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# Greenhouse Gas Mitigation Opportunities in California Agriculture

## Minimizing Diet Costs and Enteric Methane Emissions from Dairy Cows

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NICHOLAS INSTITUTE
FOR ENVIRONMENTAL POLICY SOLUTIONS

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## ABSTRACT

The study aimed to determine baseline methane emissions from California dairies and assess mitigation strategies. Two optimization models based on linear programming were developed to formulate minimum cost and minimum methane diets without compromising production. A third model uses weighted goal programming for joint minimization of dietary costs and emissions. The economic and environmental impact of using a specific agent (monensin) was also assessed. Enteric emissions ranged from 18.8 to 25.1 MJ/d. Dairies that used corn/alfalfa-based forages and cows with higher intakes and production were low emitters. The cost per unit emissions reduction ranged from \$5.02 to \$20.1/kg methane (\$239–\$956/tonne $CO_2$ equivalent) for a 1% to 25% reduction of total emissions. Various levels of trade-offs between cost and emissions reduction are possible. Up to a 9.4% reduction in $CH_4$ emissions was possible with monensin (costs ranged from \$3 to \$26/kg $CH_4$). Mitigation options need to be tested in a commercial setting before recommendation for use.

## Acknowledgments

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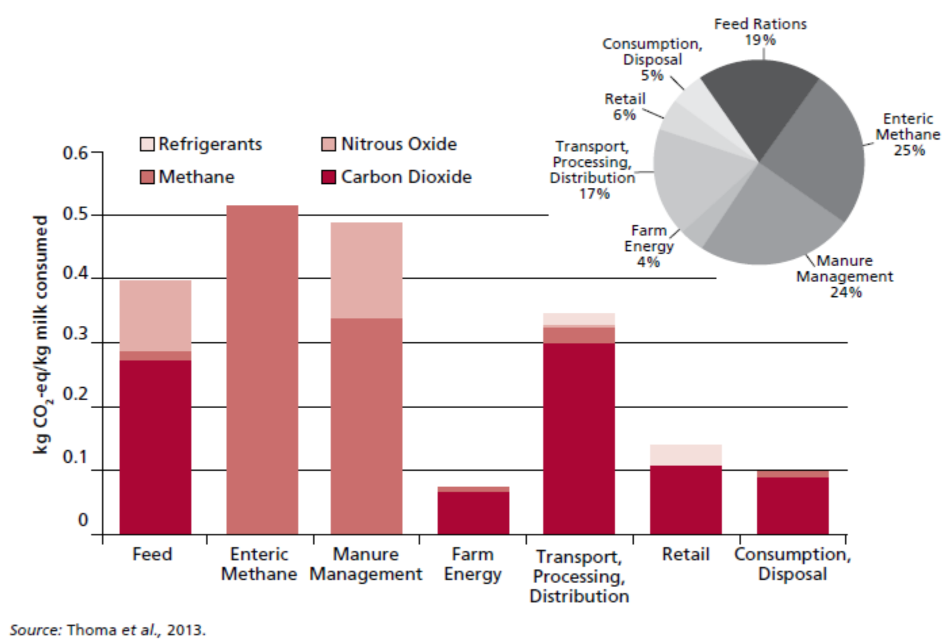
**CONTENTS**

## INTRODUCTION

Methane ($CH_4$) emissions from livestock production are a substantial source of greenhouse gas (GHG) worldwide. The livestock contribution to global anthropogenic GHG emissions ranges from 7% to 18%, depending on accounting approaches and scope (Hristov et al. 2013). According to estimates for the United States, in 2011 $CH_4$ emissions from livestock enteric fermentation and manure management accounted for 23.4% and 8.9% of $CH_4$ emissions from anthropogenic activities, respectively (EPA 2013). Life-cycle assessments of various systems have shown that on-farm emissions represent the largest contribution to the carbon footprint of dairy or beef supply chains (see, e.g., Thoma et al. 2013; Figure 1). The largest contributor to on-farm emissions is $CH_4$ from enteric rumino-reticular fermentation (Hagemann et al. 2011). In the United States, these emissions represent 67.5% of livestock $CH_4$ emissions (enteric fermentation plus manure management; see EPA 2011). However, according to California Air Resources Board (CARB), enteric $CH_4$ emissions represent about 47% of livestock-related emissions in California (CARB 2011). Addressing both enteric fermentation and manure management could reduce GHG emissions from California livestock production systems.

Gerber et al. (2013) reviewed technical options for mitigating enteric $CH_4$ emissions and showed that dietary manipulation could mitigate $CH_4$ emissions from livestock. Some of the options from the review that are relevant to California include improving feed digestibility and use of highly digestible concentrates, dietary lipid supplementation, and ionophores such as monensin and tannins (possibly from grape pomace). For reduction of greenhouse gases in manure, Gerber et al. (2013) identified mitigation options such as low protein diets (to decrease nitrogen in manure), storage time reduction, aeration, and use of stacking and anaerobic digesters. In a companion report, Owen, Kebreab, and Silver (2014) provide a detailed analysis of GHG mitigation opportunities from manure management. The Economic and Technology Advancement Advisory Committee (ETAAC 2008) report suggested that feeding to National Research Council (NRC) guidelines to optimize efficiency could reduce enteric $CH_4$ emissions. The report estimated that $CH_4$ emissions could be reduced up to 30%: 16% from NRC recommended feeding practices, 11% from specific agents, and 3% from long-term management and breeding.

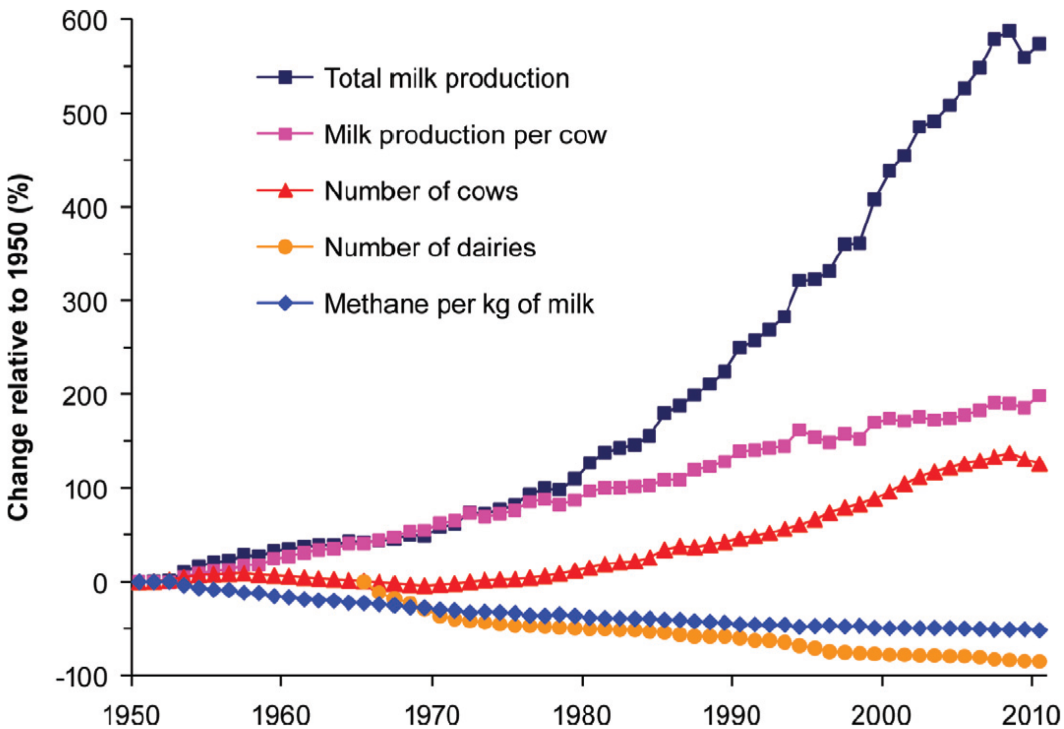
**Figure 1. Supply Chain Contribution to the Carbon Footprint of "Generic Milk" in the United States**




*Source:* Thomas et al (2013).

