Dynamic Predictive Quantization for Staggered SAR: Experiments with Real Data

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***Abstract*—Present and future spaceborne SAR missions are designed to acquire an increasingly large amount of onboard data. This is a consequence of the use of large bandwidths, multiple polarizations and the acquisition of large swath widths at fine spatial resolutions, which result in challenging requirements in terms of onboard memory and downlink capacity. In this scenario, SAR raw data quantization represents an essential aspect, as it affects the volume of data to be stored and transmitted to the ground as well as the quality of the resulting SAR products. Dynamic Predictive Block-Adaptive Quantization (DP-BAQ) is a novel technique, recently proposed by the authors, consisting in a low-complexity data compression method, and its application is particularly suitable for staggered SAR systems. DP-BAQ exploits the existing correlation among the azimuth raw data samples by applying Linear Predictive Coding (LPC). This results in a data rate reduction of up to 25% with respect to state-of-the-art SAR quantization methods. In this paper, we test and validate the potential of DP-BAQ on airborne SAR data which emulate the system scenario of Tandem-L, a DLR mission proposal for a bistatic L-Band system. For this purpose, an experimental SAR image has been acquired at L band by the airborne DLR Flugzeug-SAR (F-SAR) sensor over the Kaufbeuren area, in Southern Germany. In order to simulate the staggered SAR acquisition mode, we implemented a dedicated resampling and filtering of the data. Our analyses confirm the effectiveness of DP-BAQ for efficient data volume reduction, exhibiting a consistent and promising performance when tested on areas characterized by different land cover types and backscatter statistics.**

***Index Terms*—Synthetic Aperture Radar (SAR), raw data quantization, data volume reduction, F-SAR.**

I. Introduction

PRESENT and future spaceborne satellite SAR systems will implement advanced acquisition modes by combining innovative system architectures, such as digital beamforming (DBF) and multiple receive as well as polarization channels [1], [2]. In this paper, we focus on a SAR system operating in staggered mode, an acquisition method which allows for achieving a fine azimuth resolution of a few meters and, at the same time, to cover a wide swath up to hundreds of kilometers [3]. The staggered SAR principle foresees the presence of blind ranges (i.e., gaps) along the swath within the acquired raw data, caused by the fact that the instrument is transmitting a pulse while the radar echo is being received. By opportunely varying (i.e., staggering) the pulse repetition frequency (PRF) during the acquisition, the data gaps are non-uniformly displaced along the azimuth and range dimensions. By properly designing the PRF sequence, it is possible to reconstruct the missing raw data samples and so to achieve a continuous swath width up to hundreds of kilometers [3], [4]. For staggered SAR, the mean transmit PRF is typically larger than the one selected for conventional SAR systems in order to achieve a certain oversampling in the data. This, in turn, introduces a sufficient correlation among the azimuth samples, which is exploited for an interpolation along the azimuth dimension to reconstruct the data gaps, hence allowing for an overall increase of the resulting SAR image quality. However, as a drawback, such an oversampling in the raw data obviously increases the overall onboard data volume to be handled by the system. In particular, staggered SAR is the acquisition mode designed for Tandem-L, a highly innovative spaceborne mission proposal for the monitoring of the dynamic Earth processes [1]. The fulfillment of the complex mission goals requires the acquisition of a huge volume of daily data. Hence, the problem of reducing the amount of onboard data is of crucial importance and needs to be carefully taken into account. A possible solution for data volume reduction has been presented in [5]. It foresees a filtering of the unnecessary parts of the Doppler spectrum and achieves a considerable reduction of onboard data (up to 50%), at the cost of a significant complexity for its onboard implementation. A different approach to the problem consists in a novel quantization method, named Dynamic Predictive - Block Adaptive Quantization (DP-BAQ), which was proposed in [6] and exploits the correlation introduced by the antenna pattern in the oversampled azimuth raw data stream to reduce the amount of data to be stored on board. Simulations of the proposed method showed an achievable data volume reduction between 20% and 25% for a Tandem-L-like spaceborne staggered SAR system [7]. If compared to [5], DP-BAQ offers a reduced capability for data volume reduction but, on the other hand, it requires significantly lower onboard resources (i.e., memory and number of operations). In this

Fig. 1. DLR aircraft Dornier Do228-212, with mounted F-SAR antenna carrier (middle-end part of the fuselage).

