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Impacts of COVID-19 lockdown on private domestic groundwater sample numbers, *E. coli* presence and *E. coli* concentration across Ontario, January 2020–March 2021: An interrupted time-series analysis

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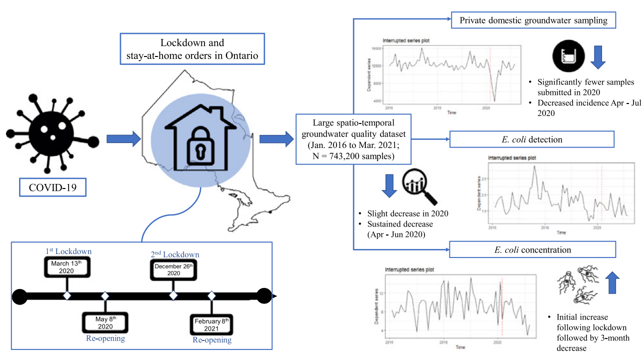
HIGHLIGHTS

- Large provincial *E. coli* sampling dataset (N = 743,200 groundwater samples) employed for time-series analyses
- Results indicate a major shift (decrease) in private groundwater sampling frequency/incidence
- COVID-19 lockdown concurred with a decreased *E. coli* detection rate in private wells.
- An immediate increase was noted in samples with "high" *E. coli* counts followed by gradual decrease.

GRAPHICAL ABSTRACT



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ABSTRACT

Approximately 1.5 million individuals in Ontario are supplied by private water wells (private groundwater supplies). Unlike municipal supplies, private well water quality remains unregulated, with owners responsible for testing, treating, and maintaining their own water supplies. The COVID-19 global pandemic and associated non-pharmaceutical interventions (NPIs) have impacted many environmental (e.g., surface water and air quality) and human (e.g., healthcare, transportation) systems over the past 15-months (January 2020 to March 2021). To date, the impact of these interventions on private groundwater systems remains largely unknown. Accordingly, the current study aimed to investigate the impact of a province-wide COVID-19 lockdown (late-March 2020) on health behaviours (i.e., private domestic groundwater sampling) and groundwater quality (via *Escherichia coli* (*E. coli*) detection and concentration) in private well water in Ontario, using time-series analyses (seasonal decomposition, interrupted time-series) of a large-spatio-temporal dataset (January 2016 to March 2021; N = 743,200 samples). Findings indicate that lockdown concurred with an immediate ($p = 0.015$) and sustained ($p < 0.001$) decrease in sampling rates, equating to approximately 2200 fewer samples received per week post-interruption. Likewise, a slightly decreased *E. coli* detection rate was observed approximately one month after lockdowns began ($p = 0.003$), while the proportion of "highly contaminated" samples (i.e., *E. coli* > 10 CFU/100 mL) was shown to increase within one month ($p = 0.02$), followed by a sustained decrease for the remainder of the year (May 2020–December 2020). Analyses strongly suggest that COVID-19 interventions resulted in discernible impacts on both well user behaviours and hydrogeological

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mechanisms. Findings may be used as an evidence-base for assisting policy makers, public health practitioners and private well owners in developing recommendations and mitigation strategies to manage public health risks during extreme and/or unprecedented future events.

1. Introduction

Approximately 30% of the Canadian population rely on groundwater for daily consumption, increasing to over 80% of the country's rural population (Government of Canada, 2019). In Ontario, it is estimated that 1.5 million individuals depend on a private groundwater source ($\approx$500,000 water wells serving a single household) (Statistics Canada, 2016). Unlike municipal water supply systems and networks, private well water quality in Ontario is unregulated, with well owners responsible for testing, treating and maintaining their domestic drinking water source (Ministry of Environment, Conservation & Parks, 2014). Well water testing is available free of charge for *Escherichia coli* (*E. coli*) and Total Coliforms through the Ontario provincial laboratories. In spite of the availability of this free service, infrequent testing behaviours have been reported (Maier et al., 2014; Ugas et al., 2019).

Groundwater and surface water are frequently contaminated with *E. coli*, a faecal indicator bacterium (FIB) widely used to assess the microbiological quality, and thus potability, of drinking water (World Health Organization, 2017). Previous geospatial analysis of private groundwater quality in Ontario, much of which is characterised by high on-site domestic wastewater treatment system (septic systems) density and extensive livestock-based agriculture, is reported as being highly susceptible to *E. coli* contamination (Krolik et al., 2013; Latchmore et al., 2020). For example, Latchmore et al. (2020) reported that, for wells tested frequently (5 times) throughout the years 2010–2017 (n > 700), an overall mean of 18% were found to be positive for *E. coli*. Additionally, recent studies from Ontario have reported season, hydrogeological setting and source depth as significant predictors of private well water contamination (Latchmore et al., 2020; White et al., 2021). Accordingly, frequent well water testing is critical for preventing consumption of contaminated private groundwater and subsequent waterborne gastrointestinal infections, particularly in light of recent estimates suggesting approximately 80,000 cases of acute gastrointestinal infection (AGI) are attributable to microbial contamination of private domestic wells per year in Canada (Murphy et al., 2016).

On March 11th, 2020, the World Health Organization officially declared the worsening COVID-19 situation a global pandemic, leading to myriad non-pharmaceutical interventions (NPI) including restrictions on national and international travel, regional/national curfews, and work from home/stay at home orders (lockdowns) in an attempt to arrest disease transmission (World Health Organization, 2020). Nationally, the Canadian government implemented travel restrictions, while provinces were responsible for implementing further, regionally-specific risk mitigation measures. The province of Ontario declared a state of emergency on March 17, 2020, necessitating closure of all non-essential business (e.g., daycares, restaurants, cinemas, private schools) and publicly-funded educational institutions, marking the first COVID-19 lockdown (Government of Ontario, 2020). A full timeline of COVID-19 NPIs in Ontario is presented in Supplementary materials (Table S1). Unsurprisingly, due to the global and unprecedented nature of the COVID-19 pandemic and ensuing NPIs, a large volume of scientific research has sought to quantify the effects of these NPIs, many of which have focused on human mental health and the natural environment, e.g., air and water quality (Selvam et al., 2020; Ingram et al., 2020; Pfefferbaum and North, 2020; Zhai and Du, 2020; Duttagupta et al., 2021; Mostafa et al., 2021). Urban centers and highly populated cities experienced dramatic reductions in vehicular and pedestrian traffic and industrial activities, leading to measured improvements in air and surface water quality (Mostafa et al., 2021; Tokatlı and Varol, 2021). Likewise, many studies have analysed the impact of COVID-19 interventions on individual and population health behaviours associated with diet, alcohol consumption, sleep and physical activity (Arora and Grey, 2020; Fu et al., 2020; McPhee et al., 2020).

