Development of a Coupled Thermal – Mechanical –
Biological Model to Simulate Temperatures and Settlement
at a Landfill in Ste. Sophie, Quebec

By

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Abstract

A fully coupled Thermal - Mechanical - Biological (TMB) model was developed in COMSOL Multiphysics to simulate temperatures and settlement observed at a Municipal Solid Waste (MSW) landfill in Ste. Sophie, Quebec. The thermal model included heat transfer and storage, aerobic and anaerobic heat generation (biological model), heat conduction at the base and heat flux due at the top due to net radiation and convection. The mechanical model was based on a viscoelastic Kelvin-Voight model. A temperature-dependent biodegradation-induced settlement term was added to the mechanical model to simulate waste settlement. A unique modelling approach was developed that allowed optimization of model parameters over a single simulation which included both filling and post-filling stages. The optimized model was able to simulate temperatures and settlement field data reasonably well. Modelling results and sensitivity analysis illustrate the need for a coupled TMB model to simulate temperature-dependent, biodegradation-induced settlement of MSW in landfills.

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Chapter 1: Introduction

1.1 Problem Definition

The management of municipal solid waste is a persistent environmental and political concern for Canadian municipalities who bear the primary responsibility for waste management (Lougheed et al. 2018). According to a global review of waste management conducted by the World Bank, the total amount of Municipal Solid Waste (MSW) generated globally could reach 2.5 billion tons per year by 2025 (Hoornweg et al. 2012). In 2016, Canada generated an estimated 33 million tons of MSW, 76.5% of which was diverted to landfills (Statistics Canada, 2016). Landfills are considered as the most common disposal option for MSW in Canada and Ontario has the highest waste disposal rate among all Canadian provinces followed by Quebec, Alberta, and British Columbia (Mohsen et al. 2019).

Statistics Canada reported that solid waste is generated at a rate of 936 kg per person per year and 729 kg of the generated waste goes to the 2000 operating landfills in the country (CCME, Giroux Environmental Consulting, & CCME, 2014). Landfills have proved to have many advantages and benefits including the stabilization of waste and waste to energy landfill gas generation. But there are many challenges associated with waste management in landfills. Some of them include finding a location for siting of a landfill, managing landfill gas production, protecting the groundwater from the threat of contamination by leachate, ensuring that the waste is stabilized, assessing the amount of settlement that can occur in the waste, assessing landfill slope stability, and the reclamation of land for other uses post closure.

It is of specific importance to assess the long-term settlement of a landfill because landfill settlement can continue over an extended period, with a final settlement reaching 20-30% of the initial fill height (Qian et al. 2002).

The climate in Canada poses another challenge for the management of MSW. During winter months, the waste collected at the curbside may be frozen by the time it is collected. If frozen waste is placed in a landfill, it can stay frozen for many months or even years due to insulation by the placement of subsequent waste layers (Bonany et al. 2013). Frozen waste does not undergo decomposition as biological activity is inhibited at cold temperatures. The mesophilic and thermophilic bacteria which are responsible for anaerobic biodegradation of waste optimally function between a temperature range of 30-40°C and 50-60°C, respectively (Rowe & Islam, 2009). This can result in a longer contaminating lifespan of a landfill as well as a slower rate of settlement in the waste. Understanding the heat transfer and heat and gas generation within a landfill situated in a northern climate can lead to better management practices for waste management operators. Enhanced biodegradation can increase the production of landfill gas which can be used in energy applications and promoting waste settlement also maximizes usable air space of the landfill, generating increased revenues for landfill operators and at the same time reducing the landfill footprint.

Accurate assessment of landfill behavior is a great challenge because of the complexity of a landfill system in which coupled thermal, hydraulic, biochemical and mechanical processes play an important role (McDougall, 2007). Therefore, for the development of any predictive tool for the estimation of landfill settlement, it is important to understand the coupled processes. This can be done by developing mathematical models to describe

these coupled processes (Collin et al. 2015). The overall goal of this thesis is to advance this insight by the development of a coupled Thermal-Mechanical-Biological (TMB) model for the simulation of temperatures and settlement at landfills located in Northern climates.

1.2 Scope of Research

A landfill in the municipality of Ste. Sophie in Quebec, Canada was instrumented with sensors during the filling stage of the landfill between 2010 and 2012, as a research project to understand the processes controlling waste stabilization in Northern climates.

Bonany et al. (2013) was the first to develop a 1D heat transfer model simulating the first two years of temperature data by considering surface heat flux, conduction from the landfill base, latent heat and heat generation.

Megalla et al. (2016) continued the work by modelling subsequent waste lifts, improving the conceptual model, and presenting a model application to illustrate the effects of different waste placement strategies on waste temperature. Doyle (2015) then proposed a quasi-thermal-mechanical-biological coupled landfill model using Bonany et al. (2013) and Megalla (2015) as a foundation. Doyle (2015) included a generalized method to include settlement in the waste in their thermal model by including mesh compression with time based on an empirical settlement model proposed by Marques et al. (2003) with parameters fit by Van Geel and Murray (2015). In addition, Doyle (2015) improved the aerobic heat generation term and varied the thermal properties of MSW with depth and time.

As an improvement upon previous modelling efforts, Berquist (2017) used the concept of waste expended energy to propose a temperature-dependent settlement term to replace

the time-dependent biodegradation-induced settlement term proposed by Park and Lee (1997) and included in Marques et al. (2003). Inclusion of a temperature-dependent biodegradation-induced settlement term better accounted for the delayed biodegradation of wastes placed in cold climates. McDonald (2018) as a part of his research, developed a geomechanical model to simulate the behavior of MSW for the same landfill using two composite compressibility models to simulate the mechanical response of MSW and the temperature-dependent biodegradation-induced (TDBI) settlement term proposed by Berquist and Van Geel (2020).

This thesis combines the thermal-biological model developed by Berquist (2017) and the mechanical model developed by McDonald (2018), thereby presenting a coupled thermal-mechanical-biological (TMB) model for the analysis of settlement and temperatures generated within the Ste Sophie landfill. Major improvements from the previous models include –

1. Developing a fully coupled thermal-mechanical-biological model that can simulate both temperatures and settlement of all MSW lifts as they are placed progressively in a landfill, in a single simulation. The thermal model developed by Berquist (2017) simulated the temperatures for distinct periods, each corresponding to the addition of an additional waste lift. This prevented the optimization of parameters over the entire simulation period.
2. Providing a direct thermal-mechanical link between the strain that can occur due to biological decomposition by modelling it as a function of energy expended by the waste.

3. Improving the thermal properties – thermal conductivity and specific heat capacity - by modelling them as a function of density which is tracked in the mechanical model, hence providing a mechanical-thermal link.
4. Optimizing the anaerobic heat generation rate and latent heat value by minimizing the sum of squared differences between the simulated and actual temperatures at the Ste Sophie landfill using approximately 10 years of data.
5. Optimizing the settlement parameters with 10 years of settlement data to assess the relative contribution of factors impacting long term settlement.
6. Conducting a sensitivity analysis on thermal properties, the anaerobic heat generation function and settlement properties to understand their relative impact on model results.

1.3 Organization of thesis

This thesis is divided into 7 chapters –

Chapter 2 provides a comprehensive literature review, with a critique and summary of previous research and modelling efforts in this area.

Chapter 3 presents a description of the setup of instrumentation on the Ste. Sophie Landfill, and the temperature, settlement, oxygen data collected to date.

Chapter 4 presents and explains the framework of the fully coupled model, the development of relationships between parameters used, and its implementation in COMSOL Multiphysics.

Chapter 5 presents the model results which include simulated temperatures and settlement, and their comparison with recorded field data, along with optimized values of thermal and mechanical parameters.

Chapter 6 presents results of sensitivity analysis done on optimized parameters.

Chapter 7 summarizes the thesis and presents the research contributions of the author along with recommendations for future work

Chapter 2: Literature

The stabilization of municipal solid waste is the result of several interdependent processes. These processes may be split up into four major parts – mechanical processes i.e. the stress-strain behavior, hydraulic processes, which are governed by transport of pore fluids, biochemical processes like biological degradation, and thermal processes which impact the temperatures of the waste (Bente et al. 2017). This chapter provides an overview on modelling studies related to the processes mentioned above - starting with a description of the approaches taken to simulate each of the biological, mechanical, hydraulic and thermal processes and followed by a description of the coupled approaches adopted by various researchers for the prediction of the constitutive behavior of MSW.

2.1 Biological Degradation

2.1.1. Aerobic Biodegradation

The aerobic phase begins just after the waste is landfilled and lasts for a few weeks at the most as the deposition of subsequent layers of waste deprives the previous ones of any oxygen. During this phase, the organic content is degraded into macromolecules by bacteria (Hubert et al. 2016). In a study to model aerobic landfills, Fytanidis et al. (2014) reviewed the different modelling approaches that can be used to simulate aerobic biodegradation of MSW. These models can vary from detailed Monod-type equations to simple first order reactions.

Megalla et al. (2016) noted that there was a strong correlation between the oxygen concentration and temperatures in the Ste Sophie landfill at instrument bundles located near the surface. Since aerobic biodegradation is highly exothermic, it leads to a significant temperature rise, sometimes rising over 60 °C (Hubert et al. 2015). Therefore,

Megalla et al. (2016) used the following quasi first order relationship to estimate the aerobic heat generation for the top one meter of waste when oxygen concentrations were recorded by the sensors in the field –

$$Q_{aer} = E_{O_2} [O_2] \quad (1)$$

where Q_{aer} is the aerobic heat generation rate (W/m^3) and is proportional to the decay rate of organics and consumption of oxygen, E_{O_2} is the rate constant, and $[O_2]$ is the oxygen concentration expressed as a percentage. To determine the value of E_{O_2} , Megalla et al. (2016) used a trial and error approach by best fitting the model temperatures to the actual Ste. Sophie temperatures during which oxygen was detected. The maximum aerobic heat generation rate during the fourth simulation periods in their model was measured as $44 W/m^3$, which was comparable to values measured in aerobic composting piles (Zambra et al. 2011). The same methodology has been adopted in this research to model aerobic biodegradation in the top 1 metre of waste lifts.

2.1.2 Anaerobic Degradation

Similar to the aerobic models, anaerobic models range from complex, multi-species, multi-reaction models requiring many parameters, to simplified models requiring fewer parameters in which many processes are represented by a lumped process. LDAT (Landfill Degradation and Transport), a comprehensive model developed at the University of Southampton in the UK (White et al. 2013), assumes the organic carbon fraction of the waste is broken into four groups: proteins, fats, carbohydrates and glucose. Hydrolysis is not simulated but a chemical equilibrium approach is used. Each group of compounds is assumed to have a solubility product that governs how much of that compound is available for biodegradation and a first order equation is used to simulate

dissolution to maintain chemical equilibrium. The biodegradation pathways are broken into three stages and each degradation pathway is simulated using a Monod type reaction. In the first stage, the proteins and fats break down into aqueous acid and acetic acid; carbohydrates into aqueous acids; and glucose into acetic acid. In the second stage the aqueous acid is converted to acetic acid and in the final stage, the acetic acid is converted into methane. Heat generation is linked to gas production. El-Fadel et al. (1996) assumed the biodegradable organic fraction within waste is lumped into three fractions: readily degradable, moderately degradable and slowly degradable. Each fraction undergoes a first order hydrolysis step. The aqueous phase organics are then converted by acidogenic bacteria to acetate and CO₂. Methanogenic bacteria convert the acetate to methane and CO₂. Both acidogenesis and methanogenesis are simulated using a Monod-type reaction. Lei et al. (2011) developed a coupled model to analyze gas flow and transport, and reaction processes of biodegradation and heat conduction in a landfill in China. They assume the biochemical degradation followed a first order reaction rate which corresponds to a first order heat release rate. The heat release rate Ω_T was described using the following equation:

$$\Omega_T = Q_{T,\infty} k(T)e^{-k(T)t} \quad (2)$$

where $Q_{T,\infty}$ is the total heat released in the biochemical reaction process, k is the generation rate coefficient related to the temperature $k(T)$ and t is the timestep.

As noted for the LDAT model, heat generation is linked to gas production from the biochemical model. Several gas production models exist for gas generation in landfills.

The US EPA's Land GEM model assumes a first order decay rate to derive a landfill gas generation model for a series of waste cells placed in a landfill (US EPA, 2005).

Hanson et al. (2008) took a similar approach and developed an exponential growth and decay function to model anaerobic heat generation (Figure 1) in MSW landfills. The constants A , B_t , C_t , and D control the peak value, the shape of the peak and rate of decay.

$$Q = A \left(\frac{t}{B_t + t} \right) \left(\frac{C_t}{C_t + t} \right) e^{-\sqrt{\frac{t}{D}}} \quad (3)$$

where Q is the heat generation rate (W/m^3), t is the time (day), A is the peak heat generation rate factor (W/m^3), B_t , C_t are shape factors (day) and D is the decay rate factor (day). The resulting heat generation equation is plotted in Figure 1 and resembles a typical landfill gas generation model.

Figure 1: Exponential growth and decay function (Hanson et al. 2008)

2.2 Mechanical Models

Several researchers have proposed mechanical models to predict the settlement of MSW considering different combinations of landfill conditions. These models can be grouped

into two types of models. The first are equations developed to estimate MSW settlement and these have been grouped as soil mechanics-based models, empirical models, rheological models and composite models incorporating biodegradation. The second approach is used in numerical models and different geomechanical models, e.g. linear elastic model, Mohr-Coulomb and Cam Clay.

2.2.1. Soil Mechanics Based Models

The first basic soil mechanics-based model of consolidation was used by Sowers (1973) to estimate the settlement of MSW. The model can be expressed as:

$$\Delta H = HC_c^* \log \left(\frac{\sigma_o + \Delta\sigma}{\sigma_o} \right) + HC_\alpha \log \left(\frac{t_2}{t_1} \right) \quad (4)$$

where ΔH is the settlement due to primary and secondary consolidation, H is the initial thickness of the waste layer, C_c^* is the primary compression ratio, σ_o is the existing overburden pressure acting at the midlevel of the layer, $\Delta\sigma$ is the increment of overburden pressure acting at the midlevel of the layer from the construction of an additional layer, C_α is the secondary compression index, t_1 is the time for completion of initial compression, t_2 is the ending period for which long term settlement of layer is desired.

2.2.2. Empirical Models

Empirical models attempt to simulate general waste behavior by adjusting the empirical parameters which are site-specific. Mostly, the mathematical functions employed are the logarithmic function, the power creep function, and the hyperbolic function. The power creep function developed by Edil et al. (1990) and the hyperbolic function developed by Ling et al. (1998) are expressed as:

$$S(t) = H_o \Delta \sigma M \left(\frac{t}{t_r} \right)^N \quad (5)$$

$$S(t) = \frac{t}{\frac{1}{\rho_o} + \frac{t}{S_{ult}}} \quad (6)$$

where $S(t)$ is settlement (m), H_o is the initial height of refuse (m), $\Delta \sigma$ is the compressive stress in kPa, t is the time since beginning of filling in day, M is the reference compressibility, N is the rate of compression, t_r is the reference time, ρ_o is the initial rate of settlement and S_{ult} is the ultimate settlement.

2.2.3. Rheological Models

Gibson and Lo (1961) assumed that the structure of soils exhibiting secondary compression behaved according to the rheological model shown in Figure 2.

Figure 2: Schematic representation of secondary compression (Gibson and Lo, 1961)

An exact solution was obtained for secondary compression of soil where the time-dependent strain $\varepsilon(t)$ was expressed as:

$$\varepsilon(t) = \Delta\sigma \left[a + b \left(1 - e^{\frac{-\lambda}{b t}} \right) \right], t > t_a \quad (7)$$

where a , b and λ are empirical parameters determined from experimental data and t_a is the time after which the applied stress becomes fully effective. Edil et al. (1990) and Liu et al. (2011) applied this model to predict long-term settlement of MSW in a landfill. The concept of viscoelasticity was used by McDonald (2018) to develop a composite compressibility model to simulate settlement at a MSW landfill located in Ste. Sophie, Canada.

2.2.4. Composite Models

Composite MSW settlement models combine different mathematical formulations which have been described earlier. A few models have been discussed in this section.

A composite compressibility model developed by Marques et al. (2003) is shown to consider all the mechanisms as well as being simple for use at landfill sites. According to this model, the strain of the MSW can be expressed as the sum of the strain from all three settlement mechanisms:

$$\varepsilon = \varepsilon_p + \varepsilon_c + \varepsilon_B \quad (8)$$

where ε is the total strain, ε_p is the strain resulting from the instantaneous applied load, ε_c is the time-dependent strain due to mechanical creep and ε_B is the time-dependent strain due to biodegradation.

