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Advances in Environmental and Engineering Research

LIDSEN Publishing Inc.

Research Article

Demonstrating Regional Climate and Meteorological Sensitivity in Landfill Methane Inventories from Historical Californian Databases

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Academic Editor: Paul Dargusch

Special Issue: Case Studies of Carbon Management in Practice

Adv Environ Eng Res
2022, volume 3, issue 4
doi:10.21926/aeer.2204054

Received: September 13, 2022
Accepted: December 12, 2022
Published: December 20, 2022

Abstract

The urgency to manage global methane emissions has been acknowledged with international pledges to reduce 2020 levels by 30% by 2030. Carbon management requires effective tools to monitor changes, including those from significant sources including waste disposed on land. The first order degradation model used to determine landfill methane emissions, has been described by researchers as highly variable, insensitive and inadequate, despite recent attempts to explain microclimate impacts on methane oxidation. The development of detailed regional inventories is hampered by these variables. The availability of historical waste management and meteorological data in California, enables a theoretical review and modelling of meteorological moisture changes with methane generation data in a region of decadal drought. This study identifies a novel approach in the modelling of regional optimisation of variable seasonal parameters of moisture and methane oxidation based on the adjustment of the methane correction factor (MCF) generally assumed to be MCF = 1 for managed sites, that is optimised as $MCF_{site} \neq 1$ as the average regional $MCF_{all\ sites}$, → 1 (Range:

<1, ≥1). Regional annual unmitigated methane emitted in December 2010 after methane recovery, oxidation and flaring is estimated at 0.40 million tonnes, falling to 0.31 million tonnes in 2011 and back to 0.40 million tonnes in 2012 ($Pr < 0.01$, $n = 370$). as meteorological conditions returned to the changing decadal norm. Meteorological and climate sensitivity is demonstrated in relation to the regional water balance, spatial distribution of landfill site moisture levels, satellite imagery of 2012 wildfire intensity ranges, the 2011 El Nino impacts and independent data sources. The method provides accurate regional methane assessments inclusive of soil and cover material oxidation. This will primarily benefit developing countries where landfill remains a dominant option, enabling the development of database linked satellite monitoring and detailed regional landfill climate emission inventories.

Keywords

Regional; climate; meteorological; sensitivity; unmitigated methane; inventory; waste models.

1. Introduction

Globally 2.5 billion tonnes of municipal solid waste (MSW) generated annually in 2014 with only about 20% of municipal waste is formally recycled. This leaves many developing countries still disposing of most of their MSW to land or elsewhere, despite a range of policy initiatives including zero waste and the circular economy. Degradation of the disposed waste presents a significant source of global methane [1]. The United States and the European Union have pledged to reduce 2020 methane emission levels by at least 30% by 2030, recognising the urgent need to manage the reduction of "… this dangerous climate pollutant over the next decade" [2].

Decadal drought affects the southwestern region of the United States [3-5] including California where researchers [6, 7] have adapted first order degradation (FOD) models to assess the relative impact of microclimate climate changes and the use of cover materials in mitigating fugitive landfill methane emissions (See discussion on the CALMIM Model and Californian State Inventory [7]). Methane assessments using FOD rate constants are based on soil moisture considerations in relation to mean annual precipitation and potential evapotranspiration [8-11].

In municipal solid waste (MSW) methane oxidation levels vary seasonally across the full range from very little to 100%. However, a default (annual) soil oxidation value of 10% is applied to sites that are managed and covered with methane oxidising material in the 2006 IPCC Waste Model [7, 10-14].

Higher moisture levels in MSW increase the rate of degradation rate. In a study in Thailand, dry season field methane emissions were found to be significantly lower than in the wet season. In this study the authors optimise the methane correction factor (MCF). a variable in the FOD equation that is used in the estimation of the proportion of degradable organic carbon (DOC), with results of methane analysed with error function analysis [15, 16].

Default site MCF estimates are based on site descriptions in the 2006 IPCC model. with a range of 1.0 to 0.4 with uncertainties ranging from 0 to10% for managed sites; a default MCF value of 1 is applied to managed sites; and at MCF = 0.4 uncertainties range from -50% to +60%. The 2005 EPA model adopts the MCF = 1 default [8, 10, 11, 17].

Landfill gas generation models have been highly variable in estimating methane with error ranges of -81% to 539% in a study on 35 Canadian landfills [18], that assessed four models including the German EPER zero order, Scholl Canyon and the LandGem model v2.01. A study on 6 landfills in South America for World Bank Clean Development Mechanism (CDM) projects including the 2006 IPCC Waste model and 2005 EPA model had a error range of 3 to 1109%. A comparison of 4 landfill models including the LandGEM, UK GasSim model and the IPCC tier 2 model had an error range of -65% to +165%. The original IPCC emission validation based on data from 9 Dutch landfills, though this was based on limited biogas recovery data [8-11, 18-21].

The error range of rate models used to estimate landfill gas decreases from zero order to first order to second order when comparing model outcomes to measured data. The zero-order error range is very high. The second-order model is claimed to be more accurate than the first-order model, is more difficult to apply. This leads to the more common use of the first-order equation [22, 23].

In a review, conclusions are drawn that the first order empirical model was insensitive to the approach taken in determining the modelling parameters and uncertainties in the quantification of the rate constant (k) and degradable organic carbon (DOC) and consider that for landfill gas generation and collection, the model is inadequate. Both the 2005 LandGem and 2006 IPPC waste models were never fully validated having been developed before the availability of landfill data on a regional scale [7, 22, 24].

In California, a regional scale online waste management database exists detailing 370 landfill sites in 2010 with 1.37 billion tons (US metrics) of waste in place. The earliest site operating from the early 1930's and 129 sites with methane recovery and treatment. Regional meteorological data collected from over 200 monitoring stations is available, with many that are close to the landfill sites that have gas recovery and treatment. Regional characterisation data, with site "other waste" variations is taken from the Walker database to provide a unique opportunity to model bespoke site waste characterisations and theoretical moisture adaptations [25-27].

This is supported by the availability of an adaptable FOD model that is based on the 2005 LandGem and 2006 IPCC models. This model has already been used in the estimation of changes to regional methane emissions due to developmental and climatic changes (desertification) in dry tropical and dry temperate climates in the Middle East and North Africa region. However, the estimated regional methane emissions recorded in these papers are likely to change due to adaptions considered and implemented in this study [9-11, 28, 29].

The purpose of this paper is to make use of the historical data availability in applying a theoretical moisture adaptation to the FOD model to rationalise and optimise the wide-ranging data errors and uncertainties in regional methane generation, assessing the sensitivity of the model to ongoing meteorological and climate conditions by comparing model outcomes with measured data.

