

Contents lists available at [ScienceDirect](http://www.sciencedirect.com/science/journal/03032434)

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

Hydrocarbon micro-seepage detection from airborne hyper-spectral images by plant stress spectra based on the PROSPECT model

Shu[a](#page-0-0)ng Huang^a, Shen[gb](#page-0-2)o Chen^{[a,](#page-0-0)}*, Daming Wang^b, Chao Zhou^{a,[c](#page-0-3)}, F. van [d](#page-0-4)er Meer^d, Yuanzhi Zhang^{[e](#page-0-5),}

^a Jilin University, Faculty of Geo-exploration Science and Technology, Changchun, 130026, China

^b China Geological Survey, Division of Petroleum Geology, Beijing, 100029, China

c National Marine Environmental Monitoring Center, Dalian, 116023, China

^d University of Twente, Faculty of Geo-information Science and Earth Observation, Department of Earth Systems Analysis, Enschede, the Netherlands

^e Chinese Academy of Sciences, National Astronomical Observatories, Laboratory of Lunar Science and Deep-exploration, Beijing, 100101, China

ARTICLE INFO

Keywords: Hydrocarbon micro-seepage Plant stressed spectra PROSPECT model Airborne hyper-spectral imaging

ABSTRACT

Hydrocarbon micro-seepage can result in vegetation spectral anomalies. Early detection of spectral anomalies in plants stressed by hydrocarbon micro-seepage could help reveal oil and gas resources. In this study, the origin of plant spectral anomalies affected by hydrocarbon micro-seepage was measured using indoor simulation experiments. We analyzed wheat samples grown in a simulated hydrocarbon micro-seepage environment in a laboratory setting. The leaf mesophyll structure (N) values of plants in oil and gas micro-seepage regions were measured according to the content of measured biochemical parameters and spectra simulated by PROSPECT, a model for extracting hydrocarbon micro-seepage information from hyper-spectral images based on plant stress spectra. Spectral reflectance was simulated with N, chlorophyll content (C_{ab}) , water content (C_w) and dry matter content (C_m) . Multivariate regression equations were established using varying gasoline volume as the dependent variable and spectral feature parameters exhibiting a high rate of change as the independent variables. We derived a regression equation with the highest correlation coefficient and applied it to airborne hyper-spectral data (CASI/SASI) in Qingyang Oilfield, where extracted information regarding hydrocarbon micro-seepage was matched with known oil-producing wells.

1. Introduction

Subterranean hydrocarbon gases may be traced to their source by locating natural hydrocarbon seepage ([Smith et al., 2004a\)](#page--1-0), gas vents that escape from underlying gas-bearing rock due to partial failure or temporary breach of the top seal, resulting in numerous changes in the rocks and soils through which they pass [\(Meijde et al., 2013;](#page--1-1) [Asadzadeh](#page--1-2) [and de Souza, 2017](#page--1-2)). At the surface, hydrocarbon seepage could be responsible for subtle differences in minerals or vegetation [\(Yang et al.,](#page--1-3) [1998;](#page--1-3) [Yang, 1999;](#page--1-4) [Smith et al., 2005](#page--1-5)). For instance, vegetation growing near hydrocarbon micro-seepage has displayed changes to its geobotany, biochemistry, and reflectance in several studies [\(Lang et al., 1985](#page--1-6); [Pysek and Pysek, 1989;](#page--1-7) [Bammel and Birnie, 1994](#page--1-8); [Yang et al., 1998](#page--1-3); [Yang, 1999;](#page--1-4) [Smith et al., 2000\)](#page--1-9). Detection of early gas seepage could thus help uncover the locations of oil and gas resources ([Scafutto and de](#page--1-10) [Souza, 2016](#page--1-10); [Scafutto et al., 2018](#page--1-11)).

Geophysical methods for oil and gas exploration mainly include

seismic exploration ([Mayerson et al., 2011](#page--1-12); [Howard et al., 2014](#page--1-13)), magnetotelluric methods [\(Zhang et al., 2014](#page--1-14); [Umirova et al., 2016](#page--1-15)), and gravitational and magnetic survey ([Tucker et al., 1985](#page--1-16); [Piskarev,](#page--1-17) [1997\)](#page--1-17). Geochemical exploration extracts hydrocarbon content through the gathering of soil, rock, water, gas, and samples from other media in a range of environments with a view to analyzing anomaly information related to oil and gas [\(Philp and Crisp, 1982;](#page--1-18) [Whittemore, 1995](#page--1-19); [Kotarba et al., 2007](#page--1-20); [Odigi and Amajor, 2010\)](#page--1-21). Comparisons of geophysical and geochemical methods have shown that remote sensing can help detect a wider range of oil and gas seepage ([Lammoglia and de](#page--1-14) [Souza, 2011](#page--1-14), [2012](#page--1-22); [2013\)](#page--1-23).

