REMOTE DETERMINATION OF MARTIAN CHLORIDE SALT ABUNDANCES.

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Abstract

Chloride salt-bearing deposits are widely distributed across the southern highlands of Mars. Because chloride salts are highly water-soluble, these deposits may be representative of the last significant period of stable liquid water at the Martian surface. Therefore, these deposits are key to understanding the fate and evolution of surface waters on Mars. Yet, little consensus exists about the formation conditions of these deposits, and their origins remain enigmatic. This is due in part because remote spectroscopic detection and quantification of many chlorides is hampered by a lack of easily discernible diagnostic absorption features. To address this issue, we present a novel Hapke radiative transfer model (RTM)-based method to estimate hydration states and salt abundances of Martian chloride salt-bearing deposits using visible/near-infrared (VNIR) reflectance spectra. VNIR laboratory spectra are used to derive water abundances of analog chloride-bearing materials, establishing an experimental basis for application of these methods to Mars. These methods are then applied to orbital Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) data to create maps of hydration state and modeled salt abundance of chloride-bearing deposits. When overlain onto high resolution 3D digital terrain models (DTMs), these methods produce the highest resolution, site-specific salt abundance maps currently available, enabling new discoveries and understanding of geologic context. As an example, deposits in the Terra Sirenum region are observed to have higher estimated salt abundances than previously recognized, exhibiting spatial variations in both abundance and surface morphology.

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Key Points:

1. Lab measurements of Mars simulant-halite mixtures were made to calculate water abundances specific to chloride bearing deposits on Mars.
2. Updated fitting parameters are used to derive hydration states and subsequently model chloride salt abundances using CRISM data.
3. Abundance maps show generally higher salt abundances of chloride salt deposits than previously determined.

Abstract

Chloride salt-bearing deposits are widely distributed across the southern highlands of Mars. Because chloride salts are highly water-soluble, these deposits may be representative of the last significant period of stable liquid water at the Martian surface. Therefore, these deposits are key to understanding the fate and evolution of surface waters on Mars. Yet, little consensus exists about the formation conditions of these deposits, and their origins remain enigmatic. This is due in part because remote spectroscopic detection and quantification of many chlorides is hampered by a lack of easily discernible diagnostic absorption features. To address this issue, we present a novel Hapke radiative transfer model (RTM)-based method to estimate hydration states and salt abundances of Martian chloride salt-bearing deposits using visible/near-infrared (VNIR) reflectance spectra. VNIR laboratory spectra are used to derive water abundances of analog chloride-bearing materials, establishing an experimental basis for application of these methods to Mars. These methods are then applied to orbital Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) data to create maps of hydration state and modeled salt abundance of chloride-bearing deposits. When overlain onto high resolution 3D digital terrain models (DTMs), these
methods produce the highest resolution, site-specific salt abundance maps currently available, enabling new discoveries and understanding of geologic context. As an example, deposits in the Terra Sirenum region are observed to have higher estimated salt abundances than previously recognized, exhibiting spatial variations in both abundance and surface morphology.

Plain Language Summary

Hundreds of chloride salt deposits are found across the southern-highlands region of Mars. Because chloride salts are highly water-soluble these deposits likely formed during the last time liquid water was on the surface of Mars. Therefore, studying these deposits may provide important clues about when, and the conditions under which, liquid water was last stable on Mars. There is little agreement on how these deposits form largely because satellite detection of many chloride salts is difficult. To address this issue, we present a new model to estimate water and salt abundances of Martian chloride salt-bearing deposits using visible/near-infrared (VNIR) spectroscopy. Lab spectra are used to derive water abundances of analog chloride-bearing materials, which are then applied to data from Mars to create maps of hydration state and modeled salt abundance of chloride-bearing deposits. When combined with high resolution 3D digital terrain models (DTMs), these methods produce the highest resolution, site-specific salt abundance maps currently available, enabling new discoveries and understanding of the geology surrounding deposits. From these maps we observe a higher estimated salt abundance than previously observed.
1. Introduction

Chloride salt bearing deposits are widely distributed across the southern highlands crust of Mars (e.g., Osterloo et al. 2008; 2010; Murchie et al., 2009, Glotch et al., 2010). Multiple studies have used remote compositional analyses of data from the Mars Odyssey Thermal Emission Imaging System (THEMIS) (Christensen et al., 2004), Mars Global Surveyor Thermal Emission Spectrometer (TES) (Christensen et al., 2001), and Mars Reconnaissance Orbiter Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) (Murchie et al., 2007) instruments to identify hundreds of these deposits (Osterloo et al., 2008; 2010; Murchie et al., 2009; Glotch et al., 2010) (Figure 1). Due to their high solubility in liquid water, chloride salts may represent the last period of stability of liquid water in the Martian surface environment (Davila et al., 2011; Hynek et al., 2015; Leask & Ehlmann, 2022). Therefore, understanding how these deposits formed is crucial to our understanding of Mars’ hydrological past. To date, the fate of surface liquid water and timing of its disappearance are poorly constrained (Bibring et al., 2006; Ehlmann & Edwards, 2014).

Various hypotheses for chloride salt deposit formation mechanisms, deposition ages, and the hydrological constraints on their brine forming environments have been suggested in prior work, however, no broad consensus on provenance has been reached (Osterloo et al. 2008; 2010; Glotch et al., 2010; 2016; Davila et al., 2011; Ruesch et al., 2012; El-Maary et al., 2013, Hynek et al., 2015; Melwani-Daswani & Kite, 2017; Leask & Ehlmann et al., 2022; Mitra et al., 2022). Many studies have suggested the formation of chloride salts from ponding of surface water runoff and/or upwelled groundwater and subsequent evaporation. Formation in Noachian-Hesperian shallow lacustrine environments was suggested by Osterloo et al., (2008; 2010), Ruesch et al. (2012), and El-Maary et al. (2013). Meanwhile, deep lacustrine environments were suggested by
Davila et al., (2011), Hynek et al. (2015), and Melwani-Daswani & Kite (2017), during the late Noachian to early Hesperian transition. Melwani-Daswani & Kite (2017) suggested Noachian-Hesperian aged lacustrine formation with chloride salts sourced from volcanically degassed HCl deposition and/or dissolution of igneous chlorapatite. Water for this process would have been sourced from shallow groundwater transport and surface water runoff. In contrast, Leask & Ehlmann (2022) proposed late Hesperian to early Amazonian formation from shallow ponding by surface water runoff related to episodic obliquity change-induced meltwater runoff. Mitra et al., (2022) hypothesized an active halogen cycle involving the reduction of oxyhalogen species (e.g., chlorates and perchlorates) to chloride by redox-sensitive elements like iron and manganese in surface water or groundwater systems. The subsequent evaporation or freezing of the chloride-containing solution could produce chloride deposits. Due to the high solubility of chloride salts, determining the origin of these deposits is difficult as they may form and be transported at any point when liquid water is stable. This could also indicate active cycling of chloride salts with multiple instances of chloride dissolution, transport, and re-deposition as some recent studies have suggested (Leask & Ehlmann, 2022; Mitra et al., 2022). High resolution maps of chloride abundance in these deposits could greatly improve our understanding of their bulk composition and how it varies within and between sites. However, the general lack of diagnostic absorption features in reflectance and emissivity spectra of many chloride salts make this challenging.

In this paper we describe a novel quantitative model developed for application to CRISM data that provides maps of hydration state (bulk water content) and chloride abundance for chloride-bearing deposits on Mars. First, we describe lab experiments used to establish a methodology to derive water content of chloride salt mixtures based on visible/near-infrared (VNIR) reflectance spectra using a Hapke radiative transfer model (RTM) (Hapke, 1981; 2012)-
based approach similar to that of Milliken & Mustard (2005). This pipeline is then applied to CRISM data to create hydration state and chloride salt abundance maps (Section 3.2.3). Finally, we showcase some potential future applications of these abundance maps combined with high-resolution digital terrain models (DTMs), which provide detailed geomorphological context of salt deposits.

![Figure 1: Global map (MDIM Viking colorized mosaic (Williams, 2010)) showing THEMIS chloride detections (black polygons) from Osterloo et al. (2010). CRISM images used for this paper are located in Terra Sirenum (black dashed line rectangle), those used for maps shown in this paper are depicted as red triangles. Close-up locations of CRISM images used to showcase chloride mapping products in this paper are shown overlain on a high resolution CTX global mosaic (credit: NASA/JPL/MSSS/The Murray Lab).](image)

### 2. Background and Motivation:

A major limiting factor in our understanding of chloride-bearing deposits is the difficulty of their spectroscopic detection. Anhydrous chlorides lack discernible diagnostic absorption
features in the VNIR (~1-4 µm) and mid-infrared (MIR) (~8-12 µm) wavelength regions (Osterloo et al., 2008; Murchie et al., 2009; Glotch et al., 2010; 2016; Jensen & Glotch, 2011; Ye & Glotch, 2019). Despite the lack of diagnostic absorptions, these materials possess unique spectral properties that can be used as proxies for their identification (Osterloo et al. 2008; 2010; Jensen & Glotch, 2011; Glotch et al., 2016; Ye & Glotch, 2019). At VNIR wavelengths, spectra of Martian chloride-bearing deposits lack narrow vibrational absorptions, exhibit red (positive) spectral slopes relative to surrounding terrain, and exhibit a weak or nearly absent 3 µm OH/H2O feature (Murchie et al., 2009; Jensen & Glotch, 2011; Glotch et al., 2016; Ye & Glotch, 2019) (Figure 2). When ratioed to spectra of the surrounding basaltic regolith, spectra of chloride deposits show an inverted (positive) 3 µm feature. This is consistent with the deposits being composed primarily of basaltic regolith mixed with nominally anhydrous chloride salt, resulting in a lower bulk hydration than that of the surrounding terrain (Osterloo et al., 2010; Jensen & Glotch, 2011; Murchie et al., 2009) (Figure 2).

**Figure 2:** Left: False-color composite (bands 304,122,41) CRISM Map Projected Targeted Reduced Data Record (MTRDR) observation FRT0000A941 covering a chloride bearing deposit (appears yellow/tan in composite). Right: CRISM spectra of chloride bearing unit (box 1), surrounding regolith (box 2) and ratio spectra showing characteristic inverted 3µm water absorption feature.
Prior analyses have primarily utilized data from the THEMIS instrument to characterize chloride salt deposits (Osterloo et al., 2008; 2010; Glotch et al., 2010; 2016). CRISM provides higher spatial (18-36 m/px) and spectral resolution than THEMIS (~100 m/px) (Figures 2 & 3). While THEMIS has been a crucial tool for the detection of chlorides, mineral quantification using THEMIS data is difficult due to its limited spectral resolution. Previous abundance estimates by Glotch et al. (2016) provided a general range from spectral matching rather than providing a quantitative model from which salt abundances are calculated. With its higher spectral and spatial resolution, CRISM data can potentially provide more reliable abundance estimates through

**Figure 3:** A) CRISM chloride salt abundance map created from CRISM image FRT0000A941 in Terra Sirenum. Salt abundance map was resized, co-registered, and overlain on CTX observation ESP_005811_1476. B) Decorrelation Stretch (DCS) image of a subsection of THEMIS observation I43011002 corresponding to region shown in A (outlined in dashed white rectangle). Note correlation between blue regions in DCS (interpreted as chlorides) and areas of high CRISM salt abundances. C) THEMIS spectra of interpreted chloride bearing (blue in DCS, square 1) terrain and surrounding regolith (magenta in DCS, square 2). Regions of mapped high salt abundance, which correlate to DCS mapped blue regions show characteristic “blue” slope shape in THEMIS spectra.
quantitative modeling (Section 3.2.3). CRISM modeled abundance maps also provide abundance
estimates at each pixel within the image, allowing for site-specific abundance estimates with a
higher granularity than possible with THEMIS.

Laboratory studies on the optical and spectral properties of hydrated minerals can provide
important analogues for understanding the spectra of similar materials on planetary surfaces.
Milliken & Mustard (2005) and Milliken (2006) performed an empirical analysis of the variability
of spectral parameters/indices as a function of water content for a variety of Mars relevant minerals
(e.g., mafic alteration products, zeolites, clay minerals, glasses, and some sulfates). One key
finding in that work was a linear correlation between water content and the effective single particle
absorption thickness (ESPAT) parameter (Hapke, 2012). In this paper, we present experimental
results that build on these prior experimental studies (Milliken & Mustard, 2005; 2007a; 2007b;
Milliken, 2006; Milliken et al., 2007), creating a suite of binary mixtures of halite and Mars soil
simulant that serve as analogs for chloride salt-bearing deposits on Mars. We provide updated
ESPAT-to-water content fitting parameters that are tailored for chloride salt-bearing mixtures.
These relationships are then used to derive salt abundances using CRISM imagery. We provide
new constraints on the hydration states and salt abundances of chloride salt-bearing deposits on
Mars using this new method. To understand the geologic implications of these updated abundances
we present a series of abundance maps overlaid onto DTMs created from higher resolution imaging
datasets (MRO Context Camera (CTX) (Malin et al., 2007) and the High-Resolution Imaging
Science Experiment (HiRISE) (McEwen et al., 2007), which together provide crucial geologic
context. We present CRISM salt map/DTM overlays that may represent distinct chloride salt
depositional environments in Terra Sirenum. These range from smaller localized perched deposits
within regional topographic lows to extensive, flat, indurated deposits. Analysis of these products
across Mars could be valuable in constraining chloride formation mechanisms, and potential future
directions are discussed further in Section 5.

