Disproportionate CH$_4$ sink strength from an endemic, sub-alpine Australian soil microbial community

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Running Title: Strong CH$_4$ uptake from unique soil microbiota

Originality-Significance Statement

Novel methanotrophic bacteria have been discovered in recent years, but few studies have examined the total known diversity of methanotrophs together with the net flux of CH_4 from soils. We used an ecosystem with a vegetation-soil gradient in the sub-alpine regions of Australia (with extremely strong consumption of atmospheric CH_4) to examine microbial and abiotic drivers of CH_4 fluxes across this gradient. Recently characterized methanotrophs, either USCα in forest and grassland soils, or oxygenic *Candidatus* Methylomirabilis sp. in the bog soil were dominant. Methanotrophs belonging to the families Methylococcaceae and Methylocystaceae represented only a small minority of the methanotrophs in this ecosystem.

Abstract

Soil-to-atmosphere methane (CH_4) fluxes are dependent on opposing microbial processes

of production and consumption. Here we use a soil-vegetation gradient in an Australian sub-

alpine ecosystem to examine links between composition of soil microbial communities, and the

fluxes of greenhouse gases they regulate. For each soil-vegetation type (forest, grassland, and

bog), we measured carbon dioxide (CO_2) and CH_4 fluxes and their production/consumption at 5-

cm intervals to a depth of 30 cm. All soils were sources of CO_2, ranging from 49-93 mg CO_2 m^{-2}

h^{-1}. Forest soils were strong net sinks for CH_4 at rates up to -413 µg CH_4 m^{-2} h^{-1}. Grassland soils

varied with some soils acting as sources and some as sinks, but overall averaged -97 µg CH_4 m^{-2}

h^{-1}. Bog soils were net sources of CH_4 (+340 µg CH_4 m^{-2} h^{-1}). Methanotrophs were dominated

by USCα in forest and grassland soils, and *Candidatus* Methylomirabilis sp. in the bog soils.

Methylocystis were also detected at relatively low abundance. The potential disproportionately

large contribution of these ecosystems to global CH_4 oxidation, and poorly understood microbial

community regulating it, highlight our dependence on soil ecosystem services in remote

locations can be driven by a unique population of soil microbes.

Keywords: carbon dioxide; methane; 16S rRNA, methanotroph; methanogen; *Methylomirabilis*;

USCalpha, *pmoA*

Introduction

Counteracting biogeochemical processes that consume or produce greenhouse gases

(GHGs) regulate whether soils act as net sources or sinks. The magnitude and spatial

distributions of these competing processes – whether across landscapes, with soil depth (Conrad

and Rothfuss, 1991; Bender and Conrad, 1994; He *et al.*, 2012), or even within soil aggregates

(Sexstone *et al.*, 1985; Ebrahimi and Or, 2016; Karbin *et al.*, 2016) – determine net release or

uptake. Soils, especially upland and older soils, are nearly always sources of carbon dioxide

(CO_2) to the atmosphere, owing to production of CO_2 via heterotrophic and root respiration,

which overwhelm slow rates of autotrophic CO_2 consumption. On the other hand, soils can

routinely be either sources or sinks for methane (CH_4) and nitrous oxide. In some cases, soils

can switch from being a net source to a net sink for CH_4 and N_2O in a matter of minutes to hours

(Harriss *et al.*, 1982; Wille *et al.*, 2008; McDaniel *et al.*, 2014; Hernández *et al.*, 2017).

Similarly, a lateral distance of just a meter or two may result in sinks becoming sources, or vice

versa (Velthof *et al.*, 1996; Priemé *et al.*, 1997; McDaniel *et al.*, 2017).

Methane is a potent greenhouse gas, 34 times as potent as CO_2, and is responsible for

~17% of anthropogenic warming (Stocker, 2013). Soil sources and sinks for CH_4 are controlled

by abundance and composition of specific microbial communities (Murrell and Jetten, 2009;

Nazaries, Murrell, *et al.*, 2013), but also regulated by abiotic factors (Sullivan *et al.*, 2010; Wu *et*

al., 2010; Wolf *et al.*, 2012). Oxidation of CH_4 to microbial biomass and CO_2 is, for example,

restricted to distinct groups of specialized methanotrophic microorganisms. Aerobic

methanotrophs belonging to the α-Proteobacteria and δ-Proteobacteria have been studied for

decades and detected across a wide range of habitats (Knief, 2015). Groundbreaking research in

recent years has uncovered previously uncharacterized methanotrophs, including acidophilic

Verrucomicrobia from the family Methylacidiphilaceae (Khadem *et al.*, 2012) and intra-

oxygenic methanotrophs, *candidatus* Methylomirabilis oxyfera, from the NC10 phylum (Ettwig

et al., 2010). In addition, more recent studies have identified USCα methanotrophs, which are

specialized atmospheric-CH_4 consuming bacteria whose activity has been known for decades but

had evaded efforts to be isolated or characterized (Pratscher *et al.*, 2018; Singleton *et al.*, 2018;

Tveit *et al.*, 2019). The first step in the biochemical pathways of CH_4 oxidation is catalyzed by

the methane monooxygenase (MMO) enzyme. The *pmoA* gene encoding a subunit of the

membrane-bound MMO (pMMO) enzyme is present in most aerobic methanotrophs and is

frequently used as a genetic marker.

Methanogenesis in soil typically requires anaerobic and low redox conditions, with

depletion of strong electronegative terminal electron acceptors, e.g. nitrate, iron. Methanogens

belong to the Euryarchaeota phylum, and produce CH_4 either from CO_2 and H_2

(hydrogenotrophic methanogenesis), acetate (acetoclastic methanogenesis), or methylated single-

C one-carbon compounds (Thauer et al., 2008). All known methanogenic pathways include the

methyl-coenzyme M reductase enzyme encoding the *mcrA* gene, which is used as a genetic

marker for methanogens in the environment. Most aerobic soils show little production of CH_4,

as evidenced by low abundance of *mcrA* genes (Hernández *et al.*, 2017).   A few recent studies

have shown that even water-logged soil profiles tend to have an aerobic upper layer that, via its

capacity for CH_4 oxidation, helps mitigate CH_4 release to the atmosphere from lower soil depths.

In some cases this layer can remove 80-97% of CH_4 produced at lower depths (Conrad and

Rothfuss, 1991; Frenzel *et al.*, 1992; Oremland and Culbertson, 1992; Sass *et al.*, 1992). In the

field, and at ecosystem spatial scales, our understanding of the drivers of soil GHG fluxes is

profoundly limited.

Local soil and vegetation gradients provide an opportunity to explore mechanisms that

regulate soil GHG fluxes (Freitag *et al.*, 2010; Krause *et al.*, 2013; Christiansen *et al.*, 2016).

Soil biogeochemical conditions (e.g. microbial substrates, reduction-oxidation potential, and soil

pH) can vary dramatically over relatively short distances despite more-or-less constant climate.

We used a forest-grassland-bog gradient located within a sub-alpine region of southern New

South Wales (Fig. 1), Australia to examine the drivers of variation in soil microbial

communities, and CO_2 and CH_4 fluxes. These soils are of particular interest given their

previously-observed, rapid rates of CH_4 oxidation in forest and grassland soils and likely

biogeochemical sensitivity to climate change. Our objective was to determine the role of soil

microbial communities in regulating the production/consumption of CH_4 across this soil-

vegetation gradient.

Results

Soil greenhouse gas fluxes and production at depth

Surface fluxes of CO_2 and CH_4 were measured once each season. Air temperatures

ranged from 3.1 to 28.3 °C, while the average soil temperature at 0-7 cm depth was 3.6 to 16.4

(Table S1). Gravimetric water content on 17 February, when microbial community analyses

were conducted, ranged from 0.25-0.79 for forest soils, 0.25-0.38 for grassland soils, and 0.9-

4.66 g H_2O g dry soil^{-1} for bog soils (Table S2). The relative differences in soil temperature and

moisture amongst soil-vegetation types during February extend to other three sampling dates

(Table S1,S2).

Mean soil-to-atmosphere CO_2 fluxes (measured *in situ*) across the soils ranged from 2.5

to 17.4 mg CO_2 m^{-2} h^{-1}, spring and summer respectively (Fig. 2A-D). Belowground, CO_2

production (measured in the laboratory) decreased with depth. CO_2 production was

predominately from top 0-5 cm of soil, with soil means ranging from 72 to 2,357 µg CO_2 g^{-1} d^{-1}.

Whereas at the 25-30 cm depth means ranged from 4 to 197 µg CO_2 g^{-1} d^{-1}. Forest and bog soils

showed significantly greater CO_2 production in summer than the grassland soil at multiple depths

($P < 0.01$, Fig. 2E), ranging from 47 to 398% greater in forest soil or 60 to 282% greater in bog

soil. Whereas, there were less pronounced differences amongst soil types in autumn, winter, and

spring.

In situ CH_4 fluxes ranged from -413 to +778 µg CH_4 m^{-2} h^{-1} (Fig. 3A-D). Absolute

fluxes, whether positive or negative, were greatest in summer compared to other seasons.