In 2012, California had about 5.35 million cattle: 1.78 million milk cows and 0.6 million beef cows (CDFA 2012). The state's cattle numbers have increased exponentially since the 1950s, but there was a small decline in 2009 (von Keyserlingk et al. 2013; Figure 2). However, cattle numbers in California appear to be rebounding; the 2012 figures represent a 2.9% increase over 2011 estimates (CDFA 2012). Therefore, emissions from livestock operations in California are a substantial source of greenhouse gases in the United States, and the examination of economic and environmental aspects of $CH_4$ mitigation strategies are necessary for the establishment of a sustainable livestock industry.

**Figure 2. Changes (Percentage Change Relative to 1950) in Total Milk Produced, Milk Production per Cow, Total Number of Dairy Cows and Dairies, and Methane Produced per Kilogram of Milk in the California Dairy Industry between 1950 and 2010**




*Source:* von Keyserlingk et al. (2013).

Due to cost considerations associated with direct emissions measurements, mathematical models of various complexity levels have been used to predict emissions from enteric fermentation (e.g., IPCC 2007; Moraes et al. 2013). However, some widely used models, such as that developed by the Intergovernmental Panel on Climate Change (IPCC 2007), cannot be used to assess mitigation options because they do not include dietary variables that influence emissions. Mechanistic models may be applicable, but due to high input requirements, they may not be applicable in practical assessment. Therefore, models that use dietary variables and require readily available inputs may be better suited for practical assessment of mitigation options. Optimization techniques have been used to model milk production system for decades (e.g., St-Pierre and Harvey 1986; Tedeschi, Fox, Chase, and Wang 2000) and in a recent study, a linear programming (LP) optimization framework was developed to assess the trade-offs between dietary costs and environmental impacts of livestock production and to estimate $CH_4$ mitigation costs through shadow prices (Moraes et al. 2012). Shadow prices of $CH_4$ emissions mitigation were derived in a hypothetical dairy herd, suggesting that substantial reductions of $CH_4$ emissions from dietary manipulation may be extremely expensive. Nevertheless, a framework for the joint minimization of $CH_4$ emissions and dietary costs, and most importantly, for the identification of the set of possible diets with various trade-off levels between emissions and cost is lacking from the literature.

The objectives of this report are to (1) determine the baseline emissions in representative California dairies, (2) quantify changes in $CH_4$ emissions and dietary costs using LP techniques from the baseline scenario when adopting either of two strategies (one to minimize dietary costs and one to minimize $CH_4$ emissions), (3) propose a programming model that combines both strategies and identifies compromises between minimizing dietary costs on the one hand and minimizing $CH_4$ emissions on the other hand, and (4) examine potential $CH_4$ mitigation through supplementation with an ionophore.

## MATERIALS AND METHODS

The study was conducted in two sequential parts. First, a large database of $CH_4$ emissions (Wilkerson and Casper 1995) was used to develop prediction models for estimating enteric $CH_4$ emissions from California dairy herds. Second, data on dietary composition, feed intake, and milk production from 40 dairies in the California Central Valley (Castillo, St-Pierre, Silva del Rio, and Weiss 2013) was used to develop a series of optimization models.

### *Prediction of Methane Emissions from California Dairy Herds*

A large database of $CH_4$ emissions in Northern American lactating cows (Wilkerson and Casper 1995) was used to fit a random regression model for predicting enteric $CH_4$ emissions from lactating cows. The database was composed of 1,111 energy balance records from 40 studies conducted from 1963 to 1995. Records represent at least four consecutive days of lactating cows in respiration chambers and were collected at the former USDA Energy Metabolism Unit at Beltsville, Maryland. The random regression model can be described as:

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{Z}_1\boldsymbol{\alpha} + \mathbf{Z}_2\boldsymbol{\xi} + \boldsymbol{\varepsilon} \qquad [1]$$

where **y** is the vector of $n$ $CH_4$ records **X, $\mathbf{Z_1}$** and **$\mathbf{Z_2}$** are design matrices relating elements of **y** to elements of **β**, **α,** and ξ**,** respectively. **β** is the vector of $p$ regression coefficients [consisting of an intercept and the linear effects of dry matter intake (DMI), dietary proportions of neutral detergent fiber (NDF), and ether extract (EE) as suggested by Moraes et al. (2013)], **α** is the vector of $p \times n_a$ animal random regression coefficients, ξ is the vector of $p \times n_s$ study random regression coefficients, and **ε** is the vector of errors. In this notation, $n_a$ and $n_s$ denote the number of animals and studies, respectively. It was assumed that **α, ξ,** and **ε** are independent and distributed as $\boldsymbol{\alpha} \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_{n_a} \otimes \mathbf{G}_1)$, $\boldsymbol{\xi} \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_{n_s} \otimes \mathbf{G}_2)$ and $\boldsymbol{\varepsilon} \sim \mathrm{N}(\mathbf{0}, \mathbf{I}_n\sigma^2)$, where **$\mathbf{G_1}$** and **$\mathbf{G_2}$** are unstructured variance covariance matrices of order $p$, **I** denotes the identity matrix, $\otimes$ is the Kronecker product, and $\sigma^2$ is the error variance. The prediction model was fitted under a Bayesian framework for which estimation was based on Markov Chain Monte Carlo methods, as described in Moraes et al. (2013). Emissions were predicted with the information (dry matter intake and dietary composition) from the baseline scenario (Castillo, St-Pierre, Silva del Rio, and Weiss 2013) using the vector of regression coefficients estimates (i.e., $\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}}$), where $\hat{\mathbf{y}}$ is the vector of predictions, **X** is the design matrix containing dry matter intake and dietary NDF and EE proportions, and $\hat{\boldsymbol{\beta}}$ is the vector of parameter estimates. This prediction model was also used to predict emissions using the solutions of the optimization models described below.