3. Materials and Methods

3.1 Laboratory Work

To emulate the spectral properties of chloride salt-bearing deposits on Mars we created a
suite of binary mixtures using Exolith Labs Mars Global Simulant (MGS-1) (Cannon et al., 2019)
and Alfa Aesar spectroscopy-grade halite (Table 1). We choose MGS-1 as it approximates the
integrated physical, chemical, mineralogical, and spectral properties of Martian regolith (Cannon
et al., 2019). We chose halite as previous studies suggest halite as the major chloride on Mars
(Bridges & Grady, 2000; Jensen & Glotch, 2011; Glotch et al., 2016; Melwani-Daswani & Kite,
2017; Leask & Ehlmann, 2022). We created mixtures of different salt abundances that ranged from
one to eighty weight percent (Table 1). Each of the mixtures was placed in a vacuum furnace (at
T~180°C) and allowed to dry overnight to remove any atmospherically contributed water before
collecting spectra.
Reflectance spectra for each of the mixtures and pure endmembers were collected over the 0.36-3.9 µm range to provide spectra over the spectral range of CRISM (Murchie et al., 2007) (following the methods of Milliken & Mustard (2005)). VNIR reflectance spectra over the 0.36 – 2.5 µm wavelength range were collected using an Analytical Spectral Device (ASD) FieldSpec3 Max spectrophotometer and referenced to a calibrated Spectralon plate. We used a Nicolet 6700 Fourier transform infrared (FTIR) spectrometer equipped with the biconical diffuse reflectance accessory to collect spectra in the 1-3.9 µm range. A CaF$_2$ beam splitter, DTGS detector, and Globar IR source were used while acquiring these data. A diffuse gold plate was used as the reference spectrum to obtain calibrated diffuse reflectance spectra. All FTIR spectra were collected under a steady flow of extra dry nitrogen gas to purge the sample chamber and to maintain a dry environment. The samples were kept in the chamber for several minutes under the flow of nitrogen gas before spectra were collected to allow any remnant weakly bound surface adsorbed H$_2$O to be purged before data collection.

Spectral data from both instruments were combined to provide spectra over the entire wavelength range mentioned above. To do so, the FTIR data were corrected using a multiplicative factor in the overlapping wavelength range to match reflectance values observed in the ASD.

<table>
<thead>
<tr>
<th>Mix ID</th>
<th>Wt.% MGS-1</th>
<th>Wt.% Halite</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMGS2-Mix1</td>
<td>99</td>
<td>1</td>
</tr>
<tr>
<td>CMGS2-Mix2*</td>
<td>95</td>
<td>5</td>
</tr>
<tr>
<td>CMGS2-Mix3</td>
<td>90</td>
<td>10</td>
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<tr>
<td>CMGS2-Mix4</td>
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<td>CMGS2-Mix6</td>
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<td>CMGS2-Mix8</td>
<td>40</td>
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</tr>
<tr>
<td>CMGS2-Mix9</td>
<td>30</td>
<td>70</td>
</tr>
<tr>
<td>CMGS2-Mix10</td>
<td>20</td>
<td>80</td>
</tr>
</tbody>
</table>

Table 1: List of Halite-MGS-1 binary mixture suite. Note Mix 2 was created but was not measured by TGA due to sample loss during transit to TGA. Mixes shown in light red (Mixes 3, 4, and 10) are assumed outliers (see sections 4.1-4.2).
spectra. The data were corrected to the ASD values as Spectralon provides a more accurate spectral reference than diffuse gold. Finally, we splice the ASD spectra to the corrected FTIR spectra to create a continuous spectrum over the 0.36-3.9 µm range.

Each sample in the suite is an intimate mixture between MGS-1 and halite. Therefore, each mixture spectrum does not behave as a linear mixture of its component endmember spectra (Mustard & Pieters, 1987; 1989; Hapke, 1981; 2012; Keshava & Mustard, 2002; Mustard & Glotch, 2019). To minimize effects of viewing geometry and multiple scattering, each reflectance spectrum was converted to units of single-scattering albedo (SSA) using the Hapke RTM (Hapke, 2012). To convert to units of SSA, we calculated surface scattering according to Hapke’s (1981, 2012) reflectance factor ($r_f$) equation.

$$r_f(i, e, g) = \frac{\omega}{4 \mu_0 + \mu} \left[ 1 + B(g) P(g) + H(\mu_0, \omega)H(\mu, \omega) - 1 \right]$$

$r_f$ is a function of the viewing geometry dependent on the incidence angle ($i$), the emergence angle ($e$), and the phase angle ($g$). Here, $\omega$ is SSA, which is solved using a look-up table approach. A set viewing geometry was used for all spectral measurements ($i = 30^\circ$, $e = 0^\circ$, and $g = 30^\circ$). $B(g)$ is the term to model the opposition effect. Since this is only a major factor for phase angles less than $20^\circ$, we adopt the assumption that $B(g)=0$. The H-function describes the multiple scattering of light. The exact solution of the H-function is an integral equation dependent on $\omega$, $\mu_0$ (the cosine of the incidence angle), and $\mu$ (the cosine of the emission angle). Following the approach of Hapke (2012), in this study it is approximated by:

$$H(x, \omega) = \frac{1}{1 - (1 - \gamma) x} \frac{1}{r_0 + (1 - 0.5 r_0 - r_0 x) \ln \left( \frac{1 + \gamma}{x} \right)}$$

where $x$ is either $\mu_0$ or $\mu$, $\gamma = \sqrt{1 - \omega}$, and $r_0 = \frac{1 - \gamma}{1 + \gamma}$. We assumed that the surface scatters isotropically and therefore the $P(g)$ function (phase function at $g$) is set equal to 1. These
assumptions are adequate approximations for simple applications of the Hapke theory (e.g., Mustard and Pieters, 1989).

Once spectra were converted to units of SSA we removed the effects of the spectral continuum and focused on the 3 μm water band depth by performing a linear continuum removal over the 1.8-3.9 μm region. Using the continuum-removed SSA spectra, we calculated the ESPAT parameter using equation 3 (Hapke, 2012).

\[ ESPAT(\lambda) = \frac{1-\omega(\lambda)}{\omega(\lambda)} \] (3)

Empirical work by Milliken & Mustard (2005) showed that ESPAT parameter values centered around the 3 μm water absorption band (at 2.9 and 3.1 μm) showed a strong linear correlation to wt.% water for a wide range of hydrated samples. Therefore, we can use Hapke’s model to convert a reflectance spectrum to SSA, calculate the ESPAT value at the wavelength of interest (Equations 1-3), and use an empirically derived linear relationship between ESPAT and wt.% H₂O to derive water abundance estimates for a given mixture.

However, the work presented in Milliken & Mustard (2005) and Milliken (2006) was done mostly for monomineralic samples (palagonite being an exception), and it did not include chloride salts. As the ESPAT parameter is dependent on the optical properties of the individual reflecting grains there is likely some variability in how it is correlated to water content in chloride salt-bearing mixtures. Therefore, to assess ESPAT-H₂O trends that are more appropriate for our suite of chloride mixtures we performed our own assessment of these relationships using our lab data.

The water content of each sample was independently measured using thermogravimetric analysis (TGA). TGA measurements were performed using a Mettler TGA/DSC 3+ instrument located at Rice University. We placed each sample in a vacuum furnace at 180 °C overnight to remove loosely bound/surface adsorbed water. Aliquots of each sample, including endmembers,
were then transferred to an airtight silica ampule before being shipped for measurement. TGA measurements were made using ~5 mg of each sample in a platinum pan over a temperature range of 50-1000 °C with a temperature ramp of 10 °C/min under a dry N\textsubscript{2} environment. Water loss from each sample primarily occurs in the 400-600 °C temperature range (Plante et al., 2009; Derkowski & Kuligiewicz, 2022) and weight loss up to this temperature is inferred as the water content for each of our samples. We assume that nearly all volatile content of our samples is water. The line of best fit between TGA measured wt.% H\textsubscript{2}O and ESPAT were used to update linear curve fitting parameters to be reflective of chloride-salt bearing deposits. These parameters and fitting relationships are used in Section 3.2.3 to estimate water content and salt abundances of chloride salt-bearing deposits from CRISM data.

3.2 Orbital Data Analysis:

3.2.1 CRISM data acquisition and calibration

The approach outlined in Section 3.1 creates a framework wherein water abundance values can be estimated from VNIR spectra using the Hapke RTM. As mentioned in Section 2, a characteristic feature of Martian chloride deposits is that they appear desiccated relative to surrounding basaltic regolith, as is apparent in the difference in their 3 μm water absorption feature (Figure 2). We utilize this variability to estimate salt abundance from CRISM data. The CRISM instrument acquires VNIR hyperspectral images covering the 0.36-3.9 μm wavelength range (Murchie et al., 2007). The CRISM images used for this study have a spatial resolution ranging between 18-36 m/pixel and a spectral sampling of 6.55 nm (Murchie et al., 2007). Using the JMARS software suite (Christensen et al., 2009) we identified CRISM Full Resolution Targeted
images overlapping regions in Terra Sirenum where chlorides were detected by Osterloo et al. (2010) and then downloaded them from the Planetary Data System (PDS). These CRISM images are in units of apparent surface I/F (the radiance detected by the instrument divided by the solar irradiance divided by π) and not in units of SSA needed to use our pipeline. To atmospherically correct these images and convert them to units of surface SSA, we used the Discrete Ordinate Radiative Transfer (DISORT) model (Stamnes et al., 1988). Full details of the implementation and application of this model to CRISM data are provided by Liu et al. (2016) and Zastrow and Glotch. (2021).

Many images were found to contain significant noise, striping, and residual atmospheric and sensor artifacts that occlude spectral signatures of interest. These artifacts and striping were found to persist through our preliminary analyses. Therefore, we applied a noise correction using factor analysis/target transformation (Thomas and Bandfield, 2017) which is described in Section 3.2.2. Once corrected, we apply the approach outlined in Section 3.2.3 to obtain hydration state and salt abundances from each scene.

3.2.2 Noise Removal: Factor Analysis/Target Transformation

Much of the processed DISORT corrected imagery was found to contain significant amounts of residual artifacts and noise, which were mitigated using the FA/TT method (Thomas & Bandfield, 2017). This method has been used previously to correct noisy data in the 1-2.5 µm range, and for target mineral detection (Liu et al., 2016; Thomas and Bandfield, 2017; Tarnas et al., 2019; 2021; Lin et al., 2021). However, this method has not been applied on CRISM imagery in the wavelength range past 2.6 µm. Since our analyses focus on water band depth in this region, we apply this technique on the data in a subset of wavelengths focused on this range.
The FA/TT method involves a two-step process: 1) factor analysis, in which the algorithm identifies the number of independently varying spectral components (eigenvectors) comprising the signal subspace of the CRISM SSA spectra, estimated using the Hysime algorithm (Bioucas-Dias & Nascimento, 2008), and 2) target transformation, in which linear combinations of the individual spectral components are used to produce an output spectrum resembling the target spectrum. Visual inspection of fit along with statistical measures such as root mean square error (RMSE) and adjusted R-squared values are used to assess the quality of fit between the target transform and the target spectra.

In our implementation we began by applying a 5 band 1-D moving boxcar filter on the spectra of each pixel, over the entire wavelength range. We extracted the first 10 eigenvectors from the smoothed CRISM SSA data using the Hysime algorithm (similar to Thomas & Bandfield, 2017; Liu et al., 2016). We then used the average spectrum of the entire scene along with the extracted eigenvectors as the independently varying spectral components for the target transformation. We used a constrained linear least squares (CLLSQ) fitting model (all components add to 1 and each component is multiplied by an abundance fraction between -1 and 1) with the eigenvectors and average scene spectrum as inputs. The final solution of the CLLSQ provides fractional abundances of each spectral component that can be used to reconstitute the image using only the first 10 eigenvectors and the scene average spectrum. If we assume that the first 10 eigenvectors contain the majority of the important spectral information within the CRISM SSA cube and that the other eigenvectors contain primarily noise, the reconstituted image should have a substantially reduced noise component. The CLLSQ abundance fractions are used to reconstitute the image using the eigenvectors and scene average and then various metrics are used to judge the effectiveness of the noise removal. The reconstituted noise removed image is compared visually
against the original DISORT-corrected SSA image. We inspected for loss of data or removal of geomorphological features. If noise removal resulted in the loss of these features, the noise removal was either performed again using a greater number of eigenvectors or the image was discarded. We also compared the scene average SSA spectra between the noise removed image and the original. We performed visual fit inspection and calculated RMSE. If the average SSA spectra were found to have a low RMSE value and a high degree of visual fit, especially around the 3 µm water absorption feature, we considered the noise removal successful. If the visual and/or statistical metrics yielded a poor fit the noise removal was either performed again using more eigenvectors or the image was discarded. An example of our noise removal method applied to CRISM imagery over a chloride salt deposit is shown in Figure 4. In this paper we present four representative CRISM derived hydration state and chloride salt abundance maps in Terra Sirenum to showcase our method and its potential future applications.