Although similar pattern of soil type persisted throughout other three seasons. Forest and

grassland soils mostly consumed CH_4 throughout the year (Fig. 3A-D), while bog soils were net

producers of CH_4 in three of four seasons (Fig. 3A-C). Belowground, most soils (including bog)

showed net CH_4 consumption at all depths to 30 cm (Fig. 3E-H). The main exception was

summer where large CH_4 production of 3838 µg CO_2 g^{-1} d^{-1} was found at 5-10 cm depth ($P =$

0.003), as well as moderate production of CH_4 by all soils at 25-30 depth ranging from 87-704

µg CO_2 g^{-1} d^{-1} (Fig. 3E). The net global warming potential, measured as CO_2-equivalents,

provides further evidence as the exceptional strength of the soil CH_4 sink in this ecosystem

(Table 1).

Archaeal and bacterial gene abundance (qPCR) during summer (17 February 2015)

There were significant differences in archaeal 16S rRNA gene abundance between soil

types, with the bog soil showing one to two orders of magnitude greater abundances than the

other two soils at multiple depths ($P < 0.060$, Fig. 4A). The abundances of bacterial 16S rRNA

genes were highly variable but did show a decrease with depth from 2.3×10^{11} to 1.6×10^{10}

copies per g soil (Fig. 4B). There were no significant differences in abundance of bacterial 16S

rRNA genes among soil types. A *pmoA* qPCR assay targeting conventional methanotrophs

belonging to the families Methylococcaceae and Methylocystaceae showed highest abundance in

the bog samples (Fig 4C).

Across the soil-vegetation gradient, GHG production at depth was positively related to

the soil-to-atmosphere flux of both gases (Fig. 5A, B). There was also evidence for GHG

production correlating with specific gene abundances across all soil types and depths. For

example, the abundance of bacterial 16S rRNA genes was linearly, positively related to CO_2

production (Fig. 5C). While, the abundance of archaeal 16S rRNA was non-linearly, positively

related to CH_4 production (3-parameter exponential equation, Fig. 5D). Interestingly, however,

we did not find significant relationships between abundances of archaea and CO_2, nor between

bacterial abundances and CH_4.

Microbial community composition and diversity during summer (17 February 2015)

Across all soils, Illumina sequencing resulted in 440,504 archaeal, 24,293,004 bacterial,

and 2,258,405 *pmoA* sequences. Both clustering and multivariate analyses (Fig. 6) show distinct

differences in bacterial 16S rRNA genes between the forest/grassland and bog soils, with less

forest and grassland soils being more similar. In the bog soils, *Betaproteobacteria* (OTU 1850)

and OTU-1522 were more abundant than in forest and grassland soils (Fig. 6A). Contrastingly,

Rhizobiales (OTU-78) and OTU-71 differentiated the forest/grassland from bog soils. A few

OTUs were uniquely abundant in the grassland soils, like the *Chloroflexi* group (especially OTU-

252, OTU-1043, OTU-249). Across multiple depths, the bog soils had greatest 16S rRNA

diversity compared to the forest and grassland soils (Fig. S1). The bog soils had greater

diversity, 10% and 42% larger Shannon diversity and richness (H' and S), than the average of

forest and grassland soils across all depths ($P < 0.001$).

This study focused on methanotroph identification by using Illumina sequencing, of

either 16S rRNA or *pmoA* genes. Both 16S rRNA and *pmoA* gene sequence data revealed that

the forest and grassland soils were dominated by USCα (Figs. 7, S2) - with nearly equivalent

abundances between the two soil types. The highest USCα relative abundance approached 1% of

all 16S rRNA genes, and decreased with depth. *Methylocystis* were the most abundant aerobic

methanotrophs detected in the bog accounting for up to 0.3% relative abundance across all

depths (Fig. 7). *Candidatus* Methylomirabilis sp., which are nitrite-dependent anaerobic

methanotrophs, increased with depth in the bog to a maximum of 1.5% relative abundance at 25-

30 cm depths. The Illumina sequencing of the *pmoA* gene resulted in distinct differences among

all three soil types, but especially between the forest/grassland and bog soils. Using *pmoA*,

USCα dominated methanotroph populations in forest and grassland soils, whereas *Methylocystis*

dominated bog soils (Fig. S2). Greater counts of USCα were mostly found at the surface of just

one bog site (B4). This bog site has greater slope along the soil-vegetation gradient and 80-1200

% greater rock content than the other bog sites across depths (B4; Table S3, Fig 1), thus greater

sand content and porosity possibly provided better habitat for methanotrophs in this bog soil.

Patterns in Community Composition and Relationships with Soil Properties

Non-metric dimensional scaling (NMDS) shows a distinct difference in bacterial 16S

rRNA genes among soil types and relationship to soil properties ($P<0.05$, Fig. 6B). The

communities in all soils showed a pattern with depth, but the bog soil had the most distinct

separation among bacterial communities with depth. Elevated CH_4 production also correlated

with depth of bog soils (Fig. 6B). The grassland soils were most positively related to clay content

of the soils, and negatively with soil moisture – these were the driest of the three soil types (Fig.

6B, Table S3). The variables arguably most related to organic matter content (dissolved organic

and total C and N, inorganic N, and CO_2 production) correlated positively with the forest soils,

and the somewhat shallow bog soil depths.

The forest *pmoA* community was relatively tightly clustered except for one sample at 10-

15 cm depth (Fig. S3A). GHG production did not correlate significantly with the *pmoA*

community, indicating differences in the microbial community are not the direct cause of

production at depth. The community composition of the Euryarchaeota showed differences

among soil types, especially between grassland and bog soils, but no trend with depth (Fig. S3B).

Both GHGs and soil properties were positively related to soil organic matter, whereas clay was

negatively related to the bog Euryarchaeota community composition. In contrast, the community

composition in the grass was positively associated with soil clay content. (Fig. S3B)

Discussion

Soil Microbial Community Composition and Links to Greenhouse Gas Fluxes

Adjacent soils, with varying soil-forming factors (especially organisms – vegetation, and

landscape position) showed distinct microbial community composition and abundance with

depth. The bog soils tended to have the greatest abundance of archaeal 16S rRNA genes (Fig.

4A). At multiple depths, the bog soils also had greater diversity in bacterial and methanotroph

communities (Fig. 4B, C). Both of these findings are most likely due to the large total organic C

content in bog soils compared to the other two – when averaged across all depths, bog soils had

41 and 128 % greater soil organic C than the forest and grassland soils, respectively (Table S3).

The greater the available sources of energy (as approximated by total C) at the base of the food

web, the larger and more diverse we might expect the microbial communities to be (Tilman *et*

al., 2001; Zhou *et al.*, 2002; Hartmann *et al.*, 2015).

The bog soils showed the greatest CH_4 production measured in this study at lower depths

(5-10 cm, Fig. 3E), which is surprising considering that at lower depths bog soils have greater

water content, i.e., likely more anoxic and methanogenic; however, this can be explained by the

increasing abundance of *Candidatus* Methylomirabilis sp. with depth (Fig. 7). *Methylomirabilis*

sp. are nitrite-dependent methanotrophs that oxidize CH_4 by the intracellular production of O_2

from the dismutation of NO (Ettwig *et al.*, 2010). Their presence in this habitat is consistent with

previous work that suggests they are common in wetland environments (Hu *et al.*, 2014). They

occur at deeper depths where nitrite is more available and exogenous O_2, which is detrimental to

their activity (Luesken *et al.*, 2012). In addition, methanogenesis might be stimulated at the 5-10

cm depth by Sphagnum rhizoids that occur just above this depth (54%, Table S3). Therefore,

high rhizodeposition at this depth could drive methanogenesis by supplying organic C for either

acetoclastic or CO_2 reduction to CH_4 (Le Mer and Roger, 2001), coupled to relatively low CH_4

oxidation. Bog soil showed that methanogen gene expression in the top 10 cm of soil correlated

linearly with the CH_4 flux, and methanotroph gene expression ratio was negatively correlated

with CH_4 flux rates at a different peat bog site (Freitag *et al.*, 2010). In aggregation, microsites of

CH_4 oxidation and CH_4 production, when coupled may explain the net production and strong

consumption of CH_4 (Bender and Conrad, 1992, 1994; Von Fischer and Hedin, 2002; Yang and

Silver, 2016).

Although not evidence of causation, patterns in soil microbial abundance and community

composition were strongly related to GHG production. Given this caveat, the CO_2 production

was best correlated with bacterial 16S rRNA abundance and CH_4 fluxes with archaeal 16S rRNA

abundance (Fig. 5). Archaeal 16S rRNA gene abundance was best related to CH_4 production

(Figs. 3E, 4C, 5E), and highlights the importance of archaeal methanogens in net CH_4 production

(Conrad, 2002; Angel *et al.*, 2012; Nazaries, Murrell, *et al.*, 2013; Hernández *et al.*, 2017).

Methanotroph relative abundance declined with depth in the forest and grassland soil

(Fig. 7), similar to the findings from other studies (Bender and Conrad, 1994; Kolb *et al.*, 2005).

USCα methanotrophs are associated with high rates of atmospheric CH_4 oxidation in well-

drained habitats lacking substantial endogenous methanogenesis (Kolb *et al.*, 2005; Chen *et al.*,

2007; Bengtson *et al.*, 2009; Kolb, 2009; Shrestha *et al.*, 2012). The bog soils only showed CH_4

consumption at the 0-5 cm depth during the summer when soil-to-atmosphere CH_4 fluxes were

highest (Fig. 3A, 3E), which corresponded to the soil depth the greatest proportion of USCα (Fig

7, S2). Thus, USCα abundance, greater O_2 availability, and lower methanogenesis in the top 0-5

cm all could contribute to the high capacity for aerobic CH_4 oxidation at the surface of bog soils.

