



Illuminating Indigenous Economic Development

Donna Feir, Rob Gillezeau, and Maggie Jones*

Department of Economics, University of Victoria

Victoria, B.C., Canada V8W 2Y2

September, 2018

Abstract

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Keywords: light density, nighttime light density, Indigenous peoples, economic development, community well-being index

JEL Classifications: I15, J15, J24

***Corresponding Author Contact:**

Maggie Jones, Dept. of Economics, University of Victoria, P.O. Box 1700, STN CSC, Victoria, B.C., Canada V8W 2Y2; E-mail: maggie.ec.jones@gmail.com.

ILLUMINATING INDIGENOUS ECONOMIC DEVELOPMENT

Donna Feir
Department of Economics
University of Victoria
dfeir@uvic.ca

Rob Gillezeau
Department of Economics
University of Victoria
gillezr@uvic.ca

Maggie E.C. Jones
Department of Economics
University of Victoria
maggie.ec.jones@gmail.com

August 31, 2018

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Acknowledgments. We would like to thank all seminar participants who provided valuable feedback for this work. We also would like to give a special thanks to Jacqueline Quinless, Kevin Milligan, Anya Hageman, Xuecao Li, and Chris Elvidge for their useful discussions and insights. All opinions expressed here are ours and any errors or omissions are ours alone.

1 Introduction

For decades, a significant challenge faced by development economists has been a lack of reliable and accurate data measuring economic activity in developing countries and regions within those countries (Henderson, Storeygard, and Weil, 2012). This has generally been of lesser concern for developed countries, which often have higher quality data. However, due to specific reporting restrictions, data on GDP per capita is not always publicly available for many small communities within developed countries. In Canada, this problem is particularly acute for Indigenous communities, where remoteness, size, and jurisdictional issues limits data collection and validation.^{1,2}

This paper proposes that publicly available satellite data that measures nighttime light density in Indigenous communities is a useful alternative to traditional indicators of economic well-being.³ There are over 1,000 Indigenous communities in Canada; however, the most comprehensive data source containing socioeconomic indicators only includes consistent data for 357 of these communities every five years over the 1990 to 2011 time period.⁴ Known as the Community Well-Being (CWB) Database, this data source includes community-level information on GDP per capita, in addition to a CWB index—akin to the Human Development Index—which assigns communities a score between 0 and 100 based on community-wide levels of education, income, labour force participation, and housing conditions.⁵ We show that nighttime light density is positively correlated with the existing measures of well-being and examine the sample selection issues that arise when evaluating economic questions using these publicly available databases. We conclude by providing three empirical examples that highlight the usefulness of using nighttime lights data relative to other publicly available datasets.

The use of nighttime light density as a measure of economic well-being allows researchers to generate a panel of well-being spanning over 20 years for communities large

¹For instance, in 2011 there were a total of 31 Indian reserves and Indian settlements that were incompletely enumerated. Reasons for the incomplete enumeration ranged from natural events that prevented data collection to a lack of permission from the community. More information can be found at: <http://www12.statcan.gc.ca/nhs-ennm/2011/ref/aboriginal-autochtones-eng.cfm>.

²This may also be of concern in other developed countries with sizeable Indigenous populations, like the United States, Australia, New Zealand.

³While our analysis focuses on Indigenous communities in Canada, nighttime light density data may be useful for assessing economic development of rural areas more generally.

⁴Communities are defined in terms of census subdivisions (CSDs) in order to be consistent with the CWB geography. CSDs are municipalities or areas that are the equivalent to municipalities such as Indian reserves. “First Nations communities” are CSDs that Indigenous and Northern Affairs Canada and Statistics Canada classify as “on-reserve”. They include all CSD types that are legally affiliated with Indian bands. Inuit communities are included in similar census definitions. See [Indigenous and Northern Affairs Canada \(2010\)](#) for details.

⁵For further discussion of this index and its relationship to the Human Development Index, see [O’Sullivan \(2011\)](#) and [Cooke \(2005\)](#).

and small. We outline a procedure based on the methodology of [Li and Zhou \(2017\)](#) that can be used to adjust the time-series for differences in the on-board calibration of satellites, from which we construct a database containing the average nighttime light density of all communities in Canada between 1992 and 2013. For reasons outlined in [Section 2](#), we exclude communities above the 60th parallel from our analyses. Using our adjusted data, we compare community-level nighttime light density to GDP per capita, the CWB index, and the CWB component scores for the set of First Nations and Inuit communities for which this these data are available.⁶ We find that nighttime light density is correlated with many of the standard measures of well-being included in the CWB database. Further, comparing the characteristics of communities that have available per capita income or CWB data to those included in the nighttime lights data reveals clear evidence of sample selection issues within the pre-existing indicators of well-being in First Nations and Inuit communities.⁷ We use three empirical applications to illustrate the relevance of the sample selection problem and the potential usefulness of nighttime lights data.

First we show that comparing trends in community well-being and GDP per capita over time, as has been done by Indigenous and Northern Affairs Canada in the past, underestimates the improvement in well-being of First Nations communities relative to non-Indigenous communities. In our second example, we find that certain historical and geographic factors are not statistically correlated with economic activity in the selected samples, but do have a statistically significant relationship with economic activity for the expanded sample. Researchers limited to using the selected samples would draw substantially different conclusions about the role of historical persistence and geographic characteristics on modern economic development than researchers using the expanded sample. Our final empirical exercise focuses on the impact of local mining intensity on the well-being of Indigenous communities using an illustrative difference-in-differences design. We show that the conclusions drawn depend on both the selected sample, as well as the frequency with which publicly available data are observed. Since the nighttime light data can be matched to other datasets that are available on an annual basis, researchers can use this additional variation in their estimations, which in turn can affect the final results. We find that night-time light density within Indigenous communities is negatively correlated with the opening of mines in surrounding territory. While we hesitate to draw conclusions about causality and emphasize these findings may not generalize to

⁶We focus on First Nations and Inuit communities, defined below, because economic development among these communities is a pressing public policy issue ([Feir and Hancock, 2016](#); [The Truth and Reconciliation Commission of Canada, 2015](#)) and publicly available data are subject to serious limitations.

⁷We argue nighttime light data are useful for overcoming this sample selection issue for smaller First Nations communities over the full time period for which these data exist, and is useful for the Inuit post-2005.

communities above the 60th parallel, we believe understanding this relationship more deeply is a policy-relevant area of future research.

Given the aforementioned sample selection issues, in addition to other advantages of nighttime light data, such as its annual availability since 1990, we suggest that nighttime light data should be considered a core outcome variable when studying economic development in Indigenous communities. In addition to the usefulness of this measure for economic research, conceptually, light may be a more palatable measure of well-being for many Indigenous cultures in comparison to GDP or the CWB index. The concept of light as a thing of value is embedded in many Indigenous and non-Indigenous creation narratives, potentially making it a measure with cross-cultural meaning beyond its ability to capture more standard economic measures of well-being (Levy, 1998; May, 1939; Miller, 2000; Rasmussen and Worster, 2009; Reid et al., 1996). In addition, satellite nighttime light data are available worldwide at a relatively fine level of detail and can be easily used to analyze any geographic unit of interest. Nighttime light data could be used to study outcomes along Indigenous-defined geographies of interest, such as asserted land claims, traditional homelands, or historical treaty boundaries. The ability to use nighttime light data to transcend political, national and standard statistical boundaries has already proven to be advantageous for the study of economic development in the African context (Michalopoulos and Papaioannou, 2013, 2014).

In Section 2, we discuss the existing data sources for measures of the economic well-being of Indigenous communities. We then introduce the nighttime light data and outline the procedure for generating a temporally consistent database of nighttime lights. Next we discuss the sample selection issues by comparing a cross section of the CWB database to a cross section of the nighttime lights data, and conclude the data section by correlating nighttime lights to other measures of well-being. Section 3 presents our three empirical examples, and we conclude in Section 4 with an overview of some of the limitations of the nighttime lights data and how we see this measure as contributing to the understanding of Indigenous economic development.

2 Existing Data Sources, Potential Sample Selection, and the Meaning of Nighttime Light Density

2.1 The Community Well-Being Index

Indigenous and Northern Affairs Canada (INAC) recognizes 618 First Nations, in addition to Inuit groups, that are associated with over 1,000 reserves and settlements through-

out the country. Both reserves and Indigenous settlements are measured at the census subdivision (CSD) level, which is comparable to a municipality. Since many of these communities are small, publicly available data on housing, labour force participation, education and wages is available for only a subset of communities. The most comprehensive public collection of economic data for Indigenous communities is the Community Well-Being (CWB) database, which is derived from the Census of Population. The primary indicator of well-being in the CWB database is a composite index between 0 and 100 that reflects a community’s overall well-being. This index, known as the Community Well-Being (CWB) Index, is similar to the United Nation’s Human Development Index, as it takes into account education, housing, labour force participation, and income to provide a comprehensive measure of well-being.⁸ The CWB Index is publicly available for all census subdivisions (CSD) in Canada that meet Statistics Canada public reporting criteria. For communities that meet slightly more stringent criteria, the individual component scores are also provided.⁹ Along with the CWB index and relevant components, these data include population, type of census subdivision—First Nation, Inuit, or non-Aboriginal¹⁰—and GDP per capita can be backed out of these data using the formula for the income component score.¹¹

Although the CWB database is the most comprehensive community level data on economic well-being in Indigenous communities, only 381 Indigenous communities had data on GDP per capita in 2011 ([Strategic Research Directorate Aboriginal Affairs and Northern Development Canada, 2015](#)), which is the most recent year for which these data are available. The composite CWB index yields a larger count of 603 Indigenous communities in the same year. However, of those communities, only 357 have consistent data from 1990 onwards. An additional drawback of these data is that they are not available annually; rather, they are available at 5 year intervals alongside the Census of Population.

The subset of communities included in the CWB database covers a substantial proportion of the on-reserve First Nation and Inuit population; however, it is a small fraction

⁸The CWB index can be downloaded from: <https://www.aadnc-aandc.gc.ca/eng/1100100016579/1100100016580>.

⁹Component scores are provided for income, education, housing, and labour force participation. They are available for communities with a population of at least 250, if the total number of unweighted individuals in the community with a component score was least 4, and the total number of weighted individuals with a component score was at least 10.

¹⁰We follow the terminology in the CWB database and use the term “non-Aboriginal” communities to refer to communities that are not associated with an Indigenous group.

¹¹The income score is constructed using the following formula:

$$inc_score = \left(\frac{\log(gdp_pc) - \log(2,000)}{\log(40,000) - \log(2,000)} \right). \quad (1)$$

of the total number of Indigenous communities in Canada.¹² Moreover, the communities included in the sample are systematically selected. The threshold population size for being included in the CWB database is 65, while being included in the GDP sample requires a population of 250 people or 40 households ([Indigenous and Northern Affairs Canada, 2010](#)). Communities are also only included in either sample if they are completely enumerated. A reserve is deemed incompletely enumerated if it is not permitted to be enumerated or if enumeration is interrupted or of insufficient quality. Inclusion also requires a non-response rate to the census questions that was less than 25%. Since many questions relating to public policy, economic development, and Indigenous well-being focus on community-level outcomes,¹³ a representative sample of these communities is required to understand the full extent of the policy under question. In particular, it is essential to have a complete distribution of community sizes in order to examine policies related to the revitalization of Indigenous communities, such as out-migration from traditional homelands. Many Indigenous value systems emphasize community level priorities and objectives ([Daes, 1995](#); [Gomez, 2007](#); [Kovach, 2010](#); [Smith, 2012](#); [United Nations, 2009](#)); thus, excluding more than half of the communities from economic analysis may be particularly troublesome for conducting economic research of meaning for Indigenous communities.

2.2 The Nighttime Light Database

Given the aforementioned constraints, luminosity data may be used as an alternative indicator of well-being for Indigenous communities. Nighttime light data have been used extensively in recent economic literature and have been shown to be good proxies for economic activity at various levels of aggregation: countries ([Lessmann and Seidel, 2017](#); [Pinkovskiy and Sala-I-Martin, 2016](#)), ethnic homelands ([Alesina, Michalopoulos, and Papaioannou, 2016](#); [Michalopoulos and Papaioannou, 2013](#)), sub- and supranational regions ([Ghosh, Powell, Elvidge, Baugh, Sutton, and Anderson, 2010](#); [Henderson, Storeygard, and Weil, 2012](#)), and even at the pixel level ([Bleakley and Lin, 2012](#)). These data are gathered by the U.S. Air Force Defence Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) from satellites that orbit the earth up to 14 times per day and collect imagery of light density on Earth between 8:30 p.m. and 10 p.m. The raw images are processed by scientists at the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Centre (NGDC) to account for fluctuations in

¹²For example, in 2011, the CWB database included well over 80 percent of the total on reserve population, although nearly 40,000 people are still excluded from these data. The sample that contains only GDP excludes another 30,000 individuals.

¹³For examples, refer to [Aragón \(2015\)](#); [Dippel \(2014\)](#); [Feir, Gillezeau, and Jones \(2017\)](#).