Figure 4: Figure depicting noise removal from CRISM data using Factor Analysis and Target Transformation (FA/TT). Panel A shows original DISORT corrected CRISM SSA image (at 3.0 µm band) and panel B shows the noise corrected CRISM SSA image. Note the removal of striping and overall improvement in visual quality of the data.
3.2.3 CRISM Data Analysis Workflow

After atmospheric removal and noise correction, we used an approach similar to that used for the laboratory spectra (Section 3.1) to obtain water abundance estimates from the CRISM data. The spectra for each pixel of the corrected images were continuum removed over the 3 μm water absorption band. ESPAT values at 2.9 μm for each pixel were then obtained using the continuum removed image cube. We chose the 2.9 μm band to be consistent with Milliken & Mustard (2005) who also used this wavelength. Further, we found that derived water abundances vary negligibly with choice of a specific band center for the water absorption band between 2.9-3.1 μm (See supplementary Figure S1). Therefore, our method is agnostic to the choice of the 3 μm water absorption band center. Once ESPAT values were calculated at each pixel, we used the linear fitting parameters that we empirically derived in Section 3.1. to calculate the water content at each pixel.

These water content maps are used to estimate salt content. To do so, we make a few simplifying assumptions. First, we assume that Martian chloride salt deposits are mixtures of an anhydrous salt such as halite and the regional basaltic regolith (Glotch et al., 2016). Secondly, we assume halite has negligible water associated with it, and therefore should not have a significant 3-micron feature. That is, the presence of halite acts to dilute the total water content of the bulk material. In our calculations we assume the densities of basalt to be 2.9 g/cm³ and halite to be 2.16 g/cm³ and assume that these values are representative of the materials present on the Martian surface. The calculation of the salt content from water content maps relies on the above assumptions and the difference in calculated water abundance between the chloride deposits and the regional basaltic regolith present in the scene.
The derived water abundance at each pixel of a Martian chloride deposit is the sum of the water contents of halite and the basaltic regolith in the CRISM scene multiplied by their fractional abundances:

\[ H_2O_{\text{Deposit}} = H_2O_{\text{halite}} \times f_{\text{halite}} + H_2O_{\text{basalt}} \times f_{\text{basalt}} \]

Since we assume that \( H_2O_{\text{halite}} \) is approximately zero, we can simplify the equation and solve for the fractions of basalt or halite:

\[ f_{\text{halite}} = 1 - f_{\text{basalt}} = 1 - \frac{H_2O_{\text{Deposit}}}{H_2O_{\text{basalt}}} \]

Here, \( f_{\text{halite}} \) is the fraction of halite and the \( H_2O_{\text{Deposit}} \) is the derived water abundance of the salt deposit, while \( H_2O_{\text{basalt}} \) is the average water abundance of the surrounding basaltic regolith. The value of \( H_2O_{\text{basalt}} \) is obtained by averaging the water content for a cluster of pixels in each scene that are representative of the average value of water content for the regolith surrounding a chloride deposit.

The above equation provides the areal fractions of halite or basalt derived from remote sensing measurements that are sensitive to the top several hundreds of micrometers of the regolith/deposit surface. If we assume that the surface areal fractions are reliably representative of volumetric abundances to some depth, then we can calculate the mass fractions of each component using assumed densities of halite and basalt using this equation:

\[ m_{f_{\text{halite}}} = \frac{\rho_{\text{halite}} \times v_{f_{\text{halite}}}}{(\rho_{\text{halite}} \times v_{f_{\text{halite}}}) + (\rho_{\text{basalt}} \times v_{f_{\text{basalt}}})} \]

Where \( m_{f_{\text{x}}}, v_{f_{\text{x}}}, \) and \( \rho_{\text{x}} \) are the mass fraction, volumetric abundance, and density of each phase. Our assumption of the areal fractions representing the volumetric abundances to some depth is likely to produce some error. Whether this assumption produces an over- or underestimate of true salt abundances would likely be influenced by the formation conditions of the salt deposits. For
example, if the deposit surfaces are efflorescent crusts or were formed as a floatation crust from evaporating brines, the surface fractions are likely higher than at depth. For highly eroded deposits however, it is possible that at greater depth abundances are higher than observed on the surface.

3.2.4 Salt Map-DTM Overlay Processing.

Our processing pipeline is a novel method to create high-resolution hydration state and salt abundance maps using CRISM data. While these data products are useful in mapping abundances and observing variation across a CRISM scene, these maps alone do not provide significant geomorphologic context for the chloride bearing deposits and their surroundings. To get a better sense of the 3D-geomorphologic context of these deposits we created salt abundance maps overlain onto DTMs generated from high-resolution imagery (Figures 8 and 10).

We used the Ames stereo-pipeline (Moratto et al., 2010) and the MarsSI online tool (Quantin-Nataf et al., 2018) to process DTMs from one HiRISE stereo pair and three CTX stereopairs that overlap with the CRISM imagery used to produce salt abundance and hydration state maps shown above. HiRISE orthorectified imagery provides 25 cm/pixel resolution while HiRISE DTMs provide 1m/pixel resolution and is the highest resolution available for Mars. However, HiRISE stereo-pairs are limited in availability and only a few HiRISE stereopairs exist over detected chloride salt bearing deposits. CTX images provide ~6 m/pixel spatial resolution and associated DTMs have a 24 m/pixel resolution. There is greater coverage of CTX stereopairs overlapping chloride salt deposits and processing times are shorter.
4. Results

4.1 Laboratory spectra of chloride bearing mixtures

Reflectance spectra of each of the chloride mixtures are shown in Figure 5a, SSA spectra are shown in Figure 5b, continuum removed SSA spectra are shown in Figure 5c, and continuum removed SSA spectra convolved to CRISM spectral sampling over the CRISM L wavelength range (1-3.9 µm) are shown in Figure 5d. An overall trend is apparent in the 3.0 µm water absorption band. As salt content increases (salt content increases from mix 1-10), the water absorption becomes shallower. In our spectra, mixes 3 and 4 appear to be outliers, falling off trend of shallowing 3µm water absorption feature with increasing salt content. They also fall off trend in our TGA analysis (section 3.1), and in our plots of band depth vs. salt content. Therefore, we
treated them as outliers for this study (see section 4.2. for further rationale) and removed them from further analyses.

4.2 TGA Measured Water Contents vs. Spectral Data

Figure 6A shows TGA-measured volatile loss of each sample which we assume as the absolute water content for each of our samples. Water content is expected to decrease as salt
content increases in our mixtures. This is generally true except for mixes 3, 4, and 10. Mixes 3 and 4 were assumed outliers based on their spectra, and going forward we also assume mix 10 as an outlier based on TGA observations. There are many potential sources of error in TGA measurement. For one, the MGS-1 simulant contains many minor components and is a non-uniform heterogeneous mixture (Cannon et al., 2017). Different aliquots of MGS used in the mixture could contain different hydrated components that could lead to disparate water contents being measured. The TGA measurements are made in a dry N₂ environment, however trace amounts of water in the N₂ flow could also be a source of error.

After removing these apparent outlier mixtures from the sample suite, the spectra fall on trend with shallowing 3µm water absorption features and band depth (Fig. 6B), and the TGA measured water contents decrease as salt content increases as is expected from prior spectral analyses (Osterloo et al., 2010; Glotch et al., 2010; 2016). Spectra of the non-outlier mixes, and

**Figure 6:** A) Plot of TGA volatile loss (~ wt.% water in samples) vs. Halite Content for the mixture suite. Outliers are plotted in red. Red trend-line shows trend using all mixtures while blue trend line shows best linear fit using outlier-removed data points. Fitting is significantly improved when using blue data points. B) shows the continuum removed SSA spectra of non-outlier mixtures. Note a clear trend in the 3 µm water absorption band: as salt content increases in the mixture the 3µm water absorption shallows. These combined observations were used to deem Mix 3, 4, and 10 from our data set as outliers.
the fitting relationships between their ESPAT values and TGA derived water abundances are shown in Figures 6 and 7.

The linear fit generated in our work differs from that in Milliken et al. (2005; 2007). We compared these parameters when used to derive water abundances from spectra of our mixtures. We find that parameters in Milliken et al. (2005; 2007) provide higher estimates of water content, especially when using fitting relationships for the 3.0 µm band. We find that our fitting relationships do not produce derived water abundances that vary significantly with choice of band center in the 2.9 - 3.1 µm range over the water absorption band. When derived water abundances are compared to TGA-derived water abundances, we observe similarly that using the fitting relationships in Milliken et al. provide an overestimate of water content (see slopes in Fig. 7). Therefore, our fitting relationships provide a more accurate estimate of water content from spectra for chloride-bearing mixtures compared with those of Milliken et al. (2005; 2006; 2007) for primarily monomineralic and highly hydrated phases.
Figure 7. A) ESPAT vs TGA Volatile Loss (assumed wt.% water) at 2.9 µm and derived fitting relationship with errors. B) ESPAT vs TGA volatile loss at 3.0 µm and derived fitting relationship with errors. Derived water abundance variation using ESPAT-$H_2O$ fitting relationships derived in Milliken et al., (2005;2007) (old) vs. those derived in A) and B) (new) at 2.9 µm (C) and 3.0 µm (D) (new). TGA derived volatile loss vs. DWA using both sets of parameters and their associated slopes. Slopes indicate how well fitting parameters predict water abundances from spectra.
4.3 Water content and Salt Abundance Maps.

Hydration state maps and chloride abundance maps for four CRISM images (FRT00010A4E, FRT0000A941, FRT00007431, and FRT0000A253) produced using the pipeline outlined in Section 3.2.3 are shown in Figure 8. To validate the model, CRISM abundance maps were compared against THEMIS decorrelation stretched (DCS) images (DCS maps were created using THEMIS bands 8,7,5) that were used previously to detect chlorides (Osterloo et al., 2008; 2010; Glotch et al., 2010). Regions appearing in blue in THEMIS DCS imagery have a characteristic blue sloping spectra in their corresponding THEMIS images, which is consistent with a mixture of chloride salt and a silicate component in MIR data (Osterloo et al., 2008; 2010; Glotch et al., 2010). High salt abundance regions in CRISM derived salt abundance maps appear well correlated with regions appearing blue in THEMIS DCS imagery (Figure 2), and their corresponding THEMIS spectra show the characteristic “blue” slope. Further, we observe regions in the DCS imagery that appear blue-green that correlate well with regions of intermediate salt content in CRISM produced salt abundance maps, which have THEMIS spectra that are consistent with a mixture of chloride salt with a higher relative silicate component.
Figure 8. A-D hydration state maps produced using CRISM images FRT00010A4E, FRT00007431, FRT0000A253, FRT0000A941 respectively overlain onto overlapping CTX/HiRISE imagery. All images used are in the Terra Sirenum region. E-H are the corresponding modeled salt abundance maps. Notice variation in salt abundances. In some cases, we see large-laterally extensive deposits with high salt abundances E/H. G shows lower abundances localized in pitted terrains specifically on the slopes of regional topographic lows.
To discern the sensitivity of hydration state and salt abundance maps to the choice of ESPAT-\textsubscript{H$_2$O} fitting relationships we produced these maps using both our fitting relationships and those used in Milliken et al. (2005; 2007) (Figure 9). We found that hydration state maps were appreciably sensitive to the choice of fitting relationships, but salt abundance maps were not. Our

**Figure 9:** Figure showing variation in Map products when using fitting parameters generated from our lab work (new) vs. those published in Milliken et al., (2005; 2007) (old). All map products shown here were created using CRISM observation FRT0000A253 and overlain onto CTX observation CTX_007446_1477_043616_1477A1. A noticeable lowering of water abundance is observed when using our parameters vs. those in Milliken et al. Differences are primarily observed in the surrounding basaltic regolith rather than in the salt deposits. Variation in salt abundances is however comparatively negligible.
fitting relationships generate a lower hydration state estimate than estimates generated by fitting relationships in Milliken & Mustard (2005) and Milliken et al., 2007 (Fig. 9). The lower derived hydration states when using our fitting relationships is uniform across the image (i.e., all pixels appear to have lower hydration states, rather than a specific unit or region). Calculated salt abundance depends primarily on the ratio of the water content of the salt-bearing regions to the surrounding regional basaltic regolith (see Section 3.2.3). This ratio remains largely unchanged regardless of choice of fitting relationships. Therefore, we find that there is no significant difference between salt abundance maps.

