on the final univariate regression models, are:

$$\frac{ds}{dw} = 100km^2 * 2(0.79 + 0.17\log(w)) * 0.17/w \qquad\qquad \text{Equation 1}$$

$$\frac{dr}{dw} = 100km^2 * (0.018 + 0.063 * 2\log(w) - 0.089 * 3\log(w)^2)/w \qquad \text{Equation 2}$$

where the factor of 100 km^2 scales to the results to units of km of feature per new well added to a 10,000ha.landscape. These relations are highly non-linear in *w* (Figure 12).

(a)

■	−0.90 : −0.34
■	−0.34 : −0.11
	−0.11 : 0.08
■	0.09 : 0.29
■	0.30 : 1.64

Raw density

CLWR

(b)

■	−0.60 : −0.13
■	−0.13 : −0.05
	−0.05 : 0.03
■	0.03 : 0.14
■	0.14 : 0.78

Raw density

(c)

■	−9.15 : −2.14
■	−2.14 : 0.07
	0.07 : 1.05
■	1.06 : 1.76
■	1.76 : 9.28

Raw density
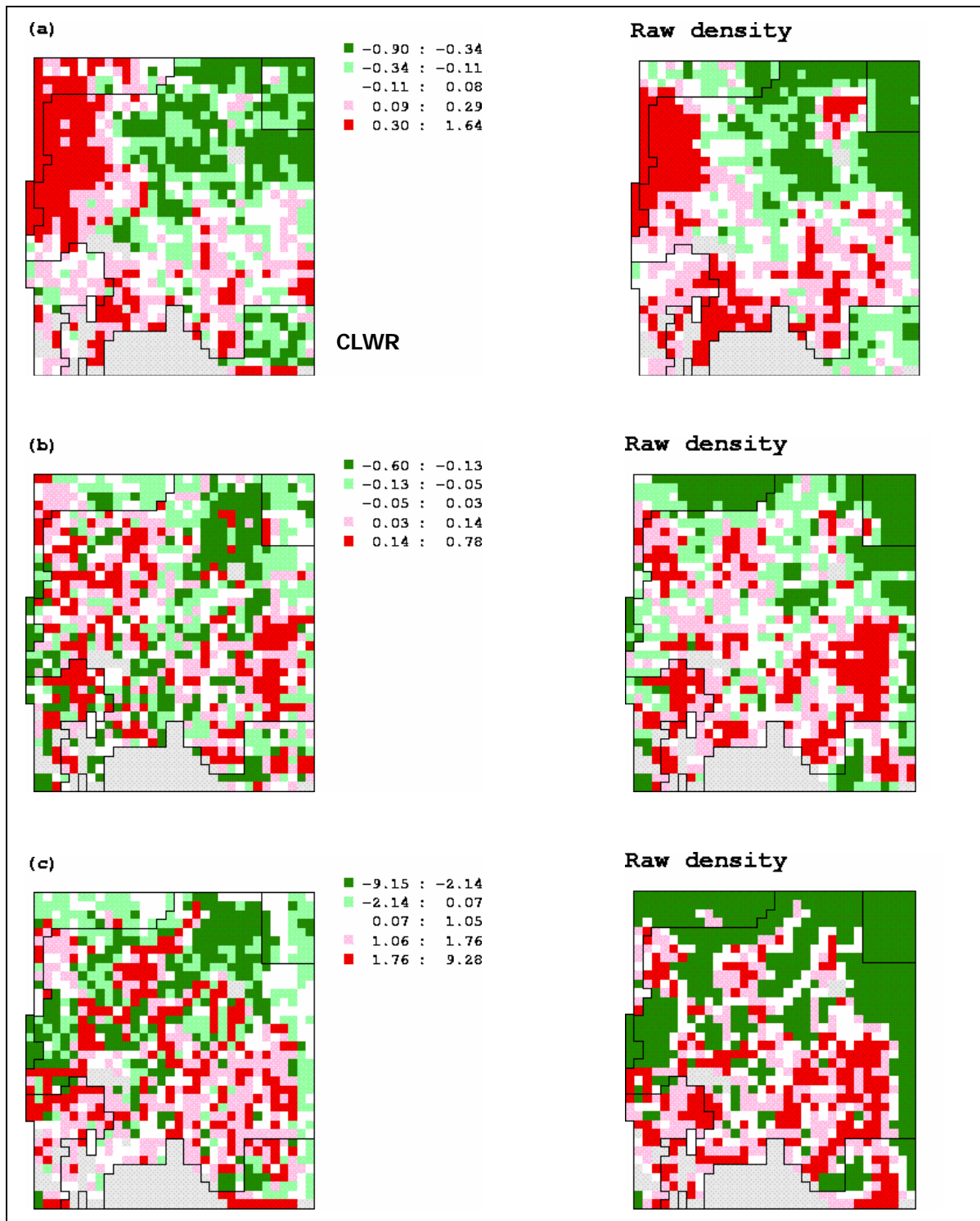
- Figure 11. The spatial distribution of residual seismic line (a) road (b) and pipeline densities (c). Areas excluded from the analysis are coloured grey, and the internal black line marks the approximate boundary of study region from Schneider et al. (2003). Values are mapped as quintiles: the 20, 40, 60 and 80% quintiles can be read from the map legends. The quintiles of the corresponding raw feature densities are mapped on the right panels: note that their ranges (not shown) differ. The Cold Lake Air Weapons Range (CLWR), at the south west corner of the region, is marked on panel (a).

As the number of accumulated wells in a landscape increases, the marginal increase in total length of seismic lines and roads decreases rapidly too, e.g., 1.55km and 0.46km respectively at $w = 30$. The present spatial distribution of estimated marginal increases is highly variable (Figure 13), especially for seismic lines. The regional means of ds/dw and dr/dw are 9.7km and 1.48km, respectively. For the 828 active townships (see Section 3.4.4 for definition), these means are 4.4km and 1.44km. For the 182 active townships with $w > 30$, the means are only 0.87km and 0.18km. If these townships are indicative of the future more developed region, we expect the marginal increases in seismic line and road densities to decline rapidly over the next few decades.
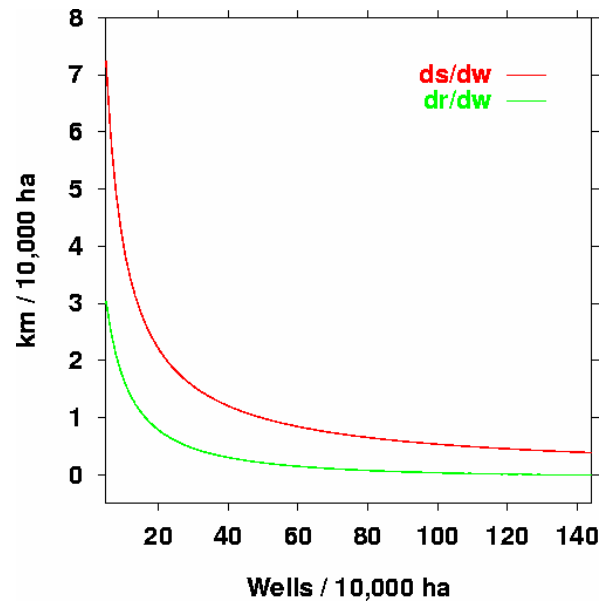
- Figure 12. Marginal increase in landscape total km of seismic lines (ds/dw, Eqn.1) and roads (dr/dw, Eqn.2) per additional well, as a function of initial well density.
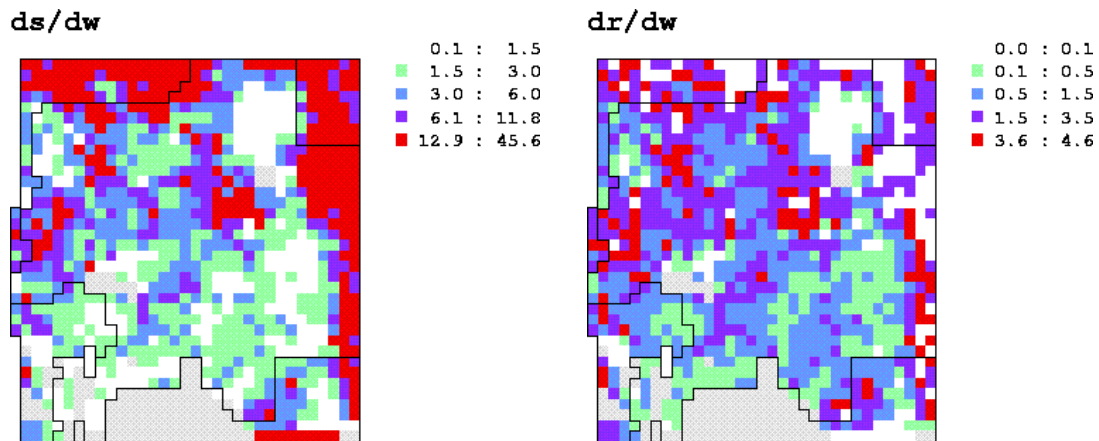
- Figure 13. Predicted marginal increase in landscape total km of seismic lines (ds/dw) and roads (dr/dw) per additional well (Equations 1 and 2) given the distribution of landscape well densities c. 2000.

