Estimating the Marginal Effect of Pits and Quarries on Rural Residential Property Values in Wellington County, Ontario: A Hedonic Approach

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Alison Grant

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ABSTRACT

Estimating the Marginal Effect of Pits and Quarries on Rural Residential Property Values in Wellington County, Ontario: A Hedonic Approach

Alison Grant
University of Guelph, 2017

Advisor: Dr. Brady Deaton
Committee: Dr. Jessica Cao
Dr. Richard Vyn

"Aggregate" material – i.e., sand, gravel, clay, and bedrock – are extracted from pits and quarries throughout Ontario. Aggregates are the number one resource extracted (by value) and used by Ontarians, and approximately $1.2 billion of aggregate material was extracted in Ontario in the last year.

While aggregate is a valued resource, the extraction of aggregate is often identified as a negative externality. Similar to other environmental disamenities mentioned in the literature – such as shale gas exploration sites, wind turbines and landfills – residents near aggregate extraction identify a host of events that can be categorized as negative externalities. Residential concerns include noise and visual disamenities, as well as environmental concerns, such as diminished water quality.

In this study, I assess the potential impacts of aggregate sites. First, I briefly introduce the perceived impacts of aggregate sites by quoting residents' concerns through newspaper articles and lobby group websites. I then utilize the hedonic model to test these claims made by residents: namely, the negative effect on property values. I estimate average changes in property values (or marginal implicit prices) in close proximity to these sites as a proxy for aggregate site

impact. When estimating these marginal implicit prices using the hedonic model, conventional covariates that describe housing and land quality are used. I also include covariates that describe the aggregate site (e.g., activity, licensed area, site type) and spatial attributes that might influence the relationship between the site and the residence (e.g., distance to nearest highway, distance to Toronto).

The data set utilized in this thesis includes over 9,000 arms-length sales of rural residential properties in Wellington County in Ontario. These property sales occur over a 12 year period: 2002-2013. Data on the 107 individual pits and quarries in Wellington County were collected through the 2013 Ministry of Natural Resources (MNR) database on licensed aggregate sites.

Across various models to test for sensitivity (i.e. flexible functional forms, varying model commands, and focused analysis on the most active sites), I do not find evidence that aggregate sites have a strong negative effect on property values in Wellington County. The empirical evidence found in this study does not support the public claims that aggregate sites are negatively affecting neighbouring property values.

DISCLAIMER

This research is based, in part, on data provided by the Municipal Property Assessment Corporation (MPAC). Any findings or recommendations expressed in this thesis are those solely of the author, Alison Grant, and not necessarily the views of MPAC.

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CHAPTER 1: INTRODUCTION

1.1 Background

1.1.1 Use of Aggregate Materials in Ontario

Aggregate materials are used for infrastructural development in the province of Ontario, and come from pits and quarries.[1] Sand, gravel, clay, and bedrock extracted from pits and quarries are used in the construction of roadways, water mains, dams, subway infrastructure, and foundations in commercial buildings. Roads and highways account for the greatest share of aggregate material uses. Figure 1A shows the uses for aggregate resources in Ontario (TOARC, 2015). For every 1 kilometre of highway built, approximately 1760 truckloads[2] are needed in its construction. One kilometre of subway line uses approximately 4,560 truckloads, and structures such as industrial buildings (like hospitals) use approximately 3,760 truckloads. On average a single person makes use of 14 tonnes of sand and gravel each year (TOARC, 2015), for example in their yard, driveway, or the construction of their home or office. The operation of aggregate pits and quarries are essential in the development of these key sources of physical infrastructure in the province.

Aggregate materials are also used in a number of manufacturing processes, including the processing of iron, steel, aluminum, and plastic. Aggregates are also key materials in manufactured products such as glass, paint, pharmaceuticals, fertilizer, floor coverings, and toothpaste. In the 2010 *State of the Aggregate Resource in Ontario Study* by the Ministry of Natural Resources (SAROS, 2010), it was estimated that the economic value of aggregate

[1] Loose material, such as sand and gravel comes from pits. Solid bedrock, such as limestone and granite, comes from a quarry. ‘Aggregate sites’ and ‘pits and quarries’ will be used interchangeably throughout this thesis.
[2] A truckload holds approximately 13 metric tonnes of gravel (TOARC, 2015).

production was $6.1 billion in gross output in 2010. The aggregate production process - including processing, transportation, and secondary industries that use processed aggregates to create new goods (such as concrete) - generated $1.8 billion in labour income, and created approximately 34,900 full-time jobs. Additionally, $3.2 billion of GDP was generated by aggregate production (SAROS, 2010). Taking this one step further, if the whole aggregate value chain is analyzed (i.e. all industries that use some form of aggregates in the production of their output goods), it is found that aggregate use generates $44.7 billion in gross production, $13 billion in labour income, 245,000 full-time jobs, and a $22 billion contribution to Canada's GDP (SAROS, 2010). The economic value of aggregate production not only is a strong contributor to GDP, it is also a large source of employment.

Primary aggregate consumption in Ontario in 2007 was 171 million tonnes. This is compared to aggregate production, which was 173 million tonnes. Most aggregates that are produced in Ontario are consumed in Ontario, meaning little aggregate primary materials are imported or exported (SAROS, 2010). In the past 20 years, Ontario has consumed over 3 billion tonnes of aggregate materials, and consumption is predicted to rise by 13 percent over the next 20 years (SAROS, 2010). In the present day, there are few known viable substitutes for aggregate materials (SAROS, 2010).

1.1.2 Concerns for Aggregate Development

Aggregate sites can also be a cause of disturbance to surrounding areas. For example, a content analysis was conducted in the 2010 *State of the Aggregate Resource in Ontario Study* of reported public comments from Ontario Municipal Board (OMB) hearings and from 31 Ministry of Natural Resources aggregate license applications. This analysis cited the three most frequently reported public complaints from property owners near aggregate sites as: truck traffic, noise, and air pollution (dust) (SAROS, 2010). When surveying a larger portion of the Ontario population (a sample including more people living far from pits or quarries), “environmental effects” emerged as the main social cost of aggregate production (SAROS, 2010). Across the 31 sample licenses, the most significant loss of land use was agricultural land. A net shift was found in land use within the sample of 31 MNR licenses. Over time, the aggregate extraction process has shifted land use from terrestrial to lake habitats (SAROS, 2010). Two of the largest impacts cited in the study analysis were bi-products of aggregate processing and the impact of physical infrastructure (i.e. buildings, roads, and dams) on the developed landscape (SAROS, 2010).

The current aggregate application review around Hidden Quarry in Rockwood, Ontario has brought forth a group called the Concerned Residents Coalition (CRC). The Wellington Advertiser newspaper (2015) cited the residents’ concerns of Hidden Quarry as “hydrogeology, species at risk, traffic, haul route, noise and blast vibrations, archeology and agriculture.” One common issue of debate is whether these aforementioned externalities influence nearby residential property values. Many people believe the sites to be loud and visually displeasing. The trucking routes can disturb school and business commuters. Bedrock quarries use blasting techniques that can be very loud and disturbing. Many residents fear that extraction activities below the water table will affect water and soil quality.

A list of concerns put out by the Concerned Residents Coalition reflects the issues discussed above (CRC, 2016). This group lists eleven concerns on their website: 1) groundwater contamination, 2) household water wells lowered, 3) blasting damage and noise, 4) potential for rocks to be launched outside designated extraction area, 5) extermination of wetlands, 6) diminished air quality, **7) decline in property values**, 8) wildlife habitat destruction, 9) traffic increase and truck haulage routes impacted, 10) visual disamenity, and 11) impact on Rockwood cultural heritage and natural landscape (CRC, 2016).

The research conducted in this thesis is particularly concerned with assessing one of the concerns (number 7) listed above: the effect of aggregate extraction on surrounding property values. There is some evidence to support this concern. For example, in some counties, the Municipal Property Assessment Corporation (MPAC)[3] reduces the assessed values of properties that are abutting aggregate sites (J. Moore, MPAC, personal communication, 2017). This reduction is based on market evidence of property value changes due to aggregate site activities, and is meant to adjust the assessed value to reflect what the property should sell for on the open market at the valuation date that MPAC uses (MPAC, 2017).

When MPAC (2017) analyzes residential properties, they look at many different site variables. Some of these include abutting or being in proximity to a railway line, a commercial property, a busy street, an industrial property, etc.[4] Aggregate sites are considered industrial properties in these analyses. Abutting and proximity to an industrial property enters significantly in MPAC's market models, so properties abutting or in proximity to a pit or quarry will receive an adjustment to the assessed value in most parts of the province. This amount will vary by market based on the sales analyses. In Wellington County, the adjustment was -3% for abutting an industrial property and -2% for proximity in 2016. The definition of proximity can vary based on the characteristic being measured and the location. In Wellington County, MPAC used a definition of: "one property removed from a pit site or across the road," for proximity. In some

[3] MPAC is the mass appraisal agency in Ontario that determines assessed value of properties for taxation purposes.
[4] Abutting is a term referring to the attribute (e.g. industrial site) sharing a common boundary with the subject property. The definition of proximity is flexible across MPAC models, but in this case it refers to the attribute being directly across or diagonally across from the subject property (MPAC, 2017).

parts of the province the definition is wider and can go as far as within one kilometer of a gravel pit. The only unique deviation from this method in Ontario occurred for the Regional Municipality of Halton and Regional Municipality of Peel property assessments. MPAC included some proposed future pits when they did their assessments (J. Moore, MPAC, personal communication, 2017). These adjustments in assessed value support the argument that some property values are diminished as a result of their proximity to pits and quarries. The reduction in assessed value for taxation is performed as a form of compensation for living nearby the pits, or for having one developed near existing property.

Zhang and Hite (2016)[5] state that pit operations include mechanical excavating, sorting, and crushing of materials. Further, they state that the environmental issues arising from gravel pit operations are the release of sediment into the waterways and air. Zhang and Hite (2016) also argue that a noise disamenity results from the use of heavy equipment and vehicles to transport materials. If the disamenities created from pits and quarries are perceived by residents living in the area, the perceptions can translate into a discount of property values. The prices of nearby houses would be reduced to compensate the buyers for accepting the disamenity.

Currently, there are few studies in Ontario with empirical work on property value changes for those residing near pits and quarries. Presently, to my knowledge, there are no peer-reviewed publications examining the effect of aggregate sites on property values. There is unpublished research by Lansink Appraisals (2014) arguing that the effect of aggregate sites on property values ranges between -8.57 and -39.36 percent in property value losses. This market study analysis looked at 19 individual property sales after the creation of a nearby pit, quarry, or haul route in southern Ontario.

[5] This study is currently available online as a conference presentation for the 2016 Southern Agricultural Economics Association Meetings, but is not yet published in the peer-reviewed literature.

1.1.3 The Case Study Area: Wellington County

The area of focus in this study is Wellington County. A list of current licensed pits and quarries in Wellington County is provided in Table A1. The Ontario Aggregate Resources Corporation (TOARC) publishes a production report listing total aggregate production by municipality. Wellington County had 107 licensed aggregate sites as of 2011, and approximately 6.5 million metric tonnes in production of aggregate material in 2015 (TOARC, 2015). Out of all the municipalities in Ontario, only 5 municipalities have more sites (by production volume) than Wellington, the largest being the Municipality of Ottawa (TOARC, 2015). Comparatively, approximately 3 million more metric tonnes were produced in the Municipality of Ottawa in 2015. Five percent of Ontario's aggregate sites are located within Wellington County (TOARC, 2015).

1.2 Research Question

The primary research question of this thesis is whether aggregate sites influence nearby property values. There are important empirical challenges that this research question raises. For example, pits differ by level of activity, and properties differ by proximity to the sites. These are key factors analysed and assessed in the empirical analysis. Municipal governments in Ontario, the Ontario Municipal Board (OMB), and rural residential[6] property owners are interested in the impacts arising from the development of pits and quarries, specifically on property values surrounding these sites. The municipal governments and OMB may utilize this information to inform the decision-making process of approval or selecting location of aggregate development

[6] Rural residential properties are those properties located in an area zoned for residential use but are located in a less densely populated area. No urban properties are designated in this group. Most aggregate sites are located in rural areas, hence why rural residential properties are used in this study.

projects. Rural residential property owners may be interested in the valuation of their home (if surrounding an aggregate site), or the valuation of surrounding properties in their township or county that are neighbouring these sites (e.g. if they are possibly deciding to move elsewhere). If there are negative and large impacts of aggregate sites on property values, this may mean that current assessments are overvalued. But, as mentioned above, MPAC already assumes this. Property appraisals performed by MPAC are adjusted according to proximity or abutting industrial property (aggregate sites are within this category). This study could provide insight into the property appraisal process for properties abutting or in proximity to aggregate sites specifically.

This study seeks to estimate any potential rural residential property value effects of living nearby an aggregate site(s), specifically in Wellington County. The findings of this research can also assist the Ontario Municipal Board (OMB) in making decisions on future development of aggregate sites in the province of Ontario. The results of this study attempt to inform municipal governments, MPAC, the OMB, community groups, and the aggregate industry. This study provides information that all of these groups can use to clarify and measure the effects of aggregate development on property values.

1.3 Method

Details of the theory and empirical methods used to answer the primary research question are fully developed in the theoretical and empirical model sections of this thesis (Chapters 3 and 4). In this section, I provide a brief summary of my methods. I estimate the hedonic price function using cross-sectional data on property sales in Wellington County between the years 2002-2013. The hedonic price function includes a dependent variable on market sales data, distance variables to identify proximity from the pit or quarry to the property, as well as all of the independent variables used to describe the value of each property. The data comes from property sales data gathered by MPAC over the 12-year period. Pit and quarry identification and location coordinates come from the Ministry of Natural Resources 2011 census data. Distance data was derived using Geographical Information Systems (GIS) linking each parcel or property sale to the nearest pit, highway 401, closest urban area, and Toronto. A key variable in the hedonic price function will be a measure of the proximity of a rural residential property to the nearest aggregate site. From this, the marginal implicit price of being located further away from a site can be estimated. A key empirical issue is addressing the extraction activity of the pits and quarries, as there is large variation in extraction levels between different pits and quarries in Wellington County.

1.4 Hypotheses

Two key hypotheses are analyzed and tested using the above outlined empirical methods:

1. Rural residential properties experience a decline in value within close proximity (i.e. three kilometres) to aggregate sites.
2. The effect of proximity to an aggregate site depends on its level of activity.

1.5 Thesis Synopsis

Chapter 2 contains a literature review; this review first addresses three prior studies on the effect of pits (gravel pits specifically) on housing values, and then more broadly addresses research on the effect of various environmental disamenities on housing values. A discussion of the novelty of this thesis is specified. Chapter 3 provides the theoretical framework of the hedonic property model that I use for measuring the property value effect, and discusses the preliminary hypotheses that I test. Chapter 4 explains the data: how it was collected, analyzed, and used. This chapter also outlines the methods used to estimate the effect of aggregate sites on surrounding property values, and the empirical model used to do so. Chapter 5 communicates the summary statistics and the results of the empirical models. Chapter 6 provides a summary and analysis of the results, as well as the implications and usefulness of these results for policy applications. I also address limitations of the data and analysis here, and suggest next steps for future research in this area.

CHAPTER 2: LITERATURE REVIEW

This literature review provides a critical assessment of prior literature in two categories: 1) studies examining the effect of gravel pits on surrounding property values, and 2) studies using the hedonic model to estimate the impact of environmental disamenities on property values. In the first section, emphasis is placed on four studies: two studies with identical hedonic models performed in Ohio and Michigan that assess the effect of gravel pits on nearby property values, and then a recent study that assesses residential property impacts of gravel pits and landfills in Ohio. These are the only known academic empirical studies that measure the effect of gravel pits on property values. This is an important discussion, because it will inform the empirical analysis described in Chapter 4. These studies were not published in a peer-reviewed journal. Hereafter, non-peer-reviewed publications are referred to as “grey literature.” The last study on gravel pits that I review does not use the hedonic model, but looks at the effect of aggregate operations on property values. In the second section I provide an overview of literature examining the effect of environmental disamenities on nearby property values, and trends in the findings across studies are presented. There is a wealth of studies that observe the effect of various environmental disamenities on property values, and only a few are chosen for this literature review. These specific studies are chosen either because the model is similar to the one used in this thesis, or because the area being studied is regionally similar.