2. Materials and Methods

2.1 Theoretical Review

2.1.1 The Role of Moisture in MSW Landfill Degradation

Methane (CH_4) is only produced when water is present in anoxic conditions generating CH_4 and carbon dioxide (CO_2) in equimolar quantities, as shown in-Eq. (1) below. It is accepted that the natural chemical stoichiometry varies in the biodegradable fraction as the generated CH_4 to CO_2 molar ratio uncertainty may vary from 0.50 the default value to 0.55 [9-11, 17]. The rate equation can be derived from a general carbohydrate formula $[C][CH_2O]_{n-1}$ which is used to represent the simplified structure of one ring of carbohydrate from empirical formulae [30, 31] to illustrate the role of moisture in creating sugars as the intermediate precursor for the degradation of organic waste.

$$[\mathrm{C}][\mathrm{CH_2O}]_{\mathrm{n}-1} + (1+\mathrm{a})[\mathrm{H_2O}] \rightarrow [\mathrm{CH_2O}]_{\mathrm{n}} + \mathrm{a}[\mathrm{H_2O}] \rightarrow {}^{\mathrm{n}}\!/_2\,[\mathrm{CH_4}] + {}^{\mathrm{n}}\!/_2\,[\mathrm{CO_2}] + \mathrm{a}[\mathrm{H_2O}] \quad (1)$$

Where: a is the additional number of water molecules to achieve 100% moisture saturation point for equimolar anaerobic digestion and n = 5 or 6. The intermediate $[CH_2O]_n$ is a sugar, a food source for the microbes in the soil that is converted in anoxic conditions to CH_4 and CO_2.

Degradation can also be considered as a zero-order rate reaction as shown in Eq. (2).

$$-\frac{d[C[CH_2O]_{n-1}]}{dt} = k\,{}^{[CH_4]}\!/_{[H_2O]} \quad (2)$$

However, the water concentration $[H_2O]$ is assumed to be sufficiently large to remain constant and is considered zero order in FOD models with $[H_2O]^0$ = 1. The classic waste FOD rate equation [11] is shown in Eq. (3).

$$-\frac{d[C[CH_2O]_{n-1}]}{dt} = k[CH_4] \quad (3)$$

In the rate determining step (hydrolysis of the carbohydrate), the relative moisture saturation is a non-constant dimensionless term. So, if b is a variable portion of water available within the waste mass that is ≤ or > (1 + a), then the adjusted proportion of CH_4 (and equimolar CO_2) emitted is regulated as the moisture saturated rate constant (k) with b/(1 + a) in Eq. (4).

$$-\frac{d[C[CH_2O]_{n-1}]}{dt} \times \frac{b}{(1\,+\,a)} = \left(\frac{b}{(1\,+\,a)}k\right)[CH_4] \quad (4)$$

Where k is the 100% moisture saturated rate constant = 0.050 [9, 10].

Let us assume that meteorological conditions in the environment are in equilibrium with the change in landfill moisture levels. Moisture changes can be measured as ETo/P, the annual evapotranspiration (ETo) and precipitation (P) ratio (ETo/P). Similar terms are used by hydrologists in the estimation of soil moisture (See review in: [32]). The non-constant water term (ETo/P) relates to the proportion of CH_4 produced as a proportion of the total theoretical default term $n/2$ CH_4 produced in Eq. (1) with the residual carbon being converted to CO_2. As ETo/P is both relative (non-constant) and dimensionless, the moisture term in the zero order Eq. (3) forms the Fickean non-constant rate constant term, inverting as P/ETo (the Aridity Index: [33]), changing to the first order equation, shown in Eq. (5).

$$-\frac{d[C[CH_2O]_{n-1}]}{dt} = k\frac{[CH_4]}{[H_2O]} = \left(\frac{1}{\frac{ET_o}{P}}k\right)[CH_4] = \left(\frac{P}{ET_o}k\right)[CH_4] \quad (5)$$

In practice, the b/(1 + a) and P/ETo term is highly variable, impacted by changing environmental conditions, inhomogeneous disposed waste composition, engineering and working practices at the landfill (See review in: [7]), as well as, for example, the loss of degradable carbon due to surface and underground fires [34].

The FOD equation is derived from the 1855 Fick's Law, the mass (Ms) of degrading solute (sugar) transferred, is defined by a non Fickean rate constant (k_{nc}) and the time (t) period (usually 1 year) to the power of n, where n = 1, due to the porosity of degradable organic substrate (Eq. (6)).

$$Ms = (k_{nc})t^{(n=1)} = \left(\frac{P}{ETo}k\right)t = \left(\frac{b}{(1 + a)}k\right)\mathrm{t} \tag{6}$$

Adding a moisture term in the exponential rate term of the FOD equation has been previously used by researchers as a hydrolysis rate constant [35]. The FOD equation, outlined in Eq. (7), used to estimate methane generation is made up of 4 terms: 'M' the mass of the disposed waste; 'L' is the biodegradable content term built around the degradable organic carbon (DOC); the MCF is normally included in 'L' – for this study it is treated as an unknown variable; and an exponential rate constant term (k) and time t = 1 (year). The equation terms are calculated in yearly intervals and summed (Σ) across operational and closure periods (See; [10, 17]).

$$\text{Methane generated} = \sum M \times (L \times MCF) \times Exp(-k_{nc}t) \tag{7}$$

There are two key highly variable terms that hinder consistency in the estimation of regional emissions.

- MCF, and
- Non-constant rate constant term – shown as K_{nc}.

The moisture related non-constant term has a logarithmic relationship with the mass of waste in Eq. (7) and with the methane gas generated.

2.1.2 Data Sources, and Site Selection Criteria Used in Modelling

The principal sources of data available were obtained from,

- The 2012 Walker database was the first comprehensive Californian waste management data base [25] that includes data on the disposal of "other wastes" such as green wastes and sewage sludge.
- The CIMIS regional meteorological database [26], with monthly data from January 2010 to December 2011 from monitoring stations near to Landfill sites.
- The Calrecycle, Californian waste characterisation report [27] provides regional characterisation of wastes disposed at sites. This is used to calculate 'L' using the DOC (Eq. (7)).
- 2006 IPCC model [10, 11] provides optimum DOC and moisture data for waste types at disposal (See: [28], Table 2) and uncertainty levels

The MSW landfill sites used for the rate calibration were selected from the waste management database [25] using the following criteria.

- Without leachate circulation (So landfill moisture changes in the landfill can be directly related to meteorological changes).
- With annual methane extraction, flaring, oxidation or recovery data

- With sufficient data for FOD modelling.

Many sites listed in [25] did not have a corresponding CIMIS meteorological monitoring station [26] nearby and only 66 sites of 129 with gas recovery were used to match the meteorological with the site waste management data.

2.2 Optimising Site MCF, Moisture Saturation and Methane Oxidation

The key premise for the moisture adaption modelling is that there needs to be a sufficient annual quantity of moisture available to generate a related quantity of methane. Figure 1 shows three charts with a wide range of variation of the site meteorological moisture saturation estimates across the WIP range.