Each strain-dependent term can be expanded as:

$$\varepsilon = C'_c \log \left(\frac{\sigma_o + \Delta\sigma}{\sigma_o} \right) + b(\Delta\sigma)(1 - e^{-ct'}) + E_{DG}(1 - e^{-dt''}) \quad (9)$$

where C'_c is the compression ratio, σ_o is the initial vertical stress, $\Delta\sigma$ is the change in vertical stress, b is the coefficient of mechanical creep, c is the rate constant for mechanical creep, t' is the time since the application of the stress increment $\Delta\sigma$, E_{DG} is the total amount of strain that can occur due to biological decomposition, d is the rate constant for biological decomposition and t'' is the time since the placement of waste in the lift. This model is notable because of its implementation. MSW is predominantly placed in a series of lifts and while doing so, since they are placed and compacted at significantly different points in time, they undergo unique settlement. The total settlement at the landfill at any time t can be expressed as the sum of settlement of each of these waste lifts.

$$S(t) = \sum_{i=1}^N \Delta H_i [\varepsilon_{Pi} + \varepsilon_{Ci}(t) + \varepsilon_{Bi}(t)] \quad (10)$$

where $S(t)$ is the settlement of the surface, N is the number of lifts in the landfill and ΔH_i is the initial thickness of the compacted lift i .

Because this approach is highly flexible, Babu et al. (2010) and Babu et al. (2011) modified this model by replacing the instantaneous compression term with a soil mechanics based elastic and plastic behavior model.

One limitation of the Marques et al. (2003) model is that the biodegradation-induced settlement term is not dependent on temperature and strictly dependent on time. This may be inappropriate for landfills operated in Northern climates as waste placed in the winter months may take months to years to reach temperatures that are optimal for biodegradation. Berquist and Van Geel (2020) introduced a temperature-dependent

biodegradation-induced (TDBI) settlement term replacing the third term in the Marques et al. (2003) model with the following:

$$\varepsilon_B = E_{DG} \left(\frac{\textit{Expended Energy}}{\textit{Total Expended Energy}} \right) \quad (11)$$

Total energy expended is a fixed value based on waste composition as defined by Hanson et al. (2013). The limitation of using this model is how to determine an expression of the ratio of the expended energy versus total expended energy with time. Berquist and Van Geel (2020) developed a thermal model that simulates the expended energy with time which they in turn, used to estimate settlement with time.

McDonald (2018) simulated the settlement at the Ste. Sophie landfill using two different models. The first model was based on the model proposed by Marques et al. (2003) with the instantaneous settlement (first term) simulated using a stress history-dependent elastic model developed in a finite element (FE) model, and the biodegradation-induced settlement (third term) using the TDBI model developed by Berquist and Van Geel (2020) and their expended energy data. The second model employed a single Kelvin-Voight viscoelastic body to simulate the mechanical processes and the TDBI model to simulate the biological process.

2.2.1 Geomechanics Models

A range of geomechanics models have been proposed to simulate the settlement of MSW. Reddy et al. (2018) used the 2D plane-strain formulation of the Mohr-Coulomb plasticity model implemented in FLAC 8.0 to simulate total strain. They incorporated Bishop's effective stress concept and linked the mechanical model to a two-phase unsaturated flow model. McDougal (2007) incorporated a Modified Cam Clay model into their settlement

model. LDAT estimates settlement or compression based on a bulk modulus of the waste which is a function of density. Time-dependent settlement is addressed by tracking the mass lost due to biodegradation. As noted in the previous section, McDonald (2018) incorporated a linear elastic model for initial compression with the modulus and Poisson's ratio as stress/strain-dependent terms. In a second model, McDonald (2018) replaced the initial compression and time-dependent mechanical settlement terms with a single Kelvin-Voight model.

2.3 Hydraulic Processes

Several approaches have been taken to simulate the flow and transport of leachate and gas in MSW. The most detailed approach involves two-phase flow model with multiple species in the aqueous and gaseous phases (e.g. Reddy et al., 2018). The flow of landfill leachate and landfill gas are governed by the following two equations, respectively.

$$\frac{\partial}{\partial t}(nS_w) = -\left(\frac{\partial q_i^w}{\partial x_i}\right) \quad (12)$$

$$\frac{\partial}{\partial t}(nS_g) = -\left(\frac{\partial q_i^g}{\partial x_i}\right) \quad (13)$$

where q_i^w and q_i^g are the Darcy flux for the water and gas phases, respectively, n is porosity and S_w and S_g are the water and gas phase saturations, respectively. The Darcy flux for each phase is given by:

$$q_i^w = -\frac{k_{rw}k}{\mu_w} \frac{\partial}{\partial x_i}(P_w - \rho_w g z) \quad (14)$$

$$q_i^g = -\frac{k_{rg}k}{\mu_g} \frac{\partial}{\partial x_i}(P_g - \rho_g g z) \quad (15)$$

Equations (12) and (13) are linked by the capillary pressure between the gas and water phases. The relative permeabilities of the water (k_{rw}) and gas (k_{rg}) phases are determined based on van Genuchten or Brooks-Corey relationships for the soil water characteristic curve for MSW.

As an example, Garg et al. (2010) developed a two-phase model to simulate gas, moisture and heat transport through a sanitary landfill. The model incorporated a four component (methane, CO₂, O₂ and N₂) gas and moisture flow through MSW coupled with temperature effects. The governing equation for the transport of each species in the gaseous mixture was described by the advection-dispersion-reaction equation as follows:

$$\varphi \frac{\partial C_i}{\partial t} = -\nabla(v_g C_i) + \nabla \cdot (D_i^s \nabla C_i) + G_i \pm R_i \quad (16)$$

where φ is the gas-filled porosity of the waste, C_i is the concentration of the i th component (mol/m³), v_g is Darcy's velocity of gas-phase (m/s), t is time (s), D_i^s is the diffusion coefficient of species i in the gas-filled porosity of the porous medium (m²/s), G_i is the generation rate for species i (mol/(m³s)), and R_i is the reaction rate of gas i (mol/(m³s)). A similar equation can be derived for the transport of multiple species in the aqueous phase. Some models only focus on leachate modelling and therefore use Richards equation for unsaturated flow (McDougall, 2007), while other focus just of gas generation and migration (Hettiarachchi et al., 2009). These and other models are discussed in more detail in section 2.5 Coupled Models.

2.4 Thermal Processes

A methodology for modelling thermal processes in a landfill was outlined by (Hanson et al. 2013) by conducting a transient nonlinear analysis to simulate the temporal variations of waste heat generation. Heat transfer was described as:

$$k_t \frac{\partial T}{\partial^2 x} + q = C \frac{\partial T}{\partial t} \quad (17)$$

where k_t is the thermal conductivity of waste (W/m.K), T is the temperature (°C), x is the distance (m), q is the rate of heat generation (W/m³), C is the volumetric heat capacity of waste (kJ/m³ K) and t is the time (s).

An exponential growth and decay function discussed in section 2.1.2. was used to model heat generation. The model was validated using field data from 2 cells – Cell D (conventional) and Cell B (bioreactor) at a landfill in Michigan, USA. This numerical model predicted the thermal behavior of landfills with site-specific heat generation rate functions and did not consider the effects of coupled hydraulic, mechanical and/or biological phenomena. In effect, Hanson et al. (2013) ignored heat transfer by leachate and landfill gas.

The previously discussed model developed by Garg et al. (2010) coupled their two-phase flow model with a thermal model which included heat transfer due to the flow of leachate and landfill gas. The heat balance equation was presented as:

$$\frac{\partial(\rho C_p T)}{\partial t} = \nabla \cdot (k \nabla T - \rho_g C_{p,g} v_g T - \rho_l C_{p,l} v_l T) + Q_h \quad (18)$$

where ρ is the average waste density (kg/m³), C_p is the mass fraction weighted average heat capacity of the waste (J/kg K), ρ_g and ρ_l are gas phase and liquid phase densities

(kg/m^3), $C_{p,g}$ and $C_{p,l}$ are constant specific heat capacities of the gas phase and liquid phase, respectively (J/kg K), k is the effective thermal conductivity of waste (W/(m K)), and Q_h is the rate of heat generation ($\text{J/(m}^3\text{day)}$).

2.5 Coupled Models

Several models have been proposed in the literature that couple different biological, mechanical, hydraulic and thermal processes. In most cases, the processes included in the models were a function of the objective of the model, e.g. gas generation and recovery, prediction of settlement, impacts of leachate recycle on gas generation, etc. There are very few models which present a fully coupled TMHB model for MSW. The following section provides an overview of some of these models.

El-Fadel et al. (1996) was one of the first, more comprehensive coupled models that incorporated the biodegradation, gas flow and heat transport. The model was developed to simulate the data collected at the Mountain View Controlled Landfill Project (El-Fadel et al., 1996b). The biological model for waste degradation included three degradable organic fractions and simulated hydrolysis, acidogenesis, acetogenesis and methanogenesis in the generation of landfill gas. Gas flow was simplified to include Darcy's law and assumed a fixed gas saturation and hydraulic conductivity. Heat transport included heat transfer through the solid waste and through advection of the landfill gas.

A conceptual framework for the integrated analysis of hydraulic, biodegradation and mechanical (HBM) behavior in landfilled waste and other biodegradable soils was presented by McDougall (2007). The hydraulic model was an unsaturated flow model, based on Richards' equation, in which the two main system variables were hydraulic pressure and moisture content. The model allowed the saturated hydraulic conductivity to

be a function of the void ratio. The biodegradation model was a modified two-stage anaerobic digestion model in which the main field variables were the volatile fatty acid (VFA) and methanogenic biomass (MB) concentrations. The mechanical model was based on established formulations of load and creep induced effects combined with mechanical consequences of decomposition. Load induced compression was based on elasto-plasticity using a modified Cam Clay model. Creep behavior was incorporated using the equivalent time method developed by Yin and Graham (1989). The impacts of biodegradation on the mechanical parameters was achieved by the introduction of a decomposition hardening multiplier which would allow for strain-softening as a function of the loss of solids and increase in void ratio due to biodegradation.

Another commonly referenced, coupled model is LDAT, a comprehensive model developed at the University of Southampton in the UK (White et al. 2013). As noted earlier, LDAT included a comprehensive biodegradation model that assumes the organic carbon fraction of the waste is broken into four groups: proteins, fats, carbohydrates and glucose. A three step, Monod-type reaction is assumed to convert the organic mass to organic acids, to acetic acid and finally methane and CO₂. They include a fully two-phase flow model based on the van Genuchten and Mualem relationships and multi-species flow and transport in the aqueous and gaseous phases. The gas and liquid contents are linked to a changing porosity simulated in the mechanical model. The mechanical model assumes a linear elastic response for primary compression and includes additional settlement due to the loss of mass due to biodegradation.

For the simulation of hydraulic, thermal and biological behavior of anaerobic bioreactor landfills during the methanogenic phase, Gholamifard et al., (2008) developed a model

incorporating concepts from hydrodynamics and microbiology. The model was composed of a two-phase flow model of leachate and biogas migration based on Darcy's law. Their biological model was two-step, hydrolysis-methanogenesis model. The organic waste was defined as three fractions: rapidly, fairly and slowly biodegradable. First order kinetics-controlled hydrolysis and Monod kinetics was used to simulate methanogenesis. The heat generation rate α_q was obtained from the hydrolysis and methane production rates as:

$$\alpha_q = \beta \frac{H_{hyd}}{M_{VFA}} \cdot \frac{dA}{dt} + \frac{H_{meth}}{M_{meth}} \cdot \frac{\alpha_b}{2} \quad (19)$$

where H is the energy released per mole of VFA/methane produced and M is the molar mass of VFA/methane, $\frac{dA}{dt}$ is the rate of hydrolysis and α_b is the biogas production rate.

To understand the effect of landfill gas pressures and moisture content on the settlement in bioreactor landfills versus dry landfills, Hettiarachchi et al. (2009) developed a HBM model. The hydraulic model included Richards equation to simulate moisture migration. The biological model considered first-order decay of four degradable fractions: rapidly degradable, moderately degradable, slowly degradable and non-degradable. A mass balance approach was used to link the biodegradation rates to gas generation rates. Gas migration was based on Darcy's law and a relatively permeability of the gas phase as a function of moisture content. However, the model did not include capillary pressure and coupled two-phase flow. The model is unique in its simulation of settlement with time. Mechanical compression, $(\Delta Z)_m$, is a function of effective stress and in their formulation, an increase in gas pressure can cause a decrease in effective stress and a rebound in settlement. The change in height due to biodegradation $(\Delta Z)_b$ is a function of the first

order degradation of the different degradable fractions in the waste and an assumed density of each fraction.

For the analysis of solid-liquid-gas interactions in landfilled MSW, a bio-hydro-mechanical coupled model was established by Chen et al. (2012). Fluid flow was modelled using two-phase flow equations. Biodegradation was simulated as a first order reaction with the decay rate as a function of moisture content. A stoichiometric equation was used to determine gas generation rates based on the degradation rates. For the mechanical model, primary compression was simulated using Terzaghi's equation. Chen et al. (2012) argued that it is difficult to differentiate mechanical creep from biodegradation-induced strain and that if the conditions are suitable for biodegradation, that biodegradation-induced settlement plays a dominant role in the long-term time-dependent settlement. Therefore, they combined mechanical creep and biodegradation-induced strain into a single time-dependent settlement term assuming an exponential decline in settlement similar to the second term in Marques et al. (2003). The author would consider this a significant simplification of settlement as the long-term settlement is not linked to biodegradation rates or temperature.

To predict biodegradation-induced settlement, Liu et al. (2011) proposed a coupled mechanical-hydraulic-gaseous model. They developed an empirical biodegradation model based on an experimental program to determine the impacts of moisture content and temperature on the degradation rate. The biodegradation rate was defined as:

$$v(T) = (AT/B) \times e^{(-T/B)} \quad (20)$$

where T is temperature and A and B are fitting parameters which are a function of temperature and moisture content. They include two-phase gas and liquid flow for the

hydraulic model. Gibson and Lo (1961)'s rheological settlement model was adapted as the mechanical model. Biodegradation-induced settlement is linked to the biodegradation term in that the loss of organic matter corresponds to a loss in solids volume which leads to additional settlement, Δh .

Reddy et al. (2018) developed a 2D coupled mathematical model to simulate the hydro-bio-mechanical processes in MSW using the finite element model FLAC 8.0. The hydraulics model is based on a fully two-phase flow model. The biodegradation model was formulated using a first-order decay model using a similar approach to the USEPA's LandGEM model. The mechanical model is based on a plain strain formulation of Mohr-Coulomb constitutive model assuming Bishop's effective stress. A series of empirical relationships were developed to relate the degree of biodegradation to various geotechnical parameters including the waste's unit weight, saturated vertical hydraulic conductivity, cohesion coefficient, friction angle, bulk modulus and shear modulus.

One advantage of the model developed by Reddy et al. (2018) in FLAC is the model's ability to assess landfill slope stability and in-plain shear behavior of composite liner and final cover systems.

So far, there has been only two fully coupled models developed, one by Bente et al. (2017) and another by Hubert et al. (2016), which include thermal, hydraulic, mechanical and biochemical (THMB) processes for degradation induced settlements in MSW landfills.

The model developed by Hubert et al. (2016) incorporates the biodegradation, mechanical and hydraulic models of McDougall (2007) into a fully coupled thermo-hydro-mechanical model originally developed for an unsaturated porous medium. The thermal model simulates the conduction of heat in the waste and advection of heat due to leachate

migration. It does not include the heat flux due to gas migration as the hydraulic model is based on Richards equation and does not simulate gas flow. The thermal properties of the waste, i.e. specific heat and thermal conductivity, are calculated based on the volume-weighted components of the waste (water, gas, solid), which may be appropriate for the specific heat but is less appropriate for the thermal conductivity. Biodegradation acts as a heat source in the thermal model and it is unclear if the coupling includes the impacts of temperature on the biodegradation rate kinetics.

The coupled THMB model developed by Bente et al. (2017) combines the stress dependency of compaction rate with density dependence and the creep rate to the solid dry bulk density. A separate description of different settlement phenomena was enabled by including the concept of effective stress, which enabled the separation of pure consolidation from compaction induced by solid mass loss. The model has been validated against a waste lysimeter experiment to demonstrate the capability of the model in estimating long term settlements for periods of up to 30 years. However, this model has not been validated using field data from a landfill.

This re-enforces the fact that while several coupled models exist in the literature, limited field data exist to validate these models. Table 1 provides a summary of the components included in the coupled models discussed in this literature.

Table 1: Summary of processes considered in models discussed in this chapter

Reference	Biological	Mechanical	Hydraulic	Gas - Flow	Thermal
El Fadel (1997)	✓			✓	✓
McDougall (2007)	✓		✓	✓	
Gholamifard (2008)	✓		✓	✓	
Hetteriarchi et al. (2009)	✓	✓	✓	✓	
Lei et al. (2011)	✓			✓	✓
Liu et al. (2011)	✓	✓	✓	✓	
Chen et al. (2012)	✓	✓	✓		
White et al (2013)	✓	✓	✓	✓	✓
Hubert et al. (2016)	✓	✓	✓		✓
Bente et al. (2017)	✓	✓	✓	✓	✓
Reddy et al. (2018)	✓	✓	✓	✓	

2.6 Characteristics of Municipal Solid Waste

2.6.1. Density

The density of MSW at the Ste Sophie landfill was determined to be 930 kg/m³ (Bonany et al. 2013). The density of MSW changes as biodegradation and compaction occur and there is a general trend towards an increase in dry unit weight with an increase in depth. The variability in data is due to the heterogeneity in the waste. Table 2 lists the MSW densities which have been cited in literature.