3.3   Principle Components Analysis of linear feature residuals

3.3.1   Structure of the components

Because the variance of the residuals differed (variances of rsqs, rr3, and rlp =0.15, 0.034, and 5.31, respectively), we used the correlation matrix to calculate principle components, which scales each residual to unit variance. The eigenvalues differed from zero ($\lambda_1 = 1.192$, $\lambda_2 = 0.957$, $\lambda_3 = 0.815$, Table 5), so it is very likely that the residuals were independent. The residuals did not reveal any sub-dimensions or secondary structures in the data (*sensu* Linacre 1999). The first two components (PCA1 and PCA2) explain 77.9% of the variation in the residuals. Because the variables (residuals from the linear models) were few and weakly correlated (Table 3), PCA did not substantially reduce the dimensionality of the problem, namely the number of variables necessary to describe linear feature densities at the township scale. However, the PCA scores and their coefficients can be used for further investigation into the relationships between linear feature and well densities. The PCA scores were each linearly independent of *w*.

3.3.2   Interpretation of the components

The coefficients of PCA1 are all negative (Table 5). Suppose the densities of all three linear feature classes were higher than expected given regression models on log(*w*): then the residuals would all be positive and the score would be negative. Negative values of PCA1, therefore, indicate an overall excess of linear features, relative to the density of wells. PCA2 loads positively on residual density of seismic lines (rsqs) and negatively on the residual density of pipelines (rlpi). The coefficient and correlation with residual road density (rr3) is negligible. Thus, PCA2 is the contrast in or difference between the relative densities of seismic lines and pipelines. Positive values of PCA2 indicate a relative excess of seismic lines and/or a relative deficit of pipelines, given log(*w*). PCA3 is the difference between the relative densities of roads and other linear features. As the coefficient for rsqs is relatively small (0.275), PCA3 could be interpreted as the contrast between the relative densities of roads and pipelines.

PCA1 could be useful as a design variable of covariate in landscape studies concerned with the effects of linear features as such. PCA2 contrasts densities of relatively narrow seismic lines and relatively wide pipelines, and so could be of use for studies concerned with the effect of linear features of different widths. PCA3 contrasts roads with pipelines, and could be used in studies of the relative effects of linear features as such and human access. For such questions, use of PCA scores in conjunction with well densities could reduce the number of experimental or design variables from 4 to 2. Equally, a selected PCA score could be used as a covariate in statistical models of landscape-scale data. We note, however, that individual model residuals should probably not be used as covariates (Freckleton, 2002).

Maps of the PCA scores (Figure 14) reveal different aspects of the industrial footprint than either the absolute or residual densities of linear features (Figure 11). For example, PCA1 de-emphasises the high absolute and relative density of seismic lines in the northwest of the

study region, and highlights high overall linear feature densities in other areas. The footprint in the northwest re-emerges in the map of PCA2 as an area of high contrast between residual densities of seismic lines and pipelines.

The PCA scores may also reveal something of the history or present stage of development of individual landscapes, and suggest where high intensities of development might be expected in the near future: see, for example, the high contrast between relative seismic and pipeline densities (PCA2) near Ft. McMurray and in the northwest of the study region. On the other hand, both PCA1 and PCA2 emphasise a difference between the Cold Lake Air Weapons Range (southeast corner of the maps) and adjacent areas. The overall footprint, and the ratio of seismic to pipeline densities, is lower there than expected given the level of resource extraction. This may reflect the differences in regulatory constraints imposed by the Department of National Defence vs. the Provincial government. If so, the relationship between the industrial footprint and resource extraction can be influenced by regulation.

• Table 5. Principal components analysis on model residuals rsqs, rr3 and rlpi.

Importance of components			
	PCA1	PCA2	PCA3
Standard deviation (λ)	1.192	0.956	0.815
Proportion of Variance	0.474	0.305	0.221
Cumulative Proportion	0.474	0.779	1.000
Loadings			
	PCA1	PCA2	PCA3
Rsqs	-0.474	0.813	0.338
rr3	-0.665	-0.079	-0.743
Rlpi	-0.578	-0.577	0.578
Correlations			
	PCA1	PCA2	PCA3
Rsqs	-0.565	0.778	0.275
rr3	-0.792	-0.075	-0.605
Rlpi	-0.688	-0.552	0.471
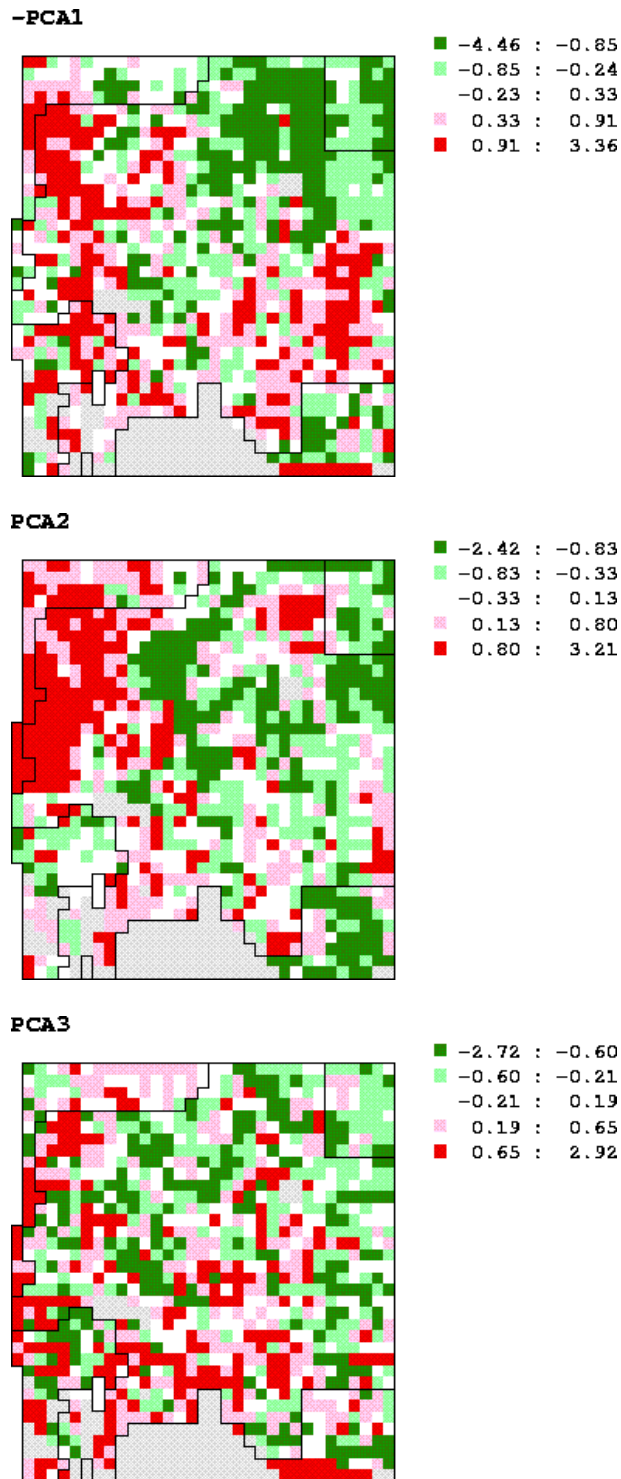
- Figure 14. Quintiles of the principal components of residual linear feature densities (Table 5). The sign of PCA1 was changed so that positive values appear as shades of red on all three maps. An interpretation of the scores is offered in the text.

