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PROGRAMA DE PÓS-GRADUAÇÃO EM SENSORIAMENTO REMOTO

ADRIANE BRILL THUM

UTILIZAÇÃO DE TÉCNICAS DE RADIOMETRIA E GEOTECNOLOGIAS NA DESCRIÇÃO DO COMPORTAMENTO ESPECTRAL DE CULTIVARES DE *VITIS VINIFERA*:

Estudo de caso na Serra Gaúcha

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Pela Banca Examinadora:

Prof. Dr. Jorge Ricardo Ducati
Orientador

Profa. Dra. Regina Célia Espinosa Modolo
(UNISINOS)

Prof. Dr. Giuliano Elias Pereira
(EMBRAPA Uva e Vinho)

Profa. Dra. Denise Cybis Fontana
(PPGSR/UFRGS)

Homologada em: __/__/____
Por:

Prof. Dr. Guilherme Garcia de
Coordenador do Program
Pós-Graduação em Sensoria
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RESUMO

A importância da Indicação Geográfica (IG), o cenário econômico aliado à preocupação com a produção de qualidade e as exigências do consumidor fizeram aumentar o uso de geotecnologias como sensoriamento remoto – SR – e *Global Navigation Satellite Systems* – GNSS – na vitivinicultura, surgindo a vitivinicultura de precisão. Entre os sensores remotos utilizados, podem ser destacados os espectroradiômetros utilizados para conhecer os espectros de reflectância que carregam informações que, potencialmente, são úteis, pois fornecem dados não destrutivos, econômicos e praticamente em tempo real. A pesquisa desenvolvida tem como objetivo geral investigar a resposta espectral de folhas, ramos, solo e rochas medidos em dois vinhedos, sua relação com a localização e resultados de análises químicas de folhas e solos dos mesmos vinhedos. O estudo foi realizado, na Região da Serra Gaúcha, no município de Nova Pádua, que se localiza à latitude 29º01'43" sul e à longitude 51º18'24" oeste, em altitudes que variam de 600 a 800 metros. Nas áreas estudadas foram escolhidas dez parcelas com as castas viníferas tintas Cabernet Sauvignon e Merlot devido à sua importância para a produção regional de vinhos finos. Foram recolhidas amostras de solo em dez parcelas de videiras selecionadas. Para obter as coordenadas precisas dos vinhedos realizou-se o georreferenciamento com a utilização um par de receptores GNSS de dupla frequência (L1/L2). Além do uso de GNSS, foi realizado um voo com veículo aéreo não tripulado (VANT), usando duas câmeras, uma delas operando no RGB e a outra com sensitividade no infravermelho, permitindo a obtenção de índices de vegetação como o NDVI. Os dados de campo consistiram em espectros de reflectância no domínio espectral entre 350 nm e 2500 nm medidos em solos e em folhas e ramos de videiras. Os espectros foram processados no *software* ViewSpec Pro, organizados em tabelas e analisados estatisticamente. A avaliação das diferenças entre as médias foi realizada pela aplicação da ANOVA, considerando o nível de 5% de significância. As técnicas multivariadas de Análise de Componentes Principais e Análise Discriminante foram executadas em dados previamente autoescalonados. Solos das parcelas e folhas de videiras foram coletadas para análise química efetuada nos laboratórios da Universidade Federal do Rio Grande do Sul – UFRGS, sendo determinadas as concentrações dos elementos N, P, K, Ca, Mg, S, Cu, Zn, Fe, Mn e B nas folhas, e de 21 parâmetros de solo (elementos químicos e atributos agronômicos) para cada uma das parcelas estudadas. Diferenças químicas significativas a um nível de confiança de 95% entre as duas áreas estudadas foram encontradas para seis atributos do solo, e os espectros de refletância médios foram separados por este mesmo nível ao longo da maior parte do domínio espectral observado. Correlações entre concentrações e reflectâncias para alguns domínios de comprimentos de onda foram encontradas, e análises por Partial Least Square Regression para dados de folhas e solos apresentaram coeficientes de correlação de Pearson $r > 0,8$. A análise discriminante aplicada aos dados de reflectância dos ramos das videiras para a separabilidade entre vinhedos e entre as variedades de uvas, alcançando acurácia superior a 90%. Como conclusões tem-se que o teor mineral de folhas e solos influenciam as respectivas reflectâncias, e quando considerados diferentes locais sua separação é possível. Os métodos relatados podem contribuir para a melhoria e consolidação das normas para Indicações Geográficas.

Palavras-chave: Resposta espectral. Espectroradiômetro. Análises química. Vitivinicultura de precisão. Geotecnologias. Solos.

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SUMÁRIO

ESTRUTURA DA TESE

A proposta da presente tese consiste na elaboração de 3 artigos científicos. Devido a isto, são apresentados cinco capítulos nos quais são abordados temas descritos a seguir.

No primeiro capítulo, são apresentados os "Aspectos Introdutórios e Metodológicos Gerais" em que são abordados assuntos como relevância e introdução ao tema, objetivos, fundamentação teórica do assunto abordado e metodologia. Os resultados e discussões são apresentados em forma de artigos nos capítulos II, III e IV.

O capítulo 2 mostra o artigo 1, publicado no *International Journal of Remote Sensing*, Volume 41 Issue 23. *The influence of mineral content on spectral features of vine leaves, International Journal of Remote Sensing*, 41:23, 9161-9179, DOI: 10.1080/01431161.2020.1798547. O artigo tem como objetivo mostrar as diferenças na resposta espectral das folhas das videiras, determinar os comprimentos de onda característicos e o conteúdo mineral, e estimar até que ponto as observações de reflectância podem ser úteis para prever as concentrações de minerais observadas nos vinhedos 1 e 2.

No capítulo 3, expõe o artigo 2 encaminhado para a Revista Brasileira de Ciência do Solo com o título: *The influence of mineral content on spectral features of soils in vineyards*, que apresenta as respostas espectrais observadas em diferentes solos dedicados à viticultura e o resultado das análises dos conteúdos minerais presentes nos solos para estimar até que ponto as reflectâncias observadas podem ser utilizadas para prever concentrações nos solos estudados.

O capítulo 4 designa-se ao artigo 3 encaminhado para a Revista Precision Agriculture, denominado: *Geotechnologies applied to precision viticulture of two areas at Serra Gaúcha, Brazil*, que pretende mostrar o levantamento georreferenciado dos vinhedos estudados para definir o contorno das áreas e parcelas, construir um conjunto de mapas de atributos agronômicos selecionados para os vinhedos e gerar mapas de índice de vegetação para essas parcelas visando a possíveis correlações entre as informações geradas.

No capítulo 5 "Considerações Finais", podem se verificar as principais conclusões referentes ao estudo de dois vinhedos na Serra Gaúcha por técnicas de radiometria, imageamento e análises químicas com base nos resultados obtidos nos artigos apresentados nos capítulos anteriores.

No Apêndice A, encontra-se o Resumo do trabalho apresentado no Congresso, reportando resultados de análise discriminante efetuada sobre rochas coletadas na área de estudo e em outras regiões.

Capítulo 1 - Aspectos Introdutórios e Metodológicos Gerais

1 INTRODUÇÃO

1.1 CONSIDERAÇÕES INICIAIS

O aumento na produção agrícola é um reflexo das transformações tecnológicas. Investir na melhoria da qualidade e da produção é o propósito da maioria dos produtores rurais, o que é alcançado com conhecimento científico e incorporação de tecnologias. Nesta perspectiva, surgiu a agricultura de precisão (AP), que tem por meta melhorar a gestão espacial e temporal das lavouras a fim de obter a maior receita e a menor despesa por área ou parcela. A AP possibilita a aplicação de insumos na quantidade e no local corretos (COELHO, 2005), com conhecimento espacial preciso, georreferenciado, utilizando diversas tecnologias, como receptores GNSS – *Global Navigation Satellite Systems* ou Sistemas Globais de Navegação por Satélite (MONICO, 2008); Sistema de Informação Geográfica – SIG (BLASCHKE; KUX, 2007; ROCHA, 2007) sensores e mapas digitais; possibilitando aplicações precisas, diminuindo os riscos, possibilitando um manejo otimizado e ampliando fronteiras (MANZATTO *et al.*, 1999; MIRANDA, 1999; CAMPO, 2000; TSCHIEDEL; FERREIRA, 2002; BRAGA, 2009; MACHADO *et al.*, 2018; DOW *et al.*, 2009; GROVES, 2013; GAY *et al.*, 2015; SOUBRY *et al.*, 2017). A vitivinicultura de precisão (VP) é uma aplicação da AP mais recente, por esta razão, necessita de desenvolvimentos derivados da pesquisa.

A Viticultura de Precisão é a precisa aplicação e gestão das operações culturais para a produção no vinhedo, visando ao aproveitamento otimizado dos recursos e à sustentabilidade, podendo se citar o conhecimento detalhado da área, características do solo, tipo de poda, fertilidade, água, pesticidas e outros recursos, permitindo ao produtor e ao enólogo a tomada de decisões e uma gestão diferenciada da vinha, levando à produção de vinhos de qualidade a partir da previsão da qualidade das uvas e da produtividade (TISSEYRE; TAYLOR, 2004; SILVA *et al.*, 2009).

Uma ferramenta importante para a obtenção de informações necessárias para a Viticultura de Precisão é o Sensoriamento Remoto (SR). O Sensoriamento Remoto pode ser entendido como um conjunto de ações técnicas que permitem a obtenção de informações sobre componentes da superfície terrestre sem a necessidade de contato direto com esses. Estas atividades envolvem a detecção, aquisição e análise por sensores remotos da energia eletromagnética emitida ou refletida por feições terrestres. O espectro de reflectância (ou a assinatura espectral), que é o registro do fluxo da radiação eletromagnética refletida por alvos terrestres, como vegetação ou solo, é característico de cada tipo de alvo, também chamado de classe (JENSEN, 2009; NOVO, 2008; MENESES, 2001). Para um dado alvo, a assinatura espectral é única, sendo formada por feições espectrais derivadas das características físicas, químicas e biológicas deste alvo específico (MENESES; ALMEIDA, 2012). De uma maneira geral, informações sobre o comportamento espectral de feições na superfície terrestre podem ser obtidas por meio de diversos meios, associados às plataformas sobre as quais operam os sensores. Estes podem ser aerotransportados, orbitais, terrestres e laboratoriais, possuindo resoluções espacial, espectral, radiométrica e temporal específicas de cada sensor. Informações sobre o comportamento espectral de alvos são coletadas em laboratório por meio de equipamentos como radiômetros, de utilização relativamente nova no Brasil, por serem equipamentos caros, razão pela qual, no caso da vitivinicultura, poucas investigações foram efetuadas até os dias de hoje.

A viticultura de precisão exige a associação das informações espectrais às feições territoriais que lhes deram origem. Para isto, é necessário um preciso levantamento de informações espaciais, ou seja, um levantamento topográfico. O avanço tecnológico dos últimos anos tem mudado as técnicas e os equipamentos utilizados nos levantamentos topográficos (ERBA *et al.*, 2005; GHILANI; WOLF, 2013; LOCH;CORDINI, 2007) com a utilização crescente de tecnologias como GNSS (SILVA; SEGANTINE, 2015; ALMEIDA, 2015; ALVES, 2013; SEEBER, 2003) e Sistemas de Aeronaves Remotamente Pilotados (RPAS) ou Veículos Aéreos Não Tripulados (UAV) (SOUZA, 2017; CASTRO JORGE; INAMASU, 2017; EISENBEISS, 2009; MOUTINHO, 2015; MUNARETTO, 2015); essas técnicas geram diversos produtos, incluindo mapas topográficos e Modelos de Elevação Digital (DEM), além de informações espaciais sobre o estado de saúde vegetal por índices de vegetação, como NDVI (Normalizado Difference Vegetation Index) ou outros (TSCHIEDEL; FERREIRA, 2002; EVERAERTS, 2008).

1.2 CONSIDERAÇÕES SOBRE A PRODUÇÃO VITIVINÍCOLA

Em nível mundial, existem, aproximadamente, sete milhões e quinhentos mil hectares de vinhas com um rendimento médio de 9.700 kg de uva por hectare. Os maiores produtores de uvas, para as mais variadas finalidades, são a China, Estados Unidos, França, Itália e Espanha. Os cinco maiores produtores de vinho são Itália, Espanha, França, Estados Unidos e China, com uma produção alta em 2018, porém, em 2019 e 2020, a produção mundial de vinho ficou abaixo da média histórica, devido às condições climáticas e à pandemia do coronavírus (OIV, 2021).

A vitivinicultura no Brasil, principalmente com relação à produção de uvas para vinhos finos, é recente quando comparada com a história dos países europeus e vem crescendo anualmente (MELO, 2012). No Rio Grande do Sul, a vitivinicultura teve seus primeiros registros em 1626, por obra do padre jesuíta Roque Gonzáles de Santa Cruz (EMBRAPA, 2017; BENTO GONÇALVES, 2018).

O Brasil colheu mais de 80 milhões de quilos de uvas de *Vitis vinifera* (IBRAVIN, 2017). O Rio Grande do Sul responde por 90% do total de vinhos finos produzidos, sendo processadas mais de 870 mil toneladas de uvas viníferas em 2017. Em 2020, a safra foi com muita qualidade, devido aos dias ensolarados e às noites com temperaturas amenas aliados ao déficit hídrico no período da colheita, já em 2021, houve safra recorde em quantidade. A Serra Gaúcha é a principal região produtora, sendo responsável por 85% da produção. O PIB (produto interno bruto), no Rio Grande do Sul, cresceu 5,5% no primeiro trimestre de 2021, apesar da pandemia do Coronavírus, graças ao agronegócio, sendo a uva a segunda responsável por este resultado, com aumento na produção de 29,2% (CANAL RURAL, 2021). A uva, em nível nacional, é a nona fruta mais produzida, com 78 mil hectares em 2018 (IBGE, 2018), mostrando a importância da viticultura no desenvolvimeto regional e na sustentabilidade econômica (MELLO, 2017) de alguns estados.

Para agregar valor à produção e comercialização do vinho no Brasil, protocolos de controle de qualidade do vinhedo à vinícola foram desenvolvidos, e, a partir de 1996, os vinhos finos produzidos em determinadas regiões passaram a ser reconhecidos como Indicações Geográficas, ou seja, vinhos finos com Denominação de Origem (DO) ou Indicação de Procedência (IP) (TONIETTO *et al.*, 2016; MENEZES, 2009). Este reconhecimento foi fundamental para o fortalecimento e a consolidação de uma identidade regional ou nacional para os vinhos brasileiros, na perspectiva de buscar competividade em nível nacional e internacional. Indicações Geográficas foram implementadas, inicialmente, na Serra Gaúcha em sub-regiões como o Vale dos Vinhedos e Monte Belo do Sul, havendo perspectivas do reconhecimento de novas regiões, como a Campanha, Serra do Sudeste e Vale do Submédio São Francisco (EMBRAPA, 2017).

1.3 ASPECTOS DO SR APLICADOS À VITICULTURA

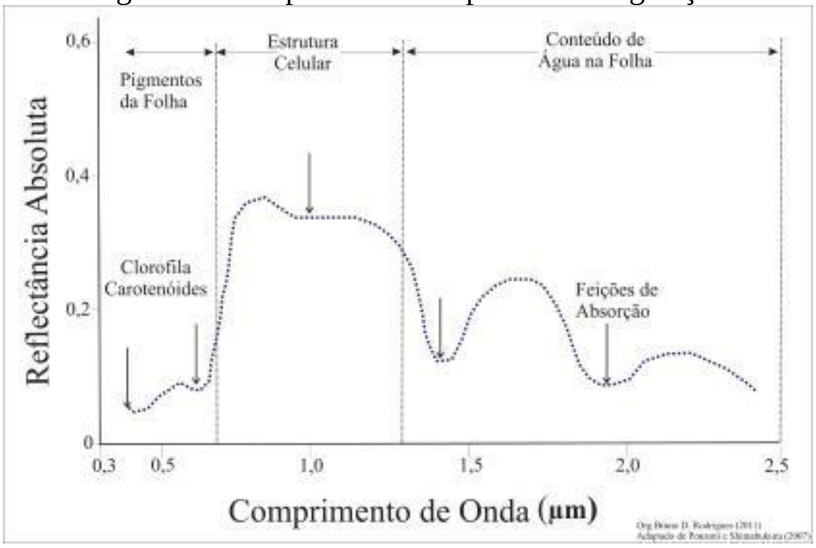
Vinhedos localizados em diferentes zonas permitem a produção de vinhos com características distintas, mesmo com castas, clone e porta-enxerto idênticos. Estas diferenças são devidas a diferenças subtis nas características físicas das vinhas, no tipo de solo, microclima, declividade, exposição solar, drenagem, capacidade de retenção de água no solo, regas e podas. Ainda em um mesmo vinhedo, variações espaciais da qualidade do solo levam a variações espaciais do vigor vegetativo, o que influencia o rendimento e a qualidade das uvas, alterando a qualidade do vinho (HOFF, 2013).

Um dos problemas enfrentados na vitivinicultura é a falta de informações espaciais detalhadas, o que leva a um manejo homogêneo, sem considerar as diferenças encontradas entre as parcelas ou no interior de uma parcela. O detalhamento de informações permite otimizar o manejo, incrementando o rendimento e a qualidade (SORT; UBALDE, 2005).

A evolução tecnológica e o surgimento de novos sensores com melhor resolução espacial, temporal e radiométrica são grandes aliados na VP, pois permite o diagnóstico de situações e o monitoramento dos vinhedos, com a possibilidade de determinar diferenças entre espécies de plantas por meio do conhecimento das características espectrais. Considerando espectros de reflectância, que podem caracterizar o estado fisiológico, potencial fotossintético e a produtividade (XUE *et al.*, 2008); observa-se que as diferenças na resposta espectral medida em folhas (CURRAN, 1989) de variedades de Vitis spp. são mais acentuadas na região do infravermelho próximo, que é associada à estrutura celular das folhas (THOMAS; GAUSMAN, 1977), do que na região do visível, diretamente relacionada com o teor de pigmentos e a atividade fotossintética (GAO, 2000; LUZ, 2005; ASSUNÇÃO, 1989; PEÑUELAS; FILELLA, 1998). De acordo com Hunt e Rock (1989), Gao (1996), Ceccato *et al.* (2001) e Ponzoni e Shimabukuro (2007), a reflectividade entre 1.300 e 2.500 nm depende, em parte, do teor de água armazenada nas células das folhas (Figura 1). A reflectividade diminui com o aumento do nível de água no tecido (sensitividade à absorção de água em 760, 970, 1450, e 1940 nm) (RIPPLE, 1986; PEÑUELAS *et al.*, 1993; PEÑUELAS *et al.*, 1997).

A estrutura celular das folhas, expressa espectralmente na região do infravermelho, é mais importante na discriminação das variedades do que no teor de pigmentos e na atividade fotossintética das plantas, expressas na região do visível (PALTA, 1990). Da Silva e Ducati (2009), estudando vinhedos no Rio Grande do Sul, demonstraram que variedades de uvas tintas e brancas poderiam ser espectralmente separadas, a causa sendo o pigmento antocianina que está presente em células das folhas de plantas de variedades tintas.

Figura 1 - Comportamento espectral da vegetação



Fonte: Ponzoni e Shimabukuro (2007)

A determinação de índice de área foliar (Leaf Area Index – LAI) utilizando sensoriamento remoto e índices NDVI (Normalized Difference Vegetation Index) também é importante na VP (POBLETE-ECHEVERRÍA *et al.*, 2017). Estes autores compararam imagens de Landsat 8, Sentinel e de VANT, com resoluções espaciais de 30m, 10m e 0,06m, respectivamente, encontrando alta correlação (r^2=0,86) entre NDVI e LAI. Estudos de NDVI na região da Campanha no RS, por Junges *et al.* (2017), para os anos de 2015 e 2016, em vinhedos de Cabernet Sauvignon, mostraram variações associadas ao solo, ao manejo dos vinhedos e às condições meteorológicas.

1.4 FATORES VITICULTURAIS E O CONCEITO DE TERROIR

A definição do conceito de terroir é uma das questões mais debatidas em enologia e viticultura. A interação dinâmica entre diversos fatores, incluindo o ambiente, o clima, as características do local, como topografia, o solo, o estado da água da videira, o enxerto, a planta da videira e as técnicas vitícolas adotadas, pode levar a que o vinho produzido num determinado espaço seja único. Diz-se, então, que o vinho é fruto de um terroir característico e que apresenta uma tipicidade (TONIETTO, 2007). Tem havido um crescente interesse em definir e quantificar objetivamente a contribuição de fatores individuais para um terroir específico (SEGUIN, 1988; TONIETTO, 2007; MIGUEL-GÓMEZ *et al.*, 2013; SABIR, 2016). Na visão de autores mais ligados à área de solos (FANET, 2004), a geologia e as características de solo são aspectos essenciais do terroir. Hoff *et al.* (2015), estudando diferentes regiões vitícolas do Rio Grande do Sul, concluíram que as diferenças relativas a rochas e ao relevo, ou seja, à geodiversidade, agregam fatores de tipicidade a cada terroir.

1.5 FATORES LIGADOS À GEOLOGIA

Rochas sofrem intemperismo físico e químico ou meteorização, fornecendo um material denominado regolito, que dá origem ao solo. Rochas expostas a condições climáticas diferentes podem formar solos diferentes, devido aos processos de decomposição de rochas distintas, sendo estes processos mais intensos em climas mais quentes.

Geologicamente, o Estado do Rio Grande do Sul está constituído por diversas regiões. Na região central, predominam rochas cristalinas designadas como Escudo Sul-Rio-Grandense; um conjunto de formações sedimentares depositadas desde o Permiano até o Jurássico que recobre as litologias do Escudo, sobrepostas e/ou intrudidas por rochas relacionadas ao magmatismo Serra Geral, de idade cretácica e que compõem a Serra Gaúcha, ou os Campos de Cima da Serra (MODENA, 2016). A região da Planície Costeira apresenta sedimentos finos cenozoicos, cuja sedimentação teve início quando do rompimento e da expansão do continente Gonduana, e consequente abertura do oceano Atlântico. Ainda são encontrados extensos depósitos aluvionáreos, distribuídos ao longo dos principais rios, como o Camaquã, as planícies do rio Santa Maria ou ao longo do delta do Jacuí e seus afluentes, seguidos de sedimentações residuais, como as Formações Santa Tecla e Tupanciretã (WILDNER *et al.*, 2005).

O magmatismo Serra Geral é dividido em nove fácies distintos, cinco relacionados ao magmatismo máfico (Fácies Gramado, Paranapanema-Ribeira, Pitanga, Esmeralda, Campo Erê e Lomba Grande) e três ao magmatismo intermediário a félsico (fácies Palmas – mesmas características do Caxias, Chapecó e Alegrete) (WILDNER *et al.*, 2005). A Fácies Alegrete é encontrada na região Oeste do RS, representada por conjuntos de derrames de composição andesítica a basáltica, dentre os quais os derrames Catalán e Cordillera comportam espessas brechas de topo cimentadas por calcitas, com quantidade subordinada de zeolitas. De maior interesse para a viticultura, por ali haver atividade vitivinícola, são as Fácies Gramado e Caxias.

A Fácies Gramado refere-se a um conjunto de derrames com espessura aproximada de 350m, aflorantes nas bordas sul e sudeste da bacia, com seção-tipo ao longo das escarpas da serra que se iniciam em Novo Hamburgo e sobem em direção a Nova Petrópolis, entre Estrela e São José do Herval, e entre Igrejinha e as proximidades de Gramado. As rochas dessa fácies são tipicamente de grão fino, afíricas a raramente microporfiríticas. Constituem-se de um arranjo de cristais de plagioclásio euédricos aos quais se somam o par de clinopiroxênios (augita-pigeonita) e quantidades esporádicas de olivinas. Como acessórios, destaca-se a presença dos óxidos de Fe-Ti (magnetita – ilmenita), apatita e quartzo. Os espaços intersticiais entre cristais encontram-se preenchidos por vidro intersertal, podendo, ocasionalmente, estar rearranjado para um mosaico de cristálitos de plagioclásio e quartzo (WILDNER *et al.*, 2005).

A Fácies Caxias corresponde a derrames superiores constituídos por riolitos e riodacitos depositados diretamente sobre os basaltos da Fácies Gramado, apresentando derrames maciços e espessos, chegando a 80 metros por derrame . Estes derrames são de composição intermediária e ácida (riodacitica), mesocráticos, granulares finos a microfaneríticos, horizontes superiores com disjunção tabular regular bem desenvolvida e raras vesículas preenchidas por sílica. Encontram-se centros de derrames maciços, e estruturas de fluxo laminar e dobras.