Table 2: Cited MSW Densities in Literature

Value (kg/m³)	Reference	Remarks
305-1733	Konig & Jessberger, (1997)	For uncompacted or poorly compacted waste to compacted waste
305-2040	Zekkos et al. (2005)	In place, MSW unit weight reported at 37 different landfills
321, 642, 963	Lukas (1992)	Values for poor, good, and best compaction
352- 725	Faitli et al. (2015)	With k varying from 0.24 to 1.15 W/m. K, from a testing cell 1.8 x 1.8 x 0.8 m deep
458 -491	Ham and Brooker (1982)	Refuse density in test lysimeters constructed with ‘normal compactive effort’ (Blieker et al. 1995)
694-1653	Landva and Clark (1990)	Excavated surface pits and measured mass and volume, includes cover and absorbed moisture (Blieker et al. 1995)
750-1640	Reddy et al. (2017)	From top to bottom of a conventional landfill subjected to coupled HBM interactions, after a post-closure period of 50 years.
750-1670	Reddy et al. (2017)	From top to bottom of a bioreactor landfill subjected to coupled HBM interactions, with prolonged leachate injection time (15-16 years)
800-1080	Reddy et al. (2017)	Initial MSW density considered from top to bottom for model simulations
825-1125	Hettiarachchi et al. (2009)	The maximum value of wet density (1125) observed at the bottom after 25 years.
1019-1326	Kavazanjian et al. (1996)	Near the ground surface at six California landfills
1326-1632	Kavazanjian et al. (1996)	At a depth of 30 m at six California landfills
1122-1286	Oweis and Khera (1982)	The minimum and maximum value for old refuse

2.6.2 Thermal Conductivity

Thermal conductivity is the quantity of heat transmitted due to a unit temperature gradient per unit time under steady-state conditions, in a direction normal to the surface of the unit area (Perry and Green, 1997). As moisture content and density in a landfill increase with depth, thermal conductivity and specific heat also increase. At the base of the landfill, waste is assumed to have a higher density than near the top. Also, since water has a significantly higher thermal conductivity than air ($0.591 \text{ W/m}\cdot\text{K}$ and $0.024 \text{ W/m}\cdot\text{K}$ for water and air, respectively), the overall thermal conductivity at the base of the landfill is expected to be higher than at the top.

Table 3 highlights the values of thermal conductivity that have been used by various researchers to model heat transfer processes in landfills. Considering that thermal conductivity of MSW varies with waste composition, density and moisture content, values in literature have ranged from 0.01 to $1.15 \text{ W/m}\cdot\text{K}$.

Table 3: Summary of Thermal Conductivities cited in the literature

Value of Thermal Conductivity (W/m·K)	Reference	Remarks
0.01 to 0.7	Hanson et al. (2000)	Probe experiments in lab and field
Varied between 0.04 and 0.22, and used 0.1	Lefebvre et al. (2001)	Thermal probe for measurement. Values measured very sensitive to where the probe is placed
0.08 or 0.058	Rees, 1980	Same as sawdust
0.23	Hanson et al. (2006)	Simulate temperatures in a landfill in Alaska
0.24-1.15	Faitli et al. (2015)	Waste samples extracted from a testing cell Landfill in Hungary. For sample sizes ranging from 400 to 1450 kg
0.3 (top 1 m of waste) & 0.67 (underlying waste)	Megalla (2015)	For MSW placed in Ste Sophie, Quebec landfill
0.3 (top 1 m of waste) & varied with time and depth for underlying waste	Megalla et al. (2016)	For MSW placed in Ste Sophie, Quebec landfill
0.35 and 0.96	Yoshida and Rowe, (2003)	For unsaturated and saturated waste respectively to simulate T in a Tokyo landfill
0.4	Gholamifard et al. (2008)	Initially from Aran (2000)
0.6- 0.8	Gholamifard et al. (2008)	Increased it -site data from France or to simulate temperatures in a landfill in France
1	Neusinger et al. (2005)	--

2.6.3. Specific Heat Capacity

The specific heat capacity describes the ability of a given mass of a substance to store internal energy while undergoing a given temperature change, but without undergoing a phase transition (Lide, 2009).

The value of specific heat within a landfill depends on the composition, density and moisture content of waste and can be approximated based on the individual components found in MSW. Table 4 lists the values of specific heat used by various researchers in the literature. Considering that specific heat varies with waste composition, density, and moisture, values in literature have ranged from 600 to 3300 J/kg·K.

Table 4: Summary of specific heat capacities cited in literature

Value of Heat Capacity (J/kg·K)	Reference	Remarks
719	Yeşiller et al. (2005), Hanson et al. (2006)	Landfill in Alaska
900-2100	Faitli et al. (2014)	Landfill in Hungary
1000 to 1100	Gholamifard et al. (2008)	Based on Meima et al. (2007)
1330 (sawdust) to 2700	Rees, 1980	For dry waste, same as sawdust, using C_p of water
1900-3000	Lefebvre et al. (2001)	Extracted waste samples from a 10 m deep waste cell
1939 to 2363	Yoshida & Rowe (2003)	For unsaturated and saturated waste, to simulate temperatures in a Tokyo landfill
1999 to 3080	Faitli et al., (2015)	--
2100	Megalla et al. (2016)	-For Ste Sophie Landfill, Quebec,
2170-2200	Houi et al. (1997), Zanetti et al. (1997)	--
$\rho \cdot C = 0.6 \times 10^6 \pm 0.12$ which corresponds to an average value of 630 to 1000	Lefebvre et al. (2000)	In a density range of 600 to 950 kg/m ³ C = Specific heat capacity ρ = density
$\rho C = 0.8 \times 10^6$ to 10×10^6	Hanson et al. (2000)	Did not provide density values

2.6.4. Latent Heat of Phase Change

The latent heat of phase change is defined as the amount of heat absorbed or released by a substance when it undergoes a phase change i.e. it is the amount of energy that must be provided to transition to a new phase per unit mass of material. In terms of waste stabilization in landfills operating in Northern climates, latent heat is required to thaw the frozen liquid fraction of the waste. Hanson et al. (2006) used values of 1.7 and 32.1 kJ/kg as the latent heat of soil and waste respectively, to model temperature profiles at a landfill in Anchorage, Alaska. Bonany et al. (2013), Megalla et al. (2016) and Berquist (2017) used values of 41.75, 37.2 and 10 kJ/kg, respectively, for their simulations of the Ste. Sophie Landfill. The latent heat of phase change was determined by using a trial and error approach by comparing the modelled and measured field data in their research efforts. In their coupled model, Yesiller et al. (2008) used 95 and 56 kJ/kg for the latent heat of waste and 59 and 10 kJ/kg for the latent heat of soil for modelling temperatures of cover systems in MSW landfills in Michigan and Alaska, respectively.

Chapter 3: Ste Sophie Field Site instrumentation and Data Acquisition

3.1 Site Details

Ste Sophie landfill is located approximately 50 km North-West of Montreal, Quebec, Canada. This area experiences a northern climate typical to Canada, experiencing temperatures as low as -30 °C in winter, and as high as +30 °C in summer. This site is permitted to receive up to 1.0 million tonnes of waste each year, which includes MSW as well as industrial, construction and demolition waste, and institutional wastes as well as automotive wastes and contaminated soils. This landfill is equipped with horizontal gas collection wells but there is no leachate recirculation. Approximately half of the collected gas is sent to a nearby pulp and paper mill as an energy source, while the other half is flared.

3.2 Placement of Instrument Bundles

Waste Management (WM) began filling the south-east corner of Zone 4 (Figure 3) with MSW in late 2009 and Van Geel's research group began installing 12 instrument bundles in two vertical columns in this zone as the landfill was filled. The first bundles were placed in November 2009, with additional bundles being installed as the waste was progressively placed from January 2010 until mid-2012. The site features compaction, with an average waste density of 930 kg/m³ achieved. The landfill is designed to have a 30% side slope and a 2% top slope.

Figure 3: Aerial view of Zone 4 of Ste Sophie Landfill (North is vertical)

Figure 4 shows an aerial view of Zone 4 at the site and the approximate location of the two vertical profiles of the bundles and the instrument shed. Each instrument bundle consists of a total earth pressure cell, oxygen sensor, moisture, and electrical conductivity sensor, a settlement sensor and the lower 4 bundles also contain a vibrating wire piezometer to record any leachate mounding.

Figure 4 : Location of Instrument shed and Bundles at the Ste Sophie Landfill (Google Earth)

Each bundle also includes two ¼” (0.625 cm) tubes contained in a single protective sheath to allow for the collection of gas and/or leachate samples. They also allowed the research team to push air out to the bundles to verify that the oxygen sensors are working properly.

All the electrical cables from the sensors feed into a single junction box on the instrument bundle and connect to a single 24 pair cable (blue cable in Figure 5), which leads back to the instrument shed and data acquisition system.

The cables connecting the instrument bundles to the data acquisition system in the instrument shed vary from 110 to 130 m in length. The 24 pair cable, the double tubing referenced earlier and the double tubing for the settlement sensor are all contained in a corrugated 2 in. (5.08 cm) flexible plastic pipe for protection.

The bundles were installed just inside the area with 2% slope to minimize the lengths of cable and tubing between the bundles and the instrument shed; the cable and tubing accounted for 40% of the costs of the instrument bundles.

Each column consists of 6 instrument bundles. At the time of installation, each instrument bundle was covered in 30-40 cm of sand for protection of the instruments. Each instrument bundle is mounted on a 60 cm x 60 cm steel plate outfitted with the following components:

- Total Earth Pressure Cell – to measure total overburden earth pressure due to waste placed above the bundle. It also measures temperature.
- Oxygen Sensor – to measure the amount of oxygen present in the gas phase (% by volume). Also measures temperature.
- Moisture and electrical conductivity sensor – to measure the moisture content of the sand covering the instrument bundle which should reflect the surrounding waste and leachate. Also measures temperature.
- Liquid Settlement sensor – to measure the change in elevation of the bundle. Also measures temperature.
- Vibrating wire piezometer (bundles 1, 2, 3 and 4 only) – to measure leachate mounding. Also measures temperature.
- Two hollow plastic lines connected to the instrument shed – to draw out leachate or landfill gas, or to inject air into the landfill.

Figure 5: Instrument Bundle used at the Ste Sophie Landfill

The instrument bundles are connected to a Campbell Scientific CR100 FlexDAQ Datalogger which is housed in an instrument shed outside the landfill footprint. Instrument data is continuously recorded at a 30-minute interval and can be downloaded either by direct connection in the instrument shed or through a remote wireless connection. Data collection from the bundles began on November 9, 2009. The following table shows the date that each set of bundles began recording data.

Table 5: Date of data collection commencement for instrument bundles

Bundles	Date of Data Collection Commencement
1 and 2	November 9, 2009
3 and 4	January 16, 2010
5 and 6	December 13, 2010
7 and 8	January 28, 2011
9 and 10	August 23, 2011
11 and 12	March 14, 2012

The author was responsible for downloading and processing the data from Ste. Sophie for the past 2.5 years. The latest data was generally downloaded at the end of each month and appended to previous files.

3.3 Location of Instrument Bundles

Instrument bundles 1 and 2 were placed on top of the leachate collection system in November 2009 (Van Geel and Murray, 2015). The first waste lift was placed over the instrument bundles in January 2010. The first layer pushed onto the leachate collection system was 1-1.5 m thick and was left uncompacted. Each subsequent layer was 30-40 cm in thickness which is compacted with 4-5 passes of a sheepsfoot roller. The landfill operators initially placed half of the first waste lift allowing for the installation of bundles 3 and 4 at the center of the first waste lift. The second half of the waste lift was then placed immediately after bundles 3 and 4 were installed. Bundles 5 and 6 were installed approximately 0.5 m below the top of the first waste lift in June 2010. The second waste lift was placed in December 2010 and the third waste lift was placed in January 2011. Bundles 7 and 8 were installed approximately 0.5 m below the top of the third waste lift in February 2011.

The first three waste lifts representing approximately 13 m of compacted waste, were placed under freezing ambient conditions. The fourth waste lift was placed in August 2011 and bundles 9 and 10 were installed in September 2011. The first portion of the fifth waste lift was placed in March 2012 and bundles 11 and 12 installed on March 13, 2012. The remainder of the fifth waste lift was placed in April and May 2012 to bring the top of the waste profile close to its final permitted elevation. Figure 6 provides a schematic of the waste lifts and locations of the instrument bundles within those lifts.

Figure 6: Waste Lift Heights and Bundle Locations

Both bundles 11 and 12 are located 10-15 m closer to the centre of the landfill to avoid impacts of the side slope of the landfill. The thickness of all waste lifts was determined by Van Geel and Murray (2015) by determining the height of waste placed above the odd and even-numbered bundles. From the quarterly survey data for June 2012, knowing the elevations of bundles 11 and 12 in June 2012 and given the survey data, the depth of waste above bundles 11 and 12 was calculated to be 2.1 m and 3.7 m respectively.

An additional pressure increase was observed in the TEPC data in November 2013 and in early October 2014. Waste Management (WM) confirmed that the final cover was placed in summer/fall of 2014 and therefore the latter increase was assumed to be due to the construction of the final cover. The cover specifications from bottom to top for Ste.

Sophie are – 300 mm sand (1×10^{-2} cm/s), LLDPE liner (1.0 mm), 450 mm sand (1×10^{-3}

cm/s), Geotextile (8oz), 150 mm top soil (WM, 2019). The increase in November 2013 was assumed to be due to regrading related to the placement of waste in Zone 5 (Figure 3) and/or because WM had spread a layer of contaminated soil above part of Zone 4 extending north from Zone 5 (Figure 3).

To confirm the placement of the final cover, the quarterly surveys were requested from WSP. The surveys indicated an approximate 1m increase in elevation above both bundles 11 and 12 during the third quarter of 2014. For the November 2013 event, the even-numbered TEPCs and settlement plots responded more than the odd-numbered TEPC and settlement plots. Given the elevations in June 2012 after the placement of lift 5 and in 2014 prior to the placement of the final cover, it appeared that soil was added.

The depth of soil added was approximated to be 0.5 m above bundle 11 and 1.5 m above bundle 12. So, a pie-shaped lift 6 was assumed to consist of soil and a uniform lift 7 which is a 1m thick soil layer for the final cover. Between 2015 and December 2018, the LIDAR data indicated additional soil had been placed and the TEPCs indicated some small increases in pressure at different times which is believed to be a result of regrading. This additional material, which is estimated to be less than 1m of soil, has been ignored in the coupled model.

Therefore, lifts 6 and 7 have been added to the model as per the diagram with appropriate densities and thermal properties for the coupled model presented in this work.

For Figure 6 presented in this section and modelling results presented in this thesis, the locations of bundles 11 and 12 were projected on the 2D cross-section that contains bundles 1 through 10. In reality, bundles 11 and 12 were installed further into the landfill to avoid the slide slopes and as a result have a greater depth of waste above them in waste

lift 5 (2.1m and 3.7m as noted earlier) than they do in the projected 2D profile. It was also discovered that the use of the survey data, which was in relation to the locations of bundles 11 and 12, may not have correctly reflected the thickness of lift 5 above bundles 9 and 10. The survey data were revisited and an updated figure is presented in Appendix A. It is recommended that future modelling efforts reflect the geometry presented in the new figure.

3.4 Existing Field Data

3.4.1 Temperature Data

Temperature profiles for all 12 bundles and the ambient temperature along with the time of placement of waste lifts are shown in Figure 7. The temperature was measured by several sensors installed on each instrument bundle which include the moisture sensor, the settlement, oxygen sensors, and total earth pressure cells. The temperature measured by the oxygen sensor was on an average approximately 0.5 °C higher than the other sensors as the oxygen sensor has a small heater to prevent condensation on the sensor device.

The maximum difference between the lowest and highest temperature readings, excluding the oxygen sensor, never exceeded 0.5° C at any time during the study, reinforcing the reliability of the temperature data. The average measured temperatures are presented, and the averages include the temperatures measured from at least two sensors as during the study some sensors have failed.

Figure 7: Temperature profiles of Bundles 1-12 from October 2009 to December 2019

Temperature will impact settlement since the biodegradation of the waste is dependent on temperature. The first three waste lifts were all placed in December or January when the ambient temperatures were below 0 °C. Therefore, the center of waste lift 1 remained below zero for 12-18 months as indicated by temperatures measured at bundles 3 and 4. The roughly 4 m of waste placed above the bundles provided enough insulation to prevent any temperature changes in response to the summer ambient temperatures during the summer of 2010.

Bundles 5 and 6 were placed near the surface of the waste lift. Being placed 0.5 m below the top of waste lift 1, they followed ambient temperature closely, with a slight time lag, indicating positive temperatures between June and December 2010 but the temperatures decrease as the ambient temperatures decreased. As the second waste lift was placed in December 2010, when bundles 5 and 6 reported near 0 °C temperatures, bundles 5 and 6 became insulated from the atmosphere and remained at those temperatures.