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letter, we demonstrate the applicability of DP-BAQ on real SAR data. A verification of the DP-BAQ on airborne data has been also presented in [8], including some modification to the technique, nevertheless, in this letter we present a more detailed performance evaluation of the method in the context of a staggered SAR spaceborne-like scenario. The raw data was acquired by the F-SAR system, the airborne SAR sensor of the Microwaves and Radar Institute of the German Aerospace Center (DLR). A picture of the F-SAR antenna system mounted on the Dornier Do228-212 aircraft is shown in Figure 1. The DLR F-SAR airborne SAR sensor represents a flexible system in order to test and optimize the design of new SAR technologies and acquisition modes with real case scenarios [9]. The F-SAR system is equipped with a variety of SAR antennas, each one employing a different radar center frequency. In this work we have considered an F-SAR acquisition at L band, with the goal to emulate a spaceborne staggered SAR acquisition, and so to validate the DP-BAQ technique on real data, by comparing the expected results obtained from theoretical simulations in [7] with the ones observed for a real SAR acquisition.

In the following Section II a background on SAR raw data quantization is briefly recalled, followed by the description of the proposed quantization method (DP-BAQ). Section III discusses the investigations on the real F-SAR data, together with the corresponding performance analysis. Finally, Section IV summarized the results and draws the conclusions.

II. Dynamic-Predictive (DP)-BAQ

The raw data acquired by a SAR sensor is typically stored in a complex two-dimensional digital matrix, where each element represents the coherent backscatter of the illuminated targets lying in the projection of the azimuth antenna beamwidth and pulse length. For conventional SAR systems, in the raw data domain the mutual correlation exhibited by neighbouring raw data samples is usually rather weak, which, together with the limited onboard computational resources available for a spaceborne system, makes onboard data compression a challenging task. Operational spaceborne SAR systems, such as TerraSAR-X and TanDEM-X, typically employ Block-Adaptive Quantizers (BAQ) [10] (or one of its variations, such as for the Sentinel-1 Flexible Dynamic (FD)BAQ [11]). BAQ represents an effective data compression method as it offers a good trade-off between signal representation quality, achievable compression ratio and overall implementation complexity. The principle of BAQ consists in grouping together range samples into blocks and adapting the decision levels of the quantizer depending on the statistics of each block. It is separately applied for the real and imaginary parts of the raw data, being the two complex components statistically independent.

The performance of a quantizer is usually measured through the signal-to-quantization noise ratio (SQNR), expressed as:

$$\mathrm{SQNR} = \Big(\sum_{i=1}^{I}|x_i|^2\Big)/\Big(\sum_{i=1}^{I}|q_i|^2\Big), \tag{1}$$

where I represents the number of considered samples, x is the received signal at the input of the quantizer, and q is the quantization error, defined as the difference between the uncompressed signal s and its quantized version s_q (i.e., $q = s - s_q$). The SQNR can be directly related to the quality of the interferometric SAR data through:

$$\gamma_{\mathrm{Quant}} = 1/(1 + 1/\mathrm{SQNR}), \tag{2}$$

being γ_{Quant} the coherence loss due to quantization [12].

Linear Predictive Coding (LPC) is an encoding method which exploits the redundant information present in the data by encoding the difference between the actual data and its prediction. Such a difference has typically a smaller entropy than the original data and can be therefore encoded with a reduced bitrate for a given target performance [13]. The applicability of LPC in SAR raw data has been firstly introduced in [14] and [15], and then further elaborated in [7] in the specific context of staggered SAR systems. The definition of a more complete encoding method named Dynamic-Predictive (DP)-BAQ for Staggered SAR data has been then presented in [7]. In the following, we briefly recall the main relevant aspects of DP-BAQ, while the detailed description of the method is reported in the referred papers.