1.6 ASPECTOS LIGADOS AO SOLO

A reflectância do solo ocorre devido a todos os constituintes minerais, concentração de óxido de ferro, umidade, matéria orgânica, granulometria, textura e estrutura, mineralogia da argila, material de origem, cor, capacidade de troca catiônica, condições de drenagem interna e a temperatura do solo, sua localização, etc. Ocasionalmente, um parâmetro específico é característico. Solos com óxido de ferro absorvem energia eletromagnética no infravermelho próximo (IVP), em torno de 900 nm. A presença de matéria orgânica não diminui a contribuição do ferro na reflectância (EPIPHÂNIO *et al.*, 1992). No visível, quanto menor a partícula de solo, maior a reflectância, sendo o silte o principal parâmetro para explicar a variação espectral, tanto no visível como no infravermelho. Já o teor de argila pode ser observado entre 1500 e 1730 nm. No infravermelho médio, são os teores de argila, carbonatos, fosfatos e sulfatos que se destacam (EPIPHÂNIO *et al.*, 1992; DEMATTÊ *et al.*, 2000; MOREIRA, 2001).

As características físicas do solo e a topografia influenciam na quantidade de água retida no solo devido às características do subsolo (ATKINSON, 2011), ou seja, o relevo tem influência na formação do solo, devido à dinâmica da água no solo (MOREIRA, 2007). Alliaume *et al.* (2017) descrevem que o conhecimento espacial das características do solo é crucial para entender as diferentes respostas das plantas e manejar os vinhedos, arrolando como fatores a serem conhecidos os teores de argila, matéria orgânica, as trocas catiônicas e a resistência à penetração. Estudos mostram que o solo influencia na resposta espectral de um vinhedo, resposta esta proveniente, essencialmente, do dossel; um exemplo são os estudos realizados na Borgonha (DUCATI *et al.*, 2014). Assim, a reflectância espectral pode ser utilizada como critério na identificação de solos. Solos mais argilosos, que retêm mais água, possuem maior humidade, o que reduz a refletância no infravermelho; já solos mais secos a aumentam. A textura, a estrutura e o conteúdo de matéria orgânica influenciam na capacidade de retenção de água no solo (BOWERS; HANKS, 1965; FANET, 2008; PITIOT; SERVANT, 2010; MARQUES *et al*., 2017).

1.7 JUSTIFICATIVA DO ESTUDO

O conhecimento do terroir é um recurso que vai permitir ao profissional do vinho gerir melhor o patrimônio do vinhedo, com adaptações de práticas agrovitícolas e enológicas, em função do vinho desejado, potencialidades do ambiente, restrições econômicas, ambientais e uso do solo. O inventário e o georreferenciamento da variabilidade local dos fatores ambientais podem auxiliar e definir as tomadas de decisões por meio das informações precisas obtidas por parcela para serem aplicadas técnica e cientificamente em estudos de vinhedos.

O estudo se justifica, pois, para afirmar se realmente ocorrem diferenças nas características da folha e do solo em função das características do subsolo e das rochas, sendo necessário estudo detalhado com base em informação espectral de ambos. Ainda existe a dúvida se as diferenças espectrais são, essencialmente, de recursos do solo, que são transmitidos à videira e às folhas de videira, sendo que, por sua vez, esse solo tem origem de rochas que podem ou não ser diferentes. Com o intuito de sanar parte dessa dúvida é que estamos propondo tal estudo, em que geotecnologias, dentre as quais técnicas de Sensoriamento Remoto, irão auxiliar na caracterização do terroir. O conhecimento detalhado do espectro por parcela pode ser um indicativo de saúde e vigor do vinhedo, além de identificar causas e adotar medidas corretivas localizadas otimizando a utilização de insumos, reduzindo custos e aumentando a produtividade, ou seja, viabilizando a sustentabilidade. Por meio de medidas radiométricas de campo ou laboratório (radiometria espectral), pode-se descrever com qual intensidade cada material, seja solo, rocha, folha (vegetação) e ramos reflete a radiação eletromagnética nos diferentes comprimentos de onda do espectro. As assinaturas espectrais servem de biblioteca espectral de alvos e auxiliam no entendimento de como cada um destes objetos irá aparecer nas imagens.

1.8 HIPÓTESE DESTE TRABALHO

Este trabalho está baseado na hipótese de que fatores ambientais, centrados essencialmente no solo, geram alterações metabólicas nas plantas de vinhas, com impacto nos espectros de reflectância destas plantas; a detecção e descrição destas alterações, expressas nos espectros de reflectância, e devidamente espacializadas, podem constituir-se em uma contribuição relevante para a Viticultura.

1.9 OBJETIVOS DO ESTUDO

1.9.1 Objetivo geral

A pesquisa tem por objetivo investigar a resposta espectral de alvos medidos em dois vinhedos, como folhas, ramos, solo e rochas, e sua relação com resultados de análises químicas de folhas e solos dos mesmos vinhedos, buscando evidenciar correlações existentes.

1.9.2 Objetivos específicos

a) Identificar as correlações entre feições espectrais medidas por radiometria com variações na composição química de folhas de vinhas e dos solos dos vinhedos;
b) Apresentar e avaliar os resultados da utilização de veículos aéreos não tripulados (VANTs) e GNSS em operações de georreferenciamento dos vinhedos estudados;
c) Testar as metodologias usadas nos distintos vinhedos, para evidenciar diferenciações espectrais dependentes de variações espaciais;
d) Buscar correlações entre as informações coletadas por meio de técnicas de análise estatística;
e) Verificar as potencialidade das geotecnologias para melhorar o manejo e a produção dos vinhedos.

2 MATERIAIS E MÉTODOS

2.1 LOCALIZAÇÃO E CARACTERIZAÇÃO DA ÁREA DE ESTUDO

O estudo foi realizado na região da Serra Gaúcha, no município de Nova Pádua, que se localiza à latitude 29º01'43" sul e à longitude 51º18'24" oeste, em altitudes que variam de 600 a 800 metros (IBGE, 2016). O clima da região é de classe Cfb no sistema Köppen-Geiger (BECK *et al*., 2018; Moreno, 1961), que significa um clima subtropical com verões amenos, e ISO IH4 IF2 no sistema MCC (Multicriteria Climate Classification) (TONIETTO; CARBONNEAU, 2004), correspondendo a um clima temperado úmido e quente com noites temperadas. A precipitação média anual é de cerca de 1736 mm sem estações chuvosas ou secas bem definidas. Os solos da região são considerados de boa qualidade para a agricultura e muitas vinícolas estão estabelecidas na região.

Nesta região, estão os vinhedos da vinícola Boscato com algumas castas viníferas, entre as quais as tintas Cabernet Sauvignon e Merlot, que são entre as mais importantes para a produção regional de vinhos finos. Nesta área situam-se dois vinhedos que incluem parcelas das duas castas mencionadas, do mesmo proprietário e submetidos aos mesmos tratamentos, o que é conveniente para este estudo. Em consequência, estes dois vinhedos, aqui denominados Vinhedo 1 e Vinhedo 2, foram escolhidos para o trabalho. Ambos vinhedos são conduzidos no sistema de espaldeira. No Vinhedo 1, foram selecionadas três parcelas de Cabernet Sauvignon e uma parcela de Merlot; no Vinhedo 2, foram selecionadas uma parcela de Cabernet Sauvignon e cinco parcelas de Merlot, havendo, para este estudo, portanto, dez parcelas destas duas castas.

2.2 MÉTODOS

2.2.1 Medidas radiométricas análise química

O estudo foi realizado nas safras de 2014/2015 e 2015/2016, em dois vinhedos, conforme descrição acima. No primeiro momento, buscaram-se informações sobre a área, visitou-se o local para o reconhecimento inicial e, com as informações do IBGE, tratadas com o *software* ArcGis, geraram-se alguns mapas para utilização posterior neste trabalho.

A mensuração da resposta espectral das folhas, lenho, solos e rocha foi efetuado com o espectrorradiômetro portátil, FieldSpec Pro FR., com auxílio do leitor *leaf clip.* Para cada alvo medido, calibrou-se o espectroradiômetro, tendo como base uma placa de referência de bário, que reflete próximo a 100% de modo uniforme ao longo do domínio espectral coberto pelas medidas, que é de 350nm a 2500nm.

Selecionaram-se duas fileiras por parcela, e foram escolhidas quatro plantas em cada fila, identificando-as com uma fita bem colorida de cada planta, foram eleitas quatro folhas totalmente desenvolvidas, sadias e completas. Optou-se por folhas dos ramos produtivos, correspondendo à primeira folha oposta ao cacho, metodologia adaptada de Dal Bó (1992) e Terra *et al.* (2003). Realizaram-se cinco medidas por folha, no mês de janeiro, início da maturação, ou seja, no período que antecedeu a safra. As medidas radiométricas foram, portanto, realizadas "*in vivo*" e "*in situ*". Utilizando a média das medidas por folha, obtiveram-se os perfis espectrais médios.

Folhas de videiras das mesmas parcelas foram coletadas para a análise química efetuada nos laboratórios da UFRGS. O conteúdo dos elementos B, Zn, Cu, S, Fe, Ca, Mn, Mg, N, K e P foi determinado para as parcelas em estudo.

Para o estudo espacial do solo, foram coletadas, em cada parcela, em média, 10 subamostras, utilizando um trado para compor a amostra do solo. Todas as amostras coletadas seguiram as orientações Comissão de Química e Fertilidade do Solo (2004). As amostras de solo e de folhas foram embaladas segundo procedimentos recomendados, etiquetadas e encaminhadas para a análise no laboratório de solos da UFRGS. Além da coleta do solo, abriram-se trincheiras, verificando-se os perfis do solo. Coletaram-se amostras de rochas no interior do vinhedo (Vinhedo II) e próximo a ele (Vinhedo I), onde se encontram afloramentos.

2.2.2 Levantamento georreferenciado

Para obter as coordenadas precisas dos vinhedos, realizou-se o georreferenciamento com a utilização de um par receptores GNSS, de dupla frequência (L1/L2). Além do uso de GNSS, foi efetuado um levantamento com Estação total e, ainda, realizado um voo com VANT um EBee UAV, usando duas câmaras, uma delas opera no RGB enquanto a outra possui sensibilidade no infravermelho, permitindo a obtenção de índice de vegetação como o NDVI .

A partir do processamento destes dados, geraram-se mapas planialtimétricos e Modelo Digital de Terreno – MDT. As informações obtidas no IBGE foram cruzadas com a base cartográfica, gerando os mapas.

O mapa de NDVI dos vinhedos 1 e 2 foram realizados no *software* ArcGis 10.5 a partir dos dados originais coletados pelo VANT. O primeiro passo foi realizar a conversão da camada raster no formato kmz para tiff, em seguida, foi realizado o recorte referente às parcelas trabalhadas de cada vinhedo (ferramenta usada “extract by masck”). O segundo passo foi atribuir as 5 classes pré-definidas no processamento, permanecendo com os máximos e mínimos, e também intervalos iguais dos valores de NDVI entre os vinhedos para fins de comparação.

2.2.3 Tratamento dos dados radiométricos

Foram organizados os dados das folhas, ramos, rochas e solos em tabelas e posteriormente realizado as análises. Como resultado são apresentados nos próximos capítulos os 3 artigos e um resumo para Congresso. O primeiro trabalho efetuado sobre os espectros de reflectância coletados em amostras de folhas de videira e ramos e os demais trabalhos produzidos sobre dados de reflectância coletados sobre amostras de rocha, solos e aplicações de geotecnologias.

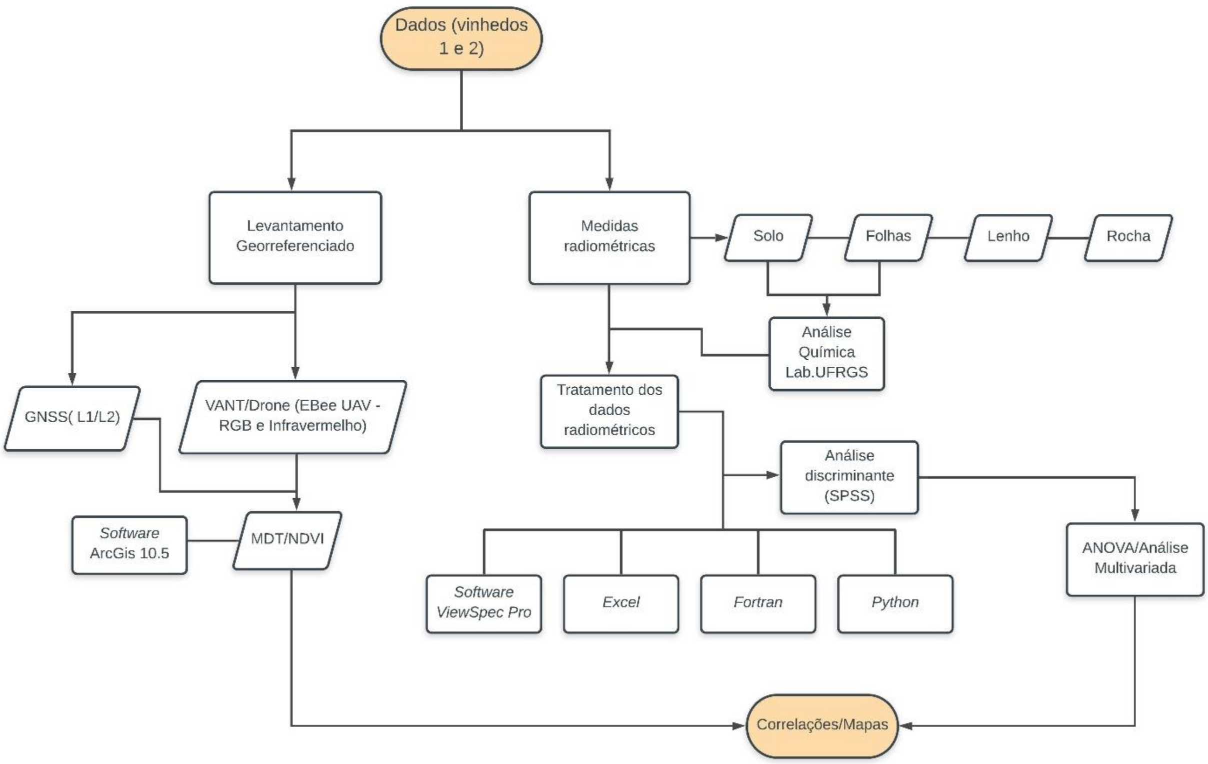
Os dados de campo consistem em espectros de reflectância medidos em folhas e ramos de videiras, solos das parcelas e rochas dos dois vinhedos com o domínio espectral medido entre 350 nm e 2500 nm, e, como os valores de reflectância são gravados a cada angstrom, um espectro tem 2151 valores de reflectância. Os espectros foram processados no *software* ViewSpec Pro, disponibilizado pela ASD, fabricante do equipamento, e organizados em tabelas em formato adequado para uso em aplicativos como o Excel. Os dados radiométricos foram analisados por meio de duas técnicas.

Na primeira técnica, os dados foram submetidos à análise discriminante. Neste caso, as classes a serem eventualmente discriminadas eram casta (Cabernet Sauvignon ou Merlot) e região (Vinhedo 1 ou Vinhedo 2). Como cada espectro, originalmente, tinha 2151 valores de reflectância, foi necessário reduzir este número (dimensão) de valores, de modo a permitir a execução da análise discriminante no aplicativo estatístico disponível, que, no caso, foi o programa SPSS. Para tanto, foi selecionado um conjunto de 30 comprimentos de onda, distribuídos ao longo do domínio espectral medido. Estes valores correspondem a feições espectrais, tanto para Cabernet Sauvignon quanto para Merlot, em que os espectros se diferenciam entre si, diferença esta detectada durante inspeção visual efetuada com o auxílio de operações de subtração ou divisão de pares de espectros, em método semelhante ao preconizado por Demattê e Nanni (2003), e Fiorio e Demattê (2009). Este banco de dados, consistindo em espectros de reflectância de folhas, para um conjunto selecionado de comprimentos de onda, foi submetido a técnicas de análise estatística.

A segunda técnica procurou colocar em relação os dados radiométricos das folhas, neste caso, as médias de cada uma das sete parcelas, com os dados das análises químicas efetuadas sobre folhas das mesmas sete parcelas. Foram efetuadas análises para quantificar a abundância, nas folhas, de onze elementos químicos. O propósito era evidenciar em quais comprimentos de onda o conteúdo químico se expressava por meio de um valor de reflectância. Neste caso, para cada comprimento de onda, pode ser gerada uma relação linear, em que a variável independente é a abundância química, e a variável dependente é a reflectância. Esta correlação foi buscada por meio da criação de um programa na linguagem FORTRAN que gerou, para cada elemento químico, 2151 relações lineares com seus respectivos valores do coeficiente de correlação R^2. Após as primeiras execuções, optou-se por eliminar as medidas entre 350 e 400 nm por serem muito ruidosas.

A avaliação das diferenças entre as médias foi realizada pela aplicação da ANOVA, considerando o nível de 5% de significância. As técnicas multivariadas Análise de Componentes Principais (ACP) e Análise Discriminante (AD) foram executadas em dados previamente autoescalonados. Metodologia semelhante foi aplicada para os outros alvos, como é detalhado nos artigos.

2.2.4 Fluxograma



Capítulo 2 – Artigo 1

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The influence of mineral content on spectral features of vineleaves

Adriane B. Thum[a,b], Diniz C. Arruda[b], Jorge R. Ducati[b], Pâmela Aude Pithan[b] and Silvia B.A. Rolim[b]

[a]Escola Politécnica, Universidade do Vale do Rio dos Sinos, São Leopoldo, Brazil; [b]Centro Estadual de Pesquisas em Sensoriamento Remoto e Meteorologia, Universidade Federal do Rio Grande do Sul, PortoAlegre, Brazil

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ABSTRACT

The reflectance spectra of vegetation carry potentially useful infor- mation that can be used to determine chemical composition and discriminate between vegetation classes. If compared with analyti- cal methods such as conventional chemical analysis, reflectance measurement provides non-destructive, economic, near real-timedata. This paper reports results from reflectance measurements performed by spectroradiometry on leaves and branches of *Vitis vinifera* L. cv. Merlot and Cabernet Sauvignon from two vineyards in south Brazil. The vineyards had different geological origins but were subjected to the same management. The objectives were to detect spectral differences between the vineyards, and to correlate these differences to variations in foliar traits like the chemical composi-tion of vine leaves. To that end, seven vine parcels were selected forreflectance measurements and chemical analyses (of eleven ele- ments) of vine leaves, and correlations between reflectance and chemical composition were looked for. An initial investigation by discriminant analysis applied to reflectance data of leaves and branches and to grape varieties as well allowed for good separation between vineyards and varieties (> 90% accuracy). By further inves- tigating the correlations between leaf chemical composition and reflectance along the wavelength domain covered by the measure- ments, we found several well-determined wavelengths with Pearson correlation coefficients $r > 0.7$. Concentrations of elements could be modelled up to 94% accuracy. These preliminary results,which have to be validated, suggest that variations in soil proper-ties induce chemical differences in vine leaves that can be detected by reflectance measurements. Applications of this observation include the assessment of the chemical content of vine leaves by spectroradiometry as a fast, low-cost alternative to chemical analy- tical methods.

1. Introduction

It is well known that vineyard geology has a remarkable influence on wine characteristics.More specifically, the nature of the bedrock and overlying soils is believed to be strongly

CONTACT Adriane B. Thum adrianebt@unisinos.br escola Politécnica, Universidade do Vale do Rio dos Sinos, SãoLeopoldo, Brazil

linked to descriptors of the wines produced from grapes of that place. This perception isdeeply associated with the 'terroir' concept, as historically and scientifically reported (van Leeuwen and Seguin 2006; Fanet 2008; White 2009), despite some criticism (Matthews 2016). Quantitative studies have been done looking for specific correlations between rock, soil, and wine, pointing to indirect factors like the soil's capacity to hold and release water(Wittendal 2004; Atkinson 2011). Other authors have focussed on the existence – or not –of a direct correlation between the chemical composition of rock and soil, and theresulting wines (Poerner et al. 2010; Maltman 2013). Between the soil and the wine is the vine plant, and some studies have looked for observable vine characteristics resulting from interaction with geology (Ducati et al. 2016; van Leeuwen et al. 2018). The spectral responses of vineyard canopies have been studied either by direct measurements or byremote sensing (Cemin and Ducati 2011; Ducati, Sarate, and Fachel 2014). The physicalobservable in these studies is the reflectance, and in this case the reflectance spectrum of vines or vineyards can be observed at different wavelength resolutions, ranging from multispectral (available in satellite images) to hyperspectral (more common at laboratory facilities). From a general point of view, it is well known that plant colours, both in visible and infrared wavelengths, are primarily due to pigments, being also impacted by nutrient availability (White 2009). This has been reported for several nutrients, and we can cite, in first place, the effects of nitrogen on vine metabolism. Metay et al. (2014) and Verdenalet al. (2019) reported as varying nitrogen supply to grapevines leads to significant alterations in carbon assimilation by tissues; since carbon availability is crucial to cell formation and growth, a correlation between nitrogen content and spectral behaviour can be expected. This perception is reinforced by the research reported by Vrignon- Brenas et al. (2019), which demonstrated that increasing amounts of nitrogen suppliedto grapevines leads to carbon accumulation; on the contrary, deficiency of nitrogen or other nutrients can induce chlorosis, similarly changing plant colours. These studies, therefore, suggest that plant tissue composition and structure is influenced by nitrogencontent. Concerning other elements important to plant metabolism, most studies werefocused on elemental dynamics in the plant and through seasons. Conradie (1981),Schreiner, Scagel, and Baham (2006) and Schreiner (2016) reported as phosphorus, potassium, calcium and magnesium move along vine tissues and seasons. Ordóñez et al. (2013) looked for correlations between reflectance and mineral content in vine leaves, obtaining significant correlations for nitrogen and phosphorus, and poorer results for other elements. The assimilation of chemical elements and other substances from the soil by plants has been studied and discussed thoroughly (Johns 2015; White and Watson2018), and concerning metals, Zhou et al. (2018) found relatively inconclusive results onthe impact of Co, Cu, Mo and Ni from mining soils and their accumulation in tissues of trees in China.

Chemical analyses can detect these elements in plant tissues, but this detection is generally done through destructive methods and may require rather long time intervalsbetween the sampling of plant material and the production of results. Still, these resultsare useful to assess descriptors of plant health and phenological stages. An alternative to the derivation of these parameters may be the direct acquisition of information from tissues using reflectance measurements. These techniques, although not as precise as chemical analysis, have some advantages, like allowing non-destructive, cost-effective,real-time data collection. Classic examples are measurements of vegetation indices like the Normalized Difference Vegetation Index (NDVI) and others (Bellvert et al. 2015; Junges et al. 2017; Poblete-Echeverría et al. 2017) related to health status and yield. Several studies had their focus on the use of techniques related to reflectance measurements applied to the detection of pigments, chemical elements or other substances in plant material, whether in leaves or in the whole canopy. Investigating Tempranillo vineyards,Martín et al. (2007) reported that iron deficiency-induced chlorosis, which can be observed in the wavelengths corresponding to the chlorophyll peak around 550 nm.Concentrating on citrus leaves, Galvez-Sola et al. (2015) used near infrared reflectancespectroscopy (NIRS) to predict leaf concentrations of N, K, Ca, Mg, B, Fe, Cu, Mn and Znwith varying accuracies. Samples from trees were also used by Nunes, Davey, and Coomes (2017) to correlate leaf reflectance to content of chlorophyll, phenolics, minerals and other components, revealing the positive potential of the technique. Mineral deficiency in grape leaves were investigated by Caramanico, Rustioni, and De Lorenzis (2017) for ironchlorosis and by Rustioni et al. (2018) for Fe, Mg, N and K deficiencies, both studiesreporting that spectral alterations can be traced back to mineral content or deficiency. It iswell known that element scarcity or excess has a crucial effect on plant development (White 2009), and methods that readily provide some information on element availability would be very useful.

Reflectance measurements using instruments like spectroradiometers have producedopen-access spectral libraries (Clark et al. 2007) for minerals and have also been reported for vegetation (Cemin and Ducati 2011; Ducati, Sarate, and Fachel 2014). The specific influence of soil on reflectance measurements has been investigated by Ducati, Bombassaro, and Fachel (2014) using satellite imagery. Studying vine parcels in Burgundy, they reported that variations in soils, which are related to grape and wine quality, have a detectable effect on vine leaf reflectance that makes it possible to classify vineyards by quality. This paper also reported that vineyard classification is still possibleeven in a winter image, with plant reflectance arising only from vine branches. Therefore,a link may exist between soil chemical parameters and reflectance, be it soil, branch or leafreflectance.