Bundles 7 and 8 were placed at the top of lift 3 when ambient temperatures were below freezing. They measure increasing temperatures, following the ambient temperatures with a slight time lag, between January 2012 and August 2012 as they are placed in close proximity to the surface. They were then insulated from the atmosphere when the fourth waste lift was placed in August 2012 at approximately 20° C. As a result, the temperatures at bundles 7 and 8 gradually increased in response to heat generation in lift 4 located above them.

Bundles 9 and 10 were installed near the top of waste lift 4. The temperatures for both these bundles rose well above ambient temperatures. The high temperatures indicate that heat must be heat generated within the waste at or near the bundles.

Gas recovery and pumping in lift 4 may have created an inward gradient drawing air into the landfill. This could extend the aerobic zone into the landfill refuse and prevent the formation of methane in the waste near the surface (Christensen et al. 1989). Correlating the temperature rise with the oxygen data presented in Figure 8; it was observed that these high temperatures resulted from aerobic decomposition.

Figure 8: Oxygen concentration and corresponding temperatures measured at the bundles 9-12

(Megalla et al., 2016)

Because of the heat generation and insulation of the waste above, temperatures remained high even through the winter months. After the installation of lift 5 in March 2012, the oxygen source from the atmosphere was cut off and the temperatures dropped to 40° C over the course of the next few days.

Bundles 11 and 12 were placed in the 5th waste lift with bundle 11 located closer to the side slope of the landfill. As noted earlier from the TEPC data, there was evidence of regrading in the vicinity of bundle 11. It is anticipated that this regrading led to the low oxygen values observed at bundle 11 from August 2013- April 2014. The oxygen concentration measured at bundle 11 appears to be linked to a corresponding increase in temperature at bundle 11.

3.4.2 Settlement Data

The settlement sensors consist of a pressure transducer at the instrument bundle which is hydraulically connected to a reference pressure recorded by a pressure transducer in the instrument shed. The instrument shed is located outside the landfill footprint and hence should not experience any settlement. The transducer at the instrument bundle is connected to the transducer at the instrument shed using the dual tubing under a single protective sheath discussed in the previous section. The tubing is filled with 50% water – 50% glycol solution to prevent freezing. Therefore, the settlement is monitored via the pressure difference between the pressure at the instrument bundle and the reference pressure in the instrument shed.

At the time of placement, this value was recorded and reflected zero settlement. An increase in the differential pressure between the settlement sensor and the instrument shed pressure indicates settling of the instrument bundle. The pressure transducers are

vibrating wire pressure transducers, corrected for temperature and have an accuracy of <0.1% full scale, which is 170 kPa (17.2 m equivalent water head); 0.1% of full scale corresponds to approximately 1.7 cm of 50% water-glycol solution at 20° C.

Figure 9: Settlement Data by Elevation

The settlement data for bundles 1 through 12 from January 2010 through December 2019 are presented in Figure 9. The vertical bars indicate the time that the seven waste lifts were placed within the landfill in the area of the instrument bundles. It is clear from the data plotted in Figure 9 that each pair of instrument bundles within the two waste profiles followed similar settlement paths with time. Elevations at bundles 2, 3 and 6 are incorrect after September 2016 because of a leak in the tubing connecting the settlement gauge to the reference pressure, a device called an accumulator, in the instrument shed. There are four accumulators in the instrument shed and unfortunately a leak in one of the tubes impacts all the pressure readings connected to that accumulator. Bundles 2, 3 and 6 are connected to the same accumulator.

The settlement results from bundles 1 and 2 indicate the base of the landfill is settling with time. The consultant involved in the design of the landfill estimated the base of the landfill may settle over 1.0 meter due to the clay unit underlying the landfill. The impact of placing a new waste lift on the settlement of the lower waste lifts can be observed as the rate of settlement increases in response to the placement of a new waste lift.

The model is built using a fixed base constraint. For this reason, the settlement recorded at bundles 1 and 2 were subtracted from all the odd numbered and even numbered bundles respectively, to normalize the settlement dataset for comparison with model results. The normalized data are presented in Figures 10 and 11.

Figure 10: Settlement Data by Elevation (Odd Bundles) – Corrected for fixed base

Figure 11: Settlement Data by Elevation (Even Bundles) – Corrected for fixed base

Settlement data from bundles 1 and 2 (Figure 9) were incorrect after June 2018 and September 2016, respectively. Normalization of settlement data of upper bundles with respect to the base required elevation data of both bottom bundles 1 and 2 through the end of the simulation period (December 2019).

After observing the data closely, it was found that the settlement of bundles 1 and 2 was negligible after April 2015. The seasonal variation observed in settlement measurements, as discussed in McDonald (2018) was ignored and a constant elevation of the bottom bundles after this date was considered for subtraction from the elevation of upper bundles to extrapolate the data beyond these dates.

Chapter 4: Elaboration of the Coupled Thermal – Mechanical – Biological Numerical Model

4.1 Introduction and Objectives

The thermal, biological and mechanical processes occurring in a landfill are complex and inter-related. Figure 12 shows the links between the processes which were modelled as a part of this research. Hydraulic processes are not included in the model; only thermal, mechanical and biological processes are considered.

Figure 12: Framework of the TMB Coupled Model

Mechanical settlement increases density of the waste which in turn impacts the thermal parameters of MSW, thermal conductivity (k) and specific heat capacity (C), which increase as the density of the waste increases, hence influencing the temperature profile throughout the waste. Biological activity in the waste is dependent on temperature and generates heat which in turn impacts the temperature of the waste. The degree of biodegradation, which is a function of the amount of expended energy, influences the amount of biodegradation induced settlement, hence providing a biological-mechanical link.

The objective of the coupled TMB model is to solve the coupled thermal, biological and mechanical equations to simulate the temperatures and settlement of the waste and to better understand the impact and importance of different parameters and processes on these predictions.

4.2 Numerical Model setup in COMSOL Multiphysics

COMSOL Multiphysics version 5.4, a commercial finite element model, was used to develop the coupled model. The following sections outline the processes and equations used to develop the coupled TMB model used to simulate the temperatures and settlements at the Ste Sophie landfill over a 10-year period. Figure 13 provides a schematic representation of the conceptual framework of the coupled TMB model.

Figure 13: Detailed framework of the TMB Coupled Model

4.3 Mechanical Component

The Solid Mechanics Interface in COMSOL Multiphysics was used to define the constitutive behavior of MSW. The input parameters to describe the properties of the linear elastic material included relationships for Young's Modulus and Poisson's Ratio. Viscoelasticity subnode in the Solid Mechanics Interface was used to include viscous stress, and this subnode required relaxation time of the dashpot as an input. The specific viscoelastic model used in the computation was a single Kelvin – Voigt viscoelastic body which can be represented by a spring in parallel with a dashpot (Figure 14).

Figure 14: Kelvin – Voigt Viscoelastic Model

The stiffness of the spring in COMSOL is defined by the shear modulus, G (kPa) which is derived from Young's Modulus E (kPa), and Poisson's ratio ν , according to the following equation.

$$G = \frac{E}{2(1 + \nu)} \quad (21)$$

Young's modulus and Poisson's ratio were made stress/strain dependent to better match the recorded displacement data at Ste. Sophie landfill. Young's modulus for MSW is thought to behave similar to soils and should increase with depth and confining stress.

This is in agreement with large scale compression tests conducted by Beaven and Powrie (1995) and Singh and Fleming (2008) (Figure 15).

Figure 15: Young's modulus from large scale compression tests (Singh, M.K. 2008)

In the field, however, waste undergoes compaction under heavy machinery after placement as a part of regular landfill operations. This loading and unloading would leave a residual stiffness in the waste and thus a starting Young's modulus above zero. Because of insufficient data to implement a correct loading sequence, the initial compaction behavior is not present in the FEM model. Therefore, a starting value of Young's modulus was included by McDonald (2018) to account for the compaction of the waste in the field. To match the trend seen in Figure 15 with the equation below, a fitting parameter N was added, which is expected to have a value between zero and one.

$$E = E_{start} + M * P_{ATM} \left(\frac{\sigma_y}{P_{ATM}} \right)^N \quad (22)$$

where E_{start} is the predefined starting value of Young's Modulus (kPa); M, N are fitting parameters, P_{ATM} is the atmospheric pressure (kPa) and σ_y is the vertical stress (kPa).

Similarly, a modification was made to the Poisson's ratio of the elastic material.

McDonald (2018) used the findings of Ramaiah and Ramana (2017) (Figure 16), who used large scale triaxial tests to study the stress-strain volume change behavior of MSW.

Figure 16: Stress-Strain Volume change behavior of MSW (Ramaiah & Ramana, 2017)

To replicate this strain dependency in the FEM, Poisson's ratio was defined by the following equation –

$$\nu = 0.1 + A * \text{abs}(\varepsilon_{axial})^B \quad (23)$$

where A, B are fitting parameters and ε_{axial} is the axial strain in the material.

Equation 21 has a starting value of 0.1 for zero axial strain and two fitting parameters – A and B. McDonald (2018) postulated that the starting value could differ depending on the true fiber content, but 0.1 was considered a moderate compromise as it achieved a good fit. The fitting parameter B should be close to 1 to produce a linear fit.

The calculation for handling of strain in the KV body can be viewed in COMSOL with the formulas included in the viscoelasticity node. The stress in the viscoelastic response, σ_q (kPa) is calculated from the elastic strain rate $\dot{\epsilon}$ (s^{-1}) as:

$$\sigma_q = 2 \eta \dot{\epsilon} = 2G\tau \dot{\epsilon} \quad (24)$$

In Equation 22, η is the viscosity of the dashpot ($kPa \cdot s$) and the relaxation time of the dashpot, τ (s) relates viscosity η ($kPa \cdot s$) with shear modulus G (kPa) by:

$$\eta = G\tau \quad (25)$$

The relaxation time of the dashpot and the type of Material Model (KV Body) are the only two inputs which the Viscoelasticity subnode requires to model the viscous response of the solid. The other parameters, E , ν and density are defined as the linear elastic material properties in the Solid Mechanics Interface. The density was input as 930 kg/m^3 .

4.3.1. Biodegradation Induced Strain and Biological – Mechanical Link

Marques et al. (2003) proposed an exponential relationship for biodegradation induced strain similar to Park and Lee (1997). The expression assumed biodegradation-induced settlement starts immediately after the waste is placed and is not temperature dependent. Temperature data from Ste. Sophie indicated that waste placed during the winter months, it could take months or years before the MSW temperature approaches ideal levels for anaerobic biodegradation.

Berquist (2017) in their thermal model simulated the temperature changes and expended energy or heat due to anaerobic biodegradation using a model proposed by Hanson et al. (2013). Berquist's model tracked the energy expended with time for waste in the landfill. The biodegradation induced settlement with time was a function of the expended energy

relative to the total expended energy, i.e. if 50% of the energy has been expended, then 50% of the biodegradation induced settlement has occurred. The simulation expressed as a fraction of expended energy over the total expended energy with time as shown in Figure 2. The ratio of expended energy to total expended energy was directly applied to the settlement model by changing the Marques et al (2003) time-dependent biodegradation induced settlement term into temperature-dependent biodegradation-induced settlement term as follows-

$$\varepsilon_B = E_{DG} \left(\frac{\text{Expended Energy}}{\text{Total Expended Energy}} \right) \quad (26)$$

where E_{DG} is the total amount of strain that can occur due to biological decomposition which was set as 0.3218 based on the work of McDonald (2018).

An external strain subnode was added to the Solid Mechanics Interface to provide this additional strain contribution to the mechanical model. In Equation 24, Total Expended Energy is a fixed value based on waste composition, which was set as 104 MJ based on the work of Hanson et al. (2013). The numerator, Expended Energy varies with time and is calculated in the Heat Transfer Interface and tracked in the Solid Mechanics Interface to calculate the total biodegradation induced strain.

Therefore, the total strain is a combination of the viscoelastic strain in the KV body, and the biodegradation-induced strain as a function of the energy expended by the waste (Figure 17).

Figure 17: Mechanical Component of the Coupled Model

4.3.2. Initial Model Parameters

For the long-term behavior of settlement of MSW, McDonald (2018) optimized all mechanical model parameters using settlement data of bundles 3 and 4 (B3, B4) and the resulting parameter set (Table 6) provided good agreement with the field data. These parameters were used as initial model parameters and were later optimized as a part of this study.

Table 6: Optimized Viscoelastic Model Parameters from McDonald (2018)

Parameter	Value
E_{DG} – Maximum biodegradation induced strain	0.32180
E_{start} – Starting Young's Modulus	1.2771E5 [Pa]
M – Young's modulus fitting parameter	1.4221
N - Young's modulus fitting parameter	0.62977
A – Poisson's ratio fitting parameter	0.88887
B - Poisson's ratio fitting parameter	0.93642
τ - Relaxation Time of the dashpot	1.4283E7 [s]

4.4 Thermal Component

Heat Transfer in Solids Interface in COMSOL Multiphysics was used to model the thermal component. Figure 18 depicts the heat transfer processes ongoing in and around the landfill which were modelled as a part of the thermal component of the coupled model.

Figure 18: Conceptual Model of the Thermal Component

At the surface, incoming solar radiation, convection with the surrounding air and outgoing longwave radiation control the surface heat flux. Within the landfill, heat can be generated under aerobic and anaerobic conditions and heat transfer within the landfill is governed by conduction through the waste.

4.4.1 Thermal Properties of MSW

4.4.1.1 Thermal Conductivity

The thermal conductivity of waste was varied as a function of density which was calculated in the mechanical interface, hence providing a thermal-mechanical link in the coupled model. The value of thermal conductivity was varied from 0.3 to 1.5 W/m·K as the density increased from 930 kg/m³ to 1700 kg/m³ in the form of the following equation:

$$k = 0.3 + \left(\frac{\rho - 930}{1700 - 930} \right) (1.5 - 0.3) \quad (27)$$

which gives:

$$k = (0.0016 * \rho - 1.1494) \text{ W} / \text{m} \cdot \text{K} \quad (28)$$

The values of thermal conductivity reflect the range of values found in the literature and are similar to the values use by Berquist (2017). The range in densities were taken from the simulation results of McDonald (2018).

4.4.1.2 Specific Heat Capacity

Like thermal conductivity, the specific heat capacity increases with increasing moisture content and density. Therefore, the specific heat capacity of waste was varied as a function of density. The value of specific heat capacity reflects the range of values found in the literature and are similar to the values used by Berquist (2017). The values were linearly varied from 1700 to 3000 J/kg·K over a density range of 930 to 1700 kg/m³. This results in the following equation:

$$C = 1700 + \left(\frac{\rho - 930}{1700 - 930} \right) (3000 - 1700) \quad (29)$$

which gives:

$$C = (1.6883 * \rho + 129.87) \text{ J/ kg} \cdot \text{K} \quad (30)$$

4.4.1.3. Latent Heat of Phase Change

Bonany (2012) estimated the latent heat of partially frozen waste in the Ste Sophie landfill by assuming that approximately one-eighth of the total waste volume was frozen water. Bonany et al. (2013b) used a final value of 38.2 kJ/kg for the latent heat of waste. Megalla (2015) used a similar method as that of Bonany et al. (2012, 2013b) and used a final value of 37.2 kJ/kg. The following formulation was used for the latent heat of phase change:

$$C_p = \begin{cases} C_s & T < 271.55K \\ \frac{L}{\Delta T} & 271.55K < T < 272.55K \\ C_l & 272.55 K < T \end{cases} \quad (31)$$

where C_s is the specific heat for frozen waste, C_l is the specific heat for non-frozen waste. When T ranges from 271.55 K to 272.55 K, the specific heat capacity of waste C_p is dependent on the latent heat L required to change the state of water or moisture from solid to liquid state or liquid to solid-state. Berquist (2017) used a value of 10 kJ/kg. The same formulation was used in the coupled model and the value was optimized along with other parameters affecting temperatures, to get a reliable estimate for latent heat values for waste placed in the Ste Sophie landfill.

4.4.2 Conduction from Underlying Soil

At the base of the landfill heat can be transferred from the underlying soil to the landfill or from the landfill to the underlying soil. Bundle 1 is located at the base of the landfill just above the leachate collection system. A linear piecewise function was fit to the temperature data collected from bundle 1 and used to prescribe the bottom boundary condition for the thermal interface (Appendix B).