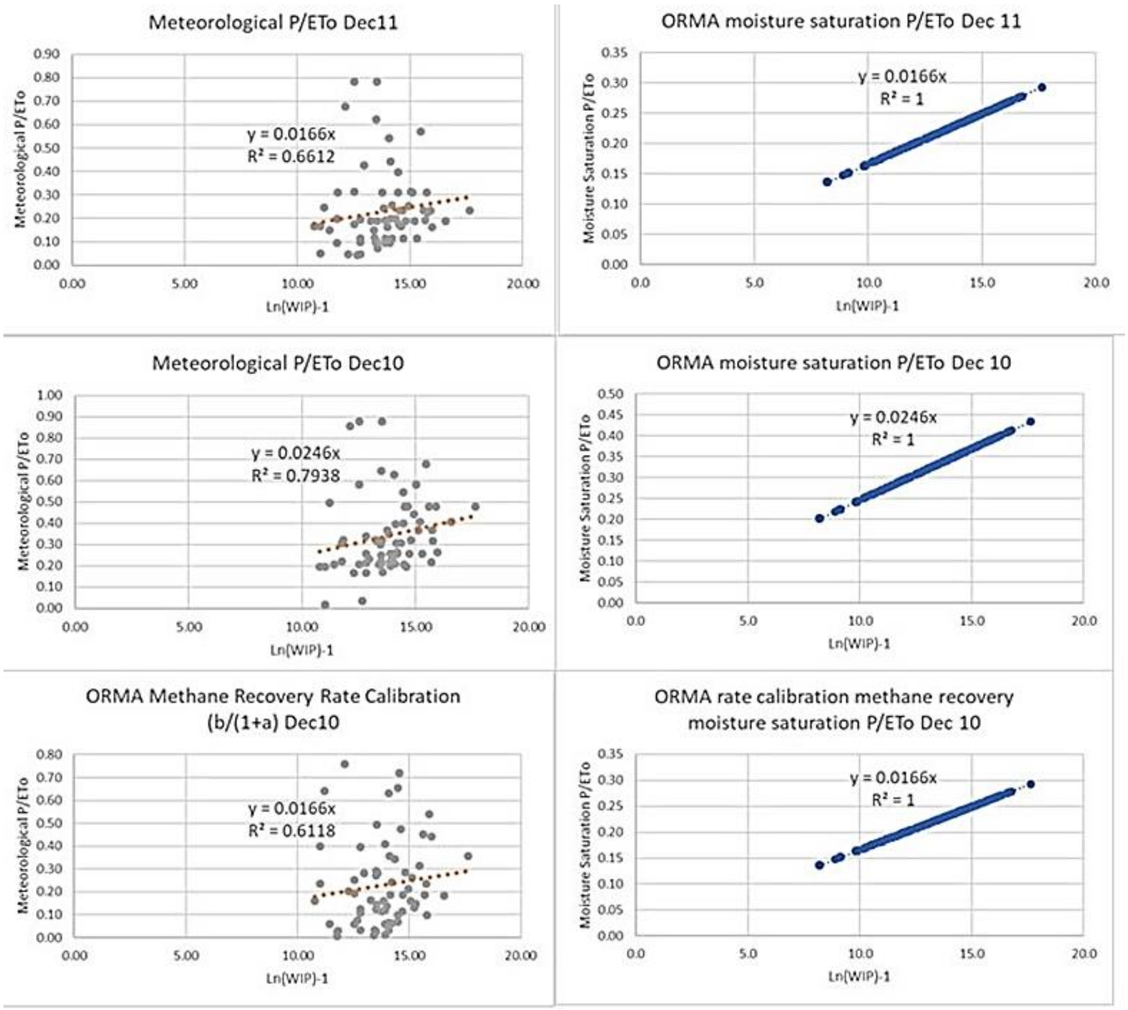

Figure 1 Optimising site and rate calibration moisture estimates.

The variation decreases (shown as R^2 increases) as moisture levels increase across all sites. To generate the rate calibration trendline that is used to estimate the methane emitted, all the data points are adjusted to MCF = 1 by iteratively changing the rate constant from 0.050 to value that generates field methane measurements (recovered, treated and adjusted for collection deficiencies and oxidation). The trendline generated optimises differences in the site MCF across the WIP range from points where generally MCF ≠ 1, though MCF = 1 is possible but a rare occurrence. The chart calibration with data points above and below the trendline optimised within the moisture saturation values creating the conditions in Eq. (8) and Eq. (9).

$$\sum \left(\frac{MCF_n}{n}\right)_{all\ sites} \rightarrow 1 \tag{8}$$

$$\sum \left(\frac{\Delta MCF_n}{\Delta t}\right)_{all\ sites} \rightarrow 0 \tag{9}$$

where 'all sites' is the number (n) of regional sites available, ΔMCF is the difference between MCF = 1 and the site MCF value and Δt = 1 (year). As shown in Eq. (9).

The CIMIS data (n = 66) [26] is used with the rate calibration data to generate optimisation charts to the following general Eq. (10) with moisture saturation as.

$$\frac{\mathrm{b}}{\mathrm{a}\,+\,1}\,\mathrm{or}\,\frac{\mathrm{P}}{\mathrm{ETo}} = \,Slope \times \,(\mathrm{Ln(WIP)} - 1) \tag{10}$$

where the Slope is the gradient of the trendline.

The equation allows the estimation of moisture saturation for all regional sites (n = 370) with WIP and the site location data [25]. The rate calibration Slope is fixed to a measured methane recovery level (n = 88), which allows an optimum regional moisture adaptation (ORMA) assessment to be made.

This gives a two-dimensional (surface) view of moisture saturation that is mass balanced with the site WIP as a proportion of the total WIP for the estimation of methane, removing the spatial bias created by the smaller (<10 million tons) 343 of 370 sites that constitute 31.9% of the total WIP [25].

The molar methane oxidation is estimated from the site annual methane by volume and landfill gas recovery data [25]. The relationship with WIP is assessed as unoxidised methane (using molar values) to allow a direct data feed into the FOD model. The proportion of methane generated at each site (n = 66) is shown in Figure 2.

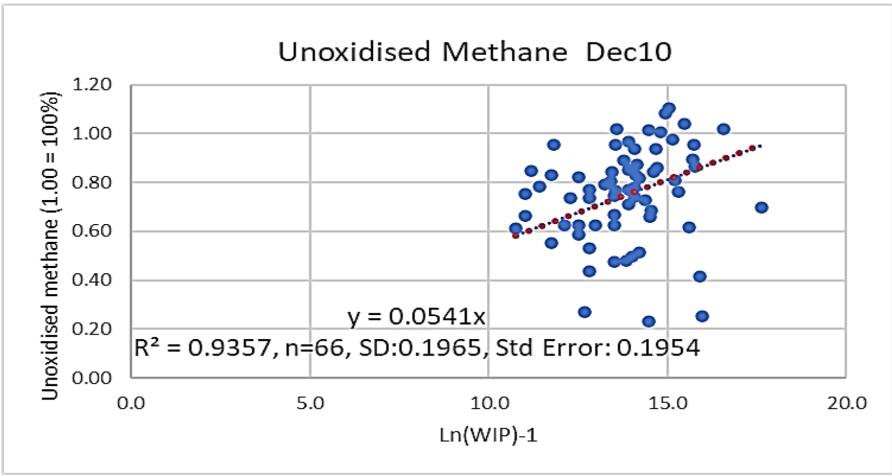

Figure 2 Optimising regional unoxidised methane in December 2010.

The molar methane oxidation is estimated from the site annual methane by volume and landfill gas recovery data [25]. The relationship with WIP is assessed as unoxidised methane (using molar values) providing a direct data feed into the FOD model. The proportion of methane generated at each site (n = 66) is shown in Figure 2.