Although *Candidatus* Methylomirabilis were highly abundant at depth, their per-cell CH_4

oxidation capacity might be lower than for aerobic methanotrophs (Luesken *et al.*, 2012).

Furthermore, the activity of *Candidatus* Methylomirabilis might have been inhibited by O_2

exposure during the subsectioning of the cores. Finally, although aerobic methanotrophs can

survive in low O_2 environments, in part by energy generation via fermentation reactions

(Kalyuzhnaya *et al.*, 2013; Kits *et al.*, 2015), the rates of CH_4 oxidation will be lower than most

well-oxygenated surface soils.

The three soils had distinct microbial community compositions, with the forest and

grassland soils being the most similar (Fig. 6, 7, S2, S3). The bog soils had greater abundances

of bacterial 16S rRNA OTU in the family *Ktedonobacterales* (OTU-1522) and an unclassified

Betaproteobacteria (OTU 1850, Fig. 6A). All soils showed a pattern with depth, but the bog

soils showed the greatest discrimination with depth (Fig. 6B). Some microorganisms in the

Ktedonobacterales have been cultured, and these are Gram-positive, aerobic, broad temperature

ranges (meso- to thermophilic), and are characterized by having multicellular filaments and

spores – similar to actinomycetes (Yokota, 2012; Yabe *et al.*, 2017). The unclassified

Betaproteobacteria are likely ammonia-oxidizing bacteria and did not play a significant role in

CH_4 oxidation (Bodelier and Frenzel, 1999). The forest soils showed greater abundance of an

unclassified *Gammaproteobacteria*, which could potentially be either methanotrophic or

ammonia-oxidizing bacteria.

Within the methanotroph community, the bog soils showed a distinctly greater abundance

of *Methylocystis* spp., *Ca*. Methylomirabilis, and unclassified proteobacterial methanotrophs (Fig

7 and S2). *Methylocystis* typically proliferate at CH_4 concentrations > 40ppm, which would

occur in bog soils where concentrations (and production) of CH_4 are greatest. A recent study

showed this is indeed the case where low-affinity methanotroph activity is dependent on high

supply of CH_4, and may trigger high-affinity activity during drought (Cai *et al.*, 2016). The

grassland and forest soils were predominately composed of *Methylocystis* and USCα (Fig 7 and

S2). The USCα, are classified as high-affinity, with apparent K_m values of 0.01-0.28, compared

to that of 0.8-32 for low-affinity methanotrophs (Shukla *et al.*, 2013). Several studies now

confirm that forest or grassland soils that have high CH_4 oxidation potential also have high

abundance of *Methylocystis* or USCα methanotrophs (Knief *et al.*, 2003; Malghani *et al.*, 2016).

There is mounting evidence, including this study, that indicate the absence/presence of specific

methanotrophic bacteria or methanotrophic community composition might be just as important

as physicochemical regulators on net CH_4 fluxes from soils (Nazaries *et al.*, 2011; Nazaries, Pan,

et al., 2013; Malghani *et al.*, 2016). Other studies show CH_4 fluxes are largely regulated by

physical processes such as substrate diffusion (Saari *et al.*, 1997; Wille *et al.*, 2008; Fest *et al.*,

2015; D'imperio *et al.*, 2017) or labile C supply (Pratscher *et al.*, 2011; Sullivan *et al.*, 2013);

however, due to the high sensitivity of methanotrophic bacteria to physicochemical conditions it

is difficult to tease these factors apart (Nazaries *et al.*, 2011; Fest *et al.*, 2015).

Our study and others (Conrad and Rothfuss, 1991; Frenzel *et al.*, 1992) show that surface

soils even in consistently wet soils (0-5 cm, Fig. 3) can be a sink not only for atmospheric CH_4,

but also a likely filter for CH_4 produced at greater depths (Cai *et al.*, 2016). Given that by some

estimates as much as 80-97% of endogenously produced CH_4 at depth is consumed before

reaching the atmosphere (Conrad and Rothfuss, 1991; Frenzel *et al.*, 1992; Oremland and

Culbertson, 1992; Sass *et al.*, 1992), the disturbance of this thin layer of soil could result in

larger net CH_4 fluxes as CH_4 produced at depth diffuses toward the atmosphere and is not

oxidized in this surface layer. The complex dynamics, high net CH_4 uptake rates of the forest

and grassland soils (Fig. 9A), and high consumption at the surface of the bog soils are all reasons

why it is crucial to understand the microbial mechanisms driving these greenhouse gas fluxes.

Australian Alps: Unique Soils with Disproportionate CH_4 Sink Strength

Across the globe, aerated upland soils provide a net CH_4 sink that ranges from 7-100 Tg

y^{-1} (Smith *et al.*, 2000), which is estimated to be up to 15% of the total global CH_4 sink

(Reeburgh, 2003; Dutaur and Verchot, 2007; Shukla *et al.*, 2013). The Australian Alps are

restricted to the southeastern corner of the mainland totaling 0.16% of Australia's area (Fig. 8).

We studied 538 ha of a 1.2M ha region, but found convincing evidence for the overwhelming

CH_4 sink strength of this region's soils (Fig. 9A).

We used a combination of foliar coverage estimates for extrapolation across the region,

climate station data to interpolate CH_4 fluxes between seasonal measurements, and range in

global sink strength from the literature (Table 2), to parameterize the disproportionate

contribution of this endemic ecosystem to the global soil CH_4 sink. While only comprising

<0.03% of global forested and grassland ecosystems, this unique Australian ecosystem could

represent 6 up to >100% of global soil methane sink (Kirschke *et al.*, 2013; Saunois *et al.*, 2016).

While it is unreasonable to expect these unique soils to make up more than 100% of the global

CH_4 sink, it illustrates the problem with the low estimates for the global soil CH_4 sink (Kirschke

et al., 2013; Saunois *et al.*, 2016; Gatica *et al.*, 2020). These soils are undoubtedly amongst the

greatest negative CH_4 fluxes observed at an hourly scale (Fig. 9A), and our data conform to other

annual CH_4 flux estimates despite the acknowledged error of these estimates with so few

observations (Gatica *et al.*, 2020; Fig. 9B). Monitoring CH_4 fluxes at high spatial and temporal

resolution in remote locations remains a major challenge.

Soils under all three vegetation types were sources of CO_2 with positive GWPs, yet

ranged from strong negative to positive GWP contributions from CH_4 (Table 1). The CH_4 sink

under grassland and forest soils provided 53% and 56% GWP offset (in negative CO_2-

equivalents) of the net CO_2 emissions respectively. All soils consumed CH_4 at 0-5 cm depth.

This is consistent with other studies showing high uptake in surface soils where O_2 is more

available (Koschorreck and Conrad, 1993; Bender and Conrad, 1994; Hütsch, 1998), even lake

sediments can show similar CH_4 oxidation profiles with depth (He *et al.*, 2012). However, many

studies find maximum oxidation rates are not near the soil surface, but 5-10 cm below (Bender

and Conrad, 1994; Hütsch *et al.*, 1994; Schnell and King, 1994; Priemé and Christensen, 1997;

Wolf *et al.*, 2012). Differences in where this maximum CH_4 consumption depth occurring are

dependent on soil texture, organic matter content, and moisture content with depth along with

substrates that are also thought to regulate CH_4 oxidation like labile C or inorganic N that are

also more available in surface soils (Priemé and Christensen, 1997; Pratscher *et al.*, 2011;

Sullivan *et al.*, 2013).

This endemic ecosystem, with an arguably disproportionate importance to the global soil

CH_4 sink (Tables 1,2; Fig. 8), are amongst the ecosystems most likely to be affected by changes

in climate, as was recently demonstrated by declines in CH_4 uptake in several long-term studies

of forest soils (Ni and Groffman, 2018). More frequent and intense forest fires are just one

global change threat to these Australian Alps soils (Adams, 2013; Adams *et al.*, 2013), with

potential positive feedbacks to climate change. We are increasingly reliant on key soil

ecosystem services to thrive on planet Earth (Jónsson and Davíðsdóttir, 2016), and

agroecosystem soils get much of the attention due to proximal benefits (i.e. crop production).

Global soil ecosystem services, however, like that of strong atmospheric CH_4 oxidation

occurring in these Australian Alps soils, are not as obvious nor as easy to value but critical for

buffering against anthropogenic climate change.

Experimental Procedures

Study Site Characteristics

Our study sites were located in an area known locally as the Snowy Plains, within the

Snowy Mountains region of southern New South Wales. The Snowy Plains are form part of the

Australian Alps montane grasslands, and lie adjacent to the Kosciuszko National Park (36º10′ S,

148º54 ′E; Fig. 1). The elevation range of the sampling area within the Snowy Plains was 1471

to 1677 masl. The mean annual temperature and precipitation are 6.4 ºC and ~1600 mm (SILO -

Queensland Government). The site remains snow-covered typically for 2-3 months of the year.