4.4 Error Analysis.

Salt abundance values are dependent on the choice of water abundance value from the surrounding regolith (Section 3.2.3). As mentioned in Section 3.2.3 this value is determined by averaging hydration state values over a square region of interest (ROI) encompassing many pixels. The ROIs selected are chosen over regions that correlate to basaltic regolith in corresponding CRISM map-projected MTRDR map products. In choosing ROIs we ensure that there is no spectral evidence of other mineral phases and hydrated components (such as ice or hydrated minerals such as clays, sulfates, etc.). However, some variability in derived water abundances of the surrounding regolith can be observed in the hydration state maps (Figure 8). To assess the degree to which salt abundance calculations are sensitive to this variability we performed a sensitivity analysis. For each CRISM image we chose three similarly sized square ROIs over different patches of surrounding basaltic regolith and used their average values to calculate salt abundances (Section 3.2.3) (Figure 10). We also calculated the mean of the hydration states from the three ROIs and calculated the salt abundances using this mean value. To better observe
resulting variability we calculated the differences at each pixel between these test salt abundance
maps and the salt abundance maps shown in Figure 8.

As expected, the estimated salt abundances vary depending on the choice of ROI (Figure
10). In images where there is little variability in the hydration state of the surrounding regolith, we
find only nominal differences (typically <5 %) in calculated salt abundances based on choice of
ROI. However, where there is a greater degree of variability in the hydration state and/or fewer
regions to select larger ROIs for surrounding regolith, the variability was higher (up to 10-12%
variability in salt abundance in select regions). Overall, we observe the most variability outside of
the salt deposits in the surrounding regolith (where the salt abundances are very low). This is likely
a result of variability in the water abundances in different regions of the surrounding basaltic
regolith. The variability caused by the choice of ROI, however, has a much lower effect on the
determined salt abundances within the salt deposits (on average <5%). Other factors such as
elevation, improper atmospheric artifact removal, and surface roughness could also account for
this variability. To assess this variability outside of the salt deposits we masked the salt deposits
and calculated the mean and standard deviation of the calculated salt abundances outside of the
salt deposits (see supplementary S1). For each image we found that the mean calculated salt
abundance outside of the salt deposit area was 2-8 wt.%. For these regions, ascribed salt
abundances are likely an artifact of the method used to determine salt abundances rather than true
abundances. Therefore, salt abundances calculated using this method is likely most reliable when
looking at abundances clearly within regions which can clearly be defined as a salt deposit while
the minor salt abundances determined outside of the salt deposits are generally not reliable.

Therefore, variability in the hydration states of the surrounding regolith is a potential
source of error in the use of this method. However, variability as a result of this is nominal and
within the bounds of reasonable error. Most reliable abundance maps will be produced where there is little variability in the hydration state of the regolith surrounding the salt deposits. For regions with greater variability, using an averaged value that captures the variability of hydration state of the surrounding deposits may produce a more reliable abundance estimate.

Figure 10. Variability in calculated salt abundance maps based on choice of ROIs used to determine average basalt water content. A-D shows difference in salt abundance based on choice of ROI for CRISM image FRT0000A941. A-C are using the average value of three different similarly sized ROIs selected in different regions across the image (approximate locations are depicted by red stars). D is using the mean value of each ROI average value to account for spatial heterogeneity. Differences are calculated by subtracting salt abundance maps created for Figure 8 to those created using ROIs shown here. E-H is a similar analysis done for CRISM image FRT00010A4E. Variability is image dependent and depends on the variability encountered in hydration states across the image. Variability is relatively low in all cases, with the greatest variability typically encountered in the outside of the salt deposit. For A-H the relatively low variability is encountered in the salt deposit with most variability typically observed outside of the deposit. Greater variability is observed in E-H, likely due to a greater degree of variability in the hydration states of the surrounding basaltic regolith.
Our mapping method relies on hydration state constraints from remote sensing data. Prior hydration state constraints from remote sensing data were designed using spectral data of a limited sample suite (Milliken & Mustard, 2005; 2007a; 2007b; Milliken, 2006; Milliken et al., 2007). Prior mapping methods have provided an invaluable method of global mapping of Mars’ water content (Milliken et al., 2007; Jouglet et al., 2007; Audouard et al., 2014) but were grounded in laboratory studies that do not represent the mineralogic diversity that has since been detected from orbital and landed missions on Mars in the past two decades (Murchie et al., 2009; Ehlmann & Edwards, 2014; Seelos et al., 2023). The fitting parameters used to estimate the surface water abundance published in these studies are likely best representative of only certain surface compositions of Mars where the mineralogy is primarily composed of the materials that were used in Milliken & Mustard, (2005; 2007a; 2007b), Milliken (2006) Milliken et al. (2007). We find that hydration state estimates can vary depending on the materials being mapped. In the work presented here, a marked difference is apparent when using chloride deposit-specific fitting parameters designed with the mineralogy of the units being mapped in mind, compared to the fitting parameters used in prior studies. One major factor that affects the derived ESPAT-H$_2$O fitting relationships is the particle size of the materials (Milliken & Mustard, 2007b). As particle size increases, the ESPAT-H$_2$O positive slope is known to decrease (Milliken & Mustard, 2007b). Therefore, an increase in particle size of measured materials would lead to a lower estimated hydration state. To account for particle size effect, Milliken et al. (2007) provided fitting relationships for two particle size ranges (<45 µm and 125-250 µm). However, it is important to note that these relationships were still derived for individual minerals rather than mixtures. The materials used in our lab studies are an aggregation of various particle sizes, which is likely to be
encountered on the Martian surface (Cannon et al., 2017). The MGS-1 consists of materials with a variety of particle size ranging from fine grain materials (<10 µm) to coarser glass beads and rock fragments (>500 µm) (Cannon et al., 2017). The MGS-1 simulant was then mixed with fine grained halite (<45 µm) to produce our samples. Therefore, the larger overall grain size of the measured materials could explain why the derived water abundances in our study are lower than when parameters published in Milliken & Mustard (2005) and Milliken et al. (2007) are used. The grain sizes of the materials we used in our lab work however are likely a better representation of the grain sizes of chloride deposit materials encountered on the surface of Mars. Use of fitting parameters that are specifically tailored to the physical properties and mineralogy of the units being mapped is warranted for improved accuracy of hydration state maps, especially on a more localized scale. However, it is also important to note that the improvement in hydration states estimates is fairly small and are within typical reasonable bounds of error that would be expected when making such measurements from orbit (in most cases difference in hydration state estimates are typically between ~1-5 wt.%). We suggest that, where known, the surface mineralogy should be considered and new fitting parameters that are specific to the observed surface composition should be used to provide the most accurate hydration state estimates of that locale. In that vein, our work provides a more accurate representation of water abundance estimates for chloride bearing regions on Mars.

While there has been significant investigation of chloride salt deposits on Mars (Osterloo et al, 2010; Glotch et al., 2010; Hynek et al., 2015; Mehwani-Daswani & Kite, 2017; Leask & Ehlmann, 2022) no quantitative high-resolution chloride abundance maps of these deposits exist. Little work has been done to fully leverage higher resolution spectral data sets such as CRISM, which can provide more reliable abundance estimates through quantitative modeling. Therefore, the mapping method presented here fills a crucial gap in high-resolution abundance maps of
chloride deposits on Mars. This mapping method can be used to produce modeled abundance maps using CRISM images, which have widespread coverage on Mars, and hundreds of CRISM images exist overlapping chloride salt deposits identified by THEMIS data (Leask & Ehlmann, 2022; Das et al., 2023). Previous abundance estimates using THEMIS by Glotch et al. (2016) provided a general range from spectral matching rather than providing a quantitative model from which salt abundances maps are calculated. CRISM-derived products have the additional benefit of having a significantly higher spatial resolution than THEMIS (18-36 m/pixel vs ~100 m/pixel). The abundance mapping method presented in this paper allows for site-specific abundance estimates with a higher granularity than possible with THEMIS.

Salt abundances determined using the method outlined here are higher (typically between 30-50 wt.% with some localized regions with abundances up to 75-80 wt.%) than those estimated in prior studies using THEMIS data (10-25 wt.%) (Glotch et al., 2016). One possible source of this discrepancy is the difference in depth of penetration of VNIR wavelengths compared to TIR. VNIR light is sensitive to the upper 100s of nm to 10s of µm of the surface while TIR wavelengths are sensitive to a comparatively greater depth (top 10-100s of µm). Higher detected salt abundances may result from induration (chloride salt deposits are likely indurated based on thermal inertia measurements (Osterloo et al., 2010)) or due to the formation of a salt crust during deposition. If these deposits formed in an evaporative setting it is possible that a salt crust was formed which may cause a higher abundance detected at very surface of the deposits. Abundance estimates in Glotch et al., were made by comparing laboratory TIR spectra of analog materials to single THEMIS spectra of a limited number of chloride deposits (8 deposits). Grain size effects in the TIR region could also have caused some uncertainty in salt abundance determination, especially in regions with higher dust cover.
Figure 11 shows two salt map-DTM overlay products, one created using HiRISE and one using CTX. These overlay products are a valuable resource for answering broader questions of chloride provenance, which is the subject of ongoing work (Das et al., 2023). These high-resolution products can be used to resolve important geologic features that cannot be resolved using coarser-resolution CRISM data alone. The overlay products in Figure 11 show substantial

![Figure 11. Example of salt map DTM overlays (Both have a vertical exaggeration of 7x). A) is an overlay created using HiRISE imagery, saltmap was generated using CRISM image FRT00010A4E overlayed onto HiRISE DTM (dteec_047413_1410_003160_1410_a01). This overlay exhibits large laterally extensive indurated chloride deposit in regional low-lying terrain. B shows a more localized smaller-scaled deposits with higher abundance centered around the slopes of regional topographic lows/pitted terrains. Saltmap was created using CRISM Image FRT0000A253 and DTM was created using CTX stereopairs (CTX_007446_1477 and CTX_043616_1477).](image-url)
variation in the morphology of the salt deposits within Terra Sirenum alone. These range from extensive, flat, indurated deposits (Fig. 11A) with high salt abundances to smaller localized deposits perched on regional topographic lows (Fig. 11B). This observed diversity in salt abundances and depositional environment may indicate disparate formation scenarios. Mapping of chloride salts across Mars using the method outlined in this paper can provide new, more detailed, site-specific constraints on chloride deposit abundance, abundance variation, hydration state, and surrounding geomorphology.

Further, DTM overlay products can be used to interpret potential water source pathways, observe geologic features of interest (e.g., channels, deltaic features, faults, etc.), constrain precursor pond/lake volumes, estimate salt deposit thicknesses, and generate total salt volume estimates. These constraints can be used to assess the feasibility of hypothesized formation mechanisms and/or be used to formulate new ones. Global scale mapping of chloride salt deposits and analysis of overlay products would greatly improve our understanding of these enigmatic deposits and is the subject of ongoing work (Das et al., 2023; 2024).

6. Conclusions.

Understanding the aqueous history of Mars is a key goal of Mars exploration. Chloride deposits represent a valuable way through which we can reconstruct Mars’ hydrologic past. Constraining formation mechanisms and ages will help better constrain the last instances of stable liquid water, hypotheses for which range from the late-Noachian to early Hesperian to periodic occurrences extending into the Amazonian. This study outlines a novel method of mapping chloride salt abundances using CRISM data. Updated lab-derived fitting parameters to estimate hydration states from remote sensing data specific to chloride-bearing regions on Mars are
presented. We then showcase a pipeline to use these lab-derived parameters to CRISM data and obtain hydration state and modeled salt abundance maps. We find that updated fitting parameters lowers hydration state estimates compared to Milliken et al. (2007). In this paper we present the first CRISM-derived modeled salt abundance maps along with high resolution DTM overlay products. These products are the first of a kind and are the highest resolution salt abundance maps produced yet. DTM overlay products show great promise and could provide an extensive global-scale view of chloride salt deposits on Mars. Further work assessing the geomorphological context of these enigmatic deposits, their variability across the widespread regions in which they occur is of immense value.