As with the moisture saturation Slope, the unoxidised methane 'Gradient' is used to estimate optimum regional post oxidation methane generation with the WIP data from the 370 sites. However, whereas annual P/ETo is available monthly, there is only one dataset of annual methane by volume available for estimation of annual methane oxidation data (December 2010) [25]. However, the *Gradient* can be iteratively modelled to the 100% unoxidized methane, which is related to the point where the molar output of CO_2 and CH_4 is equal at the 100% moisture saturation level. The empirical equation enabling a direct estimation of unoxidized methane into the FOD model from site WIP is shown in Eq. (11).

$$Gradient = (0.1617 \times Slope\ Eq.(10)) + 0.0514 \tag{11}$$

3. Results

3.1 Regional Site Distribution by Relative MSW Landfill Moisture Levels

The raw data meteorological (P/ETo) data with the rate calibration (b/(1 + a) estimate, is shown in an accumulative site distribution chart in Figure 3. Over the period from November 2010 to December 2011 there is a general drying trend with a significant drying period in the latter months of 2011.

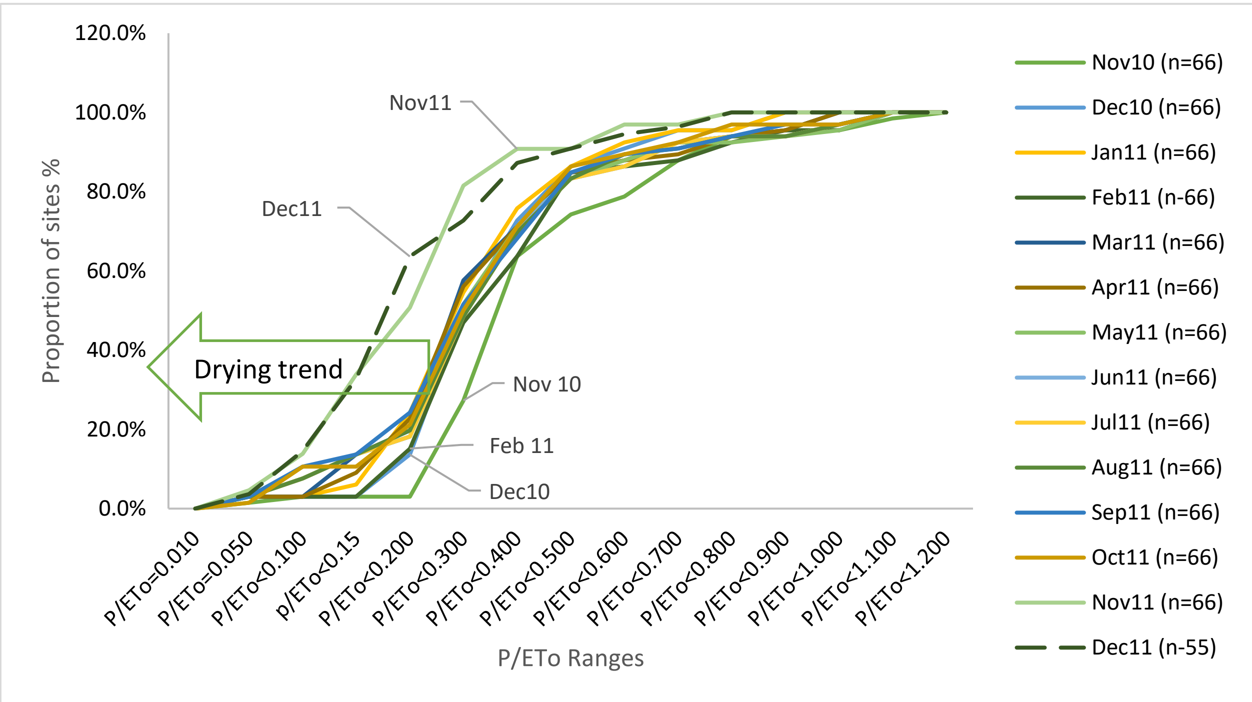

Figure 3 Regional landfill site distribution of P/ETo ranges From Nov10 to Dec11.

There is a monthly range from 63% (November 2010) to 90% (November 2011) of the sites (n = 66) that have a P/ETo below 0.40 or an average regional %MSW moisture <16.9%. These low MSW moisture levels are in the range of increased wildfire intensity 10 to 15% and high wildfire intensity levels 0 to 10% that are measured as dead fuel moisture. The increasing scale and intensity of wildfires in a region of decadal drought indicate rapidly changing climate conditions [3-5, 34, 36-38].

The coloured wildfire intensity ranges in Figure 4were used to show the environmental sensitivity of the optimised moisture saturation term as site MSW moisture (n = 370), making use of the regional (Geographic Information Systems-GIS) landfill locations [25]). Charts at high and low MSW moisture levels that occurred in November and December 2010 and 2011 are shown in Figure 4.