The area is a mosaic ecosystem containing a mixture of bog, grassland, and forest (Fig. 1)

and has been well described elsewhere (e.g. Jenkins and Adams, 2010). Alpine humus soils

(Chernic tenosol) in the region are ~400 million years old and derived from glacial moraines of

Silurian Mowomba granodiorite (Costin *et al.*, 1952). They show little horizon development in

the top 30 cm (Fig. S4). Soil are mostly sandy loams in texture, and pH ranges from ~5.3-5.7

down to 30 cm, across all sites (Table S3). Bogs are dominated by *Sphagnum spp.* and some

sparse grass cover (*Poa spp*). Grasslands are dominated mostly by *Poa hiemata* and *Poa*

costiniana. Forests are dominated by Snow Gums (*Eucalyptus pauciflora*), with the N-fixing

shrub *Bossiaea foliosa*, and some *Poa* spp. as understory and ground layers.

Experimental Design, Soil Sampling, and Gas Sampling

We used four topographic transects (from bogs and grasslands in the lowest part of the

landscape, to forests in upland areas) to guide our soil and GHG sampling (Fig. 1). After each

sampling location was determined, a 15-cm diameter (5-cm deep) PVC collar was installed for

soil GHG sampling a minimum of 1 month prior to sampling, in order to preclude artifacts

introduced by recent disturbance. We measured greenhouse gas fluxes *in situ* and collected soils

on 17 February, 25 May, 22 September, and 23 November in 2015. But in-depth microbial

sampling and analyses were conducted only on soils collected on 17 February – the time of year

for peak CH_4 production and consumption.

GHG fluxes were measured *in situ* using the static chamber method. We first placed a

3.2 L, vented, PVC chamber over the collar. Four gas samples were collected every 10-15

minutes and directly injected into a Labco Exetainer vial. Concurrent measurements of soil

moisture (Theta Probe, Delta-T DevicesTheta Probe, Cambridge, UK) and temperature (Novel

Ways, Hamilton, NZ) were taken in triplicate and averaged for each measurement location (7 cm

depth).

Immediately after completing gas sampling, the chambers were removed, and a 5-cm

diameter 30-cm deep soil core was taken directly in the center of the collar. These cores were

used for determination of soil properties, microbial community analyses, and to measure net CO_2

production and CH_4 production/consumption in the laboratory. The 30-cm soil cores were

stratified and dissected in the field with a clean knife at 5-cm intervals. At each depth, a

subsample (~ 3-5 g of soil) was immediately placed into a 2-ml Eppendorf tube, then placed in

liquid nitrogen and stored at -80 °C until DNA was extracted. The remainder of the soil core

was placed in a protective PVC sleeve, and then stored in an iced cooler until reaching the

laboratory.

Soil cores from the field were transferred to 1 L jars where they were briefly incubated at

near-ambient air temperature at the time of collection (22 °C) in order to further characterize

CO_2 and CH_4 production and consumption occurring at each depth (*sensu* Bender and Conrad,

1994). This procedure has been found to be highly related ($r^2 = 0.44$, n = 30) to *in situ* CH_4

production/consumption (Priemé and Christensen, 1997). The incubations began by placing the

relatively undisturbed soil cores into the jars, flushing them with ambient air, and then placing

the lids on the jars. The lids had Luer-lock access, and four gas samples were taken over the

short-term (3-day) incubations and placed directly into Labco Exetainer vials. Once the

incubations finished, the soils were air dried for physical and chemical analyses. The GHG

concentrations were analyzed on a gas chromatograph.

Soil Processing and Analyses

Soils were sieved (2 mm) and both rocks and roots were removed and weighed. A sub-sample was ground for total C and N analysis on a TruSpec Elemental Analyzer (LECO, St. Joseph, MI, USA). Soil texture was analyzed by using the hydrometer method (Gee and Bauder, 1986). Soil inorganic N (ammonium and nitrate) was measured by extracting 5 g of soil with 40 ml of 0.5 M K_2SO_4 shaken for 1 h and filtered with Whatman #1. These extracts were analyzed on a Lachat Injection-flow Analyzer according to standard methods (Lachat Instruments, Loveland, CO, USA). Dissolved organic C and N were analyzed on the same extracts on a Shimadzu TOC-N Analyzer (Shimadzu Scientific Instruments Inc., Columbia, MD, USA). Electrical conductivity and pH were measured on SevenMulti probe (MettlerToledo, Columbus, OH, USA) with a 1:1 (w:w) ratio with de-ionized water. Heavy elements were analyzed by X-ray fluorescence using a Niton XL3 t Ultra Analyzer meter (Thermo Scientific, Waltham, MA, USA).

DNA Extraction and Quantitative PCR

Total DNA was extracted using the NucleoSpin® Soil kit (Macherey-Nagel, Germany) by disrupting the cells by bead beating (30 s at 5.5 m s^{-1}). DNA purity and quantification were determined using a NanoDrop® Spectrophotomoter ND-1000 (Thermo Fisher Scientific, USA). DNA at a concentration of 10 ng μl^{-1} was stored at -20 °C for further molecular analysis. The abundance of bacterial- and archaeal- 16S rRNA genes as well as *pmoA* genes was performed using an iCycler Instrument (BioRad). For all assays, standards containing known number of DNA copies of the target gene were used. qPCR conditions for archaeal- and bacterial- 16S rRNA genes were based on dual-labeled probes. For bacterial 16S rRNA genes, primers Bac338F, Bac805R and Bac516P were used. For archaeal 16S rRNA genes, primers Arc 787F,

Arc1059R and Arc915P were used. Conditions for both genes were as follows: 0.5 μM of each

primer, 0.2 μM of the dual-labeled probe, 3 μl of template, 4 mM $MgCl_2$ (Sigma) and 12.5 μl of

JumpStart Ready Mix (Sigma-Aldrich). 1 μl of BSA (0.8 μg/μl) was added to archaeal 16S

rRNA gene reactions. The program used for both assays was 94 °C for 5 min, 35 cycles of 95 °C

for 30 s and 62 °C for 60 s extension and signal reading (Yu *et al.*, 2005). qPCR condition for

pmoA genes was using SYBR Green (Sigma-Aldrich) and primers A189F / mb661R. PCR

conditions were 0.667 μM of each primer, 3 μl template, 4 mM $MgCl_2$ (Sigma), 0.25 μl FITC

(1:1000), 12.5 μl of SYBR Green JumpStart *Taq* Ready Mix (Sigma-Aldrich) and 0.6 μl of BSA

(0.5 μg/μl). PCR program was 94 °C for 6 min, followed by 45 cycles of 94 °C for 25 s, 65.5 °C

20 s, 72°C 35s, 72°C 10 s plate read. The final melting curve was as follows: 100 cycles of 75-

94.8°C 6s, +0.2 °C $cycle^{-1}$ (Kolb *et al.*, 2003). Efficiencies of 99.6% for bacterial 16S rRNA

genes, 78.8 – 84.9% for archaeal 16S rRNA genes, and 77.2 – 78.5% for *pmoA* genes were

obtained, all with R^2 values > 0.99. Technical duplicates were performed for each of the

replicates.

Illumina library preparation and sequencing

MiSeq Illumina sequencing was performed for total 16S rRNA and *pmoA* genes. PCR

primers 515F / 806R targeting the V4 region of the 16S rRNA gene (approximately 250

nucleotides) were used (Bates *et al.*, 2011) with an initial denaturation at 94 °C for 5 min,

followed by 28 cycles of 94 °C for 30 s, 50 °C for 30 s, and 68 °C for 30 s and a final elongation

at 68 °C for 10 min (Hernández *et al.*, 2015). The amplification of *pmoA* genes was performed

via a semi-nested PCR approach using the primers A189F/A682R for the first round PCR

(Holmes *et al.*, 1995) as follows: 94 °C for 3 min followed by 30 cycles of 94 °C 45 s, 62 to 52

°C (touchdown 1 °C per cycle) for 60 s, 68 °C 3 min, and a final elongation of 68 °C 10 min

(Horz *et al.*, 2005). Aliquots of the first round of PCR (0.5 µl) were used as the template in the

second round of PCR using the primers A189f / A650r / mb661r in a multiplex PCR as follows:

94 °C for 3 min followed by 25 cycles of 94 °C 45 s, 56 °C 60 s and 68°C 1 min, and final

elongation of 68 °C 10 min (Horz *et al.*, 2005). Individual PCRs contained a 6-bp molecular

barcode integrated in the forward primer. Amplicons were purified using a PCR cleanup kit

(Sigma) and quantified using a Qubit 2.0 fluorometer (Invitrogen). An equimolar concentration

of the samples was pooled for each of the genes and sequenced on separate runs using 2 x 300 bp

MiSeq paired-end protocol. Library preparation and sequencing was performed at the Max

Planck Genome Centre (MPGC), Cologne, Germany. Table S4 summarizes primer sequences for

both genes and barcode sequences for each of the samples.

Bioinformatics, Data processing, GIS modeling, and Statistical Analyses

For 16S rRNA genes, quality filtering and trimming forward and reverse adaptors from

the sequences was carried out using the tool cutadapt (Martin, 2011). Forward and reverse reads

were merged using the usearch fastq_mergepairs command (Edgar, 2013). For the *pmoA* gene,

one-end run was performed, and the forward adaptor was trimmed using cutadapt. Downstream

processing was performed with UPARSE (Edgar, 2013) and UCHIME pipelines (Edgar *et al.*,

2011) following the steps detailed in Reim et al. (Reim *et al.*, 2017). For 16S rRNA genes, a

representative sequence of each operational taxonomic unit (OTU) was classified based on the

SILVA-132 16S rRNA gene database using the naïve Bayesian classifier (bootstrap confidence

threshold of 80%) in mothur (Schloss *et al.*, 2009). The *pmoA* genes were classified using the

same method, but using the *pmoA* database (Dumont *et al.*, 2014). Sequence data were deposited

in the NCBI Sequence Read Archive (SRA) under accession number PRJNA384296.