### *Optimization Modeling*

Initially, $CH_4$ emissions were estimated for the 40 dairies from Castillo, St-Pierre, Silva del Rio, and Weiss (2013) using the prediction model described above, and predictions were used to construct a baseline scenario for $CH_4$ emissions and dietary costs. Changes in emitted $CH_4$ and dietary costs when National Research Council (NRC 2001) guidelines were adopted for diet formulation were examined through a series of LP models. A comprehensive description of the implementation of the NRC (2001) model within a LP diet optimization framework is given by Moraes et al. (2012). Two major LP frameworks were constructed: a least-cost diet model and a minimum $CH_4$ model with the objective of examining changes and trade-offs of optimizations with distinct goals. Shadow prices were calculated under the least-cost diet model for which $CH_4$ was restricted through the implementation of a model constraint (as described in Moraes et al. 2012). These prices were used to estimate marginal costs of $CH_4$ emissions mitigation. Finally, a weighted goal programming model (Romero and Rehman 1989) is proposed for the joint minimization of diet costs and emissions. The goal programming framework combines the two LP models previously implemented through identification of the set of solutions with various levels of trade-offs between diet costs and $CH_4$ emissions. All optimization models were solved in the lpSolve package of the open source statistical software environment R (Buttrey 2005). That package offers an attractive software environment for implementing optimization models because it is freely available and provides tools in R such as plots and statistical analysis capabilities.

### Least-Cost Diet Model

The least-cost diet model was developed to identify least-cost diets that supply nutrients determined by the NRC guidelines (NRC 2001). Feeds used for diet optimization were from Castillo, St-Pierre, Silva del Rio, and Weiss (2013). Milk production and supplementary animal information from Castillo, St-Pierre, Silva del Rio, and Weiss (2013) were used within the NRC (2001) model for the calculation of the nutrient requirements as described in Moraes et al. (2012). Additional constraints were imposed on the NRC (2001) guidelines to ensure the formulation of feasible diets that would be readily accepted by producers. For example, some feeds in diets had maximum inclusion limits, and the proportion of dietary forage was limited from 40% to 60% (Table 1). Feed prices were collected locally in California and represent costs from February to March 2013 (Table 1), and feeds' nutrient composition was based on NRC (2001). The model was solved individually for each dairy and can be described by:

$$
\begin{aligned}
&\min z_1 = \sum_{j=1}^{n} c_j x_j \\
&s.t. \\
&\sum_{j=1}^{n} a_{ij} x_j \geq b_i \quad for\ i = 1, \ldots, m \\
&\sum_{j=1}^{n} x_j \leq d \\
&u_i \leq \frac{\sum_{j=1}^{n} x_j p_{ij}}{\sum_{j=1}^{n} x_j} \leq v_i \quad for\ i = m+1, \ldots, m+r. \\
&x_j \geq 0 \quad for\ j = 1, \ldots, n
\end{aligned}
\tag{2}
$$

where $z_1$ is the objective function value ($); $c_j$ is the price of feed $j$ ($/kg DM); $n$ represents the number of available feeds; $x_j$ is the amount of feed $j$ (kg DM); $a_{ij}$ is the content of nutrient $i$ ($i$ = 1, …, $m$) in feed $j$ (MJ, g or mg/kg DM); $b_i$ is the daily animal requirement of nutrient $i$ (MJ, g or mg); $d$ is the daily animal maximum intake capacity (kg DM), which was set at the DMI intake from the baseline scenario (DMI must be smaller than or equal to the baseline scenario); $u_i$ is the minimum dietary proportion of nutrient $i$; $p_{ij}$ is the proportion of nutrient $i$ ($i = m + 1$, …, $m + r$) in feed $j$ (kg/kg DM); and $v_i$ is the maximum dietary proportion of nutrient $i$. The dietary proportion nutrient constraint was linearized, so the model could be solved by LP techniques through multiplication of the equation denominator by its right-hand side. Such linear form of the constraint is equivalent to the original non-linear form and will generate same LP solutions with the advantage of direct interpretation of dual values. In this report, dietary NDF percentage was constrained to be greater than 25%, and dietary EE was constrained to be smaller than 7%, as suggested by NRC (2001).

**Table 1. Dietary Feed Upper Limits and Feed Costs**

| Feed | Limit[a] | Cost[b] |
|---|---|---|
| Alfalfa silage | No limit | 0.30 |
| Alfalfa hay | No limit | 0.29 |
| Almond hulls | 0.10 | 0.20 |
| Bakery waste | 0.10 | 0.42 |
| Barley grain | No limit | 0.41 |
| Barley silage | No limit | 0.16 |
| Canola meal | 0.10 | 0.47 |
| Corn gluten feed | 0.10 | 0.36 |
| Corn grain - flaked | No limit | 0.43 |
| Corn silage | No limit | 0.21 |
| Whole cotton seeds | No limit | 0.44 |
| Corn dried distillers grain | 0.10 | 0.39 |
| Grass silage | No limit | 0.13 |
| Molasses | 0.03 | 0.27 |
| Oats hay | No limit | 0.19 |
| Oats Silage | No limit | 0.16 |
| Rice Bran | 0.05 | 0.30 |
| Soybean meal | 0.15 | 0.58 |
| Sugar beet pulp | 0.15 | 0.36 |
| Tomatoes | 0.1 | 0.12 |
| Wheat hay | No limit | 0.25 |
| Wheat silage | No limit | 0.17 |
| Whey | 0.01 | 0.17 |
| Sodium Bicarbonate | No limit | 0.34 |
| Sodium Chloride | No limit | 0.14 |
| Mineral premix A[c] | No limit | 1.05 |
| Mineral premix B[d] | No limit | 0.76 |
| Mineral premix C[e] | No limit | 7.15 |

[a]In kg/kg of diet DM.
[b]In $/kg DM. Collected locally in California – From February and March 2013.
[c]Contained 15% Ca and 21% P.
[d]Contained 22.5% S, 18% K, and 11.5% Mg.
[e]Contained 3.75% Zn, 3% Mn, 1.25% Cu, and 0.25% Co.

### Minimum Methane Model

The minimum $CH_4$ model was developed to formulate diets that minimize $CH_4$ emissions while supplying nutrients required to maintain the milk production level from the Castillo, St-Pierre, Silva del Rio, and Weiss (2013) data. The model was structured similarly to the least-cost diet model with the same set of constraints specified. The difference between the least-cost diet and the minimum $CH_4$ models is that the objective function for the latter can be described as:

$$\min z_2 = \sum_{j=1}^{n} g_j x_j \qquad [3]$$

where $z_2$ is the objective function value ($CH_4$ emission factor units), and $g_j$ is the $CH_4$ emissions factor unit of feed $j$ (Emission factor units/kg DM), calculated as a linear combination of NDF and EE proportions of each feed for which the regression coefficients of Eq. [1] are the combination weights. More specifically, $g_j = \mathbf{s}_j^{\mathrm{T}} \hat{\boldsymbol{\beta}}$, where superscript T denotes transpose, $\mathbf{s}_j = \left(1, NDF_j, EE_j\right)^{\mathrm{T}}$, $NDF_j$ and $EE_j$ are the NDF and EE percentages of feed $j$, and $\hat{\boldsymbol{\beta}}$ is the vector of estimates of the regression coefficients from Eq. [1].