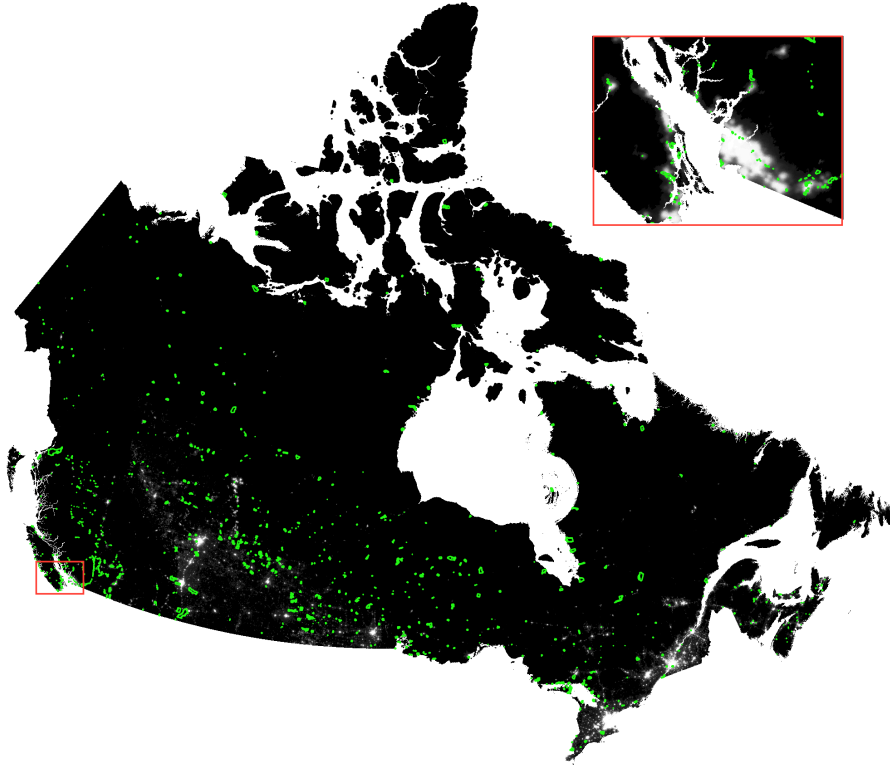


Figure 1: *This figure displays nighttime lights across Canada in 2011. Light areas represent locations with a high light density and dark locations have a low light density. CSA boundaries, from Statistics Canada, are in green. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*

light density that occur from natural phenomena such as seasonal variation in sunlight, auroral activity, and cloud-cover. All orbits are averaged over valid nights to produce a satellite-year dataset (Henderson et al., 2012). In some years more than one satellite orbits Earth, in which case light density can be averaged over both satellites.¹⁴

The DMSP-OLS nighttime light data are downloadable from the NGDC website in raster (bitmap image) form.¹⁵ They are available at 30 arc second grids, which is equivalent to an area of approximately 1 square kilometre at the equator (Pinkovski and Sala-I-Martin, 2016). We focus on the “Average Visible, Stable Lights, & Cloud Free Coverages” sample, which excludes sunlit and moonlit data, glare, observations with clouds, and auroral activity. Each pixel of the raster is assigned a value between 0 (no

¹⁴In 2011 NASA and NOAA launched a satellite carrying the first Visible Infrared Imaging Radiometer Suite Instrument (VIIRS). The VIIRS data also collects nighttime light imaging and has been noted as producing a higher quality image to the DMSP-OLS (Elvidge et al., 2017, 2013). Analyzing these data in concordance with publicly available economic data is beyond the scope of this paper but constitutes future work.

¹⁵These data can be downloaded online from <https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>.

light) and 63 (maximum light). They are available nearly globally for every year between 1992 and 2013.¹⁶ Figure 1 displays the 2011 nighttime light density across Canada along with the geographic boundaries of Indigenous communities. It is easy to identify large economic centres in the south-east, along the border with the United States, and centres in the prairies by their luminosity.

The main advantage of using nighttime light data in this context is that it can, in principle, be constructed for all communities in Canada from publicly available information consistently from 1992 onward. Given that there is selection—which we outline below—into publicly available government-based data, the nighttime lights data can be a useful alternative to these pre-existing data sources. Further, light data may be aggregated more naturally to geographic areas beyond those currently defined geographical units in existing survey data, like the census of population. This may allow Indigenous communities or researchers to draw boundaries of interest that they consider to be relevant units of study, rather than those defined by Statistics Canada. In order to make comparisons with the CWB database, we focus on the log of mean light density within the 2011 census subdivision boundaries.¹⁷

The nighttime light data suffers from two main limitations. First, comparing nighttime light data across time requires inter-annual calibration of the satellites to account for differences in the measurement of light intensity across satellites. We adjust the time series following the methodology of Li and Zhou (2017), which we outline in Appendix B. Given the effectiveness of this adjustment, we see it as a minor limitation.

The second limitation is that the nighttime lights data become erratic at high latitudes. There are several possible explanations as to why this may be the case. Extensive auroral activity, the presence of sunlight, variation in snow cover, a low number of cloud-free days, or the algorithm used to detect and filter out cloudy days have all been suggested as contributing factors to the erratic trends in nighttime lights at high latitudes (Elvidge et al., 2017).¹⁸ The explanation that can be most easily accounted for by standard econometric tools would be to adjust the nighttime light data for the number of cloud-free days, but this does not fully account for the variability of the nighttime lights data at high latitudes during the 2000-2005 time period. Appendix C provides more detail on this issue.

Since the cloud-free adjustment does not correct for the variability in the lights esti-

¹⁶The nighttime light data range from -65 to 75 degrees latitude, excluding Canada's northernmost community, Grise Fiord.

¹⁷We choose 2011 geographic boundaries since the DMSP nighttime light data are available until 2013 and 2011 is the closest census year with geographic boundary files.

¹⁸Speculation regarding the effectiveness of the algorithm used to detect and filter out cloudy days at high latitudes was communicated to us via email from C. Elvidge, August, 2018.

mate for high latitude communities prior to 2005, we follow the literature and exclude high-latitude communities in our analyses. Although the trends in lights seem to be stable for high latitude communities after 2005, we exclude them in all our estimations, so that we present estimates from a consistent sample. Specifically, we focus on communities below the 60th parallel.¹⁹ Unfortunately, this excludes the majority of Inuit communities from our time series sample. Therefore, although nighttime lights data allow researchers to look at a sample of small communities that are typically excluded from the public use census files, they are limited in their usefulness to proxy for well-being for northern communities in Canada prior to 2005.

Using the 2011 geographic boundaries to compute light density results in a total of 4,161 non-Indigenous communities, 1,039 First Nations communities and 52 Inuit communities.²⁰ In light of the aforementioned data limitations, we restrict the sample to those communities below the 60th parallel. This restriction primarily affects Inuit communities, where nighttime light was, on average, more variable during the pre-2005 time period—see Figure A1—but also affects a small number of non-Indigenous and First Nations communities. Our restricted sample contains 4,125 non-Indigenous communities (a loss of 0.87% of communities), 994 First Nations communities (-4.33%), and 13 Inuit communities (-75.00%).

In regressions where we compare the nighttime light data to the publicly available data from the CWB dataset, we focus on communities below 6,500 people because the largest First Nations community for which we have a population estimate at the census subdivision level is 6,200 and we round up to the nearest 500. In 2011, this leaves a total of 1039 First Nations communities, 52 Inuit communities, and 3,585 non-First Nations communities in the night-light sample; 557 First Nations communities, 46 Inuit communities, and 2,154 non-Aboriginal in the CWB sample; and 340 First nations communities, 41 Inuit communities, and 1,795 non-Aboriginal communities in the GDP sample.

It is important to note that the choice to include communities above the 60th parallel in this case is a result of a careful analysis of these data surrounding this time period, as well as consideration of their limitations. Researchers wishing to use the full sample of Indigenous communities should consider the time period of their analysis to ensure it is not during a period of high variability in arctic lighting. Otherwise, communities above the 60th parallel should be excluded from the analysis.

¹⁹Results using the full sample do not tend to differ substantially and are available upon request.

²⁰There were actually 53 Inuit communities in 2011; however, being above the 75 parallel, Grise Fiord is not included in the lights data, as it is located above the threshold latitude for which satellites are able to detect light.

2.3 Sample Selection Issues in the CWB Database in a Single Cross-Section

Figure 2 displays the density of the natural logarithm of nighttime lights for all First Nations, Inuit, and non-Aboriginal communities below the 60th parallel with populations under 6,500 people as identified in the 2011 Census of the Population. The results of Figure 2 are striking: a substantial mass of First Nations and Inuit communities are essentially in the dark. This is seen in the bimodal nature of the First Nation and Inuit light distribution: the first mass is at extremely low levels of light density and the second mass is to the left of the median of the non-Aboriginal light density distribution. The low light density peak is not nearly as pronounced for non-Aboriginal communities and there is substantially more mass in the right tail of the non-Aboriginal distribution of light density. This bimodal nature of the First Nations and Inuit light distribution is not driven by Inuit or northern communities. Overall, the data paint a picture of a mass of First Nations and Inuit communities with low observable levels of economic activity and a larger mass that are still somewhat less well-off than their non-Aboriginal counterparts.

It should be noted that the bimodal nature of the distribution may largely be a feature of the inability of satellites to distinguish between very low levels of light. The notion that nighttime light density data are unable to differentiate between light among very small communities has been noted in the literature (Chen and Nordhaus, 2011; Elvidge et al., 2017; Lessmann and Seidel, 2017), and it is important to recognize that nighttime light density may not be an appropriate indicator to use to study inequality between communities in the left tail of the nighttime light distribution. However, the point remains that there are a substantial number of First Nations and Inuit communities with very low levels of nighttime light emissions and this is more common among First Nations communities than non-Aboriginal communities.

In Figure 3, we display the distribution of the log of light density for First Nations, Inuit and non-Aboriginal communities, comparing the sample of communities that are included in the GDP sample, the larger CWB sample, and the full nighttime light sample. We only focus on communities below the 60th parallel. It is clear that the CWB and GDP subsamples differ from the full lights sample. In particular, restricting our analysis to only those communities in the CWB and GDP sample omits the lower mass of the light density. Given that policies are often meant to target the poorest communities or equalize funding across First Nations, Inuit and non-Aboriginal communities, this is a significant omission. From this distributional analysis, it is clear that the communities excluded from typical GDP per capita or CWB analyses differ from communities in these limited samples.

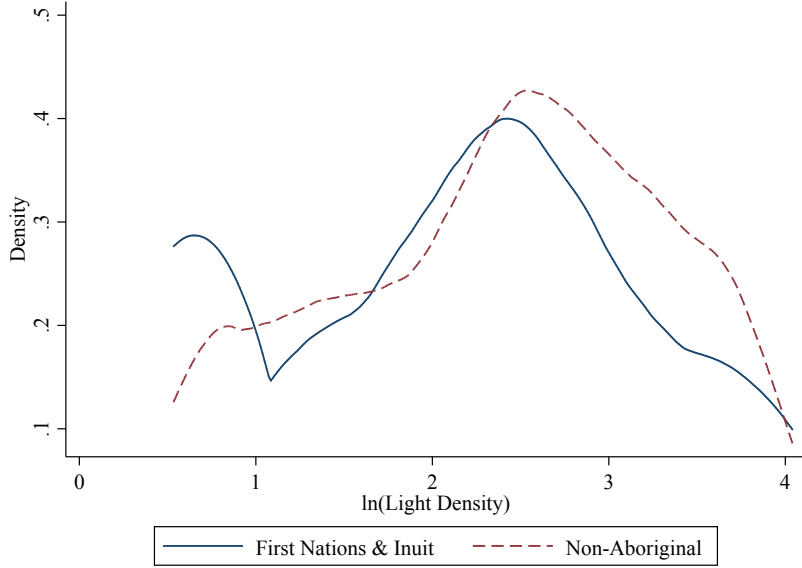


Figure 2: *The distribution of the natural log of light density at night for First Nations and Inuit communities and non-Aboriginal Communities below the 60th parallel with a population under 6,500 individuals. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*

To further examine this sample selection, in Tables 1 and 2, we report summary statistics for Indigenous communities split by the sample in which the community is found. Panel A of each table displays the summary statistics for all Indigenous communities below the 60th parallel.²¹ The population data are not available for all communities, so in panel B of each table we show the summary statistics for population size for the available communities. Table 1 compares the CWB sample to the non-CWB sample, and Table 2 compares the GDP sample to the non-GDP sample. Those in the GDP sample are necessarily in the CWB sample. The tables emphasize that smaller communities are excluded from the CWB database. In fact, the average population of communities that are excluded from the CWB database is approximately 480 people lower than the average of communities that are included in this database. This difference in population is partially reflected in a lower average light density among communities not included in the CWB database. The communities observed only in the lights sample have an average of about one standard deviation lower log light density compared to those that are included in the sample. A similar pattern holds when we compare the communities for which GDP data are available to those that are excluded from both the GDP data

²¹Our main analysis focuses on communities smaller than 6,500; however, since all Indigenous communities are smaller than 6,500 we do not need to make this restriction for tables displaying only Indigenous communities.