A USCα 16S rRNA gene sequence has recently been identified (Pratscher *et al.*, 2018),

which enabled us to search these sequences in our dataset. The 16S rRNA genes were identified

by standalone BLAST against the 16S rRNA OTUs using the USCa_MF sequence (Genbank ID

MG203879). Those OTUs with percent ID > 98% relative to the USCa_MF were positively

identified as USCα. The relative abundance of USCα in each of the samples could then be

calculated from the OTU table.

Greenhouse gas fluxes (both field and incubation) were calculated using a linear

regression, or change in the GHG over the time between gas samples. Data was screened for

normality and heterogeneity of variances, and when not conforming was log-transformed (Zuur

et al., 2010) for statistical analyses (all CO_2 and gene abundance data). All univariate statistics

were conducted in SAS (v. 9.4). Comparisons of variance among soil/vegetation types (bog,

grassland, forest) were completed using 1-way ANOVA ($\alpha = 0.05$) with transect considered

random, and depth not included in interactions since depth effects are not independent. Post-hoc

tests were completed using lsmeans, adjusted using Tukey's for multiple comparisons.

Multivariate statistics for 16S rRNA Illumina data was analyzed by using the vegan package

(Oksanen *et al.*, 2016) in R software version 3.0.1 (R Core Team, 2018). Non-metric

multidimensional scaling (NMDS) was performed using the *decostand* function for ordination of

Hellinger distances. Influence of environmental variables on the total diversity of 16S rRNA and

pmoA genes was analyzed by the *envfit* function (vegan package in R, permutations = 999).

Heatmaps were constructed with the gplots package (Warnes *et al.*, 2015). Principal components

analysis (PCA) of the Hellinger transformed data was performed using the prcomp function. The

OTUs explaining most of the differences between samples were defined as the 10 OTUs

contributing the largest absolute loadings in the first and second dimensions of the PCA,

obtained from the rotation output file (Hernández *et al.*, 2017). Hierarchical clustering of the

distance matrix used the "ward.D2" method and *hclust* function. The heatmap was constructed

using the *heatmap.2* function in *ggplots* package (Hernández *et al.*, 2017).

Using the four field-measured, hourly CH_4 fluxes we developed a model to estimate

annual CH_4 production across the Australian Alps based on number of geographic information

system (GIS) datasets. The datasets included elevation and aspect (30 m pixel) as well as daily

estimates of maximum and minimum air temperature (BOM, 2020) and soil moisture (0 – 0.1 m;

Frost *et al.*, 2018). The climate data rasters were all a 5 km pixel size. For each of the days for

that CH4 fluxes were determined in the field, the location of 12 sites was used to extract data

from each of the raster datasets using ArcGIS (V10.8, ESRI Systems, CA). This data was then

used to develop a linear regression model using R (v 4.0.2). The final linear regression model (p-

value = <0.0001, F-statistic = 14.95, adjusted r2 = 0.77) included the main factors (the ecosystem

measured; Bog, Forest & Grassland) along soil moisture and maximum air temperature and

interactions. The spatial extent of each ecosystem across the Australian Alps bioregion (IBRA7,

2012) was based on tree cover in 2015 (DEE, 2018); Forest sites were located in >20% projected

foliage cover and Grassland sites <20% projected foliage cover and the Bog sites were

considered to be within 1 m of a hydrological flow surface developed using the TauDEM

ArcGIS toolset (v5.3.7; Tarboton, 2005). This data along with average seasonal estimates of

maximum air temperature and soil moisture were then computed for the Australian Alps. In

small number of cases, individual pixels of the maximum air temperature and soil moisture

rasters exceeded the maximum/minimum points on which the linear regression model had been

developed, in which case they were forced to the maximum/minimum value. The linear

regression previously developed was then used to predict seasonal estimate of CH_4 fluxes for

each of the ecosystems measured across the Australian Alps.

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<u>Table legends</u>

Table 1. Annual estimates (mean, standard error, and range) for net ecosystem flux of carbon

dioxide and methane

Table 2. Comparison of Global and Australian Alps soil methane sink estimates

Figure legends

Figure 1. A) Location of 548 ha experiment area (inset of Australia), sampling sites within area and nearby streams. B) Landscape-level photograph of the vegetation gradient from sphagnum-dominated bog in foreground to eucalyptus-dominated forest in background. Abbreviations are F = Forest, G = Grassland, and B = Bog. The numbers after the letter represent which transect the sampling location belongs to.

Figure 2. Soil CO_2 fluxes (top panels, A-D) and production (bottom panels, E-H). Surface flux measurements and soils collected for production on 17 February (Summer,A & E), 25 May (Autumn, B & F), 22 September (Winter, C & G), and 23 November (Spring, D & H) in 2015. Mean and standard error shown (n = 4).

Figure 3. Soil CH_4 fluxes (top panels, A-D) and production/consumption (bottom panels, E-H). Surface flux measurements and soils collected for production on 17 February (Summer,A & E), 25 May (Autumn, B & F), 22 September (Winter, C & G), and 23 November (Spring, D & H) in 2015. Mean and standard error shown (n = 4).

Figure 4. Abundance of archaeal (A) and bacterial (B) 16S rRNA genes, and pmoA (C). Means and standard error are shown (n=4) for all samples.

Figure 5. Regressions between total CO_2 production and CO_2 soil-atmosphere flux (A), CH_4 production and CH_4 soil-atmosphere flux (B). Total GHG production was calculated for each soil profile as sum of production from 0 to 30 cm depth. Regressions between bacterial 16S rRNA abundance with CO_2 production (C, linear equation with log, log scale). Regression between and archaeal 16S rRNA and CH_4 production (D, 3-parameter exponential, log x-axis). Equations, chosen by best fit, are shown in each panel.

Figure 6. A) Heatmap of the most relevant OTUs derived from bacterial 16S rRNA genes. The

samples and OTUs were clustered according to Euclidean distances between all Hellinger

transformed data. The taxonomy of OTUs was determined using the Sina classifier. The colored

scale gives the percentage abundance of OTUs. B) NMDS ordination of bacterial 16S rRNA

communities based on the Bray–Curtis dissimilarity of community composition (stress =0.061).

Arrows indicate the direction at which the environmental vectors fit the best (using the envfit

function) onto the NMDS ordination space. EC, electrical conductivity; DOC, dissolved organic

carbon; DON, dissolved organic nitrogen; GWC, gravimetric water content.

Figure 7. Relative abundance of 16S rRNA genes of the dominant methanotroph groups detected

in the forest (A), grass (B), and bog (C) sites. USCα was identified by blast as described in the

methods. Methylocystis and Methylomirabilis were identified based on the Silva classifications.

Other methanotrophs include Methylomonas and Methylospira.

Figure 8. Areal coverage of Australian Alps in southeastern Australia (1.2M ha).

Figure 9. A) Hourly methane (CH_4) fluxes from this study's Forest, Grassland and Bog soils

compared to Forest and Herbaceous studies from a global meta-analysis (McDaniel et al. 2019).

10th and 90th percentile shown by bottom and top whisker. 25th and 75th percentile shown by

bottom and top of the box. Median is shown by the thin line, mean by the thick line, and outliers

are circles. The number of measurements within each boxplot are shown in parentheses. Gray

bar at -571 µg CH_4 m^{-2} h^{-1} is the greatest CH4 oxidation rate (most negative flux) ever observed

and published (Singh *et al.*, 1997). B) Figure from survey of global forest CH4 fluxes (Gatica *et*

al., 2020) with our modeled annual mean net CH4 sink from Australian Alps and range created ±

relative standard deviation from ecosystem means (Table 2).

REFERENCES

Adams, M.A. (2013) Mega-fires, tipping points and ecosystem services: Managing forests and

woodlands in an uncertain future. *For Ecol Manage* **294**: 250–261.

Adams, M.A., Cunningham, S.C., and Taranto, M.T. (2013) A critical review of the science

underpinning fire management in the high altitude ecosystems of south-eastern Australia.

For Ecol Manage **294**: 225–237.

Angel, R., Claus, P., and Conrad, R. (2012) Methanogenic archaea are globally ubiquitous in

aerated soils and become active under wet anoxic conditions. *ISME J* **6**: 847–862.

Bates, S.T., Cropsey, G.W.G., Caporaso, J.G., Knight, R., and Fierer, N. (2011) Bacterial

communities associated with the lichen symbiosis. *Appl Environ Microbiol* **77**: 1309–1314.

Bender, M. and Conrad, R. (1992) Kinetics of CH4 oxidation in oxic soils exposed to ambient air

or high CH4 mixing ratios. *FEMS Microbiol Lett* **101**: 261–269.

Bender, M. and Conrad, R. (1994) Methane oxidation activity in various soils and freshwater

sediments: Occurrence, characteristics, vertical profiles, and distribution on grain size

fractions. *J Geophys Res Atmos* **99**: 16531–16540.