### Goal Programming Model

The two previously described LP models have distinct goals: minimize diet costs and $CH_4$ emissions, which may be potentially conflicting. Consequently, there is a trade-off, i.e., minimizing diet costs may result in diets with increased $CH_4$ emissions, and minimizing $CH_4$ emissions may result in substantially expensive diets, as discussed in Moraes et al. (2012). To identify solutions for which there is a balance between achievements of individual goals, a weighted-goal programming model that combines the two previously described LP models is proposed. Goal programming belongs to the multiobjective optimization family of models that are often utilized when the decision maker is aimed at simultaneously optimizing more than one criteria of the system. Further, the weighted-goal programming model is a special case of the goal programming model that weighs the objective function to establish trade-offs between achievement of specific goals. The weighted-goal programming model uses total requirements from the 40 dairies in the construction of the feasible region in a single optimization and can be described by:

$$\begin{aligned}
&\min z_3 = \sum_{q=1}^{2} w_q \left( \frac{n_q + p_q}{t_q} \right) \\
&s.t. \\
&\sum_{j=1}^{n} c_j x_j + n_1 - p_1 = t_1 \\
&\sum_{j=1}^{n} g_j x_j + n_2 - p_2 = t_2 \\
&\mathbf{x} \in F \\
&\mathbf{x}, n_q, p_q \geq 0
\end{aligned} \qquad [4]$$

where $z_3$ is the goal programming objective function value, $w_q$ is the weight of the $q^{\text{th}}$ goal (q = 1, 2, where goal 1 is to minimize cost and goal 2 is to minimize emissions), $n_q$ and $p_q$ are the negative and positive deviation variables for goal $q$, $t_q$ is the objective target value for goal $q$, $\mathbf{x}$ is the vector of feeds, $F$ is the feasible set constrained by the technical constraints described in Eq. [2], and the other variables are the same as noted above. Further, objective target values were set as the objective function values from the two previously described LP models (i.e., $t_1 = z_1$ and $t_2 = z_2$) using the total nutrient requirements of the 40 dairies from Castillo, St-Pierre, Silva del Rio, and Weiss (2013). This model specification naturally accommodates the goal programming restriction $n_q p_q = 0$ ($q$ = 1, 2). A grid of weights for which $\sum_{q=1}^{2} w_q = 1$, as suggested by Jones and Tamiz (2010), was constructed to explore the set of efficient solutions. In essence, this grid created a factorial experiment with $w_1$ and $w_2$ varying from [1, 0] and [0, 1] in increments of 0.01. At each one of the 101 loci, the model was solved and solutions were recorded for the construction of the set of solutions. In this grid specification, when $w_2 = 0$, Eq. [4] produces the same solutions (in the diet formulation sense) as Eq. [2], and when $w_1 = 0$, Eq. [4] produces the same solution as Eq. [3]. Diet cost and emissions target levels ($t_1$ and $t_2$) can be derived from field data of specific production systems and regulatory policies schemes or can be determined as a part of the optimization. If target values are known a priori, they should be used in model optimization. When no prior knowledge about target diet costs and emissions were available (as in this report), a method based on individual optimizations of each goal (i.e., $t_1 = z_1$ and $t_2 = z_2$) was used.

## RESULTS AND DISCUSSION

### *Prediction of Methane Emissions, Dietary Costs, and Linear Programming Models*

Baseline Scenario

The fitted model for predicting $CH_4$ emissions was:

$$CH_4\ (\text{MJ/d}) = -\ 1.285\ (0.82) + 0.796\ (0.03) \times \text{DMI (kg/d)} + 0.157\ (0.02) \times \text{NDF (\% DM)} - 0.219\ (0.10) \times \text{EE (\% DM)} \quad [5]$$

where values in parentheses are the standard errors. This prediction equation provides a mean square prediction error, when internally evaluated, of 3.08 MJ/d (or 18.1% of observed mean), which suggests that the prediction model used here has a greater predictive capacity than the models assessed by Ellis et al. (2010). Quantiles of predicted $CH_4$ emissions for the Californian dairies are given in Table 2. Methane emissions ranged from 18.8 MJ/d to 25.1 MJ/d, with a median of 21.7 MJ/d, which is agreement with literature values of Holstein lactating cows (Wilkerson and Casper 1995).

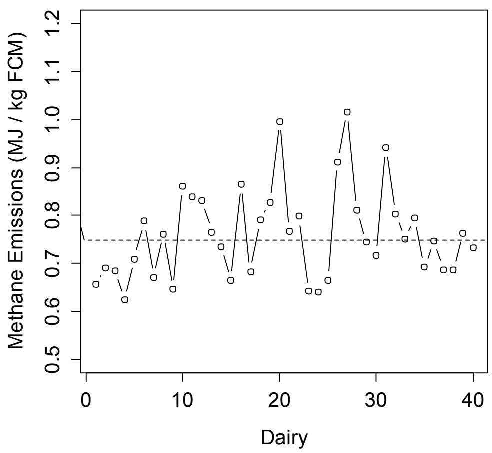
**Table 2. Predicted Methane Emissions and Dietary Costs in the Castillo, St-Pierre, Silva del Rio, and Weiss (2013) Baseline Scenario, Least-Cost Diet Scenario, and Minimum Methane Scenario in 40 Dairies, on a Cow Basis**

| | Methane emissions (MJ/d)[a] | | | | | | Diet cost ($/d)[a] | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Scenario | Median | 10th Qt. | 25th Qt. | 75th Qt. | 90th Qt. | Median | 10th Qt. | 25th Qt. | 75th Qt. | 90th Qt. |
| Castillo, St-Pierre, Silva del Rio, and Weiss (2013) | 21.7 | 20.5 | 21.3 | 22.4 | 2 3.3 | 7.8 | 6.1 | 7.2 | 8.4 | 8.6 |
| Least-cost diet | 21.7 | 20.4 | 20.9 | 23.1 | 23.8 | 4.9 | 4.2 | 4.6 | 5.4 | 5.9 |
| Minimum methane | 16.4 | 14.5 | 15.7 | 17.6 | 19.4 | 6.6 | 5.6 | 6.2 | 7.3 | 8.3 |

[a] Median, 10th, 25th, 75th, 90th quantiles.

Methane emissions in MJ/kg fat corrected milk (FCM) are presented in Figure 3 and ranged from 0.624 to 1.02 MJ/kg FCM, with a median of 0.748 MJ/kg FCM. Furthermore, calculated dietary costs in the baseline dairies ranged from 4.38 to 8.89 $/d, with a median of 7.84 $/d, which is in close agreement with California average feed costs from the first quarter of 2013 (CDFA 2013). Examination of the baseline scenario shows that the ratio $CH_4$ emissions/unit FCM varies considerably in the 40 dairies (Figure 3), suggesting that some dairies emit less $CH_4$ per unit of produced milk.

**Figure 3. Predicted Methane Emissions pre Unit of Fat-Corrected Milk (MJ $CH_4$/kg FCM) for the 40 Dairies from Castillo, St-Pierre, Silva del Rio, and Weiss (2013) Data**




*Note:* Dashed horizontal line is the median.