The vegetation anomalies caused by oil and gas seepage, which can be detected by remote sensing research, have been demonstrated in two primary ways: through indoor simulation experiments and through extraction of data from hyperspectral images. Indoor simulation experiments artificially simulating oil and gas micro-seepage environments were used to research the responses, in vegetation, of

⁎ Corresponding authors.

<https://doi.org/10.1016/j.jag.2018.09.012>

Received 19 July 2018; Received in revised form 19 September 2018; Accepted 20 September 2018 0303-2434/ © 2018 Elsevier B.V. All rights reserved.

E-mail addresses: chensb@jlu.edu.cn (S. Chen), f.d.vandermeer@utwente.nl (F. van der Meer), yuanzhizhang@hotmail.com (Y. Zhang).

biochemical parameters and spectral reflectance to oil and gas seepage ([Smith et al., 2004a](#page--1-0), [b](#page--1-24); [Noomen et al., 2008\)](#page--1-25). Hyperspectral remote sensing data are also widely applied to extract surficial information anomalies linked to oil and gas leakage ([Yang et al., 2000](#page--1-26); [Salati et al.,](#page--1-27) [2014a,](#page--1-27) [b](#page--1-28); [Asadzadeh and de Souza, 2016\).](#page--1-29) An experiment conducted on wheat, soybean, and grass found that the increase of natural gas content in soil inhibits plant growth and decreases chlorophyll content [\(Smith](#page--1-0) [et al., 2004a](#page--1-0)). Spectral responses consisted of reflectance that increased in the visible bands and decreased in the near-infrared bands. Derivative analysis identified features within the red-edge at 720–730 nm and at 702 nm. The ratio of the magnitude of the derivative at 725 nm to that at 702 nm, which was less in areas where gas was present, enabled identification of stress due to gas leakage seven days before visible indicators were apparent, as well as at the edges of gassed plots where changes were not visible ([Smith et al., 2004a](#page--1-0), [b](#page--1-24)). Gas pipeline leaks detected from the stress response of vegetation spectra using remote sensing data were verified by rapeseed spectra subjected to oil and gas and measured by an ASD handheld spectrometer ([Smith et al., 2005](#page--1-5)). As a result of the stress, the red edge position shifted toward shorter wavelengths, with the reflectance centered at 670 nm and 560 nm used to detect increases in red pigmentation in gas-exposed vegetation ([Smith et al., 2005](#page--1-5)). Further experiments were carried out in which maize plants were grown in pots, in which the plants were exposed to gas to test whether natural gas and its two main components, methane and ethane, affect vegetation reflectance in the chlorophyll and water absorption regions ([Yang et al., 1998\)](#page--1-3). Ethane caused an initial increase of 10% in spectral reflectance between 560 nm and 590 nm, as indicated by band depth analysis, followed by a decrease during the experiment. Ethane caused a reflectance shift of 1–5 nm toward longer wavelengths in the visible region, compared to control reflectance assessed by normalized band depth analysis. Methane and ethane also caused an increase in reflectance in the water absorption bands ([Yang,](#page--1-4) [1999;](#page--1-4) [Noomen et al., 2006](#page--1-30)).

The theory of radiative transfer was the basis of vegetation remote sensing [\(Yang et al., 1998;](#page--1-3) [Verhoef, 1998](#page--1-31)). Leaf reflectance and transmittance features in the 400–2500 nm range were simulated by adjusting three input variables: leaf mesophyll structure, chlorophyll content, and water content ([Jacquemoud and Baret, 1990](#page--1-32)). The PRO-SPECT model was used to estimate leaf biochemical compound specific absorption coefficients and to predict chlorophyll and water content ([Fourty et al., 1996\)](#page--1-33). To investigate the PROSPECT model's potential for allowing estimation of leaf biochemistry from space, the reflectance spectra, transmittance spectra, and biochemical and biophysical parameters of 63 fresh leaves and 58 dry leaves were measured. Predictive power changed depending on plant chemistry, with the accuracy of water content inversion found to be 95% on fresh leaves and 54% on dry leaf samples ([Jacquemoud et al., 1996](#page--1-34), [2000\)](#page--1-35), indicating that PROSPECT was influenced by dry matter content. The experiment concluded that the inversion of water and dry matter contents with transmittance is better than that with reflectance [\(Fourty and Baret,](#page--1-36) [1998\)](#page--1-36).