Future work combining observations of geomorphological variation, mass balance constraints from DTM products, and geochemical models of chloride brine forming environments would greatly benefit constraints on chloride formation mechanisms and in-turn the stability of liquid water on Mars.
Open Research

CRISM FRT, MTRDR, and DDR, CTX Stereo Pairs, and HiRISE DTM data were collected from the Planetary Data System’s Geosciences Node (https://pds-geosciences.wustl.edu/). Some CTX and HiRISE data used in this work were processed with the MarsSI (marssi.univ-lyon1.fr) application. THEMIS data were collected from the ASU Mars Space Flight Facility website (https://viewer.mars.asu.edu/viewer/themis#T=0). CRISM, CTX, HiRISE and THEMIS data were identified using JMARS (https://jmars.asu.edu/). Processed data including hydration state maps, salt abundance maps, DTMs, ROIs, lab data etc. and codes used in this work is available on our Zenodo repository (https://zenodo.org/doi/10.5281/zenodo.11391245).

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References


REMOTE DETERMINATION OF MARTIAN CHLORIDE SALT
ABUNDANCES.

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Key Points:

- Lab measurements of Mars simulant-halite mixtures were made to calculate water abundances specific to chloride bearing deposits on Mars.
- Updated fitting parameters are used to derive hydration states and subsequently model chloride salt abundances using CRISM data.
- Abundance maps show generally higher salt abundances of chloride salt deposits than previously determined.

Abstract

Chloride salt-bearing deposits are widely distributed across the southern highlands of Mars. Because chloride salts are highly water-soluble, these deposits may be representative of the last significant period of stable liquid water at the Martian surface. Therefore, these deposits are key to understanding the fate and evolution of surface waters on Mars. Yet, little consensus exists about the formation conditions of these deposits, and their origins remain enigmatic. This is due in part because remote spectroscopic detection and quantification of many chlorides is hampered by a lack of easily discernible diagnostic absorption features. To address this issue, we present a novel Hapke radiative transfer model (RTM)-based method to estimate hydration states and salt abundances of Martian chloride salt-bearing deposits using visible/near-infrared (VNIR) reflectance spectra. VNIR laboratory spectra are used to derive water abundances of analog chloride-bearing materials, establishing an experimental basis for application of these methods to Mars. These methods are then applied to orbital Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) data to create maps of hydration state and modeled salt abundance of chloride-bearing deposits. When overlain onto high resolution 3D digital terrain models (DTMs), these
methods produce the highest resolution, site-specific salt abundance maps currently available, enabling new discoveries and understanding of geologic context. As an example, deposits in the Terra Sirenum region are observed to have higher estimated salt abundances than previously recognized, exhibiting spatial variations in both abundance and surface morphology.

Plain Language Summary

Hundreds of chloride salt deposits are found across the southern-highlands region of Mars. Because chloride salts are highly water-soluble these deposits likely formed during the last time liquid water was on the surface of Mars. Therefore, studying these deposits may provide important clues about when, and the conditions under which, liquid water was last stable on Mars. There is little agreement on how these deposits form largely because satellite detection of many chloride salts is difficult. To address this issue, we present a new model to estimate water and salt abundances of Martian chloride salt-bearing deposits using visible/near-infrared (VNIR) spectroscopy. Lab spectra are used to derive water abundances of analog chloride-bearing materials, which are then applied to data from Mars to create maps of hydration state and modeled salt abundance of chloride-bearing deposits. When combined with high resolution 3D digital terrain models (DTMs), these methods produce the highest resolution, site-specific salt abundance maps currently available, enabling new discoveries and understanding of the geology surrounding deposits. From these maps we observe a higher estimated salt abundance than previously observed.
1. **Introduction**

Chloride salt bearing deposits are widely distributed across the southern highlands crust of Mars (e.g., Osterloo et al. 2008; 2010; Murchie et al., 2009, Glotch et al., 2010). Multiple studies have used remote compositional analyses of data from the Mars Odyssey Thermal Emission Imaging System (THEMIS) (Christensen et al., 2004), Mars Global Surveyor Thermal Emission Spectrometer (TES) (Christensen et al., 2001), and Mars Reconnaissance Orbiter Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) (Murchie et al., 2007) instruments to identify hundreds of these deposits (Osterloo et al., 2008; 2010; Murchie et al., 2009; Glotch et al., 2010) (Figure 1). Due to their high solubility in liquid water, chloride salts may represent the last period of stability of liquid water in the Martian surface environment (Davila et al., 2011; Hynek et al., 2015; Leask & Ehlmann, 2022). Therefore, understanding how these deposits formed is crucial to our understanding of Mars’ hydrological past. To date, the fate of surface liquid water and timing of its disappearance are poorly constrained (Bibring et al., 2006; Ehlmann & Edwards, 2014).

Various hypotheses for chloride salt deposit formation mechanisms, deposition ages, and the hydrological constraints on their brine forming environments have been suggested in prior work, however, no broad consensus on provenance has been reached (Osterloo et al. 2008; 2010; Glotch et al., 2010; 2016; Davila et al., 2011; Ruesch et al., 2012; El-Maary et al., 2013, Hynek et al., 2015; Melwani-Daswani & Kite, 2017; Leask & Ehlmann et al., 2022; Mitra et al., 2022). Many studies have suggested the formation of chloride salts from ponding of surface water runoff and/or upwelled groundwater and subsequent evaporation. Formation in Noachian-Hesperian shallow lacustrine environments was suggested by Osterloo et al., (2008; 2010), Ruesch et al. (2012), and El-Maary et al. (2013). Meanwhile, deep lacustrine environments were suggested by
Davila et al., (2011), Hynek et al. (2015), and Melwani-Daswani & Kite (2017), during the late Noachian to early Hesperian transition. Melwani-Daswani & Kite (2017) suggested Noachian-Hesperian aged lacustrine formation with chloride salts sourced from volcanically degassed HCl deposition and/or dissolution of igneous chlorapatite. Water for this process would have been sourced from shallow groundwater transport and surface water runoff. In contrast, Leask & Ehlmann (2022) proposed late Hesperian to early Amazonian formation from shallow ponding by surface water runoff related to episodic obliquity change-induced meltwater runoff. Mitra et al., (2022) hypothesized an active halogen cycle involving the reduction of oxyhalogen species (e.g., chlorates and perchlorates) to chloride by redox-sensitive elements like iron and manganese in surface water or groundwater systems. The subsequent evaporation or freezing of the chloride-containing solution could produce chloride deposits. Due to the high solubility of chloride salts, determining the origin of these deposits is difficult as they may form and be transported at any point when liquid water is stable. This could also indicate active cycling of chloride salts with multiple instances of chloride dissolution, transport, and re-deposition as some recent studies have suggested (Leask & Ehlmann, 2022; Mitra et al., 2022). High resolution maps of chloride abundance in these deposits could greatly improve our understanding of their bulk composition and how it varies within and between sites. However, the general lack of diagnostic absorption features in reflectance and emissivity spectra of many chloride salts make this challenging.

In this paper we describe a novel quantitative model developed for application to CRISM data that provides maps of hydration state (bulk water content) and chloride abundance for chloride-bearing deposits on Mars. First, we describe lab experiments used to establish a methodology to derive water content of chloride salt mixtures based on visible/near-infrared (VNIR) reflectance spectra using a Hapke radiative transfer model (RTM) (Hapke, 1981; 2012)-
based approach similar to that of Milliken & Mustard (2005). This pipeline is then applied to CRISM data to create hydration state and chloride salt abundance maps (Section 3.2.3). Finally, we showcase some potential future applications of these abundance maps combined with high-resolution digital terrain models (DTMs), which provide detailed geomorphological context of salt deposits.

**Figure 1:** Global map (MDIM Viking colorized mosaic (Williams, 2010)) showing THEMIS chloride detections (black polygons) from Osterloo et al. (2010). CRISM images used for this paper are located in Terra Sirenum (black dashed line rectangle), those used for maps shown in this paper are depicted as red triangles. Close-up locations of CRISM images used to showcase chloride mapping products in this paper are shown overlain on a high resolution CTX global mosaic (credit: NASA/JPL/MSSS/The Murray Lab).

2. **Background and Motivation:**

A major limiting factor in our understanding of chloride-bearing deposits is the difficulty of their spectroscopic detection. Anhydrous chlorides lack discernible diagnostic absorption
features in the VNIR (~1-4 µm) and mid-infrared (MIR) (~8-12 µm) wavelength regions (Osterloo et al., 2008; Murchie et al., 2009; Glotch et al., 2016; Ye & Glotch, 2019). Despite the lack of diagnostic absorptions, these materials possess unique spectral properties that can be used as proxies for their identification (Osterloo et al. 2008; 2010; Jensen & Glotch, 2011; Ye & Glotch, 2019). At VNIR wavelengths, spectra of Martian chloride-bearing deposits lack narrow vibrational absorptions, exhibit red (positive) spectral slopes relative to surrounding terrain, and exhibit a weak or nearly absent 3 µm OH/H$_2$O feature (Murchie et al., 2009; Jensen & Glotch, 2011; Glotch et al., 2016; Ye & Glotch, 2019) (Figure 2). When ratioed to spectra of the surrounding basaltic regolith, spectra of chloride deposits show an inverted (positive) 3 µm feature. This is consistent with the deposits being composed primarily of basaltic regolith mixed with nominally anhydrous chloride salt, resulting in a lower bulk hydration than that of the surrounding terrain (Osterloo et al., 2010; Jensen & Glotch, 2011; Murchie et al., 2009) (Figure 2).

Figure 2: Left: False-color composite (bands 304,122,41) CRISM Map Projected Targeted Reduced Data Record (MTRDR) observation FRT0000A941 covering a chloride bearing deposit (appears yellow/tan in composite). Right: CRISM spectra of chloride bearing unit (box 1), surrounding regolith (box 2) and ratio spectra showing characteristic inverted 3µm water absorption feature.
Prior analyses have primarily utilized data from the THEMIS instrument to characterize chloride salt deposits (Osterloo et al., 2008; 2010; Glotch et al., 2010; 2016). CRISM provides higher spatial (18-36 m/px) and spectral resolution than THEMIS (~100 m/px) (Figures 2 & 3). While THEMIS has been a crucial tool for the detection of chlorides, mineral quantification using THEMIS data is difficult due to its limited spectral resolution. Previous abundance estimates by Glotch et al. (2016) provided a general range from spectral matching rather than providing a quantitative model from which salt abundances are calculated. With its higher spectral and spatial resolution, CRISM data can potentially provide more reliable abundance estimates through

Figure 3: A) CRISM chloride salt abundance map created from CRISM image FRT0000A941 in Terra Sirenum. Salt abundance map was resized, co-registered, and overlain on CTX observation ESP_005811_1476. B) Decorrelation Stretch (DCS) image of a subsection of THEMIS observation I43011002 corresponding to region shown in A (outlined in dashed white rectangle). Note correlation between blue regions in DCS (interpreted as chlorides) and areas of high CRISM salt abundances. C) THEMIS spectra of interpreted chloride bearing (blue in DCS, square 1) terrain and surrounding regolith (magenta in DCS, square 2). Regions of mapped high salt abundance, which correlate to DCS mapped blue regions show characteristic “blue” slope shape in THEMIS spectra.
quantitative modeling (Section 3.2.3). CRISM modeled abundance maps also provide abundance estimates at each pixel within the image, allowing for site-specific abundance estimates with a higher granularity than possible with THEMIS.

Laboratory studies on the optical and spectral properties of hydrated minerals can provide important analogues for understanding the spectra of similar materials on planetary surfaces. Milliken & Mustard (2005) and Milliken (2006) performed an empirical analysis of the variability of spectral parameters/indices as a function of water content for a variety of Mars relevant minerals (e.g., mafic alteration products, zeolites, clay minerals, glasses, and some sulfates). One key finding in that work was a linear correlation between water content and the effective single particle absorption thickness (ESPAT) parameter (Hapke, 2012). In this paper, we present experimental results that build on these prior experimental studies (Milliken & Mustard, 2005; 2007a; 2007b; Milliken, 2006; Milliken et al., 2007), creating a suite of binary mixtures of halite and Mars soil simulant that serve as analogs for chloride salt-bearing deposits on Mars. We provide updated ESPAT-to-water content fitting parameters that are tailored for chloride salt-bearing mixtures. These relationships are then used to derive salt abundances using CRISM imagery. We provide new constraints on the hydration states and salt abundances of chloride salt-bearing deposits on Mars using this new method. To understand the geologic implications of these updated abundances we present a series of abundance maps overlaid onto DTMs created from higher resolution imaging datasets (MRO Context Camera (CTX) (Malin et al., 2007) and the High-Resolution Imaging Science Experiment (HiRISE) (McEwen et al., 2007), which together provide crucial geologic context. We present CRISM salt map/DTM overlays that may represent distinct chloride salt depositional environments in Terra Sirenum. These range from smaller localized perched deposits within regional topographic lows to extensive, flat, indurated deposits. Analysis of these products
across Mars could be valuable in constraining chloride formation mechanisms, and potential future
directions are discussed further in Section 5.