Reflectance measurements of plants can be performed from a wide choice of plat- forms. More proximal measurements are frequent when the focus is on precision viticul-ture, where indexes related to vegetation are derived (Bramley and Proffitt 1999; Haboudane et al. 2004; Zarco-Tejada et al. 2005, 2013). Orbital platforms have been used in studies aiming to spectrally differentiate between wine grape varieties (Cemin and Ducati 2011) or viticultural practices (Ducati, Sarate, and Fachel 2014). The results of these investigations have demonstrated that grape varieties and vineyards from different soils can effectively be spectrally separated using data acquired from remote sensing techniques. It is clear that this separability arises from differences in reflectance through the measured spectral domain, and more research is needed on the impact of soil characteristics on spectral profiles of vine leaves. Specifically, correlations between plant reflectance and mineral content, either in soil or in vine leaves, have to be more deeplyinvestigated. Therefore, the objectives of this paper are: a) to detect differences in reflectance of vine leaves observed in different soils; b) to determine characteristic wavelengths for which reflectance expresses mineral content; and c) estimate to which extent reflectance observations can be used to predict mineral concentrations in the observed vineyards.

To that end, we conducted a three-part investigation on these aspects. In order to havea clear understanding of the problem, and to minimize variations not arising from intrinsic soil variations, we limited the investigation to two vineyards located at different sites and two grape varieties. The first part of this project, presented here, focuses on reflectance ofplant material and how it is impacted by mineral content in vine leaves. Parts two and three extend the analysis to rock and soil and will be presented in separate papers.

2. Materials and methods

2.1. Study area

The study area is located in the Serra Gaúcha viticultural region, Rio Grande do Sul State, Brazil (Figure 1). A particular characteristic of the area comes from the local geology, with two formations originated at different epochs. One is the Gramado facies, formed by basalts from volcanic activity 132 million years ago; the other is the Caxias facies, formed by rhyodacites and rhyolites of more recent origin. The Caxias facies covers the Gramado facies (Melfi, Piccirillo, and Nardy 1988; Modena et al. 2016). The Gramado facies is basic, with dominance of alisols and chernosols; the Caxias facies, where argisols, nitosols andcambisols dominate, is acid with a greater (up to 70%) silica concentration from the characteristic mineral rhyolite (Modena et al. 2014; Santos et al. 2018). In spite of the fact that one facies originally covered the other, subsequent geological processes, includingerosion, led to the exposition of large parts of the underlying Gramado facies; mixing of

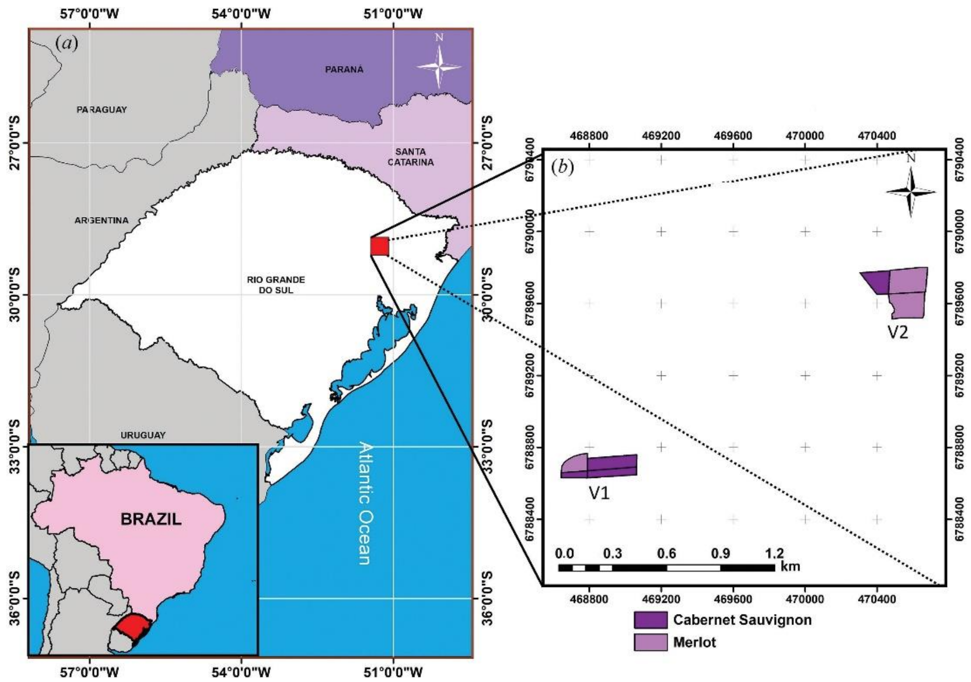

Figure 1. (a) Localization of study area. (b) Study area at Boscato Winery, where geographical coordinates are given at the Universal Transverse Mercator (UTM) projection, zone 22. Vineyard 1 isat West, Vineyard 2 at East.

facies occurs at interfaces. Presently, both facies are exposed, the Caxias facies being found at higher elevations. The geological map of the region shows this duplicity (Wildneret al. 2008; Viero and Silva 2010), and rock and soil variations can exist within distances of few kilometres, making the area especially suited for our study.

After selecting the area, we looked for two vineyards in two locations differing only in their geological conditions, meaning that ideally these areas have nearly identical viti-cultural practices and, for small distances, negligible differences in climate. We selected two vineyards of a family-owned winery, the Vinícola Boscato, which were 2 km apart. The area we call Vineyard 1 (5.38 hectares) is near the interface between the two geologicalformations, and Vineyard 2 (7.93 hectares) is further into the Caxias facies. Grape varieties included Cabernet Sauvignon and Merlot. The two vineyards have the same managementand, therefore, equivalent viticultural factors. Seven vine plots were selected: in Vineyard1 we selected three parcels of Cabernet Sauvignon and one parcel of Merlot, and inVineyard 2, one parcel of Cabernet Sauvignon and two parcels of Merlot. Vines were planted in rows (generally oriented east-west) and trained to a Guyot system. Row andplant spacing was 1.0 m × 2.7 m for both Vineyards 1 and 2. Age of vineyards was 18 years. Treatments on these vineyards were conventional, meaning that synthetic pesticides were used, besides copper-based products.

2.2. Data acquisition

Reflectance measurements of plant material (branches and leaves) were performed usingan Analytical Spectral Devices (ASD) FieldSpec 3 spectroradiometer with sensitivity through the spectral range of 350 to 2500 nm. The operation of this instrument is madethrough three sensors, each one sensitive to a spectral region: from 350 to 1000 nm at VNIR (Visible and Near InfraRed), from 1001 nm to 1800 nm for $SWIR_1$ (Short Wave InfraRed), and from 1801 nm to 2500 nm for $SWIR_2$ (PANanalytical 2015).

At pruning time (July 2015), freshly cut leafless vine branches of Cabernet Sauvignonand Merlot were collected at Vineyards 1 and 2 and brought to the laboratory. Separatedby site and variety, the branches were lined up and stacked in piles of about 20 branchesthick; this arrangement gave to the sensor a field of view composed only of branches. Measurements were made with the contact probe sensor with a sampling area of about7 cm^2, under illumination by an internal halogen light source. In a measurement, the contact probe was put in close contact with the target, illumination was activated, andfive successive spectral

acquisitions took place in about 2 s. Each acquisition was followed by a calibration measurement using a Spectralon® reference plate. For each variety andeach vineyard five measurements were performed; then the pile was rearranged and measurements were repeated. This procedure was repeated four times.
Vine leaves were measured on 18 January 2015 *in situ*/*in vivo* using the spectro-radiometer's leaf clip sensor, with an internal light source, internal calibration plate and sampling area of about 7 cm^2. The epoch of these measurements corresponds to the phenological stage when fully developed leaves are already present on vine canopy, andcoincides with stages 81 to 83 of BBCH scale for grapevines. Acquisitions occurred duringa time interval of less than 4 h for two reasons, being the first one to avoid spectraldifferences due to variations of starch content in leaves whose synthesis occurs during daytime (Zeeman, Smith, and Smith 2007; Orzechowski 2008), because starch is accumulated in chloroplasts inside leaf cells, and diurnal variations of its content couldimpact cell structure, since the process of leaf reflectance occurs inside the leaf, where thefundamental mechanism responsible for this phenomenon is the refractive index differences between the various internal leaf structures (cell walls, air spaces, chloroplasts, etc.;Walter-Shea and Norman 1991), with consequences in reflectance in the near-infrared spectral region. From these considerations, it is possible that the reflectance spectrum could have a component due to starch content, and since we were aiming to detectreflectance alterations due to other factors (soil, mineral concentration), we tried to minimize this confusing or noise factor. The second reason was to avoid large changes in leaf hydration, with impacts in stomata opening and transpiration processes which also influence cell structure.
In this acquisition mode, a part of the leaf is put between the leaf clip components. For these non-destructive measurements, data acquisition protocol was as follows: in eachvine parcel we selected two central rows; in each row, we selected four vines; and in each vine we selected four adult mid-branch leaves in the mid-canopy (about 130 cm from the ground), opposed to the grape bunches. Each leaf was sequentially measured in four different parts of the adaxial surface, avoiding the midrib. Following the procedure adopted for branches, each spectral measurement was composed of five successive acquisitions. In each vine parcel 32 leaves were measured.
The measured vine leaves were collected and put in identified plastic bags insidea refrigerated box, following the protocol recommended by Silva (2009), being trans- ported to the University's Laboratory of Soils where they underwent chemical analysis.Concentrations of elements N, P, K, Ca, Mg, S, Cu, Zn, Fe, Mn and B were determined by thefollowing analytical methods: For N, Kjeldahl digestion; for P, K, Ca, Mg, S, Cu, Zn, Fe, Mn, nitric-perchloric acid digestion/ICP-AES (Inductively Coupled Plasma – Atomic Emission Spectrometry); and for B, dry ashing digestion/ICP-AES.

2.3. Data treatments and quality estimation

The preliminary task was to produce a database of reflectance measurements. The fundamental data for this study were set to be the spectrum of a leaf, and therefore two initial treatments were done. The first one was to produce an average spectrum from the five successive acquisitions; then we calculated the average spectrum of a leaf, from the four measurements performed on different parts of each leaf. The final database was composed of 224 leaf spectra, being 128 from Vineyard 1 and 96 from Vineyard 2. Inaddition to this list of averaged spectra of individual vine leaves, we also calculated theaverage spectrum for each of the seven studied vine parcels. For branch measurements,averages were made for grape variety for Vineyard 1 and Vineyard 2. At this stage, due to noisy data in the ultraviolet part of the spectral domain, it was decided to use only databetween 400 and 2500 nm, corresponding to reflectance at 2101 wavelengths.
This investigation was aimed to the detection of differences in reflectance spectra dueto geological factors. An important concern was if such detections are at all possible, that is, if the reflectance spectra have enough quality to reveal spectral features which possibly are subtle. Addressing this issue, we estimated the quality of reflectance acquisitions through two parameters. The first one was a signal-to-ratio (SNR) assessment performed on a typical reflectance measurement made on a vine leaf, that is, an original spectrummade from five successive acquisitions, as described in the preceding Sub-Section.
The second quality assessment was derived from the fact that the investigation was strongly based on the average spectrum for each parcel. Therefore, we calculated the associated error bars to a spectrum which is the averaged reflectance of the eight plants measured in a parcel. Evaluations of the standard deviations from values derived for these eight vines were performed for two Merlot parcels, one at each Vineyard and

at the three wavelengths cited by the manufacturer as references for noise for each sensor (PANanalytical 2015): for VNIR at 700 nm, for $SWIR_1$ at 1400 nm and for $SWIR_2$ at 2100 nm.

2.4. Analytical methods

Since our prime objective at this stage was to detect the dependence of plant reflectance on spatial variations due to geological factors, we performed a discriminant analysis onboth branch and leaf databases. The role of discriminant analysis was exploratory, that is, aimed to reveal spectral differences which would ask for more detailed analysis. Theseanalyses were made, from branch data, both for grape variety and vineyard (1 and 2), and for leaf data, from the 224 leaf spectra, linked to their respective parcels.

Deeper analysis was indeed justified, and the investigation proceeded towards the possible link between localization, chemical composition, and reflectance. As mentionedin the preceding section, the presence in leaves of chemical elements, and their content, can influence leaf reflectance. How it happens is a process linked to plant metabolism.Besides, the correlation between leaf element content and reflectance, if any, can be direct or inverse. Therefore, the next step was to look for the wavelengths that best express a correlation between leaf reflectance and leaf element content. This was done by performing, for each of the 2101 available wavelengths, a linear correlation by using asdependent variable the reflectance data for each of the seven parcels, and leaf elementcontents at the same seven parcels as independent variable. Therefore, for each of theeleven chemical elements, we had 2101 Pearson correlation coefficients r, meaning thatfor each wavelength there is a corresponding linear equation between reflectance and chemical concentration. The wavelengths with higher correlations between chemical content and reflectance could be visualized in graphs of λ versus r for each element, where the λ values with higher r correspond to the wavelength domains that betterexpress element content in leaves.

In addition to this, coefficients of variation were calculated for each wavelength within the interval 400 to 2500 nm and an analysis of variance (ANOVA test) was performed todetect significant differences of chemical concentration between Vineyards 1 and 2 andbetween grape varieties.

Finally, a Partial Least Squares Regression (PLSR) analysis was performed. As input data we used the measured reflectance between 400 and 2500 nm for each one of the sevenstudied vineyards and their respective chemical concentrations, the output being predic- tions of these two parameters, to be validated by additional data in future studies. Theperformance of the PLSR model (Wold, Sjöström, and Eriksson 2001) for each chemicalelement was assessed through the Root Mean Square Error (RMSE), which is the residualbetween measured and estimated values, and the coefficient of determination R^2.

3. Results and discussion

In Figure 2(a) two typical leaf reflectance spectra are presented, which in this case are the average spectra of two Merlot parcels. It can be seen that they have regular features commonly found in healthy vegetation (Kumar et al. 2001; Jensen 2007). These spectra are different by values of up to 0.025 at some wavelengths, and reflectance values for Vineyard 1 are greater over the entire spectral domain. If these differences are real is a question which has to be analysed on the basis of quality parameters, as it was discussed in the preceding Section. SNR values were about 5900 at λ = 850 nm and 7500 atλ = 1800 nm, which are indicators of high-quality measurements (Schroeder 1999). Little fluctuation was found when an average spectrum was produced from the fourmeasurements for each leaf. With respect to error bars, standard deviations were of 0.0058, 0.0074 and 0.0064 for Vineyard 1 at 700, 1400 and 2100 nm, respectively and of 0.0035, 0.0083 and 0.0110 for Vineyard 2 at the same wavelengths. These values of error bars are typical for the whole spectra, and looking at the differences in reflectance between the two spectra of Figure 2(a), the above-mentioned error bars were smaller than these differences over most of the spectral domain. We can compare our results with those reported by Nunes, Davey, and Coomes (2017), where leaves were collected fromtrees growing in alluvial and chalk soils; the reflectance spectra in their Figure 3 show little, if any, difference. Figure 2(b) presents the coefficients of variation (CV) of our reflectance measurements over the entire spectral domain; we note that, in spite of thefact that our spectra shown in Figure 2(a) present comparatively larger differences, the CV presently reported are much smaller than the ones reported by Nunes, Davey, andCoomes (2017), which found values up to 30%, while ours are up to 17.5% at the wavelengths associated with the water bands at 1400 and 1900 nm, suggesting variationsin water content in leaves. Likewise, other larger CV values (12.5%) are associated with thechlorophyll bands around 600 nm, suggesting variations in chlorophyll content which canbe associated with nitrogen availability (Rustioni et al. 2018), the differences in N content between the studied regions being significant (Table 1). Staying with nitrogen, Brunetto et al. (2012) report as soil texture affects nitrogen content in grapevines, a perception that agrees with the fact that in the presently studied regions, soil types are different, implying in different textures. Still discussing Figure 2(b), we note that CV values are greater forVineyard 2 for all wavelengths, excepted for those corresponding to ultraviolet and at the water absorption peaks at 1400 and 1900 nm. From these considerations we were lead to conclude that differences between the spectra were above noise, in some wavelengths by fairly high values from a statistical perspective, being therefore significant. It was this perception that leads us to deeper investigations which results are reported below.

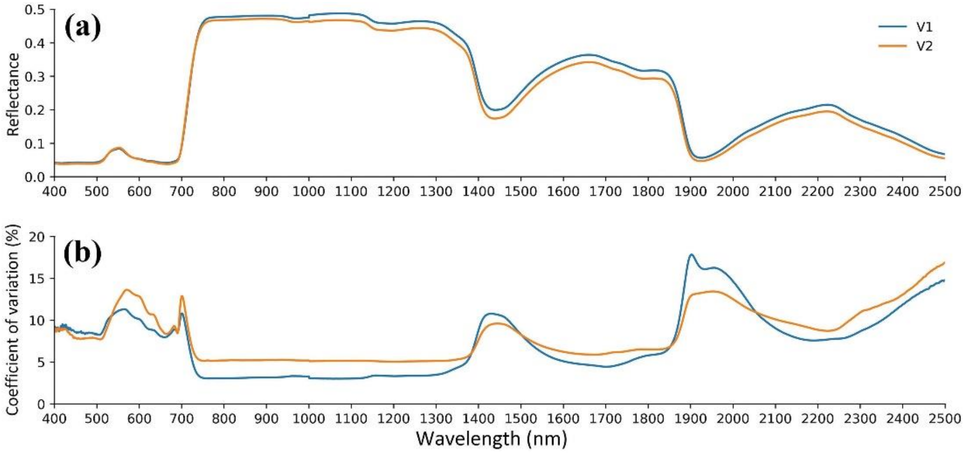

Figure 2. (a) Reflectance spectra of Vitis vinifera (Merlot) leaves from our measurements of the twostudied regions V1 and V2; (b) Coefficient of variation (%) along the measured spectral range.

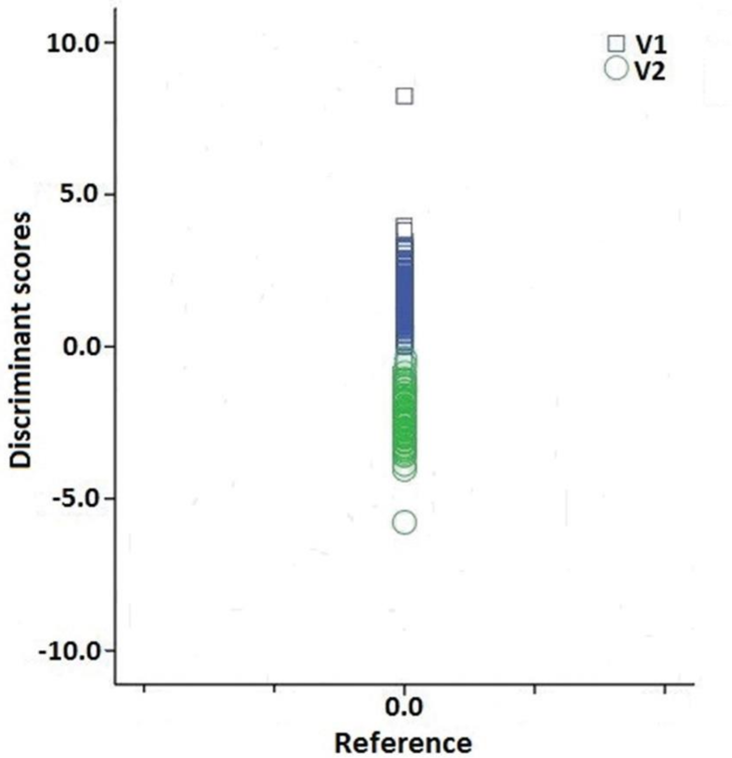

Figure 3. One-dimensional separation by discriminant analysis of leaf reflectance data. V1, Vineyard 1;V2, Vineyard 2. The x-axis contains all points in a single dimensionless, reference value.

Table 1. Chemical concentrations of elements measured in vine leaves. SD is Standard deviation; CV is Coefficient of variation; letters after mean values refer to OneWay test: p-value < 0.1, where significantdifferences are expressed by different letters. Units are (% m m^{-1}) for P, K, Ca, Mg, S and N, and (mg kg^{-1}) for Cu, Zn, Fe, Mn and B.

	Vineyard 1				Vineyard 2				
Element	Range	Mean	SD	CV (%)	Range	Mean	SD	CV (%)	Confidence level of 95%
P	0.36 to 0.49	0.41a	0.06	13.49	0.28 to 0.40	0.34a	0.06	17.62	0.32 to 0.44
K	1.40 to 2.30	1.92a	0.45	23.37	1.50 to 2.10	1.86a	0.32	17.22	1.55 to 2.24
Ca	2.40 to 3.00	2.60a	0.027	10.41	1.90 to 2.40	2.13b	0.25	11.79	2.07 to 2.72
Mg	0.52 to 0.62	0.57a	0.04	8.04	0.46 to 0.61	0.55a	0.08	14.43	0.51 to 0.61
S	0.30 to 0.41	0.34a	0.04	13.77	0.25 to 0.31	0.28a	0.03	10.78	0.27 to 0.36
Cu	9.00 to 13.00	11.25a	2.06	18.32	9.00 to 11.00	9.66a	1.15	11.94	8.89 to 12.24
Zn	442.00 to 689.00	596.25a	109.49	18.36	454.00 to 587.00	508.00a	69.94	13.79	466.63 to 650.21
Fe	140.00 to 220.00	177.75a	33.06	18.60	171.00 to 189.00	180.00a	9.00	5.00	156.53 to 200.89
Mn	845.00 to 1200.00	1034.75a	151.91	14.68	711.00 to 872.00	787.70b	80.77	10.25	765.61 to 1092.10
B	65.00 to 79.00	71.00a	6.68	9.41	62.00 to 64.00	63.00a	1.00	1.58	61.65 to 73.48
N	2.00 to 2.40	2.25a	0.17	7.69	2.50 to 3.10	2.70b	0.35	12.83	2.13 to 2.75

The part of this investigation which was focused on chemical differences between grape varieties lead to non-significant results: The ANOVA test produced p-values between 0.22 and 0.90, indicating low confidence levels for a chemical discrimination between Cabernet Sauvignon and Merlot at the studied vineyards. However, some significant results were found for chemical differences between Vineyards 1 and 2, andwe present in Table 1 information on the chemical concentrations of the eleven studiedelements in leaves for the two regions. It shows that internally to each vineyard variations of concentrations expressed by their CV have values up to 23.37%. Significant differencesto a 90% confidence level between Vineyards 1 and 2, expressed by the one-way test$p$-value < 0.1, exist for elements Ca, Mn, and N (p-values of 0.068, 0.053, and 0.070 respectively) and marginally for B (0.101). These variations in nutrient availability can impact leaf reflectance, as suggested by the discriminant analysis which was applied toreflectance data of 224 vine leaves; this technique, when applied to a set of data contain- ing only two classes, which is presently the case, leads to one-dimensional results whichare presented in Figure 3, showing a clear separation of the two studied regions with anaccuracy of 99.0%. The two classes (Vineyard 1 and Vineyard 2) are spread along the y-axis,where for graphical purposes the x-axis contains all values in a unique reference value. Such a significant separation must be understood, and environmental factors are prob- ably fundamental for the differentiation. It was reported by Poorter et al. (2009) that environmental factors like radiation, atmospheric CO_2 concentration, nutrients, water and temperature affect a specific plant descriptor which is leaf mass per area (LMA). Rustioniet al. (2017, 2018) report that varying the mineral content of N, Fe, Mn and K available to grape vines, under hydroponic conditions, lead to alterations in leaf reflectance. The presently studied vineyards share common conditions of illumination, atmosphere, water input (the vineyards are rain fed) and temperature, leaving to nutrient availability,in this case from the soil, as being the more probable differentiation factor. The two studied vineyards are grown on soils of different geological origins, as already informed in Section 2.1: Vineyard 1 grows mainly on basic basalt which gave origin to alisols and chernosols, while Vineyard 2 grows on rhyodacites and rhyolites which gave origin to argisols, nitosols and cambisols. Spectral differentiation between measurements from different regions and grape varieties has been previously reported by Karakizi, Oikonomou, and Karantzalos (2016) using high-resolution satellite images and visible and near-infrared radiometric data; overall accuracy in classification was up to 90%. From satellite images with a broader spectral range, similar accuracies were reported by Cemin and Ducati (2011), where the studied vineyards, separated by large distances, were readily discriminated. In the present paper, our two regions are close to each other (2 km apart) and therefore spatial factors prone to induce an eventual spectral difference would besubtle. However, even in this case discrimination from spectral data was possible. Such separability was already demonstrated from satellite data of a limited area in Burgundy, where vineyards were separated based on differences linked to soil factors (Ducati, Bombassaro, and Fachel 2014).

Our analysis was further pushed by means of reflectance measurements on branchescollected at pruning time. When discriminant analysis was applied to reflectance data of vine branches, separability between Vineyards 1 and 2 and between grape varieties achieved 100% accuracy (Figure 4). These results show that spectral differences between grape varieties exist and can be measured not only in vine leaves, but also in hard material like branches. This perception helps us to understand the empirical result reported in Ducati, Bombassaro, and Fachel (2014), where Pinot Noir and Chardonnay vineyards were separated based on data from satellite images acquired in winter, when only woodmaterial from vines reflects light.