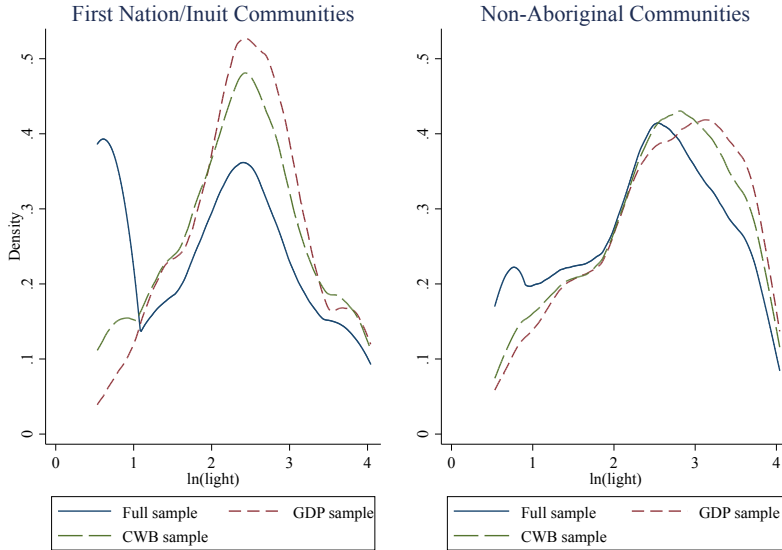


Figure 3: *The distribution of the natural log of light density at night for First Nations and Inuit communities, comparing the distribution for sub-samples of communities based on the availability of GDP per capita, CWB, and nighttime light density for communities below the 60th parallel and under 6,500 people. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*

and the CWB database.

There are notable differences in other community characteristics between samples. On average, communities that are excluded from the CWB and GDP databases are slightly less geographically isolated, as indicated by being located closer to a census metropolitan area (CMA) or from a railway station. They are located farther from historical trading posts, and are less likely to have signed a modern treaty with the federal government and are more likely to be located on rugged terrain.²²

²²Distance from historical trading posts and railway stations is computed by calculating the geodetic distance between the centroid of each CSD and the location of historical trading posts and railway stations. The historic trading post data are from from Natural Resources Canada and the location of historical railway stations is from ESRI Canada. Ruggedness is calculated using Global DEM files from the Harmonized World Soil Database v 1.2 (HWSD) from the Food and Agriculture Organization of the United Nations (Fischer et al., 2008). We overlay these files with reserve boundaries to compute the terrain ruggedness index of Riley et al. (1999).

Table 1: Sample Selection in CWB Database

	In sample	Not in sample	Difference
Panel A: CWB Sample			
Ln(avg light density)	2.33 (0.90)	1.42 (1.10)	-0.91***
Has Population Data	1.00 (0.00)	0.61 (0.49)	-0.39***
Signed modern treaty	0.02 (0.16)	0.00 (0.07)	-0.02**
Dist to closest CMA	119.00 (116.98)	103.74 (88.99)	-15.26*
Dist to historical post	110.92 (97.24)	128.59 (93.73)	17.67**
Dist to railway station	193.57 (214.60)	189.59 (231.71)	-3.98
Avg ruggedness index	356.96 (269.51)	471.21 (321.90)	114.25***
Latitude	-104.15 (19.06)	-111.96 (16.34)	-7.82***
Longitude	51.26 (3.46)	51.40 (2.97)	0.14
Observations	528	435	963
Panel B: CWB Sample with Population			
Ln(Population)	5.93 (1.00)	3.33 (1.52)	-2.60***
Population	623.10 (727.35)	142.56 (486.48)	-480.54***
Observations	528	264	963

Table 2: Sample Selection in GDP Database

	In sample	Not in sample	Difference
Panel A: GDP Sample			
Ln(avg light density)	2.46 (0.80)	1.65 (1.12)	-0.81***
Has Population Data	1.00 (0.00)	0.73 (0.44)	-0.27***
Signed modern treaty	0.04 (0.20)	0.00 (0.06)	-0.04***
Dist to closest CMA	131.06 (129.83)	102.54 (89.36)	-28.51***
Dist to historical post	99.59 (87.90)	128.65 (98.52)	29.06***
Dist to railway station	193.53 (206.96)	190.89 (229.92)	-2.65
Avg ruggedness index	350.60 (253.72)	437.82 (316.48)	87.22***
Latitude	-100.16 (18.67)	-111.47 (16.89)	-11.30***
Longitude	51.47 (3.48)	51.24 (3.12)	-0.23
Observations	323	640	963
Panel B: GDP Sample with Population			
ln(Population)	6.59 (0.66)	4.02 (1.40)	-2.57***
Population	926.92 (790.85)	143.37 (366.49)	-821.86***
Observations	323	469	963

Notes: Mean values are reported with the standard errors in parenthesis for Indigenous (First Nations and Inuit) communities only. Communities are defined by census subdivisions in order to be comparable with the CWB index. The total census population is rounded to the nearest 5. Communities with 0 people are treated as missing population information. Communities above the 60th parallel and with more than 6,500 people are excluded from the comparison. Significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

There are also sample selection issues within the CWB database. In Table A1 of the appendix, we compare communities that are observed in the CWB sample, but not in the GDP sample. We find that communities in the GDP sample are systematically rated lower on the CWB index and higher in the light density index than those who are not included in the GDP sample. The CWB index is approximately half a standard deviation higher in the communities excluded from the GDP sample and about half a standard deviation lower in log light density. Again, there are differences in levels of modern and historical geographic isolation.

2.4 What Do Lights Tell Us About Well-Being?

Nighttime light data are only helpful to circumvent the potential sample selection problem if they can be used as a meaningful measure of well-being and can be used as an outcome in policy evaluation. In this section, we show that not only are nighttime lights strongly correlated with measures of well-being in the cross-section, but they are also meaningfully correlated with changes in income within communities over time. While it has already been established that nighttime light density is meaningfully correlated with per capita income and the growth of per capita income both globally, as well as within countries with low levels of per capita income (Henderson et al., 2012), it is not well established that light measures are useful to measure growth at the regional level in relatively high income countries.²³

We begin by showing that lights and measures of well-being are correlated in the 2011 cross-section for First Nations, Inuit, and non-Aboriginal communities.²⁴ Figure 4 shows that our light density measure is positively correlated with the Community Well-Being Index (Figure 4(a)) and GDP per capita (Figure 4(b)).

In Table 3, we display the unconditional, cross-sectional elasticities between community nighttime light density and standard composite measures from the CWB database, including education, housing, labour force participation, population, GDP per capita, and the CWB index itself for both Indigenous and non-Indigenous communities below the 60th parallel. For both sets of communities, nighttime light density is positively correlated with all outcome variables and this correlation is statistically significant in all cases other than labour force participation among the Indigenous communities. These estimated correlations between economic outcomes and nighttime light density are similar to those observed in other contexts (Donaldson and Storeygard, 2016); however, in

²³Mellander et al. (2015) provides evidence that in Sweden night time light measures are a good proxy for population and establishment density but the correlation was weaker for wages.

²⁴We choose 2011 since it is the most recent year for which the CWB and its subcomponents are available.

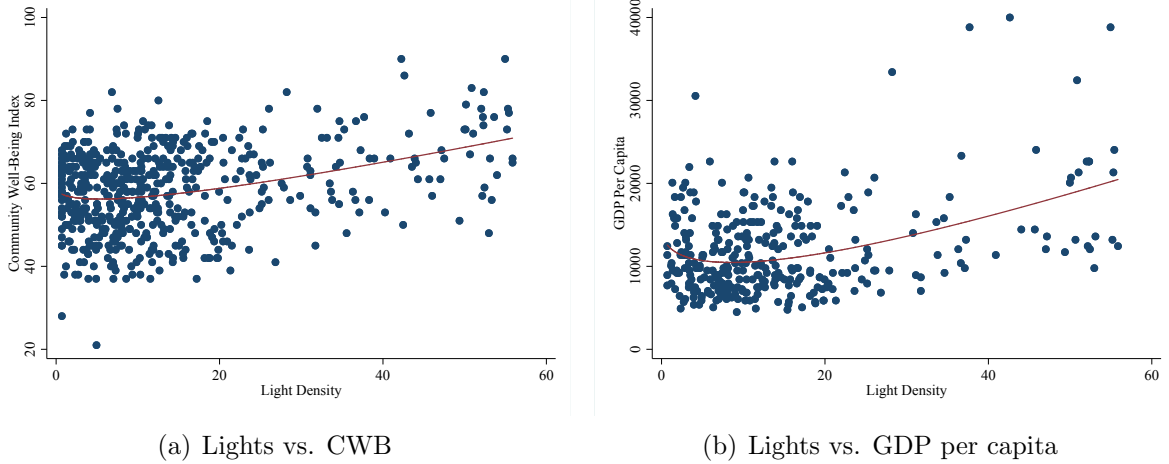


Figure 4: *This figure plots the average light density per pixel for First Nations and Inuit census subdivisions below the 60th parallel against the CWB index and GDP per capita in 2011. The nighttime lights data are available from the National Geophysical Data Centre (NGDC), and the CWB and GDP data are available from INAC.*

general, the elasticities are larger for non-Aboriginal communities.

We repeat this exercise in Table 4 where we present our elasticity estimates conditional on population size. For non-Aboriginal communities, we continue to see a positive correlation between education, housing, population, and GDP per capita and light density. As in the unconditional correlations, the correlations remain positive for First Nations and Inuit communities.

Generally, we would expect lights to be positively correlated with income to the extent that the consumption of goods and services that require light are normal goods and that productive processes require or admit light. Both of these factors may also depend on unobservables characteristics, like the price of electricity, which may vary across communities and over time and could potentially confound the estimates of elasticity in Table 3. Fortunately, we can partially account for this concern by using the time-series component of the nighttime lights and GDP data in fixed effects specifications of the following form:

$$\ln(\text{lights})_{it} = \alpha + \beta \ln(\text{GDPpc})_{it} + \phi \ln(\text{population})_{it} + \gamma_i + \zeta_t + \epsilon_{it}, \quad (2)$$

where we regress the logarithm of nighttime light density in community i at time t on the logarithm of GDP per capita and the logarithm of population. The fixed effects, γ_i and ζ_t account for time-invariant community-specific unobservable characteristics, as well as time-varying unobservables that are consistent across census subdivisions. This estimating equation gives us a sense of the extent to which changes in light intensity are correlated with income independent from changes in these unobservables.

Table 3: Elasticities of Light with Respect Other Well-being Measures in 2011

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Non-Aboriginal Communities						
ln Education	0.934*** (0.106)					
ln Housing		3.451*** (0.740)				
ln Labour Force			1.926*** (0.209)			
ln Population				0.229*** (0.008)		
ln GDP per capita					0.808*** (0.105)	
ln CWB						3.017*** (0.274)
Observations	1787	1787	1787	3551	1787	2145
Adjusted R^2	0.040	0.036	0.045	0.158	0.034	0.065
Panel B: First Nations and Inuit Communities						
ln Education	0.478*** (0.105)					
ln Housing		1.153*** (0.158)				
ln Labour Force			0.394 (0.309)			
ln Population				0.210*** (0.012)		
ln GDP per capita					0.434*** (0.105)	
ln CWB						1.028*** (0.190)
Observations	334	334	334	976	334	541
Adjusted R^2	0.059	0.127	0.002	0.224	0.047	0.044

Notes: The left hand column labels the natural log of the respective indexes. The dependent variable is the natural log of average annual nighttime light density as described in the data section. Robust standard errors in parentheses. Communities above the 60th parallel are not included in the sample. Significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We present estimates of equation 2 in Table 5, where we do not restrict Indigenous and non-Indigenous communities to have the same functional relationship between income, population and light production. This allows for the possibility of different preferences or production processes between Indigenous and non-Indigenous communities. We use all years for which both GDP and light data are available (1996, 2001, 2006, and 2011) and we cluster standard errors at the census subdivision level.

Column (1) presents pooled estimates of the elasticities, conditional on population, for Indigenous communities and non-Indigenous communities. The elasticity of lights with respect to income is 0.520 among Indigenous communities, which is comparable to the estimate of 0.446 using the single cross section in Table 4. The estimate for non-Indigenous communities is upwards of 0.82 compared to 0.49 for the single cross section. Column (2) adds year fixed effects to the specification, exploiting variation

Table 4: Elasticities of Light with Respect to Well-Being Measures Conditional on Population Size and Population Density

	(1)	(2)	(3)	(4)	(5)
ln Education	0.462*** (0.102)				
(Non-Ab==1)*ln Education	0.0932 (0.149)				
ln Housing		1.287*** (0.151)			
(Non-Ab==1)*ln Housing		1.014 (0.671)			
ln Labour Force			0.436 (0.309)		
(Non-Ab==1)*ln Labour Force			1.142*** (0.372)		
ln GDP per capita				0.446*** (0.103)	
(Non-Ab==1)*ln GDP per capita				0.0438 (0.148)	
ln CWB					1.288*** (0.183)
(Non-Ab==1)*ln CWB					0.877*** (0.331)
ln Population	X	X	X	X	X
Observations	2175	2175	2175	2175	2755
Adjusted R^2	0.770	0.773	0.780	0.766	0.716

Notes: The left hand column labels the natural log of the respective indexes and the indices interacted with a non-Aboriginal dummy variable. The dependent variable is the natural log of average annual nighttime light density as described in the data section. Robust standard errors in parentheses. Communities above the 60th parallel are not included in the sample. Standard errors are contained in the parentheses. Significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

between communities and the elasticity of lights with respect to GDP per capita decreases slightly for both Indigenous and non-Indigenous communities. Finally, column (3) adds census subdivision fixed effects, so that the identifying variation comes from changes within communities. The elasticity estimate in this specification is notably smaller than the previous estimates, suggesting that a large component of the differences in elasticity estimates between Indigenous and non-Indigenous communities comes from unobservable community-level differences.