2.1 Studies Examining the Effect of Gravel Pits on Nearby Property Values

Currently, there is anecdotal and appraisal information about changes in property values near aggregate sites but no statistical evidence at a county-wide level of such effects. Therefore, there is a lack of empirical evidence as to whether a negative property value effect occurs when an aggregate site is created and operated. Although there is a plethora of empirical analyses and research on the effects of environmental disamenities in Ontario, Canada, and worldwide (the next section provides examples of some empirical analyses and research on the effects of other environmental disamenities on property values), no peer-reviewed literature addresses the effects of aggregate pits and quarries on nearby property values in Ontario or elsewhere. To the best of my knowledge, there are four studies that look at the effect of gravel pits on property values. There are two grey literature studies that use the hedonic model to examine the effect of pits on nearby properties that I will briefly discuss: Hite (2006) and Erickcek (2006). Zhang and Hite (2016) is the third study I discuss. The authors use the horizontal sorting model to estimate effects of gravel pits and landfills on surrounding property values. I will also discuss a grey literature study that does not use the hedonic model by Lansink (2014) that assesses the effect of aggregate sites on property values in the Ontario context.

Hite (2006)[7] estimated the effect of gravel pits on nearby property values in Ohio, and found that gravel pits diminished surrounding property values. The decrease in property values that she found was observed far from the sites, exceeding two miles, indicating that the gravel pits provided a disamenity large enough to affect property values at a greater distance than two miles from a site. There are some important limitations to Hite's study. First, it was not stated in the paper whether the researcher visually checked to confirm that all of the pits included in the analysis were active during the time period studied. This is important, as some aggregate sites can be licensed, but not necessarily active in extraction activities. Second, Hite (2006) did not control for proximity to urban areas or major highways, and her broad area of study in Ohio contained both. Third, Hite (2006) specifically looks at only gravel pits (excluding quarries),

[7] This white paper study cannot be found online in the present day.

which do not provide the noise disamenity or loud blasting that bedrock quarries do. There were bedrock quarries in her study area that were not included in her investigation. I attempt to address each of these three shortcomings in my analysis: a measure of aggregate activity for each site is collected to confirm that it is indeed physically active, nearby major urban areas and major highways are taken into account, and *all* aggregate sites – from sand and gravel pits, to bedrock quarries – are examined. Lastly, this thesis provides a county-level analysis; this smaller-scale analysis pays greater attention to individual aggregate sites, as will be discussed in Chapter 4.

In the same year, Erickcek (2006) replicated Hite's (2006) hedonic property model in Richland Township, Michigan. This second study found similar property value losses from aggregate operations. Erickcek (2006) found that gravel quarrying operations had a significant negative impact on 60% of the town of Kalamazoo's properties. He noted a time factor: that the properties only declined in value at the time the quarry was established or establishing, and once a quarry had been operating for some time the effect was diminished. Erickcek's findings are consistent with those of Hite's, although he does stress the importance that the effect on property values diminishes over a pit's lifetime.

The third study on gravel pits was performed by Zhang and Hite (2016). The authors used a horizontal sorting model[8] to estimate the effect of landfills and gravel pits on surrounding residents. This study was performed in Franklin County of Ohio state and included 1592 housing transactions over a one-year period (2010). To complement this data, the authors also included household-level characteristics, such as household size, race, and income. The authors attempted to see if these household characteristics affect whether or not individuals choose to live in proximity to landfills or gravel pits. The authors found that wealthy white households live further

[8] A horizontal sorting model uses location choice as the unit of analysis (dependent variable) rather than the change in property values.

away from pits and landfills than wealthy black households. Additionally, the authors founds that a longer distance to landfill sites increased the fixed utility[9] of the household. Lastly, the authors determined that households prefer to live further away from gravel pits, yielding a 13.9% increase in willingness to pay for every additional mile away from the pit.

Lansink (2014) from Lansink Appraisals and Consulting performed a series of market price study analyses on the effect of aggregate sites in Ontario, contributing to the popular debate on this issue in the grey literature. Lansink (2014) looked at 19 hand-picked property sales in Ontario – located in the communities Beachville, Braeside, Burlington, Caledon, West Montrose, and London – that were within the geographic influence of a pit, quarry, or haul route. The diminution in price was calculated as a percentage difference in the original price and the sold price of the property, adjusted only for the passage of time. Lansink (2014) found a diminution in price between -8.57% and -39.36% for the 19 properties studied. There are shortcomings to this study, as the 19 properties were chosen, which could lead to selection bias. In contrast to Lansink (2014), I use regression analysis to examine the effect of pits and quarries on property values. Regression analysis has the advantage of explicitly controlling for other variables that may influence price. It also diminishes any selection bias, as all property sales in close proximity to aggregate sites between the years 2002-2013 are included (and not chosen by the researcher).

The results across all of these studies listed above are consistent in that negative impacts of gravel pits are found on property values. In the next section, I discuss key literature on the effect of other possible environmental disamenities – hazardous waste sites, shale gas exploration sites, wildfire occurrence, landfills and wind turbines – on property values.

[9] Fixed utility is the fixed preferences over some bundle of goods. The preferences are fixed because these preferences were not intertemporal, but were measured at one point in time.

2.2 Studies Using the Hedonic Model to Estimate the Impact of Environmental Disamenities on Property Values

There is vast known literature regarding the impact of environmental disamenities on property values. I focus on studies that use the hedonic model. Another focus of this section is a discussion of studies performed in areas that are regionally similar to Ontario (wind turbine studies), or may provide a disamenity that could be similar to aggregate operations (such as toxic waste sites, shale gas exploration sites, wildfire occurrence, and landfills). This section is split into two parts: the first section discusses studies that found a negative impact on property values. The second section describes studies that found no statistically significant impacts on property values.

2.2.1 Negative Impacts Found

Kohlhase (1991) uses the hedonic property model to analyze the effect of hazardous waste sites on property values. Her study was performed in Houston, Texas using 6,374 housing sales near 10 various toxic waste sites. She analyzes three time periods: 1976 (before the Superfund[10] list was created), 1980 (when the Superfund list was established) and 1985 (once the sites located on the Superfund list were made available to the public). Kohlhase finds that once the public was made aware that the sites were on the Superfund list, housing prices were estimated to increase at a decreasing rate up to 6.2 miles from the toxic waste site. Her findings demonstrate that toxic waste sites provide a disamenity to nearby property owners, and thus pose a negative effect on nearby property values.

[10] The United States' Environmental Protection Agency (EPA)'s Superfund program is responsible for cleaning up or restoring contaminated land and responding to environmental emergencies (EPA, 2017). Eligible sites are ranked by priority and placed on a list in the order of clean-up.

Gopalakrishnan and Klaiber (2014) also use the hedonic property model to estimate the effect of shale gas exploration sites on property values. The data came from housing market transactions from 67 municipalities in Pennsylvania. They discover a decrease in home values of 21.7% within 0.75 miles (approximately 1.2 kilometres) of the shale site. The authors find evidence that households are negatively impacted by shale gas exploration activity, but that impact depends on the proximity and intensity of the shale activity. They also identified that this effect diminishes over time, coinciding with the cessation of exploration activity.

Xu and van Kooten (2013) use the hedonic property model to determine the effects of wildfire occurrence on property values in Kelowna, British Columbia. The authors examine 10 years (2000-2010) of home sales (yielding 6, 496 observations) and the number of fires that occurred within 1, 5, and 10 kilometers from the housing parcels. The authors discover that historical wildfire occurrence has a statistically significant impact on property values, but fire size has a more significant impact than frequency (with a decrease in value of $47 per metre squared). Xu and van Kooten conclude that home buyers discount the impact of fire on their purchase if large fires occurred nearby.

Hite (2001) analyzes the effect of landfills on nearby residential real estate prices in Franklin County, Ohio, using the hedonic property model. The author identifies significant property value declines in close proximity to 4 landfills, and her results also suggest that closing a landfill would not necessarily mitigate property value impacts. Particularly, her dataset includes 2, 913 observations and indicates a 19-20% increase in average annual welfare as a result of a move 3.25 miles away from a landfill. In a similar study, Ready (2010) estimates the effect of three landfills in Berks County, Pennsylvania, that differed in size and prominence in the landscape on property values, also using the hedonic model. He includes 11,090 property sales and notes an average decrease in property value of 13.7%, and diminishes further away from the landfill. His results vastly differed across the three different landfills. Notably, the smallest landfills yielded no statistically significant effect on property values, giving rise to the question of whether landfill size plays a role in the effect on property values.

Of the environmental disamenities discussed above (toxic waste sites, shale gas exploration sites, wildfire occurrence, and landfills), negative effects on property values were found across studies. The effect varies in magnitude and scale.

2.2.2 No Effects Found

Vyn and McCullough (2014) use the hedonic property model to estimate the effect of proximity and visibility of wind turbines on rural residential and farmland property values. The study was performed in Melancthon Township, Ontario using approximately 7,000 housing market sales from 2001-2010. The authors found no statistically significant results to support the claim that property values decline with proximity or visibility of wind turbines.

Another study examining wind facilities with similar results was a paper published by Hoen, Brown, Jackson, Thayer, Wiser & Cappers (2015). The authors use the hedonic property model and data from 50,000 home sales from 2000-2014 across 9 different U.S. states. Although Hoen et al. did not use the visibility variable that Vyn and McCullough (2014) used, they also did not find statistically significant effects of wind turbines on property values. The authors find no property value effects before, after, or during construction of a wind facility. These two studies on the effect of wind turbines show no statistically significant impacts of wind facilities on property values.

2.3 Summary

In this chapter, I reviewed some of the previous empirical literature that examines the effect of disamenities on surrounding property values. Although there is a wealth of literature on environmental disamenities using the hedonic model, there are too many studies to include in this literature review. Specific studies chosen for this literature review provided some relation to this thesis. For example: the wind turbine studies were performed in an area regionally similar to the area in my study, and the shale gas exploration and toxic waste site articles include similar methods. Across all studies examined, the findings are varied: some studies find a negative impact from the environmental disamenity and others find no impact.

Across all analyses on *gravel pits* examined, the findings were quite similar: a large effect of aggregate sites on property values is identified. Four studies have been reviewed that find gravel pits as an environmental disamenity. All studies reviewed on gravel pits find a statistically significant negative effect of gravel pits on surrounding property values.

Despite the consistent findings in previous studies, there are significant shortcomings. These shortcomings, and the lack of research on this issue for aggregate sites in Ontario, are what this thesis aims to address. My study addresses the shortcomings of previous literature on the effect of gravel pits in four ways. First, I confirm that the aggregate site is indeed physically active, and provide a measure of aggregate activity. Second, nearby major urban areas and major highways are taken into account. Third, *all* aggregate sites are examined – from sand and gravel pits, to bedrock quarries. Finally, my county-level smaller-scale analysis pays greater attention to individual aggregate sites. I believe that addressing these shortcomings in prior literature, and studying this issue in a previously unstudied geographic area, will contribute novel findings to the literature on this issue.

CHAPTER 3: THEORETICAL FRAMEWORK - THE HEDONIC MODEL

3.1 Hedonic Property Model

Freeman (1993) provides a detailed explanation of hedonic demand theory. Hedonic demand theory uses revealed preferences to estimate the value of – or demand for – an item. The theory is called 'hedonics' because it encompasses the hedonistic elements, or the variables that derive a level of pleasure (utility), with respect to the dependent variable in question. This variable can be anything from property values, to wages, to willingness to pay for a specific rice variety. The specific item being researched is broken down into its independent variables - its utility-bearing attributes or constituent characteristics.

From hedonic demand theory comes the hedonic price model, which is the overarching term that explains all hedonic models that use price (of some item) as the dependent variable. A specific type of hedonic price model is the hedonic property model. In the hedonic property model, the utility-bearing attributes are categorized by the structural, neighbourhood, and environmental characteristics of the item. The structural utility-bearing attributes consist of different fixed elements of the property, such as: age, type of construction, square footage of building(s), number of bedrooms, baths, etc. The neighbourhood characteristics encompass the local property factors, such as distance to an urban area or major highway. The environmental component of the utility-bearing attributes are characteristics such as: beach-front access, forested area, or air quality.

The hedonic property model in this thesis specifically examines the influence of aggregate sites (and the possible disamentities associated with them) on property values. To see this relationship more clearly, Freeman (1993) examines the relationship between a utility maximizing individual and the marginal implicit price of an attribute. Marginal implicit prices are developed fully in section 3.2.

The theory of rents states that the value or stream of rents gained through asset (property) ownership in the future are capitalized into the present day value. Put simply, the expectations about the present and future value of the asset, or property in this case, are capitalized into the present value of the property. Freeman (1993) states that the productivity of the land - the structural, neighbourhood, and environmental attributes - determines the land's value. A utility maximizing individual is assumed to consider the value of the attributes when buying a property including positive and negative traits. Rents derived from property ownership are greater when these three attributes that determine positive productivity of a property are larger.

$$U = U(X, S_i, N_i, E_i) \tag{3.1}$$

This utility-maximizing equation assumes that demands for characteristics are independent of the prices of other goods. This utility maximizing equation can be transformed into the following equation:

$$P_{hi} = P_h (S_i, N_i, E_i) \tag{3.2}$$

The individual is denoted by "h," and the property is denoted by "i." This equation shows that the price or observed sale price of the property depends on these characteristics of the property.

An assumption is made that the rural residential area as a whole is treated like a single market for housing. The individuals in this market have information on all alternatives and are free to choose a property anywhere in the open housing market. The individual's purchase decision of rural residential location fixes for them the whole bundle of housing services that the purchased property provides. Individuals can increase the quantity of any utility-bearing characteristic by finding another location alike in all other respects but offering more of the desired characteristic. Furthermore, it is assumed that all individuals make their utility-maximizing rural residential choices given the prices of alternative housing locations (and the bundle of characteristics attached). These housing prices just clear the market given the existing stock of housing and its characteristics.

Individuals then maximize their utility subject to a specific and individual budget constraint. The budget constraint is a function of how much income an individual has (M), the specific price of the property (P_{hi}), and the price of all goods other than the asset (composite good) (P_x). This is represented in Equation (3.3).

$$M - P_{hi} - P_x = 0 \tag{3.3}$$

Property values will reflect the choices of individuals in the market, satisfying their individual utility maximization problems subject to their individual budget constraints. The first order condition (FOC) is calculated from the utility maximization problem. The environmental amenity, E_j, will be used as the example to be illustrated in the marginal implicit price equation below. The FOC of the environmental amenity (or of any characteristic) is the partial derivative of the hedonic price function, or marginal implicit price.

3.2 Marginal Implicit Prices

Hedonic modelling will be used to examine the effect of an environmental attribute by interpreting the derivative of the cross-section[11] regression equation with respect to the environmental attribute as a *marginal implicit price*, i.e. the marginal value of living further away from an aggregate site(s).

The FOC or partial derivative denotes the marginal implicit price of the specific attribute.

[11]Cross-section refers to the nature of the data, which is the observation of many characteristics (attributes of the property) at the same point in time (when the property was sold).

The marginal implicit price is the additional amount that an individual pays to move to a greater amount (or unit) of that attribute, other things being equal. The environmental attribute in question for the purpose of this thesis is the distance away from an aggregate site. Therefore, the marginal implicit price is the willingness to pay of an individual to move one unit further away from an aggregate site, other things being equal. Utility maximizing individuals allocate the structural, neighbourhood, and environmental characteristics of their property where marginal implicit price equals their marginal willingness to pay. This can be denoted by the following equation:

$$(\delta U/\delta E_j)/(\delta U/\delta X) = \delta P_{hi}/\delta E_j \tag{3.4}$$

The partial derivative with respect to E_j gives the marginal implicit price of that characteristic. An individual maximizes their utility by simultaneously moving along each price schedule, until they reach a point where their marginal willingness to pay for an additional unit of that attribute equals the marginal implicit price of that attribute.

Figure 3.1 shows the partial relationship between P_{hi} and E_j as estimated from Equation 3.2.