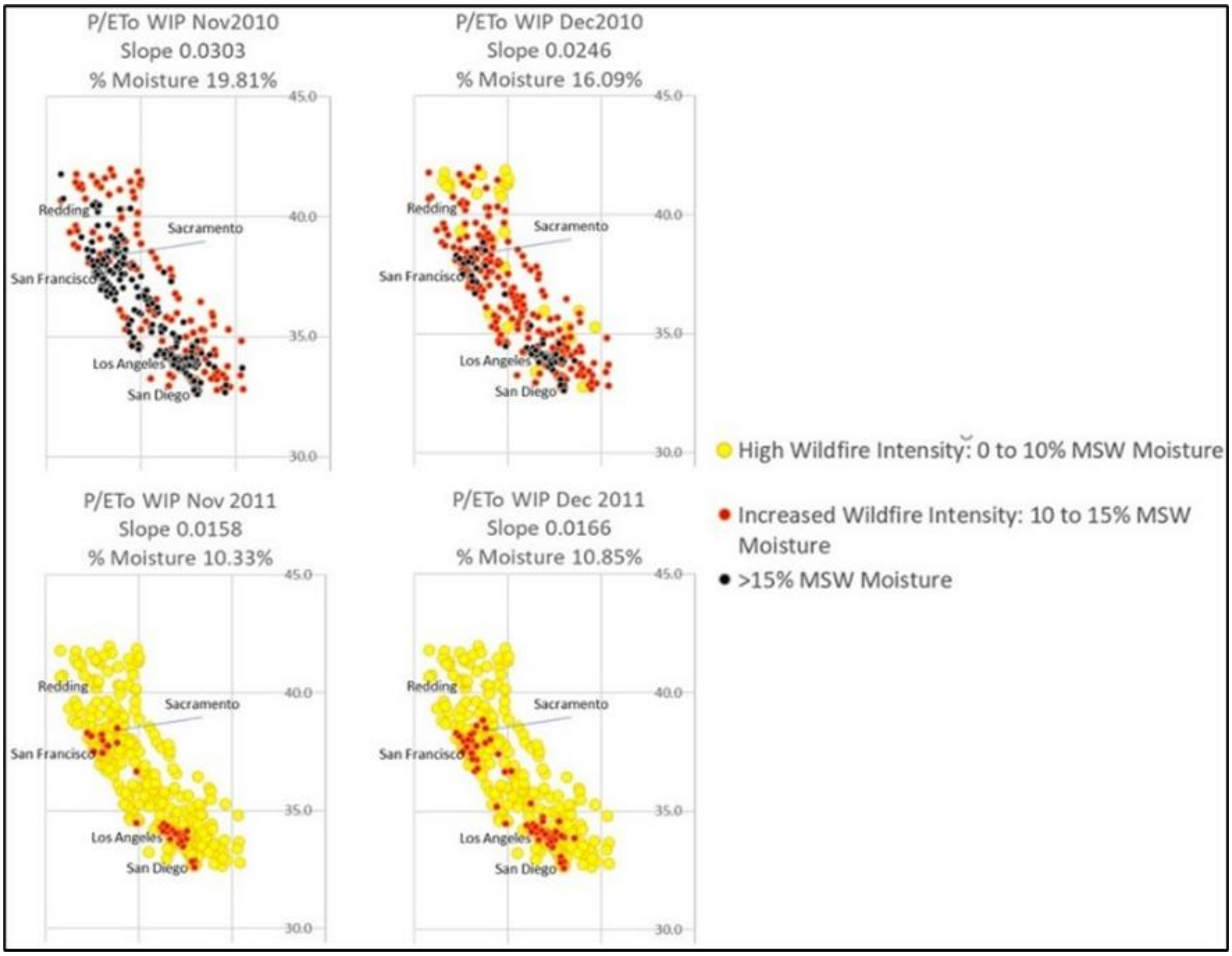

Figure 4 Regional distribution charts of Californian landfill moisture as wildfire intensity levels.

The wildfire vulnerability transformation that occurred over the next 12 months from November and December 2010 to November and December 2011 is stark, as sites change from those dominated by wildfire intensity ranges of 10 to 15% (red) and above 15% moisture (black) within 12 months, to those dominated by those with yellow, high wildfire intensity data points (0 to 10% moisture) across the whole region.

3.2 Case Study. Simulation of 2012 NASA Wildfire Intensity Image

Given the random distribution of the 370 site locations, it would seem unlikely it would be possible to reproduce key features of a satellite image of regional wildfire intensity for 2012 [39].

The chart on the left-hand side of Figure 5 was modelled by iteratively adjusting the Slope (Eq. (11)) to a value of 0.0243 where key wildfire intensity features of the 2012 NASA image were reproduced as closely as possible.

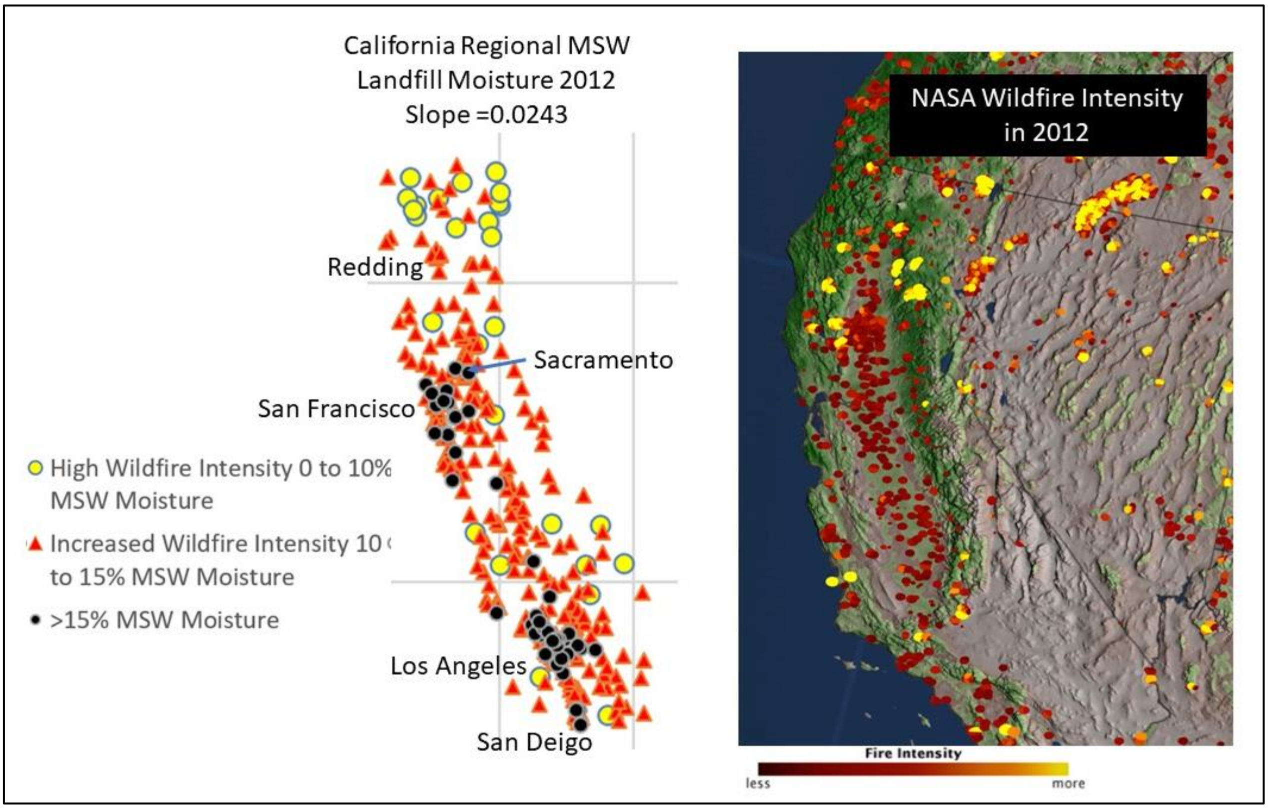

Figure 5 Modelled landfill moisture simulation of 2012 NASA Wildfire Intensity Image [39].

The distribution of high wildfire intensity in the north, with scattering of sites along the coast and to the north of Los Angeles. The central red belt of increased wildfire intensity sites in the central South Southeast to North Northwest band up and down the State, mirroring the NASA image. In San Francisco black markers (>15% moisture) with a few further to the south along the central coast area, demonstrate visual similarities, despite differences in landfill and wildfire locations, engineering, practices, sizes, MSW moisture variations, meteorological, seasonal and microclimate differences (See review on these issues in [7]) that occur across such large region.

3.3 Methane Oxidation

Due to the narrow range of the mass balanced methane oxidation charts generated from Equation 10, there is little difference in the visualisation in the spacial distribution between the highest and lowest methane oxidation values of 12.76% in November 2010 and 16.40% in December 2011. An example from a mid-range chart in April 2011 is shown in Figure 6.

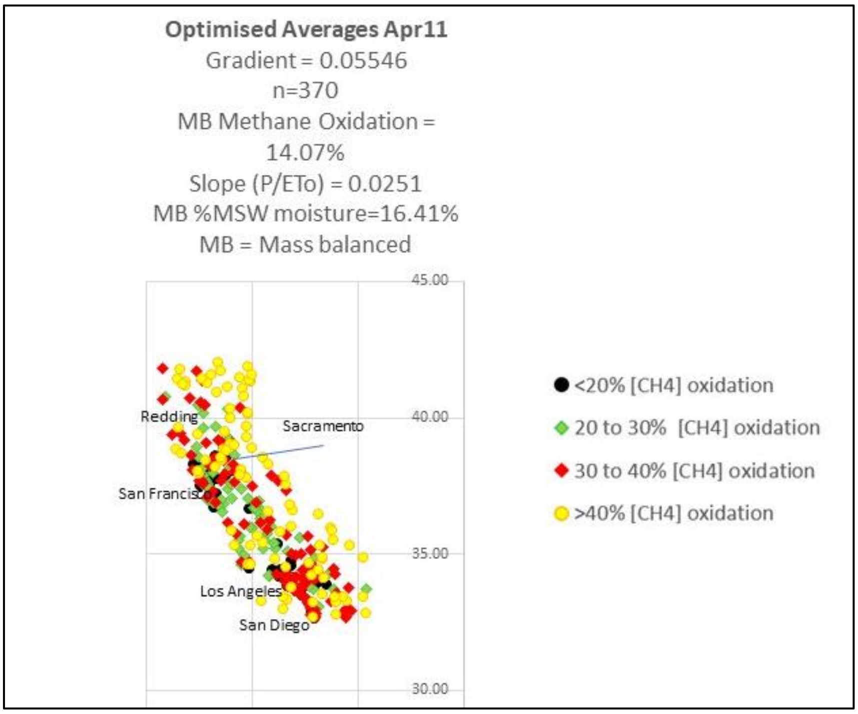

Figure 6 Site distribution with optimised methane oxidation.