Despite high global reliance on groundwater for domestic use, and numerous studies reporting the effects of NPIs on surface water resources, to date, the impact of COVID-19 interventions on groundwater quality remains largely unknown (Aravinthasamy et al., 2021; Duttagupta et al., 2021; Karunanidhi et al., 2021; Krishan et al., 2021). One study conducted in Southern India by Aravinthasamy et al. (2021) reports that concentrations of heavy metals (e.g., Fe, Mn, Ni, Cr and Pb) and biological parameters (total coliform, faecal coliform, and *E. coli*) in shallow groundwater samples decreased considerably after the lockdown period. However, most studies seeking to identify associations between COVID-19 NPIs and groundwater quality have been undertaken in or adjacent to industrial and urban areas and rely on small sample sizes. To the authors' knowledge, the impact of COVID-19 interventions on private groundwater quality in rural and remote areas has yet to be examined.

Considering the large groundwater reliant population residing in Ontario (and globally), and the unregulated nature of these supplies, examining the impacts of various mitigations strategies undertaken during the COVID-19 pandemic on health behaviours and private groundwater quality is essential for developing recommendations and mitigation strategies to manage health risks during future extreme and/or unprecedented events (e.g., extreme weather events, outbreaks). Accordingly, the current study employed a large spatio-temporal groundwater quality dataset (January 2016–March 2021; N = 743,200 samples) (1) to determine if COVID-19 lockdown impacted health behaviours (i.e., private domestic groundwater sampling) among private well users in Ontario, (2) quantify the effect of enforced COVID-19 restrictions (i.e., lockdown) on *E. coli* detection rate and (3) examine the magnitude (concentration) of *E. coli* contamination (CFU/100 mL) pre- and post-COVID-19 in Ontario.

2. Materials and methods

2.1. Private groundwater testing and quality data

The current study used the Well Water Testing Dataset (WWTD) from January 2016 to March 2021, inclusive. The WWTD comprises all results of bacteriological testing performed at the eleven provincial laboratories. Water microbiology test results from private well water samples were exported from the Well Water Testing Dataset (WWTD) in 3-month batches as CSV files for downstream processing with RStudio (v1.1.383) with R (v3.6.0). Each CSV file was pre-processed with R prior to merging pre-processed CSV files into a final dataset. The data were anonymized by selecting only the variables of interest. Time-series analyses required creating a DATE (ymd) attribute from DATE_RECEIVED by removing the time component. Quantitative analysis of *E. coli* results required replacing ">80" with "81", then coercing these variables to numeric data type. Records with duplicate sample barcodes were removed.

All submitted groundwater samples are processed and analysed for *E. coli* via direct membrane filtration and culture, in compliance with ISO/IEC Standard 170255:2017, with presumptive *E. coli* reported and enumerated to a maximum of 80 CFU/100 mL. The maximum acceptable concentration of *E. coli* in drinking water in Ontario is none detectable per 100 mL (i.e., 0 CFU/mL).

2.2. Seasonal decomposition

Seasonal decomposition was carried out in RStudio (v4.0.5) with the "forecast" package (v 8.15) using Seasonal and Trend (STL) decomposition via the LOESS (Locally Estimated Scatterplot Smoothing) method to assess

Table 1
Monthly distribution of private groundwater sample submission to Ontario provincial laboratories, January 2016 to March 2021.

Month	Samples received	%
January	42,850	5.77
February	38,432	5.17
March	52,456	7.06
April	51,096	6.88
May	79,956	10.76
June	84,101	11.32
July	93,210	12.54
August	88,251	11.87
September	68,251	9.18
October	61,867	8.32
November	51,357	6.91
December	31,373	4.22
Total	743,200	100

temporal patterns of received private groundwater sample number, *E. coli* detection rate (temporally-specific proportion of *E. coli* positive wells (i.e., the number of wells in which *E. coli* bacteria are detected relative to the number of wells in the sampled population during a specified time-period)) and *E. coli* contamination magnitude (proportion of *E. coli*-positive samples (≥1 CFU/100 mL) with >10 CFU/100 mL) over the study period. Weekly and monthly time series were calculated for each outcome. The STL method decomposes incidence data (Y_v) time-series into three separate component series: seasonal variation (S_v), overall trend over time (T_v) and residuals (R_v), whereby incidence is equal to the sum of all three trends denoted by (Cleveland et al., 1990; Boudou et al., 2021a, 2021b; Cleary et al., 2021):

$$Y_v = T_v + S_v + R_v \tag{1}$$

An additive seasonal decomposition formula was used to remove seasonality (S_v) and trend (T_v) from the overall time-series (Y_v) and filter "temporally local" variation from long-term patterns given by the residuals (R_v) so that: Residuals (R_v) = Time series (Y_v) – Seasonal trend (S_v) – Trend (T_v). Accordingly, the STL method has been employed in concurrence with interrupted time-series analysis (ITSA) as STL simulates and identifies a seasonal signal over a prolonged temporal period, which is important when examining cyclical processes (e.g., groundwater contamination), whereas ITSA is used to examine shorter time-series and specific temporal points within the series.

2.3. Interrupted time-series analysis (ITSA) modelling

Interrupted time-series analysis (ITSA) modelling was used to statistically evaluate the effect of a distinct temporal event by assessing the underlying trend of a time-series, interrupted by a specific time-point (e.g., epidemiological intervention, change in policy/legislation, etc.) (Bernal et al., 2017). ITSA was undertaken using the "itsa.model" function from the "its.analysis" package (v 1.6.0) in RStudio (v4.0.5) (English, 2019). The function runs a Type-2 Sum of Squares ANCOVA lagged dependant variable model, assessing the mean difference between non-interrupted (prior) and interrupted (post) time-periods (i.e., before and after lockdown) (English, 2019). Outputs from the model include a trimmed median F-value from which a bootstrapped p-value is derived, for both the non-lagged and lagged dependant variable. The median slope prior and post-interruption is used to assess overall interruption effect, in terms of both an immediate and sustained (>1 time-step i.e., >1 month where modelling employs monthly incidence) response. For the current study, bootstrapped models were run using 250 iterations and $\alpha = 0.05$.