The understanding of why discriminations like those shown in Figures 3 and 4 exist, under conditions where environmental factors like climate and human factors like man-agement are the same, requires examining a fundamental component of the so-called 'terroir' concept, the soil, which impacts plant metabolism (White 2009). As in the already cited studies (Ducati, Bombassaro, and Fachel 2014; Ducati, Sarate, and Fachel 2014), we have two regions with systematic differences in leaf reflectance (Figure 2(a)). Table 1 informs us that significant differences in mineral concentration in leaves exist for Ca, Mn and N, and that less significant differences also exist for the other eight measuredelements, these factors being possible reasons for the remarkable separations betweenvineyards for leaf (Figure 3) and branch reflectance data (Figure 4). Several papers havereported alterations of reflectance in vegetation caused by variations in its mineral content using a variety of techniques (Rustioni et al. (2018) for grapevines, Nunes, Davey, and Coomes (2017) for trees, Galvez-Sola et al. (2015) for citrus).

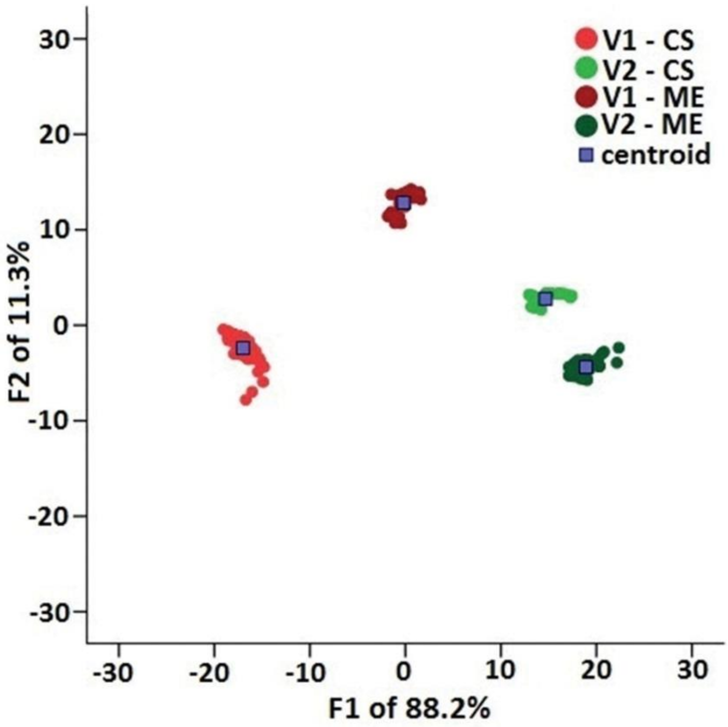

Figure 4. Discriminant analysis of branch reflectance data. V1, Vineyard 1; V2, Vineyard 2; CS, CabernetSauvignon; ME, Merlot.

Because the main objective of the study was to assess the potential of using remotesensing data to derive the chemical content of plant material, we then looked for correlations between leaf reflectance and chemical content along with the observed wavelength domain for the eleven studied elements. Some results had been reported using similar techniques. Chemical analysis and near-infrared reflectance spectroscopywere applied on samples of forages (Lavrensic, Stefanon, and Oresnik 2002) or on leavesof several tree species (Petisco, Aldana, and Mediavilla 2008); Serbin et al. (2014) reported correlations through PLSR between reflectance and chemical content in conifer leaves,and Chadwick and Asner (2016) used airborne high fidelity imaging spectroscopy (HiFIS)to find similar correlations for foliar samples of a tropical forest. However, these results donot connect chemical concentrations to reflectance at specific wavelengths, as we pre-sently report. Here, results from the correlation analysis are presented in Figure 5, where we see that for certain wavelength domains the coefficient of determination R^2 is significantly higher, going up to values close to unity, while other domains show nosignificant correlations. Since significant correlations did not show up in isolated wave-lengths, but rather along spectral bands or regions, we can admit that these correlationsare not the result of noise but do express an influence of mineral content on reflectance. An analysis of these results shows that several spectral domains are common to more than one element, as in the cases, for example, of Fe, K and Mg around 513 nm. Thismeans that leaf spectral traits at this wavelength are influenced by several elements. However, some wavelengths (or wavelength domains) are exclusive for a specific element, and close inspection of Figure 5 leads to Table 2, which informs which wavelength domains are indicators of element content, in some cases in an exclusive way considering the studied set of elements. These exclusive wavelengths are marked in Table 2 as boldcharacters.

Table 2 also provides the correlations (direct or inverse) between leaf element con-centration and reflectance at specific wavelengths. For example, the highest direct correlation between leaf Mn content and reflectance was obtained at 2108 nm(r = +0.95), while for S a value of r = −0.87 was obtained at 1013 nm, a wavelengthwhich is exclusive for sulphur considering the eleven elements presently studied. Someother wavelengths were found to be highly specific: for example, reflectance measure-ments at 529 nm were an exclusive indicator of leaf Zn content. We note from Table 2 that the exclusive wavelengths are both from VNIR and SWIR spectral regions.

Results from PLSR analysis are shown in Figure 6. The best correlations between observed and predicted values were found for elements N, Ca (R^2 = 0.94 and 0.92, respectively) and Mn (R^2 = 0.76), which are the elements with significant differences at 90% confidence level between Vineyard 1 and Vineyard 2 (Table 1). Of the presently studied elements, seven out of eleven have R^2 values higher than 0.5 and the poorer correlations were found for Fe and K; the low correlation for K coincides with the result for K reported by Chadwick and Asner (2016); on the other hand, we note that our PLSR- derived correlations have higher values that those reported by Chadwick and Asner (2016). These differences can be due to the fact that our data come from very low noisefield radiometry, while theirs come from an airborne platform. In accordance with the research reported by Nunes, Davey, and Coomes (2017), which also used PLSR, the results presently reported confirm that spectroradiometry has a high potential to detect and predict foliar traits.

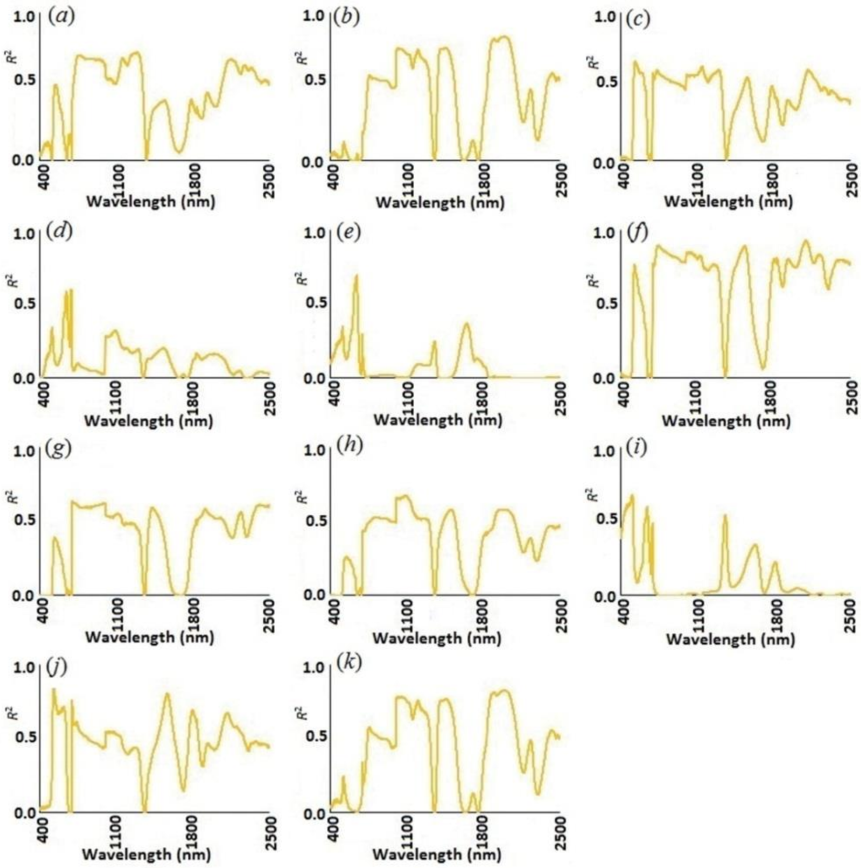

Figure 5. Correlations between leaf reflectance and chemical concentration along the measured spectral domain; (a) Boron, (b) Calcium, (c) Copper, (d) Iron, (e) Magnesium, (f) Manganese, (g) Nitrogen, (h) Phosphorus, (i) Potassium, (j) Zinc, (k) Sulphur.

Table 2. Wavelengths with higher correlations between reflectance and chemical concentration in vine leaves. λ is wavelength; r is the Pearson correlation coefficient. Wavelengths in bold characters are exclusive of their respective elements.

	Wavelength 1		Wavelength 2		Wavelength 3		Wavelength 4		Wavelength 5	
Element	λ (nm)	r	λ (nm)	r	λ (nm)	r	λ (nm)	r	λ (nm)	r
P	1040	−0.81	1102	−0.82	**1516**	0.75	**1947**	0.76	**2047**	0.75
K	513	0.82	649	0.77	693	0.69	1361	−0.71		
Ca	1035	−0.86	**1209**	−0.84	1422	0.87	1908	0.91	2017	0.91
Mg	515	0.58	642	0.83	693	0.55	1360	−0.50	**1654**	−0.57
S	761	−0.75	**1013**	−0.87	1414	0.87	1916	0.89	2012	0.91
Cu	**540**	−0.82	746	−0.77	**1154**	−0.79	1307	−0.78	**2129**	0.78
Zn	**529**	−0.91	696	−0.87	**1574**	0.89	**1806**	0.84		
Fe	517	−0.56	649	−0.77	692	−0.78	1105	−0.54		
Mn	748	−0.95	1048	−0.92	**1139**	−0.91	**2108**	0.95		
B	**781**	−0.84	**1167**	−0.82	1305	−0.85	**2160**	0.81		
N	697	0.81	**998**	0.80	**1436**	−0.77	**2411**	−0.78		

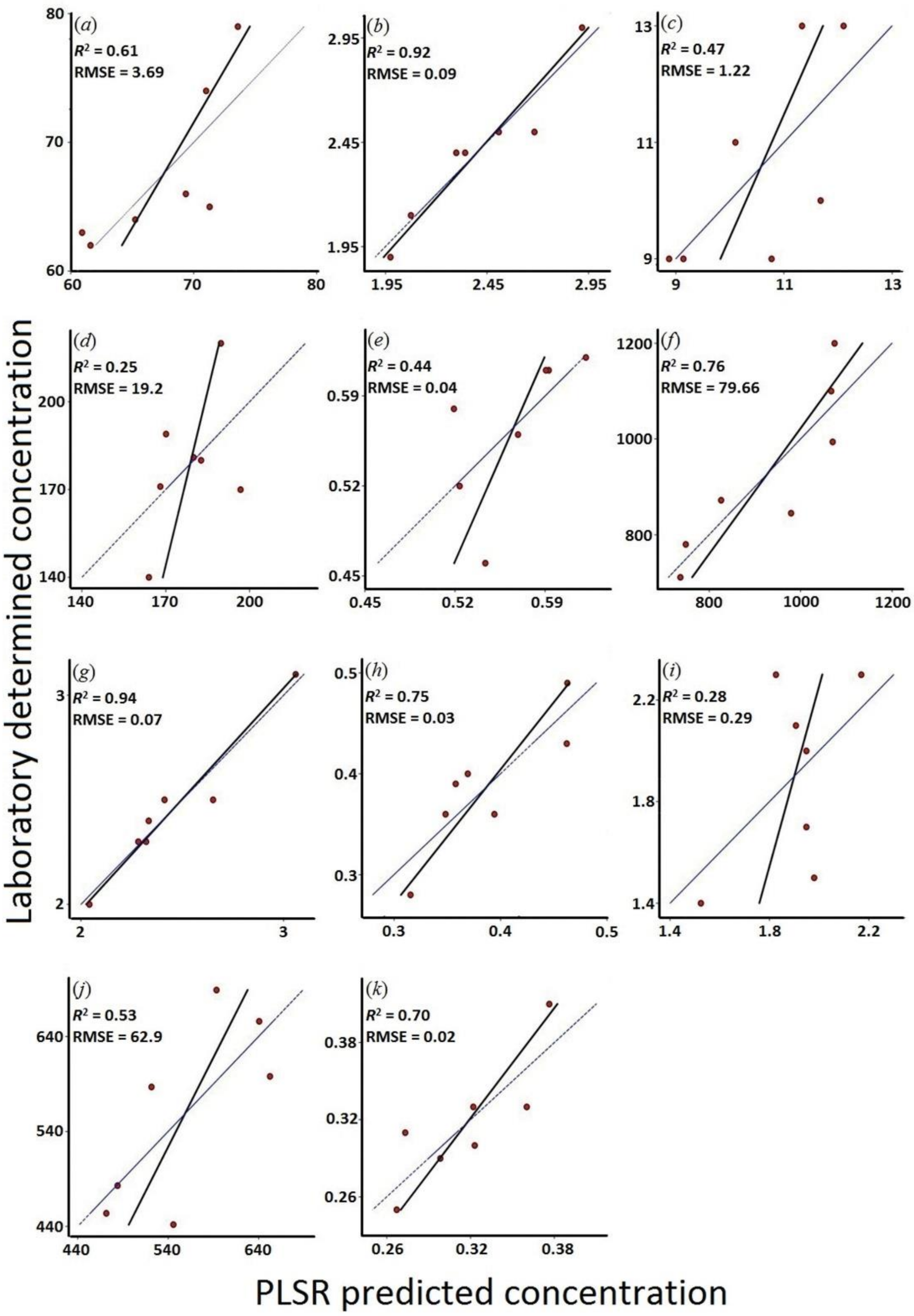

Figure 6. Scatter plots produced by PLSR of the predicted foliar traits (chemical concentrations) versusthe foliar trait data from field radiometry and chemical analysis. The dashed, blue line is the 1:1correlation. (a) Boron, (b) Calcium, (c) Copper, (d) Iron, (e) Magnesium, (f) Manganese, (g) Nitrogen, (h) Phosphorus, (i) Potassium, (j) Zinc, (k) Sulphur. Units for the x- and y-axes are (% m m-1) for P, K, Ca,Mg, S and N and (mg kg-1) for Cu, Zn, Fe, Mn and B.

As a complement to this discussion, we note that the wavelengths at which mineral content in vine leaves are expressed do not have to bear a similarity with the reflectance spectra of pure minerals. Minerals, either in elemental form or in rock aggregates, havecharacteristic spectra which are completely different of the spectra of vegetation (Clarket al. 2007). In this paper, we presented evidence that a varying mineral content in leaves leads to spectral changes, markedly in some wavelengths, which can be due to alterationsin pigment concentration, cell structure or water content in leaf tissues. The processes of nutrient assimilation by plants are mediated by their metabolism, which is a complex biological process. Therefore, reflectance spectra of pure minerals would not be expected to be observed in leaf reflectance. This observation is further reinforced by the fact thatthe correlations between leaf mineral content and reflectance can be direct or inverse (Table 2), which is an indication of the complexity of the ways plants assimilate minerals.

4. Conclusions

We presented in this paper an analytical method to detect the presence and to estimatethe content of some chemical elements in vine leaves. The method is based on non-destructive reflectance measurements and can be helpful to instrumental developments aiming to produce within-vineyard, real-time information on plant conditions ina straightforward way. It was demonstrated that leaf mineral content indeed influencesleaf reflectance, and when we consider different study sites a separation is possible. We suggest that the causes of this separation are soil differences between the studiedvineyards. Variations in mineral content are better expressed in wavelengths which arecharacteristic of each studied chemical element. And finally, a predictive capacity of our method concerning the estimation of leaf mineral content was suggested; this potentialcapability has to be tested by further studies using a new dataset. Given that only two sites were studied, and given the size of our sample, the results presently reported should be considered as preliminary, and have to be tested and eventually validated by futureexperiments based on data acquired from other places and from other epochs of the phenological cycle.

This paper has its focus on reflectance properties of vine leaves and their connectionswith differences between soils. Even if soils could be considered has being an importantfactor for wine quality, an eventual relationship, if any, of leaf reflectance properties with wine quality and/or oenological properties was not investigated.

This paper reported results from data obtained from plant material. At our Introduction,we discussed the importance of soil from a viticultural point of view, as a crucial factor tothe 'terroir' concept which points to a connection between soil and wine quality or typicity.A better understanding of the link between soil properties (chemical composition, reflectance) and these parameters in plants, presently studied, would be useful to con-tribute some quantitative data to the terroir concept. Therefore, a natural extension of this study would be to include soil data, and this will be pursued in a forthcoming paper.

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Disclosure statement

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ORCID

Silvia B.A. Rolim http://orcid.org/0000-0002-2146-9057

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CAPÍTULO 3 – ARTIGO 2

ARTIGO 2 - ENCAMINHADO PARA REVISTA

The influence of mineral content on spectral features of soils in vineyards

Adriane B. Thum[a,b*], Diniz C. Arruda[b], and Jorge R. Ducati[b]

[a]Escola Politécnica, Universidade do Vale do Rio dos Sinos, São Leopoldo, Brazil; [b]Centro Estadual de Pesquisas em Sensoriamento Remoto e Meteorologia, Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil

*corresponding author: adrianebt@unisinos.br

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ABSTRACT

Knowledge on the reflectance spectrum of soil is potentially useful since it carries information on soil chemical composition that can be used to the planning of agricultural practices. If compared with analytical methods such as conventional chemical analysis, reflectance measurement provides non-destructive, economic, near real-time data. This paper reports results from reflectance measurements performed by spectroradiometry on soils from two vineyards in south Brazil. The vineyards were close to each other, had different geological origins, but were subjected to the same management. The objectives were to detect spectral differences between the two areas, to correlate these differences to variations in their chemical composition, and to assess the technique's potential to predict soil attributes from reflectance data. To that end, soil samples were collected from ten selected vine parcels. Chemical analysis yield data on concentration of twenty-one soil attributes, and spectroradiometry was performed on samples. Chemical differences significant to a 95% confidence level between the two studied areas were found for six soil attributes, and the average reflectance spectra were separated by this same level along most of the observed spectral domain. Correlations between soil reflectance and concentrations of soil attributes were looked for, and for ten soil traits it was possible to define wavelength domains were reflectance and concentrations are correlated to confidence levels from 95% to 99%. PLSR analyses were performed comparing measured and predicted concentrations, and for fifteen out of 21 soil traits we found Pearson correlation coefficients $r > 0.8$. These preliminary results, which have to be validated, suggest that variations of concentration in the investigated soil attributes induce differences in reflectance that can be detected by spectroradiometry. Applications of these observations include the assessment of the chemical content of soils by spectroradiometry as a fast, low-cost alternative to chemical analytical methods.

Keywords: radiometry, hyperspectral data, soil reflectance, vineyard geology

1. Introduction

The importance attributed to the quality of soils as a determining factor to the quality of agricultural products depends on the product under consideration. This point of view was emmited by Matthews (2015), in a discussion of the terroir concept linked to wine quality, and so linked to winegrapes quality, as opposed of the virtually non-existent concerns linking, for example, tomatoes quality to the quality of soil where they are grown. Such an opinion, about which a debate continues (Ducati and Bettú 2012; van Leeuwen et al., 2018; Döring et al. 2020), is in opposition to the idea initially and strongly sustained by Faulkner (1943) in a seminal work on soil conservation, where he stated that the best vegetal products come from the best, healthier soils, where the meanings of "best" and "healthier" deserve, still today, precise definitions. We have here two problems: one is to have descriptors of soil, eventually useful to achieve a definition of soil quality (Riches et al. 2013) or soil health (Chaignon et al., 2003; Schindelbeck and van Es 2011; White and Watson 2018); the other is to stablish a credible link between soil descriptors (of quality) and the aim of producing better, or the best, vegetal products (Bramley and Proffitt 1999; Atkinson 2008; Preston et al. 2017). Solving these problems may have as starting points the development of techniques to display descriptors of soils and plants useful to the quality debate. Among such descriptors the chemical composition appears as a crucial piece of information, and chemical analysis is the classic technique to obtain it (Oliver et al. 2013; White 2015).

However, chemical analisys can be expensive, and the resulting information is not readily retrieved. As an alternative, at least to yield preliminary data, proximal sensing techniques like spectroradiometry have been investigated, having as basic perception the idea that certain components imprint marks on the reflectance spectra of soil or plants, allowing their detection and even their quantification. Presently, spectroscopy can be performed *in situ*, and being the case *in vivo*, yielding information in real-time, provided that reliable calibrations are available. Applied to plants, and specifically to grapevines, such perception was investigated by our research group and reported in Thum et al. (2020), where it was suggested that analisys of the reflectance spectra of vine leaves can produce information on their chemical content, with the additional result that this chemical content may be sensitive to the kind of soil supporting the vines; this work was the first part of a research project, and presently our focus is the spectral response of the soils themselves.

The characterization of minerals (Hunt and Salisbury 1970) and soils from their reflectance spectra have been described throughfully (Demattê 2002; Demattê et al. 2004; Viscarra Rossel et al. 2006), the identification of chemical, physical and mineralogical soil attributes at visible and infrared wavelengths being possible (Henderson et al. 1992; Shepherd and Walsh, 2002; Genú and Demattê 2006) as well as structure and aggregates size (Sarker et al. 2018; Shi et al. 2020). Soil class mapping is very useful for farm management (Poppiel et al. 2019), and calibrations of soil's reflectance spectra have been performed (Ge et al. 2011), while Terra, Demattê, and Viscarra Rossel (2015) compiled spectral libraries of Brazilian soils from Vis-NIR and mid-IR data. These studies give way to the perception that contributions on the knowledge of spectral information on soils are stillnecessary, aiming to increase of the usefulness of the application of radiometry to soils towards the derivation of quantitative parameters. Correlations between soil reflectance and content of minerals or other soil attributes content can be more deeply investigated, contributing to expand knowledge on domains like precision agriculture. Therefore, the objectives of this paper are: a) to detect differences in reflectance observed in different soils; b) to determine characteristic wavelengths for which reflectance expresses concentrations of minerals or other soil traits; and c) to estimate to which extent reflectance observations can be used to predict concentrations in the studied soils .

To that end, we conducted a three-part investigation on these aspects. In order to have a clear understanding of the problem, and to minimize confusion from variations not arising from intrinsic soil differences, we limited the investigation to two vineyards located at different sites. The first part of this project was reported in Paper I (Thum et al. 2020), and the research presently reported is the second part, with its focus on reflectance of soils. Subsequent analysis on the impact of soil on plant reflectance and influence of bedrock will be presented in separate papers.

2. Materials and methods

2.1. *Study area*

The study area is the same of Paper I (Thum et al. 2020) and for the sake of completeness is here briefly repeated. It is located in the Serra Gaúcha viticultural region at Rio Grande do Sul State, Brazil, with coordinates 29º01'43" South, 51º18'24" West and altitudes between 600 and 800 meters above sea level. A particular characteristic of the area comes from its geology which has two formations originated at different epochs. The first one is the Gramado facies, formed by basalts from volcanic activity 132 million years ago; the second is the Caxias facies, formed by rhyodacites and rhyolites of more recent origin. Being more recent, the Caxias facies covers the Gramado facies (Melfi, Piccirillo, and Nardy 1988; Modena et al. 2016). The Gramado facies is basic, with dominance of alisols and chernosols; the Caxias facies, where argisols, nitosols and cambisols dominate, is acid with a greater (up to 70%) silica concentration from the characteristic mineral rhyolite (Modena et al. 2014; Santos et al. 2018). Geological processes, including erosion, led to the exposition of large parts of the underlying Gramado facies, and mixing of facies occurs at interfaces. Presently both facies are exposed, the Caxias facies being found at higher elevations. The geological map of the region shows this duplicity (Wildner et al. 2008; Viero and Silva 2010), and rock and soil variations are found within distances of few kilometres, making the area especially suited for our study.

In this region we looked for two vineyards in two locations differing only in their geological conditions, meaning that ideally these areas would have nearly identical viticultural practices and, for small distances, negligible differences in climate. We selected two vineyards of a family-owned winery, the Vinícola Boscato, which were 2 km apart. The area we call Vineyard 1 (5.38 hectares) is near the interface between the two geological formations, and Vineyard 2 (7.93 hectares) is further into the Caxias facies. Grape varieties include Cabernet Sauvignon, Merlot, Touriga Nacional, Tannat and others. The two vineyards have the same management and equivalent viticultural factors, being therefore assumed that differences between soils are intrinsic and not anthropic. Internally to each vineyard variations in elevation do not exceed 10m, but significant variations in soil depth exist, as shown from preliminary soil profiling. The deepest profiles were found in Vineyard 1, where Horizon A goes up to 50cm, displaying dark brown color with occasional lighter shades, and increasing rock mixing as depth increases. At Vineyard 2, Horizons A and B have both a 10cm thickness with a larger proportion of organic matter and roots which are observed at higher elevations; soils are darker and at the shallow parts vine roots are occasionally exposed, as well as rock fragments. Parts of this Vineyard 2 present deeper soil, with Horizon A going from 0 to 30cm, Horizon B going from 30 to 70 cm, and Horizon C starting at 70 cm. As complementary information, the region's climate is of Cfb class at the Köppen-Geiger system (Beck et al. 2018; Moreno, 1961) meaning a subtropical climate with mild summers, and ISO IH4 IF2 in the MCC (Multicriteria Climate Classification) system (Tonietto and Carbonneau 2004), corresponding to an umid and warm temperate climate with temperate nights. Average annual precipitation is about 1736mm with no well-defined rainy or dry seasons. These soils are considered as being of good quality for agriculture and viticulture.