3.4 Spatial and temporal dynamics of well site density

3.4.1 Annual increments of total well counts

The total number of wells in the study region, $W(t)$, has increased steadily since the 1940s (Figure 16). As of 1999, a total of 30,028 wells had been drilled. The annual increment $dW(t)$, or the number of new wells added per year, has also increased over time (Figure 15b). The largest annual increment (2,311) occurred in 1997. Although Figure 16 may seem to suggest a marked change in the mean annual increment at about 1973, this is not in fact the case. Examining the annual per-capita rate of increase,

$$\Delta W(t) = [W(t+1) - W(t)]/W(t),$$

indicates that a change in the dynamics of well production occurred somewhat later, at about 1981 (Figure 15a). The mean rates for the intervals 1960-1981 and 1982-1999 were 0.09 and 0.043, respectively. This difference was significant (Welch two sample t-test, $p < 0.001$).

The Poisson GLM

$$\log dW(t) = -6.5 + 1.35 \log W(t) + I_{82}[3.2 - 0.25 \log W(t)] \quad \text{Equation 3}$$

(where I_{82} is an index variable for $t < 1982$) explains 58% of the deviance in the annual increments (Figure 15b). Starting at $W(1960) = 2122$, this model reproduced the observed trajectory of $W(t)$ with a mean absolute error of 6.3%. Over the interval 1981-1999, the mean absolute error was only 3.3%. Observed and simulated time series, with an 11-year projection to 2010, are shown in Figure 17. For the period 1960-1999, the dynamics of $W(t)$ are well described by a stochastic exponential growth process where the rate constant depends in part on known exogenous factors (e.g. introduction of the National Energy Program in October 1980, a global economic recession in the 1980s, and the 1990s boom). This model is purely descriptive, and should not be used to predict future dynamics. However, it demonstrates that the temporal dynamics of well development is susceptible to statistical analysis. Moreover, the data clearly do not suggest that the absolute or per-capita growth in $W(t)$ has begun to decline, and no such decline is in fact expected over the next several decades (Schneider et al., 2003).
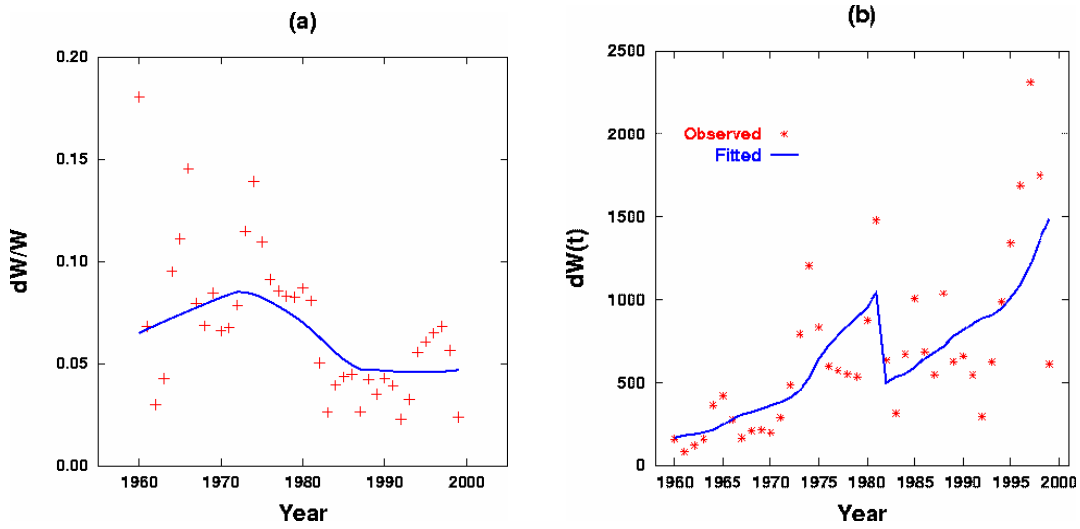
- Figure 15 Annual rates of increase d*W*(t)/*W*(t) in total well count *W*(t) for 1960-1999, with LOWESS smoother (a); annual increments d*W*(t) and fitted values of Eqn. 3 (b).
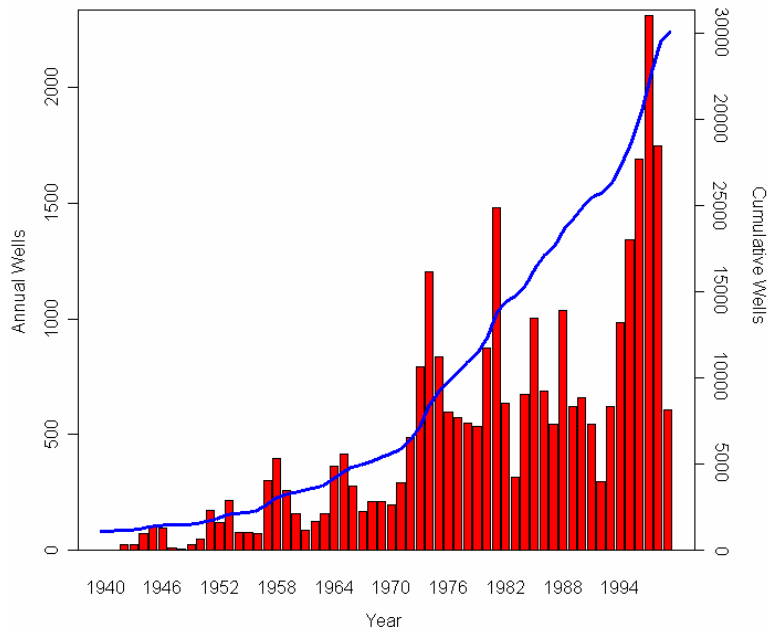
- Figure 16. Annual increments d*W*(t) of drilled wells in the study region over the interval 1940-1999 (red bars, left *y*-axis) and cumulative totals *W*(t) (blue line, right *y*-axis).
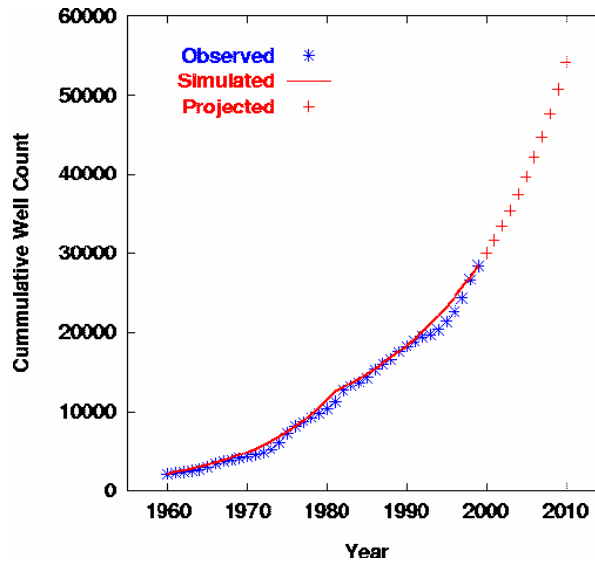
- Figure 17. A comparison of observed and simulated time-series of cumulative well counts $W(t)$ in the study region from 1960-1999, with an 11-yr projection to 2010. The simulation used a stochastic growth model (Eqn. 3) initialised from the 1960 datum.

3.4.2 Spatial/temporal patterns of well abundance

The past and present spatial distributions of wells are markedly heterogeneous at the landscape or township scale (Figure 18). The five-decade sequence of mapped well densities (1960-2000) is suggestive of a reaction-diffusion process. The diffusion component describes the spatial dynamics of contagious spread from local hotspots of high well density to nearby areas of lower or zero density. The reaction component describes local increases in well density within landscapes where some wells are already present. Further insight into these processes can be gained by mapping the periodic increments in per-township well counts. At 10yr resolution (Figure 19) we observe:

1) In 1960, most townships (68%) had no wells present, of those that did, few (9.4%) had more than 10 wells, and these were concentrated at loci in the northeast (around Ft. McKay) and the southwest (due west of Athabasca) of the study region.

2) Contagious spread from these loci into well-free landscapes during the 1960s and 1970s had accessed most of the area by 1980.

3) Since 1970, the addition of new wells has predominated over initial access, in terms of the proportion of landscapes affected.

4) This process is spatially structured: landscapes with high periodic increments tend to be concentrated in a few distinct areas within each period.