For the current study, ITSA modelling was used to assess the impact of the first phase-5 population lockdown across Ontario, which was brought into force on March 23rd 2020. Time-series were seasonally adjusted (de-seasonalised) using the "forecast" package (v8.0.5) to remove regular seasonal patterns that may bias the analysis. Dependant variables (sample number, monthly *E. coli* detection rate and monthly proportion of *E. coli*-positive samples characterised by *E. coli* > 10 CFU/100 mL) were lagged (1–3 months) to allow for naturally longer-term responses associated with groundwater contamination, i.e., delayed response between contaminant release (e.g., hazard) and dissemination/transport to the eventual receptor (private well) via various pathways (e.g., gradual recharge, preferential flow, or runoff).

3. Results

3.1. Groundwater sampling rate (health behaviours)

The employed time-series comprised 743,200 private groundwater samples, collected and submitted by private well users across the province of Ontario between January 2nd 2016 and March 31st 2021, equating to a monthly mean submission rate of approximately 12,400 samples. Monthly, seasonal and annual sample numbers are presented in Table 1 and Fig. 1; as shown (Table 1), highest monthly sample numbers are annually associated with the 4-month period May to August. The highest number of samples were submitted during 2017 (n = 156,143, 21% of total), while the lowest number of samples were received during 2020 (n = 124,692, 16.78%) (Fig. 1).

Seasonal decomposition of monthly received sample numbers (Fig. 2) indicates a distinct seasonal signal annually peaking in June (>6000 expected samples above monthly mean), while lowest sample numbers are received during November and January (≈5500 expected samples below monthly mean). A notable series of negative residuals was evident during the 3-month period April–June 2020, during which approximately

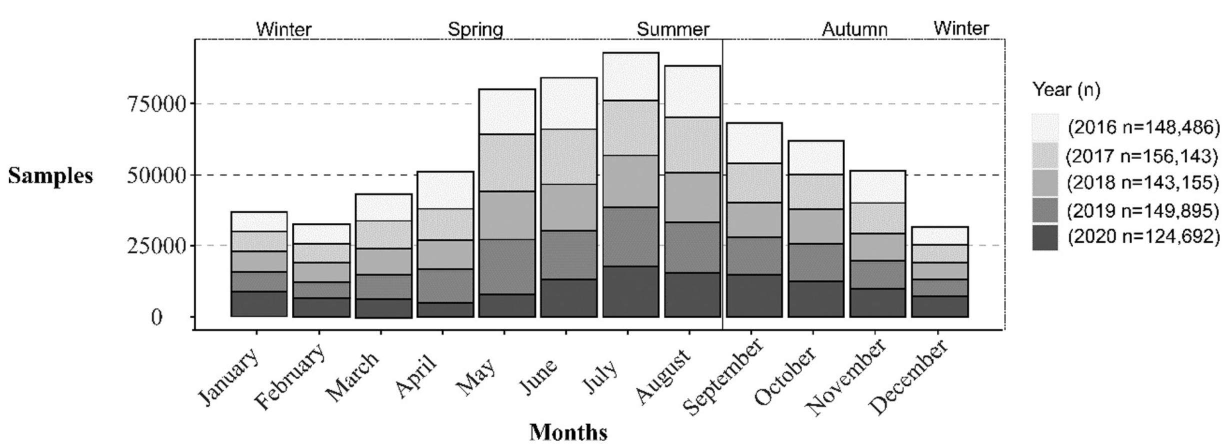

Fig. 1. Annual, monthly and seasonal distribution of private groundwater sampling numbers received by provincial laboratories, January 2016 to December 2020 (January–March 2021 removed to only present complete sampling years for clarity).

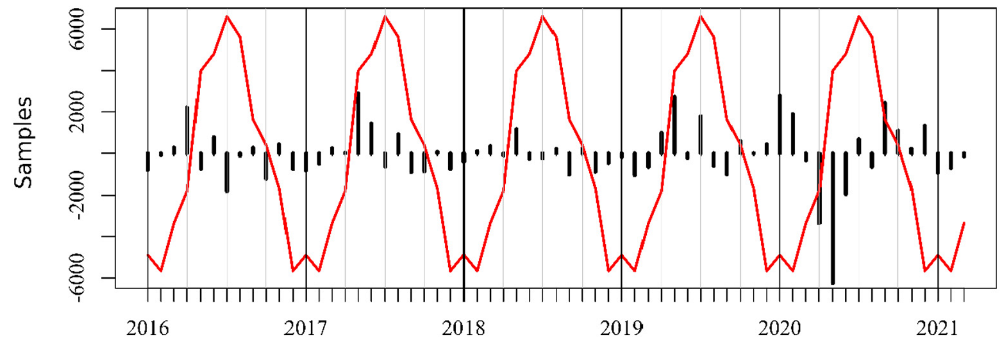

Fig. 2. Seasonal variations (red) and residuals (black) obtained via seasonal decomposition of monthly sample numbers received by provincial laboratories (January 2016–March 2021).

11,000 fewer groundwater samples than expected were received by the provincial laboratories based on the period 2016 to 2019, with this residual particularly pronounced during May 2020, with more than 6000 fewer samples (51%) than typical for that month. Subsequently, ITSA modelling was undertaken on the deseasonalised time-series to assess the effect of COVID-19 lockdown, defined as the modelled interruption point (late-March 2020), on received sample numbers (Fig. 3; Table 2). Results (Table 2) indicate a significant, immediate (interruption variable) response to the lockdown ($F = 6.221$, $p = 0.015$), followed by a significant sustained response ($F = 12.817$, $p < 0.001$), equating to a mean difference of −2190 samples per week before and after lockdown.

Table 2
Outputs from ITSA modelling of deseasonalised weekly sample numbers and first COVID-19 lockdown (late-March 2020).