Vines were planted in rows (generally oriented east-west) and trained to a Guyot system. Row and plant spacing was 1.0 m × 2.7 m for both Vineyards 1 and 2. Age of vineyards was 18 years. Treatments on these vineyards were conventional, meaning that synthetic pesticides were used, besides copper-based products. Ten vine plots were selected: in Vineyard 1 we selected four parcels, and six parcels were selected in Vineyard 2.

2.2. Data acquisition

For each one of the ten selected parcels soil samples were collected in ten randomly spaced points with help of an auger going up to 40cm deep, following the protocol recommended by Siqueira et al (1987); samples of each parcel were mixed and put in identified plastic bags, being transported to the University's Laboratory of Soils where they underwent chemical analysis. A total of 21 soil traits (chemical elements and soil attributes) were quantified for each one of the ten studied parcels, using the following methods: concentrations of elements P, K, Cu, Zn and Na were determined by Mehlich 1method; Ca, Mg and Mn by exchangeable KCl in a 1 mol l^{-1} extract; B extracted with hot water; Fe by sulfuric extraction; S by SO_4 extracted with $CaHPO_4$ at 500 mg l^{-1} of P; clay determined through densimeter method; pH in water1:1; H+Al by calcium acetate; SMP by *Shoemaker–McLean–Pratt* method; organic matter (OM) by wet digestion; *CEC (Cation Exchange Capacity) and CEC*/BS (Base Saturation) by SMP. The relations Ca/K, Ca/Mg and Mg/K were also calculated.

Samples of each one of the ten parcels were dried; the importance of monitoring the humidity content in samples subjected to spectroscopy was stressed, for example, by Bogrekcy and Lee (2006). Spectroscopic measurements were performed indoors at our laboratory using a Malvern Panalytical Spectral Devices (ASD, Westborough, MA, USA) FieldSpec® 3 spectroradiometer, which has spectral sensitivity between 350 nm and 2500 nm (Malvern Panalytical, 2020). A contact probe accessory was used in direct contact with the sample, with a surveyed area of about 7 cm^2;e note that the use of a contact probe touching the sample was one of the recommended methods by Ben-Dor, Ong, and Lau (2015). Measurements were performed as follows: soil from one of the ten samples was put in a Petri dish; a calibration *measurement was done using a Spectralon®* reference plate (Labsphere, Inc., North Sutton, NH, USA); *the contact probe was put in contact with the soil and four consecutives data acquisitions were made, in about one second; a calibration measurement was repeated. This procedure produced a preliminary spectrum, compiled by the equipment's internal software* ViewSpec Pro®. *Then the sample was stirred and a new acquisition was performed. This procedure was repeated five times for each one of the ten samples. Averages were calculated for the set of five acquisitions, producing what we called a regular spectrum which provides 2151 reflectance values between 0.0 and 1.0 at intervals of one nanometer.*

The presence in the soil of chemical elements and their content can influence soil reflectance, and therefore possible links, either direct or inverse, between localization, chemical composition, and reflectance were investigated. We looked for the wavelengths that best express a correlation between soil reflectance and leaf element content. This was done by performing, for each of the 2151 available wavelengths, a linear correlation by using as dependent variable the soil reflectance data for each of the ten parcels, and soil element contents at the same ten parcels as independent variable. Therefore, for each of the twenty-one chemical elements or soil attributtes we had 2151 Pearson correlation coefficients r, meaning that for each wavelength there is a corresponding linear equation between reflectance and chemical concentration. The wavelengths with higher correlations between chemical content and reflectance could be visualized in graphs of λ versus r for each element, where the λ values with higher r correspond to the wavelength domains that better express element content in soil.

In addition to this, coefficients of variation were calculated for each wavelength within the interval 350 nm to 2500 nm and an analysis of variance (ANOVA test) was performed to detect significant differences of chemical concentration between Vineyards 1 and 2.

Finally, a Partial Least Squares Regression (PLSR) analysis was performed. As input data we used the measured reflectance between 350 nm and 2500 nm for each one of the ten selected parcels and their respective chemical concentrations, the output being predictions of these two parameters, to be validated by additional data in future studies. The performance of the PLSR model (Wold, Sjöström, and Eriksson 2001) for each chemical element was assessed through the Root Mean Square Error (RMSE), which is the residual between measured and estimated values, and the coefficient of determination R^2.

3. Results and Discussion

The reflectance spectra of the ten studied parcels is shown in Figure 1. The displayed spectra has features typical of soils (Lillesand and Kiefer, 2000) with no notable deviations, showing the water absorption bands at 1400, 1900 and 2200 nm. Figure 2 shows the average spectra both of Vineyard 1 and Vineyard 2, with the respective coefficients of variation. Soils from the two regions are separated to a 95% confidence level: those from Vineyard 1 tend to have higher reflectance from ultraviolet wavelengths up to about 1000 nm; from 1000 nm up to 2500 nm soils from Vineyard 2 have higher reflectance.

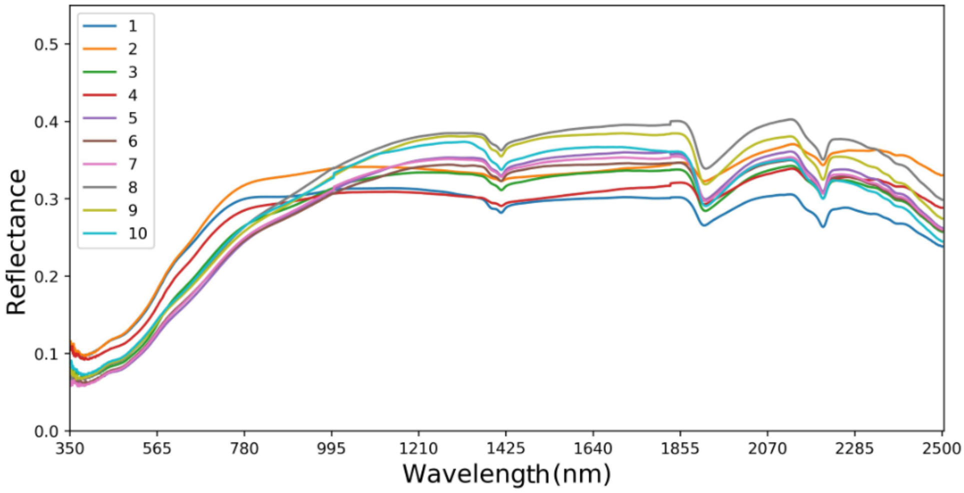

Figure 1. Average spectra of soils of studied vine parcels. Spectra one to four are from Vineyard 1, spectra six to ten from Vineyard 2.

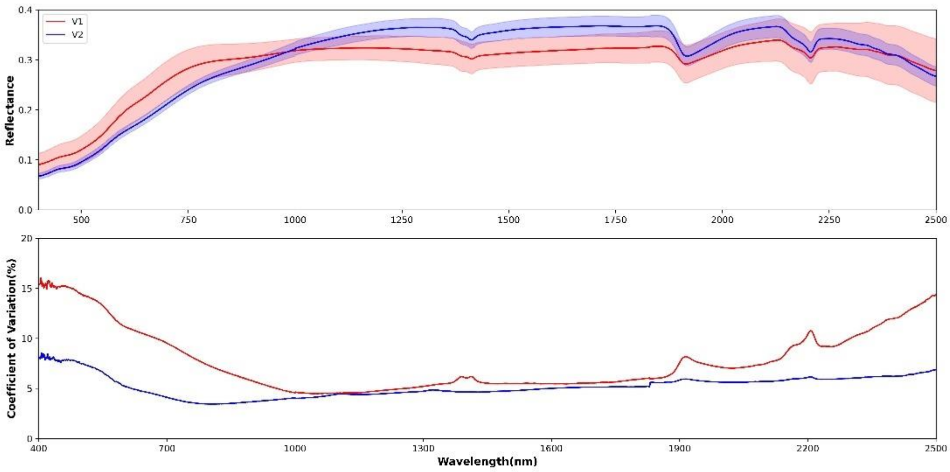

Figure 2. a) Average reflectance of Vineyards 1 and 2 with 95% confidence level. b) Coefficients of variation for both vineyards.

Results from the chemical analyses and their statistical data are presented in Table 1; for elements B, Cu, Fe, and K, and also for CEC and OM there are significant differences between the two studied areas to a confidence level of 95%, with dominance of values for Vineyard 2.

Table 1. Chemical concentrations of attributes measured in studied soils. SD is Standard deviation; CV is Coefficient of variation; letters after mean values refer to OneWay test: *p*-value < 0.05, where significant differences are expressed by different letters. Units are: B, Cu, Mn, Na, P, K, S, Zn (mg dm^{-3}); Fe (g dm^{-3}); H+Al, Ca, Mg, CEC($cmol_c$ dm^{-3}); Clay, OM, CEC/BS (%); SMP, pH, Ca/K, Ca/Mg, Mg/K are dimensionless.

	Vineyard 1				Vineyard 2				
Element	**Range**	**Mean**	**SD**	**CV(%)**	**Range**	**Mean**	**SD**	**CV(%)**	**Confidence level of 95%**
B	1.1 to 1.5	1.2a	0.2	15.5	1.6 to 1.9	1.71b	0.1	6.8	1.3 to 1.7
S	12 to 18	13.5a	3.0	22.2	15.0 to 43.0	24.5a	10.7	43.6	12.9 to 27.2
Ca	8.2 to 13.0	10.2a	2.1	20.3	11.3 to 13.9	12.4a	1.2	9.5	10.2 to 12.9
P	13.0 to 76.0	45.7a	26.2	57.3	16 to 67	37.8a	23.1	61.2	24.3 to 57.6
Zn	2.9 to 19	11.9a	6.7	56.2	6.5 to 14.0	10.3a	3.2	30.8	7.6 to 14.3
Ca/K	20.0 to 27.0	22.5a	3.3	14.7	15.0 to 22.0	18.5a	2.3	12.7	17.7 to 22.4
Ca/Mg	1.8 to 2.3	2.02a	0.2	10.2	1.7 to 2.5	1.95a	0.3	15.1	1.7 to 2.1
Cu	12.0 to 94.0	50.2a	43.3	86.3	7.2 to 16.0	10.0b	3.9	38.9	2.7 to 49.4
Fe	1.8 to 2.2	2.1a	0.2	9.5	2.4 to 3.3	2.9b	0.3	10.9	2.2 to 2.9
K	144.0 to 221.0	176.a	33.7	19.1	226.0 to 302.0	267.3b	31.8	11.9	190.7 to 271.0
Mg	4.1 to 6.6	5.05a	1.1	21.7	4.6 to 7.4	6.53a	1.1	16.6	5.0 to 6.8
Mg/K	9.0 to 14.0	11.5a	2.1	18.1	6.0 to 11.0	9.66a	1.9	19.3	8.9 to 11.8
Mn	6.0 to 12.0	7.75a	2.9	37.1	3.0 to 13.0	6.83a	3.5	51.0	4.96 to 9.43
Na	50.0 to 61.0	57.5a	5.2	9.0	39.0 to 71.0	56.3a	12.5	22.1	49.8 to 63.8
CEC	15.9 to 22.0	17.9a	3.2	17.9	20.2 to 24.9	23.4b	1.7	7.4	18.6 to 23.8
CEC/BS	83.0 to 89.0	87.2a	2.9	3.3	71.0 to 91.0	84.1a	6.9	8.2	81.3 to 89.4
Clay	38.0 to 40.0	39.0a	1.2	3.0	30.0 to 46.0	39.3a	6.1	15.6	35.8 to 42.5
OM	2.4 to 3.7	3.17a	0.6	17.5	3.6 to 4.6	4.18b	0.3	7.8	3.3 to 4.2
pH	6.1 to 6.7	6.45a	0.3	4.1	5.6 to 6.7	6.21a	0.4	6.1	6.0 to 6.5
H+Al	2.0 to 2.8	2.3a	0.4	17.0	2.2 to 6.9	3.75a	1.7	44.7	2.1 to 4.2
SMP	6.4 to 6.7	6.57a	0.2	2.3	5.6 to 6.6	6.2a	0.4	5.7	6.1 to 6.5

From inspection of Figures 1 and 2 it can be seen that soils from Vineyard 1are spectrally separated from those of Vineyard 2 to a 95% confidence level over most of the observed spectral domain, and results from Table 1 suggest that such separation has its roots in chemical differences. Such differences are not a surprise, as we have seen at Section 2.1 that soil types and profiles differ; however, presently we want to stress two perceptions. The first one is that in our investigation of the same regions through vine leaf spectroscopy (Thum et al., 2020) it was suggested that chemical and spectral differences also exist at plant level, implying that the presently detected soil differences act on plants growing from these soils in a measurable way. The second perception is on the soils themselves and how the soil differences presently detected through radiometry can be linked to what has been called "precision viticulture" or even "precision agriculture". Here we refer to what was reported, for example, by Bramley and Proffitt (1999) or by Alliaume et al (2017) concerning small spatial scale variations in vegetation indices within a vineyard due to soil variations, ultimately influencing wine quality, or by Poerner et al. (2010) concerning chemically detected differences in wines coming from vineyards growing on different soils. Both perceptions raise an awareness towards the importance of the use of radiometry to detect soil attributes or, at least, small-scale soil spatial variations, as it is suggested to be possible from our results.

Figures 3 and 4 present results from the correlations analysis for soils of all ten sampled parcels; the coefficients of determination R^2 and the associated *p*-value are shown for the 21 analysed parameters, as derived from radiometric measurements and chemical analysis.

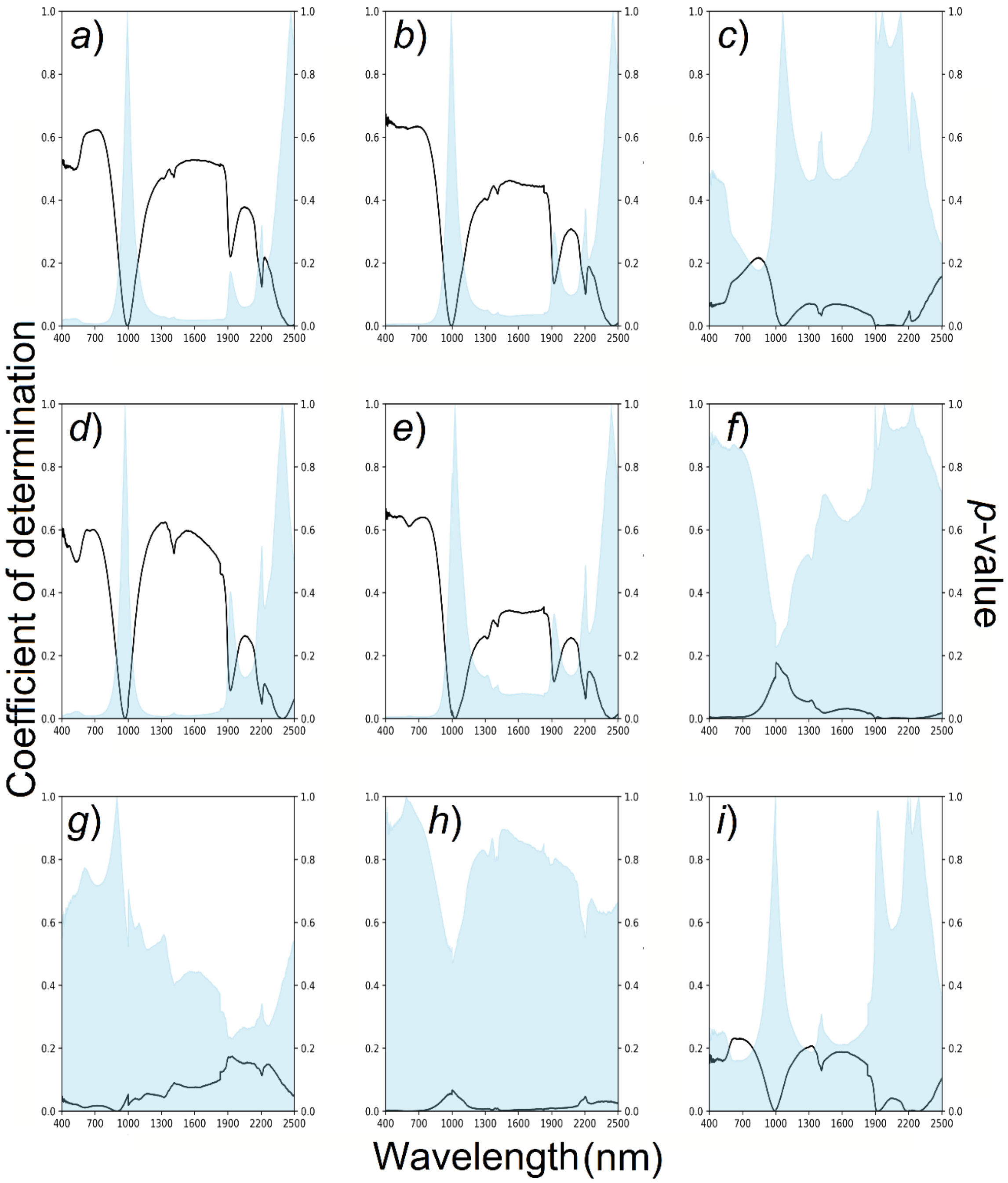

Figure 3. Coefficients of determination and *p*-values across the observed spectral domain for the elements: (*a*) Boron; (*b*) Calcium; (*c*) Copper; (*d*) Potassium; (*e*) Magnesium; (*f*) Manganese; (*g*) Sodium; (*h*) Phosphorus; (*i*) Sulfur.

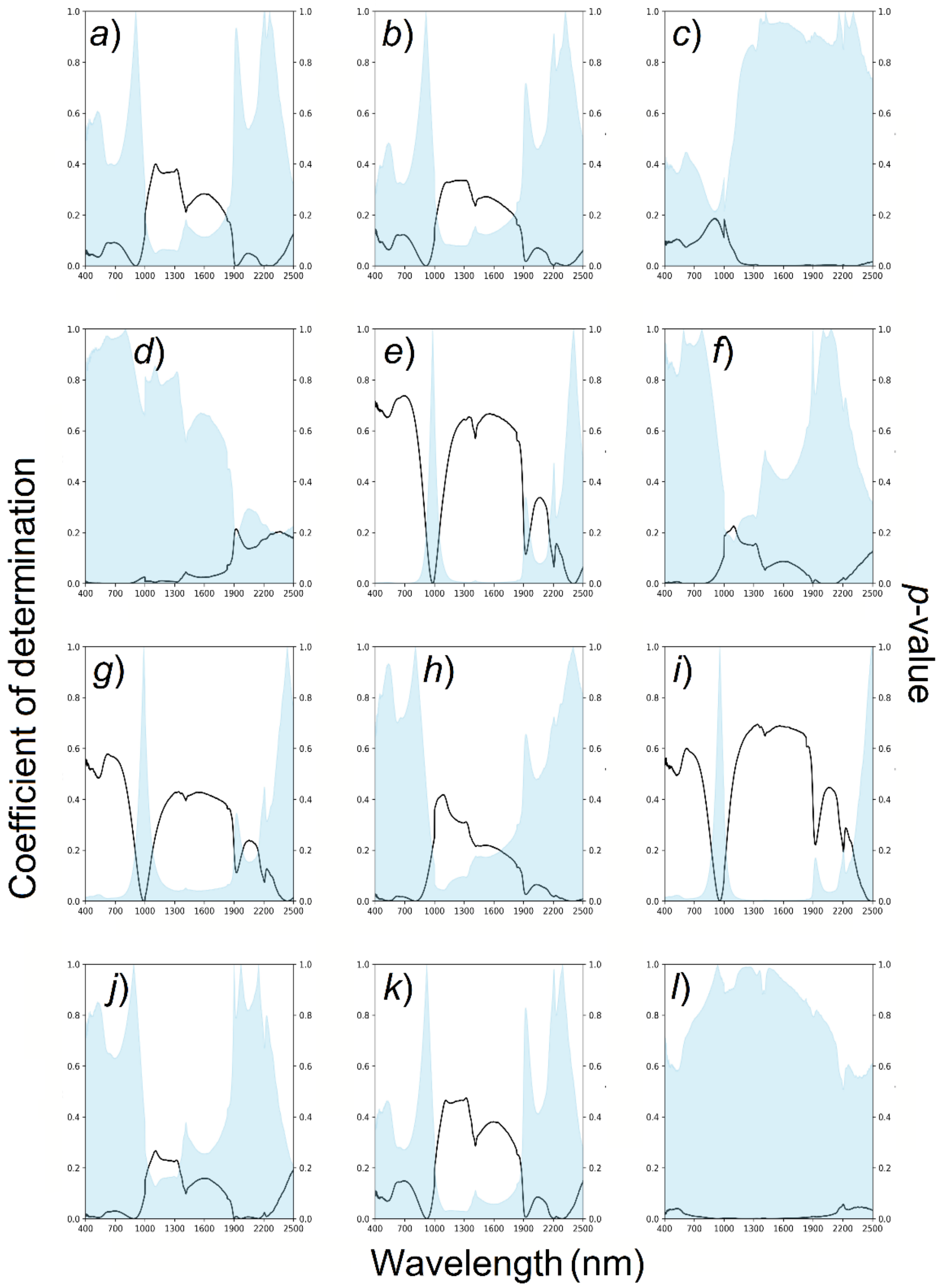

Figure 4. Coefficients of determination and p-values across the observed spectral domain for the elements and soil attributes: (*a*) H+Al; (*b*) Ca/K; (*c*) Ca/Mg; (*d*) clay; (*e*) CET; (*f*) CET/BS; (*g*) Iron; (*h*) Mg/K; (*i*) OM; (*j*) pH; (*k*) SMP; (*l*) Zinc.

Examination of Figures 3 and 4 suggest that for some wavelength domains there are correlations between reflectance and concentration with R^2 values as high as 0.7, a fact that could lead to useful applications of radiometry as a predictor of concentrations, either at the field or in laboratory. However, some preliminaty considerations ought to be made.

It is important to stress that Figures 3 and 4 are not spectra; they express values of R^2, the coefficient of determination, correlating concentration and reflectance at each wavelength. Even if they are not spectra, these Figures display features often found in reflectance spectra, being either depressions or peaks, notably around 1000, 1400, 1900 and 2200 nm; it is well-known (Tian and Philpot 2015; Bishop 2019) that water absorption in soils occurs at several bands, notedly near 960, 1150, 1400, 1900, 2200 and 2900 nm with varying intensities.

We start with the 1000nm feature. A feature at 1000 nm is frequently found in reflectance spectra obtained from FieldSpec radiometers like the one used in this study, and frequently it is an measurement artifact. It comes from the fact that spectra from such device is acquired for three spectral domains by three sensors (Malvern Panalytical 2020), each one sensitive to a spectral region: from 350 to 1000 nm for VNIR (Visible and Near InfraRed), from 1001 nm to 1800 nm for $SWIR_1$ (Short Wave InfraRed), and from 1801 nm to 2500 nm for $SWIR_2$; therefore, one of the interfaces between two domains is at 1000nm, and if a calibration was not properly performed, a step separing the spectra of shorter and longer wavelengths would be recorded at this wavelength. However, in our case, as it can be seen at Figures 1 and 2, such step is not observed, suggesting that the calibration was properly done. Therefore, the feature around 1000 nm displayed in Figures 3 and 4 is assumed to be real, being due to the measured minerals or soil attributes.

The lower R^2 values around 1000, 1400, 1900 and 2200 nm can be explained as follows: R^2 values were calculated for each wavelength value, where the involved factors were the ten reflectance values for that λ and the ten concentration values, which, obviously, are not λ-dependent but do depend on the considered vine parcel. Reflectance was measured on the soil samples, which hold variable water amounts; at the four considered wavelengths water absorption occurs, an effect whose magnitude may vary from sample to sample. That is, reflectance at these wavelengths is an expression both of mineral (or of soil attribute) content and water content. We suggest that water content in the ten samples vary to such magnitude that resulting reflectance values are more due to water absorption than to other soil components; therefore, reflectance has a large variation and is less proportional to concentration at those wavelengths. This, in our opinion, explain the low correlations, expressed by R^2, at these four wavelengths for all 21 parameters; deep depressions in R^2 are observed even in soils traits like B, Ca, K, Mg, S, Ca/K, CET, Fe, and OM which display relatively high R^2 in other spectral regions. Still in Figures 3 and 4 we can observe cases with other behaviors, like Mn and P which display peaks, not absorptions, around 1000nm, now in a context of very poor correlations between concentration and reflectance, the same being observed with Fe and Zn. It is worth to note that the three parameters linked to soil acidity, which are H+Al, SMP and pH, have nearly identical curves. Finally, we note that Bilgili et al. (2010), studying some of the soil attributes presently analysed, obtained results which are not in agreement with those reported in our Figures 3 and 4.