Four dairies in the lower 10th quantile can be considered low-$CH_4$-emitting dairies (0.65 MJ/kg FCM). Dietary characteristics and animal responses were examined to identify production characteristics that may contribute to lower $CH_4$ emissions in these four dairies, such reduced emissions level. The four dairies used corn silage and alfalfa hay as their main forage source. Three of these dairies also used oat silage as a forage source. The main concentrate sources in the four dairies were corn, barley, cotton seeds, canola, almond hulls, distillers' dried grains, and soybean meal. In these dairies, the average DMI is greater than the data median intake (23.2 kg DM/d), and two of the dairies have a dietary EE proportion greater than the data median (4.41%). Dietary NDF percentages are above the median (34.5%) in two of the dairies. In these low-emitting dairies, daily milk production is above the 90th quantile (37.4 kg/d), and in three of the dairies, fat percentage proportions are also above the median (3.58%). Finally, the milk-to-feed ratio (kg Milk/kg DMI) was above the 90th quantile (1.51 kg Milk/kg DMI) in all four dairies. Therefore, dairies that are more efficient in producing milk per unit of feed may have lower $CH_4$ emissions levels per unit of milk produced than low-producing dairies, a finding that is in agreement with Capper, Cady, and Bauman (2009) and Gerber et al. (2013). Specifically, if more efficient cows produce a larger amount of milk for a given amount of feed, they will have lower emissions per unit of milk because feed intake is the major driver of $CH_4$ emissions. In fact, as Figure 2 shows, $CH_4$ emissions in California since 1950 decreased 52% when calculated per product basis. This trend is due to a 200% increase in milk production but a just more than 100% increase in cow numbers (von Keyserlingk et al. 2013).

## Least-Cost Diet and Minimum Methane Scenarios

Predicted $CH_4$ emissions for the 40 dairies in baseline, least-cost diet, and minimum $CH_4$ model scenarios are given in Table 2. Total $CH_4$ emissions increased 0.94% for the least-cost diet scenario compared with the baseline scenario, suggesting that feeding according to the NRC guidelines would not reduce total $CH_4$ emissions. As expected, total $CH_4$ emissions decreased 23.61% in the minimum $CH_4$ scenario compared with the baseline scenario and 24.32% compared with the least-cost diet scenario. Such changes in $CH_4$ emissions were achieved through changes in dietary composition and dry matter intake.

Increased dietary fat has been suggested as a $CH_4$ mitigation tool by several studies (e.g., Martin, Morgavi, and Doreau 2010; Grainger and Beauchemin 2011) and this strategy was incorporated into the model structure through Eq.[1] because EE was one of the explanatory variables. Reducing the proportion of dietary structural carbohydrates has also been shown to reduce emissions (Moe and Tyrrell 1979). Average dry matter intake decreased from 21.2 kg/d to 18.0 kg/d from the least-cost diet to the minimum $CH_4$ scenario. Moreover, dietary NDF percentage decreased from 48% to 30% in the least-cost diet and minimum $CH_4$ scenarios. Similarly, dietary crude protein (CP) increased from 17.8% in the least-cost diet scenario to 20.6% in the minimum $CH_4$ scenario.

Feeds used for diet formulation also changed in both scenarios. For example, the major forage sources in the least-cost diet model were grass and oat silages and the major concentrates were flaked corn, soybean meal, distillers' dried grains, and tomatoes. Conversely, in the minimum $CH_4$ scenario, the major forage sources were corn and alfalfa silages, and the major concentrate sources were flaked corn, soybean meal, canola, and bakery waste. In both the least-cost diet and minimum $CH_4$ scenarios, delivery of net energy for lactation (NEL) was at or slightly above the animal requirement level, suggesting that milk production in these two scenarios would be similar.

Dietary cost in the least-cost diet and minimum $CH_4$ scenarios are given in Table 2. Total diet costs decreased 34% and 10% in the least-cost diet and minimum $CH_4$ scenarios, respectively, compared with the baseline. Total diet costs in the minimum $CH_4$ scenario increased 35.5% compared with total diet costs in the least-cost diet scenario.

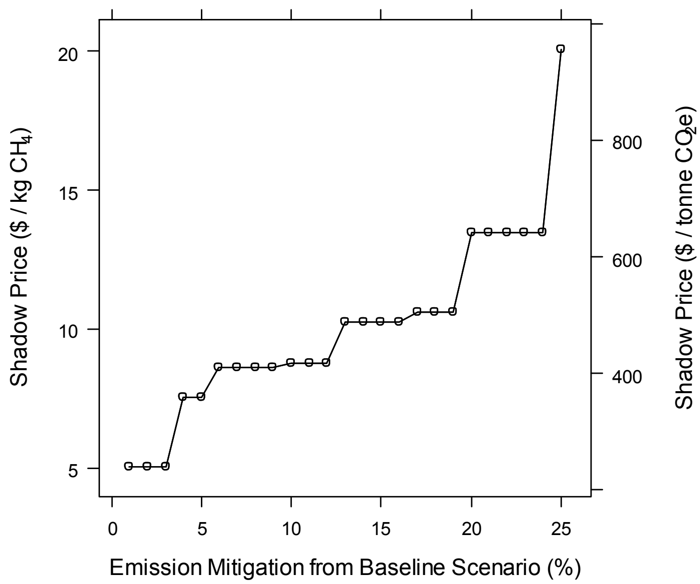
Diet costs from the LP models may underestimate actual feeding costs because a series of assumptions are implied in the LP structure. Specifically, nutrient requirements and feeds' nutrient composition are assumed to be known and error free, yet nutrient composition of feeds varies considerably (St-Pierre and Harvey 1986), and nutrient requirements within a pen of animals also vary. In practice, safety factors are used in the calculation of nutrient requirements of animals as described by Kohn (2007). Moreover, diets formulated in the computer software and the ones actually fed to animals may be quite different due to losses in the feeding process (Rossow and Aly 2013). Therefore, to meet cows' nutrient requirements, nutrients are often overprovided, resulting in diets that are more expensive than the theoretical ones optimized by LP models. Moreover, a major reason for lower diet costs from optimization models may be the assumption that all feeds are available for purchase in unlimited quantity at every dairy. In this study, it was assumed that all feeds were available in every dairy at the same price, but in the baseline scenario not all dairies used all feeds. Some feeds might not be readily available in specific regions, at least at the price assumed. These factors may partially explain the substantially lower costs of diets in the LP models than those in the baseline scenario. Nevertheless, major differences in dietary costs may be a result of the diet optimization process, which is not always used in commercial dairy production settings.

These differences in formulated and actual diet costs must be considered when comparing diet costs from the three scenarios to avoid the misleading impression that reduction of emissions from the baseline scenario to the minimum $CH_4$ scenario may not increase dietary costs. In the baseline scenario, prices of actual diets fed to animals are calculated, whereas diet prices in the other two scenarios reflect theoretical optimization results. From an economic perspective, a suitable approach for examining changes in dietary costs under a set of production restrictions, such as $CH_4$ emissions mitigation, is calculation of shadow prices.