Table 5: Fixed Effects Estimates of Elasticities of Light With Respect GDP

	Pooled (1)	Between (2)	Within (3)
ln GDP per capita	0.520*** (0.111)	0.508*** (0.112)	0.114* (0.069)
ln GDP per capita \times Non-Aboriginal	0.295** (0.129)	0.282** (0.132)	0.0216 (0.072)
ln Population	0.142* (0.074)	0.138* (0.075)	0.236*** (0.069)
ln Population \times Non-Aboriginal	0.121 (0.078)	0.124 (0.078)	-0.358*** (0.079)
Year FE		X	X
Community FE			X
Observations	9992	9992	9992
Adjusted R^2	0.106	0.107	0.968

Notes: The dependent variable in each column is the logarithm of nighttime light density. Standard errors, clustered by CSD, in parenthesis. Data included in these specifications is from 1996, 2001, 2006, and 2011. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results from the above exercise reveal that there is a robust positive correlation between nighttime light density and GDP per capita, as well as other measures of economic well being. These results provide further support that nighttime light density data are a general proxy for economic development in more rural regions of Canada for both First Nations, and non-Aboriginal communities.

3 Examples of Empirical Applications

In this section, we provide a set of empirical examples that are meant to illustrate the consequences of using the restricted samples to study economic well-being. In each example, certain restrictions have to be made in accordance with the context under examination, which suggests that there is no “one size fits all” set of rules to follow when using nighttime light data to examine economic well-being. Rather, each researcher must assess the benefits and costs associated with using nighttime light data in lieu of traditional economic indicators for their particular study.

3.1 Comparing Community Well-Being Over Time

One of the reasons that the CWB index was developed was to assess the relative well-being of communities in Canada over time. To this end, Indigenous and Northern Affairs Canada (INAC) has released a set of policy reports outlining the progression of the well-being of various types of communities over time ([Strategic Research Directorate Aborig-](#)

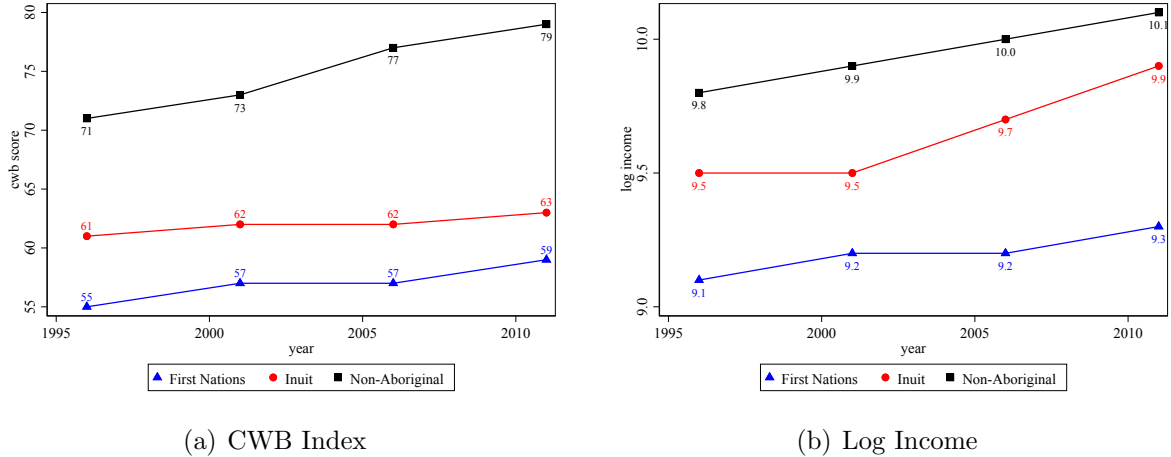


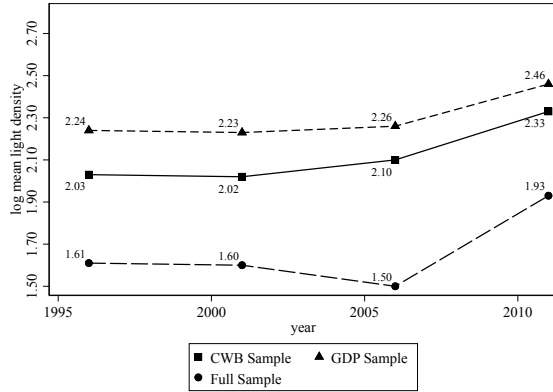
Figure 5: *CWB index and the logarithm of income over time for First Nations, Inuit, and Non-Aboriginal communities. Data are from INAC.*

inal Affairs and Northern Development Canada, 2015). For example, in 2013 they produced a report comparing the CWB index across First Nations, Inuit, and non-Aboriginal communities. Figure 5(a) and 5(b) recreate their plots.²⁵ Our analysis will focus on First Nations and non-Aboriginal communities, as they are least affected by the 60th parallel restriction. For both well-being and income, we see a general increase over time for all communities; however, both appear to have increased more for non-Aboriginal communities compared to First Nations communities. The CWB index increased by 11.3% between 1996 and 2011 in non-Aboriginal communities, while First Nations communities saw an increase in their CWB index of 7.3%. For log income, increases were roughly 3.1% for non-Aboriginal communities and 2.2% for First Nations communities, respectively.

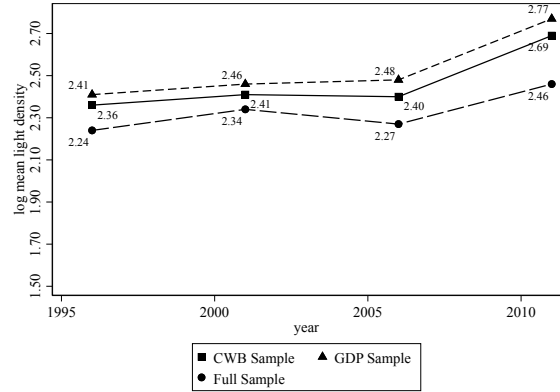
Figure 6(a) and 6(b) display the trends in log nighttime light density for each of the samples—CWB, GDP, and Lights—for First Nations and non-Aboriginal communities. We exclude communities above the 60th parallel. Restricting to the CWB sample shows comparable increases in the log of nighttime light density for First Nations and non-Aboriginal communities—14.8% versus 14.0%, respectively.²⁶ The GDP sample, which is an even smaller subset of communities, yields gains of 14.9% for non-Aboriginal communities and 9.9% for First Nations communities. When we expand to the full sample, we see that log light density actually increased by 19.9% for First Nations communities and 9.8% for non-Aboriginal communities. In this instance, conclusions based on the restricted samples may drastically understate the advancements in economic activity in

²⁵Our numbers differ slightly from the report, since we use the sample of comparable communities over time and they use the sample of communities available for each year of the study.

²⁶We do not show results for the Inuit, as the 60th parallel restriction eliminates most communities from the sample.



(a) First Nations



(b) Non-Aboriginal

Figure 6: *Logarithm of mean light density for First Nations and Non-Aboriginal communities by sample. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*

First Nations communities relative to non-Aboriginal communities. Given that these types of data trends actively inform government decision-making, this is an important difference.

3.2 Correlates of Historical Factors and Modern Outcomes

The omission of smaller communities from the CWB data may have significant implications for work in economic history and understanding path dependence from historical geography or institutions. For example, suppose we were interested in the determinants of economic well-being in Indigenous communities and hypothesized that both historical persistence and geography affect contemporary outcomes. By combining data from various historical and geographic sources, we can test this theory empirically. Table 6 displays the results of this exercise.

Table 6: Comparing Correlations Between Ln Light and Ln GDP with Economic Factors: Highlighting Sample Selection

Dep. Variable:	In GDP Sample		Not in GDP Sample	Full Sample
	ln GDP (1)	ln Lights (2)	ln Lights (3)	ln Lights (4)
ln Dist to closest CMA	-0.0985*** (0.027)	-0.326*** (0.049)	-0.317*** (0.048)	-0.320*** (0.034)
ln Dist to historical post	0.0136 (0.025)	-0.0247 (0.049)	-0.167*** (0.046)	-0.119*** (0.035)
ln Dist to railway station	0.0183 (0.022)	0.0480 (0.040)	-0.0333 (0.029)	-0.0153 (0.024)
ln Ruggedness Index	-0.0841*** (0.023)	-0.163*** (0.041)	-0.318*** (0.035)	-0.268*** (0.028)
Latitude	-0.00621 (0.008)	0.0160 (0.014)	0.0638*** (0.015)	0.0481*** (0.011)
ln Population	-0.0290 (0.034)	0.0977 (0.065)	0.150*** (0.018)	0.178*** (0.012)
Observations	323	323	640	963
Adjusted R^2	0.160	0.226	0.329	0.384

Notes: Distance from historical trading posts and railway stations is computed by calculating the geodetic distance between the centroid of each CSD and the location of historical trading posts and railway stations. Robust standard errors in parentheses. Significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The first column displays the estimates from regressing the logarithm of GDP per capita on our historical and geographic controls, while the second column displays the estimates from the same specification using the logarithm of light density as the dependent variable. In each instance, we would conclude that communities located farther from economic centres and with more rugged terrain are less economically developed, but that the two historical factors—distance to the closest historical trading post and railway stations—are not statistically correlated with contemporary economic activity.

If we focus on the subset of communities that are contained in the lights sample, but not in the GDP sample (column (3)), we find that distance to the historical trading post, latitude, and population are all statistically correlated with light density. These relationships continue to hold when we expand to the full set of lights. Since historic trading posts were often places of economic exchange, as well as where medical supplies were offered, they may have also fostered a more positive relationship between settlers and First Nations people, which has persisted into the present. This finding may lead a researcher on a much different path than they would have taken otherwise due excluding more than half the possible sample. Given this substantial difference, we believe the use

of lights data may be an invaluable tool for economic historians studying the long-run outcomes of Indigenous peoples based on historical factors or shocks.

3.3 Mining and Well-Being in First Nations Communities

Our final example pertains to the effect of mining on Indigenous communities. Canada’s mining industry currently employs over 400,000 workers and is the largest private sector employer of Indigenous peoples (Marshall, 2017). A natural question surrounding the industry is whether its proximity to many Indigenous communities has contributed to economic development within these communities. We combine estimates of mining intensity near Indigenous communities using data from Natural Resources Canada with our community well-being database and nighttime lights data to show that the answer to this question can depend crucially on both sample selection, as well as the frequency with which data are available.

We exploit variation in the entry and exit of base metal, coal, ferrous, and precious metal mines, near an Indigenous community between 2001 and 2006 to examine the effect of mining intensity on economic outcomes.²⁷ Figure A3 displays the location of mines in 2003 in relation to Indigenous communities for reference. Table 7 summarizes the variation we use in the empirical analysis. There was an average of 1.123 mines within 100km buffers of Indigenous communities for the whole sample period. This number declines drastically as the size of the buffer decreases: there was an average of 0.0932 mines within a 25km buffer of Indigenous communities during our sample period.

Our empirical strategy uses a fixed effects approach that exploits variation in mining intensity within communities. We also include year fixed effects to account for changes in overall mining intensity in Canada over time. This specification is akin to a generalized difference-in-differences framework. Our estimating equation takes the following form:

$$\ln(y)_{it} = \alpha + \beta \text{number_mines}_{it} + \gamma_i + \zeta_t + \epsilon_{it}, \quad (3)$$

where $\ln(y)_{it}$ is the natural logarithm of our outcome variable—either GDP per capita or average light density—in community i in time t . We include census subdivision fixed effects, γ_i , and year fixed effects ζ_t . The variable number_mines_{it} is our measure of mining intensity: the number of mines within 25km, 50km, 75km, or 100km buffers of the census subdivision. One concern with this measure that is relevant when using the nighttime light data is that a mining operation may generate light that is independent from the light associated with community-level economic development. If a mine is close to a

²⁷We focus on this time period as these data from Natural and Resource Canada was consistent between these years and for these specific types of mines (Wortzman, 2017).