Keeping in mind these considerations, and having from them acquired a perception of the meaning and potential of Figures 3 and 4, we looked for an application of the results there presented. To that end, we selected the elements and soil attributes that display the larger R^2 and the smaller p-values. The chosen criteria were p-values of either 0.01 or 0.05, corresponding to confidence levels of 99% or 95%, equivalent roughly to R^2 of about 0.4 or higher; in these chemicals the better correlations between concentration and reflectance are expressed along certain wavelength domains, which are given in Table 2 in terms not of R^2 but of *r*, the Pearson correlation coefficient, since *r* informs if the correlation is direct or inverse. Examination of Table 2 gives two perceptions. The first one is that all displayed correlations between reflectance and concentration are negative from 400 to about 1000nm, and at longer wavelengths correlations turn to be positive up to $SWIR_2$ at 2100nm. In a study performed on contaminated soils, Gholizadeh et al. (2015) reported that iron concentration is negatively correlated with reflectance at wavelengths shorter than 1000nm, a result which is in agreement with ours; however, their result could not be repeated in other studied sites. We also note that a similar behavior was reported in a study focused on phosphorus concentrations in sandy soils by Bogrekci and Lee (2006); however, further investigation would be necessary to an understanding of this behavior which seems to be observed only in soils, since as reported in Paper I (Thum et al. 2020, Table 2) such behavior was not observed in plants. We still note in Table 2 that at the wavelength domain between 1050nm and 1360nm we have $r = +0.63$ for H+Al, while for SMP we have $r = -0.67$; such change from positive to negative could be expected, since H+Al and SMP are inversely correlated (Escosteguy and Bissani 1999).

The second perception coming from examination of Table 2 is linked to the apparent fact that, since concentrations are correlated with reflectance at relatively high *r* values, it would be possible to predict concentrations from spectroradiometry. However, these evidences are presently preliminary, being necessary additional investigation to validation; besides, most of the wavelength domains shown in Table 2 are not exclusive of a given attribute, in a sharp contrast with our results reported in Paper I, Table 2. The potential predictive power of our results, however, is shown in Figures 5 and 6, which report PLSR analysis.

Table 2. Wavelength domains corresponding to the most significant correlations between chemical concentrations and reflectance for soils of all ten sampled vine parcels. λ is wavelength in nm; *r* is Pearson correlation coefficient; * after *r* values refers to OneWay test, *p*-value < 0.01; ** *p*-value < 0.05

	Wavelengths 1		Wavelengths 2		Wavelengths 3		Wavelengths 4		Wavelengths 5	
Attribute	λ	*r*	λ	*r*	λ	*r*	λ	*r*	λ	*r*
B	400 to 588	-0.74**	589 to 787	-0.78*	788 to 863	-0.73**	1191 to 1893	+0.72**		
Ca	400 to 770	-0.81*	791 to 869	-0.74**	1278 to 1871	+0.67**				
Fe	400 to 618	-0.75**	619 to 626	-0.77*	627 to 832	-0.75**	1241 to 1407	+0.65**	1418 to 1745	+0.64**
K	405 to 418	-0.77*	419 to 603	-0.75**	604 to 725	-0.78*	1215 to 1609	+0.79*	1610 to 1876	+0.75**
Mg	400 to 831	-0.81*	832 to 897	-0.76**						
Mg/K	1032 to 1116	-0.65**								
CEC	400 to 823	-0.84*	824 to 874	-0.74**	1108 to 1197	+0.76**	1198 to 1830	+0.81*	1831 to 1888	+0.72**
OM	400 to 813	-0.75**	1068 to 1164	-0.76**	1165 to 1861	+0.82*	1862 to 1896	+0.76**	1999 to 2140	+0.66**
H+Al	1050 to 1290	+0.63**								
SMP	1072 to 1362	-0.67**								

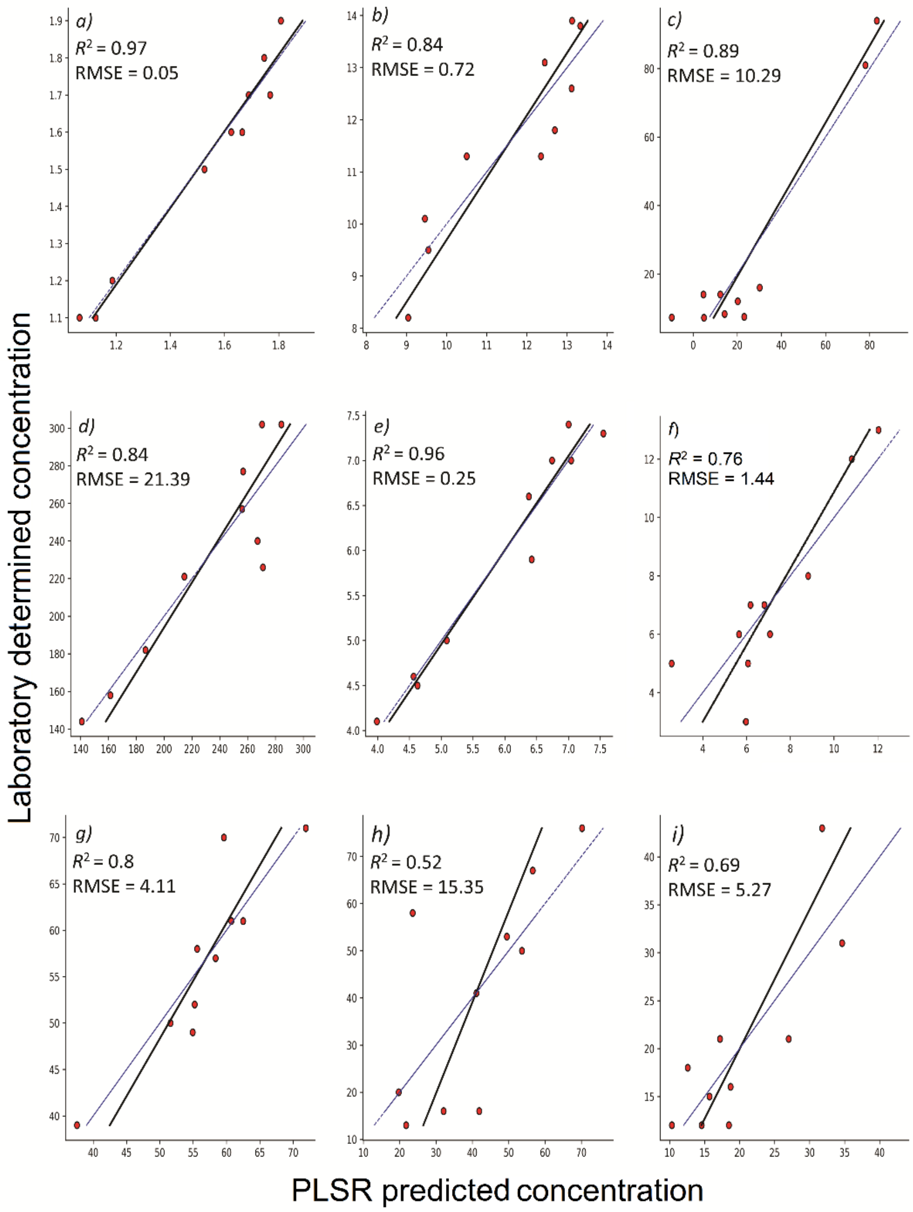

Figure 5. Scatter plots produced by PLSR of the predicted soil traits (chemical concentrations) versus the soil trait data from laboratory radiometry and chemical analysis. The dashed, blue line is the 1:1 correlation. (*a*) Boron, (*b*) Calcium, (*c*) Copper, (*d*) Potassium, (*e*) Magnesium, (*f*) Manganese, (*g*) Sodium, (*h*) Phosphorus, (*i*) Sulfur. Units for the *x*- and *y*-axes are: (mg dm^{-3}) for B, Cu, K, Mn, Na, P, and S; (cmol$_c$ dm^{-3}) for Ca and Mg.

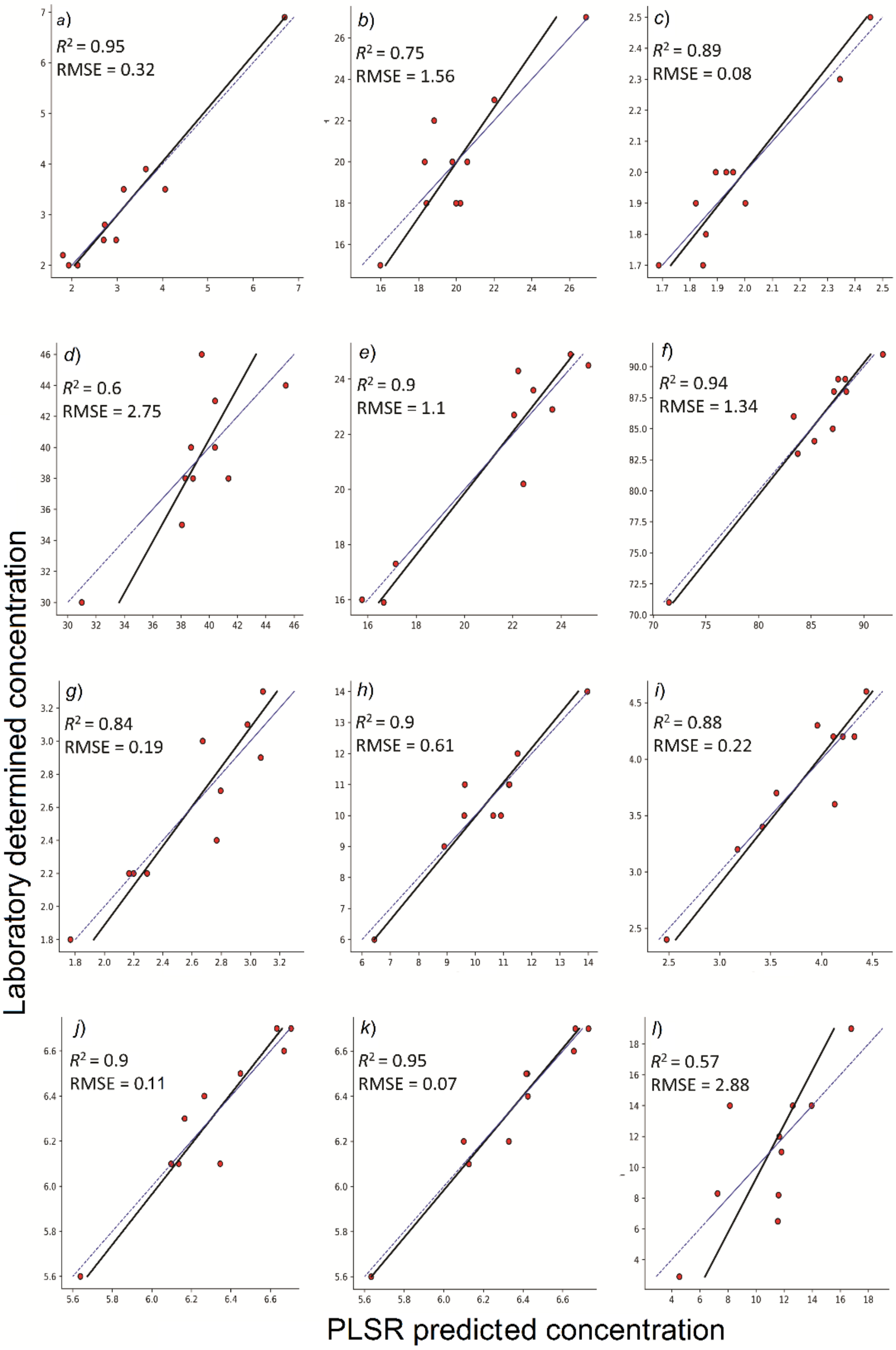

Figure 6. Scatter plots produced by PLSR of the predicted soil traits (chemical concentrations) versus the soil trait data from laboratory radiometry and chemical analysis. The dashed, blue line is the 1:1 correlation. (*a*) H+Al, (*b*) Ca/K, (*c*) Ca/Mg, (*d*) clay, (*e*) CEC, (*f*) CEC/BS, (g) Iron, (*h*) Mg/K, (*i*) OM, (*j*) pH, (*k*) SMP, (*l*) Zinc. Units for the *x*- and *y*-axes are: (mg dm^{-3}) for Zn; (cmol$_c$ dm^{-3}) for H+Al and CEC; (g dm^{-3}) for Fe; (%) for clay, CEC/BS and OM; Ca/K, Ca/M

The correlations from PLSR analysis between measured and predicted values can be divided in three groups:

a) $R^2 \geq 0.90$, which can be further divided in three sub-groups: soil elements B (R^2 = 0.97), Mg (R^2 = 0.96), and Mg/K (R^2 = 0.90); the soil acidity indices SMP (R^2 = 0.95), H+Al (R^2 = 0.95) and pH (R^2 = 0.90); and finally, CEC and CEC/BS with R^2 equal to 0.90 and 0.94 respectively;

b) $0.90 > R^2 \geq 0.80$ including Ca, Cu, K, Na, Ca/Mg, Fe and OM;

c) $0.80 > R^2 \geq 0.52$ for P, S, Mn, Zn, Ca/K, and clay.

These results from PLSR can be compared with those reported by other investigators. The similar performance for all three acidity indices could be expected, since they are correlated. In a study investigating the correlation between H+Al and SMP, both indicators of potential soil acidity, Escosteguy and Bissani (1999) reported that these two indices had a logarithmic correlation with R^2 = 0.90 accuracy. Determinations of soil attributes from radiometry through multiple linear regression were performed by Genú and Demattê (2006) with poor results (R^2 = 0.16) for pH, but better ones for CEC and CEC/BS (R^2 = 0.88 and 0.83) and for P, K, Ca and Mg as well (R^2 = 0.79; 0.67; 0.84; 0.75 respectively).

For CEC our PLSR-derived correlations have higher values that those reported by Wan et al. (2020), who used PLSR and support vector machine regression (SVMR) applied to XRF (X-ray fluorescence) spectrometry and Vis-NIR (visible and near infrared) spectroscopy to predict CEC, having obtained R^2 = 0.72 from PLRS and R^2 = 0.82 from SVMR.

Our results from PLSR analysis for OM (organic matter) report R^2 = 0.88; using a variety of spectrometers and also using PLSR, Ge et al. (2011) obtained R^2 values ranging from 0.72 to 0.94 for organic carbon, which is a related soil descriptor, while Knox et al. (2015) report R^2 values also from PLSR around 0.85 for total carbon. Nawar et al. (2016) used a spectroradiometer similar to ours to estimate organic matter and clay in salt-affected soils in Egypt; their best accuracies came from multivariate adaptive regression splines (MARS) analysis, being R^2 = 0.85 for OM and R^2 = 0.90 for clay. Terra, Demattê, and Viscarra Rossel (2015) using a FieldSpec Pro sensor and Support Vector Machine (SVM) algorithm reported what they considered reasonable performance ($0.50 \leq R^2 \leq 0.73$) for Ca, Mg, Cu and Mn, and poor results ($R^2 \leq 0.47$) for P, K, Fe and B; their best results were for clay and CEC ($0.76 \leq R^2 \leq 0.90$). Still for clay, Bilgili et al. (2010) used PLSR to correlate concentration and reflectance, reporting R^2 = 0.84; we note that the method presently reported got poor results for clay (R^2 = 0.60) compared with those of other investigators, as reported above. However, other results from Bilgili et al. (2010) for Ca, Mg, K, Ca, OM, pH and CEC had rather poor performances compared to ours.

Some comparisons can be made with our results from Paper I (Thum et al. 2020), where we investigated the correlations between reflectance of vine leaves and the mineral content of these leaves. First, the curves presented here in Figures 3 and 4 are completely different from the similar curves presented in Paper 1; second, the construction of presently reported Table 2 followed objective criteria (low *p*-value, high *r*), while a similar table in Paper I was compiled from visual inspection; third , in the investigation presently reported we found rather high correlations between measured and predicted traits (Figures 5 and 6): fifteen out of 21 soil attributes had $R^2 \geq 0.80$, while in Paper I only two elements out of 11 filled this condition. That is, compared with observations on plants, observations on soils behave differently and in some aspects perform much better; this is not a surprise, since presently we measured attributes in the soils themselves, while in Paper I we were looking for mineral traits in vegetal tissues, and citing Paper I, "The processes of nutrient assimilation by plants are mediated by their metabolism, which is a complex biological process".

4. Conclusions

In this investigation we looked for differences in reflectance measured in different soils, and our results suggest that derived significant differences in some soil attributes lead to systematic differences in reflectance which spectrally separate one region from the other. The region where the investigation was done is home to intense agriculture (viticulture), and our study areas were chosen to highlight soil differences, avoiding the influence of anthropogenic factors by considering them as mutually equivalent to all studied areas. Therefore, our results, even if having to pass through further validation, are potentially useful to precision viticulture, or to other agricultural applications, in the sense that it points to the possibility of performing spectral surveys in small areas which have homogeneous management, aiming to detect variations in soil attributes.

The results presently reported suggest that for some soil attributes there are correlations with confidence levels as high as 99% between chemical concentration and reflectance within some well-defined wavelength domains. These results and their generating method, as presented in this paper and in Paper I, are being reported for the first time, being nevertheless preliminary and having to be validated by additional investigations considering a larger sample and a wider variety of soil types. From PLRS analysis it was suggested that reflectance data can be used to predict several soil traits, to accuracies which compare well with those reported by other investigators.

Presently we investigated soils used for grape production intended for winemaking and we demonstrated, at a preliminary level, that differences between soils can be detected by their reflectance. However, no claim is made about eventual advantages of a certain content of any soil attribute on soil quality, or grape or wine quality. The authors are aware that the "terroir" concept relies heavily on soil quality to achieve the so-called "wine typicity", but are also aware that descriptors linking soil attributes to wine quality are, to date, far from being scientifically defined. A possible way to shed some light on this question would be to look for connections between soil attributes and vine leaf reflectance, an investigation that will be pursued in forthcoming papers.

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Disclosure statement

The authors declare no conflict of interest.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, ABT, upon reasonable request.

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CAPÍTULO 4 – ARTIGO 3

ARTIGO 3 – ENCAMINHADO PARA REVISTA

Geotechnologies applied to precision viticulture of two areas at Serra Gaúcha, Brazil

Adriane Brill Thum[a,b*], Diniz Carvalho de Arruda[b], and Jorge Ricardo Ducati[b]

[a]Escola Politécnica, Universidade do Vale do Rio dos Sinos, São Leopoldo, Brazil;
[b]Centro Estadual de Pesquisas em Sensoriamento Remoto e Meteorologia, Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil

*corresponding author: adrianebt@unisinos.br

ABSTRACT

The management of land parcels aiming the optimization of investments and outputs, eventually linked to increased product quality, is one of the objectives of Precision Agriculture. The gathering of data on the terrain (precise parcel areas, slopes, soil attributes, vegetation descriptors) is crucial to the fullfilement of these objectives. This paper describes a study performed on two vineyards located at the Serra Gaúcha viticultural region, in south Brazil. Based on *in situ* acquisition of information on soils chemical composition and agronomical parameters and on airborne acquisition of topographical information, besides vegetation indices, the objectives of this work were to compile a set of maps of agronomical attributes for selected vine parcels, to generate contour levels and maps of vegetation index for these parcels; and to correlate theses information to production data to gain a better, comprehensive understanding of the areas in focus, these objectives being the components of the general proposal of this paper, which is to provide an example of data integration aiming to support decisions on precise viticulture. It was shown that the studied terrains are highly variable either in physico-chemical and topographical descriptors, results that eventually can be used to management options towards standardization of products or their differentiation.

Keywords: precision viticulture; viticultural regions; vineyard NDVI; soil attributes

1. Introduction

Improvements in the management of agricultural production, aiming both larger yields and better products, are vectored by technological evolution which is one of the results of investments in scientific research. One of the better examples of such evolution is precision agriculture (PA), which uses accurate local information to achieve crop management at small and micro-spatial scales, reducing costs in fertilizers and pesticides, increasing efficiency and reducing environmental impacts (Bramley and Hamilton, 2004; McBratney et al., 2005; Acevedo-Opazo et al., 2008; Shiratsuchi et al., 2014). Geotechnologies crucial to this concept are supported by the use of position receivers linked to GNSS (Global Navigation Satellite Systems) (Dow et al., 2009; Groves, 2013) operating through several methods of positioning and processing like Real Time Kinematic (RTK) (Rizos and Han, 2003; Ekaso et al., 2020) and associated to sensors operating at ground level or airborne, the last increasingly based on Remotely Piloted Aircraft Systems (RPAS) or Unmanned Aerial Vehicles (UAV); these techniques generate several products including topographic maps and Digital Elevation Models (DEM), besides spatial information on plant health status by vegetation indices like NDVI (Normalized Difference Vegetation Index) or others (Tschiedel and Ferreira, 2002; Everaerts, 2008).

Precision agriculture allows the input of fertilizers and other agricultural products in the right amounts at the right places, and one of its recent applications is precision viticulture (PV), which allows the grape producer a precise vineyard management, leading to the production of quality grapes, optimizing costs and increasing profits (Tisseyre and Taylor, 2004). Important to these aims is the acquisition of spectral information on the vegetation associated to spatial data, such positioning being made available through GNSS and airborne sensors and imagers (Gay et al., 2015; Soubry et al., 2017). Vineyards in different places often lead to the production of different wines, even if grape varieties, clones, rootstocks and viticultural practices are identical. The differences in these cases are due to environmental factors like climate and soil, but also terrain slope, solar exposition, drainage and soil capacity to store water (Bramley and Proffitt 1999). Even inside a single vineyard spatial variations in soil features lead to spatial variations in vegetative strength, with results in grape yield and quality and, consequently, in wine quality (Atkinson 2011).

The dynamical interaction between many factors, including climate, soil, local relief and environmental features, plant characteristics, and agricultural methods, contribute to the production of goods which carry local descriptors which are frequently associated to the terroir concept (van Leeuwen and Seguin, 2006). Such considerations are often associated to certain wines, which are then called terroir wines and are considered to have typical sensorial characteristics. Several studies have focused in defining as objectively as possible the contribution of individual factors to a specific terroir (Seguin 1988; Atkinson 2011; Miguel-Gómez et al. 2013;). Soils and geology, specifically, are often described as being essential terroir components (Fanet, 2008). Studying some viticultural regions in Rio Grande do Sul

State, Brazil, Hoff et al. (2015) reported that differences related to bedrock and relief, expressing geodiversity, add typicity to products from each region, that is, to each terroir.

From the above considerations it becomes clear that the terroir concept and the aims of precision agriculture have points in common, since both are based on, or achieve to, precise descriptors of well-defined, limited land plots. At the same time, and now focusing specifically on viticulture, in many parts of the World there are regions which are relatively new to the concept, when compared to the traditional terroirs found in Europe. What was achieved in certain European regions by centuries of empirical essays (Pitiot and Servant, 2010) can, ideally, be attained in the New World by a scientific, experimental approach focused on specific vineyard parcels where, starting from the preliminary knowledge that that parcel already pruduces good grapes, a set of quantitative descriptors of soil or agronomical attributes is assembled which, eventually, would characterize that land plot as a wine terroir with its own typicity. In fact, a problem frequently found in New World viticulture is the lack of detailed spatial information, a lack which leads to a spatially homogeneous management with no regard to differences between parcels or within a parcel. Stressing what was already mentioned, spatially detailed information allows not only management optimization and gains in profit and quality, but also, as an added value, can give typicity to products.

As examples of agronomical attributes important to grape production we can mention contents of clay, organic matter, indices expressing soil acidity, and concentrations of several elements (Alliaume et al., 2017), besides terrain slope and indices expressing plant vigour. A detailed mapping of these soil traits can constitute a valuable information set to the producer, allowing precise management adapted to strategic goals of quality and profit. Therefore, the objectives of this work are: a) to build a set of maps of selected agronomical attributes for the vineyards of a chosen winery; b) to generate contour levels and maps of vegetation index for these parcels; and d) to correlate theses information to gain a better, comprehensive understanding of the areas in focus, these three objectives being the components of the general proposal of this paper, which is to provide an example of data gathering aiming to support decisions on precise viticulture.

This paper is the third of a series of studies focused on the development of methodologies, having as data souces two vineyards located at the Serra Gaúcha region, south Brazil; the first paper (Brill et al., 2020) investigated the relationship between plant reflectance and leaf mineral content; the second paper (Brill et al., 2021, in submission) was focused on soil reflectance, soil mineral content and other soil agronomical attributes. Some results from these two former papers were valued in this third paper.