Shadow prices of $CH_4$ emissions represent the marginal cost of $CH_4$ emissions mitigation through dietary manipulation and were calculated as described by Moraes et al. (2012). In short, the $CH_4$ emissions linear prediction model is used as an LP model constraint, which is set to proportionally reduce emissions at different mitigation intensities. This constraint can be thought of as an environmental regulatory policy that regulates the amount of emissions that a farm can emit. Shadow prices are then calculated in \$/unit of $CH_4$ or $CO_2$ equivalent ($CO_2e$) using a global warming potential of 21, as suggested by IPCC (2007)—that is, dividing \$/tonne $CH_4$ by 21. These prices can be used to estimate the marginal cost of reducing $CH_4$ emissions through dietary manipulation. Shadow prices of $CH_4$ emissions mitigation, i.e. cost per unit reduction of $CH_4$ emissions, ranged from \$5.02 to \$20.1/kg $CH_4$ (or \$239 to \$956/tonne $CO_2$e), representing a 1% to 25% reduction of total $CH_4$ emissions from the baseline scenario. These prices are plotted against the emissions reduction level from the baseline scenario in Figure 4.

In a carbon cap-and-trade policy scenario, producers could use $CH_4$ emissions shadow prices to determine the carbon trading value of their unit emissions reduction. Shadow prices generated in this study are substantially higher than current prices of carbon units in the California carbon credit market. Specifically, even for small reductions in $CH_4$ emissions, i.e., 1% from baseline scenario, shadow prices are much higher than current carbon credit market values for the $CO_2$ equivalent. For instance, marginal costs of $CH_4$ mitigation are around \$240/tonne $CO_2$e for a 1% emissions reduction. Moreover, for substantial emissions mitigation (greater than 15% from the baseline), marginal costs are approximately \$500/tonne $CO_2$e. Such results are in agreement with results from Moraes et al. (2012) in which substantially high shadow prices were estimated for the U.S. dairy industry in 2012.

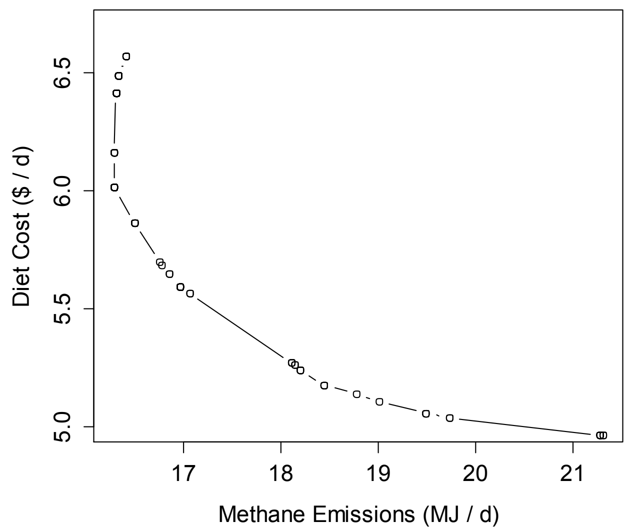
**Figure 4. Shadow Prices of Methane Emissions Mitigation through Dietary Manipulation versus Methane Reduction Percentage from the Baseline**




### *Goal Programming Model*

The goal programming model combines the two previously developed LP models and provides a set of solutions with various levels of trade-offs between reducing dietary costs and reducing $CH_4$ emissions. In comparing the least-cost diet and the minimum $CH_4$ models, it is evident that dietary costs are dramatically increased when $CH_4$ emissions are substantially reduced. Similarly, $CH_4$ emissions are increased in the least-cost diet scenario (as discussed above). Construction of the weight grid allows identification of 21 solutions for which diet costs and predicted $CH_4$ emissions are plotted in Figure 5.

**Figure 5. Methane Emissions versus Diet Costs from the Solutions of the Weighted-Goal Programming Model**




Solutions at the two extremes of the weight grid are the same as individual LP optimizations, because $w_1$ or $w_2$ are set to zero. As the weights change incrementally, solutions with different levels of goal trade-offs are identified. Proportional changes and deviations in diet costs and $CH_4$ emissions from the objective target values [$t_1$ = \$4.96/d and $t_2$ = 77.4 emission factor units ($CH_4$ = 16.4 MJ/d)] for all 21 solutions are in Table 3. This set of solutions allows selection of diets with a desired level of trade-off between a dietary costs increase and a $CH_4$ emissions reduction. For example, in the first row of Table 3, dietary costs are at their minimum set by the target level \$4.96/d, and $CH_4$ emissions are 4.90 MJ/d greater than the minimum $CH_4$ emissions [$CH_4$ = 4.90 + 16.40 = 21.30 MJ/d]. Conversely, in the last row, $CH_4$ emissions are at their minimum level of 16.40 MJ/d, and dietary costs are \$1.61/d more expensive than the target level [Cost = 1.62 + 4.96 = \$6.57/d]. The other 19 solutions represent compromised solutions, which may be chosen by the decision maker according to their trade-off limits. Explicitly, solutions at the upper part of the table reflect more weight on minimizing dietary costs, and solutions at the lower part of the table reflect more weight on emissions minimization. For example, in solution number 4 (Table 3), dietary costs are \$5.05/d, and $CH_4$ emissions are 19.49 MJ/d. In solution number 10 (Table 3), dietary costs are \$5.27/d, and $CH_4$ emissions are 18.10 MJ/d. At the lower end, in solution number 16 (Table 2), dietary costs are \$5.86/d, and $CH_4$ emissions are 16.50MJ/d.

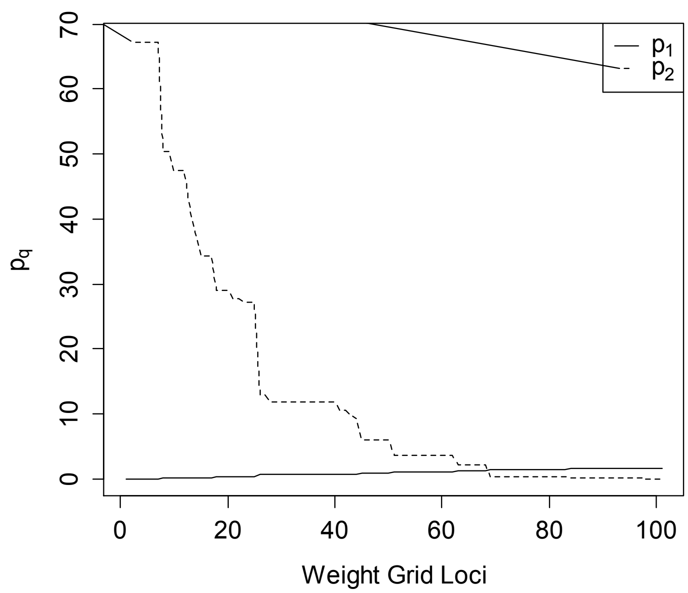
**Table 3. Diet Costs and Methane Emissions Deviations from the Individual Optimizations Objective Function Values for 23 Goal Programming Distinct Solutions**