Parameter	Value
Immediate response (i.e., within 1 week)	
Sum of squares (interruption variable)	12,494,914
F-value (interruption variable)	6.2215
p-Value (interruption variable)	0.0154
Sustained response (i.e., >1 week)	
Sum of squares (lagged variable)	25,742,546
F-value (lagged variable)	12.8177
p-Value (lagged variable)	0.0007
Pre-interruption mean (weekly samples)	12,469
Post-interruption mean (weekly samples)	10,279

3.2. Groundwater contamination rate (E. coli detection)

Annual and seasonal *E. coli* detection rates and associated contamination magnitude during the study period are presented in Table 3; as shown, highest annual contamination rates were associated with 2017 (2.12%) and 2018 (1.87%). Highest mean *E. coli* concentrations were observed during 2021 (4.62 CFU/100 mL) and 2018 (4.06 CFU/100 mL), while the highest proportions of *E. coli*-positive samples with *E. coli* > 10 CFU/100 mL were reported during 2018 (10.46% of samples with *E. coli* present). A distinct recurring seasonal pattern is evident with respect to *E. coli* detection rates among sampled private domestic wells in Ontario (Fig. 4). Highest *E. coli* detection rates typically occur during the Canadian summer and autumn, peaking during July/August, with a maximum value reported during summer 2017 (3.15%). Spring 2020 exhibited the highest mean seasonal *E. coli* concentration over the course of the 5-year study period (5.67 CFU/100 mL), in concurrence with the lowest calculated *E. coli* detection rate (1.06%). It is important to note however, that due to the sensitivity of calculated means to relatively few large outliers, this finding should be interpreted with caution, and represents the primary reason for the authors electing to use proportion of *E. coli*-positive samples >10 CFU/100 mL as an indicator of contamination magnitude. Calculated *E. coli* detection rate residuals associated with 2020 did not reveal any unusual outliers with respect to scale or timing.

ITSA modelling was undertaken on seasonally-adjusted (i.e., deseasonalised) weekly and monthly lagged (1–3 months) *E. coli* detection rates (Fig. 5). As shown (Table 4), models indicate a significant sustained negative association between the first COVID-19 lockdown (interruption) and all four lagged dependant variables, with the lowest p-value associated with a 1-month lag i.e., sustained response lasting approximately 2 months begun approximately 4–6 weeks after lockdown

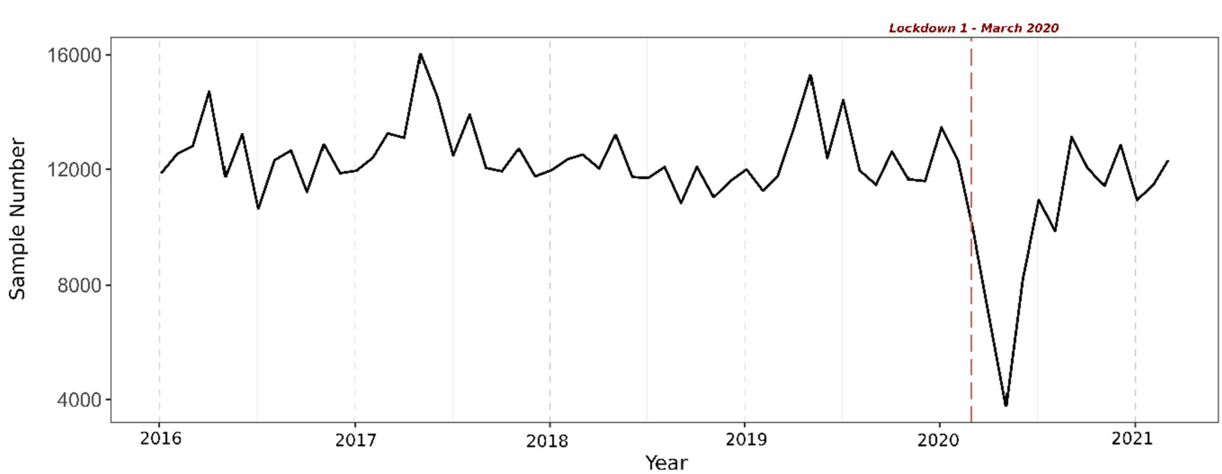

Fig. 3. Interrupted time series of monthly sample number versus first lockdown (March 2020) – Seasonally adjusted data.

Table 3
E. coli detection rate, mean concentration and mean proportion of *E. coli*-positive samples >10 CFU/100 mL delineated by year and season among private wells in Ontario, January 2016–March 2021.

		Detection rate	Mean concentration	Mean proportion of *E. coli*-positive samples >10 CFU/100 mL
2016	**Year**	**1.69**	**3.89**	**8.58**
	Spring	1.27	3.53	7.85
	Summer	2.08	4.09	9.60
	Autumn	2.12	3.78	9.29
	Winter	1.29	4.05	7.59
2017	**Year**	**2.12**	**3.98**	**9.69**
	Spring	1.34	3.53	7.69
	Summer	3.15	4.06	8.95
	Autumn	2.37	4.05	9.26
	Winter	1.64	4.25	12.85
2018	**Year**	**1.87**	**4.06**	**10.46**
	Spring	1.13	3.98	8.84
	Summer	2.44	4.18	11.12
	Autumn	2.28	3.53	8.27
	Winter	1.62	4.98	13.59
2019	**Year**	**1.67**	**3.86**	**9.26**
	Spring	1.42	3.88	8.96
	Summer	2.02	3.66	8.19
	Autumn	1.82	4.20	9.24
	Winter	1.42	3.91	10.66
2020	**Year**	**1.65**	**3.94**	**8.87**
	Spring	1.03	5.67	9.40
	Summer	2.25	3.67	8.51
	Autumn	1.94	3.48	6.87
	Winter	1.37	4.63	10.70
2021	Jan-Mar	1.05	4.62	7.15

was initiated, after which *E. coli* rates "recovered", albeit remaining within the lower range of normal throughout 2020 (pre-lockdown *E. coli* detection rate – 1.83%, post-lockdown *E. coli* detection rate – 1.69%).