As it has been mentioned in the introduction, in a staggered SAR scenario, a certain oversampling is introduced among the azimuth raw data samples to achieve a sufficient interpolation quality (and, in turn, to generate high-quality staggered SAR products) [3]. DP-BAQ aims at removing the redundant information in the data by implementing LPC along the azimuth dimension. Here, the prediction of a sample at a given discrete time instant n, $s[\mathrm{n}]$, is performed by linearly combining the N preceding samples, where N represents the *order* of the predictor. The encoded signal is then expressed as the difference between the actual sample value $s[\mathrm{n}]$ and its prediction $\tilde{s}[\mathrm{n}]$:

$$s_{\mathrm{d}}[\mathrm{n}] = s[\mathrm{n}] - \tilde{s}[\mathrm{n}]. \tag{3}$$

In particular, the prediction $\tilde{s}[\mathrm{n}]$ is derived as linear combination of the N previous samples and it can be expressed as:

$$\tilde{s}[\mathrm{n}] = \sum_{i=1}^{N}\beta_i\left(s[\mathrm{n}-i] + e[\mathrm{n}-i]\right), \tag{4}$$

where β_i represents the weight assigned to the i-th previous sample and $e[\mathrm{n}-i]$ is the corresponding quantization error. The weights β_i are defined at system design stage from the autocorrelation characteristics of the signal along the azimuth dimension, which, in turn, are related to the azimuth (Doppler) antenna pattern and the commanded PRF [7]. Finally, the set of weights which minimizes the prediction error in a mean square error (MSE)-sense is selected [13].

The amount of correlation among neighboring raw data samples is related to the azimuth oversampling factor $\mathrm{OVF_a}$, which is expressed as the ratio between the PRF and the Doppler bandwidth B_{D}:

$$\mathrm{OVF_a} = \mathrm{PRF}/B_{\mathrm{D}}. \tag{5}$$

The implementation of the proposed DP-BAQ is carried out by considering the difference between an entire range line of the acquired raw data and its computed prediction. Then, the result is encoded with BAQ along the range dimension. A

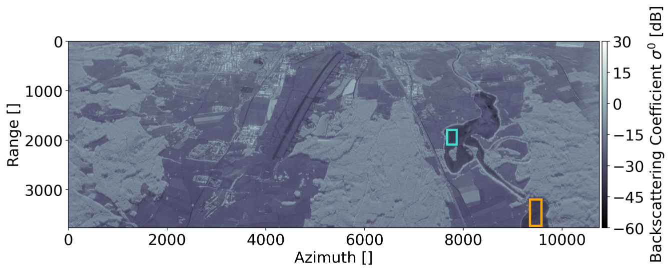


Fig. 2. SAR backscattering coefficient σ^0 of the F-SAR acquisition over Kaufbeuren in Bavaria, Germany, used for the present investigations. Different types of landcover, such as forest, crops and urban areas, can be noticed in the scene. Two small water bodies used for system noise floor (NESZ) estimation are marked by the turquoise and orange rectangles.

block length of 128 samples is considered, as it is done on the TerraSAR-X and TanDEM-X SAR satellites.

The location of the blind ranges along the azimuth is known a priori, before the data take commanding. For this reason, DP-BAQ features the possibility of dynamically adapting the prediction order and the bit allocation according to the gap positions. This allows for a finer data representation in the gap vicinity, which is then exploited during the interpolation process performed on ground before SAR focusing [7].