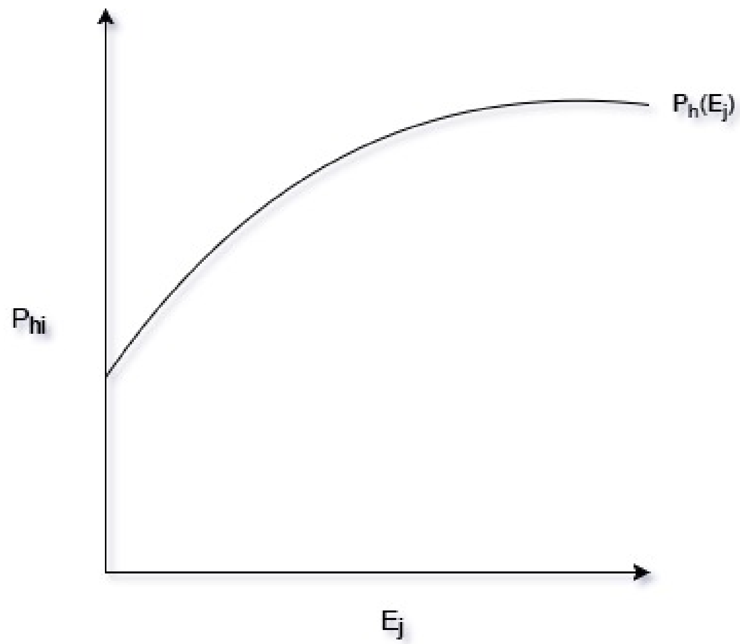


Figure 3.1: Relationship between price and the amenity

The individual's willingness to pay for an environmental attribute increases at a decreasing rate, as demonstrated in Figure 3.1 above. This means that an individual is willing to pay more for an additional unit of the environmental attribute, but as their consumption increases that willingness to pay for each additional unit decreases, until it eventually plateaus. A priori reasoning is used when depicting the slope of this curve, as it is assumed individuals are willing to pay a certain amount for a desirable attribute, but then this amount diminishes as the individual surpasses their optimal amount of that specific attribute. For example, an individual may be willing to pay some amount of money as they move further away from an aggregate site. However, this effect could diminish the further the individual moves away from the site, until the effect is no longer capitalized into the buyer's decision or some upper limit is reached.

Figure 3.2 below shows the marginal implicit price of E_j ($\delta P_{hi} / \delta E_j$), and also reflects the marginal willingness to pay curves for two individuals – k and m – who each have utility maximizing bundles of housing attributes $B_k(E_j)$ and $B_m(E_j)$.

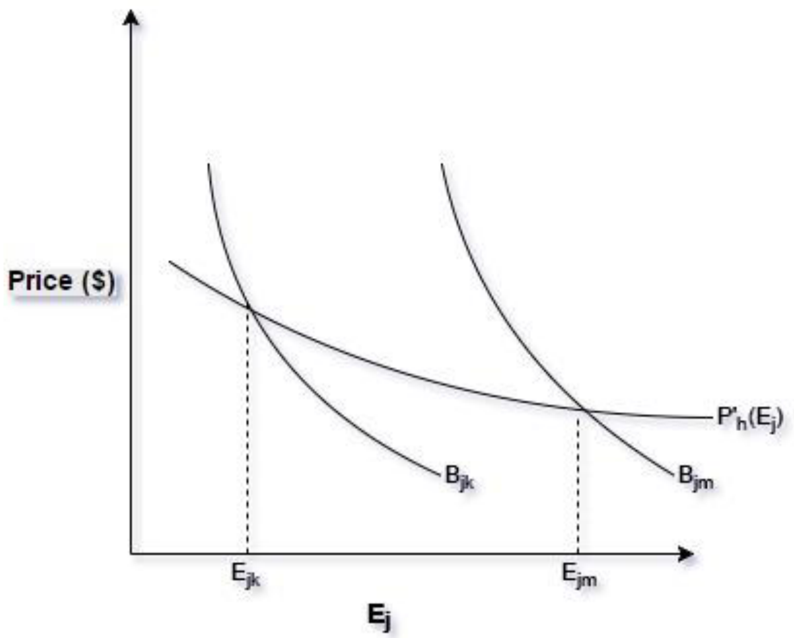


Figure 3.2: Marginal Implicit Price and Marginal Willingness to Pay

These individuals' marginal willingness to pay curves depict changes in the characteristic E_j, holding utility constant at the level achieved by maximizing utility (shown in Equation (3.3)) subject to their budget constraint (represented in Equation (3.4)). Let this maximum level of utility be at the point where both individuals have chosen property locations where their marginal willingness to pay for E_j is equal to its marginal implicit price (i.e. where the curves intersect at E_{jk} and E_{jm}). Marginal implicit prices are denoted by the partial derivative curve P'h(Ej) above.

Marginal implicit prices are estimated in this study using a hedonic price function, which will be discussed in the empirical model section. Specifically, for this thesis the hedonic model is used to estimate the marginal implicit price of residing a unit further away (or closer to) to a nearby pit or quarry.

Two hypotheses were mentioned in Chapter 1. These hypotheses are based off the theoretical framework mentioned above. The graph shown in Figure 3.1 represents my first hypothesis that rural residential properties may experience a decline in value within close proximity to aggregate sites and that this effect may diminish over time (concavity of the curve). The x axis represents the distance away from the aggregate site and the y axis represents the sale value of the property. Therefore, according to Figure 3.1, the sale price of a property rises with distance away from an aggregate site, but this effect diminishes over time after reaching a turning point. This is consistent with the prior literature mentioned in Chapter 2.

My second hypothesis states that the effect of proximity to an aggregate site may depend on its level of activity. This would involve the slope of the curve, and the turning point to which the effect diminishes. If a site had higher extraction activity, I would expect the slope of the curve to be steeper, and the effect to diminish with greater distance away from a site (the larger the extraction activity, the greater the effect on property values). In other words, the turning point of Figure 3.1 may be located further to the right on the x-axis. These hypotheses will be tested throughout the remainder of the thesis. The next chapter begins with a comprehensive review of the data used to estimate marginal implicit prices, and follows with a specification of the empirical model used to test this theory and hypotheses.

CHAPTER 4: METHODS – EMPIRICAL MODEL & DATA

This chapter outlines the data and empirical model used to evaluate the hypotheses discussed in Chapter 3. Firstly, I present a comprehensive overview of the data: how the datasets were obtained, a full description of variables used within those datasets, and definitions of specific aspects of the data. Two main datasets were used for this thesis. The first dataset consists of property sales in Wellington County and their corresponding attributes, and it was obtained from the Municipal Property Assessment Corporation (MPAC). The second dataset consists of data for all the aggregate sites in Ontario, and was obtained from the Ontario Ministry of Natural Resources (MNR). Second, the empirical model is introduced using the data previously presented. The last section of this chapter provides a description of the summary statistics.

4.1 Data

In this section, I outline a description of the data, as well as the collection process methods (if applicable). I review the data in 4 parts below: key GIS variables, property sales and attributes, aggregate sites, and the activity variable construction process.

4.1.1 Key Geographic Information Systems Variables

Geographic Information Systems (GIS) was used in this study because it allows the research to include a spatial aspect. If, for example, a property is abutting Ontario Highway 401, the property value will likely be lower than a characteristically similar home further away (because of a noise disamenity). Alternatively, because the highway 401 provides an amenity because it facilitates commuting, property values close to this highway, but far enough away to avoid noise (in close proximity but not abutting) may experience an increased home value.

Therefore, it is important to include distance variables in this type of analysis, as these variables are capitalized into a property's value. Heywood, Cornelius & Carver (2011) mention the multiple uses for GIS: capturing, storing, checking, integrating, manipulating, displaying, and analyzing geographic earth data. GIS employs computer software to pinpoint spatial components on a geographic map. GIS was used in this thesis to record the distance between the property sales and four major features: the Ontario 401 highway, the city of Toronto, the nearest urban area, and the individual aggregate sites. All distances were measured "as the crow flies," or by straight-line distance, rather than by road or trail distance. Below, I discuss each of the distance variables.

4.1.1.1 Distance from the MPAC parcel to the Nearest Aggregate Site

ArcGIS was used to measure the straight-line distance between the centroid of the MPAC parcel to the edge of the boundary of the nearest aggregate site. This was performed using the Euclidean Distance tool in ArcGIS. The location of MPAC parcels and the location of licensed aggregate sites using GPS coordinates of each parcel and site were overlaid on top of 2011 satellite imagery of Wellington County and surrounding areas to retrieve these distance variables. Distance bands using this measure were used for the main analysis in this thesis.

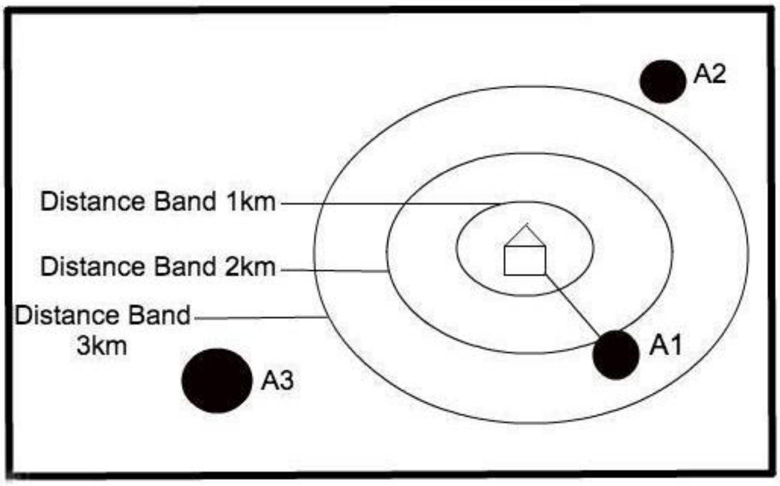
The potential impacts of aggregate sites on property values are accounted for through proximity measures. The main variables for analysis in this study are the proximity measures, as impacts are hypothesized to diminish with distance from a site. The straight-line distances from the property parcel to the closest aggregate site were grouped into distance bands using dummy variables (listed below).

Distance bands were chosen for the main analysis, instead of a continuous distance variable, because the band approach is more flexible and does not restrict the data to any functional form. Kuminoff et al (2010) study whether omitted variables seriously undermine the hedonic method's ability to accurately identify economic values. Their results suggest that large gains in accuracy can be realized by moving from the standard linear specifications (like continuous distance variables) to a more flexible framework that uses spatial fixed effects (such as distance bands). Thus, distance bands were chosen for the main analysis in this study, but a continuous distance variable, quadratic, and inverse distance measure were other functional forms used in sensitivity analysis. Distance bands of half a kilometre radii were created, with sets: 0-0.5 kilometers, 0.5-1 kilometers, etc. up to a 2.5-3 kilometers.[12] Creating these distance bands allows for varying ways to look at the data without restricting the analysis to a continuous distance variable.

All of the distance bands were constructed as dummy variables (categorized as zero or a one). For example, if an MPAC parcel was located 2.2 kilometers from an aggregate site, the distance band variable would yield a "1" for the 2-2.5 km band, and a "0" for 0-0.5, 0.5-1, 1-1.5, 1.5-2, 2.5-3, and 3+ kilometer bands. Figure 4.1 depicts a visual representation of this MPAC parcel, relative to the distance bands, with examples of aggregate sites marked A1, A2, and A3. The MPAC parcel is depicted here in the centre of the figure at a distance of 2.2 kilometers away from the aggregate site, A1. Only three 1 kilometer distance bands are drawn here to give an idea of what these bands look like conceptually. Aggregate sites A2 and A3 are drawn to show that more sites could be located in close proximity to the MPAC parcel.

[12] Number of observations within each band are provided in the summary statistics section.

Figure 4.1: Visual Representation of Distance Bands and Proximity to Aggregate Site



A density variable was not included in this analysis to supplement the distance variables. This was because the pits, once geographically clustered[13], were too far apart from one another to warrant the usefulness of a pit density variable. For example, in the figure above, A1, A2, and A3 would be included as 3 sites located within a 5km radius of the MPAC parcel, which does not occur in this dataset.

I also estimate the distance relationship in a number of other ways, including: continuous measures of distance away from the site and an inverse distance measure (indicating distance to the site). I also examine distance bands of 1 kilometre widths (as compared to 0.5km widths) and assess the sensitivity of the results. I also focus a regression to the first 3 kilometres (bands up to 3km) where the effect is expected to be most pronounced, but alternative number of bands (up to 11km)[14] are also tested. Previewing the results section, these alternative approaches yielded similar quantitative results.

[13] Clustering of the aggregate sites is discussed in the activity variable construction section.
[14] 11km is approximately the furthest distance away that the property sales extend from the aggregate sites in this analysis. An approach with bands up to 11km is tested to include all observations within bands. The results are similar to the model with bands up to 3km, so this specific analysis on bands up to 11km is not further discussed in this thesis.

4.1.1.2 Distance to the Ontario Highway 401

The computer software program ArcGIS 10.2.1 was used to measure the straight-line distance between the centroid of the MPAC parcel to the closest edge of the Ontario Highway 401. This was performed using the Euclidean Distance tool in ArcGIS. The location of MPAC parcels (each property sale in the dataset) using Global Positioning System (GPS) coordinates was overlaid on top of a 2011 satellite image to more accurately measure the centroid of the MPAC parcel to the highway.

4.1.1.3 Distance to the City of Toronto and Closest Urban Area

ArcGIS was used to measure the straight-line distance between the centroid of the MPAC parcel to the edge of the boundary of the Toronto municipal area or other nearby urban area. This was performed using the Euclidean Distance tool in ArcGIS. The location of MPAC parcels using GPS coordinates was overlaid on top of 2011 satellite imagery to more accurately measure the centroid of the MPAC parcel to the boundary of the city of Toronto.

4.1.2 Property Sales and Attributes

The Municipal Property Assessment Corporation (MPAC) provides a uniform, province-wide system of data collection of property sales in Ontario. This agency is funded by taxpayers and has a board of directors appointed by the provincial Minister of Finance. This agency provides a useful dataset on property sales and housing characteristics. This includes a record of the property sale, as well as a follow-up survey on the property's characteristics. Observed market sales are collected by MPAC, which reflect the market value of the land and its structural improvements at a specific point in time.

MPAC has provided the dataset for arms-length property sales over a 12-year period, which includes key housing characteristics assigned to each sale. Arms-length sales are those transactions that occur on the open market between a willing buyer and seller who have no prior relation to one another. Arms-lengths transactions omit any sales that occur between a father and son, for example, or a consolidation of property between relatives. It is important to only include arms-length transactions, as closed market sales may not reflect a real representation of what the property is worth in a competitive and open market. Transactions between relatives may sometimes not reflect the individual's purchase decision, as there are many other factors that can be involved with an individual purchasing a relative's property.

Twelve years (2002-2013) of rural residential property sales in Wellington County in Ontario, Canada were collected by MPAC. Wellington County was chosen for this study because a small, county-wide scale was preferred. An additional reason for focusing on Wellington County was that I live in Guelph, Wellington County, making it accessible to visit, confirm site extraction activity, and talk to the people at some of the aggregate site locations.[15]

In total this dataset includes 9,095 arms-length rural residential property sales. There are over 1,200 housing and other property characteristics in the dataset, but not all were included in the econometric analysis. Those included were attributes that were believed to contribute most to the value of a property. MPAC lists seven factors that, on average, accounted for more than 75% of a property's value in 2016 Ontario appraisals (MPAC, 2016). These key features are: location, lot dimensions, living area, age of property, quality of construction, number of bedrooms and number of bathrooms. These variables that make up 75% of a property's value were considered when choosing which variables should be used in this analysis, as described in Table 4.1. The variable names and the short-form terminology used in the econometric analysis are included in

[15] I was able to visit the Rockwood Conservation Area, where I was able to talk to some residents who live in a naeighbouring area to a pit. I was also able to discuss Wellington County aggregate sites with an MNRF (now Ministry of Natural Resources and Forestry) Aggregates Specialist for Wellington County specifically.

column 1 and 2 of Table 4.1. Column 3 provides a short definition of each property characteristic variable. All of these variables are also listed in order of placement for the regression analysis.