3.3. Contamination magnitude (proportion of E. coli-positive samples >10 CFU/100 mL)

During the study period, highest proportions of *E. coli*-positive samples >10 CFU/100 mL typically occur in late Winter (February), with proportions gradually increasing from October/November following lowest levels in mid-late Summer (August/September) (Table 3, Fig. 6). The highest proportion of highly contaminated samples were observed during winter 2018 (13.59% of *E. coli*-positive samples).

ITSA modelling of the proportion of *E. coli*-positive samples (Table 5; Fig. 7) identified a significant, immediate association (lagged by one month) between the timing of the first lockdown and the proportion of samples characterised by *E. coli* >10 CFU/100 mL samples ($p = 0.0236$). This association was linked to an immediate increase for one month, followed by a decrease, with a mean pre/post decrease based on a one-month lag of 19.6% (i.e., $(9.597 - 7.713) / 9.957 * 100$), with this response not found to be sustained ($p = 0.586$).

4. Discussion

4.1. Private domestic groundwater sampling and COVID-19 lockdown

Regular groundwater quality testing for faecal indicator bacteria (FIB) including *E. coli*, reduces the risk of consuming contaminated groundwater and subsequent waterborne infections (Murphy et al., 2017). Over the 5-year study period, highest annual sample numbers were submitted and received during the period May to August, with lowest sample numbers associated with the period December to February (Table 1). In Ontario, late spring (May) and summer months (June to August) are typically characterised by warmer weather, higher rainfall, and increasingly active agricultural practices, all of which have been shown to negatively impact private groundwater quality (Hynds et al., 2012; Atherholt et al., 2017; Latchmore et al., 2020). Higher sample numbers associated with late spring and summer may indicate a level of heightened awareness and/or risk perception among private well owners/users. Previous studies have shown that travel requirements and the distance to testing laboratories and health centers represent impediments to well water sample collection and drop-off (Munene and Hall, 2019; Colley et al., 2019), with well users less inclined to travel long distances during winter months in Ontario (Imgrund et al., 2011; Qayyum et al., 2020; White et al., 2021).

Recent studies have shown that human behaviour(s) and cognitive precursors (e.g., awareness, risk perception, attitude) to protective actions are important factors in the context of private (unregulated) domestic groundwater, as they can both mitigate and exacerbate contamination risks (Di Pelino et al., 2019; Lavallee et al., 2021). As such, understanding the impacts of enforced COVID-19 NPIs, including lockdowns and movement restrictions, on health behaviours (e.g., well water test submissions) among private well users is critical. Annual sampling distributions across the study period indicate that far fewer samples were submitted by private well users during the year 2020 (Fig. 1). Specifically, seasonal decomposition of monthly samples reveal that significantly lower sample numbers, as indicated by large negative residuals, were submitted between April and June 2020 (i.e., within one month of the first province-wide lockdown in Ontario) (Fig. 2). Furthermore, ITSA modelling reveals a significant interaction between the weekly number of samples submitted and the effect of the lockdown (Table 2); findings indicate both an immediate ($p < 0.001$) and sustained response ($p < 0.001$), with an overall decrease of ≈22% in the number of weekly samples submitted following the COVID-19 lockdown in March 2020 up until and including July 2020, starting in April 2020 (i.e., almost immediately after lockdown initiation).

Recent research has found that the COVID-19 pandemic disrupted daily routines and increased household stress among many Canadian families; a survey conducted by Carroll and Conboy (2020) reports that the key factors influencing family stress include balancing work from home with childcare and home-schooling due to school/childcare closures. Accordingly, it is likely that well users with young families were pre-occupied, in concurrence with experiencing unprecedented family-related concerns, unrelated to private well water contamination. '*The Uncontrollable Mortality Risk Hypothesis*' (UMRM) has been proposed to elucidate differences between risk perceptions related to COVID-19 and health behaviours. The UNRM specifically predicts that people with increased perceived extrinsic mortality risk (portion of mortality risk perceived to be uncontrollable) are likely less motivated to engage in positive health behaviours (Pepper and Nettle, 2014). For example, a study conducted in the UK found that perceived extrinsic mortality risk increased due to the pandemic and was associated with a reduction in healthy behaviours related to diet, physical activity, and smoking (Brown et al., 2021). The authors consider that findings from the current study may support the UNRM, with well users likely perceiving COVID-19 as a mortality risk beyond their control, resulting in lowered motivation to engage in health behaviours including private well water quality testing. This hypothesis is important to consider, as the effects of perceived extrinsic mortality risk on health behaviours among private well users may not be limited to the pandemic but could also be present during future extreme and/or unprecedented events (e.g., extreme weather events, health-related outbreaks). Furthermore, COVID-19 represents the first global pandemic to occur during the "social media age", resulting in widespread, rapid dissemination of health information and protocols. Recent studies have examined the effects of social media on risk perceptions and health behaviours during the pandemic (Liu et al., 2021; Mahmood et al., 2021). For example, a recent study by Mahmood et al. (2021), reports an association between the perceived threat(s) of COVID-19, self-efficacy (i.e., confidence in applying relevant and/or appropriate actions) and social media use. In the context of private groundwater, the authors feel that social media platforms disseminating information related to COVID-19 may have contributed to radical changes in risk perceptions (e.g., perceived threat of COVID-19), and the observed rapid decrease in test submissions.

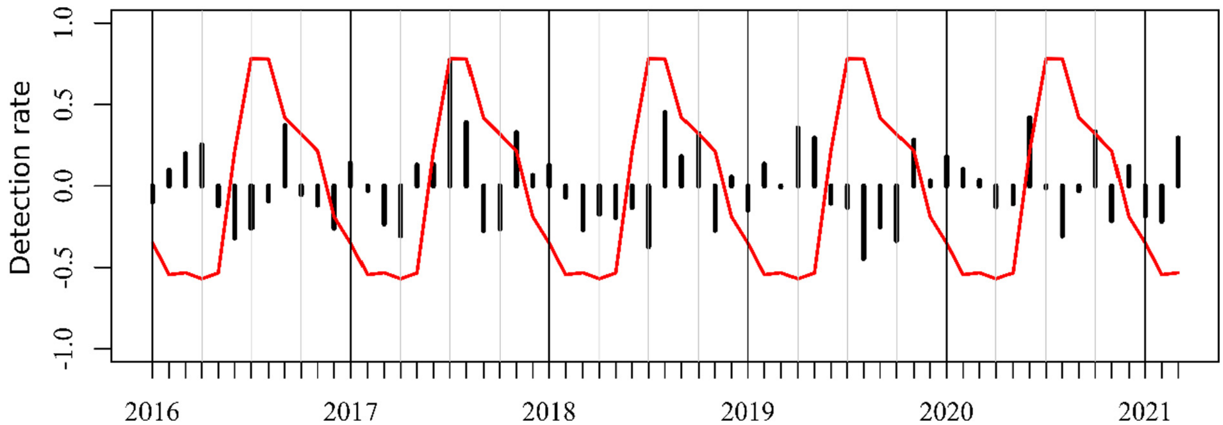

Fig. 4. Seasonal variations (red) and residuals (black) obtained via seasonal decomposition of calculated mean monthly *E. coli* detection rate among private groundwater samples received by the provincial laboratories (January 2016–March 2021).