In this analysis, we assume as reference a Tandem-L-like L-band SAR system operating in staggered SAR mode using a mean PRF of 2700 Hz and a processed Doppler bandwidth of B_{D} of about 1100 Hz. The resulting $OVF_{\text{a, stag-SAR}}$ is of about 2.4 (i.e. 140% data oversampling). For the other system parameters we refer to Table II of [7]. In this scenario, the proposed DP-BAQ resulted in a coding gain between 4 dB and 5 dB for the 4$^{\text{th}}$ order predictor. The actual gain capabilities also depend on the platform speed, antenna length and antenna pattern shape, as described in detail in [7].

III. F-SAR Experimental Data

For this work, an experimental L-band SAR acquisition over the Kaufbeuren village in Bavaria, southern Germany, has been considered. The SAR backscatter map of the imaged area is depicted in Figure 2. The F-SAR main parameters for the considered system scenario consist in a range bandwidth of 150 MHz and a PRF of about 2.5 kHz, and a range and azimuth resolution of 0.4 m and 0.6 m, respectively. An off-nadir angle of 25° to 60° allows for a swath width of 0.6 km to 6 km depending on the altitude of operation.

The data acquired by the F-SAR sensor is highly oversampled in azimuth with respect to a typical spaceborne system, in order to reduce azimuth ambiguities. For the considered acquisition, the resulting oversampling factor $\mathrm{OVF}_{a,\text{F-SAR}}$ is expressed as $\mathrm{OVF}_{a,\text{F-SAR}}$=2500 Hz/150 Hz≈19. As a consequence, the data acquired by the F-SAR system features a much higher correlation with respect to a typical staggered SAR spaceborne-like scenario. Therefore, in order to properly emulate the considered Tandem-L-like system we implemented the workflow shown in Figure 3: after range defocusing of the input data (which are already provided as input in range compressed format), we resampled the F-SAR raw data along the azimuth dimension so that the

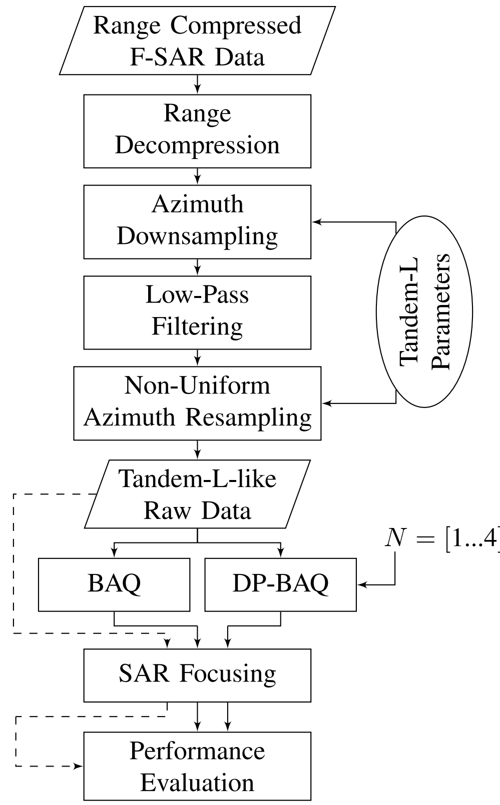


Fig. 3. Block diagram showing the processing steps taken into account in the simulation structure. The dashed line represents the uncompressed version of the data which is used as reference in the performance evaluation block.

resulting correlation between two subsequent samples (ρ_1) approximates the one of a spaceborne staggered SAR scenario, such as the one analyzed in [7], with a $\mathrm{OVF}_{\mathrm{a}}$ in the order of about 2.4 (the data is significantly downsampled in this step). Then, a low-pass filter along azimuth is applied to suppress the high frequency components from the data and to avoid possible aliasing. At this point, we performed a second resampling to reproduce a non-uniform PRF sequence along the azimuth direction, by also including the resulting blind ranges (i.e., missing samples) within the scene. The considered PRF sequence was derived from the one presented in [3], [7], such that the obtained data properly fulfill the timing requirements of the considered Tandem-L-like SAR system.