5) In all periods, well counts did not increase on many landscapes where wells were initially present.
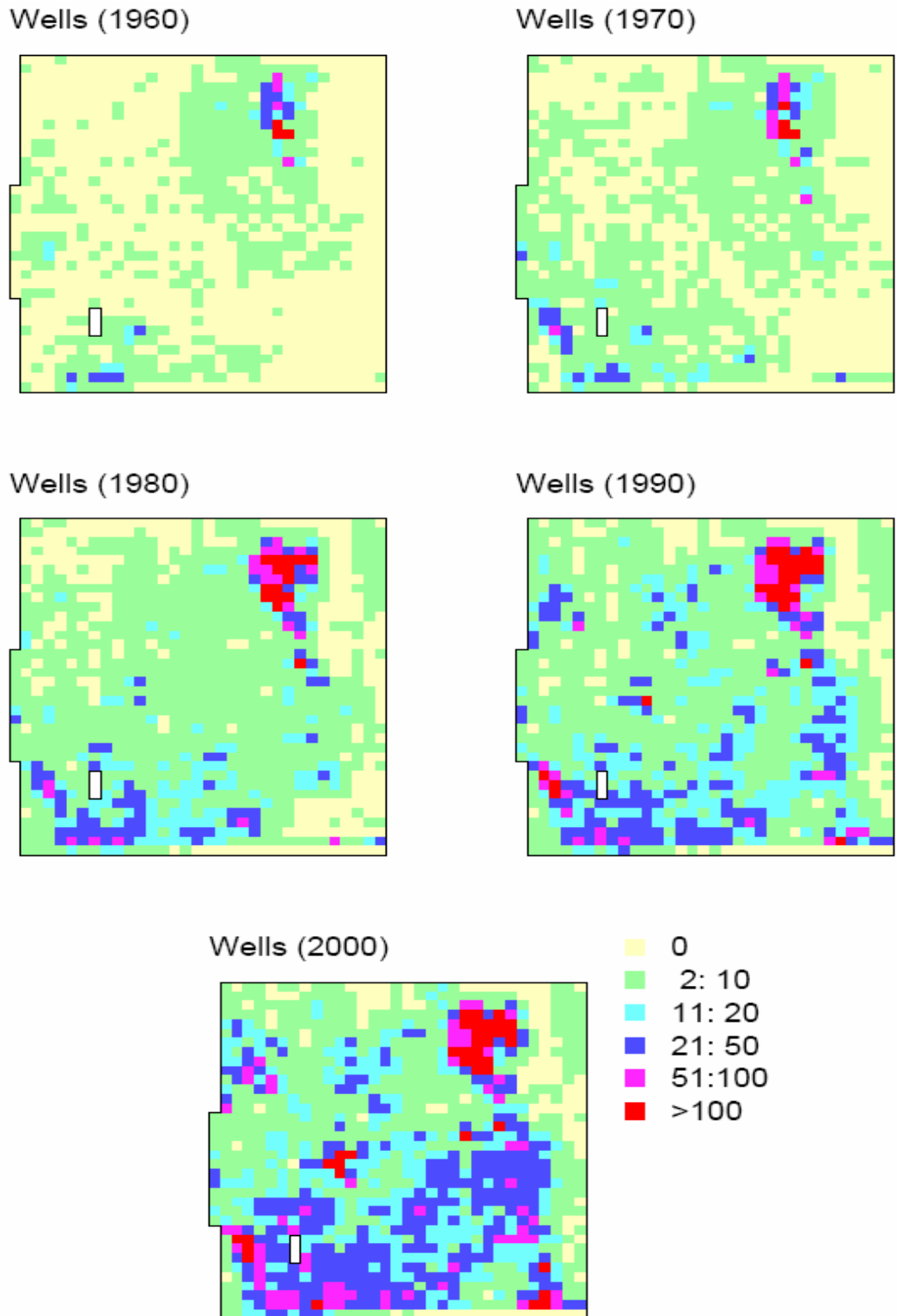
Figure 18. Time series maps of raw well counts per township within the study region, at 10-yr increments from 1960 to 2000.

Finer details are apparent when the same data are mapped at 5-yr resolution (Figure 20). Note, for example, the contagious spread into the Cold Lake Air Weapons Range at the southeast corner of the study area over three 5-yr periods beginning in 1970. Relatively fine-grained processes apparently drive the spatial and temporal sequence of well development within the study region.

- Figure 19. Ten-year increments in raw per-township well counts, from 1960 to 2000. Shades of red and green distinguish increments in townships having 0 wells (New) or at least 1 well (Add) at the beginning of an interval.