Bengtson, P., Basiliko, N., Dumont, M.G., Hills, M., Murrell, J.C., Roy, R., and Grayston, S.J.

(2009) Links between methanotroph community composition and CH4 oxidation in a pine

forest soil. *FEMS Microbiol Ecol* **70**: 356–366.

Bodelier, P.L.E. and Frenzel, P. (1999) Contribution of methanotrophic and nitrifying bacteria to

CH4 and NH4 + oxidation in the rhizosphere of rice plants as determined by new methods

of discrimination. *Appl Environ Microbiol* **65**: 1826–1833.

BOM (2020) Bureau of Meteorology. Maps. Recent and Past Conditions.

Cai, Y., Zheng, Y., Bodelier, P.L.E., Conrad, R., and Jia, Z. (2016) Conventional methanotrophs

are responsible for atmospheric methane oxidation in paddy soils. *Nat Commun* **7**:.

Chen, Y., Dumont, M.G., Cébron, A., and Murrell, J.C. (2007) Identification of active

methanotrophs in a landfill cover soil through detection of expression of 16S rRNA and

functional genes. *Environ Microbiol* **9**: 2855–2869.

Christiansen, J.R., Levy-Booth, D., Prescott, C.E., and Grayston, S.J. (2016) Microbial and

Environmental Controls of Methane Fluxes Along a Soil Moisture Gradient in a Pacific

Coastal Temperate Rainforest. *Ecosystems* **19**: 1255–1270.

Conrad, R. (2002) Control of microbial methane production in wetland rice fields. *Nutr Cycl*

Agroecosystems **64**: 59–69.

Conrad, R. and Rothfuss, F. (1991) Methane oxidation in the soil surface layer of a flooded rice

field and the effect of ammonium. *Biol Fertil Soils* **12**: 28–32.

Costin, A.B., Hallsworth, E.G., and Woof, M. (1952) Studies in pedogenesis in New South

Wales. *J Soil Sci* **3**: 190–218.

D'imperio, L., Nielsen, C.S., Westergaard-Nielsen, A., Michelsen, A., and Elberling, B. (2017)

Methane oxidation in contrasting soil types: responses to experimental warming with

implication for landscape-integrated CH4 budget. *Glob Chang Biol* **23**: 966–976.

DEE (2018) Department of Energy and Environment. Woody Cover National Forest and Sparse

Woody Vegetation Data (Version 3).

Dumont, M.G., McGenity, T.J., Timmis, K.N., and Nogales, B. (2014) Primers: functional

marker genes for methylotrophs and methanotrophs. *Hydrocarb Lipid Microbiol Protoc eds McGenity TJ, Timmis KN, Nogales B, Ed Springer-Verlag* 1–21.

Dutaur, L. and Verchot, L. V (2007) A global inventory of the soil CH4 sink. *Global Biogeochem Cycles* **21**: 1–9.

Ebrahimi, A. and Or, D. (2016) Microbial community dynamics in soil aggregates shape biogeochemical gas fluxes from soil profiles – upscaling an aggregate biophysical model. *Glob Chang Biol* **22**: 3141–3156.

Edgar, R.C. (2013) UPARSE: highly accurate OTU sequences from microbial amplicon reads. *Nat Methods* **10**: 996.

Edgar, R.C., Haas, B.J., Clemente, J.C., Quince, C., and Knight, R. (2011) UCHIME improves sensitivity and speed of chimera detection. *Bioinformatics* **27**: 2194–2200.

Ettwig, K.F., Butler, M.K., Le Paslier, D., Pelletier, E., Mangenot, S., Kuypers, M.M.M., et al. (2010) Nitrite-driven anaerobic methane oxidation by oxygenic bacteria. *Nature* **464**: 543–548.

Fest, B., Wardlaw, T., Livesley, S.J., Duff, T.J., and Arndt, S.K. (2015) Changes in soil moisture drive soil methane uptake along a fire regeneration chronosequence in a eucalypt forest landscape. *Glob Chang Biol* **21**: 4250–4264.

Von Fischer, J.C. and Hedin, L.O. (2002) Separating methane production and consumption with a field-based isotope pool dilution technique. *Global Biogeochem Cycles* **16**: 1–13.

Freitag, T.E., Toet, S., Ineson, P., and Prosser, J.I. (2010) Links between methane flux and transcriptional activities of methanogens and methane oxidizers in a blanket peat bog.

FEMS Microbiol Ecol **73**: 157–165.

Frenzel, P., Rothfuss, F., and Conrad, R. (1992) Oxygen profiles and methane turnover in a

flooded rice microcosm. *Biol Fertil Soils* **14**: 84–89.

Frost, A.J., Ramchurn, A., and Smith, A. (2018) The Australian Landscape Water Balance

model.

Gatica, G., Fernández, M.E., Juliarena, M.P., and Gyenge, J. (2020) Environmental and

anthropogenic drivers of soil methane fluxes in forests: Global patterns and among-biomes

differences. *Glob Chang Biol* **26**: 6604–6615.

Gee, G.W. and Bauder, J.W. (1986) Particle-size analysis. In *Methods of soil analysis: Part 1—*

Physical and mineralogical methods. Soil Science Society of America, American Society of

Agronomy, pp. 383–411.

Harriss, R.C., Sebacher, D.I., and Day, F.P. (1982) Methane flux in the Great Dismal Swamp.

Nature **297**: 673–674.

Hartmann, M., Frey, B., Mayer, J., Mäder, P., and Widmer, F. (2015) Distinct soil microbial

diversity under long-term organic and conventional farming. *ISME J* **9**: 1177–1194.

He, R., Wooller, M.J., Pohlman, J.W., Quensen, J., Tiedje, J.M., and Leigh, M.B. (2012)

Diversity of active aerobic methanotrophs along depth profiles of arctic and subarctic lake

water column and sediments. *ISME J* **6**: 1937–1948.

Hernández, M., Conrad, R., Klose, M., Ma, K., and Lu, Y. (2017) Structure and function of

methanogenic microbial communities in soils from flooded rice and upland soybean fields

from Sanjiang plain, NE China. *Soil Biol Biochem* **105**: 81–91.

Hernández, M., Dumont, M.G., Yuan, Q., and Conrad, R. (2015) Different bacterial populations

associated with the roots and rhizosphere of rice incorporate plant-derived carbon. *Appl*

Environ Microbiol **81**: 2244–2253.

Holmes, A.J., Costello, A., Lidstrom, M.E., and Murrell, J.C. (1995) Evidence that participate

methane monooxygenase and ammonia monooxygenase may be evolutionarily related.

FEMS Microbiol Lett **132**: 203–208.

Horz, H.-P., Rich, V., Avrahami, S., and Bohannan, B.J.M. (2005) Methane-oxidizing bacteria in

a California upland grassland soil: diversity and response to simulated global change. *Appl*

Environ Microbiol **71**: 2642–2652.

Hu, B., Shen, L., Lian, X., Zhu, Q., Liu, S., Huang, Q., et al. (2014) Evidence for nitrite-

dependent anaerobic methane oxidation as a previously overlooked microbial methane sink

in wetlands. *Proc Natl Acad Sci* **111**: 4495 LP – 4500.

Hütsch, B.W. (1998) Tillage and land use effects on methane oxidation rates and their vertical

profiles in soil. *Biol Fertil Soils* **27**: 284–292.

Hütsch, B.W., Webster, C.P., and Powlson, D.S. (1994) Methane oxidation in soil as affected by

land use, soil pH and N fertilization. *Soil Biol Biochem* **26**: 1613–1622.

IBRA7 (2012) Interim Bioregionalisation for Australia, version 7.

Jenkins, M. and Adams, M.A. (2010) Vegetation type determines heterotrophic respiration in

subalpine Australian ecosystems. *Glob Chang Biol* **16**: 209–219.

Jónsson, J.Ö.G. and Davíðsdóttir, B. (2016) Classification and valuation of soil ecosystem

services. *Agric Syst* **145**: 24–38.

Kalyuzhnaya, M.G., Yang, S., Rozova, O.N., Smalley, N.E., Clubb, J., Lamb, A., et al. (2013)

Highly efficient methane biocatalysis revealed in a methanotrophic bacterium. *Nat Commun*

4: 2785.

Karbin, S., Hagedorn, F., Hiltbrunner, D., Zimmermann, S., and Niklaus, P.A. (2016) Spatial

micro-distribution of methanotrophic activity along a 120-year afforestation

chronosequence. *Plant Soil* **415**: 1–11.

Khadem, A.F., Wieczorek, A.S., Pol, A., Vuilleumier, S., Harhangi, H.R., Dunfield, P.F., et al.

(2012) Draft Genome Sequence of the Volcano-Inhabiting Thermoacidophilic

Methanotroph <span class="named-content genus-species" id="named-

content-1">Methylacidiphilum fumariolicum Strain SolV. *J*

Bacteriol **194**: 3729 LP – 3730.

Kirschke, S., Bousquet, P., Ciais, P., Saunois, M., Canadell, J.G., Dlugokencky, E.J., et al.

(2013) Three decades of global methane sources and sinks. *Nat Geosci* **6**: 813–823.

Kits, K.D., Campbell, D.J., Rosana, A.R., and Stein, L.Y. (2015) Diverse electron sources

support denitrification under hypoxia in the obligate methanotroph Methylomicrobium

album strain BG8 . *Front Microbiol*   **6**: 1072.