We then applied two different encoding methods: BAQ and DP-BAQ at different order of prediction N. For all cases, a quantization at 2, 3, 4 and 6 bits/sample (bps) has been considered. Afterwards, we performed the SAR processing to obtain the corresponding set of focused SAR images and, finally, we evaluated the mean SQNR over the entire focused scene. The results are presented in Figure 4 for all the applied techniques and bitrates. As it can be seen, DP-BAQ outperforms the standard BAQ, as expected from the theoretical simulations in [7]. The data volume reduction for the DP-BAQ at 2 bps and 3 bps with respect to the same performance obtained by the BAQ is of 24% and 21%, respectively.

For the considered Tandem-L mission, a 4-bit BAQ is selected, as it guarantees a tolerable degradation in terms of SAR and InSAR performance (e.g., 1% of coherence loss

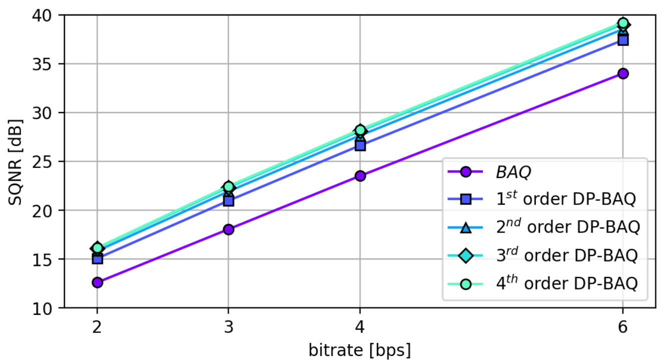
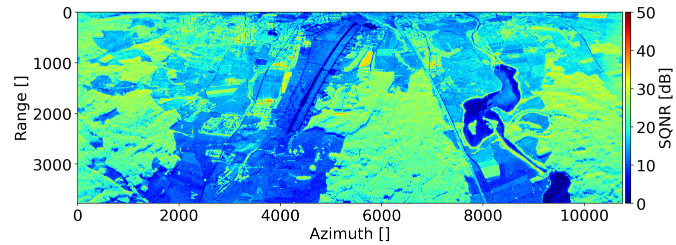


Fig. 4. SQNR calculated after the complete processing workflow of Figure 3. Different curves represent different quantization methods and bit rates.

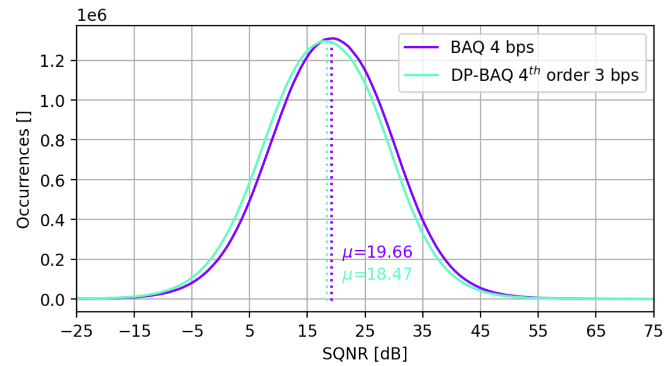
γ_{Quant} is typically observed when using this bit rate [12]). We then focused our attention on this specific case of particular interest (i.e., 4^{th} order DP-BAQ at 3 bps compared with BAQ at 4 bps) and we analyzed the SQNR for the entire F-SAR scene in Figure 2. The SQNR map for the 3-bit DP-BAQ is shown in Figure 5(a) for the DP-BAQ, together with the histograms of the SQNR (Figure 5(b)) and of the phase error (Figure 5(c)) for both the BAQ and DP-BAQ cases. We evaluated the phase error which is computed as single-look phase difference between the compressed SAR image φ_q and the reference uncompressed one φ, i.e., $\Delta\varphi = \varphi - \varphi_q$ [12]. By comparing the two compression methods, one can notice that they show a similar performance and a small bias of about 1 dB is observed, which is consistent with the results shown in Figure 4. In particular, the SQNR shows the same distribution and it depends on the backscatter of the imaged scene in a similar way for both cases: pixels showing low backscatter values (e.g., water bodies, asphalt of the airport and bare soil) are associated to lower values of SQNR, while, on the other hand, high-backscatter targets (e.g., forests and urban areas) are encoded with higher accuracy. The so called low-scatter suppression effect [7], [12] together with the more degraded amplitude and phase reconstruction of low-amplitude signals, due to the use of a Cartesian quantizer, are degrading the performance over low backscatter regions. To further investigate this effect, we also computed the average SQNR difference for different levels of SAR backscatter for the BAQ at 4 bps and the 4^{th} order DP-BAQ at 3 bps as:

$$\Delta_{\text{SQNR},\sigma_i^0} = E\left[\text{SQNR}^{4\text{ bps}}_{\text{BAQ},\sigma_i^0} - \text{SQNR}^{3\text{ bps}}_{\text{DP-BAQ},\sigma_i^0}\right], \quad (6)$$

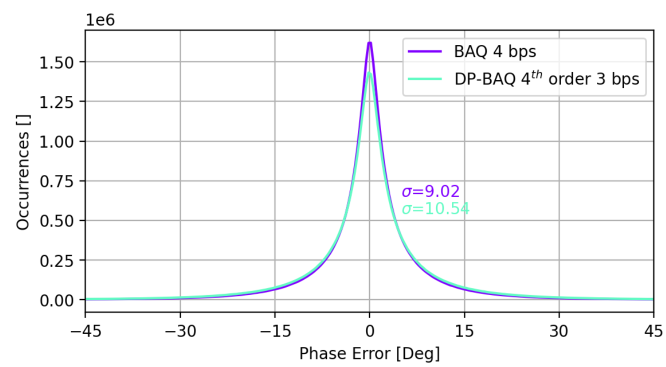
where $E[\cdot]$ represents the expectation value, σ_i is the $i-th$ interval of backscatter and the two SQNR values are expressed in dB. The result is depicted in Figure 6, together with the histogram of the backscattering coefficients. It is possible to notice that, even though the DP-BAQ is employing one bit less, the difference with respect to the BAQ is minimal for the low backscattering region (i.e., a few tenths of dB), while it becomes larger over high backscattering areas. This is due to the fact that a higher backscatter corresponds to a greater signal dynamic, hence the use of a reduced bitrate for the DP-BAQ impacts more the granular quantization noise with



(a)



(b)



(c)

Fig. 5. SQNR map for the 3-bit 4^{th} order DP-BAQ (a), SQNR histogram (b) and phase error (c) calculated for both (a) and for the BAQ at 4 bps derived for the considered F-SAR acquisition over Kaufbeuren, Germany.

respect to the 4-bit BAQ. Moreover, in this areas (typically urban areas featuring manmade structures), the statistical properties of the SAR raw signal can be different from the ones expected in presence of a fully developed speckle (i.e., white noise weighted by the antenna pattern), leading to a further degradation of the signal caused by the predictor, as it is not designed to fit these signal characteristics.

In addition, we investigated the noise equivalent sigma zero (NESZ), estimated along the range dimension, and compared once again the proposed DP-BAQ with the reference BAQ. The NESZ is calculated as the mean backscattering coefficient over calm water surfaces, where a specular reflection of the radar wave takes place and the backscattered signal recorded by the antenna is negligible. We performed this analysis on two parts of the scene where calm water bodies are present (these are delimited by the two rectangles in Figure 2), hence allowing for the estimation of the system noise floor [16]. In Figure 7