- Figure 20. Five-year increments in raw per-township well counts, from 1960 to 2000. Map conventions are as in Figure 10.
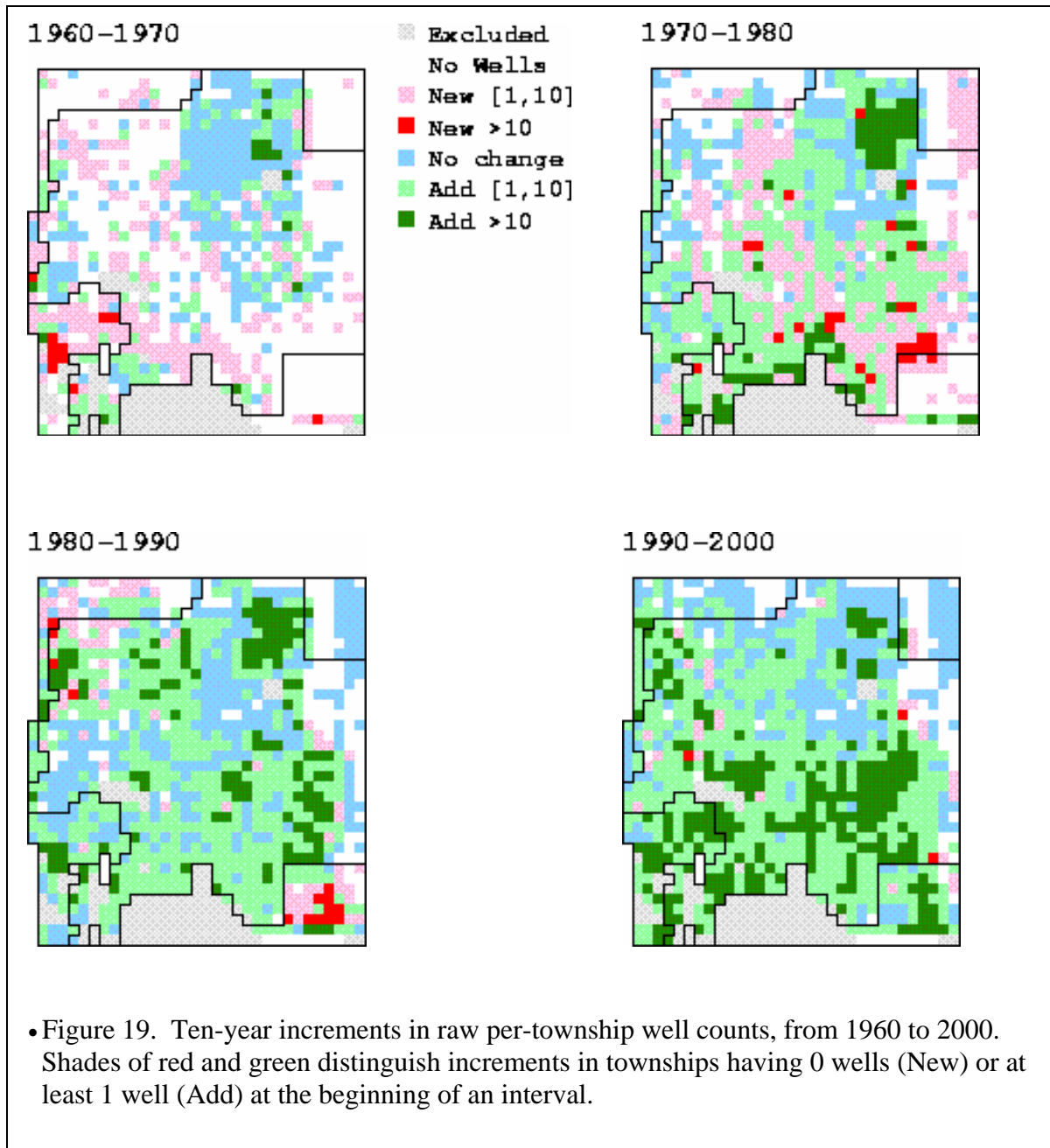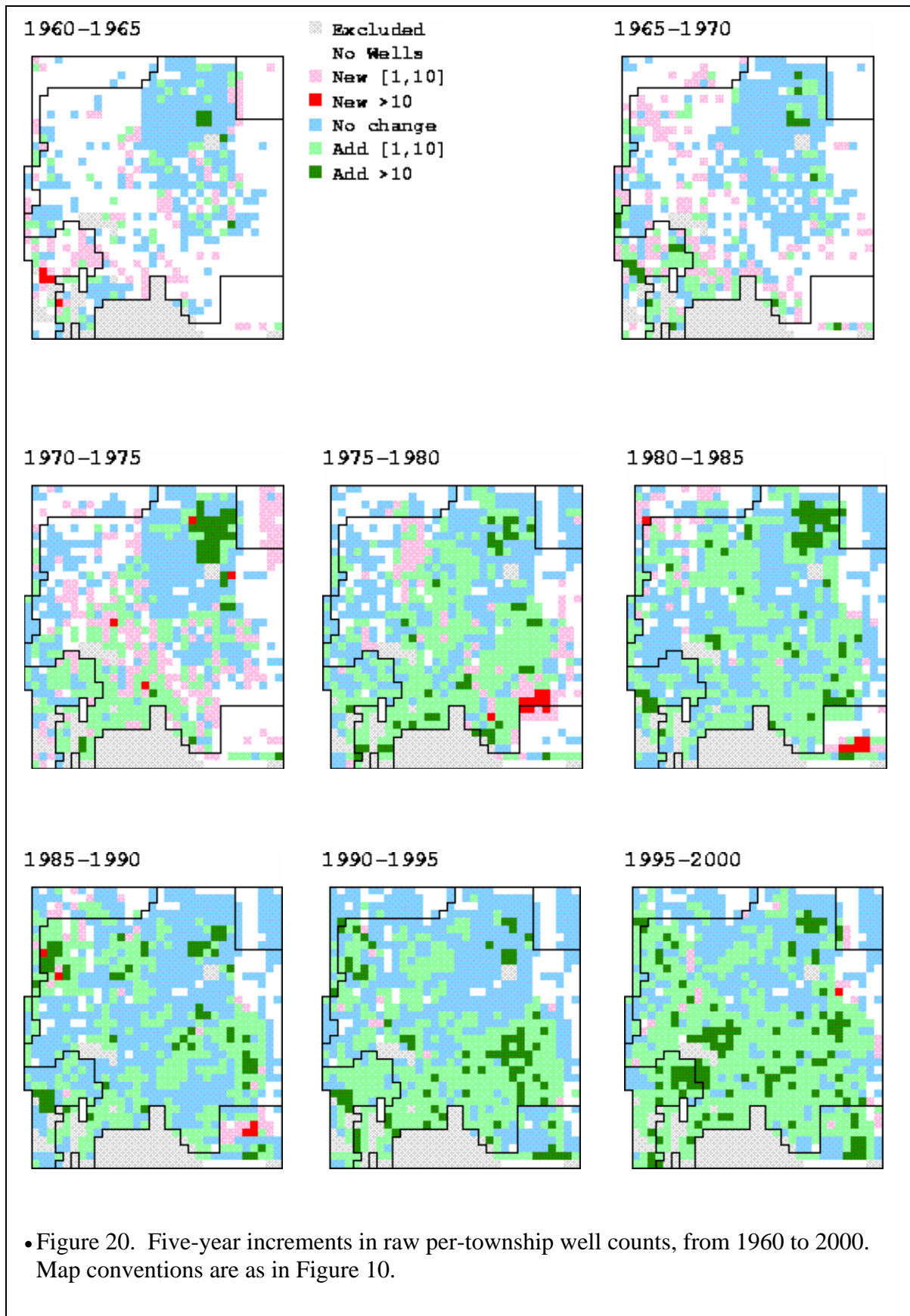
3.4.3 Abundance of well-free townships

The proportion of townships having at least one well has increased steadily from 1960 to 2000 (Figure 21). Equivalently, the number of well-free townships Z(t) has declined from Z(1960) = 720 (68%) to Z(2000) = 103 (9.9%). It is of some interest how many of these remaining well-free townships might remain in that condition, and for how long. We explored the dynamics of Z(t) by modelling the periodic loss rates:

$$\Delta Z(t) = [Z(t) - Z(t+5)]/Z(t) \qquad\qquad \text{Equation 4}$$

for eight consecutive five-year periods beginning in 1960 (Figure 21). Under standard assumptions of independence and homogeneity within periods, these rates estimate the probability in year t that a well-free township will have acquired at least one well by year $t+5$. Accordingly, we used logistic regression to model variation in $\Delta Z(t)$ over time. There was no significant relationship between $\Delta Z(t)$ and t. The estimate of $\Delta Z(t)$ was 0.22 for all periods. Assuming this loss rate, the half-life for well free townships is approximately three periods ($(1 - 0.22)^3 \approx 0.48$) or 15yr, and the expected number of well-free townships in 2015 is 49.

There was a highly significant non-linear relationship between $\Delta Z(t)$ and Z(t). The quadratic logistic regression model

$$\text{logit}(\Delta Z(t)) = -3.12 + 0.012Z(t) - 0.000014Z(t)^2 \qquad\qquad \text{Equation 5}$$

explained 80% of the deviance in $\Delta Z(t)$ (Figure 21). A quadratic model in t fit poorly in comparison (60% explained deviance, ΔAIC=24.4). Fitted rates increased rapidly during the 1960s, peaked in the1970s (0.32 and 0.31) and declined to only 0.14 in 1995 (Figure 21). The predicted rate for 2000 to 2005, given Z(t)=103, is 0.11. This pattern is presumably characteristic of the initial stages of economic development in hinterland areas. The most accessible and valuable areas are accessed first, and the mean quality of undeveloped areas must decline over time. Once 90% of the area has been at least explored, as here, one would expect the rate of new development to rapidly approach 0. The model suggests this process is far advanced in the study area. This has some implications for e.g. conservation planning. For example, the model predicts that 71 of the 103 presently well-free townships (72%) will remain in 2015 and that 50% will remain in 2035. Assuming the constant decay rate of 0.22, only 18 well-free townships (17.7%) would be expected to remain in 2035.
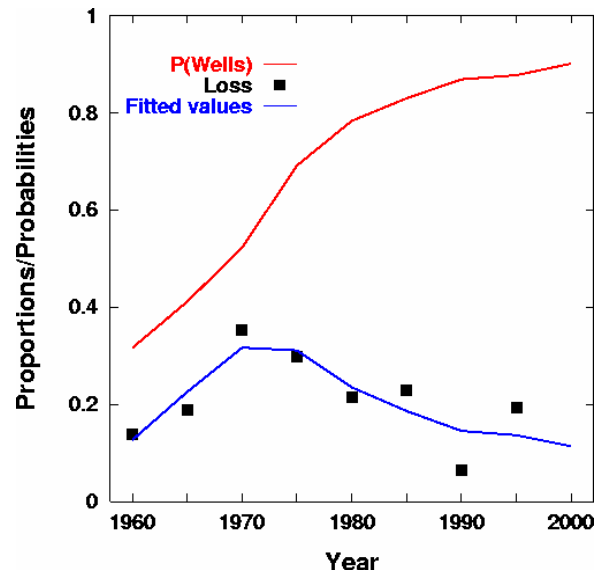
- Figure 21. The proportion P(Wells) = 1-*Z*(*t*) of 1053 sample townships with at least one well at year *t*, estimated at 5-year intervals from 1960 through 2000, the mean 5-yr loss rates ΔZ(t) of well-free townships (Loss, Eqn.4) and the fitted values of regression Eqn.5.