4.4.3 Surface Heat Flux

The net heat flux at the surface of the landfill is a function of the incoming solar radiation, the outgoing long wave radiation and the convection at the surface which can be represented as –

$$Q_{surface} = q_{solar\ radiation} + q_{convection} + q_{longwave\ radiation} \quad (32)$$

$$q_{solar\ radiation} = \epsilon Q_o \quad (33)$$

$$q_{convection} = h(T_{amb} - T_s) \quad (34)$$

$$q_{longwave\ radiation} = \epsilon \sigma (T_{amb}^4 - T_s^4) \quad (35)$$

where ϵ is the surface emissivity, Q_o is the net shortwave solar radiation, h is the convection coefficient, T_{amb} is the ambient temperature, T_s is the temperature of the surface of the waste and σ is the Stefan Boltzmann constant for black body radiation. The surface emissivity describes the amount of thermal radiation which can be emitted from an object. Its value can be between zero and one. Zero represents a perfect reflector of radiation and one indicates a perfect emitter of radiation. Both the type of material and the nature of the surface affect the emissivity of an object and affect the surface emissivity of waste. For this model, a value of 0.9 was selected (Megalla, 2015). The temperature, wind velocity and solar radiation data were obtained from Montreal - Mirabel International airport weather station which is located about 20 km southwest of the Ste Sophie landfill. A polynomial piecewise function was fit to the temperature data in order to specify the ambient temperature in the model. The convection coefficient h was estimated using the wind velocity and the equation proposed by Watmuff et al., (1977).

$$h = 2.3 + 3v \quad (36)$$

where v is the surface wind speed (m/s).

Details of the ambient temperature, and solar radiation data are provided in Appendix B. According to weather data at Montreal-Mirabel International Airport, the windier part of the year at that location lasts for 4.9 months, from December to May 3, with average wind speeds of more than 7.6 miles per hour (3.39 m/s) and the calmer time of the year

lasts for 7.1 months, from May 3 to December 5 with an average hourly wind speed of 6.0 miles per hour (2.68 m/s) (WeatherSpark, 2020). A polynomial function was fit to the wind velocity data, and used for calculations on the top of first waste lift, and after that, for the remaining waste lifts, an average wind velocity of 3 m/s was considered for all calculations.

4.5 Biological Component

4.5.1. Aerobic Heat Generation

Previous heat transfer models (e.g. Megalla et al.,2016; Berquist, 2018) were 1D and therefore aerobic heat generation was only modelled for the top of lifts 4 and 5 at the location of the odd bundles and based on the oxygen concentration measured at those bundles. By observing oxygen data obtained from the site it was confirmed that oxygen was measured at locations of bundles 9,10, 11 and 12 with all of them recording different concentrations. Aerobic heat generation was modelled at top 1 m of waste lifts 4 and 5 using the following equation:

$$Q_{aer} = m [O_2] \quad (37)$$

where m is the rate constant and $[O_2]$ corresponds to a polynomial equation fit to the oxygen concentrations measured at bundles 9, 10, 11 and 12. Details of these polynomial equations are provided in Section 4.7.3. and Appendix C. Different values for m were used at bundles 9 through 12 as the type and thickness of cover materials varied.

Therefore, different rate factors m_1 , m_2 , m_3 and m_4 were used at bundles 9, 10, 11 and 12, respectively.

The values of these aerobic rate factors were estimated during model calibration and were later optimized along with other thermal parameters.

4.5.2. Anaerobic Heat Generation

The exponential growth and decay function to model anaerobic heat generation in MSW landfills developed by Hanson et al. (2008) (Figure 18), has been used to model anaerobic heat generation in this model. The constants A , B_t , C_t , and D control the peak value, the shape of the peak and rate of decay.

$$Q_{Hanson} = A \left(\frac{t}{B_t + t} \right) \left(\frac{C_t}{C_t + t} \right) e^{-\sqrt{\frac{t}{D}}} \quad (38)$$

where H is the heat generation rate (W/m^3), t is the time (day), A is the peak heat generation rate factor (W/m^3), B_t , C_t are shape factors (day) and D is the decay rate factor (day).

Figure 19: Exponential growth and decay function Q_{Hanson} (Hanson et al. 2008)

Hanson et al. (2013) then expressed the heat generation rate as a function of the expended energy. By integrating this function over time, they obtained a plot of heat generation as a function of expended energy (Figure 19).

Figure 20: Heat generation as a function of expended energy proposed by Hanson et al. (2013) ($Q_{\text{Hanson_Scaled}}$) and 6th order polynomial applied by Megalla et al. (2016).

To simplify its implementation in COMSOL Multiphysics, Megalla et al. (2016) fit a 6th order polynomial to this heat generation vs expended energy curve ($Q_{\text{Hanson_Scaled}}$) (Figure 20).

$$\begin{aligned}
 Q = & -1.53 \times 10^{-10}E6 + 5.549 \times 10^{-8}E5 - 7.878 \times 10^{-6}E4 \quad (39) \\
 & + 5.513 \times 10^{-4}E3 - 1.948 \times 10^{-2}E2 \\
 & + 0.2940E + 0.1
 \end{aligned}$$

The same approach for modelling heat generation as a function of expended energy has been used in the coupled model. Instead of using a 6-degree polynomial, a look up table was set up based on values calculated by integrating Hanson's equation (Equation 39).

The look up table will be referred to as $Q_{\text{Hanson_Scaled}}$ in the equations that follow.

The heat generation rates are a function of temperature as illustrated in Figure 21.

Figure 21: Gas and Heat Generation Curves for two temperatures as a function of time (left) and Heat Generation curves at two temperatures as a function of expended energy (right)

Hanson proposed a dual-ramped heat generation function as shown in Figure 22. To incorporate this function into COMSOL Multiphysics, (Megalla, 2015) fit a parabolic relationship to the linear ramp function with a maximum scaling factor occurring at 40° C and no heat generation below 0° C or above 80 ° C (Figure 22).

$$\begin{array}{ll} 0 & T < 0^{\circ}\text{C} \\ -6.62 \times 10^{-4} T^2 + 4.15 \times 10^{-1} T - 63.95 & 0^{\circ}\text{C} < T < 80^{\circ}\text{C} \\ 0 & T > 80^{\circ}\text{C} \end{array} \quad (40)$$

Figure 22: Dual-ramped anaerobic heat generation function used by Hanson et al. (2013) and Quadratic fit used by Megalla et al. (2016).

Megalla et al. (2016) multiplied the quadratic dual ramped-heat generation function (Equation 40) by the temperature function with the heat generation rate equation as a function of expended energy (Equation 39) to obtain a 3D Heat generation plot dependent on waste age and temperature. Figure 23 shows the final function used by Megalla et al. (2016) to model the anaerobic heat generation in the St Sophie landfill.

Figure 23: 3D function used by Megalla et al. (2016) to model the anaerobic heat generation at Ste. Sophie landfill.

For this study, the dual-ramped function of Hanson et al. (2013) was used (Figure 22). The Dual Ramped Function (DRF) was set up in COMSOL Multiphysics as a step function. To improve the model fit, Berquist (2017) added an anaerobic heat generation adjustment factor, H to allow the user to adjust the peak heat generation rate in the model. Berquist (2017) adjusted the value of H using a trial and error approach to minimize the sum of squared differences between modelled and measured temperatures. The same approach: i.e. the use of an anaerobic heat generation adjustment factor, H , has been used in the coupled model. Therefore, anaerobic heat generation (Q_{anaer}) can be expressed as:

$$Q_{anaer} = H * Q_{Hanson_Scaled} * DRF \quad (41)$$

The Expended Energy is tracked with time in the model and can be represented by the following equation:

$$\text{Expended Energy} = \int_0^t Q_{anaer} \quad (42)$$

The governing equation for the thermal model then becomes:

$$\nabla(k\nabla T) + Q_{surface} + Q_{aer} + Q_{anaer} = \rho C \frac{dT}{dt} \quad (43)$$

4.6 Model Geometry

The coupled model is built in 2D to model both the heat transfer and mechanical behavior of the landfill. A 2D model geometry used by McDonald (2018) was modified to replicate a cross-section of the Ste Sophie landfill (Figure 6). The model shows 5 waste lifts; the 6th pie-shaped lift consists of soil and lift 7 is a 1 m thick soil layer for the final cover.

Data probes are defined in the model at the estimated initial heights of the instrument bundles. These probes track temperature, settlement, heat generation and expended energy at the instrument bundle location with time. These probes were used to output the results of the model and compare them with the data obtained from the instrument bundles in the field. The model geometry and probe locations are illustrated in Figure 24. Table 7 shows the elevations of the instrument bundles in the waste profile.

Table 7: Elevation of instrument bundles

Bundle	Elevation (m)	Bundle	Elevation (m)
1	72.5	2	72.5
3	75.684	4	75.684
5	78.297	6	78.212
7	86.114	8	86.387
9	90.326	10	90.275
11	95.783	12	95.733

Figure 24: FEM Model geometry with probes

The size of the mesh was prescribed ‘fine’ in COMSOL, which resulted in a maximum element size of 1.95 m and a minimum element size of 0.011 m. A boundary layer mesh was added at the interface of each domain and is discussed in the following section.

4.6.1. Boundary Conditions and Initial Conditions

For the mechanical model, the lower boundary of the model is fixed for all displacements, the top boundary is free to displace, and the side boundaries are subjected to vertical displacement only. The initial density of the waste was 930 kg/m³.

As noted earlier Berquist (2017) simulated the first seven years of data at Ste. Sophie using 7 different simulation periods, each one representing the addition of a waste lift, which made it impossible to optimize parameters over the entire 7 year period as at the onset of each simulation period, the results from the previous simulation were used as initial conditions for the new simulation period.

McDonald (2018) in the development of his geomechanics model, devised a unique method to include all the lifts from the beginning of the simulation and hence could optimize the settlement parameters over the entire 7-year period. To do this, gravity was initially set to zero for all the lifts. Then as a waste lift was placed, the gravity term within that lift was increased from 0 to 9.806m/s^2 over a two-week period to simulate the placement of the waste lift in the field.

To implement a similar approach for the thermal interface was challenging given that the heat flux boundary conditions at the top of each layer had to be present even when the waste lift was inactive. Initially technical support at COMSOL indicated that to set up the boundary conditions needed for the landfill, the Thermal Module from COMSOL was needed and even with this module, they were not sure it would work properly. After reviewing some on-line cases studies and further discussion with technical support, it was recommended to include a boundary layer mesh at the interface and to assign very low values of k ($10^{-5} \text{ W/m}\cdot\text{K}$) and high values of C ($10^5 \text{ J/kg}\cdot\text{K}$) in the inactive layers. The surface flux boundary due to short and long wave radiation and convection, could then be implemented as a source/sink just below the boundary layer. This allowed the model to simulate the entire 10 years of data as one simulation and allowed for the optimization of

the desired parameters (e.g. peak heat generation rate) over the entire simulation. The resulting mesh can be seen in the Figure 25.

Figure 25: FEM Model Mesh

The bottom boundary was set up as a prescribed temperature boundary with a linear piecewise function fit to the temperature measured at bundle 1 which lies at the bottom of the waste profile. The side boundaries were defined as zero heat flux boundaries. The initial temperatures for each lift were set to the initial temperatures at placement (Table 8).

Table 8: Composition, Date of Placement, and Initial Temperature of Lifts

Lift	Composition	Date of Placement	Day	Initial Temperature (°C)
1	MSW	January 2, 2010	1	-1.70
2	MSW	December 15, 2010	341	-1.80
3	MSW	January 14, 2011	371	-3.00
4	MSW	August 12, 2011	577	25.0
5	MSW	May 4, 2012	807	25.2
6	Soil Cover	November 11, 2013	1332	12
7	Soil Cover	September 23, 2014	1627	17

The thermal properties of MSW used in the model have been listed in Table 9.

Table 9: Material input parameters considered for the Thermal Interface

Parameter	Value
Density of waste at placement	930 kg/m ³
Thermal conductivity of MSW	Function varying with density - Varied from 0.3 to 1.5 W/(m·K)
Specific Heat Capacity of MSW	Function varying with density - Varied from 1700 to 3000 J/(kg·K)
Latent Heat of Phase Change	37200 J/kg
Density of Soil Cover	1800 kg/m ³
Thermal conductivity of Soil	1.5 W/(m·K)
Specific Heat Capacity of soil	1200 J/(kg·K)

4.7. Summary of Equations used in the Model

The following section provides a summary of TMB model equations set up in COMSOL Multiphysics.

4.7. 1. Mechanical Model

The input parameters needed to define the Viscoelastic model in COMSOL Multiphysics are E (kPa), ν and τ (s). E and ν are calculated using the equations that follow and τ is an input parameter. E_{start} and τ are optimized and P_{ATM} , M , N , A and B are initially set to the values from McDonald (2018). σ_y (kPa) and ε_{axial} are calculated in the geomechanics model; as is the waste density, ρ (kg/m³), due to settlement.

$$E = E_{start} + M * P_{ATM} \left(\frac{\sigma_y}{P_{ATM}} \right)^N \quad (44)$$

$$\nu = 0.1 + A * \text{abs}(\varepsilon_{axial})^B \quad (45)$$

The biodegradation-induced strain is calculated using:

$$\varepsilon_B = E_{DG} \left(\frac{\text{Expended Energy}}{104 [MJ]} \right) \quad (46)$$

where E_{DG} , or the maximum biodegradation-induced strain, is optimized and Expended Energy with time is calculated in the thermal model.

4.7.2. Thermal Model

The governing equation for the thermal model is:

$$\nabla(k\nabla T) + Q_{surface} + Q_{aer} + Q_{anaer} = \rho C \frac{dT}{dt} \quad (47)$$

where $Q_{surface}$ is the sum of q_{solar} radiation, $q_{convection}$ and $q_{longwave}$ radiation which are calculated using the following equations:

$$q_{solar \text{ radiation}} = \epsilon Q_o \quad (48)$$

$$q_{convection} = h(T_{amb} - T_s) \quad (49)$$

$$q_{longwave \text{ radiation}} = \epsilon \sigma (T_{amb}^4 - T_s^4) \quad (50)$$

where ϵ , Q_o , h , T_{amb} , and σ are input parameters or functions and T_s , which is the surface temperature, is solved by the thermal model.

Thermal conductivity, k , and specific heat, C , are a function of density, ρ , which is calculated in the mechanical model. The relationships used for k (W/m·K) and C (J/kg·K) follow:

$$k = 0.3 + \left(\frac{\rho - 930}{1700 - 930} \right) (1.5 - 0.3) \text{ W/m}\cdot\text{K} \quad (51)$$

$$C = 1700 + \left(\frac{\rho - 930}{1700 - 930} \right) (3000 - 1700) \text{ J/kg}\cdot\text{K} \quad (52)$$

Q_{aer} and Q_{anaer} are calculated in the biological model.

4.7.3. Biological Model

Aerobic heat generation at the top of waste lifts 4 and 5 when oxygen is recorded at bundles 9 and 10 and bundles 11 and 12, respectively, are given by:

$$Q_{aer} = m1 [O_2] \text{ at bundle 9} \quad (53)$$

$$Q_{aer} = m2 [O_2] \text{ at bundle 10} \quad (54)$$

$$Q_{aer} = m3 [O_2] \text{ at bundle 11} \quad (55)$$

$$Q_{aer} = m4 [O_2] \text{ at bundle 12} \quad (56)$$

where the oxygen concentration, $[O_2]$ at bundles 9, 10, 11 and 12 are input as time-dependent functions and $m1$, $m2$, $m3$ and $m4$ are optimized.

Anaerobic heat generation is modelled using:

$$Q_{anaer} = H * Q_{Hanson_Scaled} * DRF \quad (57)$$

where H is the anaerobic heat generation adjustment factor, which is optimized in the model. Q_{Hanson_Scaled} is Hanson's heat generation model and DRF is Hanson's dual ramp function; both are fixed and input into the model. The model also calculates the expended energy with time using:

$$Expended\ Energy = \int_0^t Q_{anaer} \quad (58)$$

The Expended Energy is used in the biodegradation-induced settlement term of the mechanical model.

The coupled TMB numerical model was set up to run in a single simulation for the analysis of both temperature and settlement of all waste lifts. The model tracks temperature, expended energy, heat generation and other properties for each mesh element over the entire domain.

COMSOL Multiphysics, in most cases, uses an adaptive time-stepping scheme to solve time-dependent problems, which means that the software automatically adjusts the timestep size to maintain the desired Relative Tolerance. In addition, the software automatically determines a set of solver settings which are reasonable for the combination of physics involved, but these can be modified. For this model, the step-size entry which controls the times at which the data are output was selected as 1 day.

Chapter 5: Model Simulation and Optimization Results

To establish an initial model simulation, the thermal parameters from Berquist (2017) and settlement parameters from McDonald (2018) were used. The model results were similar to the temperatures simulated by Berquist (2017) and the settlements simulated by McDonald (2018) but not the same as several improvements were made to the model and the model is now fully coupled. Model improvements included corrections to the boundary conditions, probe locations, the addition of lifts 6 and 7 as soil layers and other smaller changes. Berquist (2017) manually adjusted the thermal properties for each simulation, whereas the fully coupled model has the thermal properties as a function of density, which is calculated in the mechanical model. In addition, the biodegradation-induced settlement in the mechanical model is directly linked to the temperatures and expended energy simulated in the thermal model. This model, with the parameters from Berquist (2017) and McDonald (2018), was used as the initial conditions for the optimization simulation. The sections that follow provide the results from the optimization study. Chapter 6, which follows, outlines the results of the sensitivity study.