Knief, C. (2015) Diversity and habitat preferences of cultivated and uncultivated aerobic

methanotrophic nacteria evaluated based on pmoA as molecular marker. *Front Microbiol* **6**:

1346.

Knief, C., Lipski, A., and Dunfield, P.F. (2003) Diversity and activity of methanotrophic bacteria

in different upland soils. *Appl Environ Microbiol* **69**: 6703–6714.

Kolb, S. (2009) The quest for atmospheric methane oxidizers in forest soils. *Environ Microbiol*

Rep **1**: 336–346.

Kolb, S., Knief, C., Dunfield, P.F., and Conrad, R. (2005) Abundance and activity of uncultured

methanotrophic bacteria involved in the consumption of atmospheric methane in two forest

soils. *Environ Microbiol* **7**: 1150–1161.

Kolb, S., Knief, C., Stubner, S., and Conrad, R. (2003) Quantitative detection of methanotrophs

in soil by novel pmoA-targeted Real-Time PCR assays. *Appl Environ Microbiol* **69**: 2423–

2429.

Koschorreck, M. and Conrad, R. (1993) Oxidation of atmospheric methane in soil:

Measurements in the field, in soil cores and in soil samples. *Global Biogeochem Cycles* **7**:

109–121.

Krause, S., Meima-Franke, M., Hefting, M.M., and Bodelier, P.L.E. (2013) Spatial patterns of

methanotrophic communities along a hydrological gradient in a riparian wetland. *FEMS*

Microbiol Ecol **86**: 59–70.

Luesken, F.A., Wu, M.L., Op den Camp, H.J.M., Keltjens, J.T., Stunnenberg, H., Francoijs, K.,

et al. (2012) Effect of oxygen on the anaerobic methanotroph 'Candidatus Methylomirabilis

oxyfera': kinetic and transcriptional analysis. *Environ Microbiol* **14**: 1024–1034.

Malghani, S., Reim, A., von Fischer, J., Conrad, R., Kuebler, K., and Trumbore, S.E. (2016) Soil

methanotroph abundance and community composition are not influenced by substrate

availability in laboratory incubations. *Soil Biol Biochem* **101**: 184–194.

Martin, M. (2011) Cutadapt removes adapter sequences from high-throughput sequencing reads.

EMBnet J **17**: pp-10.

McDaniel, M.D., Kaye, J.P., and Kaye, M.W. (2014) Do "hot moments" become hotter under

climate change? Soil nitrogen dynamics from a climate manipulation experiment in a post-

harvest forest. *Biogeochemistry* **121**: 339–354.

McDaniel, M.D., Simpson, R.R., Malone, B.P., McBratney, A.B., Minasny, B., and Adams,

M.A. (2017) Quantifying and predicting spatio-temporal variability of soil CH4 and N2O

fluxes from a seemingly homogeneous Australian agricultural field. *Agric Ecosyst Environ*

240: 182–193.

Le Mer, J. and Roger, P. (2001) Production, oxidation, emission and consumption of methane by

soils: A review. *Eur J Soil Biol* **37**: 25–50.

Murrell, J.C. and Jetten, M.S.M. (2009) The microbial methane cycle. *Environ Microbiol Rep* **1**:

279–284.

Nazaries, L., Murrell, J.C., Millard, P., Baggs, L., and Singh, B.K. (2013) Methane, microbes

and models: fundamental understanding of the soil methane cycle for future predictions.

Environ Microbiol **15**: 2395–2417.

Nazaries, L., Pan, Y., Bodrossy, L., Baggs, E.M., Millard, P., Murrell, J.C., and Singh, B.K.

(2013) Evidence of microbial regulation of biogeochemical cycles from a study on methane

flux and land use change. *Appl Environ Microbiol* **79**: 4031–4040.

Nazaries, L., Tate, K.R., Ross, D.J., Singh, J., Dando, J., Saggar, S., et al. (2011) Response of

methanotrophic communities to afforestation and reforestation in New Zealand. *ISME J* **5**:

1832–1836.

Ni, X. and Groffman, P.M. (2018) Declines in methane uptake in forest soils. *Proc Natl Acad Sci*

115: 8587–8590.

Oksanen, J., Blanchet, F.G., Kindt, R., Legendre, P., Minchin, P.R., O'Hara, R.B., et al. (2016)

vegan: Community Ecology Package.

Oremland, R.S. and Culbertson, C.W. (1992) Evaluation of methyl fluoride and dimethyl ether

as inhibitors of aerobic methane oxidation. *Appl Environ Microbiol* **58**: 2983–2992.

Pratscher, J., Dumont, M.G., and Conrad, R. (2011) Assimilation of acetate by the putative

atmospheric methane oxidizers belonging to the USCα clade. *Environ Microbiol* **13**: 2692–

2701.

Pratscher, J., Vollmers, J., Wiegand, S., Dumont, M.G., and Kaster, A. (2018) Unravelling the

identity, metabolic potential and global biogeography of the atmospheric methane-oxidizing

Upland Soil Cluster α. *Environ Microbiol* **20**: 1016–1029.

Priemé, A. and Christensen, S. (1997) Seasonal and spatial variation of methane oxidation in a

Danish spruce forest. *Soil Biol Biochem* **29**: 1165–1172.

Priemé, A., Christensen, S., Dobbie, K.E., and Smith, K.A. (1997) Slow increase in rate of

methane oxidation in soils with time following land use change from arable agriculture to

woodland. *Soil Biol Biochem* **29**: 1269–1273.

R Core Team (2018) R: A language and environment for statistical computing.

Reeburgh, W.S. (2003) Global methane biogeochemistry. *Treatise on geochemistry* **4**: 347.

Reim, A., Hernández, M., Klose, M., Chidthaisong, A., Yuttitham, M., and Conrad, R. (2017)

Response of methanogenic microbial communities to desiccation stress in flooded and rain-

fed paddy soil from Thailand. *Front Microbiol* **8**: 785.

Saari, A., Martikainen, P.J., Ferm, A., Ruuskanen, J., De Boer, W., Troelstra, S.R., and

Laanbroek, H.J. (1997) Methane oxidation in soil profiles of Dutch and Finnish coniferous

forests with different soil texture and atmospheric nitrogen deposition. *Soil Biol Biochem*

29: 1625–1632.

Sass, R., Denmead, O.T., Conrad, R., Freney, J., Klug, M., Minami, K., et al. (1992) Exchange

of methane and other trace gases in rice cultivation. *Ecol Bull* 199–206.

Saunois, M., Bousquet, P., Poulter, B., Peregon, A., Ciais, P., Canadell, J.G., et al. (2016) The

global methane budget 2000–2012. *Earth Syst Sci Data* **8**: 697–751.

Schloss, P.D., Westcott, S.L., Ryabin, T., Hall, J.R., Hartmann, M., Hollister, E.B., et al. (2009)

Introducing mothur: open-source, platform-independent, community-supported software for

describing and comparing microbial communities. *Appl Environ Microbiol* **75**: 7537–7541.

Schnell, S. and King, G.M. (1994) Mechanistic analysis of ammonium inhibition of atmospheric

methane consumption in forest soils. *Appl Environ Microbiol* **60**: 3514–3521.

Sexstone, A.J., Revsbech, N.P., Parkin, T.B., and Tiedje, J.M. (1985) Direct measurement of

oxygen profiles and denitrification rates in soil aggregates. *Soil Sci Soc Am J* **49**: 645–651.

Shrestha, P.M., Kammann, C., Lenhart, K., Dam, B., and Liesack, W. (2012) Linking activity,

composition and seasonal dynamics of atmospheric methane oxidizers in a meadow soil.

ISME J **6**: 1115–1126.

Shukla, P.N., Pandey, K.D., and Mishra, V.K. (2013) Environmental determinants of soil

methane oxidation and methanotrophs. *Crit Rev Environ Sci Technol* **43**: 1945–2011.

SILO - Queensland Government.

Singh, J.S., Singh, Smita, Raghubanshi, A.S., Singh, Saranath, Kashyap, A.K., and Reddy, V.S.

(1997) Effect of soil nitrogen, carbon and moisture on methane uptake by dry tropical forest

soils. *Plant Soil* **196**: 115–121.

Singleton, C.M., McCalley, C.K., Woodcroft, B.J., Boyd, J.A., Evans, P.N., Hodgkins, S.B., et

al. (2018) Methanotrophy across a natural permafrost thaw environment. *ISME J* **12**: 2544–

2558.

Smith, K.A., Dobbie, K.E., Ball, B.C., Bakken, L.R., Sitaula, B.K., Hansen, S., et al. (2000)

Oxidation of atmospheric methane in Northern European soils, comparison with other

ecosystems, and uncertainties in the global terrestrial sink. *Glob Chang Biol* **6**: 791–803.

Stocker, D.Q. (2013) Climate change 2013: The physical science basis. *Work Gr I Contrib to*

Fifth Assess Rep Intergov Panel Clim Chang Summ Policymakers, IPCC.

Sullivan, B.W., Kolb, T.E., Hart, S.C., Kaye, J.P., Hungate, B.A., Dore, S., and Montes-Helu, M.

(2010) Wildfire reduces carbon dioxide efflux and increases methane uptake in ponderosa

pine forest soils of the southwestern USA. *Biogeochemistry* **104**: 251–265.