Much recent study has been assessed the utility of high spectral remote sensing technology to detect abnormal vegetation information as a tool for finding underground oil pipeline leaks. To detect potential vegetation stress caused by pipeline leaks, two AVIRIS data sets from oil spill areas were analyzed and the reliability of polynomial fitting, Lagrangian interpolation, and spectral mixture analysis examined [\(Li](#page--1-37) [et al., 2005\)](#page--1-37). Vegetation under the influence of gas seepage showed a red edge "blue shift" that signaled a spill site around a leaking pipeline in a HyMap hyper-spectral image ([Van der Wer](#page--1-38)ff et al., 2007). Red side position (REP) and the Lichtenthaler index (R440/R740) were both used to detect the long-term effects of oil and gas seepage on vegetation. The Lichtenthaler index distinguished between bare soil and vegetation and allowed mapping of all four seeps in the area from a Probe-1 image ([Noomen et al., 2012\)](#page--1-39).

Oil and gas pipeline leaks are usually large and visible; an abnormal

halo diameter is usually tens of meters and accompanied by visual phenomena, such as yellowing of vegetation [\(Bayramov et al., 2012](#page--1-40)). But the distribution of micro-seepage is much less obvious. It may be necessary to detect micro-seepage information from radiative transfer models based on the biochemical parameters of vegetation rather than on visible spectral shifts. Previous research on plants influenced by oil and gas has found certain abnormal phenomena, such as slow growth, decreased chlorophyll content, and red edge "blue shifts", but previous studies focused on spectral changes and changes to biochemical parameters independently, without considering both jointly for analysis applying spectroscopic principles regarding spectral changes ([Yang](#page--1-3) [et al., 1998;](#page--1-3) [Smith et al., 2004a](#page--1-0); [Li et al., 2005](#page--1-37); [Smith et al., 2005](#page--1-5)). That biochemical changes in plants responding to environmental stress can be detected using spectral signatures suggests that it should be possible to locate hydrocarbon micro-seepage sites that are affecting plant biochemistry in their zone of influence.

In this paper, we describe the building of a model based on the stressed vegetation spectra associated with conditions of hydrocarbon micro-seepage that thus allows detection of the locations of oil and gas through analysis of spectral anomalies. This model provided a method for the exploration of oil and gas resources. We used the PROSPECT model to measure wheat spectral anomalies affected by hydrocarbon micro-seepage under laboratory conditions. Plant leaf mesophyll structure and C_{ab} , C_w , and C_m content during simulated oil and gas micro-seepage were key biochemical responses, providing spectral signals as predicted by PROSPECT. This is able to construct a model to extract hydrocarbon micro-seepage information from hyper-spectral images based on plant spectral responses to stress. The regression equation with the highest correlation coefficient between spectral characteristic parameters and the volume of gasoline was applied to extract hydrocarbon micro-seepage data at oil-producing wells in Qingyang Oilfield, China.

2. Theory

2.1. Hydrocarbon micro-seepage theory

Hydrocarbon micro-seepage is a phenomenon whereby gaseous light hydrocarbons, such as methane, ethane, propane, and butane, are generated and migrate almost vertically from subsurface oil/gas reservoirs to the surface ([Rasheed et al., 2012](#page--1-41); [Wu et al., 2014](#page--1-42)). Longterm hydrocarbon micro-seepage can cause a diverse array of mineralogical and chemical changes, including conversion of mixed-layer clays and feldspars to clay minerals, ferric reduction, and an increase in carbonate content [\(Fig. 1](#page--1-43); [Chen et al., 2017\)](#page--1-44).

Vegetation can be affected by natural gas in many ways. When gas is taken up by a plant via its root system, for example, it may be metabolized or passed through the plant in the transpiration stream. Alternatively, it may alter the soil environment so that plant stress is a secondary effect of the leaking gas [\(Smith et al., 2004b](#page--1-24)). An increase of natural gas content in the soil would inhibit the growth of plants and decrease their chlorophyll content [\(Smith et al., 2004a](#page--1-0)).

2.2. The model

PROSPECT model is based on generalized "plate model", which was proposed by Allen ([Allen et al., 1969](#page--1-45)). It is assumed that scattering is described by a spectral refractive index (n) and a parameter characterizing leaf mesophyll structure (N). Absorption is modeled using chlorophyll content (C_{ab}) , water content (C_w) , dry matter content (C_m) , and the corresponding specific spectral absorption coefficients (K) ([Jacquemoud and Baret, 1990](#page--1-32); [Fourty and Baret, 1998\)](#page--1-36). If a leaf is modeled as a rough surface plate, light will scatter isotropically on it. Hemispherical reflectance and transmittance are inverted with a solid angle (Ω) rather than isotropic parallel light [\(Schaepman-Strub et al.,](#page--1-46) [2006\)](#page--1-46). $Ω$ is determined by the maximum incidence angle $(α)$ relative to Download English Version:

<https://daneshyari.com/en/article/11028670>

Download Persian Version:

<https://daneshyari.com/article/11028670>

[Daneshyari.com](https://daneshyari.com)