3.4 The El Nino Impact

The El Niño-Southern Oscillation is an impact that affects or interfaces with weather systems in regions, such as the US east coastal region. The Oceanic El Nino Index (ONI) is one measure of this affect that generates cooler drying conditions. The ONI impact shown in Figure 7 as an average of annual anomalies over a 5-year period. ONI values may change up to two months after the initial "real time" value is posted and is made up of historical NOAA data [40]. The low point between October and December 2011 coincides with the extreme dry spell in at the end of 2011 (Figure 4).

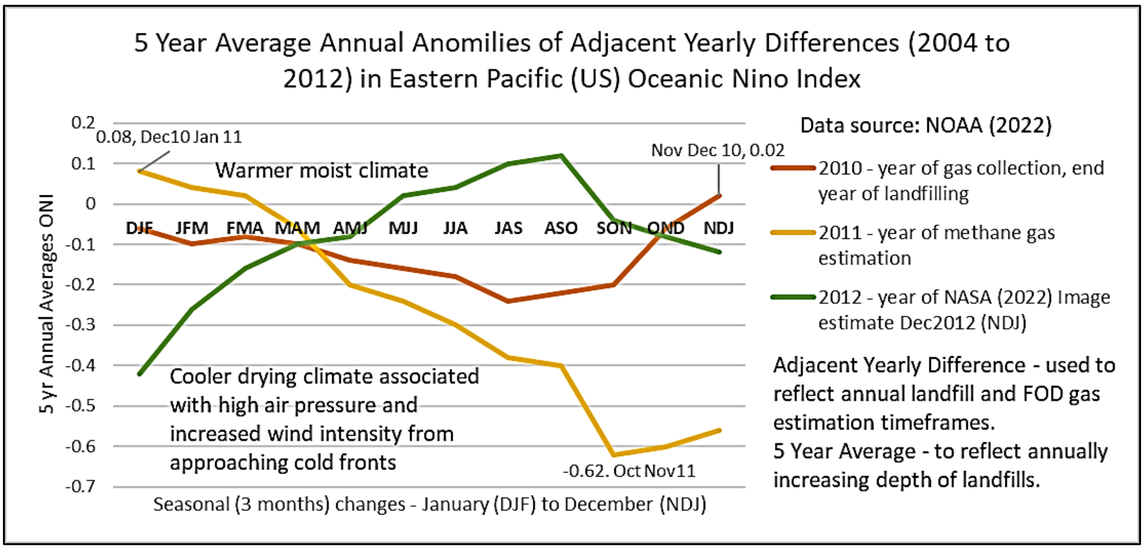

Figure 7 Annual anomaly changes in Oceanic Nino Index (ONI).

The following year 2012 was a very intense period for wildfires in California with significant increases in areas burned in comparison to 2011 [38] an ongoing trend that has continued into the present [34].

3.5 Data Analysis of Optimal Regional Moisture Adaptation

There are a wide range of uncertainties related to the application of the FOD model listed in the IPCC (2006, Table 3-Table 5) [10]. The ORMA process adopted in this study, optimises the dimensionless non-constant moisture saturation term and indirectly the MCF within the non-constant rate constant term. The impact of this is shown in Table 1 which shows that Slope (Equation 9), the moisture saturation and the MSW moisture are within the 99% confidence range, despite a major natural event occurring at the end of 2011. The 2012 NASA wildfire intensity satellite imagery [39] confirms there is less than 1% chance of the results being random (Pr < 0.01) illustrating the climate and meteorological sensitivity of the Slope, the primary modelling tool.

Table 1 Data analysis of moisture saturation and methane oxidation tools.

	Range or Mean	χ2	**DoF (n-1) & (No of datasets)	Probability (Key Variables)	Data Source
Slope (Moisture saturation)					
*ORMA Nov2010 to Dec2011	0.0303 to 0.0166	0.00765875	(4-1) (14)	Pr<0.01 (4)	WIP [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
NASA (2012) [39] Wildfire intensity	0.0243	1.89×10^{-8}	(5-1) (2)	Pr<0.01 (5)	NASA [39], WIP [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty[9-11, 17]
Moisture saturation					
*ORMA Nov2010 to Dec2011	0.4694 to 0.2448	0.00635982	(3-1) (14)	Pr<0.010 (3)	ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
MSW moisture					
*ORMA Nov2010 to Dec2011	10.33 to 19.81%	0.00280387	(4-1) (14)	Pr<0.01 (4)	WIP [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9,10,11,17]
NASA (2012) [39] Wildfire intensity	15.89%	1.24×10^{-7}	(5-1) (2)	Pr<0.01 (5)	NASA [39], WIP [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
Gradient (Unoxidised methane)					
*ORMA Nov2010 to Dec2011	0.0541 to 0.0563	0.00011574	(5-1) (14)	Pr<0.01 (5)	Methane by Vol [25], WIP [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
ORMA Dec2012 - NASA (2012)	0.05533	2.17×10^{-10}	(5-1) (2)	Pr<0.01 (6)	NASA [39], Methane by Vol [25], WIP [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]

[39] Wildfire intensity					
Oxidised methane					
*ORMA Nov2010 to Dec2011	12.67% to 16.19%	0.00817788	(5-1) (14)	Pr<0.01 (5)	Methane by Vol [25] WIP [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
ORMA Dec2010	14.19%	$4.5x10^{-6}$	(6-1) (2)	Pr<0.01 (5)	NASA [39], Methane by Vol [25], WIP [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
ORMA Dec2012 - NASA (2012) [39] Wildfire intensity	14.27%	$2.02x10^{-8}$	(6-1) (2)	Pr<0.01 (6)	NASA [39], Methane by Vol [25], WIP[25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
* CALMIM Dec2010 [7]	12.92%	0.00127903	(6-1) (2)	Pr<0.01 (6)	Spokas et al. [7], Methane by Vol [25], WIP[25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]

Notes: * χ2 referenced to mean value of meteorological moisture saturation charts Nov10 to Dec11. ** DoF: Degrees of Freedom.

The Gradient used to estimate the unoxidised methane (Equation (10)) is very sensitive over a very narrow range 0.0541 to 0.0563, though can be extended from 0.0000 to beyond 0.0563) with the narrow range of methane oxidation falling well within the 99% confidence limits. The CALMIM December 2010 methane oxidation level [7] falls between the ORMA November and December 2010 estimates and within the 99% confidence limits.