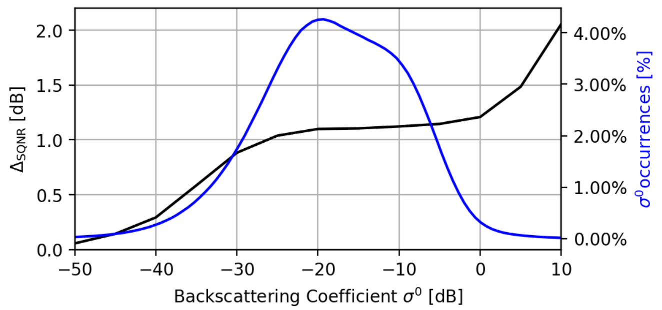


Fig. 6. Δ_{SQNR} calculated between the 4-bit BAQ and the 4$^{\text{th}}$ order 3-bit DP-BAQ as function of the SAR backscattering coefficient (black), and the histogram of the backscattering coefficients (blue).

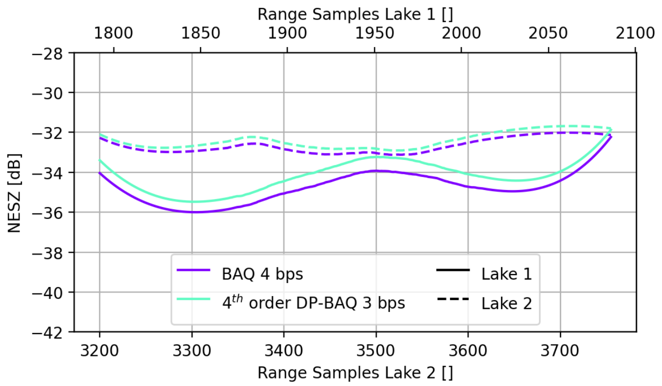


Fig. 7. Noise Equivalent Sigma Zero (NESZ) calculated on the two lakes (solid lines and dashed lines) delimited by the turquoise and orange rectangles in Figure 2, respectively. The 3-bit (4$^{\text{th}}$ order) DP-BAQ case shows comparable performance in terms of NESZ with respect to BAQ at 4 bps.

we show the NESZ curves along the range dimension: the NESZ has been calculated for each range line of the selected areas and then averaged through all the available azimuth samples. The results are depicted for the BAQ and the 4$^{\text{th}}$ order DP-BAQ at 4 bps and 3 bps, respectively. In Figure 6 the backscatter values lower than the NESZ occur in a rather small percentage of the pixels of about 6%. Due to the rather rare occurrence, they do not affect the derivation of the NESZ. By observing the results, it is possible to see once again that the 4-bit BAQ provides results which are similar to those obtained with the DP-BAQ at 3 bps. Moreover, the DP-BAQ allows for an additional 20%-25% of data volume reduction, hence confirming the suitability of the proposed method for the effective and optimized encoding of staggered SAR raw data.

IV. Conclusions

In this paper we applied the recently developed SAR raw data compression method called Dynamic Predictive (DP)-BAQ on an L-band experimental SAR data acquisition of the DLR airborne F-SAR sensor over the Kaufbeuren area, Germany. The significant oversampling of the raw data allowed us to resample the raw data matrix in order to emulate the signal statistics of a Tandem-L-like spaceborne staggered SAR system. We performed a comparison between the proposed DP-BAQ and a state-of-the-art BAQ. The obtained results confirm the expected performance of the theoretical simulation discussed in [7]. In particular, the 4$^{\text{th}}$ order DP-BAQ at 3 bps achieves on average an SQNR which is very similar to the one of the BAQ at 4 bps. We also calculated the SQNR for different landcover types and backscatter levels and a consistent performance has been observed. Finally, we estimated the system noise floor (NESZ) along range in correspondence of the two small water bodies present in the acquisition, verifying the comparable image quality provided by the two compression methods at different bit rates. Our investigations suggest that the DP-BAQ represents a suitable quantization method for onboard data volume reduction for spaceborne staggered SAR systems, achieving an additional data volume reduction between 20% and 25% with respect to a state-of-the-art BAQ, by guaranteeing a comparable data quality.

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