2. Materials and methods

2.1. Study area

The study area is located in the Serra Gaúcha viticultural region at Rio Grande do Sul State, Brazil, with coordinates 29º01'43" South, 51º18'24" West and altitudes between 600 and 800 meters above sea level. In this region we looked for two vineyards in two locations with nearly identical viticultural practices and, given the small distance between them, negligible differences in climate. We selected two vineyards two kilometers apart at Nova Pádua municipality, belonging to a family-owned winery, the Vinícola Boscato. The area we call Vineyard 1 (5.38 hectares) has altitudes from 666 to 688m, and Vineyard 2 (7.93 hectares) has altitudes from 747 to 785m. Grape varieties include Cabernet Sauvignon, Merlot, Touriga Nacional, Tannat and others. The two vineyards have the same management and equivalent viticultural factors, being therefore assumed that differences between soils are intrinsic and not anthropic; significant variations in soil depth exist, as shown from preliminary soil profiling. As complementary information, the region's climate is of Cfb class at the Köppen-Geiger system (Moreno, 1961; Beck et al. 2018) meaning a subtropical climate with mild summers, and ISO IH4 IF2 in the MCC (Multicriteria Climate Classification) system (Tonietto and Carbonneau, 2004), corresponding to an umid and warm temperate climate with temperate nights. Average annual precipitation is about 1736mm with no well-defined rainy or dry seasons. Soils in the region are considered as being of good quality for agriculture and viticulture and many wineries are stablished there.

Vines were planted in rows (generally oriented east-west) and trained to a Guyot system. Row and plant spacing was 1.0 m × 2.7 m for both Vineyards 1 and 2. Age of vineyards was 18 years. Treatments on these vineyards were conventional, meaning that synthetic pesticides were used, besides copper-based products. The soil under vines and between vine rows is in general partially covered by low vegetation, that is, soil tends to be not bare. Ten vine plots were selected: in Vineyard 1 we selected three parcels of Cabernet Sauvignon and one of Merlot, and in Vineyard 2 we selected one parcel of Cabernet Saufignon and five parcels of Merlot.

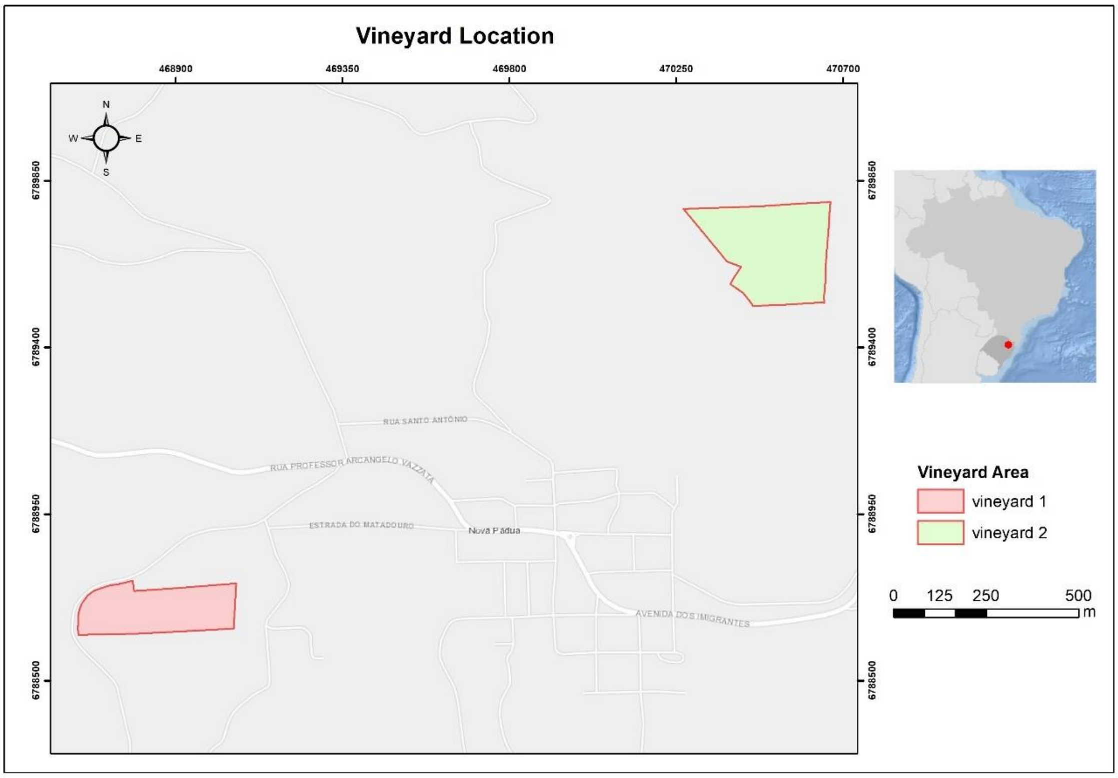

Figure 1. Localization map of study area, where geographical coordinates are given at the Universal Transverse Mercator (UTM) projection, zone 22.

2.2. Soil sample collection

For each one of the ten selected parcels soil samples were collected in ten randomly spaced points with help of an auger going up to 40cm deep, following the protocol recommended by Siqueira et al (1987). Samples of each parcel were mixed and put in identified plastic bags, being transported to the University's Laboratory of Soils where they underwent chemical analysis. A total of 21 soil traits (chemical elements and soil attributes) were quantified for each one of the ten studied parcels, using the following methods: concentrations of elements P, K, Cu, Zn and Na were determined by Mehlich 1method; Ca, Mg and Mn by exchangeable KCl in a 1 mol l^{-1} extract; B extracted with hot water; Fe by sulfuric extraction; S by SO_4 extracted with $CaHPO_4$ at 500 mg l^{-1} of P; clay determined through densimeter method; pH in water1:1; H+Al by calcium acetate; SMP by Shoemaker–McLean–Pratt method; organic matter (OM) by wet digestion; CEC (Cation Exchange Capacity) and CEC/BS (Base Saturation) by SMP. The relations Ca/K, Ca/Mg and Mg/K were also calculated. Maps for each vineyard were compiled for each one of these 21 soil traits, showing ranges of their values in a scale of five color shades.

2.3. Soil profiles

Soil profiles were acquired through the digging of trenches. Rock samples were collected in outcroppings near Vineyard I, and internally to Vineyard II.

2.4. Georeferencing

Positional data was obtained from GNSS receptors L1/L2 Topcon, models HiPer+ (used as fixed base with 6 hours tracking) and HiPer II (as rover with 94 acquired points). Data processing was performed through Precise Point Processing (PPP), a service made available by IBGE (Instituto Brasileiro de Geografia e Estatística – Brazilian Agency of Geography and Statistics), and also using Topcon's home software Topcon Tools V 8.2.3.

2.5. Data from UAVs

Data on both vineyards was acquired by an eBee UAV. Flights were performed on December 23, 2016, a sunny, clear summer day. Flight altitudes in both cases were about 110 meters. Two cameras were used: For Red, Green and NIR (Near Infrared), a Canon Power Shot 110, giving an Average Ground Sampling Distance (GSD) of 5.27cm; for RGB, a Canon IXUS 127 HS, giving a GSD of 5cm. From the acquired images, maps showing NDVI distribution along the studied vineyards were generated, as well as planialtimetric maps e Digital Elevation Models (DEM).

2.6. Final database

The final database available for the study was composed of: chemical analysis of parcels inside the studied vineyards; soil profiles; positional data; planialtimetric and NDVI maps; and Digital Elevation Models.

Additional information provided by the winery managers about the selected vine parcels is given in Table 1.

Table 1. Grape varieties in each vine parcel of Vineyard 1 or Vineyard 2 and respective areas and grape yields, year 2017. Grape varieties are Cabernet Sauvignon (CS) and Merlot (Me).

Vineyard/parcel	Area, m^2	Yield, kg/m^2	Grape variety
1/1	7896.51	0.63	CS
1/2	17797.82	0.39	CS
1/3	9149.82	0.50	CS
1/4	5116.75	0.17	Me
2/5	3884.84	0.79	Me
2/6	4382.13	0.23	Me
2/7	6914.66	0.61	Me
2/8	6756.85	0.89	Me
2/9	7654.33	1.20	Me
2/10	6683.80	0.52	CS

3. Results

3.1. Maps of concentrations of measured soil traits

Figures 2 to 8 display the distribution of values of measured soil traits across the surfaces of Vineyards 1 and 2.

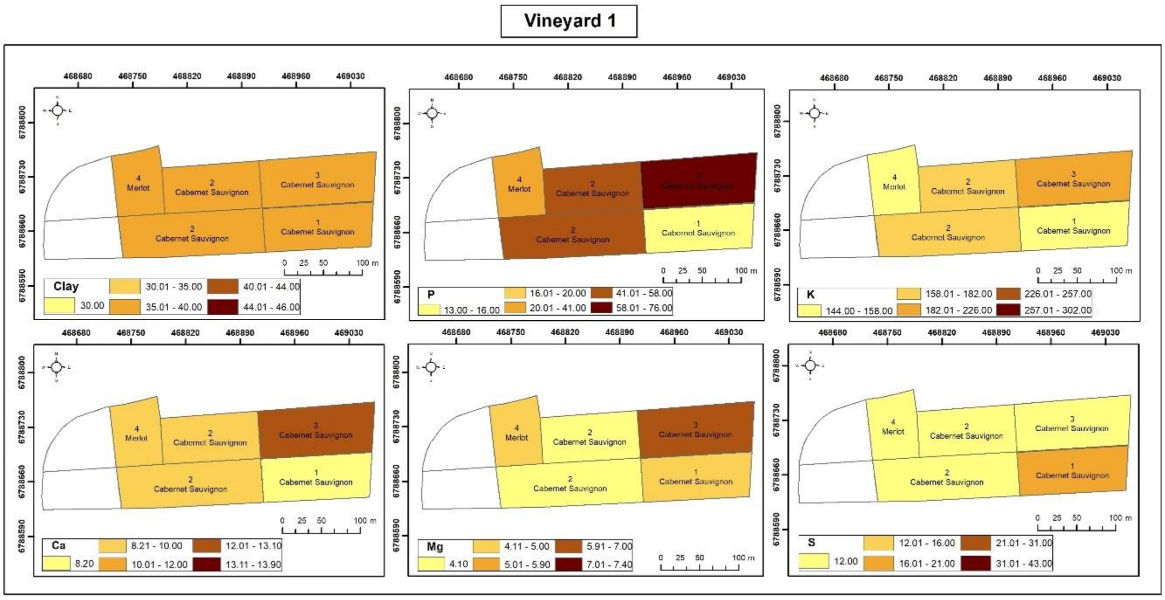

Figure 2. Values of soil traits clay, P, K, Ca, Mg, and S for Vineyard 1.

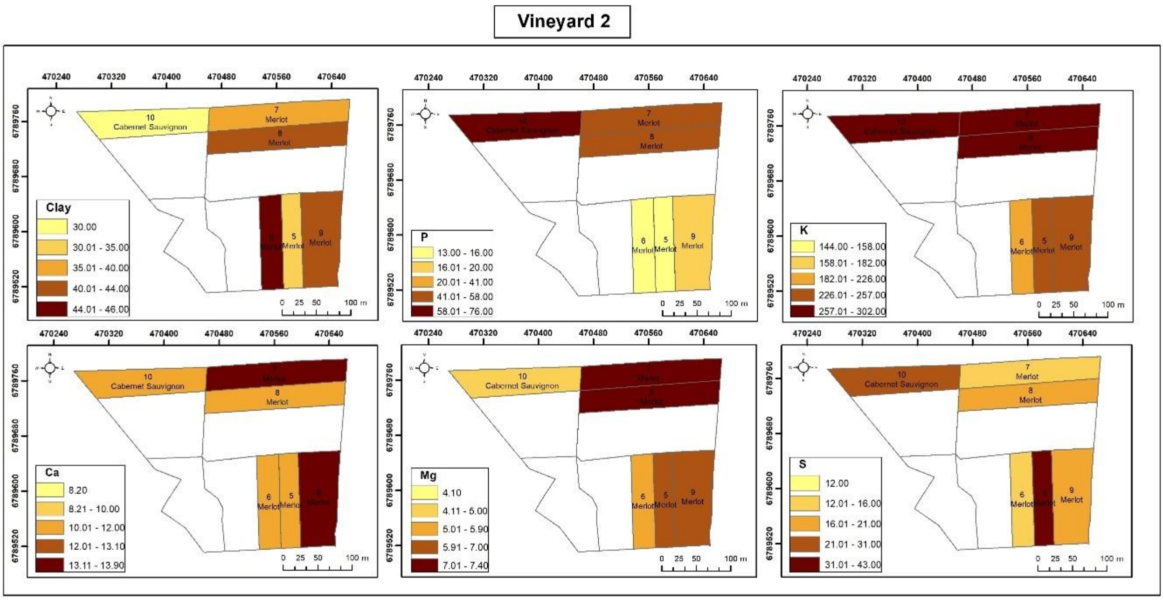

Figure 3. Values of soil traits clay, P, K, Ca, Mg, and S for Vineyard 2.

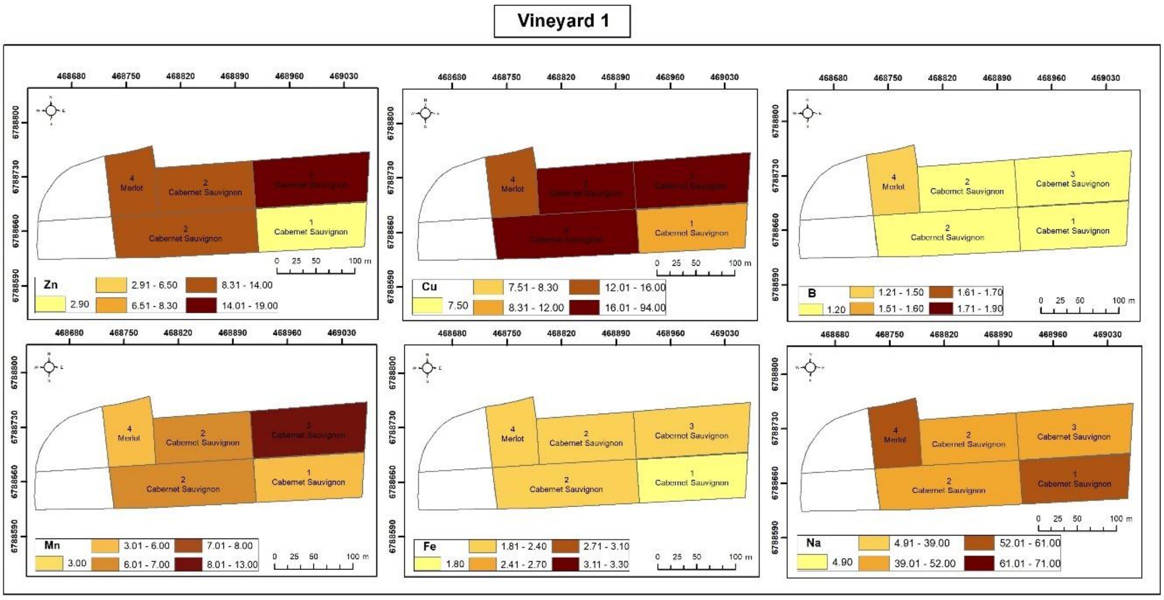

Figure 4. Values of soil traits Zn, Cu, B, Mn, Fe, and Na for Vineyard 1.

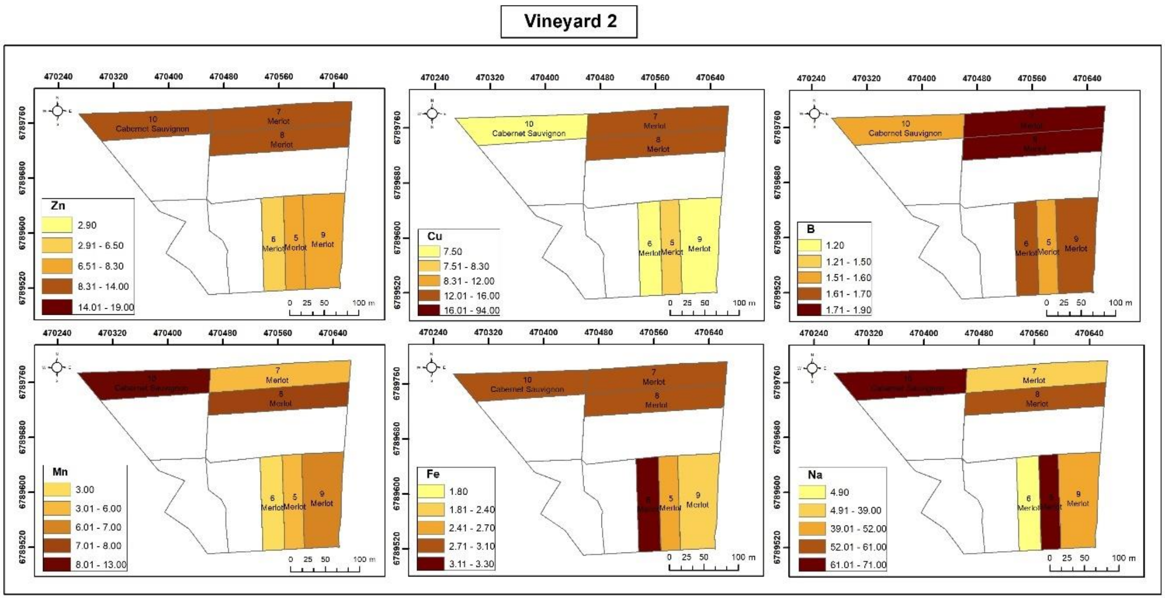

Figure 5. Values of soil traits Zn, Cu, B, Mn, Fe, and Na for Vineyard 2.

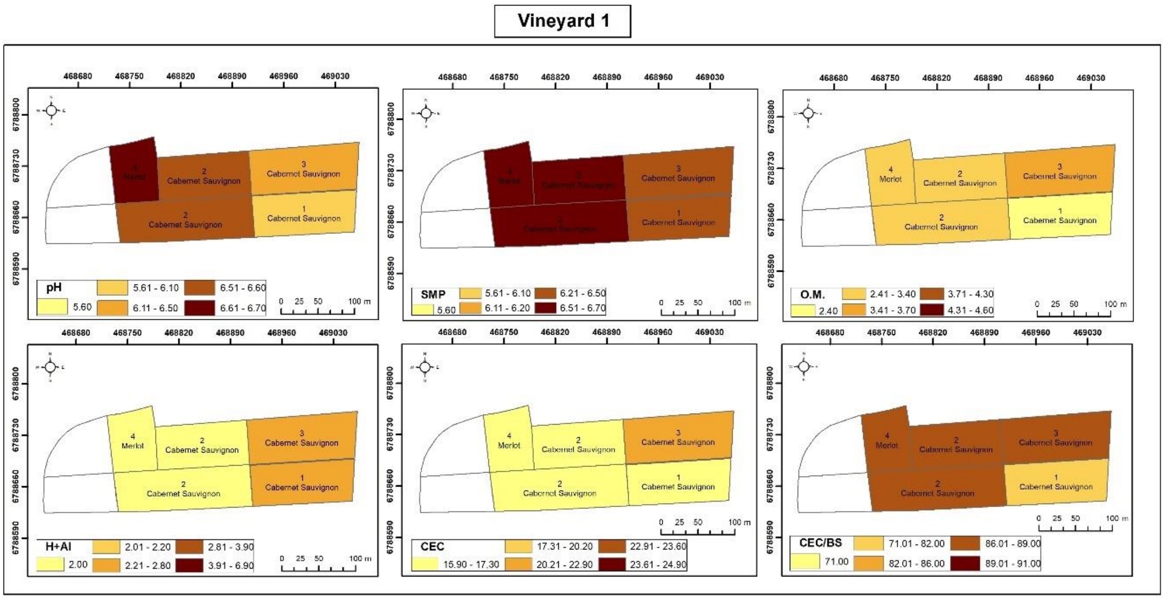

Figure 6. Values of soil traits pH, SMP, OM, H+Al, CEC and CEC/BS for Vineyard 1.

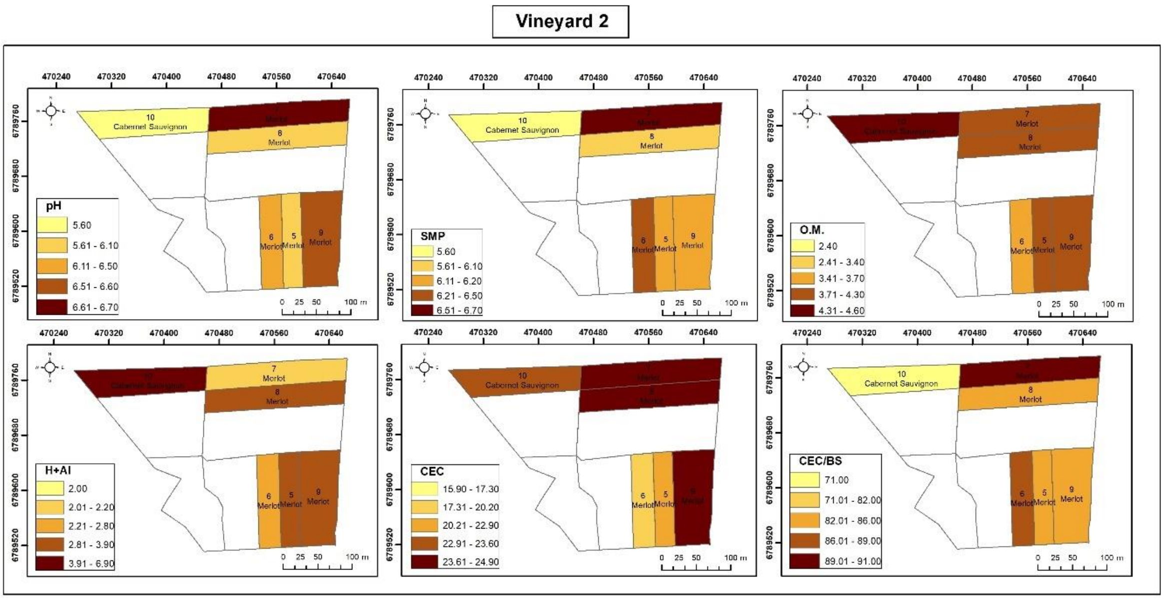

Figure 7. Values of soil traits pH, SMP, OM, H+Al, CEC and CEC/BS for Vineyard 2.

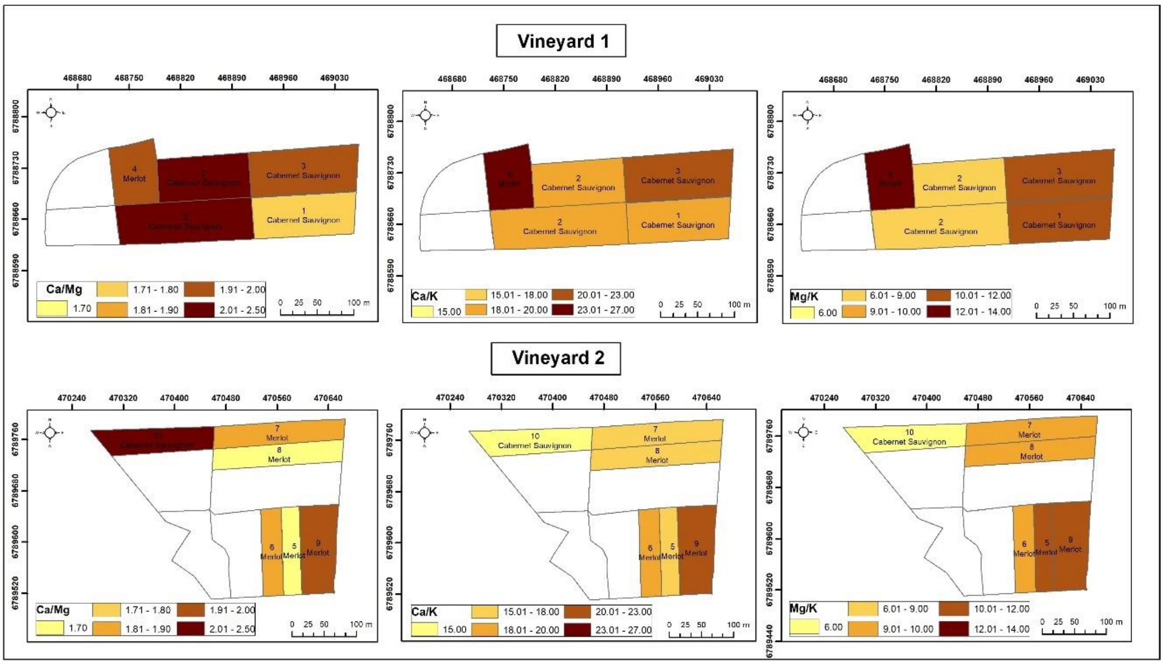

Figure 8. Values of soil traits Ca/K, Ca/Mg and Mg/K for Vineyards 1 and 2.