3.4 Optimised Regional Moisture Adjusted (Orma) Methane Modelling

The spatial distribution of the OMAR December 2012 landfill moisture estimates in Figure 5, matched with the NASA (2012) wildfire intensity image [39] shows a return to the relative annual meteorological regional norms with 1.65 million tonnes of post oxidation methane generated in December 2010 and 1.66 million tonnes in 2012 (Pr < 0.01, n = 370). The 2011 El Nino cycle dropping post oxidation methane generation to a minimum of 1.21 million tonnes in November rising to 1.26 million tonnes in December (Figure 8) as the cooler drying cycle fades away (Figure 7) into the warmer moist climate conditions across 2012.

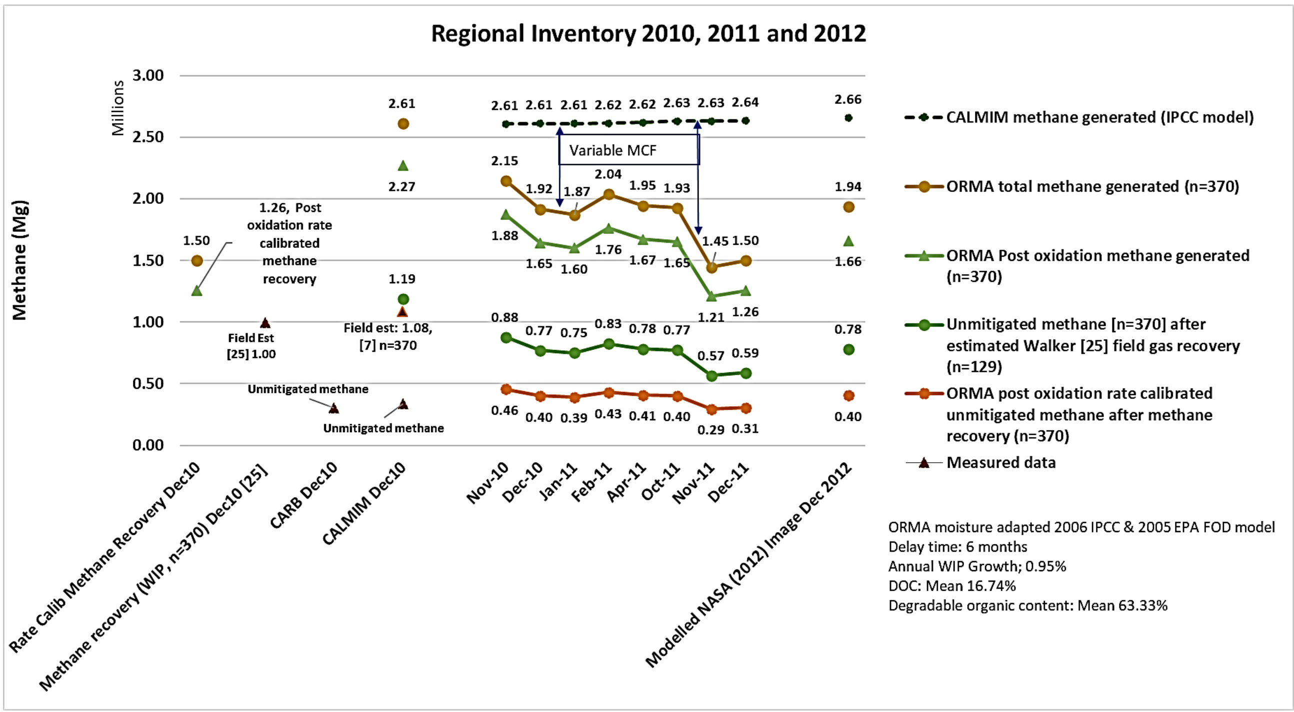

Figure 8 Optimised regional methane inventory as monthly rolling (12-month) averages.

Regional methane generation drops significantly with soil drying with an increase in methane oxidation [5, 6, 41, 42]. Results from this study show a regional methane oxidational range from 12.67% to 16.19% in the period from November 2010 to December 2011 (Pr < 0.01, n = 370, Table 1). The highest oxidation levels occurring in a significant drying period in the last quarter of 2011 relative to the ONI assessment in Figure 7. Figure 9 estimates the regional annual landfill disposal site water balance significantly dropping to 141 in November 2011, with a small rise to 147 million m^3 in December 2011, correlating well with the lower methane generation estimates in this period.

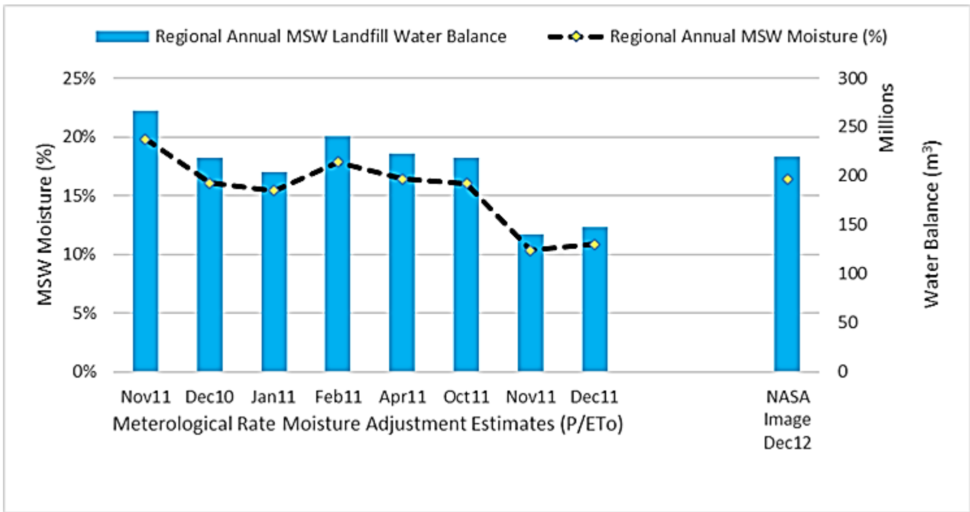

Figure 9 Optimised regional rolling annual water balance and %MSW moisture.

The estimated regional methane recovered in December 2010 is estimated at 1.26 million tonnes. This is based on OMAR simulations of the 129 sites where the methane is collected and or treated and included the largest site at Puente Hills in Los Angeles. This site was left out was omitted from the regional methane gas analysis of 1.08 million tonnes in [7]. The CALMIN methane recovery estimate is higher at 1.19 million tonnes, based on available inventory data also in [7]. A mass balanced estimate of 1.00 million tonnes is based on WIP and methane gas measures (n = 129, WIP = 89.1%) in the Walker database [25]. All these measures falling within the 99% confidence range (Pr < 0.01).

The rate calibrated ORMA post oxidation unmitigated methane after methane recovery of 0.40 million tonnes is at levels close to, though higher than the CARB (0.30 million tonnes) and CALMIM (0.34 million tonnes) estimates that form the Californian CALMIM Inventory [7]. These are based measures of fugitive surface emission data collected from a small number (10) of case study sites. LGCE would also be a factor which would increase the CALMIN estimate to within 1% of the OMAR result. The monthly ORMA estimates fall well within in the 99% confidence range (Pr < 0.01) shown in Table 2.

Table 2 Data analysis of OMAR methane estimations.