3. Materials and Methods

3.1 Laboratory Work

To emulate the spectral properties of chloride salt-bearing deposits on Mars we created a
suite of binary mixtures using Exolith Labs Mars Global Simulant (MGS-1) (Cannon et al., 2019)
and Alfa Aesar spectroscopy-grade halite (Table 1). We choose MGS-1 as it approximates the
integrated physical, chemical, mineralogical, and spectral properties of Martian regolith (Cannon
et al., 2019). We chose halite as previous studies suggest halite as the major chloride on Mars
(Bridges & Grady, 2000, Jensen & Glotch, 2011; Glotch et al., 2016; Melwani-Daswani & Kite,
2017; Leask & Ehlmann, 2022). We created mixtures of different salt abundances that ranged from
one to eighty weight percent (Table 1). Each of the mixtures was placed in a vacuum furnace (at
T~180°C) and allowed to dry overnight to remove any atmospherically contributed water before
collecting spectra.
Reflectance spectra for each of the mixtures and pure endmembers were collected over the 0.36-3.9 µm range to provide spectra over the spectral range of CRISM (Murchie et al., 2007) (following the methods of Milliken & Mustard (2005)). VNIR reflectance spectra over the 0.36 – 2.5 µm wavelength range were collected using an Analytical Spectral Device (ASD) FieldSpec3 Max spectrophotometer and referenced to a calibrated Spectralon plate. We used a Nicolet 6700 Fourier transform infrared (FTIR) spectrometer equipped with the biconical diffuse reflectance accessory to collect spectra in the 1-3.9 µm range. A CaF₂ beam splitter, DTGS detector, and Globar IR source were used while acquiring these data. A diffuse gold plate was used as the reference spectrum to obtain calibrated diffuse reflectance spectra. All FTIR spectra were collected under a steady flow of extra dry nitrogen gas to purge the sample chamber and to maintain a dry environment. The samples were kept in the chamber for several minutes under the flow of nitrogen gas before spectra were collected to allow any remnant weakly bound surface adsorbed H₂O to be purged before data collection.

Spectral data from both instruments were combined to provide spectra over the entire wavelength range mentioned above. To do so, the FTIR data were corrected using a multiplicative factor in the overlapping wavelength range to match reflectance values observed in the ASD

<table>
<thead>
<tr>
<th>Mix ID</th>
<th>Wt.% MGS-1</th>
<th>Wt.% Halite</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMGS2-Mix1</td>
<td>99</td>
<td>1</td>
</tr>
<tr>
<td>CMGS2-Mix2*</td>
<td>95</td>
<td>5</td>
</tr>
<tr>
<td>CMGS2-Mix3</td>
<td>90</td>
<td>10</td>
</tr>
<tr>
<td>CMGS2-Mix4</td>
<td>80</td>
<td>20</td>
</tr>
<tr>
<td>CMGS2-Mix5</td>
<td>70</td>
<td>30</td>
</tr>
<tr>
<td>CMGS2-Mix6</td>
<td>60</td>
<td>40</td>
</tr>
<tr>
<td>CMGS2-Mix7</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>CMGS2-Mix8</td>
<td>40</td>
<td>60</td>
</tr>
<tr>
<td>CMGS2-Mix9</td>
<td>30</td>
<td>70</td>
</tr>
<tr>
<td>CMGS2-Mix10</td>
<td>20</td>
<td>80</td>
</tr>
</tbody>
</table>

Table 1: List of Halite-MGS-1 binary mixture suite. Note Mix 2 was created but was not measured by TGA due to sample loss during transit to TGA. Mixes shown in light red (Mixes 3, 4, and 10) are assumed outliers (see sections 4.1-4.2).
spectra. The data were corrected to the ASD values as Spectralon provides a more accurate spectral reference than diffuse gold. Finally, we splice the ASD spectra to the corrected FTIR spectra to create a continuous spectrum over the 0.36-3.9 µm range.

Each sample in the suite is an intimate mixture between MGS-1 and halite. Therefore, each mixture spectrum does not behave as a linear mixture of its component endmember spectra (Mustard & Pieters, 1987; 1989; Hapke, 1981; 2012; Keshava & Mustard, 2002; Mustard & Glotch, 2019). To minimize effects of viewing geometry and multiple scattering, each reflectance spectrum was converted to units of single-scattering albedo (SSA) using the Hapke RTM (Hapke, 2012). To convert to units of SSA, we calculated surface scattering according to Hapke’s (1981, 2012) reflectance factor ($r_f$) equation.

$$r_f(i, e, g) = \frac{\omega}{4 \mu_0 + \mu} \left\{ [1 + B(g)] P(g) + H(\mu_0, \omega) H(\mu, \omega) - 1 \right\}$$  \hspace{1cm} (1)$$

$r_f$ is a function of the viewing geometry dependent on the incidence angle ($i$), the emergence angle ($e$), and the phase angle ($g$). Here, $\omega$ is SSA, which is solved using a look-up table approach. A set viewing geometry was used for all spectral measurements ($i = 30^\circ$, $e = 0^\circ$, and $g = 30^\circ$). $B(g)$ is the term to model the opposition effect. Since this is only a major factor for phase angles less than 20°, we adopt the assumption that $B(g)=0$. The H-function describes the multiple scattering of light. The exact solution of the H-function is an integral equation dependent on $\omega$, $\mu_0$ (the cosine of the incidence angle), and $\mu$ (the cosine of the emission angle). Following the approach of Hapke (2012), in this study it is approximated by:

$$H(x, \omega) = \frac{1}{1 - (1-\gamma)x [r_0 + (1-0.5r_0-x) \ln \left( \frac{1+y}{x} \right) ]}$$  \hspace{1cm} (2)$$

where $x$ is either $\mu_0$ or $\mu$, $\gamma = \sqrt{1-\omega}$, and $r_0 = \frac{1-\gamma}{1+\gamma}$. We assumed that the surface scatters isotropically and therefore the $P(g)$ function (phase function at $g$) is set equal to 1. These
assumptions are adequate approximations for simple applications of the Hapke theory (e.g., Mustard and Pieters, 1989).

Once spectra were converted to units of SSA we removed the effects of the spectral continuum and focused on the 3 µm water band depth by performing a linear continuum removal over the 1.8-3.9 µm region. Using the continuum-removed SSA spectra, we calculated the ESPAT parameter using equation 3 (Hapke, 2012).

\[
ESPAT(\lambda) = \frac{1 - \omega(\lambda)}{\omega(\lambda)}
\]  

Empirical work by Milliken & Mustard (2005) showed that ESPAT parameter values centered around the 3 µm water absorption band (at 2.9 and 3.1 µm) showed a strong linear correlation to wt.% water for a wide range of hydrated samples. Therefore, we can use Hapke’s model to convert a reflectance spectrum to SSA, calculate the ESPAT value at the wavelength of interest (Equations 1-3), and use an empirically derived linear relationship between ESPAT and wt.% H₂O to derive water abundance estimates for a given mixture.

However, the work presented in Milliken & Mustard (2005) and Milliken (2006) was done mostly for monomineralic samples (palagonite being an exception), and it did not include chloride salts. As the ESPAT parameter is dependent on the optical properties of the individual reflecting grains there is likely some variability in how it is correlated to water content in chloride salt-bearing mixtures. Therefore, to assess ESPAT-H₂O trends that are more appropriate for our suite of chloride mixtures we performed our own assessment of these relationships using our lab data.

The water content of each sample was independently measured using thermogravimetric analysis (TGA). TGA measurements were performed using a Mettler TGA/DSC 3+ instrument located at Rice University. We placed each sample in a vacuum furnace at 180 °C overnight to remove loosely bound/surface adsorbed water. Aliquots of each sample, including endmembers,
were then transferred to an airtight silica ampule before being shipped for measurement. TGA measurements were made using ~5 mg of each sample in a platinum pan over a temperature range of 50-1000 °C with a temperature ramp of 10 °C/min under a dry N₂ environment. Water loss from each sample primarily occurs in the 400-600 °C temperature range (Plante et al., 2009; Derkowski & Kuligiewicz, 2022) and weight loss up to this temperature is inferred as the water content for each of our samples. We assume that nearly all volatile content of our samples is water. The line of best fit between TGA measured wt.% H₂O and ESPAT were used to update linear curve fitting parameters to be reflective of chloride-salt bearing deposits. These parameters and fitting relationships are used in Section 3.2.3 to estimate water content and salt abundances of chloride salt-bearing deposits from CRISM data.

3.2 Orbital Data Analysis:

3.2.1 CRISM data acquisition and calibration

The approach outlined in Section 3.1 creates a framework wherein water abundance values can be estimated from VNIR spectra using the Hapke RTM. As mentioned in Section 2, a characteristic feature of Martian chloride deposits is that they appear desiccated relative to surrounding basaltic regolith, as is apparent in the difference in their 3 μm water absorption feature (Figure 2). We utilize this variability to estimate salt abundance from CRISM data. The CRISM instrument acquires VNIR hyperspectral images covering the 0.36-3.9 μm wavelength range (Murchie et al., 2007). The CRISM images used for this study have a spatial resolution ranging between 18-36 m/pixel and a spectral sampling of 6.55 nm (Murchie et al., 2007). Using the JMARS software suite (Christensen et al., 2009) we identified CRISM Full Resolution Targeted
(FRT) images overlapping regions in Terra Sirenum where chlorides were detected by Osterloo et al. (2010) and then downloaded them from the Planetary Data System (PDS). These CRISM images are in units of apparent surface I/F (the radiance detected by the instrument divided by the solar irradiance divided by \( \pi \)) and not in units of SSA needed to use our pipeline. To atmospherically correct these images and convert them to units of surface SSA, we used the Discrete Ordinate Radiative Transfer (DISORT) model (Stamnes et al., 1988). Full details of the implementation and application of this model to CRISM data are provided by Liu et al. (2016) and Zastrow and Glotch. (2021).

Many images were found to contain significant noise, striping, and residual atmospheric and sensor artifacts that occlude spectral signatures of interest. These artifacts and striping were found to persist through our preliminary analyses. Therefore, we applied a noise correction using factor analysis/target transformation (Thomas and Bandfield, 2017) which is described in Section 3.2.2. Once corrected, we apply the approach outlined in Section 3.2.3 to obtain hydration state and salt abundances from each scene.

3.2.2 Noise Removal: Factor Analysis/Target Transformation

Much of the processed DISORT corrected imagery was found to contain significant amounts of residual artifacts and noise, which were mitigated using the FA/TT method (Thomas & Bandfield, 2017). This method has been used previously to correct noisy data in the 1-2.5 \( \mu m \) range, and for target mineral detection (Liu et al., 2016; Thomas and Bandfield, 2017; Tarnas et al., 2019; 2021; Lin et al., 2021). However, this method has not been applied on CRISM imagery in the wavelength range past 2.6 \( \mu m \). Since our analyses focus on water band depth in this region, we apply this technique on the data in a subset of wavelengths focused on this range.
The FA/TT method involves a two-step process: 1) factor analysis, in which the algorithm identifies the number of independently varying spectral components (eigenvectors) comprising the signal subspace of the CRISM SSA spectra, estimated using the Hysime algorithm (Bioucas-Dias & Nascimento, 2008), and 2) target transformation, in which linear combinations of the individual spectral components are used to produce an output spectrum resembling the target spectrum. Visual inspection of fit along with statistical measures such as root mean square error (RMSE) and adjusted R-squared values are used to assess the quality of fit between the target transform and the target spectra.

In our implementation we began by applying a 5 band 1-D moving boxcar filter on the spectra of each pixel, over the entire wavelength range. We extracted the first 10 eigenvectors from the smoothed CRISM SSA data using the Hysime algorithm (similar to Thomas & Bandfield, 2017; Liu et al., 2016). We then used the average spectrum of the entire scene along with the extracted eigenvectors as the independently varying spectral components for the target transformation. We used a constrained linear least squares (CLLSQ) fitting model (all components add to 1 and each component is multiplied by an abundance fraction between -1 and 1) with the eigenvectors and average scene spectrum as inputs. The final solution of the CLLSQ provides fractional abundances of each spectral component that can be used to reconstitute the image using only the first 10 eigenvectors and the scene average spectrum. If we assume that the first 10 eigenvectors contain the majority of the important spectral information within the CRISM SSA cube and that the other eigenvectors contain primarily noise, the reconstituted image should have a substantially reduced noise component. The CLLSQ abundance fractions are used to reconstitute the image using the eigenvectors and scene average and then various metrics are used to judge the effectiveness of the noise removal. The reconstituted noise removed image is compared visually
against the original DISORT-corrected SSA image. We inspected for loss of data or removal of
gemorphological features. If noise removal resulted in the loss of these features, the noise
removal was either performed again using a greater number of eigenvectors or the image was
dispatched. We also compared the scene average SSA spectra between the noise removed image
and the original. We performed visual fit inspection and calculated RMSE. If the average SSA
spectra were found to have a low RMSE value and a high degree of visual fit, especially around
the 3 µm water absorption feature, we considered the noise removal successful. If the visual and/or
statistical metrics yielded a poor fit the noise removal was either performed again using more
eigenvectors or the image was discarded. An example of our noise removal method applied to
CRISM imagery over a chloride salt deposit is shown in Figure 4. In this paper we present four
representative CRISM derived hydration state and chloride salt abundance maps in Terra Sirenum
to showcase our method and its potential future applications.