Table 7: Mining summary statistics by year

	2001	2002	2003	2004	2005	2006	Total
N. mines w/in 100km	1.050 (1.537)	1.165 (1.670)	1.106 (1.601)	1.111 (1.539)	1.142 (1.592)	1.167 (1.652)	1.123 (1.599)
Share w/ entrant w/in 100km	·	13.60 (34.30)	1.192 (10.86)	3.376 (18.07)	2.781 (16.45)	2.284 (14.95)	3.873 (19.30)
Share w/ exit w/in 100km	·	1.192 (10.86)	7.944 (27.06)	2.582 (15.87)	0.397 (6.293)	0.794 (8.882)	2.152 (14.51)
N. mines w/in 75km	0.617 (1.117)	0.709 (1.274)	0.667 (1.216)	0.665 (1.169)	0.684 (1.210)	0.694 (1.236)	0.673 (1.205)
Share w/ entrant w/in 75km	·	10.13 (30.19)	0.596 (7.700)	1.986 (13.96)	1.490 (12.12)	1.390 (11.71)	2.598 (15.91)
Share w/ exit w/in 75km	·	0.695 (8.313)	5.065 (21.94)	1.986 (13.96)	0.0993 (3.151)	0.596 (7.700)	1.407 (11.78)
N. mines w/in 50km	0.268 (0.666)	0.297 (0.746)	0.289 (0.740)	0.290 (0.720)	0.295 (0.725)	0.297 (0.740)	0.289 (0.723)
Share w/ entrant w/in 50km	·	2.880 (16.73)	0.298 (5.453)	0.794 (8.882)	0.596 (7.700)	0.596 (7.700)	0.861 (9.238)
Share w/ exit w/in 50km	·	0.0993 (3.151)	1.291 (11.29)	0.695 (8.313)	0.0993 (3.151)	0.497 (7.032)	0.447 (6.670)
N. mines w/in 25km	0.0834 (0.344)	0.0963 (0.375)	0.0943 (0.370)	0.0943 (0.357)	0.0973 (0.363)	0.0933 (0.353)	0.0932 (0.360)
Share w/ entrant w/in 25km	·	1.291 (11.29)	0.0993 (3.151)	0.298 (5.453)	0.298 (5.453)	0.0993 (3.151)	0.348 (5.886)
Share w/ exit w/in 25km	·	0 (0)	0.397 (6.293)	0.199 (4.454)	0 (0)	0.596 (7.700)	0.199 (4.453)

Notes: Means reported with standard deviations in parentheses. We do not include communities above the 60th parallel in this table. “N. mines w/in 100km” refers to the average number of mines within a 100km buffer surrounding the community in the given year. “Share w/ entrant w/in 100km” refers to the share of communities who had at least one more mine in the 100km buffer surrounding their community in the given year compared to the previous year. “Share w/ exit w/in 100km” refers to the share of communities who had at least one fewer mine in the 100km buffer surrounding their community in the given year compared to the previous year. All share variables are expressed in percent form, so that a mean of 2.88 should be read as 2.88 percent, and 0.0993 should be read as 0.0993 percent. 2001 does not include information on the share of entrants and exits, as it is the first year of our sample.

community, then this may interfere with the interpretation of our results. To alleviate this concern, we also report results using donut-shaped buffers that are equivalent to the number of mines within a 100km buffer minus the number of mines within a 25km buffer. Figure A4 provides an example of how such a buffer is constructed.

Tables 8 display our main results from this exercise. Each panel employs a different measure of mining intensity and the columns vary based on the dependent variable used, the years included in the estimation, and whether we are looking at the restricted GDP sample, or the full lights sample. Beginning with Column (1) of Panel A, we show the results of estimating equation 3, where we use the number of mines in a 75km donut buffer surrounding one’s community as our measure of mining intensity. Column (1) uses the logarithm of GDP per capita as the dependent variable and our data cover 2001

and 2006, as these are the years for which data on GDP per capita is available. In this specification, we find that there is no statistically significant relationship between mining and GDP per capita.

Column (2) uses the same sample of communities but estimates equation 3 with the logarithm of nighttime lights as the dependent variable. We again find no statistically significant relationship between mining intensity and light density, although the coefficient estimate has flipped signs. In Column (3) we expand the sample to cover all communities in the nighttime lights sample, but we continue to use the 2001 and 2006 data only. Here we see the coefficient is larger in magnitude and statistically significant at the one percent level. Our results would suggest that for each additional mine in a 75km donut buffer from one's community is associated with an 8.74% decline in light intensity.

In the final column, we use variation from all years between 2001 and 2006. One of the advantages of the nighttime lights data is that it is available annually, so that it can be matched with other annual data, like the the location of mines, to take advantage of additional variation in the data. Column (4) suggests that this additional variation is important, both for the precision of the coefficient estimates and also the magnitude of the estimate. We find that each additional mine in a 75km donut buffer around one's community is associated with an 11.57% decline in light density. This finding suggests that we are losing variation that is important for the conclusions drawn when we use data that is collected in 5 year intervals.

Panel B, which uses the number of mines in a 100km donut buffer surrounding communities as a measure of mining intensity, paints a similar picture, although the results are smaller in magnitude. This is not surprising, given that we might expect mines closest to one's community to have the largest effect on community-level economic activity. Panel C and D focus on mining within 75km and 100km buffers of each community, and are closer to 0 than the donut buffer estimates, as would be expected if an unobservable like electricity usage were positively correlated with both the number of mines in a region and light density. We do not find any statistically significant effects of mining intensity using 25km and 50km buffers. These results can be found in Table A2

The community-level effects of resource development should be an important consideration for governments and businesses, alike. However, we caution interpreting the results as the causal effects of mining on Indigenous communities. For example, it could be the case that the decline in light density in relation to mining intensity is the result of out-migration from Indigenous communities to mining sites. The intention of our example is only to illustrate how both sample selection and the frequency of data collection can affect the results of economic analyses. As such, we have not matched our data to other covariates which may confound our estimates, nor have we implemented a causal

Table 8: Effect of Mining on Development

Sample:	GDP Sample		Full Sample	
	2001,2006	2001,2006	2001,2006	All Years
Years Used:				
Dep. Variable:	ln GDP	ln Lights	ln Lights	ln Lights
	(1)	(2)	(3)	(4)
Panel A: 75km Donut Buffer				
N. Mines 75km Donut	0.00283 (0.026)	-0.0408 (0.041)	-0.0915* (0.055)	-0.123*** (0.047)
Adjusted R^2	0.010	0.084	0.028	0.076
Panel B: 100km Donut Buffer				
N. Mines 100km Donut	0.0124 (0.025)	-0.0274 (0.025)	-0.0512 (0.040)	-0.0597* (0.035)
Adjusted R^2	0.011	0.084	0.027	0.075
Panel C: 75km Buffer				
N. Mines 75km	-0.00717 (0.019)	-0.0204 (0.031)	-0.0794* (0.045)	-0.112*** (0.042)
Adjusted R^2	0.010	0.082	0.028	0.076
Panel D: 100km Buffer				
N. Mines 100km	0.00419 (0.021)	-0.0187 (0.022)	-0.0497 (0.035)	-0.0592* (0.033)
Adjusted R^2	0.010	0.083	0.027	0.075
Observations	631	631	2014	6042

Notes: These tables display fixed effects estimates of the effect of mining on economic development in Indigenous communities. We do not include communities above the 60th parallel. Standard errors clustered by census subdivision in parentheses. “N. Mines 75km Donut” are the number of mines within a 75km buffer from the community, excluding those mines in the closest 25km buffer; “N. Mines 75km” are the number of mines within a 75km buffer from the community. All columns also include time dummies. Significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

research methodology, other than controlling for community and year fixed effects. We also have not included communities north of the 60th parallel whose economies may be most impacted by mining activities. Finally, we have not provided a rigorous analysis of the channels that may be driving the negative relationship between mining and light density and leave this to future work.

4 Discussion

Nighttime light data are not without limitations. Just as income, education, and labour force participation are not perfect measures of well-being or economic activity, neither are nighttime light data. For example, the economic assumption underlying the use of light density to proxy for economic activity is that lighting is a normal good (Donaldson and

Storeygard, 2016). Although this may seem like a natural assumption, this point may merit additional consideration in the Indigenous context. For example, if a community's shared values lead them to actively resist forms of economic activity that generate light pollution or activities that may damage the natural state of their traditional territories — e.g., dams, wind farms, or certain types of natural resource exploration — then a lack of light density or measured income does not serve as a proxy for dysfunction and therefore does not necessarily signal a poor quality of life. Alternatively, if Indigenous community members are more likely to engage in traditional activities, like hunting and fishing, then nighttime light density will underestimate the economic well-being in these communities. In addition, if communities are defined by their membership rather than by their geographical boundaries, light data may be less useful. For example, if we are interested in the economic well-being of a specific First Nation, then their membership may live in cities and outside of reserves and light density would only account for those living in the reserve. Thus, any findings using light or other existing measures of well-being, like the CWB index, should take these points into account.

We have highlighted how nighttime light data are not useful for analyzing changes in economic activity between 2000 and 2005 in communities in the northernmost parts of the country, where light measurements are more erratic, or for differentiating between very low levels of economic activity. An additional limitation is that nighttime lights are neither perfectly correlated with CWB or with GDP, meaning that they still represents something beyond either of these two measures of well-being. This should not discourage researchers from using nighttime light data, rather it should be taken into consideration when interpreting the results of analyses that use the nighttime lights data. Taken together, while we see light data as a valuable alternative in the Canadian context to traditional measures of economic activity, we suggest that it be used as much as possible as part of complementary set of measures.

It is our hope that this work will encourage scholars in economics and elsewhere in the social sciences studying economic and quality-of-life outcomes for Indigenous communities to turn to nighttime light density data as an important data source. It is clear that light density is a strong proxy not just for GDP per capita in Indigenous communities, but also for a broader composite of indicators encompassed by the Community Well-Being Index. Most importantly, for scholars working with publicly available data on First Nations communities, we have demonstrated that there is a substantial sample selection problem with the CWB and GDP per capita samples. Going forward, scholars will need to tackle this approach econometrically, perhaps through a Heckman selection model, or through the use of alternative data sources, like the nighttime light density data.

We decided to write this piece while studying the long-term impacts of the near-

extermination of the bison in the Great Plains (Feir et al., 2017). Light data was particularly valuable as the bison roamed across many low population regions that are excluded from traditional economic well-being databases. Authors looking to study the long-run impacts of historical shocks or geography on Indigenous outcomes should view light density as a reasonable present-day outcome. Another potential use of these data is in the evaluation of government programs targeted to First Nations and Inuit communities in the areas of housing, infrastructure, and other forms of economic development that could be reflected in these figures.

When researchers are considering using any form of publicly available data regarding Indigenous peoples in Canada, whether the CWB database or data derived from satellites, there needs to be an awareness that this data, and therefore the research, does not clearly fall under the principles of OCAP (Ownership, Control, Access, and Possession) put forward by the First Nations Information Governance Centre (Schnarch, 2004). Given this, researchers should exercise additional reflection about the potential benefits and harms of their research for the communities included in their analysis. While the use of nighttime light data may increase the potential for culturally relevant and beneficial economic research, the broader goals of reconciliation and engagement must always be kept in mind.

References

- Alesina, A., S. Michalopoulos, and E. Papaioannou (2016). Ethnic inequality. *Journal of Political Economy* 124(2), 428–488.
- Aragón, F. M. (2015). Do better property rights improve local income?: Evidence from First Nations’ treaties. *Journal of Development Economics* 116, 43–56.
- Bleakley, H. and J. Lin (2012). Portage and path dependence. *The Quarterly Journal of Economics* 127(2), 587–644.
- Chen, X. and W. D. Nordhaus (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences* 108(21), 8589–8594.
- Cooke, M. (2005, January). The First Nations community well-being index (cwb): A conceptual review. Technical Report R2-400/2005E-PDF, Strategic Research and Analysis Directorate Indian and Northern Affairs Canada, Ottawa.
- Daes, E.-I. (1995, 1). Draft principles and guidelines for the protection of the heritage of Indigenous peoples. Technical Report UN Doc. E/CN.4/Sub.2/1995/26, Special Rapporteur for the Sub-Commission on the Promotion and Protection of Human Rights.

- Dippel, C. (2014). Forced coexistence and economic development: Evidence from Native American reservations. *Econometrica* 82(6), 2131–2165.
- Donaldson, D. and A. Storeygard (2016). The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives* 30(4), 171–198.
- Elvidge, C. D., K. Baugh, M. Zhizhin, F. C. Hsu, and T. Ghosh (2017). VIIRS night-time lights. *International Journal of Remote Sensing* 38(21), 5860–5879.
- Elvidge, C. D., K. E. Baugh, E. A. Kihn, H. W. Kroehl, E. R. Davis, and C. W. Davis (2017). Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. *International Journal of Remote Sensing* 18(6), 1373–1379.
- Elvidge, C. D., K. E. Baugh, M. Zhizhin, and F. C. Hsu (2013). Why VIIRS data are superior to DMSP for mapping nighttime lights. *Proceedings of the Asia-Pacific Advanced Network* 35, 62–69.
- Feir, D., R. Gillezeau, and M. E. C. Jones (2017). The slaughter of the bison and reversal of fortunes on the Great Plains. *University of Victoria Working Paper, DDP 1702*.
- Feir, D. and R. L. Hancock (2016). Answering the call: A guide to reconciliation for quantitative social scientists. *Canadian Public Policy* 42(3), 350–365.
- Fischer, G., H. van Velthuisen, M. Shah, and F. Nachtergaele (2008). Global agro-ecological zones assessment for agriculture (gaez 2008).
- Ghosh, T., R. L. Powell, C. D. Elvidge, K. E. Baugh, P. C. Sutton, and S. Anderson (2010). Shedding light on the global distribution of economic activity. *The Open Geography Journal* 3, 148–161.
- Gomez, N. (2007). Healing hidden wounds. *Cultural Survival Quarterly* 31(3), 3–15.
- Henderson, J. V., A. Storeygard, and D. N. Weil (2012). Measuring economic growth from outer space. *American Economic Review* 102(2), 994–1028.
- Indigenous and Northern Affairs Canada (2010, September). The community well-being (cwb) index: Methodological details. Technical report, Strategic Research Directorate, Ottawa. <http://www.aadnc-aandc.gc.ca/eng/1100100016585/1100100016598>.
- Kovach, M. E. (2010). *Indigenous methodologies: Characteristics, conversations, and contexts*. University of Toronto Press.
- Lessmann, C. and A. Seidel (2017). Regional inequality, convergence, and its determinants – A view from outer space. *European Economic Review* 92, 110–132.
- Levy, J. E. (1998). *In the Beginning: The Navajo Genesis*. University of California Press.
- Li, X. and Y. Zhou (2017). A stepwise calibration of global dmsp/ols stable nighttime light data (1992–2013). *Remote Sensing* 9(6), 637.