Table 4.1: Variable Names with Definition and Short-Form Model Label

Variable	**Short-Form**	**Short Definition**
Property Sale ($)	sale_amt	Property sale amount
Area of Structure(s) (square feet)	area_tot	Total floor area of home/structure
Lot Size (Acres)	lotsize_ac	Total lot size of the property
Distance to 401 Highway (km)	edist_carto_1	Distance from the MPAC parcel to the closest major highway (400 series or expressway)
Distance to Toronto (km)	cdst_pc_2011_toronto	Distance from MPAC parcel to the city of Toronto
Distance to Closest Urban Area	cdst_pc_2011_gte_100k	Distance from MPAC parcel to the closest urban area (as defined by the 2011 census)
Number of Bathrooms	baths	Variable indicating the number of bathrooms within the structure (half baths included)
Number of Fireplaces	fireplcs	Variable indicating the number of fireplaces located in the structure
Number of pools	pool	Dummy variable indicating whether or not there is a pool (including indoor and outdoor) located on the property
Age of structure(s)	age	Age of the structure(s)
House Quality Index	quality	Quality of structure rated by MPAC 0-10
Finished Basement	finbsmt	Dummy variable: finished basement = 1, absence of finished basement = 0
Air conditioning	aircond	Dummy variable: air conditioning = 1, absence of air conditioning = 0
Year the Structure(s) was sold	sy2003, sy2004, sy2005, sy2006, sy2007, sy2008, sy2009, sy2010, sy2011, sy2012, sy2013	Dummy variables indicating the property sale year (dummy variable omitted is sale year 2002)
Distance Bands	band_0km_halfkm, band_halfkm_1km, band_1km_1halfkm, band_1halfkm_2km, band_2km_2halfkm, band_2halfkm_3km	Distance bands indicating the straight-line distance (radii) from the nearest aggregate site, in distance categories (3+ km category dummy omitted)
Distance from Aggregate Site (km)	distancekm	Distance from MPAC parcel to the closest proximal aggregate site
Squared Distance from Aggregate Site (km^2)	distancekm2	Squared distance from MPAC parcel to the closest proximal aggregate site
Distance to Aggregate Site (km)	invdistance	Inverse distancekm (1/distancekm)
Township Fixed Effects	Erin, WellN, Mapleton, Puslinch, Guelph-Eramosa, Well	Dummy variables indicating the township the property was sold in (Erin Township, Wellington North, Mapleton Township, Puslinch Township, Guelph-Eramosa Township, and Wellington Centre). The Township of Minto was omitted.

Distance variables (distance to nearest highway, distance to Toronto, distance to the closest urban area, and distance to a pit/quarry) are measured through GIS. Fixed effects are included to account for yearly changes in property values (year dummy variable) and the township the property was sold in (township dummy variables). This is to account for any changes within property sales specific to individual townships.

4.1.3 Aggregate Sites

There are 107 aggregate sites in Wellington County. The sites were collected from the 2011 MNR census data, and are included in order of ALPS ID (pit identifier number) in Table A1 in the Appendix. This table provides a pit and quarry inventory of all of the licensed pits as of 2011 in Wellington County. It provides the ALPS ID, as well as the characteristics of each site, including: the adjoining sites that make up the cluster, location, license type, and license area. The average individual pit or quarry license size is 336,734 square metres, while the maximum individual site license size is 1,882,271 square metres and the minimum individual site license size is 13,645 square metres. It is important to note that these values are the licensed areas, not the actual extraction areas. [16] The activity variable provides a measurement of aggregate site activity which can be used instead of the licensed area. The reasons for this are outlined in the next section: activity variable construction.

4.1.4 Activity Variable Construction

Aggregate extraction levels vary depending on the location, aggregate company, available aggregates and available area. Knowing this, it can be hypothesized that property

[16] Licensed area provides a very different average, max, and min, than the actual active area (shown in the next section). The average active area is approximately 151,000 square metres (compared to 337,000 in licensed area), the maximum active area is 600,000 square metres (compared to the 1.9 million in licensed area), and the minimum active area is 0 metres squared (compared to approximately 14,000 in licensed area). This further highlights the importance of a providing aggregate site activity in the analysis, rather than licensed area. (It is important to note that these values are the aggregate sites before they are clustered by geographical proximity.)

values may experience different impacts, depending on the level of extraction activity that is present within an aggregate site. This activity measure is an attempt to differentiate the pits by size or extraction area, instead of treating all pits equally or using their license sizes to differentiate them. Below, I explain why license sizes may not be the best measure of aggregate site extraction activity, and how extraction area might be a better measure when predicting actual site activity. Previewing the empirical model section, I am able to specify smaller subsamples of property sale observations in proximity to the most highly active pits in Wellington County.[17]

The Ministry of Natural Resources (MNR) data on all aggregate site licenses provided maximum tonnage allowances for each of the aggregate sites. This information on licenses does not give specific insight into the measure of actual extraction activity, only the size of the license area and maximum activity – or output tonnage – that is allowed. These variables may be proxy measures of activity, or they may not. The Ontario Aggregate Resources Corporation (TOARC) collects tonnage and revenue data from aggregate companies, as the tonnage of aggregates being removed from each site is taxed. Unfortunately, this data is confidential and not publicly available. To remedy this, an alternate method to estimate extraction activity was used: geospatial satellite imaging.

In this section I discuss the construction of a measure of aggregate activity for each pit and quarry. As I detail below, this activity measure identifies the average loose gravel or bedrock area exposed on a pit or quarry over the period of analysis. While using an overlaid map[18] of 2011 MNR registered aggregate sites, I compiled the actual disturbed land areas of those registered pits over the 12-year time period of the MPAC dataset: 2002-2013.

In many cases, a subset of pits and quarries are in close proximity to each other. As

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[17] Identified in the results as Model 2.

[18] The boundaries of 2013 aggregate sites were placed on top of the AAFC Annual Crop Inventory satellite images to show the exact location of the licensed area compared to the actual disturbed land area.

discussed below, I cluster pits and quarries that are abutting each other, allowing me to identify aggregate sites by a cluster of pits and/or quarries. Given these two measures, I then identify the degree of activity by cluster by adding up all of the areas of the pits abutting each other. This method – i.e., exposed area and size – is used as a measure of actual area of activity that is present in Wellington County. Additional detail on the process of obtaining the average area is provided in the following sections: 4.1.3.1 Average Aggregate Site Areas using GIS, and 4.1.3.2 Clustering Geographical Areas to Depict Actual Extraction Activities.

My empirical approach, discussed in the next section, takes advantage of this measure to focus analysis towards prices of rural residential houses that are located close to *highly active clusters*: pits and quarries in close proximity to each other with a relatively high average area of gravel and bedrock exposed over the time period analyzed. After providing analysis that utilizes all property sales and aggregate sites in Wellington County, I specifically focus analysis towards property sales observations where the nearest site is one of the eight most active clusters of pits in Wellington County.

Obtaining a measure of activity was crucial: of the 58 geographical clusters in Wellington County, 6 of those clusters were considered to have no activity present. The most active cluster was over 2.7 million square metres and the least active (not including zero activity) was only 20 square metres.[19] There is large variation in aggregate activity in Wellington County. Below, I go into detail on how I collected the areas of these each of these sites, and further, their corresponding geographical clusters.

4.1.3.1 Average Aggregate Site Areas using GIS

The AAFC geospatial satellite imaging from the Annual Crop Inventory provides images

[19] I visited both of these sites to confirm this information.

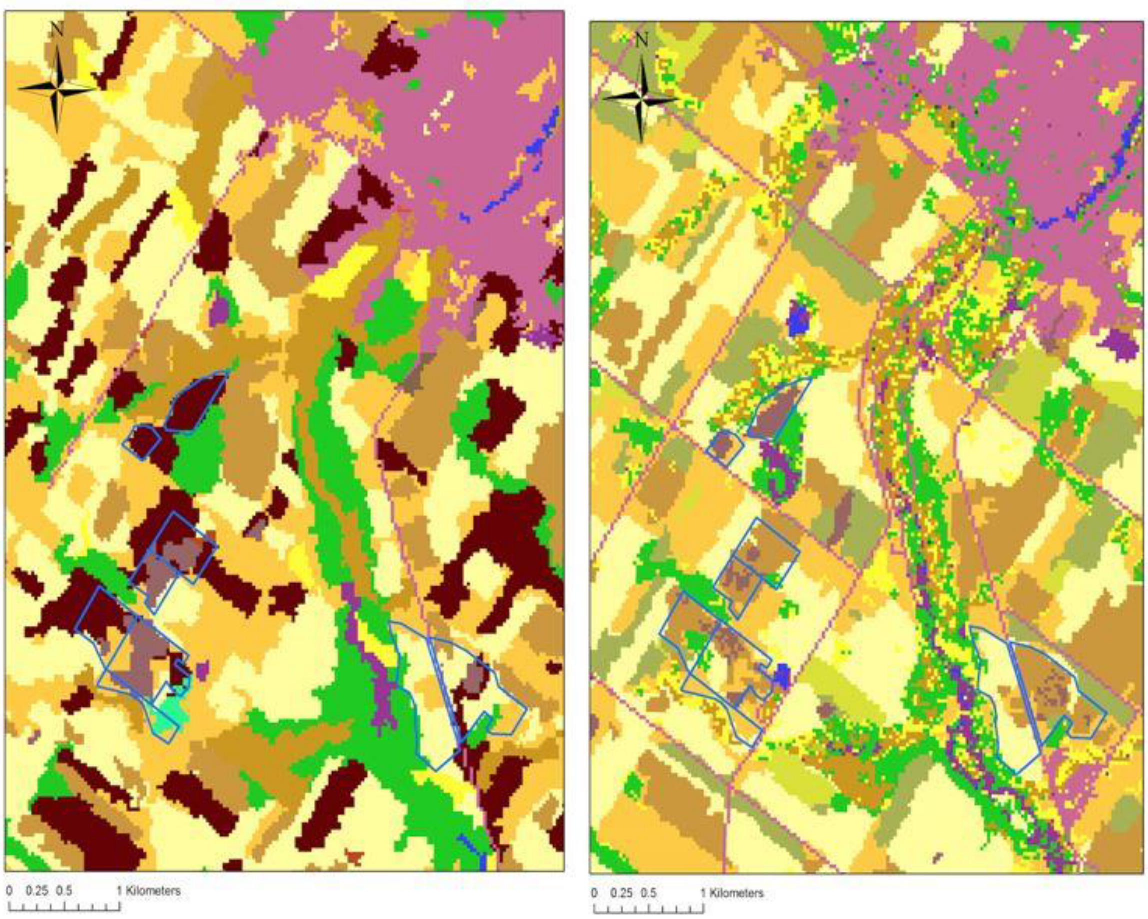
time-stamped in 2011, 2012, 2013, 2014, and 2015 (and will be provided yearly after) for all of Wellington County. This satellite map shows all the different types of crops in different colours, as well as urban areas, buildings, forests, and grasslands coverage. This is important when looking at aggregate sites to see the land's official use. Specifically, the land use under which pits and quarries are identified is "Exposed Land/Barren", and is a light brown colour. "Exposed Land/Barren" is the classification for land that is predominately non-vegetated and non-developed by structures. This includes: glacier, **rock, sediments**, burned areas, rubble, mines, and other naturally occurring non-vegetated surfaces. This land-use classification excludes fallow agriculture. Upon visual examination of the sites in Wellington County, I concluded that an aggregate site disturbed area is most likely listed under the classification of "Exposed Land/Barren". The other colours provide information regarding the crop, forest, or grassland around the site. This information is located in the legend provided in the "Data Product Specification of the AAFC Annual Crop Inventory" (AAFC, 2015).

Two geospatial imaging systems were used to measure activity. The use of two systems was necessary because together they cover the period of 2002-2013. (This is the period I examine in my empirical analysis of rural residential sales.) The AAFC Annual Crop Inventory provides data beginning in 2011, so a separate data collection system was needed for the time preceding this. The Agricultural Resource Inventory for Southern Ontario provides the same detail as the Annual Crop Inventory, but the satellite images are time-stamped at times between 2000 to 2002. Because the arms-length property sales MPAC dataset provides housing transactions from 2002-2013, the 2000-2002 Agricultural Resource Inventory provides images from approximately the beginning of the MPAC dataset, and the 2011, 2012, and 2013 Annual Crop Inventories provide the images from the end of the MPAC dataset and two years after. Therefore, if a pit or quarry is seen to be actively extracting aggregates in the 2011 images, but not in the 2000, it can be confirmed that the pit became active within that time period. If a pit shows activity in both images, it can be confirmed that it has been generally active within the entire period of the MPAC dataset. If a pit shows no activity but farming, forestry, or grassland in all images, then the pit is deemed inactive in extraction, and was therefore grouped in a category of pits with zero activity.

An overlay of the registered aggregate sites licensed area from the 2011 Ministry of Natural Resources and Forestry (MNRF) data was placed on top of the Annual Crop Inventory map. This overlay is seen using borders, which are in blue, shown in Figure 4.2 below. By placing the boundaries of the sites in our MNRF dataset over top of this map, the growth, shrinkage, or inertness of pits over time can be viewed, and can then be compared to the active licensed area. A measurement of the classified land area "Exposed Land/Barren" was calculated using the map's ruler[20] for each time period 2000-2002, 2011, 2012, and 2013. Once the land area was calculated, an average area calculation was executed over 2002-2013, which matches the property sales and characteristics dataset given by MPAC.

[20] The map's ruler is a GIS term, and is what calculates the distance between two given points. An area calculation can be given by connecting multiple points together.

Figure 4.2: Southwest of Elora, Wellington County, 2011 vs. 2015



Legend: Dark Grey: “Cereals”, Light Grey: “Exposed Land/Barren” or pit/quarry

It is important to note in the figure above that these sites within the blue boundaries had active licenses in 2011, which does not necessarily mean that the licensed area had any extraction activity occurring at the time. The licensed aggregate sites with no activity are listed as “0” for extraction activity area. For instance, if an aggregate site listed under the MNR data is considered “ACTIVE” in its licensing, the Annual Crop Inventory geospatial imaging provides the detail of what type of land use is occurring at the point of time that the imaging was created. For example, in Figure 4.2 above, the two top left “ACTIVE” pits in the MNR database are depicted as corn farms in the 2011 Annual Crop Inventory. The land use transforms from cereal crop production to barren land (gravel and sand). The best example of this is the top left grouping of two pits, which transformed from farms to extraction sites within a few years, and may provide information into the possible effect on property values in a specific time period. These pits, which are obviously not active in production (i.e. no sand or gravel is being extracted), can then be listed as "0" for average extraction area, or "activity," as it is listed in the analysis.

This method of visually confirming site activity was used after visiting a few aggregate sites that were listed as "ACTIVE" in the dataset (meaning the license was active) but where companies or government agencies had yet to develop the land, or extract from the site in any way.[21] For example, I traveled to one aggregate site that had an active license, but when I arrived (in May of 2016) I found that the entire parcel of land was under farming operations. In my analysis this parcel would be identified as having zero activity.

Table A1 in the Appendix shows the licensed area of each pit or quarry, and this can be compared to average pit size. The license sizes for individual sites (not clustered) ranged from approximately 14,000 square metres to almost 2 million square metres, whereas the average size of a site (not clustered) using this activity method ranged from 0 square metres to only 600,000 square metres. This confirms further that there are large range differences in pit activity area and license area, even though a correlation calculation shows aggregate site active area and licensed area to share a correlation coefficient of 0.71.

There are shortcomings of this method of identifying activity. One potential shortcoming is that the satellite images do not give information on other effects that may vary by activity. These include, noise level, truck traffic, the time of day that extraction occurs, etc. In addition, if

[21] I visited a number of sites to assess this method. Specifically, using this method, I identified 3 sites that were inactive. When I visited each of these sites, I was able to visually confirm that there was no aggregate activity on the site.

an aggregate company took a break from extraction for a few years but left rock piles on the land a site with little activity might be identified as having high activity.[22]

4.1.3.2 Clustering Geographical Areas to Depict Actual Extraction Activities

Many of the aggregate sites in Wellington County are in close proximity to each other. For this reason they are "clustered" according to geographic proximity. Prior to clustering, there were 107 individual aggregate sites in Wellington County. Following this procedure, this number is effectively reduced to 58. The range of numbers of individual aggregate sites that were combined to form clusters were 2-14 sites. There were many remaining individual sites that were not clustered or were not in close proximity to other sites. In the remainder of this section, I provide additional details on the 58 clusters of licensed sites. A visual example of a specific cluster is provided in Figure 4.3. These are pits located in Aberfoyle, which are owned by the same company, but have 14 different licenses.[23] Aggregate companies extract different areas at different times, and this is the broad reasoning for holding separate licenses in different areas and time periods.