Figure 4: Figure depicting noise removal from CRISM data using Factor Analysis and Target Transformation (FA/TT). Panel A shows original DISORT corrected CRISM SSA image (at 3.0 µm band) and panel B shows the noise corrected CRISM SSA image. Note the removal of striping and overall improvement in visual quality of the data.
3.2.3 CRISM Data Analysis Workflow

After atmospheric removal and noise correction, we used an approach similar to that used for the laboratory spectra (Section 3.1) to obtain water abundance estimates from the CRISM data. The spectra for each pixel of the corrected images were continuum removed over the 3 µm water absorption band. ESPAT values at 2.9 µm for each pixel were then obtained using the continuum removed image cube. We chose the 2.9 µm band to be consistent with Milliken & Mustard (2005) who also used this wavelength. Further, we found that derived water abundances vary negligibly with choice of a specific band center for the water absorption band between 2.9-3.1 µm (See supplementary Figure S1). Therefore, our method is agnostic to the choice of the 3 µm water absorption band center. Once ESPAT values were calculated at each pixel, we used the linear fitting parameters that we empirically derived in Section 3.1. to calculate the water content at each pixel.

These water content maps are used to estimate salt content. To do so, we make a few simplifying assumptions. First, we assume that Martian chloride salt deposits are mixtures of an anhydrous salt such as halite and the regional basaltic regolith (Glotch et al., 2016). Secondly, we assume halite has negligible water associated with it, and therefore should not have a significant 3-micron feature. That is, the presence of halite acts to dilute the total water content of the bulk material. In our calculations we assume the densities of basalt to be 2.9 g/cm³ and halite to be 2.16 g/cm³ and assume that these values are representative of the materials present on the Martian surface. The calculation of the salt content from water content maps relies on the above assumptions and the difference in calculated water abundance between the chloride deposits and the regional basaltic regolith present in the scene.
The derived water abundance at each pixel of a Martian chloride deposit is the sum of the water contents of halite and the basaltic regolith in the CRISM scene multiplied by their fractional abundances:

\[ H_2O_{\text{Deposit}} = H_2O_{\text{halite}} \times f_{\text{halite}} + H_2O_{\text{basalt}} \times f_{\text{basalt}} \]

Since we assume that \( H_2O_{\text{halite}} \) is approximately zero, we can simplify the equation and solve for the fractions of basalt or halite:

\[ f_{\text{halite}} = 1 - f_{\text{basalt}} = 1 - \frac{H_2O_{\text{Deposit}}}{H_2O_{\text{basalt}}} \]

Here, \( f_{\text{halite}} \) is the fraction of halite and the \( H_2O_{\text{Deposit}} \) is the derived water abundance of the salt deposit, while \( H_2O_{\text{basalt}} \) is the average water abundance of the surrounding basaltic regolith. The value of \( H_2O_{\text{basalt}} \) is obtained by averaging the water content for a cluster of pixels in each scene that are representative of the average value of water content for the regolith surrounding a chloride deposit.

The above equation provides the areal fractions of halite or basalt derived from remote sensing measurements that are sensitive to the top several hundreds of micrometers of the regolith/deposit surface. If we assume that the surface areal fractions are reliably representative of volumetric abundances to some depth, then we can calculate the mass fractions of each component using assumed densities of halite and basalt using this equation:

\[ mf_{\text{halite}} = \frac{\rho_{\text{halite}} \times vf_{\text{halite}}}{(\rho_{\text{halite}} \times vf_{\text{halite}}) + (\rho_{\text{basalt}} \times vf_{\text{basalt}})} \]

Where \( mf \), \( vf \), and \( \rho \) are the mass fraction, volumetric abundance, and density of each phase. Our assumption of the areal fractions representing the volumetric abundances to some depth is likely to produce some error. Whether this assumption produces an over- or underestimate of true salt abundances would likely be influenced by the formation conditions of the salt deposits. For
example, if the deposit surfaces are efflorescent crusts or were formed as a floatation crust from evaporating brines, the surface fractions are likely higher than at depth. For highly eroded deposits however, it is possible that at greater depth abundances are higher than observed on the surface.

3.2.4 Salt Map-DTM Overlay Processing.

Our processing pipeline is a novel method to create high-resolution hydration state and salt abundance maps using CRISM data. While these data products are useful in mapping abundances and observing variation across a CRISM scene, these maps alone do not provide significant geomorphologic context for the chloride bearing deposits and their surroundings. To get a better sense of the 3D-geomorphologic context of these deposits we created salt abundance maps overlain onto DTMs generated from high-resolution imagery (Figures 8 and 10).

We used the Ames stereo-pipeline (Moratto et al., 2010) and the MarsSI online tool (Quantin-Nataf et al., 2018) to process DTMs from one HiRISE stereo pair and three CTX stereopairs that overlap with the CRISM imagery used to produce salt abundance and hydration state maps shown above. HiRISE orthorectified imagery provides 25 cm/pixel resolution while HiRISE DTMs provide 1m/pixel resolution and is the highest resolution available for Mars. However, HiRISE stereo-pairs are limited in availability and only a few HiRISE stereopairs exist over detected chloride salt bearing deposits. CTX images provide ~6 m/pixel spatial resolution and associated DTMs have a 24 m/pixel resolution. There is greater coverage of CTX stereopairs overlapping chloride salt deposits and processing times are shorter.
4. Results

4.1 Laboratory spectra of chloride bearing mixtures

Reflectance spectra of each of the chloride mixtures are shown in Figure 5a, SSA spectra are shown in Figure 5b, continuum removed SSA spectra are shown in Figure 5c, and continuum removed SSA spectra convolved to CRISM spectral sampling over the CRISM L wavelength range (1-3.9 µm) are shown in Figure 5d. An overall trend is apparent in the 3.0 µm water absorption band. As salt content increases (salt content increases from mix 1-10), the water absorption becomes shallower. In our spectra, mixes 3 and 4 appear to be outliers, falling off trend of shallowing 3µm water absorption feature with increasing salt content. They also fall off trend in our TGA analysis (section 3.1), and in our plots of band depth vs. salt content. Therefore, we
treated them as outliers for this study (see section 4.2 for further rationale) and removed them from further analyses.

4.2 TGA Measured Water Contents vs. Spectral Data

Figure 6A shows TGA-measured volatile loss of each sample which we assume as the absolute water content for each of our samples. Water content is expected to decrease as salt
content increases in our mixtures. This is generally true except for mixes 3, 4, and 10. Mixes 3 and 4 were assumed outliers based on their spectra, and going forward we also assume mix 10 as an outlier based on TGA observations. There are many potential sources of error in TGA measurement. For one, the MGS-1 simulant contains many minor components and is a non-uniform heterogeneous mixture (Cannon et al., 2017). Different aliquots of MGS used in the mixture could contain different hydrated components that could lead to disparate water contents being measured. The TGA measurements are made in a dry N$_2$ environment, however trace amounts of water in the N$_2$ flow could also be a source of error.

After removing these apparent outlier mixtures from the sample suite, the spectra fall on trend with shallowing 3µm water absorption features and band depth (Fig. 6B), and the TGA measured water contents decrease as salt content increases as is expected from prior spectral analyses (Osterloo et al., 2010; Glotch et al., 2010; 2016). Spectra of the non-outlier mixes, and

![Figure 6](image)

**Figure 6:** A) Plot of TGA volatile loss (~ wt.% water in samples) vs. Halite Content for the mixture suite. Outliers are plotted in red. Red trend-line shows trend using all mixtures while blue trend line shows best linear fit using outlier-removed data points. Fitting is significantly improved when using blue data points. B) shows the continuum removed SSA spectra of non-outlier mixtures. Note a clear trend in the 3 µm water absorption band: as salt content increases in the mixture the 3µm water absorption shallows. These combined observations were used to deem Mix 3, 4, and 10 from our data set as outliers.
the fitting relationships between their ESPAT values and TGA derived water abundances are shown in Figures 6 and 7.

The linear fit generated in our work differs from that in Milliken et al. (2005; 2007). We compared these parameters when used to derive water abundances from spectra of our mixtures. We find that parameters in Milliken et al. (2005; 2007) provide higher estimates of water content, especially when using fitting relationships for the 3.0 µm band. We find that our fitting relationships do not produce derived water abundances that vary significantly with choice of band center in the 2.9 - 3.1 µm range over the water absorption band. When derived water abundances are compared to TGA-derived water abundances, we observe similarly that using the fitting relationships in Milliken et al. provide an overestimate of water content (see slopes in Fig. 7).

Therefore, our fitting relationships provide a more accurate estimate of water content from spectra for chloride-bearing mixtures compared with those of Milliken et al. (2005; 2006; 2007) for primarily monomineralic and highly hydrated phases.
Figure 7. A) ESPAT vs TGA Volatile Loss (assumed wt.% water) at 2.9 µm and derived fitting relationship with errors. B) ESPAT vs TGA volatile loss at 3.0 µm and derived fitting relationship with errors. Derived water abundance variation using ESPAT-H$_2$O fitting relationships derived in Milliken et al., (2005;2007) (old) vs. those derived in A) and B) (new) at 2.9 µm (C) and 3.0 µm (D) (new). TGA derived volatile loss vs. DWA using both sets of parameters and their associated slopes. Slopes indicate how well fitting parameters predict water abundances from spectra.
4.3 Water content and Salt Abundance Maps.

Hydration state maps and chloride abundance maps for four CRISM images (FRT00010A4E, FRT0000A941, FRT00007431, and FRT0000A253) produced using the pipeline outlined in Section 3.2.3 are shown in Figure 8. To validate the model, CRISM abundance maps were compared against THEMIS decorrelation stretched (DCS) images (DCS maps were created using THEMIS bands 8,7,5) that were used previously to detect chlorides (Osterloo et al., 2008; 2010; Glotch et al., 2010). Regions appearing in blue in THEMIS DCS imagery have a characteristic blue sloping spectra in their corresponding THEMIS images, which is consistent with a mixture of chloride salt and a silicate component in MIR data (Osterloo et al., 2008; 2010; Glotch et al., 2010). High salt abundance regions in CRISM derived salt abundance maps appear well correlated with regions appearing blue in THEMIS DCS imagery (Figure 2), and their corresponding THEMIS spectra show the characteristic “blue” slope. Further, we observe regions in the DCS imagery that appear blue-green that correlate well with regions of intermediate salt content in CRISM produced salt abundance maps, which have THEMIS spectra that are consistent with a mixture of chloride salt with a higher relative silicate component.
Figure 8. A-D hydration state maps produced using CRISM images FRT00010A4E, FRT00007431, FRT0000A253, FRT0000A941 respectively overlain onto overlapping CTX/HiRISE imagery. All images used are in the Terra Sirenum region. E-H are the corresponding modeled salt abundance maps. Notice variation in salt abundances. In some cases, we see large-laterally extensive deposits with high salt abundances E/H. G shows lower abundances localized in pitted terrains specifically on the slopes of regional topographic lows.
To discern the sensitivity of hydration state and salt abundance maps to the choice of ESPAT-H₂O fitting relationships we produced these maps using both our fitting relationships and those used in Milliken et al. (2005; 2007) (Figure 9). We found that hydration state maps were appreciably sensitive to the choice of fitting relationships, but salt abundance maps were not. Our

**Figure 9:** Figure showing variation in Map products when using fitting parameters generated from our lab work (new) vs. those published in Milliken et al., (2005; 2007) (old). All map products shown here were created using CRISM observation FRT0000A253 and overlain onto CTX observation CTX_007446_1477_043616_1477A1. A noticeable lowering of water abundance is observed when using our parameters vs. those in Milliken et al. Differences are primarily observed in the surrounding basaltic regolith rather than in the salt deposits. Variation in salt abundances is however comparatively negligible.
fitting relationships generate a lower hydration state estimate than estimates generated by fitting relationships in Milliken & Mustard (2005) and Milliken et al., 2007 (Fig. 9). The lower derived hydration states when using our fitting relationships is uniform across the image (i.e., all pixels appear to have lower hydration states, rather than a specific unit or region). Calculated salt abundance depends primarily on the ratio of the water content of the salt-bearing regions to the surrounding regional basaltic regolith (see Section 3.2.3). This ratio remains largely unchanged regardless of choice of fitting relationships. Therefore, we find that there is no significant difference between salt abundance maps.