4.2. E. coli detection and COVID-19 lockdown

Due to the unprecedented nature of the COVID-19 pandemic and ensuing NPIs, no evidence-base exists for the likely effect of this global event on private groundwater quality. The authors hypothesized that *E. coli* detection rates may increase given the amplified usage of private well water increasing drawdown, thus potentially increasing the zone of contribution and therefore the 'zone of influence', in concurrence with increased domestic wastewater production, which may have in some cases overwhelmed onsite wastewater treatment systems.

Prior to the COVID-19 lockdown, calculated monthly mean *E. coli* detection rates ranged from 1.67% to 2.12%, with a slight decrease (1.65%) found during 2020, thus mirroring those reported by Latchmore et al. (2020) who calculated a mean single sample detection rate of 2% between 2010 and 2017 across Ontario. Several studies have previously noted that lower sampling numbers inherently result in lower detection rates (i.e., decreasing denominator in concurrence with decreasing or unchanged numerator for detection rate calculation), conversely as groundwater sample sizes increase annually, calculated detection rates will remain unchanged or increase (Atherholt et al., 2015; Ugas et al., 2019; Latchmore et al., 2020). Results indicate that the lowest calculated *E. coli* detection rate occurred during spring 2020 (Table 3; Fig. 4), in concurrence with a significantly reduced pattern of sample submission (Fig. 2) (e.g., approximately 6000 fewer samples received in June 2020 than expected based on seasonal decomposition). Accordingly, decreased sample numbers during lockdown may potentially misrepresent private well water quality across the province via sampling bias (e.g., historically *E. coli*-positive source owners more/less likely to submit samples as usual), leading to confounded calculated detection rates, however it was not possible to assess the effect of sampling bias as a primary or partial driver of *E. coli* detection rates in the current study as data are not available at the individual (household) level. Nonetheless, the current study comprised a total of 743,200 private groundwater samples over approximately 5 years, 125,000 of which were received and analysed during 2020, thus representing the largest study seeking to examine the impact of COVID-19 lockdown(s) on *E. coli* detection and concentration in private well water. Notwithstanding, based on predictive calculations from Latchmore et al. (2020), the authors consider that an *E. coli* detection rate during a "normal" spring period would fall within the range 1.5–1.8%, and thus 50–80% higher than that observed during spring 2020.

Results of interrupted time series indicate a statistically significant sustained decrease ($p < 0.05$) in *E. coli* detection rates from May to July 2020 following the COVID-19 lockdown in March 2020, although this response was not immediate (Table 4). For example, mean *E. coli* detection decreased from 1.83% before lockdown to 1.59% two months following lockdown. Notably, Ontario experienced an atypically cold three-month period from March to May 2020, resulting in a 'polar vortex' bringing snowfall to Ontario in early May (Government of Canada, 2020). The spatiotemporal (i.e., seasonal) variability of *E. coli* detection in private groundwater is well documented in the scientific literature (Atherholt et al., 2015; Mosley, 2015; Latchmore et al., 2020; O'Dwyer et al., 2021). Indeed, the 2016 drought experienced in Ontario represents a likely driver for *E. coli*

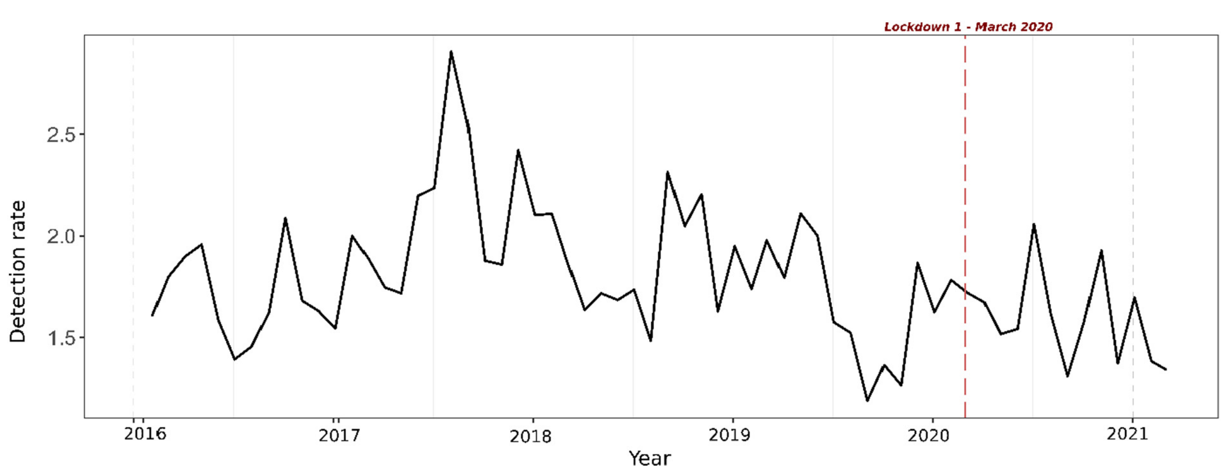

Fig. 5. Interrupted time series for detection rate of *E. coli* & first lockdown (March 2020) – Seasonally adjusted data, 1 month lag.

Table 4
Outputs from ITSA modelling for seasonally-adjusted monthly *E. coli* detection rate (lagged from 1 to 3 months) and the first COVID-19 lockdown (March 2020).