[22] I visited 5 out of the 8 highest activity clusters to ensure that they were active.

[23] The triangles in Figure 4.3 depict the number of sites within that area. The claim that fourteen different licenses are present comes from adding the triangles together: 5 + 3 + 3 + 3 = 14.

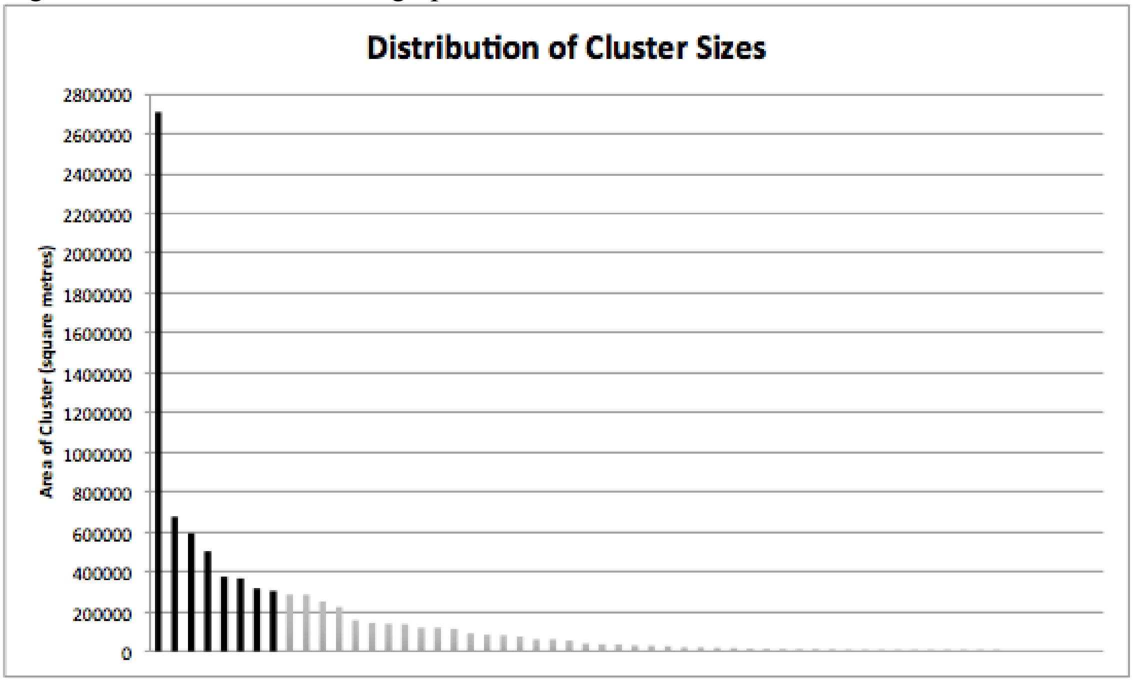
Figure 4.3: Most Active Cluster in Wellington County: Aberfoyle.

Table A2 in the Appendix shows the geographical clusters, noting their total areas, once all individual pits or quarries are added together, and the rank from large to small of all geographical clusters in Wellington County. The mean size of aggregate sites, by cluster, is approximately 151,000 square metres, but the median is approximately 33,000 square metres. The standard deviation is approximately 371,000. The minimum cluster size is 0 and the maximum is approximately 2.7 million square metres. Given this information, it is known that the distribution of average extraction area, or activity, is highly skewed or right-tailed.[24] Most aggregate clusters have smaller average areas, with the highly active clusters being large outliers.

[24] "Right-tailed," means that the right side of the distribution is longer than the left side. More observations (e.g. aggregate site active areas) are located to the left of the distribution (e.g. smaller active areas). Right-tailed distributions have a mean located to the left of the peak, whereas a normal distribution (equal tails) has a mean located in the centre of the peak.

This was confirmed by graphing the distribution of activity. This graph is provided in Figure 4.4 below. The top 8 most active clusters are shown in bold on the graph.

Figure 4.4: Distribution of Geographical Cluster Sizes



The top eight geographic clusters of pits and quarries were chosen for this study because the distribution of average extraction area is right-tailed. Only pits that were above 300,000 square meters were selected (high outliers), which presents a sample of the most highly active pits. The purpose of selecting only these highly active pits is to provide comparative analysis to the full sample. After providing results for the full sample, I test whether the highest extraction activity has an effect on property values when focusing the analysis to only these most active pits and quarries. The geographic clusters shown in bold in Table A2 in the Appendix are those 8 clusters with the highest extraction activity areas. It is also very important to note that the pit and quarry clusters were not distributed in close proximity to one another. Hence, a rural residential property would most likely not be affected by more than one geographical cluster.

The summary statistics for the subsample (properties for which the closest aggregate site is one of the top 8 most active pits or quarries) are listed in Table 4.4. The analysis of the top 10 and 12 most active clusters are also modeled in the sensitivity analysis section for comparison, and produce similar results. Focusing on the top 8 clusters removed many observations in the analysis, so top 10 and 12 cluster regressions were performed and produced very similar results. The top 10 and top 12 models use only observations in proximity to pits or quarries that are greater than 250,000 or 200,000 square metres, respectively. These are also points on the right tail of the distribution of activity graph, seen in Figure 4.4, meaning that these clusters also represented high activity aggregate sites. Eight clusters were selected for the main analysis in order to focus on a smaller number of the most highly active pits. They were also sites that were visited, so a confirmation of extraction activity in 2015 was given, to add another level of accuracy.

Previewing the results section, two models are used. One model uses the entire dataset (9,095 observations) and the second model incorporates extraction activity: using only those property sales where the nearest pit or quarry is in one of the top 8 clusters (796 observations). More detail on this restricted analysis is provided in the empirical model section. This is how the activity variable, or extraction activity, is incorporated into the analysis.

4.2 Empirical Model

4.2.1 Regression Analysis

Regression analysis is a statistical technique used to analyze data with a dependent variable and one or more independent variables (Greene, 2012). Equation (4.1) shows the format of a basic regression function. Y is the dependent variable and is a function of the independent variables. The independent variables are X_1 through X_k, where k can be any number of independent variables that are needed to explain the dependent variable. ε denotes the error term, or residual disturbance, and encompasses anything that the independent variables cannot explain about the dependent variable. This can also be explained as the combined effect of any omitted variables. There will always be an error term because no equation can include every single factor that describes it. Equation (4.2) shows the regression written in a different form, where the betas, β, are included. Beta is a coefficient that specifies the relationship between the variable X, and the dependent variable, Y. For instance, β_2 specifies the relationship between the variable X_2 and Y. This basic regression forms the basis for the hedonic property model to be used for this thesis.

$$Y = f(X_1, X_2, \ldots, X_k) + \varepsilon \tag{4.1}$$

$$Y = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \varepsilon \tag{4.2}$$

Using the hedonic property model, I can estimate marginal implicit prices. The hedonic model developed for the purpose of estimating the impact on property values of aggregate site proximity and activity is specified by Equation (4.3):

$$PRICE_i = \alpha + \beta_1 PROP + \beta_2 LOC + \beta_3 TIME + \beta_4 TOWN + \beta_5 BANDS + \varepsilon_i \tag{4.3}$$

Where:
PRICE = sale price for property i
PROP = vector of property structural attributes, including number of bathrooms, square footage of house, acreage of property, fireplace, pool, etc.
LOC = vector of distances to provincial highway 401, Toronto, and closest urban area
TIME = sale year dummy variables
TOWN = township dummy variables
BANDS = vector of distance bands: 0-0.5km, 0.5-1km, 1-1.5km, 1.5-2km, 2-2.5km, 2.5-3km
α = intercept term
β = estimating coefficients
ε = error term

The alpha ('α') term is the constant added to the regression to allow for flexibility. Essentially, there is value in the property existing, even in the absence of all of the explanatory variables (such as bedrooms, bathrooms, or any other value-adding attributes). The coefficients

β_1, β_2, etc. explain the relationship between, for example, the number of bathrooms and the sale price of the property. The 'number of bathrooms' variable is an example of a structural attribute. If the coefficient or beta in this example is positive, this means that property values increase when the number of bathrooms are increased. In this regard, the number of bathrooms would be a value-added attribute of the property. In contrast, if the coefficient or beta was negative, the independent variable would be considered a value-reducing attribute. For example, the age of the property is hypothesized to have a negative sign: the older a property, the smaller the property value. There are many more independent variables than this simple example, as my model seeks to control for as many factors that affect a property's value as possible. The specifics of all variables used in the empirical model, and the attribute groupings seen in Equation (4.3) are all discussed above in the data section, and further in the table of summary statistics below.

I estimate two models in my primary analysis, which include (1) Model using distance bands, and (2) Focused model on a subsample of sales in close proximity to the 8 most active aggregate sites. More detail on the specifics of these models are outlined in Chapter 5.

A logarithmic functional form is used for these models,[25] which is consistent with hedonic models in the literature (e.g. Vyn and McCullough 2014; Deaton and Vyn 2010; Irwin 2002). This is a flexible functional form that has performed well in the literature, particularly for models where spatial fixed effects are used to control for omitted variable bias (Kuminoff, Parmeter, and Pope 2010). Multiple functional forms were tested (i.e. log, semi-log, no logs) and from these tests it was concluded that sign, magnitude, and significance of the coefficients were very similar across forms, noting that results are not sensitive to functional form. From this, a

[25] Not all explanatory variables are logarithmically transformed, including the distance variables in question. Decisions about which variables to leave in their original form follow the general rules of thumb outlined in Woolridge (2006). The variables that have been transformed with ln() are noted in Table 5.1 of Chapter 5.

logarithmic transformation was selected to most easily report the results.

All of the models listed above are also median or quantile regressions. While the method of least squares produces results that estimate the conditional mean of the dependent variable given certain values of the explanatory variables, quantile regression produces results that estimate the conditional median, or other quantiles of the dependent variable. The reason for using the median regression is the high amount of skewness and kurtosis in the data. Kurtosis measures the heaviness of the tails in the distribution, and a value greater than 3 (which is a normal distribution), depict data that possesses heavy tailed distributions. The sales data for this study has a kurtosis value of 16.49, which is extremely high. Mean regressions are more affected by outliers, which is why a median regression approach was chosen. A mean regression using a robust command was also performed, and is detailed in the sensitivity analysis section. In conclusion, the primary qualitative results are unchanged across different functional forms or estimation approaches.

4.3 Summary of Descriptive Statistics

Table 4.2 and Table 4.3 describe the summary statistics; 4.2 includes the entire dataset and 4.3 focuses in on the observations included in the model for the top 8 most active clusters of aggregate sites.

Table 4.2 lists the dependent variable and each independent variable used in the regression analysis. The mean, standard deviation (SD), minimum value, and maximum value are also listed. The average value of rural residential properties sold in Wellington County between the years 2002-2013 was approximately $281, 000. Summary statistics for property and location variables, sale year dummy variables (with 2002 omitted)[26], township fixed effects (with Minto Township omitted), and distance bands (with everything above 3km omitted) are depicted in Table 4.2. It can be noted that the furthest property sale away from an aggregate site was approximately 11 km. The analysis of these variables will be discussed in Chapter 5.

Table 4.2: Summary Statistics of Variables included in the Hedonic Model (Full Sample n=9,095)

		Description	**MEAN**	**MEDIAN**	**SD**	**MIN**	**MAX**
Dependent Variable							
	Sale Price	Sale price of property ($)	$281,045.40	$243,000.00	$159,367.70	$203.00	$2,900,000.00
Property and Location Variables							
	Total Area	Total floor area of house (square feet)	1621.0840	1433.50	656.6263	192.0000	5981.0000
	Lot Size	Size of property (acres)	1.6119	0.2523	5.4298	0.0000	116.1600
	Distance to Hwy 401	Distance to Hwy 401 (km)	26.3548	24.2430	13.2150	0.0000	61192.0000
	Distance to Toronto	Distance to Toronto (km)	60.7580	61.9681	22.3237	15.7987	112.0212
	Distance to Urban	Distance to nearest city or town (km)	25.7753	17.6751	18.6218	0.0000	76.6584
	Bathrooms	Number of bathrooms	1.7464	1.5	0.7615	0	10.5
	Fireplaces	Number of fireplaces	0.5172	0	0.6564	0	4
	Pool	*=1 if pool exists on property	0.0631	0	0.2432	0	1
	Age	Length of time from when structure was built (years)	40.6841	28	39.1629	0	188
	Quality	House quailty index (0-10)	6.1309	6	0.5249	1	9
	Basement	*=1 if there exists a furnished basement	0.3957	0	0.4890	0	1
	Air	*=1 if house is air conditioned	0.3265	0	0.4689	0	1
Time Variables							
	SY2003	*= 1 if property sold in the year 2003	0.1175	0	0.3221	0	1
	SY2004	*= 1 if property sold in the year 2004	0.1218	0	0.3271	0	1
	SY2005	*= 1 if property sold in the year 2005	0.1160	0	0.3203	0	1
	SY2006	*= 1 if property sold in the year 2006	0.1109	0	0.3140	0	1
	SY2007	*= 1 if property sold in the year 2007	0.1210	0	0.3262	0	1
	SY2008	*= 1 if property sold in the year 2008	0.0955	0	0.2939	0	1
	SY2009	*= 1 if property sold in the year 2009	0.0808	0	0.2848	0	1
	SY2010	*= 1 if property sold in the year 2010	0.0412	0	0.1987	0	1
	SY2011	*= 1 if property sold in the year 2011	0.0312	0	0.1740	0	1
	SY2012	*= 1 if property sold in the year 2012	0.0308	0	0.1728	0	1
	SY2013	*= 1 if property sold in the year 2013	0.0129	0	0.1128	0	1
Township Variables							
	Erin	*= 1 if property is in the township of Erin	0.1482	0	0.3553	0	1
	Wellington North	*= 1 if property is in the township of Wellington North	0.1191	0	0.3239	0	1
	Mapleton	*= 1 if property is in the township of Mapleton	0.0459	0	0.2095	0	1
	Puslinch	*= 1 if property is in the township of Puslinch	0.0765	0	0.2658	0	1

[26] In order to account for differences in sale years, a sale year dummy variable was created. This attempts to account for any changes that occur over time, such as inflation. As an extra robustness check, a regression was run with month categories, to account for both changes in sale month and year over the entire time period of 2002-2013. The results yielded similar findings to the main findings in this thesis.

	Guelph-Eramosa	*= 1 if property is in the township of Eramosa	0.1258	0	0.3315	0	1
	Wellington Centre	*= 1 if property is in the township of Wellington Centre	0.3796	0	0.4853	0	1
Aggregate Distance Bands							
	0-0.5km	*= 1 if property is within 0-0.5km of an aggregate site	0.0464	0	0.2104	0	1
	0.5-1km	*= 1 if property is within 0.5-1km of an aggregate site	0.0538	0	0.2257	0	1
	1-1.5km	*= 1 if property is within 1-1.5km of an aggregate site	0.0798	0	0.2710	0	1
	1.5-2km	*= 1 if property is within 1.5-2km of an aggregate site	0.0982	0	0.2976	0	1
	2-2.5km	*= 1 if property is within 2-2.5km of an aggregate site	0.0997	0	0.2996	0	1
	2.5-3km	*= 1 if property is within 2.5-3km of an aggregate site	0.0926	0	0.2899	0	1

Note: Omitted dummy variables in the time, township, and distance band categories are 2002, Town of Minto, and 3+ km, respectively.

The accuracy of the estimated effects within each band, as well as the likelihood of detecting significant impacts, is affected by the number of observations. In order to demonstrate that there are sufficient observations within each band, I provide the number of observations within each distance band in Table 4.3. This is compared with the number of observations within each distance band in the subsample, which will be explained following the table.