3.2. Soil profiles

Results from soil profiling were as follows: The deepest profiles were found in Vineyard 1, where Horizon A goes up to 50cm, displaying dark brown color with occasional lighter shades, and increasing rock mixing as depth increases. At Vineyard 2, Horizons A and B have been observed at higher elevations; both have a thickness of about 10cm with a larger proportion of organic matter and roots; soils are darker and at the shallow parts vine roots are occasionally exposed, as well as rock fragments. Parts of this Vineyard 2 present deeper soil, with Horizon A going from 0 to 30cm, Horizon B going from 30 to 70 cm, and Horizon C starting at 70 cm.

3.3. Results from UAV flights

Concerning position accuracy of flight positioning with respect to ground control points, RMS errors were about 4cm in X, 2cm in Y and 6cm in Z. Additional information on the accuracy is given in Table 2 for some control points.

Table 2. Positions of some ground control points obtained by GNSS (Relatório de Precisões) and positions of same points acquired during UAV flight (Imagem Obtida).

PONTOS DE CONTROLE NO SOLO COMPARATIVO ENTRE RELATÓRIO DE PRECISÕES / IMAGEM OBTIDA COORDENADAS UTM								
IDENTIFICAÇÃO	RELATÓRIO DE PRECISÕES		IMAGEM OBTIDA		DIFERENÇAS OBTIDAS			
	NORTE (m)	ESTE (m)	NORTE (m)	ESTE (m)	ΔY	ΔX	$\sqrt{\Delta y^2 + \Delta x^2}$
16	6.789.644,430	470.460,028	6.789.644,447	470.459,971	-0,017	0,057	0,060
17	6.789.533,652	470.472,686	6.789.533,697	470.472,609	-0,045	0,077	0,089
18	6.789.519,128	470.541,172	6.789.519,185	470.541,088	-0,057	0,084	0,102
19	6.789.521,810	470.640,690	6.789.521,824	470.640,591	-0,014	0,099	0,100
20	6.789.660,429	470.655,461	6.789.660,391	470.655,526	0,038	-0,064	0,075
21	6.789.785,957	470.662,031	6.789.785,969	470.662,023	-0,012	0,008	0,015
22	6.789.784,030	470.508,029	6.789.784,031	470.507,974	-0,001	0,055	0,055
23	6.789.769,142	470.278,028	6.789.769,134	470.277,975	0,008	0,053	0,053
24	6.789.646,182	470.383,801	6.789.646,098	470.383,691	0,084	0,110	0,138

Figure 9 displays the RGB images of both vineyards obtained by the UAV flights.

Figure 9. RGB images of studied areas obtained by UAV flights.

Figure 10 gives the contour lines corresponding to the DEM generated from the UAV flights.

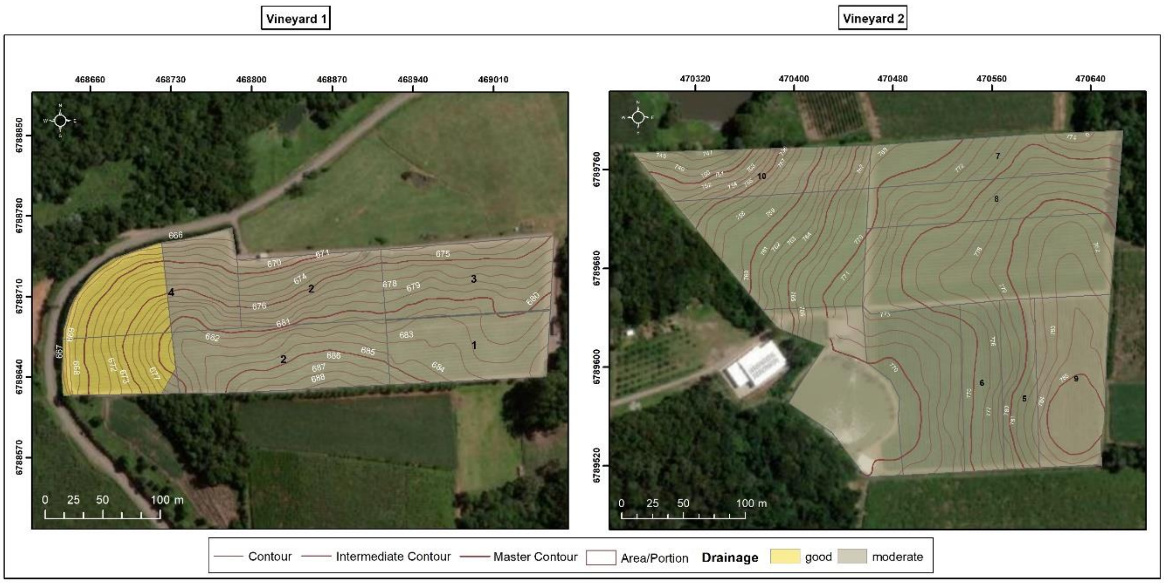

Figure 10. Contour lines for studied areas, equidistant to one meter.

Figures 11 and 12 display the NDVI maps for the studied areas.

Figure 11. Map of distribution of NDVI values for Vineyard 1.

Figure 12. Map of distribution of NDVI values for Vineyard 2.

4. Discussion

We'll start our discussion by analyzing the results displayed in Figures 2 to 8, which are the amounts or concentrations of 21 soil attributes. This will be done it in two ways: first, we'll discuss the distribution of these soil traits; afterwards, we'll discuss the vine parcels.

To assess the variability ot these traits across the vineyards we stablished a "variability parameter" calculated from the values from 1 to 5 of the concentration intervals displayed in Figures 2 to 8. As result, only 3 (P, Ca, Zn) out of the 21 measured soil traits had larger variability in Vineyard 1, which is, therefore, much more homogeneous. We note from inspection of Figure 10 that internal variation in altitude is 22 meters in Vineyard 1, and 38 meters in Vineyard 2; together with the fact that measured soil profiles (Section 3.2) in Vineyard 1 are deeper across that vineyard, this points for a possible reason of the larger variability of soil traits in Vineyard 2, since shallower soils in rugged terrain would tend to put the surface in closer contact with deeper horizons and the bedrock, these two zones acting as mineral suppliers.

Some variations in soil traits called our attention. One of the more intense internal variations is for element P in both vineyards, where on Vineyard 1 there is no apparent systematic variation of P with terrain slope or steepness. However, such correlation appears to exist in Vineyard 2, with higher P concentrations being found at lower altitudes even if terrains there are steeper. Clay content is quite homogeneous in Vineyard 1, and varies wildly in Vineyard 2, where we note that the higher concentrations are not associated with higher or lower altitudes, thus rulling out, in a preliminary analysis, possible erosion processes. In the other hand, organic matter (OM) is quite homogeneous across both areas, even if, interestingly, OM content is higher at the higher terrains of Vineyard 2. We also note that some attributes generally more associated with vine management, like P and K (as fertilizers), Cu (as fungicide) and Ca (as lime to control acidity) have either small or equivalent variations in both vineyards.

Analysis of values or concentrations of soil attributes in Figures 2 to 8 was now associated with data from Table 1 and data on NDVI and terrain slopes from Figures10 to 12 in order, presently, to discuss the vine parcels individually. Before proceeding, however, we note that the RGB images displayed in Figure 9 show that in some parts of Vineyard 1 there is a lack of vines, while vine cover in Vineyard 2 seems to be more homogeneous.

Parcel 1 in Vineyard 1 (Cabernet Sauvignon, CS) is relatively flat, is poor in those soil attributes which are considered as macro-nutrients important to vegetation yield (P, K, OM) and has higher acidity. Grape yield itself is average for the estate.

Parcel 2 in Vineyard 1 (CS) is rather uneven but display higher soil attributes. However, grape yield is low. The NDVI image shows large variations in plant vigour.

Parcel 3 in Vineyard 1 (CS) is relatively flat, has high concentrations, NDVI has large variations, and yields are average.

Parcel 4 in Vineyard 1 (Merlot, Me) has a steep slope, has attributes typical of poorer soils, a very low NDVI, and the lowest yield of the studied parcels.

Going now to Vineyard 2, Parcel 5 (Me) seems to have richer soils on a flat, lower terrain with low NDVI. Yields are high.

Parcel 6 in Vineyard 2 (Me) is rather flat with poorer soils and, perhaps for being at a lower position, has a higher NDVI. However, yields are very low.

Parcel 7 in Vineyard 2 (Me) has a higher position, is relatively flat and carries concentrations typical of richer soils. NDVI is lower. Yield is average, and this parcel is described by the owners as being one of the best in quality grapes.

Parcel 8 in Vineyard 2 (Me) is also between the best in quality, having also a high yield. Terrain is high and steep, soil attributes are richer, and NDVI is low.

Parcel 9 in Vineyard 2 (Me) is the highest in the property. Even then, NDVI is higher than in the neighbourhood, soils are rich and yield is the highest.

Finally, Parcel 10 in Vineyard (CS) is the lowest and steepest in this vineyard, soil is richer and with lower acidity, NDVI has large variations, and yelds are quite low. The owners report low quality of grapes from this parcel.

From the above perceptions we make the following considerations:

1. soils of these two estates vary considerably in all the measured parameters, and such variations do not, apparently, seem to be correlated with parcel altitude or steepness. The agitated geological history of this region is possibly responsible for this variation even in very small spatial scales. Across the studied parcels there are many patches were NDVI is low or has large variations.

2. grape quality seems to have no clear correlation with yield, an observation that goes along with what was stated by Matthews (2015), putting in doubt the widely accepted view of “lower yields, better quality”.

3. the large variations in soil attributes, yields, and quality do not, apparently, favor actions toward an uniformization of the estates aiming the production of homogeneous grapes. However, the information presently generated does point to the possibility of defining limited spaces for higher-quality grapes and higher-profitable wines (Bramley and Proffitt, 1999), one of the basis of the concept of precision viticulture.

We feel it would be worth to mention that these findings carry some agreement with what was reported in Thum et al., 2020, a paper that dealt with reflectance data from vine leaf measurements from the same vineyards presently studied. In that paper, it was found that Vineyard 1 could be accurately separated from Vineyard 2 from their leaf reflectance data. Likewise, further studies from the soil reflectance of these two regions, supported by chemical analyses, lends additional weight to the intrinsic differences between the regions (Thum et al., 2021, in submission). Presently we have reported data which reinforces the perception of differences between the two vineyards, with the addition of information on internal variability within each area.

5. Conclusions

We have seen in this study as an ensemble of information, some factual (yields and geology) and some extracted from the terrain (chemical concentrations, vegetation indices, slopes) can be associated to produce a comprehensive picture of a specific área. Cartographical surveys associated with images from UAVs lead to the production of Digital Elevation Models, maps of NDVI and other spatial information which can be used to correlate terrain data with vegetation parameters. Position accuracies at centimeter level can be attained, exceeding the basic requisites of precision agriculture. Additional data on the soil, as chemical concentrations, are also fundamental to assess which directions should be taken on management.

Quantitative descriptions of developing viticultural regions are mandatory requisites for the granting of a formal status of "Viticultural Areas", following different rules in different countries; we cite as examples the norms in Brazil (Tonietto et al., 2016) for geographical indications (G.I), in the United States (Pogue 2017) for recognizing American Viticultural Areas (AVAs) or in Portugal (Miguel-Goméz et al., 2013) for D.O. in the Douro region. It is our hope that the methods presently reported might represent a contribution to the improvement and consolidation of these norms.

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CAPÍTULO 5 – CONSIDERAÇÕES FINAIS

5 CONSIDERAÇÕES FINAIS

Foi apresentado neste estudo um método analítico para detectar a presença e estimar o conteúdo de alguns elementos químicos nas folhas e nos solos de videiras. O método baseia-se em medidas de reflectância não destrutivas e pode ser útil para desenvolvimentos instrumentais com o objetivo de produzir informações dentro do vinhedo em tempo real e sobre as condições da planta de forma simples. Variações no conteúdo mineral são melhor expressas em determinados comprimentos de onda, que são característicos de cada elemento químico analisado.

Os resultados de refletância medida nos solos sugerem que diferenças significativas derivadas em alguns atributos do solo levam a diferenças sistemáticas na refletância que separam espectralmente uma região da outra. A região na qual a investigação foi realizada é um local de intensa agricultura (viticultura), e as áreas de estudo foram selecionadas para destacar as diferenças de solo, evitando assim, a influência de fatores antrópicos, considerando-os mutuamente equivalentes a todas as áreas estudadas. Portanto, os resultados obtidos, mesmo tendo que passar por uma validação adicional, se apresentam potencialmente úteis para a viticultura de precisão ou para outras aplicações agrícolas, no sentido de que aponta para a possibilidade de realização levantamentos espectrais em pequenas áreas que possuem manejo homogêneo, visando detectar variações nos atributos do solo. Os resultados atualmente relatados sugerem que, para alguns atributos do solo, há correlações com níveis de confiança de até 99% entre a concentração química e refletância dentro de alguns domínios de comprimento de onda bem definidos.

A partir da análise de PLRS, foi sugerido que os dados de refletância podem ser usados para prever várias características do solo, para precisões que se comparam bem com aqueles relatados por outros investigadores. No entanto, nenhuma indicação é feita sobre eventuais vantagens de um determinado conteúdo de qualquer atributo do solo na qualidade do solo, ou na qualidade da uva ou do vinho. Os autores estão cientes de que o conceito de "terroir" depende da qualidade do solo para alcançar a chamada "tipicidade do vinho", mas são também cientes de que os descritores que ligam os atributos do solo à qualidade do vinho estão, até a presente data, longe de serem definidos cientificamente. Uma possível maneira de lançar alguma luz sobre esta questão seria procurar conexões entre atributos do solo e refletância da folha da videira, uma investigação que será perseguida em estudos futuros.

O estudo mostra um conjunto de informações reais, como rendimentos e geologia, e algumas extraídas do terreno, como concentrações químicas, índices de vegetação e declives, que podem ser associados para produzir uma imagem abrangente de uma área específica. Levantamentos cartográficos associados a imagens de VANTs levam à produção de Modelos Digitais de Elevação, a mapas de NDVI e a outras informações espaciais que podem ser usadas para correlacionar dados de terreno com parâmetros de vegetação. As precisões de posição ao nível do centímetro foi atingida, excedendo os requisitos básicos da agricultura de precisão. Dados adicionais sobre o solo, como concentrações químicas, também são fundamentais para avaliar quais rumos devem ser tomados no manejo.

Foi possível concluir também que as descrições quantitativas das regiões vitícolas em desenvolvimento são requisitos obrigatórios para a atribuição do estatuto formal de "Zonas Vitícolas", obedecendo a regras diferentes em distintos países; como exemplo, estão as normas no Brasil para Indicações Geográficas (IG).

Esses resultados e o método, conforme apresentado nos artigos, estão sendo relatados pela primeira vez, no entanto, considerando que apenas dois locais foram estudados, e examinado o tamanho da amostra, os resultados atualmente relatados devem ser validados, e aconselham-se experimentos futuros, com base em dados adquiridos em outros locais e em outras épocas do ciclo fenológico.

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APÊNDICE A - TRABALHO APRESENTADO EM CONGRESSO

Thum, A.B.[1]; Carvalho, D.[2]; Ducati,J.R.[2] ; Rolim,S.B.A.[2]

[1]Universidade do Vale do Rio dos Sinos/Universidade Federal do Rio Grande do Sul; [2]Universidade Federal do Rio Grande do Sul

RESUMO: O clima subtropical e úmido, juntamente com altitudes superiores e solos com características basálticas, com noites de temperaturas amenas ou baixas, são fatores que influenciam a produção de uvas na Serra Gaúcha, considerada, atualmente, como sendo a maior e mais importante região vinícola do Brasil, responsável por 85% da produção nacional de vinhos conforme os dados do Instituto Brasileiro do Vinho (IBRAVIN). Os vinhos finos produzidos nessa região possuem grande potencial de mercado devido à sua qualidade. A Indicação Geográfica (IG) é um registro conferido aos produtos ou serviços característicos do local de origem pelo Instituto Nacional de Propriedade Industrial (INPI) e composto por duas modalidades que são a Indicação de Procedência (IP) e a Denominação de Origem (DO). Nas IGs são consideradas as características específicas da região, ou seja, todos os fatores naturais e humanos, construindo o conceito de terroir, que envolve características e qualidades do solo, que sofre influência das rochas, considerando-se ainda o relevo, altitude e temperatura da região, quantidade e regularidade de luz solar, incidência de chuva, vento e umidade e ação humana. O conhecimento dessas características é importante para os vitivinicultores para auxiliar no manejo da produção. Dentre as diversas ferramentas utilizadas para estudar os terroir está o Sensoriamento Remoto. O objetivo do trabalho é utilizar a assinatura espectral dos solos de duas feições geológicas da região de estudo, a fácies Caxias e a fácies Gramado, e verificar se é possível através de análises estatísticas separar o cluster das rochas dos vinhedos, considerando que na faixa do visível até o infravermelho próximo a separabilidade das unidades é dificultada pela falta de feições de absorção bem definida no espectro eletromagnético. As amostras de rochas foram coletas em quatro vinhedos, distribuídos em três municípios. No momento da coleta as amostras foram identificadas e posteriormente levadas até o laboratório da Universidade Federal do Rio Grande do Sul – UFRGS para realizar as medidas. Para as medidas da assinatura espectral utilizou-se o espectrorradiômetro FieldSpec pertencente ao Programa de Pós-Graduação em Sensoriamento Remoto. Esse banco de dados foi utilizado na entrada dos valores de reflectância na análise estatística multivariada. As funções discriminantes canônicas foram usadas para determinar as variáveis independentes e seus respectivos pesos canônicos. A matriz de correlação foi utilizada para o agrupamento das observações. A análise estatística multivariada mostrou-se eficiente no estudo. Através das funções discriminantes canônicas foi possível separar as unidades básicas (o Fácies Caxias), rochas vulcânicas pertencentes à formação Serra Geral.

PALAVRAS-CHAVE: ROCHA, COMPORTAMENTO ESPECTRAL, VINHEDO.

48º CONGRESSO BRASILEIRO DE GEOLOGIA
AS GEOTECNOLOGIAS E O SÉCULO XXI

ANÁLISE MULTIVARIADA DO COMPORTAMENTO ESPECTRAL DE ROCHAS VULCÂNICAS EM QUATRO VINHEDOS

Thum, A.B.[1]; Carvalho, D.[2]; Ducati,J.R.[2] ; Rolim,S.B.A.[2]

[1]Universidade do Vale do Rio dos Sinos/Universidade Federal do Rio Grande do Sul; [2]Universidade Federal do Rio Grande do Sul

INTRODUÇÃO

O clima subtropical e úmido, juntamente com altitudes superiores e solos com características basálticas, com noites de temperaturas amenas ou baixas, são fatores que favorecem a produção de uvas na Serra Gaúcha. Atualmente a Serra gaúcha é considerada a maior e mais importante região vinícola do Brasil, sendo responsável por 85% da produção nacional de vinhos conforme os dados do Instituto Brasileiro do Vinho (IBRAVIN). Os vinhos produzidos nessa região possuem grande potencial de mercado devido à qualidade dos vinhos finos ali produzidos. A Indicação Geográfica (IG) é um registro conferido aos produtos ou serviços característicos do local de origem, pelo Instituto Nacional de Propriedade Industrial (INPI) e composto por duas modalidades que são a Indicação de Procedência (IP) e a Denominação de origem (DO). Na denominação de origem são consideradas as características específicas da região, ou seja, todos os fatores naturais e humanos, atualmente chamado de *terroir*. O *terroir* envolve características e qualidade do solo, o solo que sofre influência das rochas. Considera-se o relevo, altitude e temperatura da região, quantidade e regularidade de luz solar, incidência de chuva, vento e umidade e ação humana. O conhecimento dessas características é importante para os vitivinicultores para auxiliar no manejo da produção. Dentre as diversas ferramentas utilizadas para estudar os *terroir*, o sensoriamento remoto é uma alternativa. Os vinhedos se encontram a maioria na região da Serra, onde temos predomínio de rochas do Fácies Caxias e do Fácies Gramado. O magmatismo Serra Geral é dividido em nove fácies distintos, cinco relacionados ao magmatismo máfico (Fácies Gramado, Paranapanema-Ribeira, Pitanga, Esmeralda, Campo Erê e Lomba Grande) e três ao magmatismo intermediário a félsico (fácies Palmas – mesmas características do Caxias, Chapecó e Alegrete) (Wildner et al., 2005). O objetivo do trabalho é utilizar a assinatura espectral de rochas do fáceis Caxias e do fáceis Gramado e verificar se é possível através de análises estatísticas identificarem o cluster das rochas dos vinhedos, considerando que na faixa do visível até o infravermelho próximo a separabilidade das unidades é dificultada pela falta de feições de absorção bem definida no espectro eletromagnético.

Figure 1. Equipamento e materiais analisados

METODOLOGIA

As amostras de rochas foram coletas em quatro vinhedos, distribuídos em três municípios. No momento da coleta as amostras foram identificadas e posteriormente levadas até o laboratório da Universidade Federal do Rio Grande do Sul – UFRGS para realizar as medidas. Para as medidas da assinatura espectral utilizou-se o espectrorradiômetro FieldSpec pertencente ao Programa de Pós-graduação em Sensoriamento Remoto. A calibração do espectroradiômetro foi realizada a cada medida realizada, tendo como base uma placa de referência de bário, que reflete 100% da incidência da radiação eletromagnética. Os dados de campo foram processados no software ViewSpec Pro, disponibilizado pela $ASD_{Inc.}$ Esse banco de dados foi utilizado na entrada dos valores de reflectância na análise estatística multivariada. As funções discriminantes canônicas foram usadas para determinar as variáveis independentes e seus respectivos pesos canônicos. A matriz de correlação foi utilizada para o agrupamento das observações

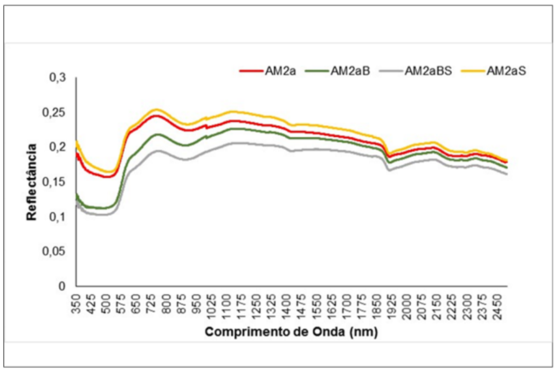

Figure 2. Resposta espectral de algumas das amostras coletadas.

RESULTADO

Das rochas vulcânicas o basalto é a rocha mais importante da crosta terrestre, constituem toda a parte superior da crosta oceânica ao lado de extensas províncias com milhares de quilômetros quadrados em áreas continentais. A caracterização dos diferentes tipos de basalto leva em consideração principalmente os aspectos de alcalinidade, relação entre álcalis e o teor de magnésio. São rochas máficas mais ou menos afaníticas, aparência escura, estrutura maciça, vesicular, amigdaloidal, escoriácea ou celular e com teor variável de fenocristais. A utilização de técnicas de Sensoriamento Remoto tem se mostrado útil no mapeamento e identificação de características e variáveis e que auxiliam no conhecimento das diferenças existentes na mesma vinha e na vitivinicultura de precisão, o que vem a confirmar o que foi descrito por (Bramley et al. 2006). O conhecimento da resposta espectral das rochas utilizando o espectro radiômetro tem sido aplicado para ampliar a biblioteca espectral e como suporte para pesquisas com imagens de satélite. Nas curvas espectrais obtidas aplicou-se técnicas estatísticas que auxiliaram na redução da dimensionalidade dos dados e proporcionou um agrupamento das rochas de forma eficiente. O tratamento mostrou-se adequado na separação de tipos diferentes de rochas com base nos espectros radiométricos. O resultado da análise do comportamento espectral das rochas coletadas e a estimativa da importância das feições de absorção bem como sua posição e forma ao longo do espectro eletromagnético, se feita de modo visual, implica em diferentes graus de subjetividade, já com o emprego de técnicas estatísticas multivariadas além de eliminar qualquer interpretação subjetiva, permite melhor lidar com a dimensionalidade dos dados gerados. Os resultados da pesquisa mostram que os comprimentos de ondas são classificados *a priori* como variáveis independentes. As funções discriminantes canônicas podem e devem ser usadas para determinar as variáveis independentes e seus respectivos pesos canônicos. A matriz de correlação é utilizada para o agrupamento das observações, sabendo-se que as correlações (Diagonal principal da matriz) e as misturas entre classes são demonstradas e avaliadas conforme o índice de acertos, a acurácia global.

CONCLUSÕES

A análise estatística multivariada mostrou-se eficiente no estudo. Através das funções discriminantes canônicas foi possível separar as unidades básicas (o Fácies Caxias), rochas vulcânicas pertencentes a formação Serra Geral.

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