5.1 Optimization of Thermal and Mechanical Model Parameters

The Optimization module and Optimization study step in COMSOL Multiphysics can be used to formulate an inverse problem to determine the values of a set of parameters that provide simulated data which best matches the field data. The objective function for the optimization study was to minimize the squared differences between the simulated and field temperature and settlement data. The field data used in the optimization study included the temperature data of bundles 3 to 12 (Figure 7) and the settlement data from bundles 3 to 12 (Figures 10 & 11). Table 10 lists the parameters optimized in this study.

Table 10: List of Optimized Parameters

Parameter	Description
H	Anaerobic heat generation adjustment factor
L	Latent heat of phase change
m1, m2, m3, m4	Rate constants for aerobic heat generation
E _{DG}	Maximum biodegradation induced strain
τ	Relaxation time of dashpot
E _{start}	Starting Young's Modulus

The first step was to optimize the thermal parameters (anaerobic heat generation adjustment factor (H) , latent heat of phase change (L) and the aerobic rate constants (m1, m2, m3, m4)) and the mechanical parameters (maximum biodegradation induced strain (E_{DG}), relaxation time of the dashpot (τ) and E_{start} (starting Young's modulus)) together.

Figure 26 and 27 present results of optimized temperatures at odd and even bundles using both temperature and settlement data. Model predictions with respect to actual bundle temperatures are not in good agreement. Even though the temperatures at lower bundles 3, 4 and 6 match very well with the field data, the temperatures at all upper bundles are underpredicted. It is not clear why the model converged to an optimized value for H of 0.4. Megalla et al. (2016) used the Hanson's model as is (i.e. H=1.0) and found this provided a good fit in their efforts to calibrate the model. Berquist (2017) found a value of H = 0.5 to provide reasonable fit.

One reason Berquist (2017) arrived at a lower value than Megalla et al. (2015) is they had more field data (7 years versus 4.6 years) and a higher value of H predicted that the bundles would reach their maximum temperatures before the maximum temperatures were observed in the field.

However, that still does not explain why the optimized model underestimated the temperature at most locations and one would expect an increase in H would provide a better fit to all the data (i.e. underestimate some and overestimate others). The COMSOL optimization module is discussed further after the presentation of the settlement results.

Figure 26: Results of Optimized Temperatures at odd bundles : Using Temperature and Settlement data, Optimized $H = 0.4$, Optimized $L = 40556 \text{ J/kg}$

Figure 27: Results of Optimized Temperatures at Even Bundles : Using Temperature and Settlement data, Optimized Parameters: $H = 0.4$, $L = 40556 \text{ J/kg}$

Figures 28 and 29 present the modelled settlement vs the settlement data from the field settlement sensors. The modelled settlement behavior is similar to that observed in the field. The field settlements have been corrected for the fixed base by subtracting the settlement of bundles 1 and 2 from the elevation of odd and even numbered bundles, respectively.

Figure 28: Results of Simulated Settlement at Odd bundles : Using Temperature and Settlement data, Optimized Parameters : $E_{start} = 137616$ Pa, $\tau = 14460318$, $E_{DG} = 0.3013$

Figure 29: Results of Simulated Settlement at Even Bundles : Using Temperature and Settlement data, Optimized Parameters : $E_{start} = 137616$ Pa, $\tau = 14460318$, $E_{DG} = 0.3013$

The coupled model yields good predictions for both short-term and long-term settlement behavior for the optimized run. Sharp increases in the rate of settlement at each bundle can be observed because of the placement of subsequent waste lifts due to primary compression. The rate for settlement provided by the viscoelastic component allows a smooth transition between the instantaneous settlement as well as the long-term time-dependent settlement behavior of waste. The resulting fit of the lower bundles 3,5,7 and 4,6,8 is best among the optimization results but the settlement of the upper bundles is overpredicted with the difference in the simulated and field data increasing with bundle height.

The fact that the settlement dataset provided a better fit to field data than the temperature dataset, indicates that the objective function to minimize squared differences of settlement prediction was dominating over the objective function to minimize temperatures at the bundle locations. To probe into the reason for this occurrence, similar studies for multi-objective optimization in COMSOL were studied (Zheng et al. 2015). It was found that when several types of measurements are considered in the optimization problem concurrently, the objective function can be described as a multi-objective optimization function of the form:

$$\text{minimize } F(X) = \text{minimize } (f_1(X), f_2(X), \dots, f_n(X)) \quad (59)$$

where $F(X)$ is the vector of the objective functions and $f_m(X)$, $m = 1, 2, \dots, M$ is the m th objective function (Deb, 2001). For example, $f_1(X)$, $f_2(X)$, $f_3(X)$ and $f_4(X)$ can be the squared difference between modelled and measured values of temperature at bundle 3, temperature at bundle 5, settlement at bundle 3, settlement at bundle 5, and so on.

X is the vector of the model parameters adjusted during the optimization (Table 11), $X = \{x_1, x_2, \dots, x_n\}$. The objective functions of a multi-objective optimization are a part of a multidimensional objective space. Different objective functions often conflict with each other and the possibility of satisfying all the goals at the same time is very low.

Therefore, a set of Pareto optimal solutions is yielded by the multi-objective optimization (Pareto 1897, Cohon 1978, Deb 2001). The Pareto optimal solutions are defined as –

$$\forall k \in [1, m] \quad f_k(X^{(i)}) \leq f_k(X^{(j)}) \quad (60)$$

$$\exists k \in [1, m] \quad f_k(X^{(i)}) < f_k(X^{(j)}) \quad (61)$$

This formulation implies that the solution $X^{(i)}$ is no worse than $X^{(j)}$ in all objectives and $X^{(i)}$ is strictly better than $X^{(j)}$ in at least one objective. Then the solution $X^{(i)}$ is said to dominate $X^{(j)}$. A solution is said to be Pareto optimal if it is not dominated by any other solution in the solution space (Zheng et al. 2015).

To explain this, looking at the results we can observe that a lower $H = 0.4$ provided a strictly better result for the temperatures at lower bundles and hence was the dominant solution. Also, regarding the settlement results, an $E_{DG} = 0.3013$ was a better fit for the lowermost bundles, and hence it dominated the solution in the optimization study.

The temperature and settlement objectives themselves are found to be conflicting with each other. To resolve this issue, it was proposed that the model be optimized for temperature parameters and settlement parameters separately. The optimization framework hereafter adopted, has been described in Figure 30.

Figure 30: Model Optimization Framework

5.2 Thermal Parameters Optimized using Temperature Data Only

Optimizing thermal parameters H , L and the aerobic rate constants (m_1 , m_2 , m_3 , m_4) yielded results of $H = 0.691$ and $L = 39372$ J/kg. Comparing the results in Figures 31 and 32 with the temperature results from section 5.1, it can be observed that the modelled results improved significantly. The fit for temperatures at the lowermost bundles is not as good as it was in the previous simulation, but overall, the sum of squared differences for these results were reduced by 39.9%. These optimized parameters were further used to optimize the mechanical parameters in the next step.

Figure 31: Optimized Temperatures using Temperature data only – Odd Bundles: Using Temperature data only, Optimized Parameters: $H = 0.691$, $L = 39372$ J/kg

Figure 32: Optimized Temperatures using Temperature data only – Even Bundles: Using Temperature data only, Optimized Paramters: $H = 0.691$, $L = 39372$ J/kg

5.3 Settlement Parameters Optimized using Optimized Temperature Parameters

When settlement parameters E_{DG} , E_{start} and τ were optimized using optimized temperature parameters from the previous step, the results of the optimization are presented in Table 11 and Figures 33 and 34.

Table 11: TMB Model Optimized mechanical parameters vs Parameters from McDonald (2018)’s

Viscoelastic Model

Parameter	Initial Value McDonald (2018)	Optimized Value	Relative Change
E_{DG} (maximum biodegradation induced settlement)	0.3218	0.3306	+2.73%
E_{start} (starting Young’s modulus)	127710 Pa	136490 Pa	+6.87%
τ (relaxation time)	14283000 s	13171000 s	-7.78%

Figure 33: Results of Simulated Settlement at Odd bundles : Using Settlement data only, with
Optimized Temperature parameters Results : $E_{\text{start}} = 136490 \text{ Pa}$, $\tau = 13171000 \text{ s}$, $E_{\text{DG}} = 0.3306$

Figure 34: Results of Simulated Settlement at Even bundles : Using Settlement data only, with
Optimized Temperature parameters : Results : $E_{\text{start}} = 136490 \text{ Pa}$, $\tau = 13171000 \text{ s}$, $E_{\text{DG}} = 0.3306$

Table 11 compares the values of optimized parameters from McDonald (2018)’s viscoelastic model with the results obtained in the study under consideration in this section. Even though the optimized results vary by no greater than 7.78%, in this model, the settlement is over predicted. This difference can be attributed to the fact that McDonald (2018) adjusted the location of all probes in the model results by the values in Table 12 as he believed the initial probe locations were incorrect.

Table 12: Probe adjustment done by McDonald (2018) per bundle (m)

B3	B5	B7	B9	B11
+0	+0.2	+0.6	+0.3	+3.2
B4	B6	B8	B10	B12
+0	+0.5	+0.8	+0.5	+3.5

Data probes are positioned in the model for monitoring settlement from the start of the simulation i.e. these probes start recording displacement before the ‘true’ installation of the instrument bundles. These adjustments were done by McDonald (2018) to synchronize the predicted settlement with the measured field data by a linear shift so that the elevation change overlaid the field data elevations. Bundles 11 and 12 required the largest shift because their settlement is based on the settlement of all the layers below and if this settlement is overpredicted, there is a significant difference between the probe elevation and the ‘true’ elevation when the bundles were installed. In addition, it was also discovered that the probes for these two bundles were positioned incorrectly in the Viscoelastic model of McDonald (2018). The location has been corrected in this model, and no probe adjustment has been made to these results. Therefore, settlement is overpredicted and the concerns remain related to the COMSOL optimization.

Another reason for the differences between the optimized parameters herein and those of McDonald (2018) is the expended energy with time using the in the biodegradation-induced settlement term. McDonald (2018) used expended energies with time from Berquist (2017) and fit gamma functions to the results which were input into the model. According to those functions, the amount of energy expended by the waste at the end of a 10-year period (3650 days) was less than that expended by the waste in the coupled model. Figures 35 and 36 present the expended energies with time simulated in the current model and used by McDonald (2017), respectively.

Figure 35: Energy Expended (MJ) vs Time (Days): Results from TMB Coupled Model

Figure 36: Energy Expended (MJ) vs Time (Days): Values used by McDonald (2017) in their Viscoelastic Model for calculating Biodegradation induced settlement

As observed in the optimization results discussed in this section, the objective functions for minimizing the sum of squared differences for settlements at all bundle locations provided a better fit for the lower bundles 3,5 and 4,6 and was strictly better than all other objectives, therefore it was the dominating solution and led to poor fits for the higher bundles. At this point, it seemed reasonable to manually adjust E_{DG} to a value which minimized the sum of squared differences between model and field data.

Manual adjustment of E_{DG} was done based on varying values of E_{DG} and finding the value which minimized the sum of the squared error of bundles 3-8. Settlement data of bundles 9 and 10 indicated that these were impacted by placement of waste in Zone 5 (Van Geel and Murray, 2015). When installed, bundles 11 and 12 were not placed in the same two vertical columns as the other bundles and were shifted towards the centre of the landfill to allow for coverage under the side slope (McDonald, 2018). Therefore, only data from bundles 3-8 was considered to finalize E_{DG} . The results have been presented in the next section.

5.4 Biodegradation Induced Strain (E_{DG}) finalized by reducing sum of squared differences

The following section presents settlement results for all bundles for the manually adjusted value of $E_{DG} = 0.24$ and optimized settlement parameters from the previous step.

Figure 37: Elevations of odd bundles - $E_{DG} = 0.24$ finalized by minimizing sum of squared differences between modelled and field data manually

Figure 38: Elevations of even bundles - $E_{DG} = 0.24$ finalized by minimizing sum of squared differences between modelled and field data manually

Table 13 compares the settlement parameters from this model with those published by McDonald (2018). With the exception of E_{DG} , the values are reasonably close (within 7.8%). Note McDonald (2018) did not face the same issues with the COMSOL optimization as they only optimized on the settlement of bundles 3 and 4 and used these values to validate the model using the settlements at the remaining bundle locations. In addition, an E_{DG} value of 0.24 better reflects values published in the literature (e.g. Park and Lee 1997, Marques et al. 2003).

Table 13: TMB Model Optimized mechanical parameters vs Parameters from McDonald (2018)’s Viscoelastic Model

Parameter	Initial Value	Optimized Value	Relative Change (%)
E_{DG} (maximum biodegradation induced settlement)	0.3218	0.24 (Manual adjustment)	-25.42
E_{start} (starting Young’s modulus)	127710 Pa	134690 Pa	+5.46
τ (relaxation time)	14283000 s	13171000 s	-7.78
M	0.6277	0.66644	+6.17
N	1.4221	1.4783	+3.95
A	0.88887	0.9284	+4.44
B	0.93642	0.96134	+2.66

5.5 Temperature Parameters Optimized again with final settlement parameters

As the final step in optimization, temperature parameters were optimized again, with the final settlement parameters. The results of this final optimization are included in Table 14, along with the parameters from previous studies. Megalla (2016) and Berquist (2017) did not include aerobic heat generation at bundles 10 and 12 in their 1D models.

Therefore, columns for values corresponding to initial values of m2 and m4 have been left blank.

Table 14: Optimized Thermal Parameters

Parameter	Initial Value	Source	Optimized Value	Relative Change (%)
H	0.5	Berquist (2017)	0.7243	+44.86
L	37800 J/kg	Megalla (2016)	39372 J/kg	+4.15
m1	14	Megalla (2016)	24.8	+43.54
m2	-	-	18.5	-
m3	14	Megalla (2016)	21.4	+34.57
m4	-	-	7.9	-

Figures 39 and 40 present the final optimized temperatures for the odd and even bundles, respectively.

Figure 39: Optimized temperatures at odd bundles – Using temperature data and final settlement parameters: Results: H = 0.7247, L = 39372 J/kg

Figure 40: Optimized temperatures at even bundles – Using temperature data and final settlement parameters: Results: $H = 0.7247$, $L = 39372 \text{ J/kg}$

Table 15 highlights the values of sum of squared differences for objective function for temperature and settlement modelled in each of the steps taken in optimization process presented in Figure 30. Steps 1 through 5 refer to each of the models which resulted from each of the steps of the optimization framework.

Table 15: Sum of squared (ssq) differences with respect to field data

Step	Optimized Parameters T indicates Temperature and S indicates Settlement	Ssq Difference for Temperature Data	Ssq Difference for Settlement Data	Difference in ssq with respect to Model 1 (%) (Temperature)	Difference in ssq with respect to Model 1 (%) (Settlement)
1	Both T and S	1220803	1544857	--	--
2	Only T	626290	1549361	-48.69	+29.15
3	Only S with optimized T	689785	1548821	-43.49	+25.66
4	E _{DG} Adjustment	648267	1545256	-46.89	+2.58
5	T optimized again	635543	1545532	-47.94	+4.37

Results from Step 1 clearly do not present an acceptable solution because temperature results do not match field data, as represented in Figures 26 and 27 even though settlement results match reasonably well with the field data.

When only thermal parameters are optimized using temperature data in Step 2, the fit to temperature data improves significantly, but settlement results worsen by 29.15%. The reason the squared differences for the settlement results increase is because the thermal model optimization caused H to increase from 0.4 to 0.691, which impacts the expended energy with time and therefore, the biodegradation-induced settlement with time. Step 3 improves settlement results by only 3.49% but at the same time increases the squared difference for temperature by 5.2%.

Step 4 significantly improves settlement results, because E_{DG} was manually adjusted and E_{DG} controls long term settlement behavior of MSW. The final optimization in Step 5 shows slight improvement in temperature results, and slight worsening of settlement results with respect to the previous step. The interpretation, which holds true for all

optimization steps, is that all optimization results indicate that the target objective function (i.e. temperature results when only thermal parameters are optimized) in an optimization run will improve the fit to field data significantly, however, this is often at the expense of the fit other target objective function (i.e. settlement).

Many studies on multi-objective optimization suggest that in such a case, the model developer needs to arrive at a compromise solution which satisfies the primary goal of the modelling study. In the development of this coupled model, the primary goal was to obtain a set of thermal and mechanical parameters that give a reasonable fit to both temperature and settlement data which has been achieved by following the designed framework, and hence the final solution of Step 5 is considered as the optimized model and serves as the base case scenario for the parameter sensitivity study that follows.

Chapter 6: Model Sensitivity Analysis

A sensitivity analysis was performed on the thermal and settlement parameters of the model. The aim of the sensitivity analysis was to provide an indication as to the effect that each of these parameters has on the model predictions.