- Marshall, B. (2017). Facts and figures 2018: Facts and figures of the Canadian mining industry. Technical report, The Mining Association of Canada.
- May, H. G. (1939). The creation of light in genesis 1:3-5. *Journal of Biblical Literature* 58(3), 203–211.
- Mellander, C., J. Lobo, K. Stolarick, and Z. Matheson (2015). Night-time light data: A good proxy measure for economic activity? *PloS one* 10(10), e0139779.
- Michalopoulos, S. and E. Papaioannou (2013). Pre-colonial ethnic institutions and contemporary African development. *Econometrica* 81(1), 113–152.
- Michalopoulos, S. and E. Papaioannou (2014). National institutions and subnational development in Africa. *Quarterly Journal of Economics* 129(1), 151–213.
- Miller, J. (2000). *Tsimshian Culture: A Light Through the Ages*. University of Nebraska Press.
- O’Sullivan, E. (2011, September). The community well-being index (cwb): Measuring well-being in First Nations and Non-Aboriginal communities, 1981-2006. Technical Report R3-170/2-2012E-PDF, Strategic Research Directorate Aboriginal Affairs and Northern Development Canada, Ottawa.
- Pinkovskiy, M. and X. Sala-I-Martin (2016). Lights, camera... income! Illuminating the national accounts-household surveys debate. *The Quarterly Journal of Economics* 131(2), 579–631.
- Rasmussen, K. and W. Worster (2009). *Inuit Folk-tales. Adventures in new lands*. IPI Press.
- Reid, B., W. Reid, and R. Bringhurst (1996). *The Raven Steals the Light*. University of Washington Press.
- Riley, S. J., S. D. DeGloria, and R. Elliot (1999). A terrain ruggedness index that quantifies topographic heterogeneity. *Intermountain Journal of Sciences* 5(4), 23–27.
- Schnarch, B. (2004). Ownership, control, access, and possession (ocap) or self-determination applied to research: A critical analysis of contemporary First Nations research and some options for First Nations communities. *International Journal of Indigenous Health* 1(1), 80.
- Smith, L. T. (2012). *Decolonizing Methodologies: Research and Indigenous Peoples*. Otago University Press.
- Strategic Research Directorate Aboriginal Affairs and Northern Development Canada (2015, April). The community well-being index: Well-being in First Nations communities, 1981-2011. Technical Report R3-170/2-2014E, Ottawa. <https://www.aadnc-aandc.gc.ca/eng/1345816651029/1345816742083>.

The Truth and Reconciliation Commission of Canada (2015). *Summary of the Final Report of the Truth and Reconciliation Commission of Canada*. McGill-Queen's University Press.

United Nations (2009). *State of the world's indigenous peoples*, Volume 9. United Nations Publications.

Wortzman, R. H. (2017). Natural resource development and First Nations in Canada: Estimating the impacts of mining on reservation community well being. Master's thesis, The University of Victoria.

Compliance with Ethical Standards:

Funding: No grants or other external funding was used for this project.

Conflict of Interest: The authors declare that they have no conflict of interest.

A Additional Tables and Figures

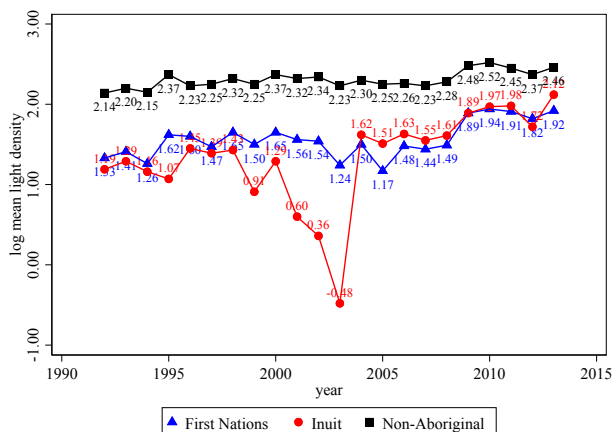


Figure A1: *Log of the estimated average nighttime light density within census subdivisions split by First Nations, Inuit, and non-Aboriginal communities. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*

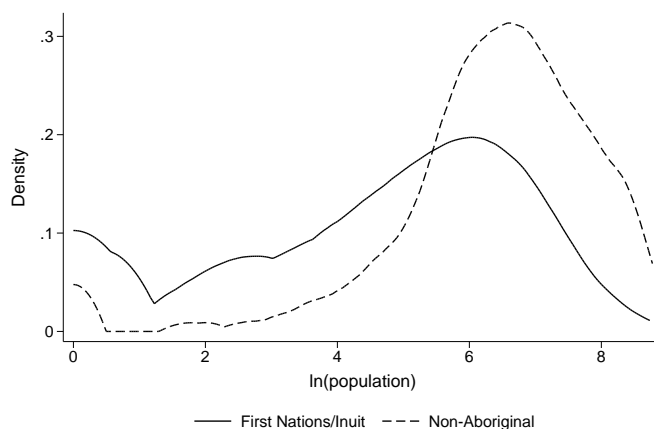


Figure A2: *This figure plots the distribution of the natural log of population for First Nations and Inuit communities and for non-Aboriginal communities. The sample is limited to communities with a population of less than 6,500. Data are from INAC.*

Table A1: Summary Statistics: Sample Selection within the CWB Database

	In GDP sample	Not in GDP sample	Difference
Ln(avg light density)	2.46 (0.80)	2.13 (1.01)	-0.33***
CWB Index	56.38 (10.81)	60.96 (8.96)	4.58***
Has population data	1.00 (0.00)	1.00 (0.00)	0.00
Signed modern treaty	0.04 (0.20)	0.00 (0.00)	-0.04***
Dist to closest CMA	131.06 (129.83)	100.00 (90.30)	-31.05**
Dist to historical post	99.59 (87.90)	128.78 (108.21)	29.19**
Dist to railway station	193.53 (206.96)	193.63 (226.62)	0.10
Avg ruggedness index	350.60 (253.72)	366.98 (293.02)	16.37
Latitude	-100.16 (18.67)	-110.42 (17.99)	-10.25***
Longitude	51.47 (3.48)	50.92 (3.41)	-0.55
Observations	323	205	528

Notes: Mean values are reported with the standard errors in parenthesis for Indigenous (First Nations and Inuit) communities only. Communities are defined by census subdivisions in order to be comparable with the CWB index. Communities above the 60th parallel and with more than 6,500 people are excluded from the comparison. Significance stars: * 0.05 ** 0.01 *** 0.001.

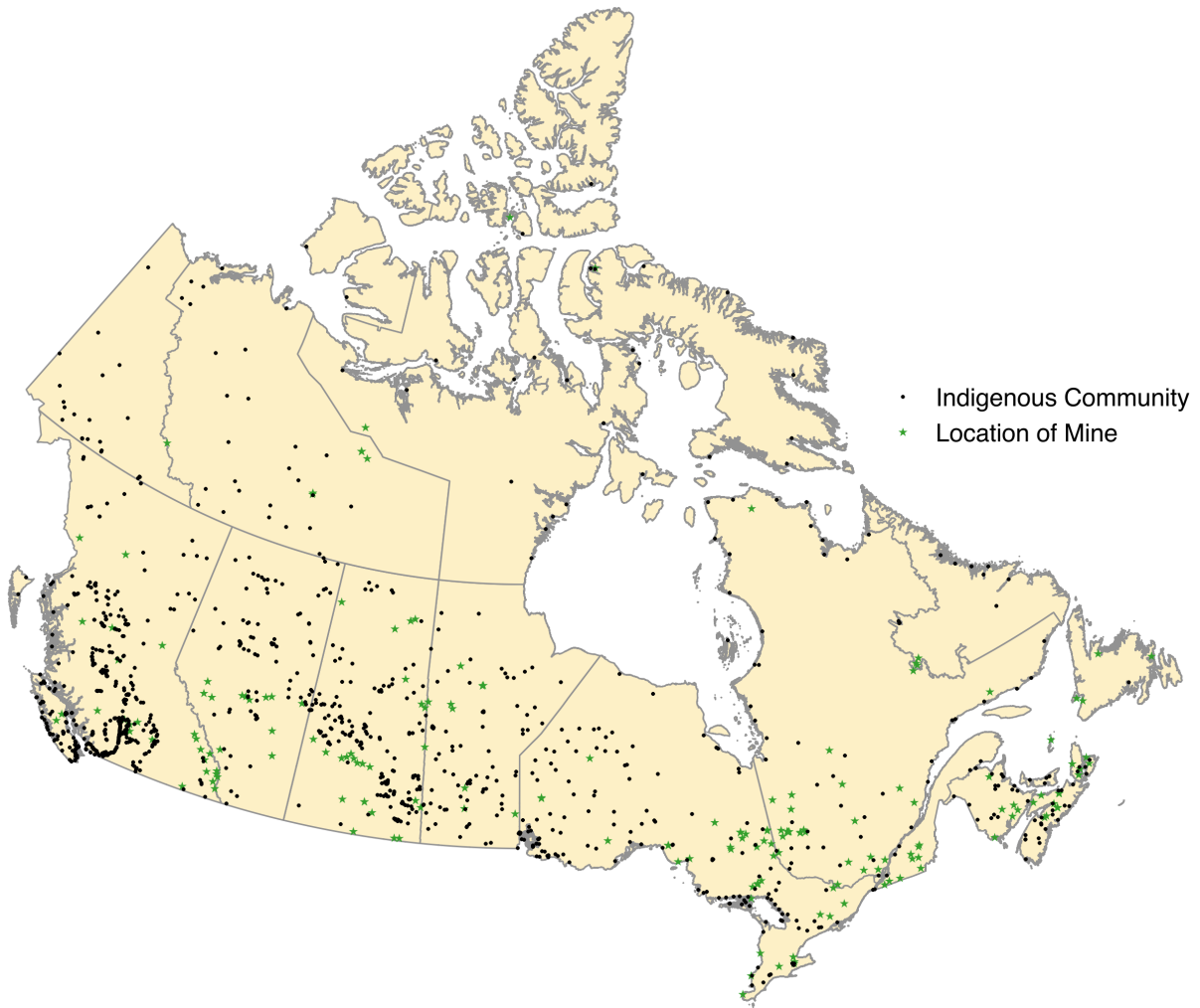


Figure A3: *The location of basemetal, coal, ferrous, and precious metal mines in 2003 in relation to Indigenous communities across Canada. Mining data are from Natural Resources Canada.*

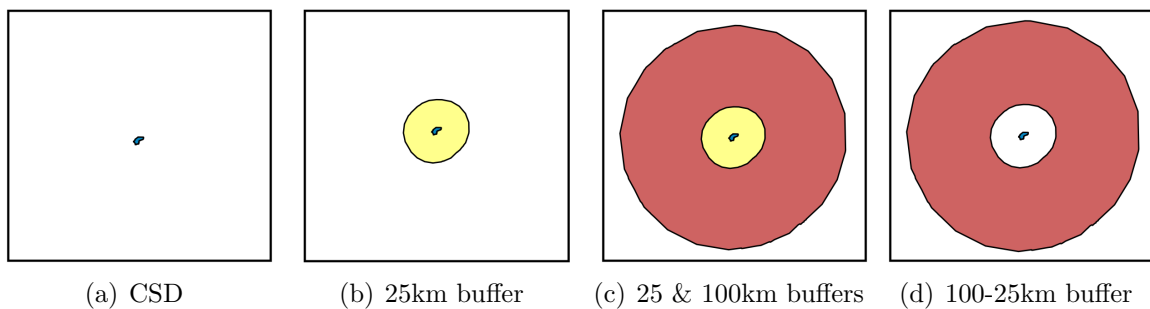


Figure A4: *An example of the construction of “donut” buffers using the Big Horn 144A reserve from Alberta. We begin by constructing separate 25km and 100km buffers around all census subdivisions, and then subtract the 25km buffer from the 100km buffer to obtain the number of mines within the “donut” shaped area surrounding the census subdivision. Mining data are from Natural Resources Canada.*

Table A2: Effect of Mining on Development

Years Used: Dep. Variable:	GDP Sample		Full Sample	
	2001,2006 ln GDP (1)	2001,2006 ln Lights (2)	2001,2006 ln Lights (3)	All Years ln Lights (4)
Panel A: 50km Donut Buffer				
N. Mines 50km Donut	0.0345 (0.045)	-0.00883 (0.056)	0.0928 (0.082)	0.0614 (0.081)
Adjusted R^2	0.012	0.081	0.026	0.074
Panel C: 25km Buffer				
N. Mines 25km	-0.0338 (0.025)	0.0132 (0.047)	-0.0639 (0.082)	-0.0604 (0.096)
Adjusted R^2	0.012	0.081	0.025	0.074
Panel D: 50km Buffer				
N. Mines 50km	-0.00137 (0.026)	0.00228 (0.034)	0.0218 (0.052)	0.0112 (0.062)
Adjusted R^2	0.010	0.081	0.025	0.074
Observations	631	631	2014	6042

Notes: These tables display fixed effects estimates of the effect of mining on economic development in Indigenous communities. We do not include communities above the 60th parallel. Standard errors clustered by census subdivision in parentheses. “N. Mines 50km Donut” are the number of mines within a 50km buffer from the community, excluding those mines in the closest 25km buffer; “N. Mines 50km” are the number of mines within a 50km buffer from the community. All columns also include time dummies. Significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Li and Zhou (2017) Satellite Adjustment

We apply the methodology outlined in Li and Zhou (2017) to construct a time series of nighttime light density across Canada. The Li and Zhou (2017) adjustment is a stepwise calibration of the nighttime light data between 1992 and 2013. Their proposed methodology uses all pixels across the globe; however, we adjust their methodology slightly to calibrate our data series specifically for Canadian census subdivisions. Using their original dataset does little to change our results.