	Range or Mean	χ2	*DoF (n-1). (No of datasets)	Probability (Variables)	Data source and variables
Methane recovery					
ORMA Dec2010 Rate Calibration	1,256,278	0.01381	3 (4-1) (12)	Pr<0.01 (5)	WIP [25], Methane Recovery [25], MCF [rate constant Calibration], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
Walker (2012), Mass Balance [25]	998,624	0.004287	2 (3-1) (1)	Pr<0.01 (3)	WIP [25], Methane recovery [25], Landfill gas recovery [25]
CALMIM data [7]	1,084,133	No data	No data	Pr<0.001	CALMIN Inventory [7]
Slope					
CALMIM Gas recovery WIP chart ([7]; Figure 1, Gradient 'a')	998,624	No data	No data	Pr<0.001 (?)	Spokas et al [7]
Unmitigated methane of all methane generated					
ORMA 2010 to 2011	455,439 to 305,978	0.000212	5 (6-1) (15)	Pr<0.01 (6)	WIP [25], Methane by volume [25], Landfill gas recovery [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
ORMA Dec2012 and NASA (2012)	405,000	8.78×10^{-6}	6 (7-1) (2)	Pr<0.01 (7)	NASA [39], WIP [25], Methane by volume [25] Landfill gas recovery [25],

[39] Wildfire Intensity					ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
CARB 2010 [7] with OMAR unmitigated methane	301,748	0.012812	6 (7-1) (13)	Pr<0.01 (7)	CARB [7] WIP [25], Methane by volume [25] Landfill gas recovery [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]
CALMIM 2010 [7] with OMAR unmitigated methane	337,430	0.005287	6 (7-1) (13)	Pr<0.01 (7)	CALMIN [7] WIP [25], Methane by volume [25] Landfill gas recovery [25], ETo [26], P [26], 0.50-0.55 Molar uncertainty [9-11, 17]

Notes: *DoF: Degrees of Freedom.

The sensitivity of monthly (12 monthly rolling averages) estimates of methane emitted in the ORMA model to meteorological changes, is well illustrated in Figure 8 & Figure 9. The sensitivity to climate is illustrated in the detail provided in the 2012 ORMA total methane and post oxidation methane estimates from the NASA satellite image of wildfire intensity levels [38] that were made with no prior knowledge of methane emissions in 2012. The El Nino minimum and inflection point between October and November 2011 (Figure 7) provides an additional indication of climatic sensitivity to oscillatory events with a similar pattern of changes in landfill methane generated in the same period (Figure 8).

The findings in the review [22] that the FOD model was insensitive in determining the modelling parameters, uncertainties and inadequate in determining landfill gas generation and collection, summarised the need for a new approach and set out a significant challenge for this study.

The availability of measured data from the databases [25-27] and other referenced sources such as historical NASA satellite imagery [39] and El Nino data [40]. has been essential in modelling realistic estimates of methane and post oxidation methane generated, as well as in the estimation of recovered methane from the calibration modelling. This is supported a relative fix between the rate calibration of methane recovered and meteorological determined moisture saturation levels in the waste.

From early development of the moisture related methane generation hypothesis, it became likely that the moisture levels estimated within the landfills would include the moisture within the landfill cover material acting as a transfer medium, homogenising the landfill moisture levels that generate the sugar solutes for microbial degradation.

The optimisation process illustrated in Figure 1 and Figure 2, averages out the gains and deficiencies of landfill moisture and MCF uncertainties. The full impact of the OMAR approach became apparent in Figure 8 where the MCF, an unknown variable in the moisture optimisation is identified as the difference in the methane generated between the OMAR and CALMIM models.

The OMAR 'Slope' moisture trendline optimization, generates the conditions $MCF_{site} \neq 1$ as $MCF_{all\ sites} \rightarrow 1$, moving on from the error function analysis [16] with the multi variable analysis used in this study and invalidating the constant rate constant FOD models such as CALMIM that is based on the

2006 IPCC Waste model [10, 11] that does not apply the necessary Fickean non-constant rate constants.

The results of this study do not support a proposition tested (by [7]) “refuting the current hypothetical linkage of biogas generation (ko) to climate”. This statement is a misunderstanding of the non-constant nature of the rate constant. The meteorological and climate sensitivity derived theoretically and demonstrated in this study re-stablishes the essential linkage for methane generation directly to moisture levels in the disposed waste, supported by consistently high confidence in levels shown in estimates of methane recovery and unmitigated methane levels, These have been verified with reference to associated (organisational) and independent sources including Californian State Inventory in [7], Calrecycle data [7, 9, 25], CIMIS [26], NASA [39] and NOAA [40].

Subject to future confirmation of these results in other regions, it looks very likely that the ORMA non constant rate constant moisture adaption can used to address the concerns of inadequacies and insensitivity [22] enabling the modification of the primary FOD models including the 2006 IPCC Waste model [10, 11] and the 2005 EPA model [9] for regional assessments.

4. Conclusion

Considering the urgency to reduce global methane levels by 2030, a key purpose of carbon management is to develop, assess and utilize tools that provide accurate methane data that can be used to record and monitor both regional and global emissions particularly where there are significant variances or data gaps.

Key findings from this regional Californian study involving a theoretical review of the moisture relationship with methane generation and soil oxidation were successfully used in the adaption of a flexible multi-variable FOD model to estimate regional methane generated and mitigated accurately. The results for moisture, methane oxidation and methane generation were analysed against measured data from researchers and independent sources that included satellite imagery and El Nino data. Both climate and meteorological sensitivity to moisture changes is demonstrated in the modelling, case studies and the figures shown in this paper.

Using FOD adaptations, rate calibration, optimisation techniques and equations outlined in this study, it is likely other researchers will be able to quickly estimate regional methane emissions across other regions with varying climate (dry and wet, temperate and tropical).

The OMAR model using basic location, meteorological and waste management data linked up to satellite or drone sensor monitoring systems could provide live estimates of moisture, wildfire intensity and the quantification of unmitigated methane emitted from regional landfills.

For mainly developing countries, where landfilling remains the dominant waste management option, the findings will enable the development of detailed waste emission inventories at country and with international cooperation at regional level. Such, monitoring will inform wider carbon management strategies and provide a means of monitoring, baselining carbon (methane) mitigation strategies, plans and targets affecting waste landfill disposal.

Acknowledgments

I would like to thank CIMIS [26] in California for their assistance in allowing a non-resident researcher of the USA to access their meteorological database and detailed meteorological monitoring station data. Without this assistance, this study would have ended 3 years ago.

Author Contribution

Paul Dumble: All the literature review, theoretical review and moisture concept development; Study data sourcing and collation; Variable FOD model adaptation and methodology; Identification and development of optimisation, calibration and modelling processes; Data analysis, writing up and responding to peer reviewers.

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Permission for non-commercial and educational use of NASA imagery [39] shown in Figure 7 at https://www.nasa.gov/multimedia/guidelines/index.html.

Walker (2012) database [25] in Spokas et al., (2015) [7] permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited details at https://online.ucpress.edu/elementa/article/doi/10.12952/journal.elementa.000051/112713/From-California-dreaming-to-California-data.

Competing Interests

The author has declared that no competing interests exist.

Database

All databases and sources accessed and used in this modelling study are available through websites or weblinks in the reference section.

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