1. To understand the contribution of biodegradation induced settlement in comparison with initial and time-dependent mechanical settlement, a simulation was performed by setting E_{DG} (biodegradation-induced strain) = 0.
2. Using the base model with $E_{DG} = 0$, a sensitivity analysis was performed to understand the contribution of E_{start} and τ by increasing the values of these parameters by 20%.
3. Anaerobic heat generation adjustment factor (H) in the base model was 0.7243. The model was tested with an H value of 0.5 and 0.3. The model was run for a lower anaerobic heat generation adjustment factor with the expectation that the peak temperatures at the bundles will shift to later times.
4. The temperature dependence of heat generation in the base model was modelled according to the dual-ramped heat generation function used by Hanson et al. (2013) where the maximum heat generation occurred in a temperature range of 30-50 °C, with the maximum heat generation rate varying from 0 to 1 during a 0-30 °C temperature transition. The coupled model was tested with a varied temperature range by shifting the range of temperature dependence to 10 – 30 °C and analyzing its impact on temperatures modelled at the bundle locations.

5. Snow cover on the surface of waste lifts would affect the heat gained, lost or transferred. A sensitivity analysis was performed to assess this impact. Snow cover would insulate the surface of the landfill and decrease the heat transferred by convection and longwave radiation. It would increase albedo at the surface of the landfill, hence decreasing the solar radiation absorbed at the surface. To incorporate this effect in the model, for all winter months, the radiation flux and convection were set to zero and temperature at the boundary was set to 0 °C. Data collected for the green-roof on the Canal Building on Carleton University's campus indicates that the temperature below the snowpack remains at 0 °C when a snowpack exists.
6. In the base model, the specific heat capacity and thermal conductivity vary linearly with density. The specific heat capacity ranges from 1700 to 2100 J/kg·K and the thermal conductivity ranges from 0.3 to 1.5 W/m·K over a density range of 930 – 1700 kg/m³. The minimum and maximum values of C and k were varied to understand the impacts of these relationships on the temperatures simulated by the model. The model was tested for four scenarios: the minimum k increased by 20%, minimum C increased by 20%, maximum k decreased by 20% and maximum C decreased by 20%.
7. Temperatures at the topmost bundles, bundles 11 and 12, were underpredicted in the base model and the simulated temperatures appear to be impacted by the ambient temperatures more than the observed temperatures in the field. To better understand this, a sensitivity analysis was done by lowering the thermal

conductivity of soil in lifts 6 and 7, which should reduce the impacts of ambient temperatures on these bundles.

For all sensitivity analyses, results for odd bundles have been shown except for Analysis 6 where the observed change in model results was more pronounced for even bundles than odd bundles. Remaining figures are provided in Appendix D.

6.1. Model Sensitivity Analysis Results

6.1.1. Effect of excluding biodegradation induced strain in modeling settlement

Figure 41 shows the results when total amount of strain that can occur due to biological decomposition (E_{DG}) is turned off during the model simulation effectively removing the TDBI settlement.

Figure 41: Coupled Model $E_{DG} = 0$, results of elevation of odd bundles

Figure 42 shows the elevations for just bundles 3 and 5 to illustrate the importance of including temperature dependence for the biodegradation-induced settlement term in the model. Recall that bundles 3 and 5 were installed in the first waste lift which was placed in the winter months.

Figure 42: Elevations of Bundles 3 and 5, indicating the importance of including biodegradation induced strain in the model

For bundle 3, both models predict similar settlements for the first 4 years. Just before the placement of lift 6 around October 2013, the coupled model begins to predict an increased rate of settlement in comparison to the model where E_{DG} is set equal to 0.

Referring to the temperature data (Figure 39), it can be observed that temperatures begin to rise up to 10 °C around that time. As the temperature rises at bundle 3, the rate of anaerobic biodegradation starts to increase, and therefore TDBI settlement also starts to occur, which is why the two models begin to differ in their predictions at this time.

Between October 2013 and October 2016, the field data indicate an increase in the rate of settlement. The coupled TMB model is able to simulate this rate of increase in settlement as temperatures increase. A similar trend is noted for the simulated settlement at bundle 5.

The TMB base model still does not predict biodegradation induced settlement starting at the same time as the field data because the rise in modelled temperatures is delayed. In the field, temperatures at bundle 3 rise above 10 °C after 3.5 years whereas in the model, this rise does not occur until 4.5 years. The same effect is observed for bundle 5.

Improvement upon the anaerobic heat generation function is required, so that the temperature rise occurs at the same time as it does in the field. This has been discussed in the section 6.1.4 and 6.1.5 where sensitivity on the heat generation function is carried out. It is also important to note that the TDBI settlement is responsible for a majority of the long-term time-dependent settlement. As noted in the literature review, Chen et al. (2012) argued that the biodegradation-induced settlement was the dominate process for long-term settlement. The settlements simulated by the KV model match the initial settlement rates well but level off rather quickly (i.e. within a year of the placement of an additional load).

6.1.2. Sensitivity on starting Young's Modulus

The starting stiffness of the spring in the KV model is controlled by E_{start} . To study the sensitivity of the model predictions to this value, the value of E_{start} in the base model was increased by 20%. The results are presented in Figures 43 to 47. The results indicate that an increase in E_{start} has the greatest impact on the upper bundles, bundles 11 and 12, which is expected as they reflect the cumulative settlement of all the waste lifts below. It is also important to note that increasing E_{start} by 20%, has the greatest impact on the early predictions of settlement.

Figure 43: Starting Young's Modulus +20% – Results for Bundle 3

Figure 44: Starting Young's Modulus +20% – Results for Bundle 5

Figure 45: Starting Young's Modulus +20% – Results for Bundle 7

Figure 46: Starting Young's Modulus +20% – Results for Bundle 9

Figure 47: Starting Young's Modulus +20% – Results for Bundle 11

6.1.3. Sensitivity on relaxation time of the dashpot

The relaxation time of the dashpot controls the time it takes for the dashpot in the KV body to dissipate, i.e. it controls the effective span of the time-dependent response in mechanical settlement.

The results of this sensitivity analysis are presented in Figures 48 and 49 and indicate that the model is not very sensitive to this parameter if you only consider a 20% increase in the relaxation time. Increasing the relaxation time significantly to allow the mechanical settlement to occur over a longer time will lead to a poor fit to settlement data at early times in response to the change in load due to the placement of another waste lift.

Figure 48: Relaxation time sensitivity analysis – Results for Bundle 5

Figure 49: Relaxation time sensitivity analysis – Results for Bundle 7

6.1.4. Lowering Anaerobic Heat Generation Rate (H)

The anaerobic heat generation adjustment factor (H) allows the user to lower the maximum anaerobic heat generation rate. The same amount of total energy is still expended from the waste, but the rate at which this happens is decreased, and therefore it takes longer for this energy to be expended. As explained in the model framework, this anaerobic heat generation function was developed using the work of Hanson et al. (2013). As observed in the results of the base model, even though the optimized temperature parameters provide a good result in reducing the sum of squared differences between the model and the field data, the temperature results do not match the temporal trends in the field data very accurately. Temperatures at bundles 3, 5 and 7 are underpredicted for the first 4 years and overpredicted after that. Similar results are observed for bundles 4, 6 and 8. It is also important to note when the simulated and field temperatures reach their peak values. For most of the lower bundles, the field temperatures have just peaked or appear to be approaching their peak values in the field. In contrast, the optimized model is predicting an earlier peak as it is trying to simulate the earlier rise in temperatures observed in the field. If the maximum heat generation rate is decreased (i.e. a lower H), the peak temperatures are shifted to later times and better match the rate of temperature increase observed in the field (Figures 50 to 54).

This may be attributable to the heat generation relationship implemented in the model. The model includes the heat generation model used by Hanson et al. (2013) for Cell D, which is for a cell operated under conditions similar to those at Ste. Sophie (i.e. no leachate recycle).

The current implementation in the model only allows the user to scale the curve by the value H effectively increasing or decreasing the peak heat generation rate of Hanson et al. (2013)'s model. The total expended energy is fixed at 104 MJ and the shape of the curve cannot be changed. As observed in Figures 50 to 54, lowering the anaerobic heat generation factor from 0.7247 to 0.5 and 0.3 reduces the predicted temperatures and shifts the peak temperatures to later times. However, lowering H had little impact on the temperatures at bundle 11 implying that the temperatures at bundle 11 are controlled more by the surface processes given its proximity to the landfill surface.

Figure 50: Sensitivity on H – Temperatures at Bundle 3

Figure 51: Sensitivity on H – Temperatures at Bundle 5

Figure 52: Sensitivity on H – Temperatures at Bundle 7

Figure 53: Sensitivity on H – Temperatures at Bundle 9

Figure 54: Sensitivity on H – Temperatures at Bundle 11

6.1.5. Shift in ramp function for temperature dependence from 0 - 30 °C to 10 - 30 °C

To account for temperature, Hanson et al. (2013) proposed a ramped heat generation function (Figure 22). Their function had the heat generation rates increase from 0 to the maximum heat generation rate as the temperature increased from 0 to 30 °C.

In this sensitivity simulation, this linear ramp function was changed to delay the heat generation with waste temperatures by shifting the initial ramp from 0 - 30 °C to 10 - 30 °C so that no heat generation occurs when waste temperatures are below 10 °C. Figure 55 shows the results of the sensitivity analysis.

Figure 55: Temperatures at odd bundles – Shift in Ramp function for temperature dependence

Shifting the ramp function, delays temperature rise at all bundles by a few months and the time it takes to reach peak temperatures before they fall. This shift improves temperature results at bundle 7, providing a better fit to field temperatures after October 2015, but worsens the results for lower bundles 3 and 5.

6.1.6. Sensitivity on Surface emissivity in winter

Figures 56 and 57 present results of sensitivity analysis when the radiation flux and convection were set to zero and temperature at the surface was set to 0 °C during winter from November 15 to April 15 each year.

Figure 56: Temperatures at odd bundles – Sensitivity on surface emissivity

Figure 57: Temperatures at even bundles – Sensitivity on surface emissivity

Table 16 lists the values of difference in squared error of the sensitivity analysis observed for temperatures at all bundle locations with respect to the base model. The impact observed at all lower bundles is small as these bundles are only exposed to the ambient temperatures for periods of less than a year and this duration of snow cover may not be for more than a couple of months. On the other hand, bundles 11 and 12 lie closest to the surface and are impacted by snow cover insulation from the time of their placement (May 2012) till the end of the simulation (7 years). When comparing the results at bundles 11 and 12 over the final 3-4 years of the simulation with the base case, the presence of the snow cover reduced the decline in temperatures during the winters and hence the temperatures are greater and closer to those observed in the field.

Table 16: Difference in sum of squared error with respect to the base model for each bundle - Variation of Surface Emissivity

	B3	B5	B7	B9	B11	B4	B6	B8	B10	B12
Emissivity	-9.11	-2.06	11.83	47.84	8.69	-5.66	3.12	-0.73	1.32	-10.48

6.1.7. Sensitivity on Maximum and Minimum Specific Heat Capacity and Thermal Conductivity

Figures 58 to 61 present the sensitivity results for varying thermal conductivity and specific heat capacity. Results for only even bundles have been presented in this section because the maximum observable differences by changing C and k were observed at these bundles. The results for odd bundles have been presented in Appendix D.

The thermal parameters, thermal conductivity, and specific heat capacity are functions of density. The minimum and maximum values of thermal conductivity mapped over minimum and maximum density of waste are 0.30 and 1.5 W/m·K. These values were increased and decreased by 20% respectively to understand the effect of this range on the

model predictions. The model was tested with a minimum thermal conductivity of 0.36 and a maximum value of 1.20 W/m·K. Similarly, the minimum and maximum values of specific heat capacity as a function of density were changed from 1700 to 2040 J/kg·K and from 3000 to 2400 J/kg·K, respectively. The sensitivity of each change was measured by comparing the squared error of each sensitivity model run to the squared error of the base model. Displayed in Table 17 are the differences in total sum of squared error for odd and even bundles for the sensitivity analysis compared to the base model. These values are also presented as a percentage difference in the sum of squared differences relative to the base model. Negative values imply a reduction in error, and positive values mean increase in error.

Table 17: Difference in sum of squared error with respect to the base model for each bundle. - Variation of thermal conductivity and specific heat capacity

	B3	B5	B7	B9	B11	B4	B6	B8	B10	B12
Dec max C	20.79	34.24	16.30	19.94	12.39	27.08	42.16	38.39	-2.79	-0.28
Dec max k	24.23	48.07	13.10	-26.01	1.57	-8.22	2.47	7.52	-22.40	-12.70
Inc min C	-8.34	25.15	33.37	42.94	-10.31	-38.86	-47.10	-16.12	24.37	-2.63
Inc min k	-4.37	12.53	12.40	47.29	10.31	0.39	1.26	-10.55	24.52	5.83

As can be observed in Table 18, and Figures 58-61, adjusting the minimum and maximum C and k values worsened results for all cases except for Case 3 where minimum thermal conductivity is increased by 20%.

Table 18: Difference in sum of squared error with respect to the base model for odd bundles, even bundles and overall difference: Variation of thermal conductivity and specific heat capacity

	Model Run	Sq error (odd)	Difference (%)	Sq error (odd)	Difference (%)	Overall Sq error	Overall Difference (%)
Case	Base	323704.50		311838.70		635543.10	
1	Dec max C	389558.20	16.90	391525.60	20.35	781083.90	18.63
2	Dec max k	365937.90	11.54	291574.00	-6.95	657511.80	3.34
3	Inc min C	351015.20	7.78	275749.30	-13.09	626764.50	-1.40
4	Inc min k	376248.80	13.97	323941.80	3.74	700190.60	9.23

Figure 58: Case 1 - Temperatures at even bundles – C max -20%

Figure 59: Case 2 -Temperatures at even bundles – k max -20%

Figure 60: Case 3 -Temperatures at even bundles - C min +20%

Figure 61: Case 4- Temperatures at even bundles – k min +20%

For the first case, maximum specific heat capacity is decreased by 20%. Decreasing the maximum C value would impact heat storage at the base of the landfill where the densities are greatest. This was not observed as the error is increased at the lower bundles.

For the second case, when maximum thermal conductivity is decreased for the greatest waste density, it is expected that less heat could exit the base of the landfill as this is where densities are greatest. Similar to the first case, no improvement in error is observed for bundles near the base of the landfill.

For the third case, when minimum specific heat capacity at the top of the landfill is increased, the maximum improvement in results is observed. The improvement is more pronounced for even bundles than odd.

For the last case when minimum thermal conductivity at the top of the landfill is increased, improvement of results is observed only for bundles 3 and 8.

For all scenarios there doesn't appear to be a consistent trend leading to the improvement of predicted temperatures for the lower bundles or for the upper bundles. Increasing the minimum value of C for lower densities indicates the largest reduction in errors with 6 of the 10 bundles indicating a lower sum of squared differences in comparison to the base case, however, there is no clear conceptual argument why this occurred. It is not clear how increasing C for the lower densities near the surface would result in improved results at bundles located near the base of the landfill (B3, B4 and B6).

6.1.8. Lowering thermal conductivity of soil cover

Figures 62 and 63 show results of temperatures predicted at bundles 11 and 12 when thermal conductivity of soil cover is reduced by 20% and 50% respectively.

Figure 62: Variation of Thermal Conductivity of Soil Cover: Results for Temperature at Bundle 11

Figure 63: Variation of Thermal Conductivity of Soil Cover: Results for Temperature at Bundle 12

Reduction in thermal conductivity of the cover soil by 20% improves the temperatures measured at bundles 11 and 12 by 22.69% and 54.83% respectively and a reduction by 50% reduces the squared errors by 50.0% and 125.64% for bundles 11 and 12, respectively. An improvement was expected as lowering the thermal conductivities in the topsoil layers will reduce the heat flux and reduce the impact of ambient temperatures on the bundles closest to the surface.

Table 19: Variation of thermal conductivity of cover soil – Difference in sum of squared error of temperatures at Bundle 11 and Bundle 12 with respect to the base model

	B11	B12
k 1.2	-22.69	-54.83
k 0.75	-50.10	-125.64

In summary, the sensitivity analyses did provide some insight as to how certain parameters impact the simulated results.

1. Setting E_{DG} to zero clearly illustrated the contribution of biodegradation-induced settlement to the long-term settlement predicted in the model.
2. The optimized E_{start} and τ provided a good fit to short-term settlement in response to the placement of an additional waste lift. Altering these values gave the expected results but did not improve the predicted settlements at early or late times.
3. As anticipated, lowering the peak heat generation rate (H) was able to shift the peak temperatures to later times as observed in the field data but significantly underestimated the temperatures.
4. Adjusting the ramp function such that the anaerobic heat generation was delayed until the temperatures reached 10 °C gave the expected results and did not improve the simulation.
5. Determining the impact of the surface boundary condition and the potential impacts of a snow cover did improve the results at later times for bundles 11 and 12.
6. Adjusting the minimum and maximum values for k and C for the minimum and maximum densities did not provide insight into how these relationships might improve the simulation results.
7. As expected, reducing the thermal conductivity of the cover soil did improve the simulation of the temperatures at bundles 11 and 12 near the top of the waste profile

Chapter 7: Conclusions, Limitations and Recommendations for Future Work

7.1. Conclusions

A fully coupled Thermal – Mechanical – Biological (TMB) numerical model was developed in COMSOL Multiphysics to simulate temperatures and settlements of MSW at a landfill in Ste Sophie, Quebec. The thermal properties of MSW – thermal conductivity and specific heat capacity - were modelled as functions of density. The concept of viscoelasticity was used to model the mechanical response of MSW and biodegradation-induced settlement was modelled as a function of energy expended by the waste.