| Solution | Δ Diet Cost ($/d) | Δ Diet Cost (%) | Δ Methane (MJ/d) | Δ Methane (%) |
|---|---|---|---|---|
| 1 | 0.0000 | 0.0 | 4.9049 | 29.9 |
| 2 | 0.0002 | 0.0 | 4.8770 | 29.7 |
| 3 | 0.0763 | 1.5 | 3.3272 | 20.3 |
| 4 | 0.0933 | 1.9 | 3.0864 | 18.8 |
| 5 | 0.1451 | 2.9 | 2.6053 | 15.9 |
| 6 | 0.1768 | 3.6 | 2.3733 | 14.5 |
| 7 | 0.2134 | 4.3 | 2.0412 | 12.4 |
| 8 | 0.2783 | 5.6 | 1.7882 | 10.9 |
| 9 | 0.2998 | 6.0 | 1.7338 | 10.6 |
| 10 | 0.3082 | 6.2 | 1.7023 | 10.4 |
| 11 | 0.6042 | 12.2 | 0.6534 | 4.0 |
| 12 | 0.6314 | 12.7 | 0.5616 | 3.4 |
| 13 | 0.6852 | 13.8 | 0.4438 | 2.7 |
| 14 | 0.7226 | 14.6 | 0.3692 | 2.3 |
| 15 | 0.7377 | 14.9 | 0.3448 | 2.1 |
| 16 | 0.8998 | 18.1 | 0.0920 | 0.6 |
| 17 | 1.0525 | 21.2 | -0.1153 | -0.7 |
| 18 | 1.1985 | 24.2 | -0.1247 | -0.8 |
| 19 | 1.4539 | 29.3 | -0.0992 | -0.6 |
| 20 | 1.5249 | 30.7 | -0.0724 | -0.4 |
| 21 | 1.6110 | 32.5 | 0.0000 | 0.0 |

*Note:* Δ Diet Cost ($/d) is the difference between the actual goal programming solution and the target diet cost ($t_1$ = $4.96/d), Δ Diet Cost (%) is the proportional change in diet cost from the target value diet cost, Δ Methane (MJ/d) is the difference in methane emissions between actual goal programming solutions and target methane emissions ($t_2$ = 77.41 emissions factor units ($CH_4$ = 16.40 MJ/d)), and Δ Methane (%) is the proportional change from the target methane emissions.

The weight grid implemented in this study generated 101 solutions of which 21 are distinct, as described above. Deviational variables are plotted versus the weight grid loci (Figure 6) for an examination of the process of identifying the set of feasible solutions. It is evident that the proportional decrease in $w_1$ causes the increase in $p_1$, leading to an increase in dietary costs and decrease in $CH_4$ emissions. Similarly, the sequential increase in $w_2$ also leads to formulation of more expensive diets and reduced $CH_4$ emissions. The changes in $CH_4$ emissions and dietary costs are a result of formulation of different diets that supply nutrients according to the NRC (2001) daily nutrient requirements.

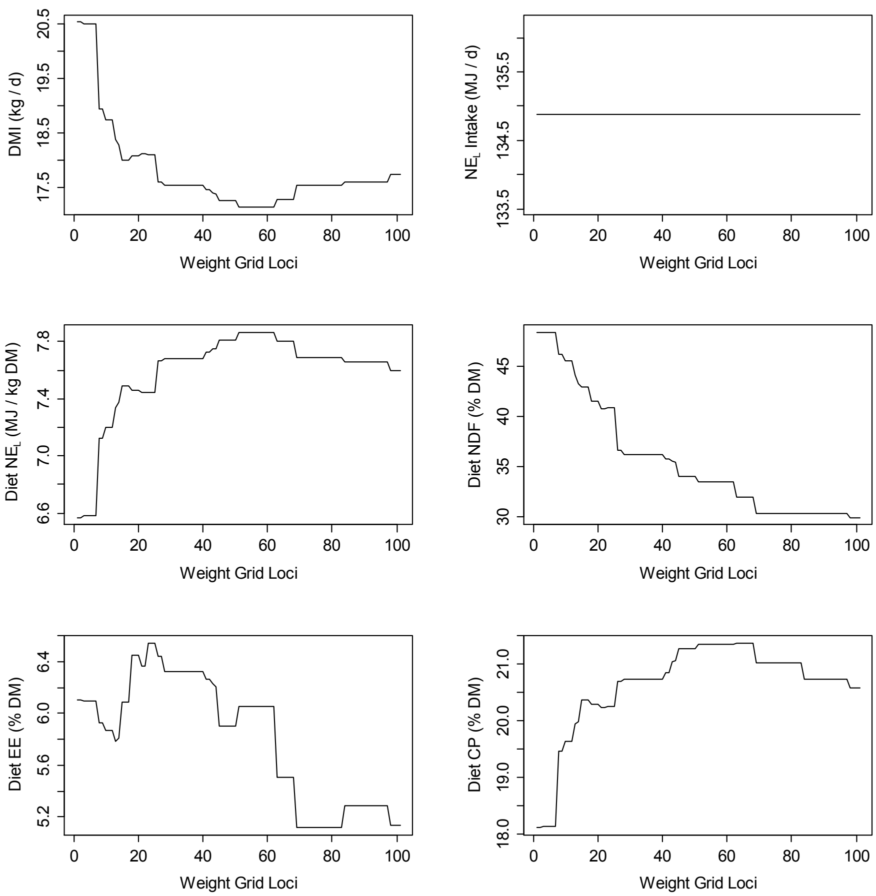
**Figure 6. Deviational Variables of the Weighted-Goal Programming Model versus the Weight Grid Loci**




*Note:* $p_q$ denotes the positive deviational variable from the $q^{th}$ goal (minimize dietary cost or minimize methane emissions). Deviational variables represent deviations from the goal programming solution to the target level: $p_1$ ($/d) represents the deviation in dietary cost from its target, and $p_2$ (emissions factor units calculated as a linear combination of ether extract and neutral detergent fiber of the feed) represents deviations from the target methane emissions factors. The x-axis is the loci of the weight grid starting with objective function weights of (1, 0) until (0, 1) with sequential 0.01 increments.

The delivery of nutrients in each solution point is greater than or equal to the animal requirement set by the NRC (2001) model and can be achieved at different combinations of dry matter intake and diet nutrient density. For example, DMI, net energy for lactation intake and diet content, and dietary contents of NDF, CP and EE are plotted against the weight grid loci in Figure 7. When $w_1$ decreases and $w_2$ increases (weight grid loci goes from 1 to 101), greater weight is placed on reducing $CH_4$ emissions rather than on minimizing dietary costs. Therefore, DMI is reduced because it is the major determinant of enteric $CH_4$ emissions. Similarly, for a reduced feed intake, dietary NEL and CP contents are increased to meet an animal's nutrient requirement at a lower intake level. Conversely, the NDF proportion of the diet is decreased because an increase in the proportion of dietary structural carbohydrates is often associated with increased $CH_4$ emissions. Notably, delivery of NEL is constant over different solutions and is delivered at the exact requirement level for every model solution, suggesting that cows receiving these 21 diets may produce similar amounts of milk. Similarly, diets delivered RDP at the exact animal requirement level for every solution point, and they delivered RUP at the requirement level in 16 of the 21 diets. In the remaining diets, RUP was fed above the requirement, which may lead to a potential increase in nitrogen excretion.