3.4.4 Abundance of inactive townships

In 1980, 825 townships had at least one well. Of these, 121 (14.7%) had no new wells added by 1999 (Figure 22,23). We will call these townships "inactive." We measured activity as $p_A(t)$, the proportion of townships having at least one well at time t to which one or more wells were added by time t+5. Activity has been >40% for every 5-yr period since 1970 (Figure 13). Interpreting the $p_A(t)$ as probabilities, as in 3.4.3, we fit the logistic regression model

$$p_A = -3.2 + 7.9 p_W - 4.6 p_w^2 \qquad \text{Equation 6}$$

where $p_w(t) = 1 - Z(t)/1053$ is the proportion of townships with at least one well at time t. The model explains 66% of the deviance in p_A (Figure 22). The fitted activity probabilities are approximately 0.54 for every period since 1980. If the process adding wells to landscapes was random and spatially independent, the expected number of inactive townships would be 825 * $(1\text{-}0.54)^4 = 37$ and the probability of there being 60 or more would be only 0.00014. Most of the 121 inactive townships must therefore be distinct in some way. Perhaps the results of the initial exploration c.1970 (Figure 11) were disappointing.

Combining Equations 5 and 6, we estimated the "access probability" or the probability that a randomly chosen landscape will acquire at least one new well over the next five years, to be

$$((1053\text{-}104)*0.54 + (104 * 0.11) / 1053 = 0.50$$

or 50%. Assuming the 121 presently inactive townships remain inactive over the next five years, the access probability for the 828 presently active townships is 0.62. Any ecological studies planned for such townships should anticipate some level of development by the energy sector during the course of the study.
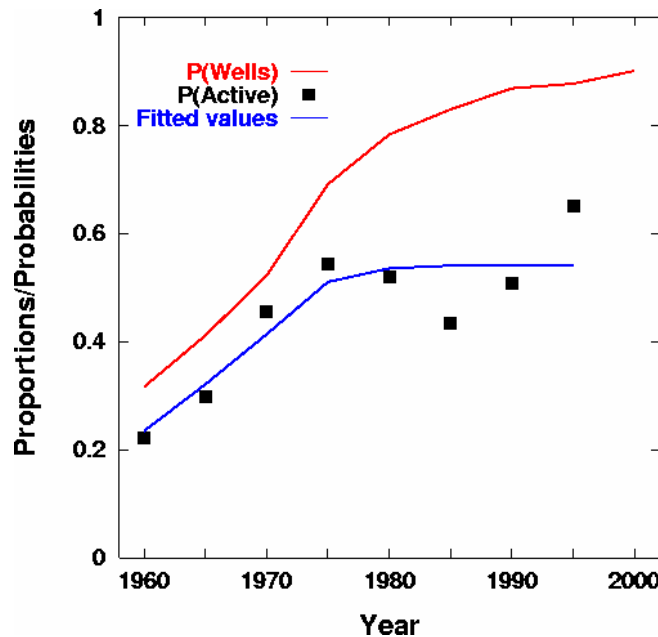
- Figure 22. The proportion P(Wells) of 1053 sample townships with at least one well at 5-year intervals from 1960 through 2000, the observed proportions p_A of active townships and the fitted proportions of Equation 6.

3.4.5   The industrial footprint on well-free and inactive townships

The inactive and well-free townships are concentrated along the remote northern and eastern fringes of the study region (Figure 23), with the exception of one cluster of inactive townships apparently associated with a large wetland complex southwest of Ft. McMurray. The mean well count in the inactive townships was 5.4, and only 8 of them had more than 10 wells. In comparison, the remaining 828 "active" townships had a mean well count of 30.3 in 2000. As well-free and inactive townships are spatially associated, it seems probable that whatever hydrocarbon reserves they may overlie are not currently worth developing.

As of 2000, considering well-free and inactive townships together, a substantial 221 (21.4%) of the sample townships remained relatively free of one component of the industrial footprint, namely wells. Mean densities of all linear feature classes were also lower than in active townships, by factors of 3 or more (Table 6). The overall characteristics of the industrial footprint may differ between well-free and inactive townships. Inactive townships have a mean PCA1 of 0.69, indicating that linear feature densities are lower than expected even given the low well densities. There is no such trend in well-free townships. The mean PCA2 and PCA3 scores are significantly non-zero for both well-free and inactive townships, which suggests a systematic pattern in the relative densities of seismic lines and pipelines (PCA2) and of roads and pipelines (PCA3). These townships remain relatively unaffected by industrial development, although probably few of them could be regarded as pristine.

• Figure 23. Spatial distribution c. 2000 of townships with well counts of 0 (No Wells), townships with non-zero counts that have not increased since 1980 (Inactive), and Active townships having well-counts below or above their average of 30.
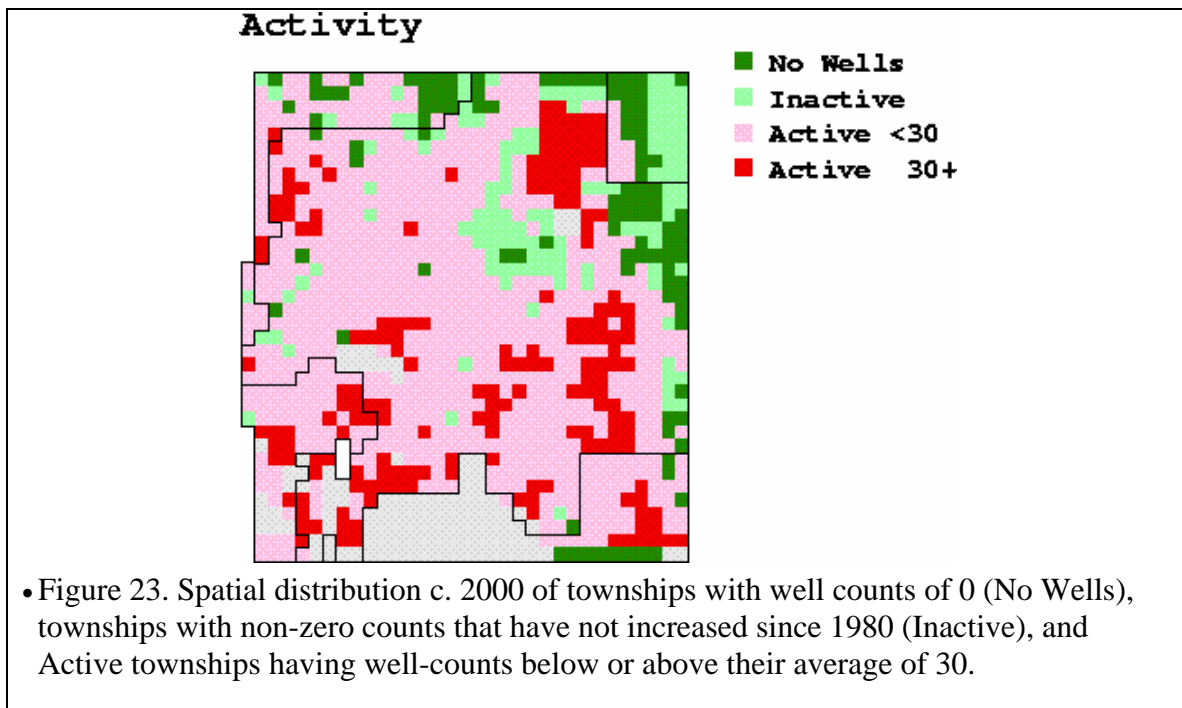
• Table 6. Mean absolute well counts (*W*), PCA scores and densities of seismic lines (*s*), roads (*r*) and pipelines (p) for well free townships (with no wells c. 2000), inactive townships (those having no new wells since 1980) and the remaining active townships.

	W	PCA1	PCA2	PCA3	*s*	*R*	p
Well free (n=104)	0.0	−0.10	−0.44	0.22	0.51	0.04	0.07
Inactive (n=121)	5.4	0.69	−0.27	0.31	0.63	0.09	0.02
Active (n=828)	30.3	−0.09	0.09	0.02	1.83	0.37	0.27

3.4.6 Trends in per-township well counts

Time-series well counts from a random sample of 20 townships (Figure 24) do not suggest that many townships are approaching an upper limit on cumulative well counts. The relation between per-township five-year increments and initial well density was non-linear, as expected (Table A.6). For the five-year interval 1990-1995, the resulting curve is best described as a flat parabola (Figure 25). The maximum expected increment of 12.3 wells per township is at an initial density of 74 wells per township. The model explains 28% of the deviance. Similar results are found for other intervals (e.g. 1995-2000, 1990-2000). Although these models fit the data rather poorly, they support the following general conclusions:

1) There is some evidence that mean periodic increments in per-township well counts decline at high well densities;

2) There is some evidence of an upper limit on per-township well counts;

3) The maximum periodic increment occurs at relatively high well densities;

4) Present well densities in most active townships are far below the density of maximum mean increment;

5) At least over the next few decades, it seems likely that most new wells will be created in the 828 (79%) active townships identified in the previous section.