Table 4.3: Observations within each distance band in the Full Sample and Subsample

Distance Band	Number of Observations	Distance Band	Number of Observations
0-0.5 km	426	0-0.5 km	90
0.5-1 km	494	0.5-1 km	119
1-1.5 km	732	1-1.5 km	182
1.5-2 km	901	1.5-2 km	118
2-2.5 km	915	2-2.5 km	132
2.5-3 km	850	2.5-3 km	101
3+ km	4777	3+ km	54
Whole sample (n = 9,095)		(Subsample n = 796)	

Eight geographic clusters of pits and quarries were chosen for model 2 (the subsample) because the distribution of average extraction area was right-tailed.[27] Only pits that were above 300,000 square meters were chosen, which presents a sample of the most highly active pits. This

[27] "Right-tailed," means that the right side of the distribution is longer than the left side. More observations (e.g. aggregate site active areas) are located to the left of the distribution (e.g. smaller active areas). Right-tailed distributions have a mean located to the left of the peak, whereas a normal distribution (equal tails) has a mean located in the centre of the peak.

is explained in further detail in the data section above. It is also important to note again that – other than the geographical clusters – the pits and quarries were not distributed in close proximity to one another. Hence, a rural residential property is not expected to be affected by more than 1 geographical cluster. The summary statistics for properties for which the closest aggregate site is one of the 8 most active pits are listed in Table 4.4. The analysis of this top 8 cluster will be explored in Chapter 5.

Table 4.4: Summary Statistics of Variables included in the Hedonic Model (Top 8 Cluster n=796)

	Description	MEAN	MEDIAN	SD	MIN	MAX
Dependent Variable						
Sale Price	Sale price of property ($)	$221,191.80	$204,000	$90,208.15	$85,000.00	$625,000.00
Property and Location Variables						
Total Area	Total floor area of house (square feet)	1962.9280	1732.00	875.7119	550.0000	5414.0000
Lot Size	Size of property (acres)	2.1545	0.75	6.6027	0.0000	85.7200
Distance to Hwy 401	Distance to Hwy 401 (km)	13.9001	8.318	15.2054	0.0000	53.9270
Distance to Toronto	Distance to Toronto (km)	41.0162	33.5495	21.1633	21.4167	98.5007
Distance to Urban	Distance to nearest city or town (km)	19.0981	11.4183	17.3126	0.0000	67.1073
Bathrooms	Number of bathrooms	2.0169	2	0.9226	1	7.0
Fireplaces	Number of fireplaces	0.7553	1	0.7263	0	4
Pool	*=1 if pool exists on property	0.1223	0	0.3279	0	1
Age	Length of time from when structure was built (years)	37.1136	27	36.6983	0	161
Quality	House quailty index (0-10)	6.4101	6	0.7181	4	9
Basement	*=1 if there exists a furnished basement	0.4250	0	0.4947	0	1
Air	*=1 if house is air conditioned	0.4869	0	0.5001	0	1
Time Variables						
SY2003	*= 1 if property sold in the year 2003	0.1136	0	0.3175	0	1
SY2004	*= 1 if property sold in the year 2004	0.1311	0	0.3377	0	1
SY2005	*= 1 if property sold in the year 2005	0.0911	0	0.2880	0	1
SY2006	*= 1 if property sold in the year 2006	0.0999	0	0.3000	0	1
SY2007	*= 1 if property sold in the year 2007	0.1236	0	0.3293	0	1
SY2008	*= 1 if property sold in the year 2008	0.0774	0	0.2674	0	1
SY2009	*= 1 if property sold in the year 2009	0.0674	0	0.2509	0	1
SY2010	*= 1 if property sold in the year 2010	0.0537	0	0.2255	0	1
SY2011	*= 1 if property sold in the year 2011	0.0637	0	0.2443	0	1
SY2012	*= 1 if property sold in the year 2012	0.0487	0	0.2154	0	1
SY2013	*= 1 if property sold in the year 2013	0.0237	0	0.1523	0	1
Township Variables						
Erin	*= 1 if property is in the township of Erin	0.3271	0	0.4695	0	1
Wellington North	*= 1 if property is in the township of Wellington North	0.0855	0	0.2798	0	1
Mapleton	*= 1 if property is in the township of Mapleton	0.0025	0	0.0498	0	1
Puslinch	*= 1 if property is in the township of Puslinch	0.4771	0	0.4998	0	1
Guelph-Eramosa	*= 1 if property is in the township of Eramosa	0.0372	0	0.1893	0	1
Wellington Centre	*= 1 if property is in the township of Wellington Centre	0.0446	0	0.2066	0	1
Aggregate Distance Bands						

	0-0.5km	*= 1 if property is within 0-0.5km of an aggregate site	0.1115	0	0.3150	0	1
	0.5-1km	*= 1 if property is within 0.5-1km of an aggregate site	0.1475	0	0.3548	0	1
	1-1.5km	*= 1 if property is within 1-1.5km of an aggregate site	0.2255	0	0.4182	0	1
	1.5-2km	*= 1 if property is within 1.5-2km of an aggregate site	0.1462	0	0.3535	0	1
	2-2.5km	*= 1 if property is within 2-2.5km of an aggregate site	0.1636	0	0.3701	0	1
	2.5-3km	*= 1 if property is within 2.5-3km of an aggregate site	0.1252	0	0.3311	0	1

Note: Omitted dummy variables in the time, township, and distance band categories are 2002, Town of Minto, and 3+ km, respectively.

Again, the number of observations within each distance band are important to the accuracy of the results. A full description of the number of observations within each band in the top 8 cluster are located in Table 4.3.

The observations within each band decrease by approximately 300-800 observations from the full sample to the subsample. Each band in the subsample has at least 90 observations within it, and each band has between 90-190 observations. The bands are consistent in that no band has a considerably large amount of observations comparatively to another band.

The full sample and subsample are referred to as Model 1 and Model 2, respectively, in the next chapter. The differences in these two model specifications are discussed and subsequently, the implications of the differences in these two models' results are discussed in Chapter 6.

CHAPTER 5: RESULTS

This chapter presents the results of the two hedonic property models discussed in Chapter 4. The chapter will be broken down into four sections: one section for each model, a section on sensitivity analysis and robustness checks, and a final section for misspecification discussion.

Two separate hedonic models are analyzed for rural residential properties: (1) Model using distance bands, and (2) The same model limited to properties located closest to one of the 8 most active pit or quarry clusters.

5.1 Model 1 & 2 Results and Interpretation

The regression results shown in Table 5.1 identify the coefficients on each variable, and their corresponding significance. Robust standard errors are also reported. Two additional statistical measures are reported, which are the adjusted R^2 and the sample size. The adjusted R^2 for the first regression is 0.6260, which means that approximately 63% of the total variation in the property sales dataset is accounted for in this specific model. Greene (2012) notes that R^2 measures the total proportion of the total variation in the dependent variable that is accounted for or explained by variation in the independent variables. Adjusted R^2 is used instead of regular R^2 because it is more precise - when more variables are added, the value decreases. The sample size is also reported to depict the change in sample size across models.

Table 5.1. Estimated Coefficients for the hedonic models

	Model 1: Base		Model 2: Activity	
	Coefficient	Robust Std Err	Coefficient	Robust Std Err
Variable				
Property and Location Variables				
ln(Total Area)	0.3112***	0.0087	0.3009***	0.0273
ln(Lot Size)	0.1195***	0.0018	0.0999***	0.0059
ln(Distance to Hwy 401)	-0.0210**	0.0067	0.0340***	0.0045
ln(Distance to Toronto)	-0.1073***	0.0137	-0.0051	0.0742
ln(Distance to Urban)	-0.0300***	0.0042	-0.0200	0.0169
Bathrooms	0.0322***	0.0037	0.0325**	0.0102
Fireplaces	0.0262***	0.0030	0.0204*	0.0088
Pool	0.0468***	0.0083	0.0317	0.0173
Age	-0.0014***	0.0001	-0.0009***	0.0002
Quality	0.1446***	0.0055	0.1963***	0.0157
Basement	0.0463***	0.0037	0.0610***	0.0126
Air	0.0314***	0.0038	0.0168	0.0115
Time Variables				
SY2003	0.0593***	0.0076	0.0865***	0.0194
SY2004	0.1520***	0.0075	0.1364***	0.0259
SY2005	0.2348***	0.0083	0.2085***	0.0326
SY2006	0.2918***	0.0070	0.3100***	0.0223
SY2007	0.3544***	0.0071	0.3462***	0.0250
SY2008	0.3894***	0.0071	0.3802***	0.0243
SY2009	0.3738***	0.0079	0.3823***	0.0212
SY2010	0.4653***	0.0099	0.4613***	0.0365
SY2011	0.4880***	0.0152	0.4875***	0.0346
SY2012	0.5122***	0.0148	0.4913***	0.0684
SY2013	0.5719***	0.0172	0.5375***	0.0329
Township Variables				
Erin	0.3371***	0.0193	0.3848**	0.1398
Wellington North	0.0825***	0.0097	-0.0705	0.1047
Mapleton	0.2222***	0.0129	0.3270*	0.1612
Puslinch	0.3005***	0.0275	0.4307***	0.1306
Guelph-Eramosa	0.3174***	0.0182	0.3082*	0.1285
Wellington Centre	0.3176***	0.0118	0.2066	0.1067
Aggregate Distance Bands				
0-0.5km	0.0320***	0.0082	0.0210	0.0255
0.5-1km	0.0470***	0.0072	0.0111	0.0251
1-1.5km	0.0484***	0.0074	-0.0081	0.0247
1.5-2km	0.0424***	0.0073	0.0218	0.0281
2-2.5km	0.0411***	0.0078	0.0333	0.0272
2.5-3km	0.0486***	0.0068	-0.0053	0.0264
Constant	9.5345***	0.1060	8.3625***	0.4332
R-squared	0.6260		0.6894	
Number of Sales	9,095		796	

Notes: Asterisks (***, **, *) indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Omitted dummy variables in the time, township, and distance band categories are 2002, Town of Minto, and 3+ km, respectively.

All models listed were run with robust[28] commands, creating a regression that provides standard errors adjusted for heteroscedasticity.[29] A robust regression adjusts the value of the standard errors to take into account issues concerning heterogeneity and lack of normality, and was used in this case to account for these issues. This particular robust command used specifies how to estimate the variance-covariance matrix corresponding to the parameter estimates and reported standard errors are the square roots of the variances (diagonal elements).

The disamenity effects of pits and quarries is hypothesized to be increasing with both proximity to the site and activity of the site. Therefore, the coefficient for the distance variables representing aggregate site impacts is expected to be negative. The band closest to the aggregate site (0-0.5 km) was predicted to have the highest negative effect, and that negative effect was expected to diminish as the distance bands went further out. This negative effect was expected to be greater across all bands for the more active pits (top 8 most active geographical clusters).

Based on the results, this hypothesis was rejected; significant negative price effects on properties in close proximity to aggregate sites in Wellington County are not found. Further, within close proximity (half a kilometer) to these sites, significant positive price effects are found. In the first band (0-0.5 km), the effect is +3.2% in property value. These effects across all bands are approximately an increase in 3-4% of the property's value, as shown in Table 5.1. When focusing the model on only the top 8 most active pits in the county, the coefficients either lose strength in the positive effect or flip signs to become negative; however, these results are not statistically significant. This direction of the change in the coefficients is consistent with theory: if it is expected that pits and quarries have an effect on property values, then when site activity is

[28] The command in Stata is vce(robust).
[29] Heteroskedasticity occurs when the variability of a variable is unequal across the range of values of a second variable that predicts it (i.e. there could be sub-populations that have different variabilities from others).

considered, the change in the coefficients moves in a direction that removes the positive effect.

The results for the property, location, time, and township variables are consistent across all models. The variables that positively impacted price were total area of the structure(s), lot size of the property, number of bedrooms, fireplaces, pools, higher quality index of the house, finished basement, and air conditioning. The variables that negatively impacted price were distance to highway 401, distance to Toronto, distance to urban area, and age of the house. The exception of consistent results across models is two distance variables becoming insignificant once the model is restricted to the top 8 most active sites: distance to Toronto and distance to nearest urban area. These two variables were tested for correlation – which yielded approximately 0.76 – which could influence their results. If independent variable coefficients are highly correlated, one variable could be explaining variation encompassed in another, and vice versa.

An examination of variance inflation factors (VIF) was run to test the possible issue of multicollinearity. Most variables did not indicate a VIF value greater than 10, which is the turning point where there is cause for concern (Gujarati 1995). The variables that possessed a VIF value greater than 10 were three township variables and distance to Toronto. The three township variables were used as fixed effects to control for properties located in different townships. These townships are Erin, Puslinch, and Guelph-Eramosa.

The results of the other township fixed effects variables indicate some variation in prices across these townships for rural residential properties, which may account for any influence of spatially varying omitted variables. The time variables are consistent with what was expected: an increase in price for each sale year.

This analysis highlights the importance of including site activity when assessing the effect of aggregate sites on property values. The first model can be termed “naïve,” because there is an omitted variable – the measure of aggregate site activity. The actual disturbed land area is quite different from the licensed aggregate area provided in the MNR data set. Out of 58 geographic clusters of aggregate sites in Wellington County, 6 of those clusters were considered to have no activity present from 2002-2013. The most active cluster was almost 3 million square metres and the least active (not including zero activity) was only 3,800 square metres. There is very large variation in aggregate activity in Wellington County, and that is why it is so important to include this when attempting to model the effect on property values.

To address some of the model limitations and their potential influence on the sensitivity of the results, a number of alternate model specifications were examined, including: tests for robustness and heteroskedasticity, differing sizes of high activity geographic clusters, constraining the regression to a 3km radius, and 1km distance bands (as opposed to 0.5km). Each of these alternate specifications is discussed below, following a discussion of the results of the 2 main models.[30] The results for the sensitivity analysis are shown in the next section.[31]

5.2 Sensitivity Analysis

Attempting to address a number of issues and limitations in the data set and the empirical approach, several alternate model specifications were used for sensitivity analysis. The results of each specification are compared to those of models 1 and 2 in Table 5.2.[32] The alternate model

[30] Sensitivity analysis shown here is only focused on model 1, as alternate specifications of the other models yielded very similar results.
[31] Sensitivity beyond what is shown in section 5.2 was performed. Some other model specifications performed were distance bands up to 11km (max), constraints at 1km, 2km, and 5km, as well as an interaction variable between activity and distance. These models are not shown for simplicity purposes, as all mentioned provided consistent results with the main models.
[32] Only the results of the distance variables are shown in these tables, as the results for all other variables are consistent with those from the original models.

specifications were specifically chosen to test the robustness of the results, and are listed below:

(1) a. Functional Form: Quadratic,
    b. Functional Form: Quadratic with Activity,
(2) a. Functional Form: Inverse Continuous Distance,
    b. Functional Form: Inverse Continuous Distance with Activity,
(3) Mean Robust Regression,
(4) a. Top 10 Geographical Clusters,
    b. Top 12 Geographical Clusters,
    c. Aberfoyle Cluster,
(5) 1km Discrete Distance Bands,
(6) Constraining the regression at 3km, and
(7) Narrowing the regression to only active pits (removing zero activity).

These are all discussed in detail following Table 5.2.