**Figure 7. Dry Matter Intake, Net Energy for Lactation Intake, and Diet Composition versus the Goal Programming Weight Grid Loci**




*Note:* NE$_L$ is the net energy for lactation, NDF is the neutral detergent fiber diet percentage, EE is the ether extract diet concentration, and CP is the crude protein diet percentage. The x-axis is the loci of the weight grid, starting with objective function weights of (1, 0) until (0, 1) with sequential 0.01 increments.

***Reductions in Methane Emissions and Costs through Specific Agents***

ETTAC (2008) suggested that specific agents have the potential to reduce $CH_4$ emissions by 11%. Recent reviews have comprehensively explored mitigation options for reducing $CH_4$ emissions (Hook, Wright, and McBride 2010; Gerber et al. 2013) and identified use of ionophores as a potential mitigation tool. To investigate further $CH_4$ emissions reductions (and associated costs) not accounted for in optimization models described above, this study examined utilization of monensin, the anti-methanogenic effect of which has been suggested as an effective $CH_4$ mitigation dietary strategy (Appuhamy et al. 2013). The authors estimated a mean reduction of 7 g $CH_4$/d (or 0.39 MJ/d, using the heat of combustion of $CH_4$ as 55.65 MJ/kg) in emissions from animals supplied with 21 mg monensin/kg DMI (Appuhamy et al. 2013). Monensin costs (from February and March 2013 in California) were approximately \$0.10/g. Using the average DMI from the Castillo, St-Pierre, Silva del Rio, and Weiss (2013) baseline scenario of 23.3 kg DM/d, a dairy cow would consume approximately 489 mg/d of monensin, resulting in a daily cost of about \$0.05/cow. In this context, the cost of mitigating $CH_4$ emissions through the use of monensin would be \$7/kg $CH_4$ (or \$0.12/MJ $CH_4$) for the average cow in this study's baseline scenario.

Appuhamy et al. (2013) describe a dose effect in the following equation: mean difference between animals receiving monensin versus control group (g/d) = –12 – 1.1 × [Dose (mg/kg DMI) – 21 (mg/kg

DMI)]. This study examines the proportional reductions from the Castillo, St-Pierre, Silva del Rio, and Weiss (2013) baseline scenario, the least-cost diet, and the minimum $CH_4$ scenarios by using 25 monensin doses between the minimum and maximum doses from Appuhamy et al. (2013). A vector of values from 11 to 35 with increments of 1 mg/kg DMI was created, and the mean difference for each element of this vector was calculated. Reductions in $CH_4$ emissions ranged from 1 to 27.4 g/d (0.05 to 1.52 MJ/d). In the baseline scenario, the reductions represent 0.25% to 7.0% in $CH_4$ emissions. The mitigation cost at these emissions reduction levels ranged from $3 to $26/kg $CH_4$. In the least-cost diet scenario, such reductions in emissions with the use of monensin would represent reductions of 0.24% to 7.1% at costs of $3 to $23/kg $CH_4$. Finally, in the minimum $CH_4$ scenario, proportional reductions with the use of different doses of monensin would range from 0.34% to 9.4% with associated mitigation costs of $2 to $20/kg methane.

Before these results are applied to the large range of dairies in the United States, several points should be addressed. First, reductions of $CH_4$ emissions in Appuhamy et al. (2013) are assumed to be linearly related to monensin dose; these reductions may not hold in datasets for which dietary and animal variables are outside the ranges of the studies analyzed. Second, only monensin purchase costs, not storage and feeding costs, are included in this study's calculations. One assumption of these calculations is that dairies in the baseline scenario did not start off using monensin, but this assumption cannot be tested by the Castillo, St-Pierre, Silva del Rio, and Weiss (2013) data. Third, monensin may also affect energy metabolism, milk composition, DMI, health, and reproduction (see reviews by Duffield, Rabiee and Lean 2008a,b,c). Governmental regulation on monensin utilization in livestock production varies dramatically worldwide, from a complete ban to a set limit on allowable dose.

## RECOMMENDED WORK

Some work for consideration includes:

- More comprehensive data collection, including a random sample of dairy farms within a state, would increase the robustness of this study's analysis, which due to duration/funding limitations relied on readily available data. Inclusion of additional farms, more complete feed analysis (i.e., analyzed samples collected from farms), and accurate diet costs would improve the reliability of results. Moreover, more intensive data collection would allow the framework to be extended to stockers and feedlot cattle.
- Most mitigation option studies have been conducted in isolation, and very few in vivo experiments have studied synergy/antagonism among mitigating agents. When adopting mitigating practices related to animal nutrition, decreasing the concentration of one nutrient will lead to increasing the concentration of another. For example, decreasing dietary protein may increase the concentration of dietary carbohydrates and result in increased $CH_4$ production. This result may be counterbalanced by decreased $N_2O$ emissions when manure is applied to soil. Therefore, future studies should take a holistic approach, which includes analysis of feed, manure (volume and content), and level of production (milk or meat).
- Mathematical models that predict emissions not only from animals but also from manure management specific to California conditions should be developed to assess mitigation options. These models should include prediction of manure volume and quality for proper estimation of emissions potential. This prediction should be based on field studies of the California production (both animal- and manure-related) system.
- Studies of the $CH_4$-mitigating effects of monensin should include the benefits of increasing the efficiency of dietary energy conversion into products, thereby allowing assessment of the true cost of monensin supplementation.
- Dietary interventions, such as lipid and concentrate supplementation, must be carefully balanced against their potential negative impact on fiber digestibility, feed intake, and animal productivity.

Because lipid supplementation may have an influence on emissions, studies should examine saturated fat versus unsaturated fat supplementation and modes of action.

- In California, grape pomace could be used as cattle feed. Grape pomace contains tannins that have been shown to reduce enteric $CH_4$ production. However, in high quantities, tannins impair nitrogen metabolism. Therefore, in vivo experiments in California should be conducted to investigate the level of tannin (grape pomace) that should be fed to cattle to optimize production and emissions reduction.

## CONCLUSIONS

Methane emissions were estimated and dietary costs calculated for 40 dairies in the California Central Valley. Two LP models were implemented to assess changes in dietary costs and potential reductions in $CH_4$ emissions through dietary manipulations when formulating diets according to NRC guidelines. Emissions were found to increase slightly when formulating least-cost diets and were substantially reduced when the optimization goal was to formulate diets for a minimum $CH_4$ emissions level. Methane emissions mitigation costs were assessed through shadow prices and were particularly high when compared with prices in current carbon markets. To combine the two previously developed LP models and jointly minimize emissions and dietary costs, a weighted-goal programming model was proposed. Such a model uses a weighing scheme in the objective function for the identification of a set of solutions with various trade-off levels between the two goals. The weight grid generated a set with 21 distinct solutions from which the decision maker can choose the solution with the desired level of trade-off. Potential further reductions in $CH_4$ emissions with monensin supplementation were examined and its associated costs were computed.

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