6) There is no evidence that present well densities in these townships places any limit on the number of new wells that can be added.

7) The accumulation of high total well counts within a township is generally a gradual process that takes place over several decades.
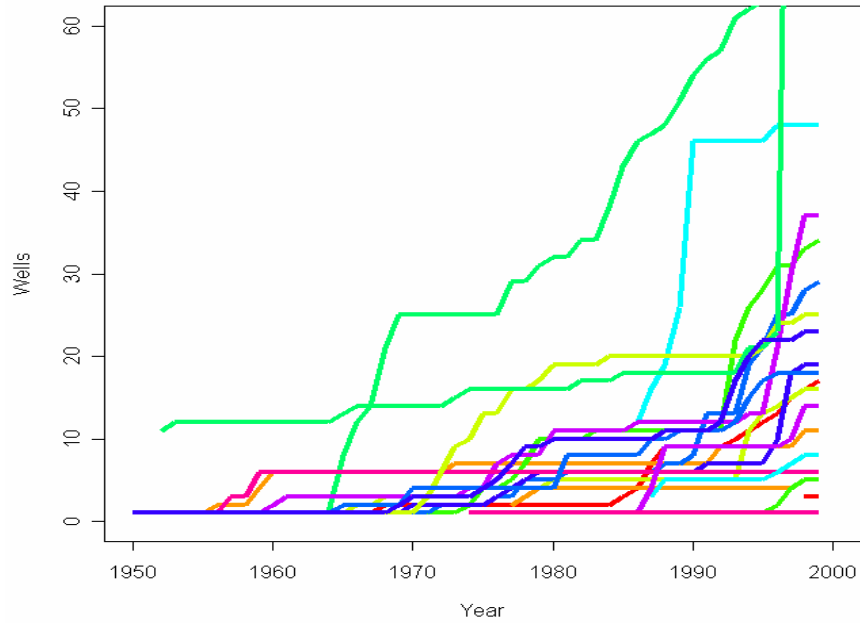
• Figure 24. Cumulative well counts (1950-2000) for 20 randomly selected townships.

Years are 1990-95
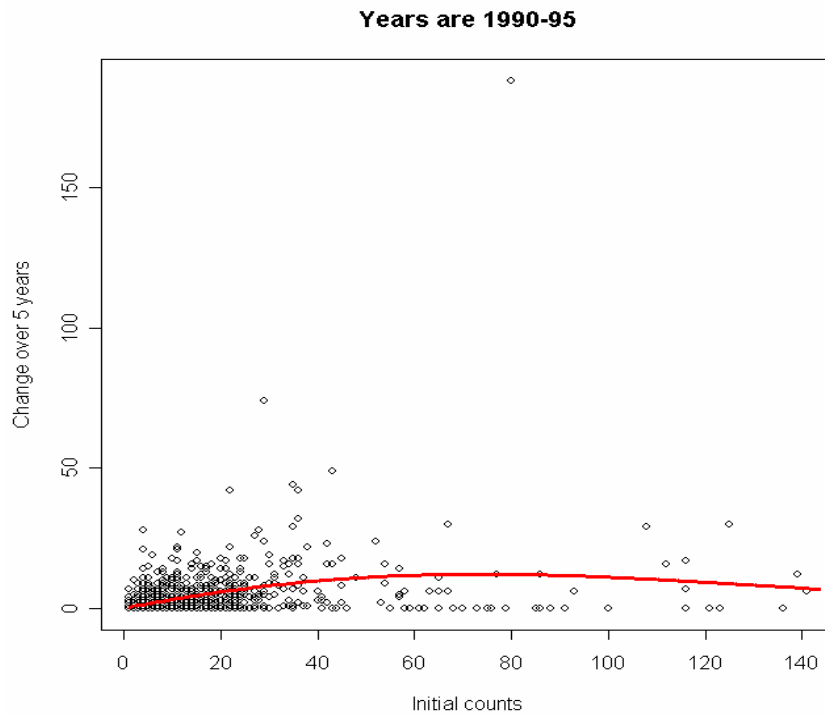
• Figure 25. Five-year (1990-1995) increments of raw per-township well counts against the initial (1990) counts. The fitted Poisson regression model (Table A.6) of the data is plotted in red.

4   Discussion

The development trajectory seen in northeast Alberta since the middle of the 20th century may foreshadow the future of the entire Western Sedimentary Basin (Schneider et al 2003), which is approximately coextensive with the boreal mixedwood ecoregion (Rowe, 1972). The results of this study should be directly applicable to the rest of Northern Alberta and could be extended to areas in north-eastern British Columbia where the energy sector is in an earlier stage of development.

4.1   Relations between well and linear feature densities

At the landscape or township scale ($\approx$10,000ha) univariate linear regression models on the log density of drilled wells explained from 31% to 48% of the variation in the density of four linear feature classes (seismic lines, total roads, industrial roads, and pipelines). Therefore, the density of wells may be used as a surrogate for the industrial footprint of the energy sector in northeast Alberta. Moreover, spatial dynamic models of linear feature density may be derived from spatial dynamic models of well density. The weakest relationship (R^2=0.31) was between well and seismic line densities. This is not surprising; there may be temporal lags between episodes of seismic exploration and drilling. In general, seismic exploration precedes drilling and road building. The PCA analysis of model residuals identified three interpretable and potentially useful components: 1) the sum scaled excess or deficit linear feature density relative to well density; 2) a contrast between residual densities of seismic lines and pipelines; and 3) a contrast between residual densities of roads and pipelines. The second component can be interpreted as an index of the stage of industrial development. For example, a high density of seismic lines relative to wells and a low relative pipeline density may be indicative of an area in the early stages of exploration, as is seen in the northwest of the study region (Figures 11 and 14).

The spatial pattern of model residuals and Principle Components pointed to some anomalies in within the Cold Lake Air Weapons Range, at the southeast corner of the study region. The relationship between linear feature densities and resource extraction seems strikingly different there compared to immediately surrounding areas. We conjecture that this may reflect differences in the regulatory environment between a closely controlled military base and lands under Provincial jurisdiction. If that is correct, further analysis might suggest the range of future outcomes that could be achieved under alternate regulations.

The non-linear relations between densities of wells and linear features have major implications for landscape or regional simulation modelling. For example, Schneider et al. (2003) used an exogenous model of well site creation to simulate alternate trajectories of the industrial footprint in NE Alberta. They assumed a constant marginal rate of increase in seismic line length, of 3km per new well. This could lead to a significant over-prediction of future linear feature densities. For example, at a well density of 200 wells per 10,000ha, the models of section 3.1 imply a seismic line density of 2.86 km/km^2, or an average of 1.43km of seismic lines per well. This is less than 50% of the density given Schneider et al's constant rate of increase. Moreover, spatial variation in the distribution of wells could have a marked effect on the total density and spatial distribution of seismic lines, and energy sector roads (see Figure 13). Our analysis did not account for reclamation or the higher seismic line densities

associated with *in situ* heavy oil extraction. Nevertheless, we suggest that marginal rates of increase, such as developed in section 3.3, are more appropriate for projecting future densities of linear features under trajectories of industrial development.

Schneider et al (2003) note that there are several kinds of wells, including conventional oil, conventional natural gas, and wells for *in situ* extraction of heavy-oil deposits. The importance of this distinction was not fully appreciated when this study was initiated, in early 2001. We expect that most wells in our dataset were conventional wells, but we do not know where localized *in situ* drilling has taken place prior to 2000. Most remaining conventional reserves in our study region are reportedly natural gas, but the relative importance of *in situ* extraction is predicted to increase dramatically over the next few decades. If the patterns of geophysical exploration, road construction and pipeline networks associated with *in situ* heavy oil extraction are significantly different from those of conventional oil and gas, our statistical models will not be applicable on future landscapes. Similarly, we could not distinguish between successful, unsuccessful and decommissioned wells, not account for multiple wells drilled at the same location within a township.