Parameter	No lag	1-month lag	2-month lag	3-month lag
Immediate response (within 1 month)				
Sum squares (interruption variable)	0.154	0.217	0.151	0.134
F value (interruption variable)	1.936	2.756	1.884	1.687
p-Value (interruption variable)	0.169	0.102	0.175	0.199
Sustained response (>1 month)				
Sum squares (lagged variable)	1.105	1.186	1.133	1.137
F value (lagged variable)	13.873	15.077	14.135	14.297
p-Value (lagged variable)	0.0004	0.0003	0.0004	0.0004
Mean before interruption	1.834	1.836	1.838	1.842
Mean after interruption	1.605	1.596	1.630	1.649

Table 5
Results from the interrupted time-series for the proportion of *E. coli*-positive samples >10 CFU/100 mL and first lockdown (March 2020) – Seasonally adjusted data.

Output	No lag	1-month lag	2-month lag	3-month lag
Immediate response (within 1 month)				
Sum squares (interruption variable)	27.280	39.280	14.780	12.240
F value (interruption variable)	3.694	5.404	1.974	1.773
p-Value (interruption variable)	0.060	0.0236	0.165	0.188
Sustained response (>1 month)				
Sum squares (lagged variable)	4.780	2.180	5.480	7.190
F value (lagged variable)	0.647	0.300	0.732	1.042
p value (lagged variable)	0.425	0.586	0.396	0.312
Mean before interruption	9.53141	9.597	9.497	9.589
Mean after interruption	8.057253	7.713	8.419	8.587

detection rates and the mean proportion of *E. coli*-positive samples being notably lower than usual during this 12-month period (Table 3) (Latchmore et al., 2020). For example, O'Dwyer et al. (2021) recently reported a post-drought *E. coli* detection rate of 24.3% among sampled private wells in Ireland, compared to 9.5% during the drought event, while the Latchmore et al. (2020) study found an annual detection rate of 1.4% associated with the drought year of 2016, which was significantly lower all other years during the 8-year. Thus, the irregularity and unpredictability of discrete extreme weather events and lack of private well water sampling during the initial lockdown period (March to July 2020) may explain the notable decline in *E. coli* detection as agricultural activities were delayed and/or ceased due to below freezing temperatures and a lack of precipitation (Atherholt et al., 2017). Moreover, the authors consider that, based on model findings, it is likely that private groundwater usage (domestic reliance) increased relatively rapidly due to stay at home orders, thus resulting in increased pumping and subsequent drawdown. Accordingly, increased "flushing" and/or dilution in and through domestic wells and their zone of influence may result in decreased *E. coli* detection rates relatively soon after the first COVID-19 lockdown began. Alternatively (or concurrently), extended pumping and drawdown may reduce the effective pathogen load reaching groundwater sources due to multiple, primarily hydraulic, drivers – an increased zone of contribution will inevitably result in extended subsurface pathways and thus residence times in the unsaturated zone leading to increased attenuation via filtration and/or natural pathogen die-off rates. Similarly, a shift in the timing of recharge (and pathogen load) reaching the water table may cause a lagged temporal effect, while more limited connectivity to contaminant sources (e.g., on-site sanitation) due to watertable drawdown may lead to decreased subsurface pathogen loading (Shani et al., 2013; Zhu et al., 2019).

4.3. E. coli magnitude and COVID-19 lockdown

Unlike *E. coli* detection rates, results of time-series analysis indicate that the proportion of *E. coli*-positive samples >10 CFU/100 mL increased within one month of the first lockdown in March 2020 ($p = 0.0236$), however, this effect was not sustained, and was almost immediately followed by a subsequent decrease (May–June). It may be presumed that a significant increase on private well water reliance (i.e., pumping/drawdown) and on-site domestic sewage treatment (i.e., septic systems) followed the first lockdown as individuals were instructed to stay at home, potentially leading to a rapid increase in the proportion of *E. coli*-positive samples (>10 CFU/100 mL) i.e., increased drawdown and 'zone of influence' potentially resulting in lower general detection rates among a majority of wells, but higher contamination magnitude among a specific sub-sample. This effect may not have been sustained due to the easing of restrictions from June onwards (Table S1), likely alleviating the pressures placed on on-site domestic sewage and drinking water systems. Additionally, the end of lockdown may have altered private well owners' motivation to test their well water, as they attempted to return to normal routines. The gradual end of COVID-19 interventions and the effect on private groundwater quality represents a notable gap in the literature, as most recent studies are limited to small sample sizes before and during lockdown periods and few, if any, examine private well water quality in high income countries.

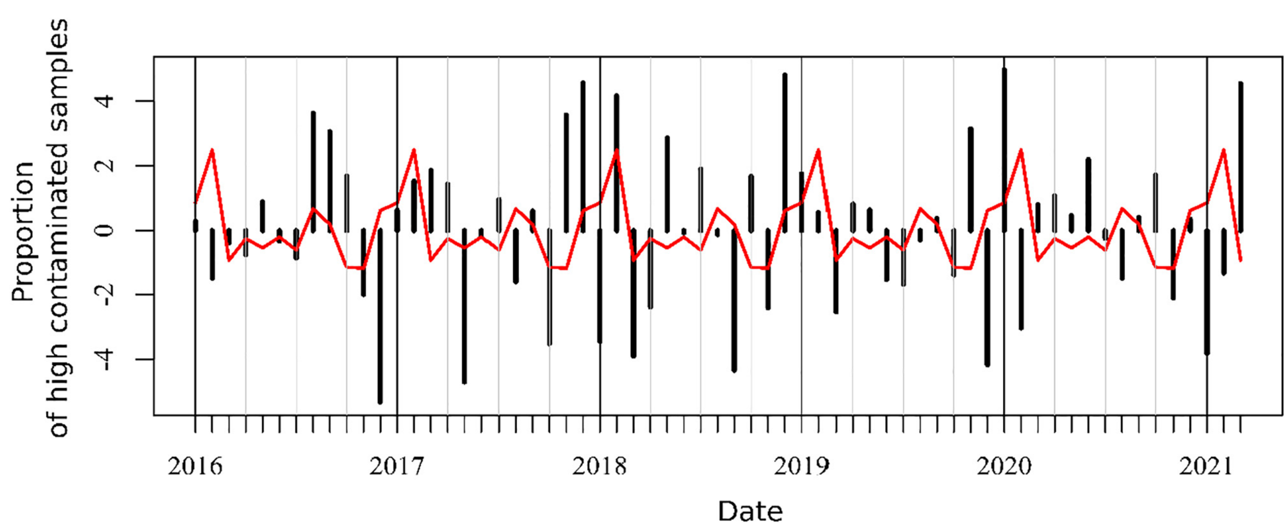

Fig. 6. Seasonal variations (red) and residuals (black) obtained via seasonal decomposition of the proportion of *E. coli*-positive samples >10 CFU/100 mL (January 2016–March 2021).