The basic idea behind the calibration is that the nighttime light estimates from the 6 satellites that orbited the globe during 1992 and 2013 are not temporally consistent and therefore adjustments must be made to account for these differences. Table A3 displays the years in which each satellite was in orbit. In some years only one satellite was in orbit, while other years had two satellites in orbit. Figure A5 shows mean nighttime light density across all census subdivisions in Canada, by satellite, where it is clear that there are large differences in recorded light across satellites. The Li and Zhou (2017) framework is a 5-step procedure to adjust for these differences across satellites.

Step 1 accounts for the systematic underestimation of F14 by assuming a quadratic relationship between satellite F12 and F14. Consider the following equation:

$$\log(\text{mean_lights})_i^{F12} = \alpha_0 + \alpha_1 \log(\text{mean_lights})_i^{F14} + \alpha_2 \left(\log(\text{mean_lights})_i^{F14} \right)^2 + \epsilon_i, \quad (\text{A1})$$

where, i indexes the census subdivision and Fxx refers to the satellite. We are essentially regressing the log of mean light density within each census subdivision in Canada, as measured by satellite F12, on the log of mean light density and its square, as measured by satellite F14. We must restrict the sample to include only those years for which we have data from both F12 and F14, that is, 1997, 1998, and 1999. The coefficient estimates, $\hat{\alpha}_0$, $\hat{\alpha}_1$, and $\hat{\alpha}_2$ are then combined with the F14 data from all years to obtain a predicted value of nighttime light density. This results in an upward shift in the trend in nighttime light density from F14 as displayed in Figure 6(a).

The second step in the procedure accounts for the drop in luminosity measured by F15 between 2003 and 2007. This step estimates a quadratic relationship between the calibrated F14 values for 2003 and the F15 values in 2003-2007, and then uses the coefficient estimates to predict light density for 2003-2007 for F15. This adjustment can be seen in Figure 6(b).

Step 3 is a two-step adjustment. First, the trend in nighttime lights is not consistent within satellite F16, so this is accounted for by calibrating all years within F16 using Sicily, Italy as a reference. Following the literature, Sicily is chosen due to its relatively stable economic activity and light density over this time period. As 2007 was the brightest year for Sicily, it is chosen as the reference year. Since Li and Zhou (2017) have already performed this computation, we use their coefficient estimates from Table 2 directly to adjust our series. As an example, 2004 F16 data are adjusted as follows:

$$\widehat{\log(\text{mean_lights})}_{i,2004}^{F16} = 0.1194 + 1.2265 * \log(\text{mean_lights})_{i,2007}^{F16} - 0.0041 * \left(\log(\text{mean_lights})_{i,2007}^{F16} \right)^2$$

2004 through 2009 are adjusted similarly. Figure 6(c) displays these estimates.

The second adjustment in step 3 accounts for the fact that even after the within-F16 adjustment, F16 still underestimates light density relative to the calibrated F15 satellite.²⁸ Following a similar procedure as step 1 and step 2, we estimate the relationship between the unchanged F16 2007 values and a quadratic in the F15 2007 values in order to shift the F16 values upwards.²⁹ Figure 6(d) displays these results.

The final step adjusts satellite F18 to be consistent with the overall trend in nighttime lights. We regress the calibrated values of F16 in 2009 on a quadratic in F18 in 2010 and then construct our predicted values, as in step 1 and step 2, from the coefficient estimates. Figure 6(e) displays this final adjustment.

The series we use throughout the paper uses the estimated nighttime light values for each satellite, where we average the estimated lights over years in which there are two satellites. The final trend line showing how average nighttime lights have evolved across all census subdivisions in Canada can be found in Figure 6(f).

Table A3: Yearly List of Satellites in Orbit

Year	Satellite		
1992	F10		
1993	F10		
1994	F10	F12	
1995		F12	
1996		F12	
1997		F12	F14
1998		F12	F14
1999		F12	F14
2000		F14	F15
2001		F14	F15
2002		F14	F15
2003		F14	F15
2004		F15	F16
2005		F15	F16
2006		F15	F16
2007		F15	F16
2008			F16
2009			F16
2010			F18
2011			F18
2012			F18
2013			F18

²⁸This problem is less of a concern for Canada, than for the global distribution of lights.

²⁹Recall that 2007 was used as the reference year in step 3a.

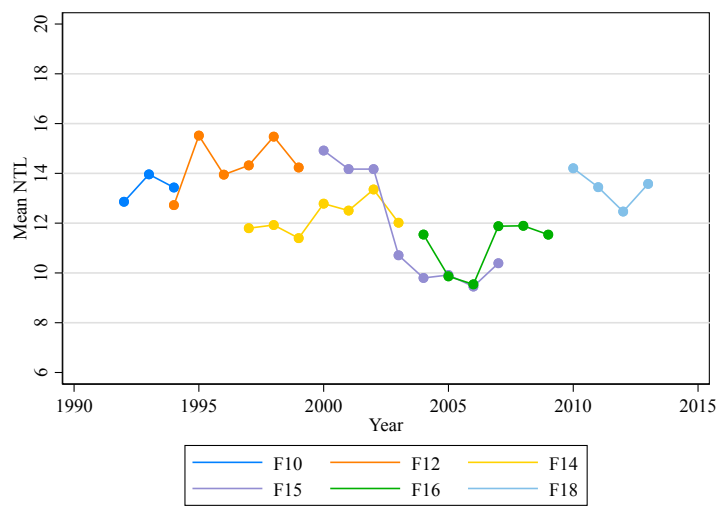
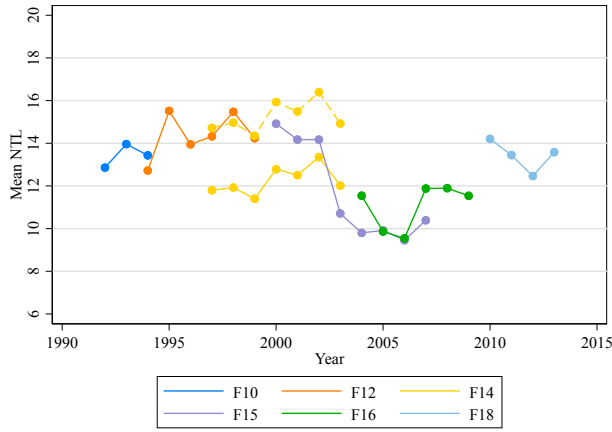
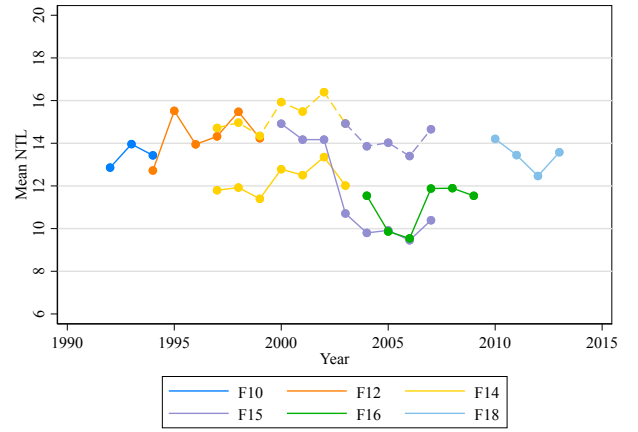


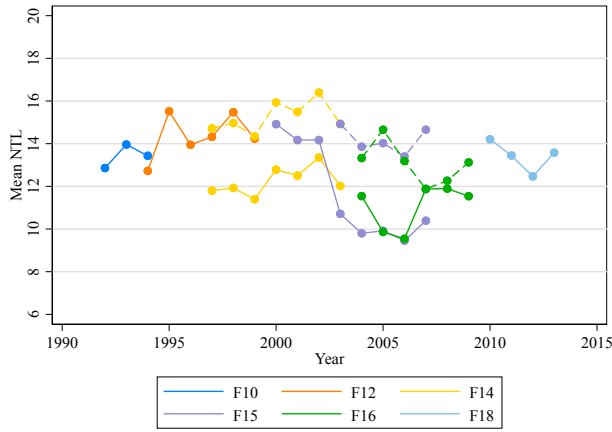
Figure A5: Average nighttime light density by satellites over time. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).



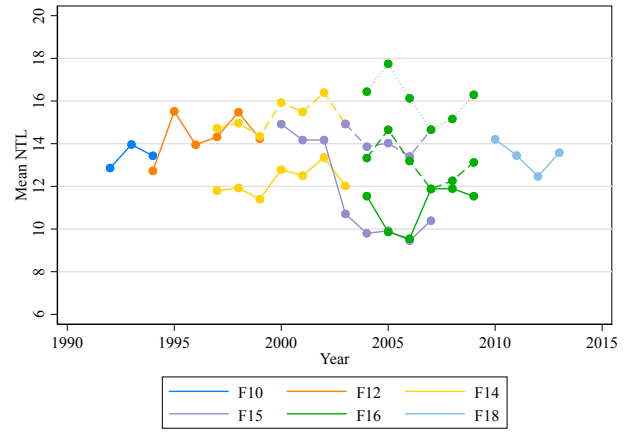
(a) Step 1: underestimation of F14



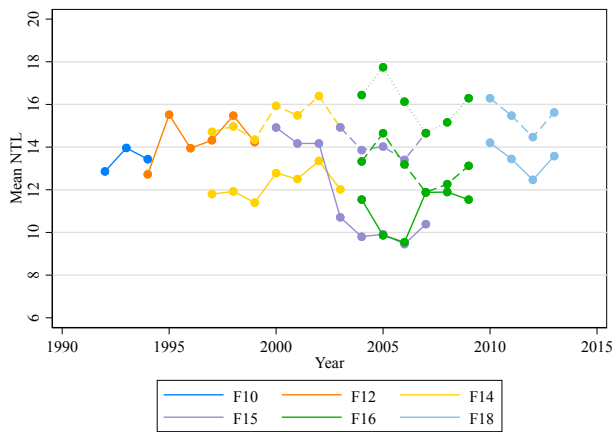
(b) Step 2: underestimation of F15, 2003-2007



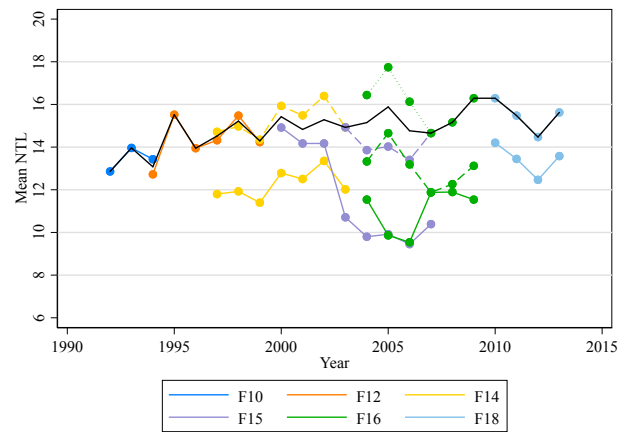
(c) Step 3a: inter-temporal calibration of F16



(d) Step 3b: underestimation of F16



(e) Step 4: overestimation of F18, 2010



(f) Final Estimate

Figure A6: Stepwise calibration of the nighttime light data between 1992 and 2013 using the methodology outlined in (Li and Zhou, 2017). The nighttime lights data are available from the National Geophysical Data Centre (NGDC).