Our analysis did not account for spatial autocorrelation or other spatial dependencies in the data or in the process of industrial development, although all reported univariate correlations between feature densities remained significant when spatial autocorrelation was accounted for (Haining 1990, §6.3.2 and 8.1.1). Violations of isotropy and stationarity assumptions are perhaps more serious. For example, the distributions of Provincial roads and, more importantly, of pipelines show a conspicuous directional trend. Clearly, the density of pipelines within a landscape depends not only on the local number of producing wells, but also on the location of that township within a highly structured network that is oriented towards major centres outside the study region.

4.2   Spatial and temporal dynamics of drilled well abundances.

The dynamics of well drilling from 1960—2000 is well described by a simple stochastic population growth model. Schneider et al (2003, Figure 2) used such a model to project a 700% or 8-fold increase in the cumulative number of drilled wells over a 30 yr period 2000-2030. This implies an annual per-capita growth rate of approximately 7.2% [$(1+0.072)^{30} =$ 8.05]. However, we found evidence that this rate had changed c.1981, from approximately 9.8% to 4.8%. Projecting the current rate over 30yr, we would expect only a 300% or 4-fold increase in total well abundance. Although simple stochastic models can describe the short-term dynamics of this system, their reliability can be improved by including appropriate covariates.

Time-series maps of cumulative total well counts and of 10 and 5yr periodic increments over the interval 1960-2000 revealed clear spatial and temporal structure in the behaviour of the energy sector. Although the pattern of development may appear chaotic in the short term, it is obvious that underlying regularities exist which could be described by various statistical and analytical methods. We suggest that some variant of a reaction/diffusion process might be a developed as a neutral model of this process, for use in low-resolution spatial dynamics simulation models (see e.g. Cumming and Armstrong 2001, Cumming and Vernier 2002). The Western Sedimentary Basin is considered mature, which means that the locations of most

reserves are known. Thus, much more sophisticated models from the geophysical literature could be applied.

Further analysis showed that the rate of geographic expansion by the energy sector peaked sometime in the early 1970s and has declined steadily since that time. As of 1999, 9.8% of landscapes in the study region had no recorded wells, and at least some of these are likely to remain free of energy sector development for several decades, if not permanently. An additional 11.5% of landscapes had been inactive since 1980. That is, some wells had been drilled in these landscapes prior to 1980 but not since. The overall industrial footprint is relatively light in these well-free and inactive townships. They represent the only controls for the ecological effects of the industrial footprint that exist in northern Alberta. We recommend that urgent steps be taken to protect some of these areas from any further development.

The existence of these landscapes has some implications for simulation modelling and cumulative impacts assessments: future energy sector developments and expansion of the industrial footprint will not be spatially homogenous, but will rather be concentrated within less than 80% of the total study region. In this portion of the region, the number of wells and rate of well construction is increasing. Of a random sample of 20 townships, less then half showed any sign of having reached a maximum well density. Consequently, we should expect steady increases in infrastructure density within landscapes that are already well developed and fragmented (AEP 1998).

Acknowledgements

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Appendix

Table A.1: Summary of regression of square-root seismic line density against log well density.

```
Call:
lm(formula = sqrt(s) ~ w, data = pdata)

Residuals:
    Min      1Q    Median     3Q      Max
-0.897346 -0.278699 -0.005051  0.240580  1.642529

Coefficients:
         Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.790274   0.020540   38.48   <2e-16 ***
w           0.169684   0.007684   22.08   <2e-16 ***
---
Signif. codes:  0 `***' 0.001 `**' 0.01 `*' 0.05 `.' 0.1 ` ' 1

Residual standard error: 0.3848 on 1051 degrees of freedom
Multiple R-Squared: 0.3169,    Adjusted R-squared: 0.3163
F-statistic: 487.7 on 1 and 1051 DF,  p-value: < 2.2e-16
```

Table A.2: Summary of linear regression of total road density r against log well density.

```
Call:
lm(formula = r ~ w, data = pdata)

Residuals:
    Min      1Q    Median     3Q      Max
-0.662854 -0.122271  0.003151  0.114431  0.822505

Coefficients:
         Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.065070   0.010258   6.343 3.34e-10 ***
w           0.108387   0.003838  28.244  < 2e-16 ***
---
Signif. codes:  0 `***' 0.001 `**' 0.01 `*' 0.05 `.' 0.1 ` ' 1

Residual standard error: 0.1922 on 1051 degrees of freedom
Multiple R-Squared: 0.4315,    Adjusted R-squared: 0.431
F-statistic: 797.7 on 1 and 1051 DF,  p-value: < 2.2e-16
```

Table A.3: Summary of polynomial regression of total road density *r* against log well density.

```
Call:
lm(formula = r ~ w + I(w^2) + I(w^3), data = pdat)

Residuals:
    Min     1Q  Median     3Q    Max
-0.59831 -0.10871 -0.02955  0.10883  0.78287

Coefficients:
          Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0338628 0.0106466  3.181  0.00151 **
w           0.0179891 0.0127477  1.411  0.15849
I(w^2)      0.0633281 0.0066987  9.454  < 2e-16 ***
I(w^3)     -0.0088630 0.0008752 -10.127  < 2e-16 ***
---
Signif. codes:  0 `***' 0.001 `**' 0.01 `*' 0.05 `.' 0.1 ` ' 1

Residual standard error: 0.1835 on 1049 degrees of freedom
Multiple R-Squared: 0.4826,    Adjusted R-squared: 0.4812
F-statistic: 326.2 on 3 and 1049 DF,  p-value: < 2.2e-16
```

Table A.4: Summary of polynomial regression of industrial road density on log well density.

```
Call:
lm(formula = r.i. ~ w + I(w^2) + I(w^3), data = pdat)

Residuals:
    Min     1Q  Median     3Q    Max
-0.50564 -0.10322 -0.02677  0.10318  0.74452

Coefficients:
          Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0338573 0.0102698  3.297  0.00101 **
w           0.0281903 0.0122966  2.293  0.02207 *
I(w^2)      0.0533938 0.0064616  8.263 4.24e-16 ***
I(w^3)     -0.0080818 0.0008442 -9.573  < 2e-16 ***
---
Signif. codes:  0 `***' 0.001 `**' 0.01 `*' 0.05 `.' 0.1 ` ' 1

Residual standard error: 0.177 on 1049 degrees of freedom
Multiple R-Squared: 0.4312,    Adjusted R-squared: 0.4295
F-statistic:   265 on 3 and 1049 DF,  p-value: < 2.2e-16
```

Table A.5: Summary of linear regression of log pipeline density against log well density

```
Call: lm(formula = log(p.i.) ~ w, data = pdata)

Residuals:
   Min    1Q  Median   3Q    Max
-9.1505 -1.5812  0.4618  1.5873  9.2832

Coefficients:
        Estimate Std. Error t value Pr(>|t|)
(Intercept) -7.10613   0.12306  -57.74   <2e-16 ***
w            1.38792   0.04604   30.15   <2e-16 ***
---
Signif. codes:  0 `***' 0.001 `**' 0.01 `*' 0.05 `.' 0.1 ` ' 1

Residual standard error: 2.306 on 1051 degrees of freedom
Multiple R-Squared: 0.4637,    Adjusted R-squared: 0.4632
F-statistic: 908.9 on 1 and 1051 DF,  p-value: < 2.2e-16
```

Table A.6: Poisson regression model of five-year increments in per-township well counts (delta) against initial counts (init) for 1990-1995.

```
Call: glm(formula = delta ~ init + I(log(init)) + I(init^2), family = poisson,
    data = initd, subset = init < 145)

Deviance Residuals:
   Min     1Q  Median    3Q     Max
-4.9550 -1.8605 -0.9393  0.5128  26.0083

Coefficients:
           Estimate Std. Error z value Pr(>|z|)
(Intercept) -9.476e-01  8.705e-02 -10.886   <2e-16 ***
init        -3.317e-03  4.323e-03  -0.767   0.4430
I(log(init)) 9.409e-01  5.404e-02  17.410   <2e-16 ***
I(init^2)   -6.368e-05  2.670e-05  -2.385   0.0171 *
---
Signif. codes:  0 `***' 0.001 `**' 0.01 `*' 0.05 `.' 0.1 ` ' 1

(Dispersion parameter for poisson family taken to be 1)

   Null deviance: 8429.3  on 1003  degrees of freedom
Residual deviance: 6067.3  on 1000  degrees of freedom
AIC: 7837.7
%Dev = 0.28
```