Sullivan, B.W., Selmants, P.C., and Hart, S.C. (2013) Does dissolved organic carbon regulate

biological methane oxidation in semiarid soils? *Glob Chang Biol* **19**: 2149–2157.

Tarboton, D.G. (2005) Terrain analysis using digital elevation models (TauDEM). *Utah State*

Univ Logan.

Thauer, R.K., Kaster, A.-K., Seedorf, H., Buckel, W., and Hedderich, R. (2008) Methanogenic

archaea: ecologically relevant differences in energy conservation. *Nat Rev Microbiol* **6**:

579–591.

Tilman, D., Reich, P.B., Knops, J., Wedin, D., Mielke, T., and Lehman, C. (2001) Diversity and

productivity in a long-term grassland experiment. *Science (80-)* **294**: 843–845.

Tveit, A.T., Hestnes, A.G., Robinson, S.L., Schintlmeister, A., Dedysh, S.N., Jehmlich, N., et al.

(2019) Widespread soil bacterium that oxidizes atmospheric methane. *Proc Natl Acad Sci*

116: 8515 LP – 8524.

Velthof, G.L., Jarvis, S.C., Stein, A., Allen, A.G., and Oenema, O. (1996) Spatial variability of

nitrous oxide fluxes in mown and grazed grasslands on a poorly drained clay soil. *Soil Biol*

Biochem **28**: 1215–1225.

Warnes, G., Bolker, B., and Lumley, T. (2015) gplots: various R programming tools for plotting

data. R package version 2.6.0.

Wille, C., Kutzbach, L., Sachs, T., Wagner, D., and Pfeiffer, E.M. (2008) Methane emission

from Siberian arctic polygonal tundra: Eddy covariance measurements and modeling. *Glob*

Chang Biol **14**: 1395–1408.

Wolf, K., Flessa, H., and Veldkamp, E. (2012) Atmospheric methane uptake by tropical montane

forest soils and the contribution of organic layers. *Biogeochemistry* **111**: 469–483.

Wu, X., Yao, Z., Brüggemann, N., Shen, Z.Y., Wolf, B., Dannenmann, M., et al. (2010) Effects

of soil moisture and temperature on CO2 and CH4 soil–atmosphere exchange of various

land use/cover types in a semi-arid grassland in Inner Mongolia, China. *Soil Biol Biochem*

42: 773–787.

Yabe, S., Sakai, Y., Abe, K., and Yokota, A. (2017) Diversity of Ktedonobacteria with

Actinomycetes-Like Morphology in Terrestrial Environments. *Microbes Environ* **32**: 61–70.

Yang, W.H. and Silver, W.L. (2016) Net soil-atmosphere fluxes mask patterns in gross

production and consumption of nitrous oxide and methane in a managed ecosystem.

Biogeosciences **13**: 1705.

Yokota, A. (2012) Cultivation of uncultured bacteria of the class Ktedonobacteria in the Phylum

Chloroflexi. *Makara J Sci* **1**: 1–8.

Yu, Y., Lee, C., Kim, J., and Hwang, S. (2005) Group-specific primer and probe sets to detect

methanogenic communities using quantitative real-time polymerase chain reaction.

Biotechnol Bioeng **89**: 670–679.

Zhou, J., Xia, B., Treves, D.S., Wu, L.-Y., Marsh, T.L., O'Neill, R. V, et al. (2002) Spatial and

resource factors influencing high microbial diversity in soil. *Appl Environ Microbiol* **68**:

326–334.

Zuur, A.F., Ieno, E.N., and Elphick, C.S. (2010) A protocol for data exploration to avoid

common statistical problems. *Methods Ecol Evol* **1**: 3–14.

Table 1. Annual estimates (mean, standard error, and range) for net ecosystem flux of carbon dioxide and methane

Ecosystem	% of 548 ha Watershed*	Net Ecosystem Flux	
		CO_2	CH_4
		CO_2-equivalents g m^{-2} y^{-1}	
Forest	8-75	911 ± 165	-506 ± 22
Grassland	25-91	484 ± 50	-259 ± 38
Bog	1	646 ± 109	256 ± 82
		CO_2-equivalents kg ha^{-1} y^{-1}	
Total Watershed		5207 to 8031	-2762 to -4391

Table 2. Comparison of Global and Australian Alps soil methane sink estimates

Measurement	Values		
Ecosystems Areal Coverage			
Global forest+grassland ecosystems (millions of ha)	5,100		
Areal coverage of Australian Alps – Figure 8 (millions of ha)	1.23		
Fraction of Australian Alps to global forest+grassland (%)	0.024		
Soil CH$_4$ Sink Estimates	**Low Estimate**	**Best Estimate**	**High Estimate**
Global CH$_4$ Soil Sink[†] *(Tg y^{-1})*	-9	-30	-100
Mean annual Australian Alps CH$_4$ sink[‡] (kg ha^{-1} y^{-1})	-4.2	-19.2	-33.2
Australian Alps Contribution to Global CH$_4$ Sink (%)	**Low Estimate**	**Best Estimate**	**High Estimate**
Low estimate (-6.2 kg ha^{-1} y^{-1})	69	21	6
Best Estimate, or our projection (-19.2 kg ha^{-1} y^{-1})	213	64	19
High estimate (-32.3 kg ha^{-1} y^{-1})	359	108	32

[†]: Low and Best Estimates from Kirschke et al. (2013) and Saunois et al. (2016). Other estimates have a high estimates of -100 Tg y^{-1} (Smith et al. 2000)

[‡]: Based on forest foliage imagery, soil temperatures and moisture estimates, and CH$_4$ modeling described in Experimental Procedures. High and Low estimate from +/- relative standard deviation from ecosystem means.

Fig. 1. **A)** Location of 548 ha experiment area (inset of Australia), sampling sites within area and nearby streams. **B)** Landscape-level photograph of the vegetation gradient from sphagnum-dominated bog in foreground to eucalyptus-dominated forest in background. Abbreviations are F = Forest, G = Grassland, and B = Bog. The numbers after the letter represent which transect the sampling location belongs to.

Fig. 2. Soil CO_2 fluxes (top panels, **A-D**) and production (bottom panels, **E-H**). Surface flux measurements and soils collected for production on 17 February (Summer,**A & E**), 25 May (Autumn, **B & F**), 22 September (Winter, **C & G**), and 23 November (Spring, **D & H**) in 2015. Mean and standard error shown (n = 4).

Fig. 3. Soil CH$_4$ fluxes (top panels, **A-D**) and production/consumption (bottom panels, **E-H**). Surface flux measurements and soils collected for production on 17 February (Summer, A & E), 25 May (Autumn, **B** & **F**), 22 September (Winter, **C** & **G**), and 23 November (Spring, **D** & **H**) in 2015. Mean and standard error shown (n = 4).

Fig. 4. Abundance of archaeal (**A**) and bacterial (**B**) 16S rRNA genes, and *pmoA* (C). Means and standard error are shown (n=4) for all samples.

Fig. 5. Regressions between total CO_2 production and CO_2 soil-atmosphere flux (**A**), CH_4 production and CH_4 soil-atmosphere flux (**B**). Total GHG production was calculated for each soil profile as sum of production from 0 to 30 cm depth. Regressions between bacterial 16S rRNA abundance with CO_2 production (**C**, linear equation with log, log scale). Regression between and archaeal 16S rRNA and CH_4 production (**D**, 3-parameter exponential, log x-axis). Equations, chosen by best fit, are shown in each panel.

Fig. 6. **A)** Heatmap of the most relevant OTUs derived from bacterial 16S rRNA genes. The samples and OTUs were clustered according to Euclidean distances between all Hellinger transformed data. The taxonomy of OTUs was determined using the Sina classifier. The colored scale gives the percentage abundance of OTUs. **B)** NMDS ordination of bacterial 16S rRNA communities based on the Bray–Curtis dissimilarity of community composition (stress =0.061). Arrows indicate the direction at which the environmental vectors fit the best (using the *envfit* function) onto the NMDS ordination space. EC, electrical conductivity; DOC, dissolved organic carbon; DON, dissolved organic nitrogen; GWC, gravimetric water content.

Fig. 7. Relative abundance of 16S rRNA genes of the dominant methanotroph groups detected in the forest (**A**), grass (**B**), and bog (**C**) sites. USCα was identified by blast as described in the methods. *Methylocystis* and *Methylomirabilis* were identified based on the Silva classifications. Other methanotrophs include *Methylomonas* and *Methylospira*.

Fig. 8. Areal coverage of Australian Alps in southeastern Australia (1.2M ha).

Fig. 9. **A)** Hourly methane (CH_4) fluxes from this study's Forest, Grassland and Bog soils compared to Forest and Herbaceous studies from a global meta-analysis (McDaniel et al. 2019). 10th and 90th percentile shown by bottom and top whisker. 25th and 75th percentile shown by bottom and top of the box. Median is shown by the thin line, mean by the thick line, and outliers are circles. The number of measurements within each boxplot are shown in parentheses. Gray bar at -571 μg CH_4 m^{-2} h^{-1} is the greatest CH_4 oxidation rate (most negative flux) ever observed and published (Singh et al., 1997). **B)** Figure from survey of global forest CH_4 fluxes (Gatica et al. 2020) with our modeled annual mean net CH_4 sink from Australian Alps and range created ± relative standard deviation from ecosystem means (Table 2).