C A Closer Look at the Relationship Between Light Density and Latitude

Figure A7 plots the logarithm of the estimate of average nighttime light density over time for all census subdivisions in Canada by latitude. The trends in census subdivisions located in the 60th to 75th parallels are highly variable. This problem is particularly acute for the period between 2000 and 2005.

Figure A8 provides a closer examination of the issue. It displays the composite nighttime light images for the city of Yellowknife and surrounding reserve, Detah, for 2000-2004. Blue pixels represent high light density areas, while yellows represent decreasing light density, and red represents no light. Yellowknife is the largest city in the Northwest Territories, with an urban population of just over 16,500 people in 2001, and should appear in the nighttime lights data; however, as we see from 2001-2003, there is no detectable light in this region.

Light density may be erratic at high latitudes for a variety of reasons. One possibility that may be accounted for relatively easily using econometric techniques is that high latitude areas tend to have fewer cloud-free days. Since the yearly nighttime light data are produced by averaging light density over the number of cloud-free days, areas with fewer cloud-free days will naturally have noisier estimates of light density. Figure A9 displays the relationship between the average number of cloud-free days and latitude for 2000-2005, the period for which light density seems to be most erratic during our sample.

It is evident that the number of cloud-free days declines with latitude, but nothing in Figure A9 suggests that this relationship differs dramatically across years. Nevertheless, we residualize our estimate of nighttime light density by regressing the logarithm of average light density in community i in time t on the number of cloud free days in community i in time t , and predicting the residuals from this specification. We display the estimate of residualized log light density over time and by latitude in Figure A10, which does little to alleviate the erratic behaviour of light density during 2000 and 2005. Since the cloud adjustment does not correct the erratic pattern in lights between 2000 and 2005, we recommend researchers exclude these communities during this time period. To be consistent across all our analyses, we exclude communities above the 60th parallel.

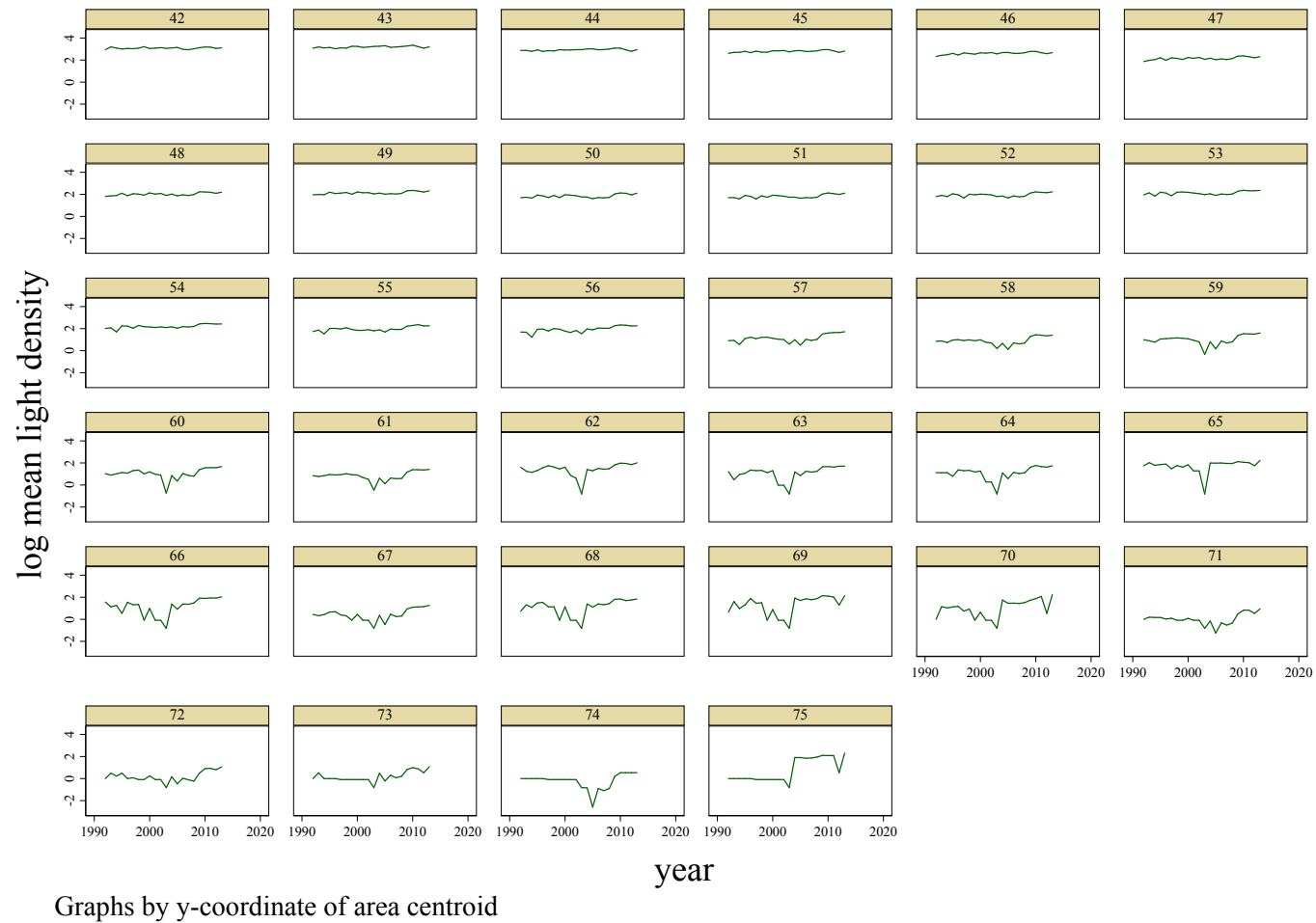


Figure A7: *Logarithm of estimate of average nighttime light density by latitude of centroid of census subdivision. Sample includes all census subdivisions in Canada. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*

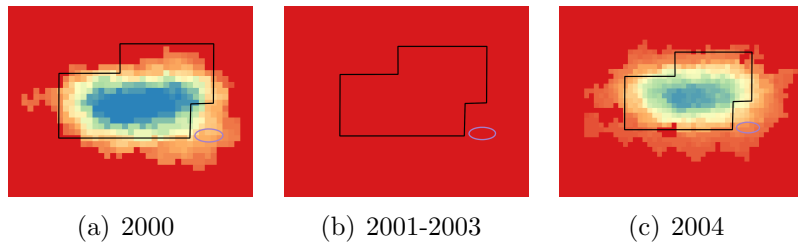


Figure A8: *Nighttime light density for the city of Yellowknife, NWT (black border) and the Indian reserve, Detah (purple border). Blue represents the brightest pixels, yellows are decreasing light density, and red represents no light. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*

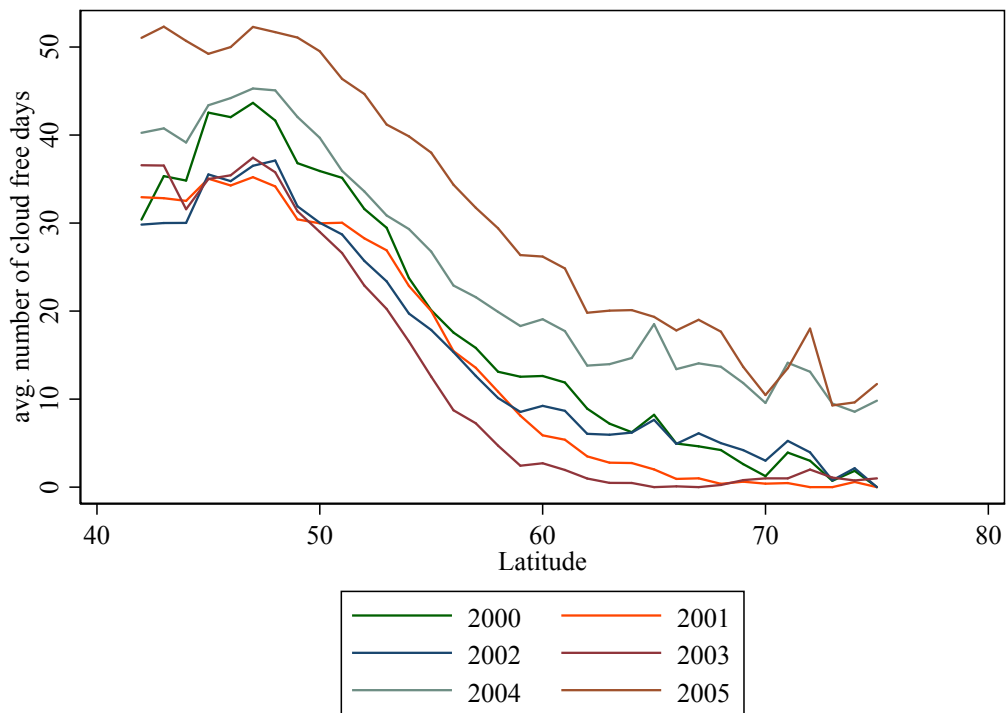


Figure A9: *Average number of cloud-free days for all communities in Canada by latitude and year. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*

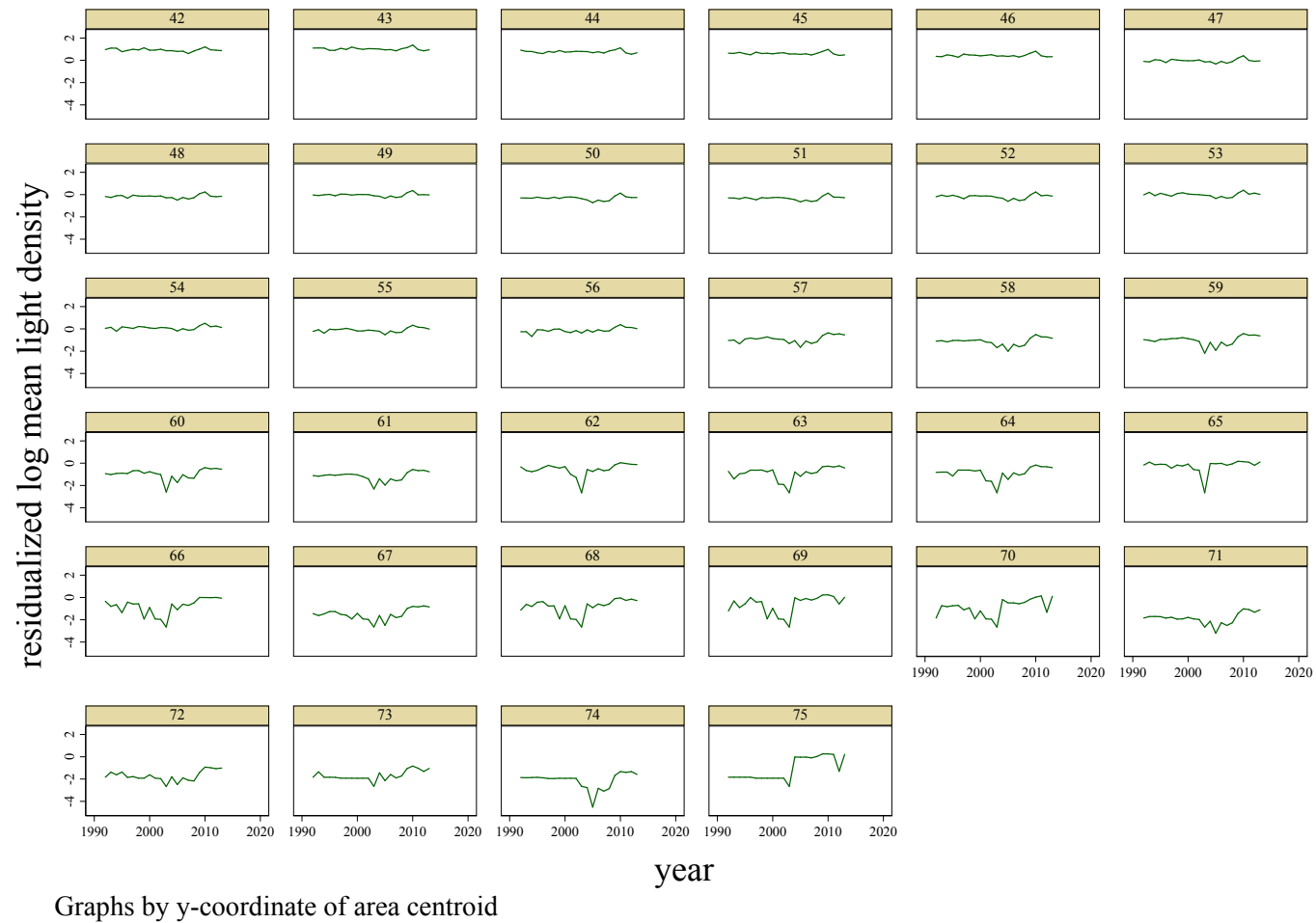


Figure A10: *Logarithm of estimate of average nighttime light density by latitude of centroid of census subdivision. Sample includes all census subdivisions in Canada. The nighttime lights data are available from the National Geophysical Data Centre (NGDC).*