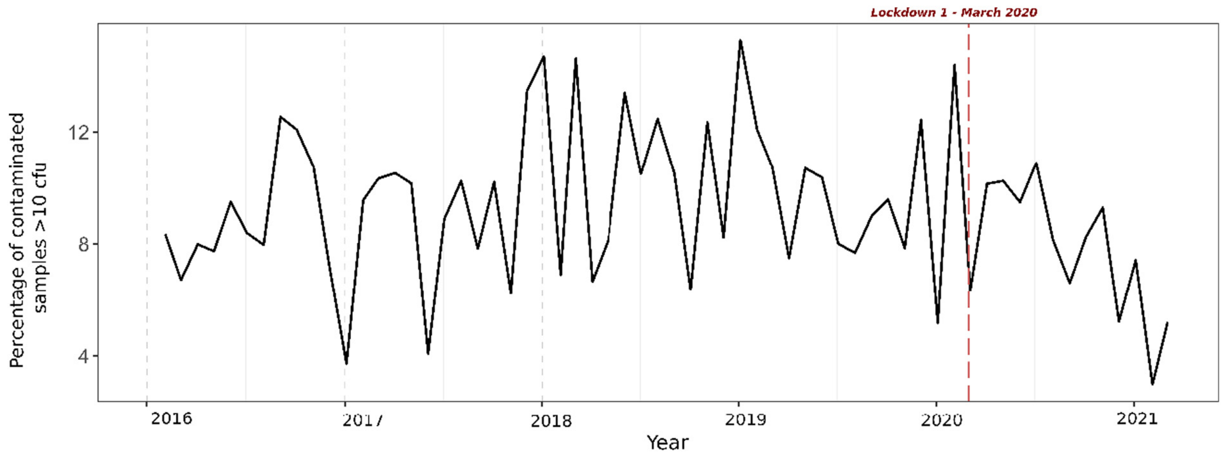

Fig. 7. Interrupted time series for the proportion of *E. coli*-positive samples >10 CFU/100 mL & first lockdown (March 2020) – Seasonally adjusted data, 1 month lag.

Other studies of the effect of COVID-19 NPIs on groundwater microbial quality report that faecal coliform presence and concentration increased during lockdown periods due to increased domestic sewage production (Tri and Qadir, 2020; Duttagupta et al., 2021). As for detection rate, the delayed groundwater response of 1–2 months following the March 2020 lockdown highlights the fluid, "creeping" (i.e., temporally lagged) nature of groundwater contamination mechanisms. Previous studies attempting to predict *E. coli* presence in private well water have reported a range of antecedent precipitation periods as being significantly predictive ranging from as little as two days up to as much as four months following significant rainfall events (Howard et al., 2003; Bauer et al., 2013; Boudou et al., 2021a, 2021b). Further, *E. coli* has been shown to survive in high concentrations in the subsurface environment for extended periods at varying temperatures (Cook and Bolster, 2007; Sidhu and Toze, 2012; Sidhu et al., 2015). The delayed response observed in the current study may be a product of the first COVID-19 lockdown coinciding with abnormally cold conditions from March to May 2020 decreasing microbial transport in the subsurface environment. The aforementioned and unprecedented 'polar vortex' was followed by a major thaw and significant rainfall as temperatures returned to seasonal averages (15 °C - 20 °C), increasing FIB transport and mobility to and within the subsurface (Hynds et al., 2014; Atherholt et al., 2017).

5. Conclusion

Data from 743,200 private groundwater samples submitted between January 2016 and March 2021 were employed to determine the effect of the first province-wide NPI (i.e., lockdown/stay at home order) on private well water in Ontario. It is not immediately clear what effect the pandemic and subsequent restrictions had on private groundwater quality in rural and remote areas of the province. The nature and timing of extreme weather events (e.g., polar vortex) during the COVID-19 lockdown period in Ontario make it difficult, if not impossible, to independently (and accurately) assess the effects of each individual event (and indeed their overlap/co-occurrence) on *E. coli* presence and magnitude in private well water. Further, given the retrospective nature of the study and the lack of regulation associated with private groundwater wells, it is difficult to directly assess the overarching impact of the restrictions. Specifically, the responsibility to maintain and manage the quality of private drinking water sources depends solely on the well user; however, during lockdown periods and stay at home orders, a noticeable difference in private domestic groundwater sampling was found, potentially resulting in a higher burden of waterborne infections during a period when medical/healthcare capacity was already stressed well beyond normal capacity. Further research is needed to determine key variables associated with testing behaviours (e.g., risk perceptions) and the impact they have on such practices during and after major national and global events. Findings leave little doubt that human behaviours, as they relate to groundwater contamination, are characterised by a significantly quicker and more marked response than groundwater contamination mechanisms themselves. As such, the authors highlight the importance of understanding health behaviours/protective health actions among private well users during extreme and unprecedented events, to design evidence-based health risk communication strategies that can be implemented in the early stages of these situations. While the COVID-19 pandemic and the nature and timing of associated NPIs varied globally, the authors consider that the spatial extent of the study area (>1 million km^2) and the highly diverse climatic, hydrological and geological settings comprised within the study area result in findings being readily transferable to other communities, regions, and/or countries characterised by large groundwater reliant populations and/or similar groundwater contamination drivers.

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CRediT authorship contribution statement

TL, SL and MB designed and performed the experiments, derived the models and analysed the data. KMcD developed and formatted all datasets, SB, PH and AM developed the overarching study idea and approach and acquired all study data. TL and SL wrote the manuscript in consultation with MB, KMcD, SB, PH and AM.

Declaration of competing interest

The authors can confirm they have no conflict of interests to declare.

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