The anaerobic heat generation adjustment factor and latent heat of phase change were optimized to generate a reasonable fit to the temperature data observed at the Ste Sophie landfill. The optimization of mechanical parameters also led to a reasonable prediction of the settlement data.

The contributions of this research can be summarized as follows:

1. This is the first study to develop and use a coupled model to simulate waste temperatures and settlement during the filling stages of a landfill. How the placement of the waste lifts was simulated in the model, allowing for the optimization of the thermal and mechanical parameters over the entire 10-year simulation, is unique and was a definite challenge. McDonald (2018) was able to implement this for the mechanical model, however, it was a challenge to incorporate this into the coupled thermal model.

2. The dataset itself and the simulation of 10 years of temperature and settlement data using a TMB coupled model is a significant contribution for two reasons. First, there are no similar detailed data sets that include the filling stages and that extend for a period of ten years. In most field studies, sensors placed in the waste failed within the first few years. The author was responsible for downloading and processing the last two and half years of data. Second, many modelling studies in the literature have used laboratory studies or post-closure field studies of a shorter duration to assess the processes and parameters that impact waste stabilization. To simulate 10 years of field data using a coupled TMB model allows for greater insight and confidence in the understanding of the complex and coupled processes occurring in landfills. This is compounded by the fact that this site was located in a Northern climate with temperatures ranging from -30°C to $+30^{\circ}\text{C}$ which will impact the waste temperatures at placement and ambient temperatures that form the model boundary conditions. While several coupled models exist in the literature, limited field data exist to validate these models.
3. The model was able to demonstrate the impacts of temperature on the biodegradation-induced settlement observed in the field and the need for a coupled TMB model to illustrate the coupling of the thermal and mechanical models to simulate the temperature-dependent, biodegradation-induced settlement.

4. This study continued to build on the earlier research and modelling efforts by Bonany, Megalla, Doyle, Berquist and McDonald in Dr. Van Geel's research group. The results illustrate the long-term impacts of placing waste under frozen conditions on the future waste temperatures and waste stabilization. The longer period over which data were collected and the ability to optimize parameters over a single 10-year simulation, provide greater confidence in the thermal and mechanical parameters and allow for a more complete understanding of the coupled processes.
5. The sensitivity simulations provided additional insight into the impacts of various parameters and model assumptions on the predicted temperatures and settlement.

7.2. Limitations of the Model

1. The model does not include a hydraulic component to simulate gas and leachate migration. Leachate recycle was not conducted in Zone 4 at Ste. Sophie. Moisture will have infiltrated prior to the placement of the landfill cover and the moisture profile with depth will impact the thermal properties of the waste. Landfill gas extraction pumps generate suctions less than 1m water column outside the landfill. Given the depth of waste and limited gas pressures, it is anticipated that unsaturated conditions and the range in water suctions will have had limited impact on settlement.
2. Mechanical properties of MSW are expected to change with variation in temperature. In addition, the strength parameters of frozen versus unfrozen waste will differ. This model does not consider temperature dependence on variation of

elastic properties of MSW (Young's Modulus, Poisson's Ratio, Shear Modulus) to model their stress- strain behavior.

3. This model does not consider different values of thermal properties of waste – thermal conductivity and specific heat capacity for waste placed above and below freezing temperatures. Thermal conductivity of a substance will depend on its phase. For example, thermal conductivity of solids is expected to increase with temperature. A similar effect is observed for gases as molecular collisions increase with temperature leading to higher thermal conductivity. For liquids, thermal conductivity decreases with increase in temperature, but pure water is an exception. Similarly, specific heat capacity often varies with temperature and is different for each state of matter. Considering variation of thermal properties of MSW with temperature would further improve the model.

7.3. Recommendations for Future Work

1. With regards to the function used to model anaerobic heat generation for this model, improvement is required as discussed in Chapters 5 and 6. This model employed an anaerobic heat generation function using site-specific waste characteristics of a landfill in Michigan, USA (Hanson et al. 2003). A more generic model should be developed and optimized to better represent the heat generation rate at the Ste Sophie landfill. One improvement might involve considering the organic fraction as a readily degradable fraction and a less readily degradable fraction as other researchers have done. This may allow the model to better replicate the earlier increases in temperature observed in the field which the current model underestimated.

2. The findings of the sensitivity analysis indicate that the temperature results, specially at the upper bundles 11 and 12 will improve if the thermal conductivity of the soil cover is reduced and/or the impact of snow cover is considered. These changes should be applied in further development of this work for model improvement.
3. Addressing the model limitations outlined in Section 7.2 would further improve the model framework.

Appendices

Appendix A

Clarification on Model Geometry – Location of Bundles 11 and 12

For the modelling results presented in this thesis, the locations of bundles 11 and 12 were projected on the 2D cross-section or profile that contained bundles 1 through 10. Upon reflection, this is not ideal or appropriate. Bundles 11 and 12 were installed further into the landfill to avoid the slide slopes and as a result have a greater depth of waste above them in waste lift 5 (2.1m and 3.7m as noted in section 3.3) than they do in the projected 2D profile. It was also discovered that the use of the survey data, which was in relation to the locations of bundles 11 and 12, may not have correctly reflected the thickness of lift 5 above bundles 9 and 10. The survey data were revisited and the results are presented here. It is recommended that future modelling efforts reflect this geometry. It is also recommended that if bundles 11 and 12 are to be used in comparing simulated and field data, that a 3D model be used. If a 2D simulation is used, the temperature and settlement data for bundles 11 and 12 should not be used. The reason the model did not effectively simulate the temperature data at bundles 11 and 12 is there is less cover soil when bundles 11 and 12 are projected on to the 2D profile and hence the greater impact of ambient temperatures observed in the model. The settlement data is also impacted as the actual settlements are impacted by a greater depth of waste at the actual locations, whereas when bundles 11 and 12 are projected on to the 2D profile, the total depth of waste is less and the simulated settlement would be less. A revised 2D profile is provide in Figure A1.

Figure A 1: Updated Model Geometry - Lifts 5, 6 and 7

The thicknesses of the first four waste lifts are consistent with Van Geel and Murray (2015) and were used in this thesis. The quarterly survey data were revisited to better understand or estimate the thicknesses of waste lift 5 and the lifts above.

In an effort to reconstruct what happened after the placement of lift 5, the TEPC data were revisited. There appears to be increases in total earth pressure in Nov 2013 (regrading), Oct 2014 (final cover), Sept 2015 (potentially regrading or a layer of contaminated soils) and Aug 2016 (potentially regrading or a layer of contaminated soils). The practice of WM placing soil on top of Zone 4 can be observed in Figure 4. If the quarterly survey data above B1-9 and B2-10 are plotted, an estimate of the thickness of soil lifts placed in Nov 2013, Oct 2014, Sept 2015 and Aug 2016 can be assessed. The results of this assessment are provided in Table A1.

Table A 1 Estimated lift thicknesses above B9 and B10 based on quarterly survey data

Time	Coverage above B9	Lift thickness	Coverage above B10	Lift thickness
Prior to lift 5	0.5		0.5	
After lift 5	6.18	5.68	7.44	6.94
After Nov 2013 (lift 6)	6.59 (7.59-1.0)	0.41	10.37 (11.37-1.0)	2.93
After Oct 2014 (cover – lift 7)	7.59	1.0	11.37	1.0
After Sept 2015 (lift 8)	8.11	0.52	12.11	0.74
After Aug 2016 (lift 9)	8.49	0.38	12.38	0.27

A similar exercise was conducted of lift thickness above B11 and B12 and the results are presented in Table A2.

Table A 2 Estimated lift thicknesses above B11 and B12 based on quarterly survey data

Time	Coverage above B11	Lift thickness	Coverage above B12	Lift thickness
After lift 5	2.31 (2.1 earlier)		3.84 (3.7 earlier)	
After Nov 2013 (lift 6)	2.46 (3.46 - 1.0)	0.15	4.78 (5.78 – 1.0)	0.94
After Oct 2014 (cover – lift 7)	3.46	1.0	5.78	1.0
After Sept 2015 (lift 8)	est. 4.23	0.77	est. 6.24	0.48
After Aug 2016 (lift 9)	4.45	0.22	7.04	0.8

Given the lift thicknesses in Table A1 at locations B9 and B10, the lift thickness at the boundaries of the domain were estimated. The top of waste lift 5 was assumed to be linear and therefore the elevations at B9 and B10 were extrapolated out to the boundaries such that the thickness of lift 5 is 5.35 and 7.77 at the left and right boundary, respectively. Lift 6 was assumed to be a pie-shaped lift based on the elevations at B9 and

B10. The final cover (lift 7) was assumed to be 1m thick. This can be observed in Figure A2.

Figure A 2: Schematic illustrating how lifts 5, 6 and 7 were determined

Lifts 8 and 9 in Table A1 and A2 are less than 1.0m. If future modelling efforts wish to include these in the model simulation, the data are provided to construct these lifts.

Appendix B

Model Boundary Conditions

The ambient temperature data measured at Mirabel International Airport, which is located 20 km from Ste Sophie, Quebec, was fit to nth order polynomials and the average ambient temperatures were used in the source/sink terms for calculation of convection and long wave radiation at the top of each waste lift. The equations were fit by carrying out non-linear regression analysis in R, which is a programming language and software environment for statistical computing and graphics. Figures B1 and B2 present the actual ambient temperature plots in grey and temperature polynomial functions used in the model from January 16, 2010 till December 31, 2019. Equations for these polynomials are presented in Table B1 that follows.

Figure B1: Polynomial piecewise functions fit to Ambient Temperature Data (Day 0 to Day 1993)

Figure B2: Polynomial piecewise functions fit to Ambient Temperature Data (Day 1993 to Day 3617)

Table B1: Equations for piecewise polynomial functions used to model ambient temperatures

Top of Lift	Day	Equation (t is in seconds)
1 and 2	0 to 405	$265.4589686849076 + 2.572387955262286E-7*t + 2.782223695538531E-13*t^2 - 6.108334170947532E-21*t^3 - 6.584673516947357E-28*t^4 + 2.490920229380915E-35*t^5 - 2.226365088493868E-43*t^6$
3	405 to 576	$5.558591632967984E4 - 7.508812848956013E-3*t + 4.235557934320917E-10*t^2 - 1.271724904693685E-17*t^3 + 2.143842285963297E-25*t^4 - 1.922852162246038E-33*t^5 + 7.162075774653254E-42*t^6$
4	577 to 806.65	$-3.652906870996538E5 + 3.775590887429392E-2*t + -1.619786293065404E-9*t^2 + 3.694115162554429E-17*t^3 + -4.721943074608643E-25*t^4 + 3.206173322935282E-33*t^5 + -9.030545867716718E-42*t^6$
5	806.65 to 1331.155	$3.275299739398933E5 - 2.12127776357629E-2*t + 5.658655765246267E-10*t^2 - 7.94821682135249E-18*t^3 + 6.197968016847486E-26*t^4 - 2.543283104908195E-34*t^5 + 4.288937090067391E-43*t^6$
6	1332 to 1626.075	$-2.526979594192106E6 + 9.8905352638468E-2*t - 1.544192946490241E-9*t^2 + 1.202301315078701E-17*t^3 - 4.66843515299718E-26*t^4 + 7.232507446619861E-35*t^5$
7	1627 to 1992	$-2.797459755292065E6 + 8.666215348934436E-2*t - 1.069869770122543E-9*t^2 + 6.579404096090884E-18*t^3 - 2.015399553803627E-26*t^4 + 2.459846253009323E-35*t^5$
7	1993 to 2358	$5.916142121595137E6 - 1.615839050740668E-1*t + 1.763054308445681E-9*t^2 - 9.605146951233616E-18*t^3 + 2.612699739161592E-26*t^4 - 2.83851976659349E-35*t^5$
7	2359 to 2724	$1.040321045282328E7 - 2.302737585376007E-1*t + 1.989220876850813E-9*t^2 - 8.13842882367683E-18*t^3 + 1.403264004123926E-26*t^4 - 1.971528350447272E-44*t^6$
7	2725 to 3090	$3.234769458603945E7 - 6.278831280913311E-1*t + 4.756681340187121E-9*t^2 - 1.706857155429509E-17*t^3$

In addition to the above, the bottom boundary condition in the model was defined as a prescribed temperature boundary based on measured temperatures at bundle 1.

Temperature data from bundle 1 was fit to a linear piecewise function which is represented in Figure B4. Equations for these linear piecewise functions are presented in Table B2 that follows.

Figure B4: Linear piecewise functions fit to Temperature measured at Bundle 1

Table B2: Equations used to describe the prescribed temperature boundary in the model – Day 0 corresponds to January 16, 2010

Day	Equations for Temperature (K), Time t in seconds
0 to 215	273.3
215-539	$0.0365*t + 265.46$
539-1026	$-0.0058*t + 288.27$
1026-1626	$0.0077*t + 274.39$
1626 – 1703	$0.1314*t + 73.31$
1703-1724	$-0.1297*t + 517.9$
1724-1783	$-0.1297*t + 517.9$
1783-1871	$0.0679*t + 177.28$
1871-2217	$0.0026*t + 288.96$
2217-2372	$-0.0096*t + 315.88$
2372-3640	$0.0038*t + 284.21$

Appendix C

Equations for Aerobic Heat Generation

Aerobic heat generation was modelled in the top 1 m of lifts 4 and 5 at times when oxygen was recorded at bundles 9, 10, 11 and 12 in the field. The following equations were used to model aerobic heat generation at these bundle locations:

$$Q_{aer} = m1 [O_2] \text{ at bundle 9}$$

$$Q_{aer} = m2 [O_2] \text{ at bundle 10}$$

$$Q_{aer} = m3 [O_2] \text{ at bundle 11}$$

$$Q_{aer} = m4 [O_2] \text{ at bundle 12}$$

where m1, m2, m3 and m4 are aerobic rate constants and $[O_2]$ represents the polynomial function fit to oxygen concentrations measured at these bundle locations. These equations are presented in Table C1.

Table C1: Polynomial equation for oxygen concentration at bundle locations

Location	Equations for $[O_2]$
Bundle 9	$m1 * (-2.391 * 10^{-4} * t^2 + 3.461 * 10^{-1} * t - 1.22 * 10^2)$
Bundle 10	$m2 * (117199.851613916 - 1000.13755705178 * t + 3.542388392231 * t^2 - 0.00666635966725664 * t^3 + 0.0000070306531875626 * t^4 - 0.0000000039401985206 * t^5 + 0.000000000009167765 * t^6)$
Bundle 11	$m3 * (1.889943 * 10^{-1} * t - 6.613117 * 10^{-5} * t^2 - 1.329587 * 10^2)$
Bundle 12	$m4 * (-25292.5309338842 + 141.387689223269 * t - 0.328395195636628 * t^2 + 0.000405595599115514 * t^3 - 0.00000028091023180754 * t^4 + 0.00000000010343309076 * t^5 - 0.0000000000001581783 * t^6)$

Appendix D

Model Sensitivity Analysis Results

D.1 Sensitivity on Starting Young's Modulus – Results for Even Bundles

Figure D 1.1: Starting Young's Modulus +20% – Results for Bundle 4

Figure D 1.2: Starting Young's Modulus +20% – Results for Bundle 6

Figure D 1.3: Starting Young's Modulus +20% – Results for Bundle 8

Figure D 1.4: Starting Young's Modulus +20% – Results for Bundle 10

Figure D 1.5: Starting Young's Modulus +20% – Results for Bundle 12

D.2 Lowering peak heat generation rate (H)

Figure D 2.1: Sensitivity analysis on H – Modeled temperatures at Bundle 4

Figure D 2.2: Sensitivity analysis on H – Modeled temperatures at Bundle 6

Figure D 2.3: Sensitivity analysis on H – Modeled temperatures at Bundle 6

Figure D 2.4: Sensitivity analysis on H – Modeled temperatures at Bundle 8

Figure D 2.5: Sensitivity analysis on H – Modeled temperatures at Bundle 12

D.3. Shift in ramp function for temperature dependence of heat generation

Figure D 3.1: Temperatures at even bundles – Base Model

Figure D 3.4: Sensitivity analysis on ramp function for temperature dependence – Modeled temperatures at even bundles

D.4. Sensitivity on thermal conductivity and specific heat capacity

Figure D 4.1 Temperatures at odd bundles - Base Model

Figure D 4.2 Temperatures at odd bundles - C max decreased by 20%

Figure D 4.3 Temperatures at odd bundles – k max decreased by 20%

Figure D 4.4 Temperatures at odd bundles - C min increased by 20%

Figure D 4.5: Temperatures at odd bundles - k min increased by 20%

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