Table 5.2. Comparison of the coefficients for the distance variables across alternate model specifications (standard errors in parentheses)

Distance Variable	Primary Model 1 (No Activity)	Primary Model 2 (Activity)	(1a) Functional Form: Quadratic	(1b) Quadratic with Activity	(2a) Functional Form: Inverse	(2b) Inverse Distance with Activity	(3) Mean Robust	(4a) Top 10 Cluster	(4b) Top 12 Cluster	(4c) Aberfoyle Cluster	(5) 1km Bands (larger band width)	(6a) 3km Constraint	(6b) 3km Constraint with Activity	(7) Only Active Pits
0-0.5km Band	0.0320***	0.0210					0.0835***	0.0269	0.0147	0.0563	0.0378***	-0.0263**	0.0213	0.0265*
	(0.0082)	(0.0255)					(0.0196)	(0.0227)	(0.0203)	(0.0464)		(0.0101)	(0.0194)	(0.0109)
0.5-1km Band	0.0470***	0.0111					0.01073***	0.0043	-0.0141	-0.0666	(0.0068)	-0.0178	0.0144	0.0322***
	(0.0072)	(0.0251)					(0.0175)	(0.0192)	(0.0171)	(0.0443)		(0.0102)	(0.0205)	(0.0092)
1-1.5km Band	0.0484***	-0.0081					0.0654***	0.0106	-0.0185	0.0132	0.0457***	-0.0127	0.0023	0.0464***
	(0.0074)	(0.0247)					(0.0140)	(0.0200)	(0.0184)	(0.0388)		(0.0090)	(0.0186)	(0.0086)
1.5-2km Band	0.0424***	0.0218					0.0657***	0.0263	-0.0145	-0.0099	(0.0060)	-0.0250**	0.0261	0.0430***
	(0.0073)	(0.0281)					(0.0127)	(0.0199)	(0.0190)	(0.0426)		(0.0088)	(0.0202)	(0.0088)
2-2.5km Band	0.0411***	0.0333					0.0590***	0.0364	-0.0009	0.0109	0.0453***	-0.0120	0.0421*	0.0437***
	(0.0078)	(0.0272)					(0.0129)	(0.0202)	(0.0204)	(0.0419)		(0.0092)	(0.0203)	(0.0088)
2.5-3km Band	0.0486***	-0.0053					0.0561***	0.0305	0.0303	0.0031	(0.0058)			0.0495***
	(0.0068)	(0.0264)					(0.0134)	(0.0202)	(0.0168)	(0.0422)				(0.0066)
Distance			-0.0172***	0.0154										
			(0.0036)	(0.0191)										
Distance^2			0.0009	-0.0049										
			(0.0004)	(0.0052)										
Inverse Distance					0.0020*	0.0052								
					(0.0010)	(0.0040)								
R-squared	0.6260	0.6858	0.6258	0.6888	0.624	0.6887	0.6297	0.6648	0.5626	0.6318	0.6260	0.6558	0.6952	0.6246
n	9,095	796	9,095	796	9,095	796	9,095	1,161	1,460	403	9,095	4,287	737	6,998

Note: Asterisks (***, **, *) indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2.1 Functional Form: Quadratic and Quadratic with Activity

Using a quadratic regression (with one variable measuring the continuous distance away from a pit and another squaring this distance) produces similar results to the distance bands approach. This functional form was used for sensitivity in order to see if functional form changed from the main results. A 1.72% decrease in property value is found when moving each kilometer further away from a pit, which is consistent with the main models. When focusing the model on only the top 8 most active pits in the county, no statistically significant results of any price effect are found.

5.2.2 Functional Form: Inverse Continuous Distance with and without Activity

Like the quadratic functional form, this functional form was used for sensitivity in order to see if using an inverse distance variable changed the results. Using a regression with an inverse distance variable (distance to the pit) produced similar results to the distance bands approach. A 0.2% increase in property value when moving one unit (a kilometer) closer to a pit was found, which is consistent with the main models. The result indicates that property values increase slightly with proximity to the nearest pit. When focusing the model on only the top 8 most active pits in the county, the coefficients lose strength in the positive effect; but these results are not statistically significant. This direction of the change in coefficients is consistent with theory: if it is expected that pits and quarries have an effect, then when activity is considered the coefficient moves in a direction that removes that positive effect.

5.2.3 Mean Robust Regression

As mentioned in the last chapter, the method of least squares produces results that estimate the conditional mean of the dependent variable given certain values of the explanatory variables. The median or quantile was used in the main models above, which produced results that estimated the conditional median (rather than the mean). This alternate model specification was used to compare to the main models. The results were similar to the median regressions, but provided more positive property value effects (between a 5-10% increase in value).

5.2.4 Top 10 and 12 Geographical Clusters and Aberfoyle Cluster (Most Active Site)

Realizing that focusing on the top 8 clusters removed many observations in the analysis, top 10 and 12 cluster regressions were performed and produced very similar results. Both clusters yielded no statistically significant results in all bands. The top 10 and top 12 models use only observations in proximity to pits or quarries that are greater than 250,000 or 200,000 square metres, respectively. These are also points on the right tail of the distribution of activity graph, seen in Figure 4.4, meaning that these clusters also represented high activity aggregate sites. The Aberfoyle cluster was also modeled in order to focus on one large cluster; this is the most active aggregate site in Wellington County.[33] No statistically significant impacts were found in all distance bands, which is consistent with the result that, once accounting for activity, aggregate sites have no statistically significant effects on property values.

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[33] Since the Aberfoyle cluster has high property values in close proximity, as well as a rehabilitation plan underway, it is hypothesized that possibly Aberfoyle could be providing an amenity value in some areas, rather than a disamenity. A regression was also run with all observations with the omission of properties nearby Aberfoyle. The result was similar to the main findings; a slight positive increase in property values in proximity to aggregate sites.

5.2.5 1km Discrete Distance Bands

As an alternative to the discrete distance bands of a half-kilometre width, distance bands using a one kilometre width were also used, up to 3 kilometres. The bands were 0-1, 1-2, and 2-3 km for the nearest aggregate site. Assuming that aggregate sites have a negative effect on property value, and this effect diminishes further away from the site, the distance bands were expected to be negative, with declining magnitudes with distance from the nearest aggregate site. However, as with the half-kilometre distance band width model, the price effects are actually positive – with approximately a 3-4% increase in property values in each band.

5.2.6 Constraining the regression at 3 kilometres

A regression constrained at 3km is used to test my hypothesis that no effects should be present after 3km, from personal experience.[34] The only occurrence of statistically significant negative price effects are found when constraining the model to a 3km radius away from the aggregate sites. This is only found when modeling the entire dataset, and not restricting the model to just those 8 highly active pits. Within the 0-0.5 km band and the 1.5-2 km band, an approximate 2.5% decrease in property values is found. This negative price effect is relative to prices in the 2.5-3 km band, which is the omitted band. All other distance bands also have a negative sign, but lack statistical significance.

5.2.7 Narrowing regression to only active pits (removing zero acitvity)

This regression was conducted to test the hypothesis that possibly only active pits and quarries may have an effect on property values. The results from this model are consistent with

[34] My personal experience is that I could no longer hear or see a pit or quarry from 3 kilometres away.

the narrative presented by the data in the original model: slight positive effects, but these effects are smaller (approximately 2-3%) once removing those observations in proximity to the 6 geographic clusters that had no activity on site.

5.3 Misspecification Analysis/Robustness Checks

5.3.1 Heteroskedasticity - Bootstrapping

A bootstrapped standard errors regression was also performed to further account for heteroskedasticity[35] in the models. Bootstrapping is essentially random sampling with replacement. Taking many random samples may account for the sub-populations that have different variabilities from others. Bootstrapping the standard errors assigns a measure of accuracy to the original estimates.

The estimated results are robust to some types of misspecification and to heteroskedasticity of the errors. This may account for issues concerning heterogeneity and lack of normality. The result of the bootstrapped standard errors regression were consistent with the main model results.

[35] Heteroskedasticity occurs when the variability of a variable is unequal across the range of values of a second variable that predicts it (i.e. there could be sub-populations that have different variabilities from others).

CHAPTER 6: DISCUSSION

This chapter summarizes the findings of chapter 5 and discusses the implications of those findings. Any potential errors, omissions, or limitations of the study are addressed here. The section includes a short discussion on the possibilities for future research stemming from this study.

6.1 Major Findings

In response to concerns raised by various organizations regarding the potential effects of aggregate sites on neighbouring property values, and to a lack of peer-reviewed literature on this issue, this thesis estimates the impacts of pits and quarries on rural residential property values in Wellington County.

While aggregate is a valued resource, the extraction of aggregate is often identified as a negative externality. Similar to other resource extraction issues – such as shale gas exploration sites studied in Gopalakrishnan and Klaiber (2013) and gravel pits assessed in Zhang and Hite (2016) – nearby residents identify a host of events associated with aggregate extraction that can be categorized as negative externalities. Residential concerns include noise and visual disamenities, as well as environmental concerns, mainly around water quality. The conflict of interests between aggregate extraction and residential interests often results in disagreement. As a result, there has been media attention and lobby groups forming around some aggregate sites in Wellington County.

Currently, there is only anecdotal and appraisal information about changes in property values near aggregate sites in Ontario (Lansink 2014). Despite the anecdotal nature, this study features heavily into specific individual examples of property sales near pits where the property values have changed. The Lansink (2014) study assesses several stand-alone sales nearby different pits, rather than average pit impacts over large areas. Unfortunately, there is very little literature outside Ontario examining this issue.

This thesis adds to the literature on the effects of aggregate sites by utilizing a hedonic approach, which has not been used for all types of aggregate sites (pits and quarries). I am aware of only four studies that estimate the impact of gravel pits: Hite (2006), Erickcek (2006), Zhang and Hite (2016), and Lansink (2014). The novelty of my study is threefold: (1) Distance to major urban areas, Toronto, and a major highway are controlled for in the model, (2) county-level analysis, as well as individual aggregate site analysis is performed, and most importantly, (3) a measure of aggregate extraction activity is included in my analysis.

The main narrative that these results address is the importance of including an aggregate site's activity when analyzing their impacts. The Ministry of Natural Resources and Forestry main database for licensed aggregate sites include all pits and quarries that are under an active license, however an active license does not necessarily mean that a pit is active in extraction activities. This analysis presents a "naive" model (where no pit identifiers or activity is included in the model), which is then compared with a model that includes a measure of activity. Once activity is accounted for, and once the model focuses on only those pits that are under high extraction activities, the results provide no evidence of aggregate site impacts on rural residential property values. This result of no property value impacts is further confirmed when constraining the model to the most active geographical cluster in Wellington County: Aberfoyle.

Two hypotheses were mentioned in Chapter 1, and further in Chapter 3. My first hypothesis is that rural residential properties may experience a decline in value within close proximity to aggregate sites and that this effect may diminish over time. My second hypothesis states that the effect of proximity to an aggregate site may depend on its level of activity. If a site had higher extraction activity, I would expect the slope of the willingness to pay curve in Figure 3.1 to be steeper, and the effect to diminish with greater distance away from a site (the larger the extraction activity, the greater the effect on property values). These hypotheses were tested, and were effectively rejected, as small positive effects (instead of negative) were seen in the full sample, and no statistically significant effects were found in the subsample of high activity clusters. There is no evidence in this analysis to support the claim that properties within Wellington County experience a decline in close proximity to aggregate sites.

The results in Chapter 5, which included the primary models and sensitivity analysis, were conclusive. The primary models indicated no statistically significant impacts within 3 kilometres away from aggregate sites once aggregate activity was accounted for. The sensitivity analysis was consistent with these results.

6.3 Implications

In the first chapter, I stated that the results of this study attempt to inform municipal governments, community groups, MPAC, the OMB, and rural residential property owners. This research can benefit each of these stakeholder groups. The municipal governments and OMB may utilize this information to inform the decision-making process of approval of aggregate development projects in specific locations. Rural residential property owners may be interested in the valuation of surrounding properties in their township that are neighbouring these sites. Further, MPAC already assumes that property owners experience a disamentity abutting or in proximity to pits. This study could provide insight into the property appraisal process for properties nearby aggregate sites. This is outlined in further detail below.

The community group that opposes the Hidden Quarry, the Concerned Residents Coalition (CRC), in Rockwood, Ontario, lists “decline in property values,” as a major concern on their website. The research conducted in this thesis is particularly concerned with assessing this concern – the effect of aggregate extraction on surrounding property values. If the disamenities created from pits and quarries are perceived by residents living in the area, the perceptions can translate into a discount of property values. The prices of nearby houses would be reduced to compensate the buyers for accepting the disamenity.

A form of compensation is already given through property taxes. MPAC currently adjusts property appraisal values for taxation purposes for those who are abutting or in close proximity to sites. In Wellington County, the adjustment was -3% for abutting an industrial property and -2% for proximity in 2016. My study seems to suggest that these adjusted values could be unnecessary in Wellington County specifically, as significant negative effects are not found from being located nearby aggregate sites. The extraction activity measure used in my study could be useful to MPAC to include in their models that determine property appraisals around these sites. This study provides some insight into the property appraisal process. As five percent of Ontario's aggregate sites are located within Wellington County alone, this is an important contemporary issue. The large number of sites within Wellington County, and the current pending proposals for even more development in the county, suggest that the property appraisal process surrounding these sites may have to be periodically refined and approved to support the individual circumstances – time, location, and nature of the development.

The primary research question of this thesis was whether aggregate sites influence nearby property values. Pits differ by level of activity, and properties differ by proximity to the sites. A key empirical issue is addressing the extraction activity of the pits and quarries, as there is large variation in extraction levels between different pits and quarries in Wellington County. Geographical clusters added in the models are an attempt to improve this estimate of aggregate site impact. This method of using average area of activity from mapping systems, as well as clustering individual sites abutting each other, can be used in other studies looking at the impact of these sites. This method provides useful insight to the actual extraction activity present. This method also adds confidence in the results, as extraction activity is hypothesized to play a role in any effect on property values.

This study provides information that some stakeholder groups – Municipal governments, the OMB, community groups, MPAC, and rural residential property owners – can use to understand the effects of aggregate development on property values, as outlined above. In addition to this, the methods for obtaining aggregate site activity can help inform future research in this area as it attempts to remedy the issue in the empirical analysis of companies holding licenses, but choosing not to extract.

6.2 Limitations and Areas of Future Research

Several areas for future research can be proposed from the findings of this study. Due to some sensitivity of results when using differing functional forms, and the strength in statistical significance varying with alterations to the model, pragmatic research in this area is recommended. Looking at pits and quarries on a case-by-case basis, rather than looking at an average effect across an entire county or province may produce more accurate results. This specified analysis may be tedious to do in practice for mass appraisal purposes. In my study, I was able to test one model that included only those observations that were proximal to the Aberfoyle geographical cluster. I realized that it takes time to test and run regressions for each individual site.

One potential area for future research is that this public perception of future development could have affected property values around licensed aggregate sites that had zero activity (and no license yet). For example, the threat of a site being developed in the future may have some impact on property values. This makes sense intuitively if there had been public knowledge that an area of land could be a potential future aggregate site. Future study on proposed pits (that have not been licensed yet), rather than just active or licensed pits, could be explored.

Some of these aggregate sites in the dataset are very close to urban areas. For instance, the city of Guelph has four neighbouring clusters of pits. However, no properties within Guelph's city limits are included in this analysis, because these sales were not classified as rural residential. Including properties that are considered residential properties may add another layer to this analysis.

In addition to the property types, the time period included in the data may have played a role in the outcome of the results. This included twelve years of property sales between the years 2002-2013, which includes periods of time where pits became active and inactive. Further analysis into the pre- and post- extraction may be explored. Additionally, the dataset only includes properties that have been sold within that time period – if a property was not sold, any loss in value cannot be accounted for. Further, the date listed as the sale date for each property is not necessarily the date that the property sold, but is the closing date. This could have an effect on the models, as some properties are actually sold months before closing. This is impossible to ameliorate with the current data set, as it is the only date that is provided by MPAC, and is the best available predictor of when the property was actually sold. Perhaps gaining insight into the dates the properties actually sold may help this analysis.

Geographical information systems (GIS) was used to create all of the distance variables: distance to the nearest aggregate site, distance to Toronto, distance to nearest urban centre, and distance to the 401 highway. For the distance to the nearest aggregate site measure, the straight-line distance was calculated from the middle of the property to the edge of the nearest aggregate site. For large pits, this may be far away from any actual disamenity, and may just be close to a licensed area that could have zero activity. The geographical clusters added in the models are an attempt to improve this calculation. All of these possible shortcomings addressed above could be first points of exploration in future research. In the future, the methods outlined in this thesis can also be applied to other counties or geographical areas.

This analysis has taken on the substantive task of estimating the impact of aggregate sites on nearby rural residential property values, which attempts to address the gap in the current academic literature. As there are current Ontario Municipal Board hearings in Wellington County and beyond regarding the proposals of future aggregate sites, this is an important contemporary issue. As aggregate material is essential to our daily life (the average person makes use of 14 tonnes of aggregate material each year), this will continue to be a subject of importance into the future.