4.4 Error Analysis.

Salt abundance values are dependent on the choice of water abundance value from the surrounding regolith (Section 3.2.3). As mentioned in Section 3.2.3 this value is determined by averaging hydration state values over a square region of interest (ROI) encompassing many pixels. The ROIs selected are chosen over regions that correlate to basaltic regolith in corresponding CRISM map-projected MTRDR map products. In choosing ROIs we ensure that there is no spectral evidence of other mineral phases and hydrated components (such as ice or hydrated minerals such as clays, sulfates, etc.). However, some variability in derived water abundances of the surrounding regolith can be observed in the hydration state maps (Figure 8). To assess the degree to which salt abundance calculations are sensitive to this variability we performed a sensitivity analysis. For each CRISM image we chose three similarly sized square ROIs over different patches of surrounding basaltic regolith and used their average values to calculate salt abundances (Section 3.2.3) (Figure 10). We also calculated the mean of the hydration states from the three ROIs and calculated the salt abundances using this mean value. To better observe
resulting variability we calculated the differences at each pixel between these test salt abundance
maps and the salt abundance maps shown in Figure 8.

As expected, the estimated salt abundances vary depending on the choice of ROI (Figure
10). In images where there is little variability in the hydration state of the surrounding regolith, we
find only nominal differences (typically <5%) in calculated salt abundances based on choice of
ROI. However, where there is a greater degree of variability in the hydration state and/or fewer
regions to select larger ROIs for surrounding regolith, the variability was higher (up to 10-12%
variability in salt abundance in select regions). Overall, we observe the most variability outside of
the salt deposits in the surrounding regolith (where the salt abundances are very low). This is likely
a result of variability in the water abundances in different regions of the surrounding basaltic
regolith. The variability caused by the choice of ROI, however, has a much lower effect on the
determined salt abundances within the salt deposits (on average <5%). Other factors such as
elevation, improper atmospheric artifact removal, and surface roughness could also account for
this variability. To assess this variability outside of the salt deposits we masked the salt deposits
and calculated the mean and standard deviation of the calculated salt abundances outside of the
salt deposits (see supplementary S1). For each image we found that the mean calculated salt
abundance outside of the salt deposit area was 2-8 wt.%. For these regions, ascribed salt
abundances are likely an artifact of the method used to determine salt abundances rather than true
abundances. Therefore, salt abundances calculated using this method is likely most reliable when
looking at abundances clearly within regions which can clearly be defined as a salt deposit while
the minor salt abundances determined outside of the salt deposits are generally not reliable.

Therefore, variability in the hydration states of the surrounding regolith is a potential
source of error in the use of this method. However, variability as a result of this is nominal and
within the bounds of reasonable error. Most reliable abundance maps will be produced where there is little variability in the hydration state of the regolith surrounding the salt deposits. For regions with greater variability, using an averaged value that captures the variability of hydration state of the surrounding deposits may produce a more reliable abundance estimate.

**Figure 10.** Variability in calculated salt abundance maps based on choice of ROIs used to determine average basalt water content. A-D shows difference in salt abundance based on choice of ROI for CRISM image FRT0000A941. A-C are using the average value of three different similarly sized ROIs selected in different regions across the image (approximate locations are depicted by red stars) D is using the mean value of each ROI average value to account for spatial heterogeneity. Differences are calculated by subtracting salt abundance maps created for Figure 8 to those created using ROIs shown here. E-H is a similar analysis done for CRISM image FRT00010A4E. Variability is image dependent and depends on the variability encountered in hydration states across the image. Variability is relatively low in all cases, with the greatest variability typically encountered in the outside of the salt deposit. For A-H the relatively low variability is encountered in the salt deposit with most variability typically observed outside of the deposit. Greater variability is observed in E-H, likely due to a greater degree of variability in the hydration states of the surrounding basaltic regolith.
5. Discussion.

Our mapping method relies on hydration state constraints from remote sensing data. Prior hydration state constraints from remote sensing data were designed using spectral data of a limited sample suite (Milliken & Mustard, 2005; 2007a; 2007b; Milliken, 2006; Milliken et al., 2007). Prior mapping methods have provided an invaluable method of global mapping of Mars’ water content (Milliken et al., 2007; Jouglet et al., 2007; Audouard et al., 2014) but were grounded in laboratory studies that do not represent the mineralogic diversity that has since been detected from orbital and landed missions on Mars in the past two decades (Murchie et al., 2009; Ehlmann & Edwards, 2014; Seelos et al., 2023). The fitting parameters used to estimate the surface water abundance published in these studies are likely best representative of only certain surface compositions of Mars where the mineralogy is primarily composed of the materials that were used in Milliken & Mustard, (2005; 2007a; 2007b), Milliken (2006) Milliken et al. (2007). We find that hydration state estimates can vary depending on the materials being mapped. In the work presented here, a marked difference is apparent when using chloride deposit-specific fitting parameters designed with the mineralogy of the units being mapped in mind, compared to the fitting parameters used in prior studies. One major factor that affects the derived ESPAT-$\text{H}_2\text{O}$ fitting relationships is the particle size of the materials (Milliken & Mustard, 2007b). As particle size increases, the ESPAT-$\text{H}_2\text{O}$ positive slope is known to decrease (Milliken & Mustard, 2007b). Therefore, an increase in particle size of measured materials would lead to a lower estimated hydration state. To account for particle size effect, Milliken et al. (2007) provided fitting relationships for two particle size ranges ($<45 \, \mu\text{m}$ and 125-250 $\mu\text{m}$). However, it is important to note that these relationships were still derived for individual minerals rather than mixtures. The materials used in our lab studies are an aggregation of various particle sizes, which is likely to be
encountered on the Martian surface (Cannon et al., 2017). The MGS-1 consists of materials with a variety of particle size ranging from fine grain materials (<10 µm) to coarser glass beads and rock fragments (>500 µm) (Cannon et al., 2017). The MGS-1 simulant was then mixed with fine grained halite (<45 µm) to produce our samples. Therefore, the larger overall grain size of the measured materials could explain why the derived water abundances in our study are lower than when parameters published in Milliken & Mustard (2005) and Milliken et al. (2007) are used. The grain sizes of the materials we used in our lab work however are likely a better representation of the grain sizes of chloride deposit materials encountered on the surface of Mars. Use of fitting parameters that are specifically tailored to the physical properties and mineralogy of the units being mapped is warranted for improved accuracy of hydration state maps, especially on a more localized scale. However, it is also important to note that the improvement in hydration states estimates is fairly small and are within typical reasonable bounds of error that would be expected when making such measurements from orbit (in most cases difference in hydration state estimates are typically between ~1-5 wt.%). We suggest that, where known, the surface mineralogy should be considered and new fitting parameters that are specific to the observed surface composition should be used to provide the most accurate hydration state estimates of that locale. In that vein, our work provides a more accurate representation of water abundance estimates for chloride bearing regions on Mars.

While there has been significant investigation of chloride salt deposits on Mars (Osterloo et al., 2010; Glotch et al., 2010; Hynek et al., 2015; Melwani-Daswani & Kite, 2017; Leask & Ehlmann, 2022) no quantitative high-resolution chloride abundance maps of these deposits exist. Little work has been done to fully leverage higher resolution spectral data sets such as CRISM, which can provide more reliable abundance estimates through quantitative modeling. Therefore, the mapping method presented here fills a crucial gap in high-resolution abundance maps of
chloride deposits on Mars. This mapping method can be used to produce modeled abundance maps using CRISM images, which have widespread coverage on Mars, and hundreds of CRISM images exist overlapping chloride salt deposits identified by THEMIS data (Leask & Ehlmann, 2022; Das et al., 2023). Previous abundance estimates using THEMIS by Glotch et al. (2016) provided a general range from spectral matching rather than providing a quantitative model from which salt abundances maps are calculated. CRISM-derived products have the additional benefit of having a significantly higher spatial resolution than THEMIS (18-36 m/pixel vs ~100 m/pixel). The abundance mapping method presented in this paper allows for site-specific abundance estimates with a higher granularity than possible with THEMIS.

Salt abundances determined using the method outlined here are higher (typically between 30-50 wt.% with some localized regions with abundances up to 75-80 wt.%) than those estimated in prior studies using THEMIS data (10-25 wt.%) (Glotch et al., 2016). One possible source of this discrepancy is the difference in depth of penetration of VNIR wavelengths compared to TIR. VNIR light is sensitive to the upper 100s of nm to 10s of μm of the surface while TIR wavelengths are sensitive to a comparatively greater depth (top 10-100s of μm). Higher detected salt abundances may result from induration (chloride salt deposits are likely indurated based on thermal inertia measurements (Osterloo et al., 2010)) or due to the formation of a salt crust during deposition. If these deposits formed in an evaporative setting it is possible that a salt crust was formed which may cause a higher abundance detected at very surface of the deposits. Abundance estimates in Glotch et al., were made by comparing laboratory TIR spectra of analog materials to single THEMIS spectra of a limited number of chloride deposits (8 deposits). Grain size effects in the TIR region could also have caused some uncertainty in salt abundance determination, especially in regions with higher dust cover.
Figure 11 shows two salt map-DTM overlay products, one created using HiRISE and one using CTX. These overlay products are a valuable resource for answering broader questions of chloride provenance, which is the subject of ongoing work (Das et al., 2023). These high-resolution products can be used to resolve important geologic features that cannot be resolved using coarser-resolution CRISM data alone. The overlay products in Figure 11 show substantial

**Figure 11.** Example of salt map DTM overlays (Both have a vertical exaggeration of 7x). A) is an overlay created using HiRISE imagery, saltmap was generated using CRISM image FRT00010A4E overlayed onto HiRISE DTM (dteec_047413_1410_003160_1410_a01). This overlay exhibits large laterally extensive indurated chloride deposit in regional low-lying terrain. B shows a more localized smaller-scaled deposits with higher abundance centered around the slopes of regional topographic lows/pitted terrains. Saltmap was created using CRISM Image FRT0000A253 and DTM was created using CTX stereopairs (CTX_007446_1477 and CTX_043616_1477).
variation in the morphology of the salt deposits within Terra Sirenum alone. These range from extensive, flat, indurated deposits (Fig. 11A) with high salt abundances to smaller localized deposits perched on regional topographic lows (Fig. 11B). This observed diversity in salt abundances and depositional environment may indicate disparate formation scenarios. Mapping of chloride salts across Mars using the method outlined in this paper can provide new, more detailed, site-specific constraints on chloride deposit abundance, abundance variation, hydration state, and surrounding geomorphology.

Further, DTM overlay products can be used to interpret potential water source pathways, observe geologic features of interest (e.g., channels, deltaic features, faults, etc.), constrain precursor pond/lake volumes, estimate salt deposit thicknesses, and generate total salt volume estimates. These constraints can be used to assess the feasibility of hypothesized formation mechanisms and/or be used to formulate new ones. Global scale mapping of chloride salt deposits and analysis of overlay products would greatly improve our understanding of these enigmatic deposits and is the subject of ongoing work (Das et al., 2023; 2024).

6. Conclusions.

Understanding the aqueous history of Mars is a key goal of Mars exploration. Chloride deposits represent a valuable way through which we can reconstruct Mars’ hydrologic past. Constraining formation mechanisms and ages will help better constrain the last instances of stable liquid water, hypotheses for which range from the late-Noachian to early Hesperian to periodic occurrences extending into the Amazonian. This study outlines a novel method of mapping chloride salt abundances using CRISM data. Updated lab-derived fitting parameters to estimate hydration states from remote sensing data specific to chloride-bearing regions on Mars are
presented. We then showcase a pipeline to use these lab-derived parameters to CRISM data and obtain hydration state and modeled salt abundance maps. We find that updated fitting parameters lowers hydration state estimates compared to Milliken et al. (2007). In this paper we present the first CRISM-derived modeled salt abundance maps along with high resolution DTM overlay products. These products are the first of a kind and are the highest resolution salt abundance maps produced yet. DTM overlay products show great promise and could provide an extensive global-scale view of chloride salt deposits on Mars. Further work assessing the geomorphological context of these enigmatic deposits, their variability across the widespread regions in which they occur is of immense value.

Future work combining observations of geomorphological variation, mass balance constraints from DTM products, and geochemical models of chloride brine forming environments would greatly benefit constraints on chloride formation mechanisms and in-turn the stability of liquid water on Mars.
CRISM FRT, MTRDR, and DDR, CTX Stereo Pairs, and HiRISE DTM data were collected from the Planetary Data System’s Geosciences Node (https://pds-geosciences.wustl.edu/). Some CTX and HiRISE data used in this work were processed with the MarsSI (marssi.univ-lyon1.fr) application. THEMIS data were collected from the ASU Mars Space Flight Facility website (https://viewer.mars.asu.edu/viewer/themis#T=0). CRISM, CTX, HiRISE and THEMIS data were identified using JMARS (https://jmars.asu.edu/). Processed data including hydration state maps, salt abundance maps, DTMs, ROIs, lab data etc. and codes used in this work is available on our Zenodo repository (https://zenodo.org/doi/10.5281/zenodo.11391245).

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References


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