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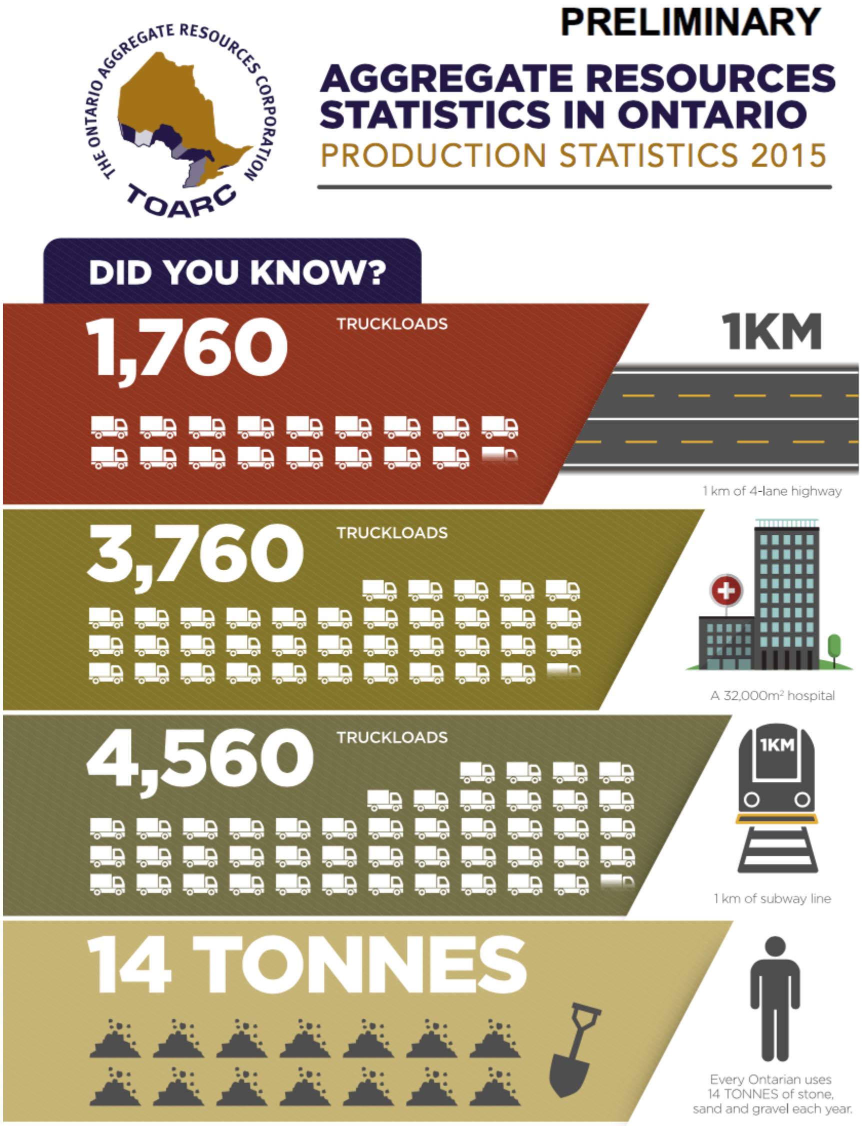
APPENDIX

Figure A1: Uses of Aggregate Resources in Ontario



Source: The Ontario Aggregate Resources Corporation (TOARC, 2015)
Notes: A truckload is about 13 metric tons in this 2015 report.

Table A1: Pit and Quarry Inventory in Wellington County

#	Pit Identifier Number (with Geographic Cluster)	PIT (P) QUARRY (Q) BOTH (B)	LOCATION	LICENSE AND MAX ANNUAL TONNAGE	LICENSED AREA
1	3595 (neighbouring 10606, 80956, 624233, 3634, 3685, 3686)	P	Marsville	Class A 53400	9.2 ha
2	3685 (neighbouring 10606, 80956, 624233, 3634, 3686, 3595)	P	Marsville	Class A 90700	33.08 ha
3	3686 (neighbouring 10606, 80956, 624233, 3634, 3595, 3685)	P	Marsville	Class A 900000	162.33 ha
4	4469	P	Mt Forest	Class A 120000	38 ha
5	4491 (neighbouring 15477, 102306, 4719, 4522, 625192)	P	Mt. Forest	Class A 800000	40.5 ha
6	4495 (neighbouring 4514, 4765)	P	Minto	Class A 100000	39.9 ha
7	4508	P	Mt. Forest	Class B 20000	1.3 ha
8	4511	P	Minto	Class B 20000	5.3 ha
9	4513	P	Minto	Class A 40000	9.85 ha
10	4514 (neighbouring 4495, 4765)	P	Minto	Class A 20000	12.7 ha
11	4519	P	Teviotdale	Class A 100000	27 ha
12	4522 (neighbouring 15477, 102306, 4719, 4491, 625192)	P	Mt Forest	Class A 500000	47 ha
13	4622	P	Clifford	Class A 40000	25 ha
14	4638	P	Lakelet	Class A 50000	12.3 ha
15	4682	P	Palmerston	Class A 50000	10.82 ha
16	4765 (neighbouring 4495)	P	Minto	Class A 100000	80.97 ha
17	4875	P	Keldon	Class A 100000	7.8 ha
18	4878	P	Mt Forest	Class A 30000	10 ha
19	4958 (neighbouring 4961)	P	Mt Forest	Class A 100000	24.5 ha
20	4960	P	Mt Forest	Class A 125000	18.2 ha
21	4961 (neighbouring 4958)	P	Mt Forest	Class A 100000	10.5 ha
22	5015	P	Mt Forest	Class A 30000	12.9 ha
23	5054	P	Mt Forest	Class A 100000	10.8 ha
24	5110	P	Mt Forest	Class A 90000	18.26 ha
25	5462	P	Georgetown	Class A unlimited	6.28 ha
26	5465 (neighbouring 5563, 5520, 5483, 5734, 5631, and south of 401 - 5497, 624864, 625284, 17600, 624952, 5738, 5737, 10671)	P	Aberfoyle	Class A unlimited	34.01 ha

27	5472 (neighbouring 15473)	P	Brucedale	Class A unlimited	22.28 ha
28	5482 (neighbouring 5610, 5654, 625189)	B	Guelph	Class A 1,000,000	89.8 ha
29	5483 (neighbouring 5563, 5520, 5465, 5734, 5631, and south of 401 - 5497, 624864, 625284, 17600, 624952, 5738, 5737, 10671)	P	Aberfoyle	Class A 500000	33.6 ha
30	5490	P	Guelph	Class A 400000	32.21 ha
31	5514	B	Guelph	Class A 2,000,000	142.34 ha
32	5520 (neighbouring 5563, 5483, 5465, 5734, 5631, and south of 401 - 5497, 624864, 625284, 17600, 624952, 5738, 5737, 10671)	P	Aberfoyle	Class A unlimited	115.7 ha
33	5531	P	Erin	Class A 500000	44.96 ha
34	5537 (neighbouring 46162)	P	Hespeler	Class A 300000	48.43 ha
35	5549 (neighbouring 6747, 5570)	P	Hawkesville	Class A 1,300,000	93.15 ha
36	5551	P	Rockwood	Class A 20000	11.75 ha
37	5552	P	Rockwood	Class A 20000	4.94 ha
38	5563 (neighbouring 5520, 5483, 5465, 5734, 5631, and south of 401 - 5497, 624864, 625284, 17600, 624952, 5738, 5737, 10671)	P	Aberfoyle	Class A 454000	32.4 ha
39	5569 (neighbouring 124155, 5696, 625138, 19333, 27777, 625212)	P	Elora	Class A 300000	27.14 ha
40	5578 (neighbouring 39158)	P	Fergus	Class B 20000	19.12 ha
41	5579	P	Fergus	Class A 25000	20.25 ha
42	5581 (neighbouring 92916, 5660, 5595, 5678)	P	Elora	Class A 500000	27.14 ha
43	5587	P	Cedar Valley	Class B 20000	9.64 ha
44	5588	P	Elmira	Class A 75000	4.45 ha
45	5592	P	West Montrose	Class A 100000	22.9 ha
46	5598	P	Erin	Class A 725600	102.06 ha
47	5602	P	Erin	Class A 925000	136.4 ha
48	5609	P	Aberfoyle	Class A 1,000,000	78.1 ha
49	5610 (neighbouring 5482, 5654)	P	Guelph	Class A 273000	17.3 ha
50	5611	P	Erin	Class B 20000	8.1 ha
51	5616 (neighbouring 5546, 5480, 5492)	P	Acton	Class A 750000	58.6 ha
52	5618	P	Riverstown	Class A 75000	5.25 ha
53	5631 (neighbouring 5520, 5483, 5465, 5734, 5563, and south of 401 - 5497, 624864, 625284, 17600, 624952, 5738, 5737, 10671)	P	Aberfoyle	Class A 1,000,000	8.1 ha
54	5635	P	Mt Forest	Class B 20000	6.31 ha

55	5640 (neighbouring 5686)	P	Arthur	Class B 20000	26.73 ha
56	5645	P	Riverstown	Class A 40000	9.49 ha
57	5646	P	Belwood	Class A 50000	10.13 ha
58	5653	P	Puslinch	Class A 300000	6.37 ha
59	5654 (neighbouring 5482, 5610, 625189)	P	Guelph	Class A 350000	35.64 ha
60	5664	P	Goldstone	Class B 20000	5.15 ha
61	5677	P	Moorefield	Class A 100000	32.7 ha
62	5684 (neighbouring 624375)	P	Floradale	Class B 20000	4.5 ha
63	5685	P	Erin	Class A 454000	41.51 ha
64	5686 (neighbouring 5640)	P	Arthur	Class A 100000	16.61 ha
65	5702	P	Brucedale	Class A 250000	56.6 ha
66	5703	P	Rockwood	Class A 30000	33.5 ha
67	5708	P	Riverstown	Class A 100000	7.49 ha
68	5709 (neighbouring 15338)	P	Guelph	Class A 45000	14.57 ha
69	5710 (neighbouring 20212, 20749, 624889, 625710, 129817)	P	Guelph	Class A 341000	141.45 ha
70	5715	P	Ponsonby	Class A 100000	16.4 ha
71	5726 (neighbouring 625260)	P	Shiloh	Class A 175000	19.36 ha
72	5732	P	Kenilworth	Class B 20000	9.92 ha
73	5733	P	Mimosa	Class A 75000	13 ha
74	5734 (neighbouring 5520, 5483, 5465, 5631, 5563, and south of 401 - 5497, 624864, 625284, 17600, 624952, 5738, 5737, 10671)	P	Aberfoyle	Class A 600000	7.03 ha
75	5737 (neighbouring 5520, 5483, 5465, 5631, 5563, and south of 401 - 5497, 624864, 625284, 17600, 624952, 5738, 5734, 10671)	P	Aberfoyle	Class A 1,000,000	5.6 ha
76	5738 (neighbouring 5520, 5483, 5465, 5631, 5563, and south of 401 - 5497, 624864, 625284, 17600, 624952, 5737, 5734, 10671)	P	Aberfoyle	Class A 2,000,000	188.6 ha
77	6524 (neighbouring 21666, 6525)	P	Belfountain	Class A unlimited	36.6 ha
78	9491	P	Mt Forest	Class B 20000	1.9 ha
79	15338 (neighbouring 5709)	P	Guelph	Class A 100000	11.71 ha
80	15343	P	Erin	Class A 750000	49.5 ha
81	15473 (neighbouring 5472)	P	Brucedale	Class A 300000	44.49 ha
82	15477 (neighbouring 4491, 102306, 4719, 4522, 625192)	P	Mt Forest	Class A 300000	18.06 ha

83	17600 (neighbouring 5520, 5483, 5465, 5631, 5563, and south of 401 - 5497, 624864, 625284, 5738, 624952, 5737, 5734, 10671)	P	Aberfoyle	Class A 500000	37.1 ha
84	19333 (neighbouring 124155, 5696, 625138, 5569, 27777, 625212)	P	Elora	Class A 150000	10.3 ha
85	19862 (neighbouring 624934)	P	West Montrose	Class A 150000	5.36 ha
86	20085	P	Aikensville	Class A 1,000,000	96.32 ha
87	20212 (neighbouring 5710, 20749, 624889, 625710, 129817)	P	Guelph	Class A 500000	101.6 ha
88	20214	P	Lake Belwood	Class A 100000	41.5 ha
89	20733	P	Elora	Class A 100000	19.7 ha
90	20749 (neighbouring 5710, 20212, 624889, 625710, 129817)	P	Guelph	Class A 500000	23.03 ha
91	22021 (neighbouring 19352, 20207)	P	West Montrose	Class A 150000	2.9 ha
92	27777 (neighbouring 124155, 5696, 625138, 5569, 19333, 625212)	P	Elora	Class A 250000	17.3 ha
93	39158 (neighbouring 5578)	P	Oustic	Class A 100000	10.21 ha
94	46162 (neighbouring 5537)	P	Hespeler	Class A 100000	31.92 ha
95	55317	P	Maryhill	Class A 200000	37.87
96	69856	P	Mt Forest	Class B 20000	3.1 ha
97	80956 (neighbouring 10606, 3595, 624233, 3634, 3685, 3686)	P	Marsville - close to Orangeville	Class A 500000	60.8 ha
98	92916 (neighbouring 5581, 5660, 5595, 5678)	P	Elora	Class A 200000	31.6 ha
99	124155 (neighbouring 5569, 5696, 625138, 19333, 27777, 625212, 601761)	P	Elora	Class A 350000	17.4 ha
100	126455	P	Mt Forest	Class A 300000	12.9 ha
101	129817 (neighbouring 20212, 20749, 624889, 625710, 5710)	P	Guelph	Class A 750000	74.64 ha
102	603781 (neighbouring 624994)	P	Elora	Class A 350000	33.79 ha
103	624864 (neighbouring 5520, 5483, 5465, 5631, 5563, and south of 401 - 5497, 17600, 625284, 5738, 624952, 5737, 5734, 10671)	P	Aberfoyle	Class A 1,000,000	16.26 ha
104	624994 (neighbouring 603781)	P	Elora	Class A 370000	34.14 ha
105	625006	P	Palmerston	Class A 100000	8.4 ha
106	625108	P	Palmerston	Class A 150000	12.24 ha
107	625189 (neighbouring 5654, 5482)	P	Guelph	Class A 750000	59.1 ha

Table A2: Geographic Clusters of Aggregate Sites in Wellington County

ALPS ID(s)	**AREA OF CLUSTER (M^2)**	**RANK (large to small)**
5465, 5563, 5520, 5483, 5734, 5631, 5497, 624864, 17600, 5738, 5737, 10671	**2708606**	**1**
5710, 20212, 20749, 129817	**676969**	**2**
4491, 15477, 102306, 4719, 4522	**593719**	**3**
5609	**502875**	**4**
5569, 124155, 5696, 19333, 27777	**376200**	**5**
5581, 92916, 5595, 5678	**368213**	**6**
5514	**316800**	**7**
5602	**304200**	**8**
15343	286819	9
5598	286031	10
5531	249863	11
20085	223875	12
5472, 15473	156038	13
20691	143438	14
5685	138713	15
5482, 5610, 5654, 625189	137081	16
5677	120150	17
5709, 15338	119813	18
5726	114413	19
5702	91744	20
4495, 4514, 4765	82688	21
5640, 5686	80606	22
5652	74363	23
625108	60582	24
4469	60581	25
4513	54225	26
5645	39994	27
20733	36394	28
5715	35888	29
126455	30431	30
603781, 624994	29475	31
5637	27281	32
5611	21656	33
5646	21544	34
5490	19406	35
5731	17944	36
5661	14794	37

5578, 39158	13838	38
5618	12938	39
4511	12488	40
5708	12431	41
4519	12150	42
5703	10125	43
69856	9900	44
4504	8944	45
5579	7706	46
5664	6525	47
4508	5850	48
5587	5738	49
5635	5456	50
48576	4950	51
9491	3825	52
5551	0	53
5552	0	53
5732	0	53
5733	0	53
20214	0	53
55317	0	53